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UNCERTAINTY OF DAYLIGHTING PERFORMANCE OF MANUAL SOLAR SHADES AND ITS INFLUENCE ON LIGHTING ENERGY

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ABSTRACT

Occupant behaviour significantly influences building energy consumption. This paper is devoted to studies the uncertainty of daylighting performance and lighting energy of manual solar shades on the south facade. A developed stochastic model for manual solar shades was used for co-simulation by BCVTB. Results show that uncertainty of shade action was not suppressed by the shade behaviour model with very weak relationship between different simulation outputs. Uncertainty of daylighting performance is 15.08 % while lighting energy uncertainty is 10.38 %. Although this level of energy uncertainty is not very significant, it influences economic analysis of manual solar shades and therefore, occupant related uncertainty should be taken into consideration when predicting energy performance of manual shades.

Keywords: Building Controls Virtual Test Bed (BCVTB), manual solar shades, uncertainty, daylighting performance, lighting energy

1. INTRODUCTION

Shading devices can be used to control solar gains, adjust daylight levels in the room and eliminate glare and high contrast [1]. Fixed shading devices such as horizontal overhang, vertical fins are widely used in the building envelope to block unwanted solar radiation in summer. However, they also block a significant amount of direct and diffuse daylight in winter and they are not effective under cloudy skies. While for movable shading devices, they can be adjusted to changing outdoor conditions. Thus, movable solar shades have been widely used in buildings either manually controlled or operated by the building automation system. Although automated solar shading system provides a high efficient control of thermal, daylight and glare, its high initial and maintenance costs are still major impediments for its widespread use in hot summer and cold winter zone of China. Therefore, manually operated roller shades are widely used in China, especially in glazed office buildings [2].

Manual solar shades highly rely on occupants' control and thus the prediction of daylighting and energy performance of manual shades should take into account behaviour characteristics, since research works have indicated that building energy consumption is influenced not only by engineering technology, but also by cultural concepts, occupant behaviour, social equity etc. Evidence suggests that occupant behaviour plays a defining role in influencing the total energy consumption [3]. For example, Labat et al [4] carried out numerical estimation and sensitivity analysis of the energy demand for six industrial buildings in France. They found that the computed value of the energy demand for heating and cooling was sensitive to input parameters related to the use of the building rather than to the ones describing the envelope. Building research in recent years has shown differences between the actual and predicted energy performance of buildings. Some of these differences have been attributed to the effect of occupants' behaviour [5]. A study by Haldi et al [6] quantified the impact of occupants' behaviour on building energy demand. Different oc-

Table 1. Characteristics of the Office Room

Parameter	Value
Location	Ningbo city in China, latitude: 30°, longitude: 120°
Room orientation	South
Dimension	Room: (4×4×3) m, Window: (3.8×2.8) m
Window and shading device	Clear double-pane window + manually controlled external shading. A white roller top-down shade with 30 % polyester and 70 % PVC is considered and the visual transmittance is 0.2.
Daylight sensor position	The red point in Fig. 1
Daylighting performance index	Hours of useful daylight illuminance (UDI: (300–2000) lx) [11]
Intensity of radiation	11W/m^2 for daylight illuminance < 300 lx

cupant behaviour models have been integrated within an urban energy modelling tool, called CitySim. The results show that occupants' behaviour has a significant impact (of the order of a factor of two) on buildings' energy demands.

Although a few researches reported the influence of occupant behaviour (manual shades) on energy performance [7, 8], the blind models adopted in these research works were not applicable to manual solar shades with partial shade states (the current studies either consider only two blind states (fully open and fully closed) or are based on unusual shading systems with motorized control. For example, Reinhart [9] simulated building energy performance based on the Lightswitch-2002 model. However, this model can be used only to predict the lighting energy performance, and daylighting performance uncertainty due to occupant behaviour on blinds cannot be simulated by this model. Moreover, the research findings cannot be directly applied in buildings in hot summer and cold winter zone of China due to the differences in shade types and behaviour characteristics.

