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DEVELOPMENT AND VALIDATION OF A PREDICTIVE ALGORITHM FOR NEAR-OPTIMAL CONTROL OF VENETIAN BLINDS

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ABSTRACT

Application of integrated centralized control systems in buildings has been shown to be a very promising option to reduce energy consumption. The focus of this paper is on automated day-lighting systems which can modulate window blinds and electrical interior lights for maintaining the proper illumination levels and saving significant electrical energy in buildings.

The algorithm proposed involves developing a preliminary baseline strategy for near-optimal blind slat angle settings for venetian blinds. We describe the predictive algorithm and validate the algorithm through experimental studies in both a virtual test cell as well as in an actual test room which have three separate sets of venetian blinds. The baseline strategy involves using a detailed lighting simulation program to predict illumination levels during selected days of the year and specific times of the day. The simulations are done by modifying the angels of blinds individually by pre-selected increments. It is then shown that this baseline data when properly extrapolated is adequate to predict near-optimal blind angles for most of the hours during the rest of the year.

The study presented in this paper lays the foundation towards the development of an innovative integrated lighting control algorithm for high performance buildings using distributed sensors which will be described in a subsequent paper.

INTRODUCTION

There is a growing concern about buildings' energy consumption and its impacts on environment [1]. In the last decade, several environmental reports have raised public awareness about the energy use and its consequences on environment and provided a better understanding of energy use characteristics in buildings, [2]. A significant part of the energy consumption is due to the growing demand for better indoor comfort in buildings, [3]. Buildings typically have a long life span, lasting for 50 years or more. It is, therefore, crucial to make sure that existing buildings are operated and maintained properly during their life time. In addition, application of effective energy efficient concepts on new buildings to reduce energy consumption and improve the level of comfort for occupants, is another key strategy. Studies have indicated that, in a building, 10-30% energy savings could be achieved through existing and cost effective equipment and operational technology available today. This savings fraction can double if cutting edge research ideas and transformational multidisciplinary research results are applied on buildings, [4-14]. In this context, efficient intelligent control strategies are key design elements, and main motivation and focus of this paper.

Furthermore, daylight is a basic need of human beings. It is generally known that daylight is able to affect physical, physiological and psychological conditions of occupants. During the last few years, architects and design professionals started to recognize the importance of introducing natural lighting into buildings and its positive impact on the work environment. Recent studies reveal a correlation between environmental lighting and human performance and health, with positive results [15]. What is known, is that insufficient or inappropriate light exposure can disrupt standard human rhythms which may result in adverse consequences for performance, safety and health, [16-21].

To provide the optimum amount of daylight in a building based on visual and thermal comfort aspects, and reduce energy consumption, designing the proper daylighting systems and strategies play a very important role. A coordinated control strategy which integrates daylighting with electric lighting systems leads to substantial lighting energy savings in existing as well as new buildings. Results of one of the first studies demonstrate the impacts of manual control of window blinds on annual energy consumption. In this particular study, it is suggested that a blind system by itself, without a proper control strategy, will not contribute to significant energy savings, [22].

There are several research studies which investigated and developed different prediction methods to determine the optimal blind slat angle settings for the occupants, [23- 25]. Although these studies provide useful models and detailed guidelines to optimize the daylight, view and visual comfort, most of them are limited to specific solar latitude and geographical location. Moreover, in some of the control approaches where many design aspects such as daylighting, artificial lighting and comfort are integrated together, the nature of the control algorithm becomes very complicated which leads to complexity of the control system and difficulties in application. Operation and maintenance of such systems in buildings requires many hours of experts' time and long delays in commissioning of the system. In addition, many of these research studies display integrated systems that are not responsive to different changes in the building shape and size and also in different climatic conditions, [26-28]

This paper reports on a simulation-based study to establish a control baseline to predict the near-optimal blind slat angles inside an office space which is then validated on an actual test-room environment.

