MULTIVARIATE PREDICTIVE WINDOW BLIND CONTROL MODELS FOR INTELLIGENT BUILDING FAÇADE SYSTEMS

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ABSTRACT

This paper presents results from a window blind usage field study that was conducted in California, USA. In this study, the measurements of physical environmental conditions were cross-linked with participants' window blind controlling preferences (n=83). A total of seven predictive window blind control multivariate logistic models were derived. As hypothesized, the probability of a window blind closing event increased as the magnitude of physical environmental and confounding factors increased ($p < .01$). The main predictors were window/ background luminance level and vertical solar radiation at the window. The confounding factors included MRT, direct solar penetration, and participants' self-reported sensitivity to brightness. The results showed that the models correctly predict between 84 – 89 % of the observed window blind control behavior. This research extends the knowledge of how and why building occupants manually control window blinds in private offices, and provides results that can be directly implemented in energy simulation programs.

KEYWORDS

Venetian blinds, occupants' control, control model, intelligent façade

INTRODUCTION

Research on intelligent building façade systems has traditionally been focused on two major goals; to reduce total building energy consumption and to continuously satisfy occupants' comfort and satisfaction. While results from previous studies suggest that the energy performance of office buildings with integrated automated window blinds and lighting control is superior to those with static glazing systems (Lee et al. 1998, Roche 2002), anecdotal evidence has mounted concerning occupants' dissatisfaction with automated systems (Mahone 1989, Jain 1998, Stevens 2001). In order to solve the occupants' dissatisfaction problem, researchers have tried to gain more understanding on how and why building occupants controlling window blinds.

Thus far, although limited in observation and identification methods, researchers were able to distinguish blind usage patterns between façade orientations and sky conditions (Rubins et al. 1978, Rea 1984, Inoue 1988, Foster and Oreszczyn 2001). A few studies monitored window blind movements and physical environmental conditions simultaneously. By correlating window blind movement and physical environmental data, researchers were able to derive window blind control rules based on simple predictors such as solar radiation (Inoue et al. 1988, Newsham 1994, Reinhart 2001), and workplane illuminance (Vine et al. 1998). Most recently, adaptive-fuzzy control, in which the position of window blinds are determined based on the optimization of multivariable predictors (solar radiation, visual comfort, thermal comfort) have been developed and simulated with a test façade model (Assimakopoulous et al. 2004, Park et al. 2004).

Even though recent algorithms include many variables, they are theoretically derived rather than derived from actual practice, and therefore their capacity to reflect building occupants' preferences when implemented in actual buildings can be challenged. Only the models from Inoue et al. (1988) and Reinhart (2001) were derived from actual observations. Clearly, more field investigation is needed in order to understand the manual operation of window blinds. This research, therefore, investigates how building occupants control their window blinds, focusing on the interaction between environmental domains that are directly regulated by window blinds, the lighting and thermal environments. The ultimate goal of this research is to develop predictive manual control models that can be used as a function in energy simulation programs, and to provide the basis for the development of future automated shading systems that better respond to users' preferences.

METHOD

Research Participants

This research reports data which were gathered from 25 building occupants (11 males and 14 females) who work in air-conditioned buildings in Berkeley, California. All participants perform managerial or clerical position within the institution and have full control of their window blinds despite the type of office they occupy (private or cubicle). All participants use computer (mostly with Cathode Ray Tube type video display terminal) to conduct their daily task. Most of research participants sat facing a sidewall (window wall is to their left or right) or a window and wall corner. Only 20% of the total participants sat with their back against a window.

Study Variables

In this study, the dependent variable was the participants' window blind closing preferences which was identified as want no change (0) or want to close (1). For independent variables, only those variables that used to estimate visual or thermal comfort and provide a measure of the physiological/psychological variability of an individual participant or previously mentioned in window blind research literature were included.

For visual comfort variables, luminance data were obtained from the High Dynamic Range (HDR) imaging program called PHOTOLUX (which is available as a licensed product). The HDR images were captured at the seated location of each participant, looking toward a window wall at 1.2 m (4 ft) from the floor. A detailed calibration report of this technique can be found Inkarojrit (2004).