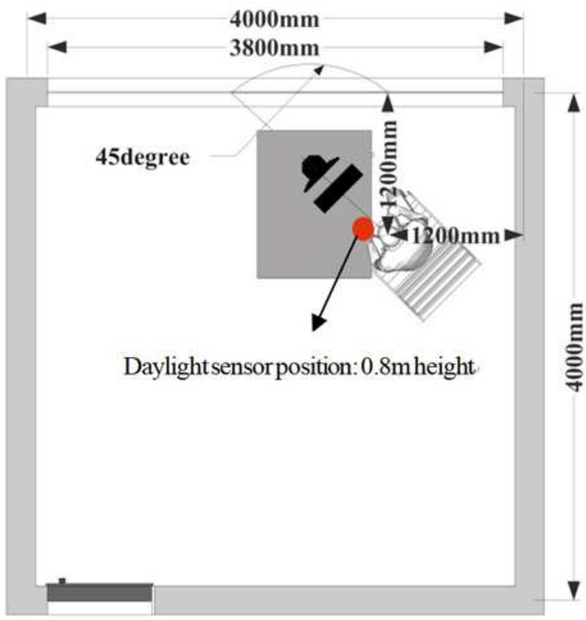

Fig. 1. Room model showing the workplace position (upward direction represents south)

To analyze the impact of occupant uncertainty of shade control behaviour on building performance, a stochastic model for west-facing facades developed in a previous study [2] based on field measurements was used in this paper. Energy savings compared to regular windows, thermal [10], daylight [11] and visual performance [12] have already been researched. This work is a continuation of the previous study and the focus is the uncertainty of occupant behaviour on solar shades and its influence on daylighting and lighting energy performance.

2. METHODOLOGY

2.1 Stochastic Model of Manual Solar Shades

A typical office room model was used in this paper. Its dimension is (4×4×3) m with a (3.8×2.8) m window on the south facade as shown in Fig. 1. The characteristics of the office room including the setting of manually controlled external shading devices and daylighting sensor position are shown in Table 1.

To investigate the uncertainty of daylighting performance of manual solar shades and its influence on lighting energy consumption, the stochastic model developed in a previous study by the author [2] was used in this paper. The model was constructed based on field measurements of a typical high-rise glazing building in hot summer and cold winter zone of China. In this model, the occupants' stochastic behaviour of solar control was divided into 5

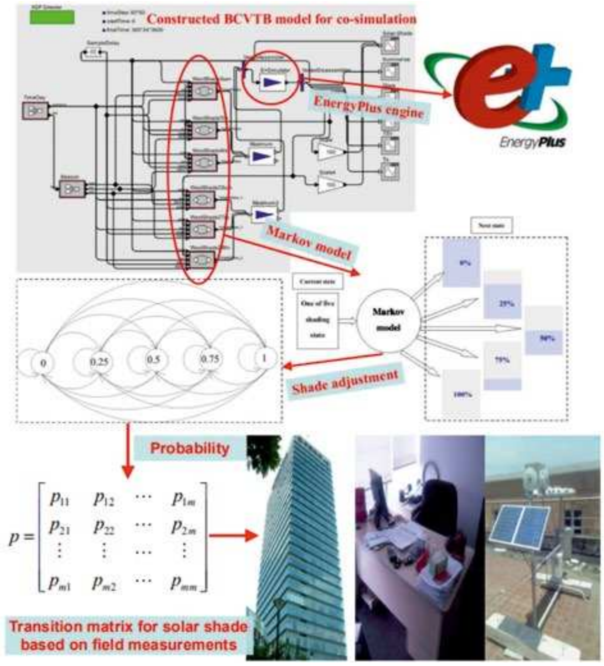

Fig. 2. A graphic illustration of the applied method for co-simulation of daylighting performance of manual solar shades