OBJECTIVES

As mentioned earlier, the prediction method is the first step of designing an adaptive integrated control strategy which provides an initial base-line for optimal for blind angle settings in the office space.

The strategy is developed on a small scale virtual test cell that represents a small office space. A set of daylighting simulations inside the virtual model was performed as input for the prediction algorithm which predicts the near-optimal blind angle settings for three venetian blinds. The main objective of this step was to predict the near-optimal settings in order to achieve a uniform daylight level on the defined work plane.

METHODOLOGY

Simulations

The prediction approach is based on simulated data inside a small scale model which represents an office area. The test room model was built in ArchiCAD [29] and then imported to Relux Professional lighting software [30] for further analysis. The small scale virtual test bed model was built to investigate daylighting situation and pertains to a 4 by 4 by 4 feet office area with three 1 by 1.3 feet windows on the North, West and South walls (Figure 1). In addition, all interior walls and ceiling are out of Birch wood and the floor is furnished with a grey carpet. All three windows have a clear glass with 80% transmittance and are equipped with matte aluminum blinds. The interior frames of the windows are also made of matte aluminum. The blinds slat angles are set on different degrees in order to control the amount of daylight entering the test cell. All measured lighting levels where calculated on a horizontal work-plane inside the test cell which represented the actual working surface in an office.

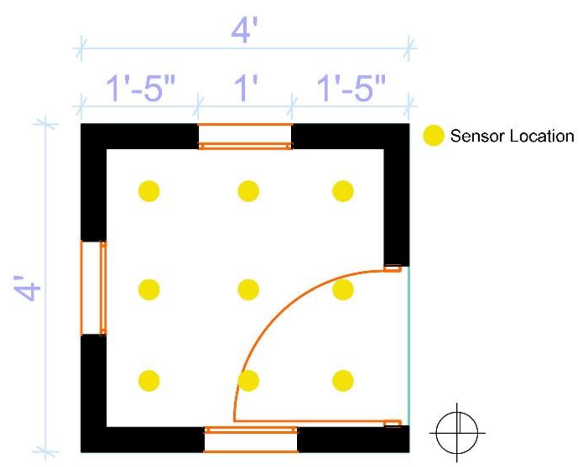

Figure 1. Virtual test cell plan and sensor locations for phase I of the study, (Test cell size: 4×4×4 feet).

The calculations were done for Phoenix, Arizona (33° 27' 0" N, 112° 4' 0" W) for clear sky according to International Commission on Illumination, (CIE), which refers to less than 30 % cloud cover, or none. To measure the daylight levels on the work plane, nine virtual light sensors were placed in the test cell to read the illuminance. Figure 1 shows the sensor placement in the model.

As stated earlier, the intent of the simulated-based approach was firstly, to optimally regulate blind slat angles in order to achieve a unified light level on the defined work plane based on the desired-lux level which was set as 250 lux (IESNA Standard level for general office work at floor level) in this phase of study. Secondly, to reduce the simulation time and automate the approach, simulation sets were limited to a minimum number of runs. These limited simulations include three different days that capture the variability of the solar movement over the year and day in summer, winter and fall, (summer and winter solstice and autumnal equinox days): June 21, September 22 and December 21.

In addition, the simulation was done for three hours each day namely 10am, 12pm and 2pm, which capture the daily solar path inside the virtual office.

The daylight simulations ran with only one window open with different blinds' slat angles one at a time with other two windows closed. We assumed that illuminance level at a specific area is additive and the total lighting for the case whereas all three windows are open was calculated as the sum of the solar radiation contribution from separate simulation cases including north, west or south window open with different slat angles. All three windows were equipped with interior blinds (matte aluminum) which were movable from 0º (fully open) to 90º (fully closed) in 15º intervals (Figure 2). The reason for applying only downward slat angles was that it allows the occupants to have a view out, even if it is only a view of the sky. This will improve the level of visual comfort in the prediction algorithm.