For thermal comfort variables, temperature data were gathered from a HOBO standalone data logger (HOBO H8-007-02) equipped with narrow-range temperature sensor cable. Each air temperature (T_{air}) sensor probe was housed inside a cylindrical Mylar radiation shield (1.5- inch diameter) to protect the probe from direct radiation gain. For globe temperature (T_{glo}), each temperature sensor probe was placed inside a 1.5 in. (38mm) matte gray ping pong ball. The HOBO data logger and temperature probes were mounted to a pole at 1.1 m (3.6 ft) from the floor in order to measure the temperature at the neck position of a normal person in sitting position. Mean Radiant Temperature (*MRT*) values were approximated from the globe and air temperature. The equation for MRT under still air was:

$$MRT = T_{air} + [(T_{glo} - T_{air}) \cdot 2] \qquad (1)$$

In addition, this research monitored the vertical solar radiation in which the pyranometer was mounted to the interior face of the window glass at approximately 1.22 m (4 ft) from the floor (see Figure 1).

Accounting for physiological and psychological differences between individuals, the seven-point scale variable called self-reported sensitivity to brightness (L_{sen}) was generated. Another variable that was analyzed is the presence of direct solar penetration (*Disun*).

Figure 1 Location of the pyranometer that was mounted to the interior face of the window glass at approximately 1.22 m (4 ft) from the floor.

Experimental Procedure

Each participant was surveyed 1 to 4 times within one-day period (at approximately every 2 hours). The research protocol includes opening window blinds at building occupants' workstation at the beginning of the test. After a brief period of adaptation (5-10 minutes), participants were asked to rate their preference for window blind movement (want no change or want to close) on a web-based survey. The window blind closing preferences were crossed check with an actual window blind movement that was monitored with a string potentiometer which was attached to the bottom of the blind. Physical environmental data at the time of the survey were then matched with the window blind closing preference for further statistical analysis.

Data Analysis

Because of a limited number of participants, an applied longitudinal data analysis technique called the Generalized Estimating Equation (GEE), which takes into account within-subject covariates, was chosen. Logistic models, which have been used in previous research to explain control behavior for electric lights, windows, and blinds (Hunt, 1979; Nicol, 2001; Reinhart and Voss, 2003), plays a major role in the derivation of predictive window blind control models in this research. A logistic model is appropriate because the results can be interpreted as probability function or threshold value, measured at p = 0.5. These characteristics are suitable for representing how window blinds are controlled in energy simulation programs and in actual automated blind systems.

Table 1 Descriptive Statistics of Selected Independent Variables by Window Blind Closing Preference

Variable	Want no change				Want to close				
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	***t* value**
L_{glo}	2.38	0.19	2.10	2.79	2.71	0.33	2.12	3.42	4.50**
L_{win}	2.97	0.26	2.43	3.43	3.30	0.27	2.68	3.76	5.03**
L_{mxwin}	3.61	0.29	3.03	4.11	4.05	0.28	3.39	4.53	6.37**
SOL	1.21	0.35	0.61	2.03	1.74	0.52	0.71	2.55	4.25**
MRT	72.41	2.70	68.00	79.40	74.18	3.45	64.20	82.90	2.11*

*$p < .05$, **$p < .01$

Table 2 Summary of Multiple Logistic Regression Analysis Predicting Window Blind Closing Events