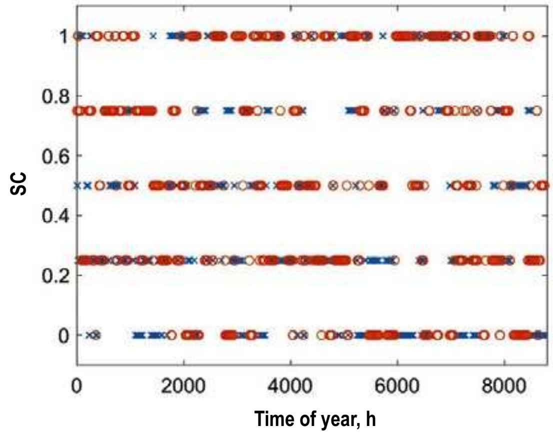

Fig. 3. Hourly SC values of two example simulations during the whole year (o represents simulation N1 and x represents simulation N2)

discrete solar shading positions (fully shaded, 75 % shaded, 50 % shaded, 25 % shaded and fully open). Corresponding values of external shading coefficient (SC) are 0, 0.25, 0.5, 0.75 and 1 respectively. And the adjustment of solar shades was predicted based on the current shade state and solar intensity on the facade (since it is the driving factor according to cumulative odds logit regression) using a first order and discrete-time Markov chain method, which produces Markov chain transition matrix (the probability of solar shade changes from the current state to the next one) for coupling with EnergyPlus. A brief description of how this stochastic model is constructed and the co-simulation is conducted can be seen in Fig. 2. More detailed information of this stochastic model and the co-simulation can be found in the previous paper [2].

2.2. Uncertainty Index

2.2.1. Shade control behaviour

In this paper, uncertainty means the stochastic adjustment of shade devices due to occupant behaviour, which results in the difference of SC value between occupants and thus the resulting building energy difference. The index used to assess how well the relationship between two variables (here hourly SC values between different simulations) is correlation coefficient, which varies between +1 and –1. A value of +1 indicates a perfect positive correlation between the two variables, –1 represents totally negative correlation and 0 corresponds to an absence of linear correlation. Since SC values in this paper are discrete and ordinal, Spearman rank correlation, a non-parametric test, is used. The Spearman rank correlation test does not carry any assumptions about the distribution of the data and thus is appropriate for correlation analysis for SC values.

2.2.2. Daylighting performance and lighting energy

For uncertainty of daylighting performance and lighting energy, the probability density function (PDF) was used to fit the data. In this paper normal distribution was adopted (since the following analysis confirmed the normal distribution of the data) which uses a two-parameter family of curves. The first parameter, μ, is the mean. The second parameter, σ, is the standard deviation. And the normal PDF of the energy data $f(x)$ can be expressed as:

$$f(x)=\frac{1}{\sigma\sqrt{2\pi}}\exp(\frac{-(x-\mu)^2}{2\sigma^2}). \qquad (1)$$

Using the above fitting analysis, the distribution of hours of useful daylight illuminance (UDI) can be determined and then 95 % confidence interval of daylighting uncertainty (hours of UDI) can be calculated as follows according to the properties of normal distribution:

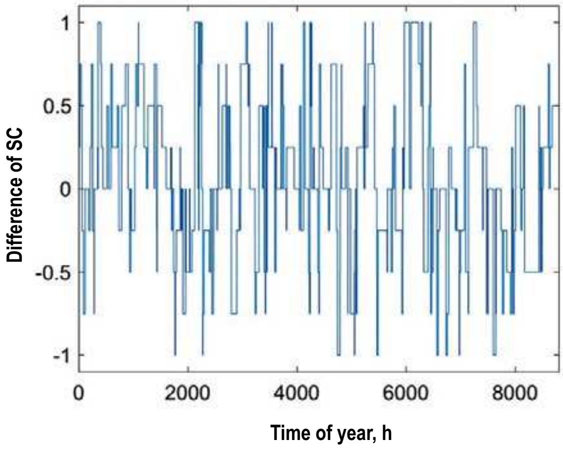

Fig. 4. Hourly difference of SC values of two example simulations during the whole year