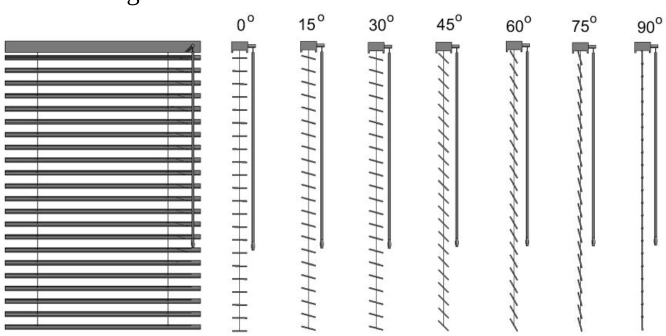

Figure 2. Different blind slat angle settings applied in this study.

Analysis

The daylight simulations for three chosen days which were run for all possible combinations that include all three window settings which are 7^3=343 (seven different angle positions and three windows) different combinations. A computer code was written to investigate the optimal blind slat settings based on uniform light level on work plane. The following section describes the calculation method for this step.

<u>Calculation of "Total Error" values for all blinds' setting combinations:</u> The control objective was to find the best blind slat settings for three windows that provides the most uniform illuminance level the work plane. A target of 250 Lux was defined to compare all simulated data provided by 9 sensors on the work plane for each combination. To achieve this goal, a Total Error (TE) value was calculated for each setting combination as:

$$\boldsymbol{TE} = \sqrt{(\boldsymbol{y_{desired}} - \overline{\boldsymbol{y}})^2 + \boldsymbol{MSE}} \quad (1)$$

Where Mean Square Error (MSE) is defined as:

$$\boldsymbol{MSE} = \frac{\sum_{i=1}^{n}(\boldsymbol{y_i} - \overline{\boldsymbol{y}})^2}{\boldsymbol{n-1}} \quad (2)$$

With:

y_i: measured light level in lux by 9 sensors installed on the work plane

$\overline{y}$: Average illuminance level of all sensors in lux

n: number of sensors

$y_{desired}$: Desired illuminance level in test cell model in lux

The definition of TE implies that smaller values indicate to a more uniform illuminance situation on the work plane and larger values point to significant differences between 250 desired lux level and illuminance levels read by 9 sensors on the work plane. The total error values were calculated for all possible blind setting combinations inside the test cell model which are 7^3 = 343 combinations, (3 windows and 7 blind stat settings for each window, (0º, 15º, 30º, 45º, 60º, 75º, 90º) on June 21st, September 22nd and December 21st. The fitness function was set to find the optimal combination for blind settings with smallest total error.

As seen in Figure 3 to Figure 5, about 80% of all blind setting combinations show a TE value in a range of 90 to 200 which indicates to a less uniform illuminance situation in the test cell on June 21st. However, for each hour, there are a few combinations with the smallest total error value, (TE values 60 to 80) which represent the near-optimal blind setting combination for those specific hours on June 21st.

Similar conclusions were reached for to September and December, [31]. About 90% of all blind setting combinations show a TE value in a range of 90 to 200 which indicates to a less uniformed illuminance situation in the test cell. However, for each hour, there are a few combinations with the smallest total error value (TE values 80 to 90) which represent the near-optimal blind setting combination for those specific hours on September 22st. These blind slat angle combinations are then picked by the algorithm as best predicted optimal settings.

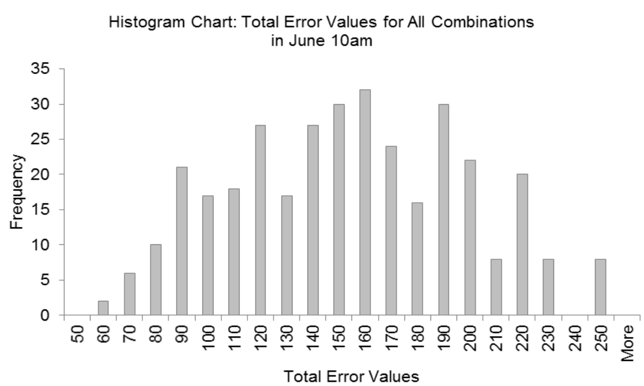

Figure 3. Histogram Charts of total error values for all combinations in June 10am.