No.	Variable	Standard Regression				GEE	
		β, α	R^2	**% Correct**	**AIC**	**β, α**	**Wald Statistics**
M1	L_{win}	-5.76	0.69	89.0	48.2	-5.82	58.67*
	L_{mxwin}	5.96				6.20	
	SOL	3.30				3.29	
	L_{sen}	1.22				1.22	
	Constant	-13.94				-14.66	
M2	*SOL*	3.09	0.62	86.3	50.8	3.22	13.82*
	L_{sen}	1.22				1.22	
	Constant	-8.71				-8.94	
M3	L_{mxwin}	5.19	0.53	84.0	61.3	4.87	21.77*
	MRT	0.25				0.25	
	Constant	-36.87				-35.92	
M4	L_{mxwin}	4.47	0.57	84.3	62.2	4.76	31.33*
	L_{sen}	0.72				0.72	
	Constant	-20.25				-20.66	
M5	L_{glo}	5.22	0.53	84.3	66.2	5.31	20.02*
	L_{sen}	0.86				0.86	
	Constant	-16.11				-16.35	
M6	L_{win}	2.18	0.52	86.7	68.8	2.44	20.68*
	Disun	1.98				1.89	
	L_{sen}	0.80				0.79	
	Constant	-10.07				-10.87	
M7	L_{win}	3.57	0.47	84.3	71.4	3.77	21.92*
	L_{sen}	0.68				0.68	
	Constant	-13.38				-14.04	

*$p < .01$

RESULTS

Descriptive Information

Table 1 presents descriptive statistics for each independent variable by window blind closing preference. A log-transformation was applied to each skewed variable, except for Mean Radiant Temperature (*MRT*). The *t* test for independent means was conducted and the results confirmed that each environmental condition was significantly higher (when blinds were fully opened) when participants wanted to close their blinds versus no change.

Multivariate Models

Results from the window blind usage survey that were conducted prior to the field study showed that window blind closing behavior was influenced by a combination of visual and thermal reasons (Inkarojrit 2004). Therefore, multivariate models of window blind closing behavior were derived by using multiple logistic regression techniques.

Table 2 summarizes the results from the two multiple logistic regression techniques. Models were ranked based on the Akaike Information Criterion (AIC), a statistical model fit measure in which the model with the lowest AIC is considered to be the best.. A total of 7 multivariable logistic regression models were derived ($p < .01$). Model M1 was derived by the backward elimination technique. Models M2 to M7 were derived by the forward selection technique. The percentage of correct prediction (% correct) was also used to justified the model's goodness-of-fit. The backward elimination model (Model M1) has the highest percentage of correct prediction (89.0%). Other multivariate models were found to have the lower percentage of correct prediction (84.0-86.7%).

In order to interpret the results, the probability of window blind closing event could be estimated by applying the regression coefficient and constant from Table 2 to the following equation:

$$P(X) = \frac{e^{-(\alpha + \sum \beta_i X_i)}}{1 + e^{-(\alpha + \sum \beta_i X_i)}} \tag{2}$$

where

P(X) Probability of window blind closing

α, β estimated regression coefficients

Using Model M2 as an example, the probability of window blind closing events could be estimated as a function of vertical solar radiation at window (*SOL*) and occupants' brightness sensitivity (L_{sen}) from the following equation:

$$P(X) = \frac{e^{-(-8.94 + [3.22 \cdot SOL] + [1.22 \cdot L_{sen}])}}{1 + e^{-(-8.94 + [3.22 \cdot SOL] + [1.22 \cdot L_{sen}])}} \tag{3}$$

Graphical representation of this model is shown in Figure 2.