$$CI = \overline{X} \pm t_{n-1,\alpha/2} \frac{\sigma}{\sqrt{n}}, \qquad (2)$$

where $\overline{X}$ is the mean of the output data from the replications, n is the number of replications, t_{n-1}, $_{\alpha/2}$ is the value from Student's t-distribution with (n-1) degree of freedom and a significance level of $\alpha/2$. A significance level (α) of 5 % is selected in this paper. That gives a 95 % probability the value of the true mean lies within the CI interval. To have a percentage value of uncertainty rather than an absolute one, CI was further divided by the mean value.

2.3. Number of Repeated Simulations

Since energy simulation based on the shade behavioural model generates different outputs, repeated simulations are needed to understand the possible distribution of the output parameters. As described in [13], additional simulation time needed for replicates can be considered as a weakness. Thus, this paper calculates the required minimum number of simulations in order to achieve a converged solution according to the graphical method recommended in [14]. The graphical method plots the cumulative mean of the simulation output data and thus, after sufficient replications, the graph will become a flat line with no upward or downward trend. The number of replications required is defined by the point at which the line becomes flat. Based on the above analysis, uncertainty of daylighting performance (hours of UDI since it is an important index in determining daylight performance [11]) as well as lighting energy consumption can be determined.

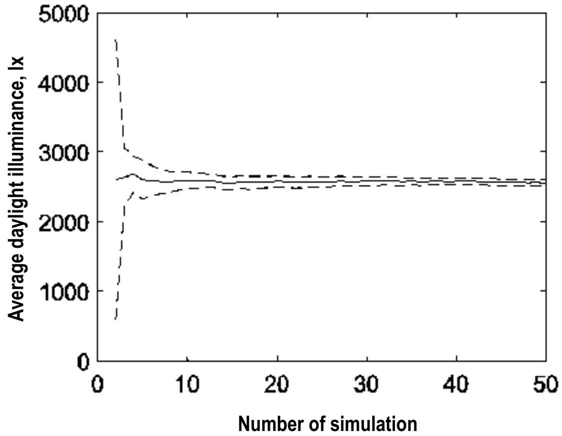

Fig. 5. Convergence of annual average daylight illuminance (the solid line indicates the mean value while the dashed lines indicate 95 % confidence interval)

3. RESULTS AND DISCUSSION

3.1. Uncertainty of Shade Control

3.1.1. Comparison of two example simulations

Two example simulations were given in this section to illustrate the behaviour uncertainty. In each simulation time step, a random number is sampled from a continuous uniform distribution between 0 and 1 and compared with the Markov chain transition matrix (see section 2.1) and thus different hourly SC sequences were generated using the same shade behaviour model as described and shown in Fig. 2. Fig. 3 gives hourly SC values of two example simulations (simulation N1 and simulation N2) during the whole year. It can be seen that SC differs significantly between the two simulations with different fluctuation trends. Fig. 4 further presents the SC differences between these two simulations. Due to the stochastic characteristics of occupant behaviour, the occupant uncertainty can be easily observed with most of times SC difference being not 0 (mainly between about –1 to 1). This difference directly influences final energy performance and therefore, a single simulation run is not capable of capturing energy uncertainty due to occupant behaviour.

3.1.2 Required simulation runs

The minimum number of required simulations for a converged solution is determined based on the graphical method and the results are show in