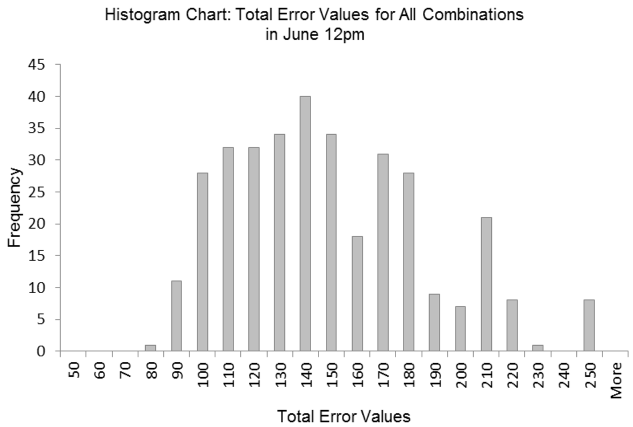

Figure 4. Histogram Charts of total error values for all combinations in June 12pm.

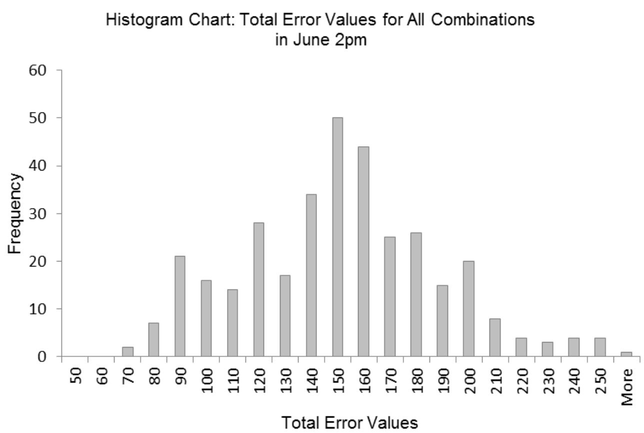

Figure 5. Histogram Charts of total error values for all combinations in June 2pm.

The results for December 21st indicate to larger values of TE among the 343 blind combinations, [31]. The reason for this could be the reduced daylight availability in winter time, thus the lower illuminance levels in the test cell. The few combinations with the smallest total error value (TE values 60 to 80) represent the optimal blind setting combination on December 21st.

One of the important aspects in controlling the blinds in an optimized setting is visual comfort. The amount of change in the blind slat angle in each setting needs to be minimized to avoid the distraction caused by blinds motor noise and visual discomfort. To achieve this goal, a cost function was defined that takes into account the total error values and the magnitude of changes in blinds slat angle. The cost function contains a factor α which is meant to weigh the relative importance of the total error and slat angle changes for the next setting.

$$\textit{Cost function} = (1-\alpha)TE + \alpha\sqrt{\frac{(A_i - A_x)^2 + (B_i - B_x)^2 + (C_i - C_x)^2}{3 \times 90^2}} \quad (3)$$

Where the variables are defined as follows:
α: Weight factor
A_i: Current blinds slat angle for window A (north-side)
B_i: Current Blinds slat angle for window B (west-side)
C_i: Current blinds slat angle for window C (south-side)
A_x: Optimal blinds slat angle for window A
B_x: Optimal blinds slat angle for window B
C_x: Optimal blinds slat angle for window C

The cost function has to be made as small as possible in order to maintain the most uniform lighting situation on the work plane with the smallest changes from one blind slat setting to the next one. When α=0, the cost function value equals to the smallest TE value without taking the slat angle changes into consideration. On the other, for α=1, the TE value weight factor is ignored and the objective would be to maintain the blind slat angle settings constant and to keep the cost function value close to zero. In other words, if α is 1 the blinds will be set on their optimal predicted setting based on smallest TE values in the morning, but then they will stay on the same position for the rest of the day.