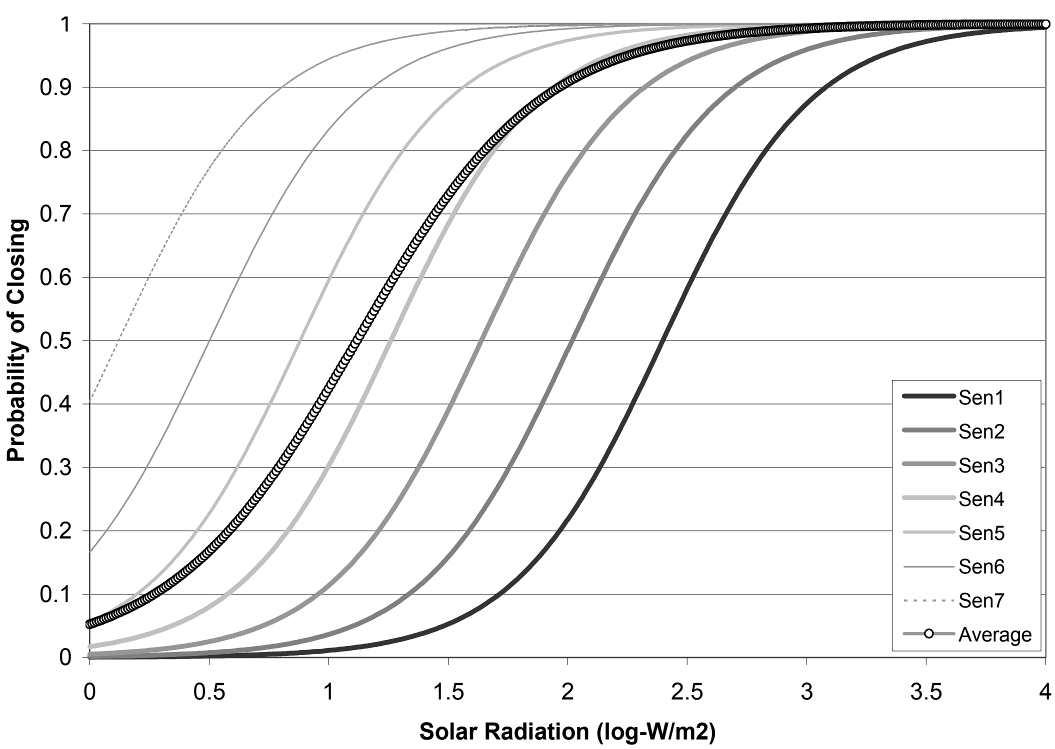

Figure 2 Model M2, logistic model of window blind closing as a function of vertical solar radiation (SOL) and brightness sensitivity (L_{sen})

DISCUSSION

Selection of the Best Model

Based on the different evaluation criteria, this study suggests that window blind control models can predict blind closing events with varying degree of accuracy. To answer the question of which model is the best, the difference between explanatory and exploratory modes of model selection must be understood.

In exploratory research, the goal is simply to find a good set of predictors. On the other hand, in explanatory research, theory determines which variables are in the model in explanatory research. This dissertation was designed to be both exploratory and explanatory.

As exploratory research, a total of 7 logistic models were derived in this paper. Using the evaluative criteria, Nagelkerke's r^2 and AIC, the best model consists of 4 independent variables. As explanatory research, limitations from the actual implementation will determine whether the models are appropriate for use. For example, models which have the self-reported brightness sensitivity as one of the predictors may not be suitable for use in energy simulation programs but will likely be very useful in future automated blind systems.

To answer the question of the best model, researchers must understand how the model will be used and what (or how many) parameters can or cannot be provided in the model. For example, while the model with four predictor variables (Model M1) is considered to be the best, the computational process in an actual automated window blind control algorithm may be expensive and time-consuming. The second best (Model M2), which consists of only two variables, could be substituted. The two-variable models will likely to take less computational time while providing a comparably high percentage of correct predictions. Alternatively, if the interaction effect of window brightness and temperature needs to be examined, model M8 should be used. Finally, researchers and manufacturers may consider using models with only one variable, which will be very easy to implement in current automated window blind control systems and energy simulation programs.

It should be noted that the model selection criteria in this study were calculated from standard logistic regression because the output from the Generalized Estimating Equation (GEE) technique does not include any criterion for the measurement of strength or accuracy of the model other than the Wald statistics.

Interpretation of logistic regression coefficients

The effects of the independent variables in logistic regression have multiple interpretations. This section discusses interpretations of logistic regression coefficients in terms of odds, probabilities and threshold value.

1. Odds

The odds is the ratio of the probability that an event will occur over the probability that the same event will not occur. The odds can be expressed by the following equation:

$$\text{Odds} = P(X) / [1-P(X)] \qquad (3)$$

where P(X) denotes the probability of the event of interest, which is equal to the logistic model as defined in Equation 1. The interpretation of odds comes from transforming the logistic regression coefficients by taking the exponent or antilogarithm of the logistic regression coefficients and predictor variables.