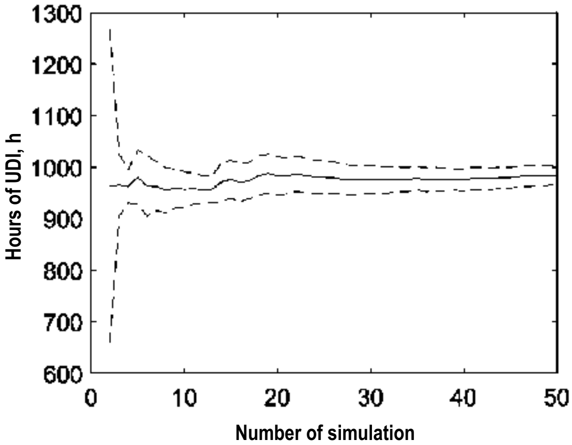

Fig. 6. Convergence of hours of UDI (the solid line indicates the mean value while the dashed lines indicate 95 % confidence interval)

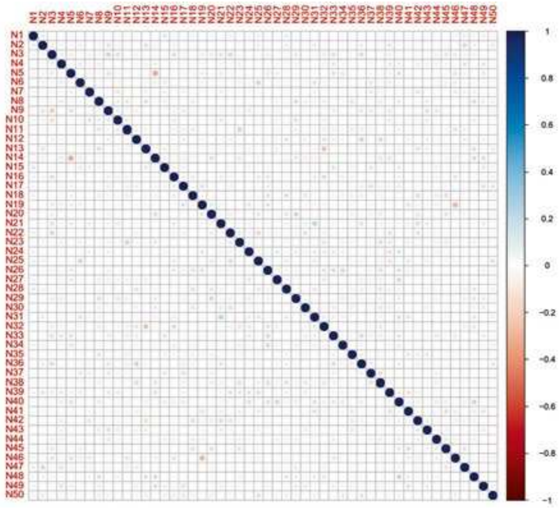

Fig. 7. Correlation coefficient of hourly SC values between each two simulations

Figs. 5, 6. It can be seen that after 20 simulations, annual average daylight illuminance reaches a converged solution while for the hours of UDI it is about 25 simulations. To have a better uncertainty evaluation, 50 simulation runs were selected in this paper. It should be noted that this amount of required simulations is based on the shade behaviour model in this climate region. Other researchers [13] reported a higher number of required simulations when simulating more types of occupant behaviours (a combination of shade adjustment, window opening and thermostat setting etc.). Therefore, generally a smaller number of repeated simulations is required if less types of occupant behaviours are considered. If other shade behaviour models are considered, the number of required simulation runs may be different from this research and it is suggested to be determined by using the graphical method described in section 2.3.

3.1.3 Correlation between repeated simulations

Based on 50 simulation runs, Fig. 7 presents Spearman correlation coefficient of hourly SC values between each two simulations. In this figure, the areas of circles represent the absolute values of corresponding correlation coefficients (a larger area of circles indicates a stronger correlation between simulations). On the principal diagonal line, the areas of circles are the largest with Spearman correlation coefficient of being 1 since the calculation is based on the same simulation. For non-diagonal elements, the distribution of correlation coefficients is illustrated in Fig. 8. It can be seen that correlation coefficients of hourly SC values are close to 0 with only a few values reaching about 0.2 /-0.2, which means

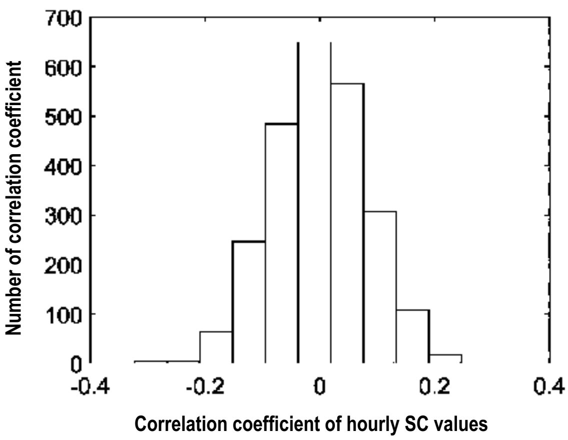

Fig. 8 Distribution of correlation coefficient of hourly SC values between 50 simulations (only non-diagonal elements in Fig. 7 are included in this figure)