Table 1 illustrates the optimal blind slat setting angles based on smallest total error with α=0 where the algorithm operates only based on only smallest total error values without taking the blind slat angle changes into account. In this case, the cost function value is equal to the total error value.

One of the interesting points in Table 1 is the average illuminance values of 9 sensors on the work plane. The selected blind slat angle combinations for the three windows in all three days indicate an average illuminance very close to the desired illuminance level which is 250 lux. This indirectly attests to the accuracy of the prediction algorithm.

Table 1
Optimal blind slat angle settings for three simulation days based on smallest cost function with α=0.

Time	TE	Ave. Lux	Window A North	Window B West	Window C South	Cost Function Value
June 10am	56	241	0	90	0	56
June 12pm	78	224	0	30	30	78
June 2pm	69	240	60	75	0	69
Sep. 10am	75	258	45	15	0	75
Sep.12pm	71	235	45	0	15	71
Sep. 2pm	81	251	0	15	15	81
Dec. 10am	73	233	45	90	0	73
Dec. 12pm	74	234	45	0	15	74
Dec. 2pm	60	248	45	0	15	60

Near-Optimal Control Setting Prediction

A prediction method based on smallest (best) cost function values has been developed which includes two different approaches in order to predict best blind slat angle settings for three windows in the test cell model during a year and also during a chosen day. Thus, the prediction approach is divided into two different categories:

- Yearly prediction approach
- Daily prediction approach

<u>Yearly prediction approach:</u> For yearly predictions of the best blind settings, the weight factor α in the cost function equation is equal to zero ($\alpha = 0$) since the amount of changes in blind slat angles are not significantly important for yearly prediction. Based on this fact, the cost function was defined based on the best TE values and the initial condition of all blinds have been set to zero, (Window A=0^o, Window B=0^o, Window C=0^o).

In this approach, TE values for the three simulated months, (June, September and December) were used to predict the near-optimal blind settings for each randomly selected month. Figures show that if the optimal blind situation for three windows for each month were to be applied on other 11 months of the year at the exact time of the day, the setting would also be one of the near-optimal settings for at least two month before and two months after that month. For example, the best simulated settings for December 10 am are (45^o, 90^o, 0^o). The same setting would also be optimal for 10 for January, February, October and November, since the difference between TE values is not significant (smaller than 10%).

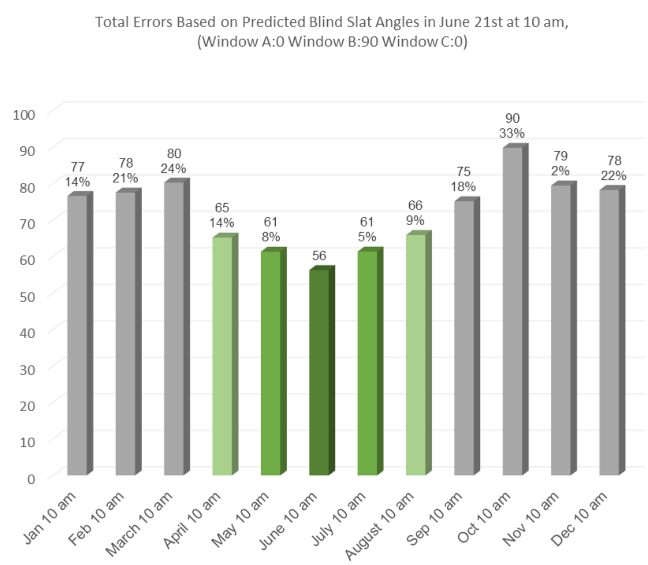

Figure 6. Yearly prediction approach based on June 21st, 10am. The highlighted months show that by applying the optimal setting of June 21st on the same time of other 11 months the TE values for two months before and after June are very close to optimal setting's TE value.