An equivalent explanation is that the regression coefficient (β_i) represents the change in log odds that would result from a one-unit change in the variable *i* when other variables are fixed. By definition, a logit is a log odds, so that the difference between two logits is the same as the different between two log odds. The interpretation of log odds is particularly useful if one would want to summarize the odds of an event for a categorical variable such as direct solar penetration. This study found that when the direct sun is present, the chance of closing the blinds is 3.6 times higher than when there is no direct sun.

2 Probabilities

The second interpretation of the logistic model involves translating log odds or odds to probabilities. Since the relationships between independent variables and probabilities are non-linear and non-additive, they cannot be fully represented by a single coefficient. The effects on probability have to be identified at a particular value (of an independent variable) or a set of values. The choice of values depends on the concerns of the researcher and the nature of data.

In this study, a few examples of window blind control models which express probability of closing as a function of predictor variables were. By translating the regression coefficients into a probability curve, researchers can estimate a specific predictor value at a certain probability value (such as a threshold value) without complex calculations.

3 Threshold value

The last interpretation of the regression coefficients is threshold value. The threshold is a theoretical construct that indicates the particular stimulus value at which the binary variable goes from 0 to 1. Threshold is often defined as the stimulus value at the probability equal to 50% on the logistic function.

In addition, because the threshold value is defined as the value at a specific probability (50%), it can be inferred that when vertical solar radiation at the window reaches 13 W/m^2, 50% of all window blinds will be closed (i.e. the average window blind occlusion value equal 50).

Modeling Window Blind Movement

Window systems in DOE-2 and EnergyPlus can have shading devices such as blinds, pull-down shades, or drapes. Shades can be fixed or movable. Movable shades can be controlled by specifying a schedule. In addition, the shade can be controlled to deploy if the trigger variable exceeds the set point. Basically, window blinds in DOE-2 and EnergyPlus can be controlled by three methods;

1. Scheduled Controls - Fixed time schedules dictate when a shade is open or closed.

2. Threshold Controls – Shades open or close depending on the conditions during the simulation

3. Probabilistic Control - There is a probability that occupants respond correctly to conditions in the building (thresholds) and open or close shades accordingly.

Example of allowed trigger variables (predictor variables) include solar radiation incident on the window and Daylight Glare Index.

The window blind control model is incorporated into the daylighting module of EnergyPlus.. At the outermost level, the simulation manager controls the interactions between all simulation loops from a sub-hour level up through the user selected simulation period.

Contribution to the Building Energy Simulation

This study makes four major contributions to the building energy simulation.

1. The window blind control models were derived from empirical study. It is anticipated that by using the values from derived models, the window blind control behavior will be represented more accurately.

2. In addition to the threshold value, the window blind control rule can be expressed as a probability function. Using Model L2 as an example, all window blinds could be closed when the vertical solar radiation exceeds 15 W/m^2. However, instead of closing all the window blinds, a researcher can specify, based on the probability function, that when the solar radiation exceeds 15 W/m^2, only half of the window blinds are closed.

3. There are many alternative models to choose from in additional to those based only on solar radiation. As mentioned earlier, the percentage of correct predictions increases as the number of parameters in the model increases. Researchers may consider using models with more than one predictor variable to increase the simulation accuracy.

4. If the distribution of occupants' self-reported sensitivity to brightness is known, then differential control of blinds can be simulated, leading to more accurate prediction of energy usage.

Implementation of control models as the basis for future automated window blind systems

The major goal in this study was to provide a basis for the development of future automated shading systems that respond to the users' satisfaction and preferences. Through analysis, it can be seen that this goal can be realized by using the threshold values or probability functions that were derived from various window blind control models.

Existing automated window blind systems are controlled by simple control rules such as time of day or direct solar penetration. The threshold values in this study were derived from luminance, solar radiation, and temperature. This enables the window blinds to be adjusted according to changing environmental and climatic variations. The control rules can also be applied to workspaces on the north façade, where there is no direct solar penetration.

In addition, factors such as temperature and individual sensitivity to brightness could be integrated into the model. This integration addresses the interaction effect of the visual environment, thermal environment, and building occupant, which helps the automated window blinds to be controlled more accurately.