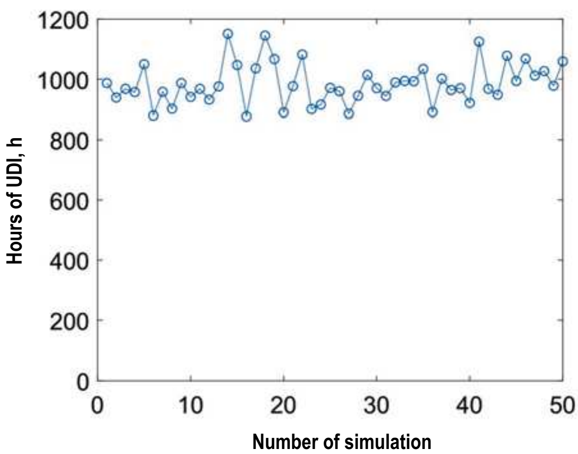

Fig. 9. Hours of UDI for each simulation

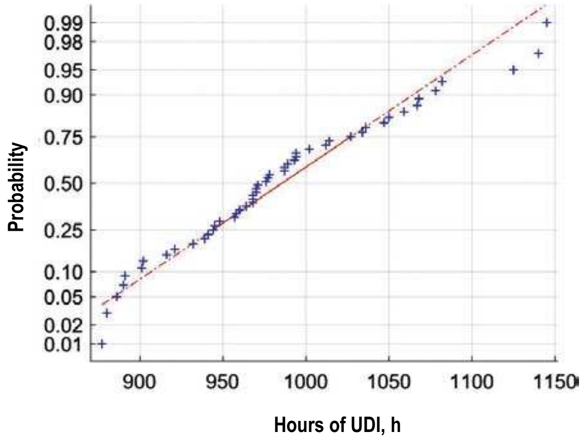

Fig. 10. Normal probability plot of hours of UDI

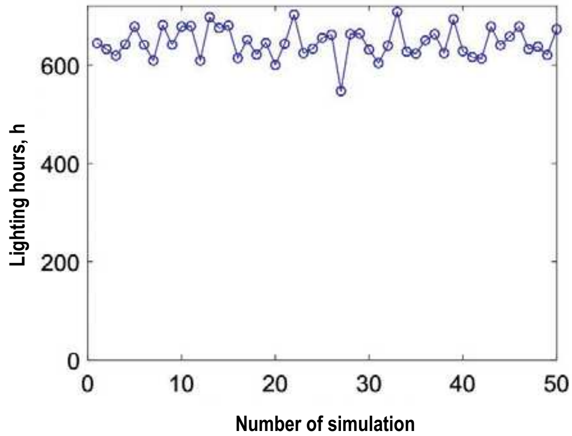

Fig. 11. Lighting hours for each simulation

no or very weak correlation. Therefore, uncertainty of shade action was not suppressed by the shade behaviour model and, thus, this model can be used to conduct uncertainty analysis of daylighting and lighting energy performance.

3.2 Daylight Uncertainty

Fig. 9 gives hours of UDI for each simulation. It can be seen that this value fluctuates among different simulation runs with a variation range of about 800–1200, which means a relatively large uncertainty (about (1200–800)/800×100 % = 50 % for the extreme situations). To further investigate the likely distribution of hours of UDI, a normal probability plot was given in Fig. 10. It can be seen that the data points approximately lie on or near the straight line, indicating a likely normal distribution. Furthermore, a more rigorous statistical test of normality of these energy data was conducted by Shapiro–Wilk test [15]. The test shows that the p-value is higher than 0.05 (a threshold value), indicating the null hypothesis cannot be rejected and the data are normally distributed. According to the equations described in section 2.2.2 uncertainty of daylighting performance (hours of UDI) was calculated and its value is 15.08 %, which means an error of about 15 % may exist if occupant behaviour on solar shades is not taken into consideration when predicting daylighting performance.