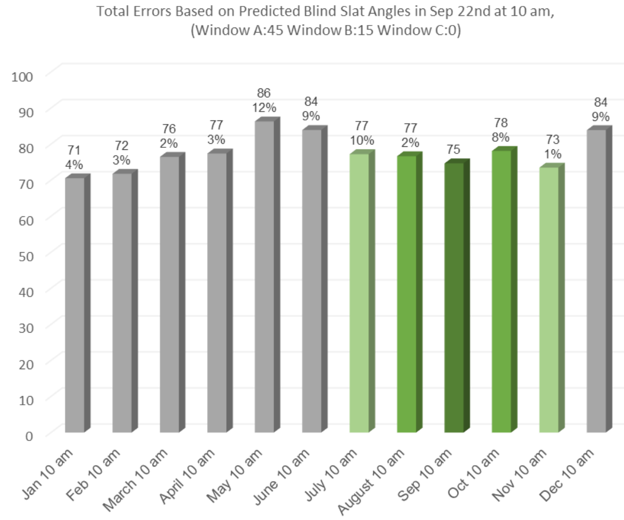

Figure 7. Yearly prediction approach based on September 22st, 10am. The highlighted months show that by applying the optimal setting of September 22st on the same time of other 11 months the TE values for two months before and after September are very close to optimal setting's TE value.

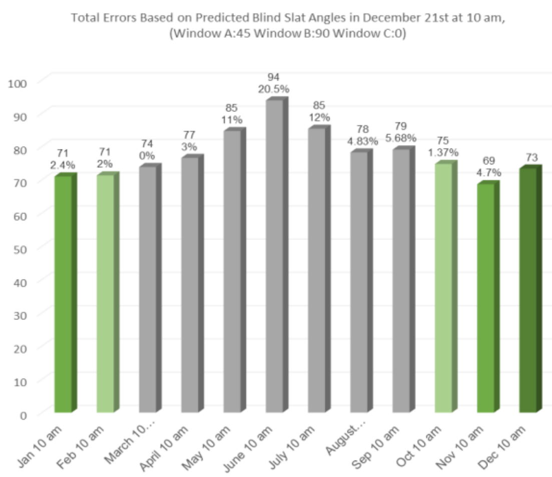

Figure 8. Yearly prediction approach based on December 21st, 10am. The highlighted months in green show that by applying the optimal setting of December 21st on the same time of other 11 months the TE values for two months before and after June are very close to optimal setting's TE value.

<u>Daily prediction approach:</u> To predict the near-optimal blind setting during a day and based on initial limited simulation runs, the weight factor α plays a very important role in the cost function, since it is responsible for changes in the blind slat angles thereby affecting visual comfort. Based on these criteria, the impacts of different values of α on cost function and optimal blind settings for three windows in June, September and December have been investigated. Furthermore, different values of weight factor α (0, 0.25, 0.5, 0.75) have been applied to the cost function to investigate their impact on optimal predicted blind slat angles and total error values. The results indicate that in all three simulated days when α=0.25 the optimal blind slat

settings for windows A, B and C (and also the total error values) are closest to the ideal situation when α=0. Therefore, for daily prediction approach, choosing α=0.25 would result in optimal TE values while meeting the requirement minimum blind slat angle changes. In this case cost function will be as follows:

$$\boldsymbol{Cost\ function} = (\mathbf{1}-\mathbf{0.25})\boldsymbol{TE} + \mathbf{0.25}\sqrt{\frac{(\boldsymbol{A_i}-\boldsymbol{A_x})^2+(\boldsymbol{B_i}-\boldsymbol{B_x})^2+(\boldsymbol{C_i}-\boldsymbol{C_x})^2}{\mathbf{3}\times\mathbf{90^2}}} \qquad (4)$$

Based on the above cost function, the optimal blind slat angles for June, September and December months have been calculated for each window as illustrated in Figure 9 to 11.

The daily prediction method assumes that the start and final setting of blinds are zero degree (fully open blinds). Then, by interpolating the blind slat angle values at start point (9am), three simulated values (10am, 12pm and 2pm) and end point at 4pm, the blind angle values for rest of the hours are predicted. Such an interpolation is a line that connects the given points to each other.