Another example of threshold value implementation is that the threshold value can be used in the procurement specification of automated window blind systems. These specifications detail performance requirements for all aspects of a technology and enable manufacturers to understand the full scope of their involvement on a project. For example, one of the goals specified in the procurement specification for an automated window shade for the new New York Times Headquarters was to maintain a glare free environment (LBNL, 2005). To achieve this goal, the threshold value for the average luminance of the unobstructed portion of the window wall was set to 2000 cd/m^2 (reflecting the IES 1:10 luminance ratio between task and remote surfaces).

Another approach to provide the basis for future automated shading systems is to express window blind control as a probability function. Review of literature in the area of intelligent window blind control systems showed that many studies utilize fuzzy control systems, Genetic Algorithms, and neural networks to the reduce energy consumption (Guillemin & Morel 2001, Athienitis & Tzempelikos 2002, Kolokotsa 2003). In these studies, window blinds were controlled based on threshold values or on optimization of one or more of the following variables: window luminance, solar radiation, illuminance level, solar position, indoor temperature, and season (Guillemin & Molteni 2002, Assimakopoulos et al. 2004, Park et al. 2004).

Because predictors in the abovementioned studies can be expressed as a threshold value or degree of membership (in fuzzy control theory), the models derived in the current study can be easily interpreted into many usable threshold values and cumulative distribution functions (e.g. logistic functions) and probability density functions (PDF) for use in fuzzy control systems.

Additional consideration for the derived models

It should be noted that the statistical analysis performed in this study aims to rule out null hypothesis and accept research hypothesis. As a consequence, a compromise between a model's bias and variance versus the number of estimated parameters in the model were made. In this study the models were derived through stepwise regression techniques to find the model with the least number of predictor parameter. Occasionally, this results in an unpredictable phenomenon such as those shown in Figure 2 where the closing probability is more than 0 when there is no solar radiation.

A possible explaination for this phenomenon comes from the window blind usage survey (Inkarojrit, 2004) which shows that window blinds were closed for multiple reasons (to reduce brightness from window, to reduce glare, to increase visual privacy). In this case, single predictor such as solar radiation in Model M2 may not be the best representative predictor that can explain the integration between all possible factors that influence the control of window blinds. Therfore, future work should look into the integration of physical and non-physical criteria in detail.

CONCLUSION

This study investigated how and why building occupants control window blinds in private offices. Data were collected from participants who occupied offices with Venetian blinds in Berkeley, California. These data supported the research hypothesis that the probability of window blind closing event was found to increase as the magnitude of monitored physical environmental conditions increase.

In this research, seven multivariate predictive window blind control models were derived as a function of interior luminance characteristics, transmitted vertical solar radiation, temperature and direct solar penetration. In addition, the data suggested that the internal psychological factor, the participants' self-reported brightness sensitivity, influence the window blind control behavior. With their probabilistic nature and simple measurable luminous and thermal based variables, it is expected that these predictive models can be easily implemented in the building energy simulation programs and provide the basis of future automated window blind control systems.

The results presented in this study are merely a snapshot of how building occupants control window blinds based on a specific group of participants in particular climatic and contextual conditions. Many factors, such as LCD screen that emit higher task luminance, that could potentially influence window blind control behaviors were not considered in this study. This research concludes that future work is still needed to develop control models that maintain satisfaction while allowing the energy-saving potential of intelligent façade systems can be fully realized.

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NOMENCLATURE

L_{win} Average luminance of the window or source luminance (cd/m^2)

L_{glo} Background luminance defines as the average luminance of the interior room surfaces (including window) and calculated as luminance averaged over the hemisphere of view (cd/m^2)

L_{mxwin} Maximum luminance of the window (cd/m^2)

T_{air} Air temperature (°F)

T_{glo} Globe temperature (°F)

MRT Mean radiant temperature (°F)

L_{sen} Self-reported sensitivity to brightness on a seven-point scale ranging from lease sensitive (1) to most sensitive (7)

Disun The presence of direct solar penetration falling on research participant

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