3.3 Uncertainty of Lighting Energy

Electric lighting is required when daylight illuminance is less than 300 lx according to lighting design standard for office buildings in China. Therefore, lighting energy can be determined according to daylighting performance, and thus the number of lighting hours (hours of daylight illuminance<300 lx) for each simulation is calculated and illustrated in Fig. 11. It can be seen that the number of lighting hours is mainly between 600 and 700. Meanwhile, normal probability plot of lighting hours was also presented in Fig. 12. It can be seen that the data points approximately lie on or near the straight line. Moreover, the Shapiro–Wilk test shows that the p-value is higher than 0.05, indicating that the data are normally distributed. Therefore, normal fitting according to the equation (1) was conducted and the percentage uncertainty of lighting energy was calculated according to the equation (2) based on the lighting energy intensity described in Table 1. The result shows that the lighting energy uncertainty is equal to 10.38 %. Although this level of energy uncertainty is not very significant and less than uncertainty of daylighting performance, it influences economic analysis (such as

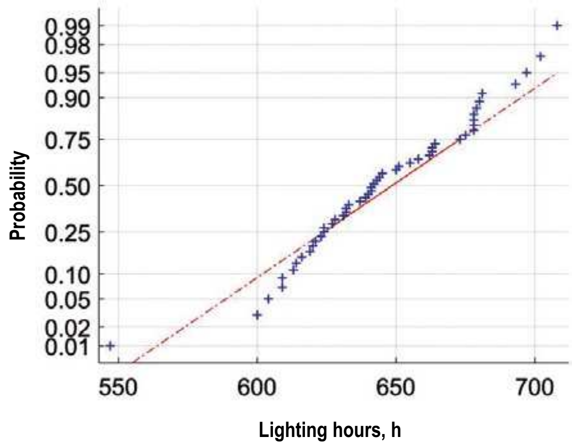

Fig. 12. Normal probability plot of lighting hours

payback period) of manual solar shades and, therefore, occupant related uncertainty should be taken into account when predicting energy performance of manual shades.

Without consideration of occupant behaviour, inappropriate choices may be selected when comparing different energy saving measures (such as clear windows with manual shades vs. low-emitting windows without solar shades). For example, energy simulation is required during building design stage and a predicted energy saving of 50 % must be met according to China's building energy design standards. Even if a simulated building energy saving is only 1 % less than 50 %, better building energy saving measures than those already used in simulated building must be adopted to achieve at least this 1 % improvement in order to meet the mandatory design standards. Therefore, an energy uncertainty of about 10 % can lead to a big difference on the choice of building energy saving measures and there is a need for consideration of energy uncertainty due to occupant behaviour. However, it is challenge for implementation of accurate energy uncertainty analysis in mandatory design standards since existing shade behaviour models are still being developed for research purpose and cannot be directly applied to building design stage. Nevertheless, some improvement strategies may be considered in design standards for better prediction of energy uncertainty instead of assuming simple shade control scenarios (e.g. fully closed or fully open, which is unrealistic occupant behaviour), which typically predict a single deterministic energy performance. For example, using representative SC values (e.g. lower and upper limits of 75 % confidence interval) for simulation according to Fig. 3. This strategy provides the possible intervals of energy performance and the uncertainty level. Besides, more reasonable simulation settings regarding manual solar shades are also required in design standards. However, possible improvements in design standards need to be further investigated and calibrated using more field measurement data in future works.

4. CONCLUSION

This paper gives an uncertainty analysis of daylighting performance and lighting energy of manual solar shades. A stochastic model developed in a previous study was used in this paper for co-simulation. Results show that uncertainty of shade action was not suppressed by the shade behaviour model with very weak relationship between different simulation outputs (SC values). Uncertainty of daylighting performance is 15.08 % while lighting energy uncertainty is 10.38 %. Although this level of energy uncertainty is not very significant, it influences economic analysis of manual solar shades and, therefore, occupant related uncertainty should be taken into consideration when predicting energy performance of manual shades. Otherwise, inappropriate choices may be selected when comparing different energy saving measures.

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