To validate the daily prediction approach, the blind slat angles for some randomly picked hours have been predicted from the three set of graphs. Then, in order to determine the accuracy level of predicted values, a daylight simulation was run for those randomly chosen times. Total error values, average illuminance levels and blind slat settings of these chosen points have been compared to the best optimal situation conducted from the actual simulation data for those hours as shown in Tables 2 and 3.

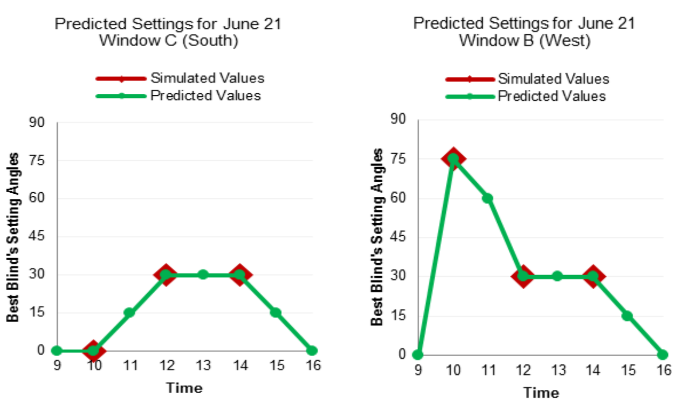

Figure 9. Predicted blind slat settings for the whole day, based on optimal settings in June 21, (10am, 12pm and 2pm) with α=0.25 in the cost function.

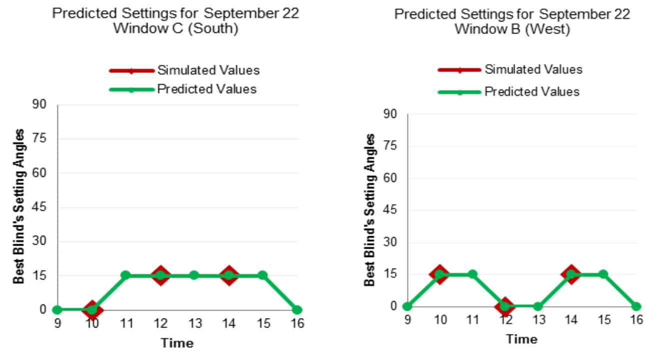

Figure 10. Predicted blind slat settings for the whole day, based on optimal settings in September 22, (10am, 12pm and 2pm) with α=0.25 in the cost function.

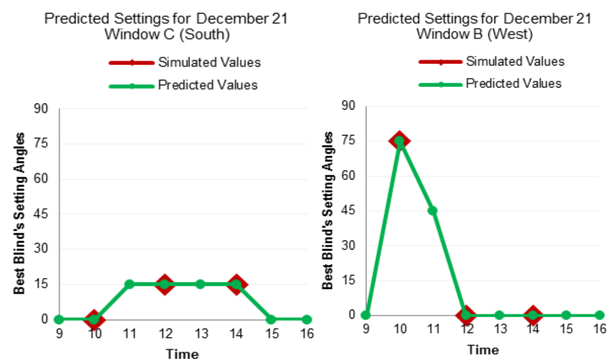

Figure 11. Predicted blind slat settings for the whole day, based on optimal settings in December 21, (10am, 12pm and 2pm) with α=0.25 in the cost function**.**

Table 2

Validation of predicted blind settings for June 21st , 9am, 11am and 1pm with comparing them to the best optimal settings resulted from actual simulation data for the same times with α = 0.25.

June 21st	Time	TE	Ave. Lux	Window A (North)	Window B (West)	Window C (South)
Predicted Data	9am	56	241	0	0	0
Simulated Data	9am	64	264	0	15	0
Predicted Data	11am	91	180	0	60	15
Simulated Data	11am	98	258	0	60	30
Predicted Data	1pm	73	233	0	30	30
Simulated Data	1pm	76	243	0	30	30

Table 3
Validation of predicted blind settings for December 21st 9am, 11am and 1pm with comparing them to the best optimal settings resulted from actual simulation data for the same times with α = 0.25.

December 21st	Time	TE	Ave. Lux	Window A (North)	Window B (West)	Window C (South)
Predicted Data	9am	99	295	0	0	0
Simulated Data	9am	88	246	30	30	0
Predicted Data	11am	94	187	45	45	15
Simulated Data	11am	90	189	45	60	15
Predicted Data	1pm	60	248	45	0	15
Simulated Data	1pm	60	248	45	0	15

We note from Table 2 and Table 3 that the total error values and average illuminance levels of blind settings based on daily prediction method and actual simulations on June 21st and December 21st are very close. The compared values indicate to a very small difference in total errors, average illuminance levels and blind slat angles between simulated and predicted data. This difference in TE values is about 15%, in average illuminance levels is about 10% and is ≤ 15° in blind slat angles. The experimental result confirm that the daily and yearly prediction approach is accurate when applied on randomly chosen days/month. The values suggest that the predicted optimal blind settings are providing the optimal average light levels and the most uniform lighting situation on the work plane in the virtual test cell environment.

Validation of Predicting Control Algorithm

To further validate the proposed control algorithm, it was implemented on a bigger scale test room. The virtual daylight model was then calibrated and fine-tuned based on actual measured data in test room which pertains to an 8 by 8 by 8 feet office area with seven 21 by 32 inches windows on the North, East, West and South walls (Figure 12).

The active (in use) windows on north and west sides were equipped with two commercial SmartBlinds. The blinds were controlled through a computer remote system by a script written in C++ which could regulate and set the blind slat angles based on control algorithm commands.

Figure 12. The view of test room on the roof of design building north in Tempe campus.

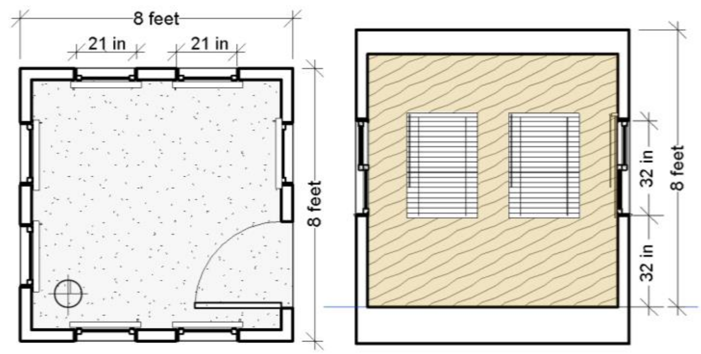

Figure 13. Plan and section of the test room.

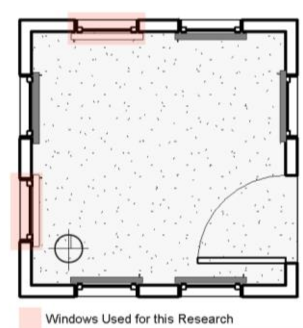

Figure 14. Active and inactive windows in test room.

Figure 15. View of windows inside test room with measuring equipment.

After the virtual model was set up, the developed blind slat control algorithm was implemented on the test room based on three limited day simulation method and calculation of total error for each blind combination. The near-optimal predicted blind angles have been implemented on the blinds on test room for a chosen day and the lighting situation inside the test room was investigated.

Calibration of RadianceIES Lighting Model: To verify the reliability of the lighting program used, the actual daylight levels in test cell have been measured on April 29th from 9am to 5pm. The actual illuminance levels in test room have been measured and recorded by 9 wireless sensor motes distributed in the room similar to the 9 sensor locations. These measured data have then been compared to simulated illuminance data. Some small changes were made to the virtual model materials in order to fine tune the data to match the experimental measurements.

Measured and simulated illuminance data resulted from motes inside the test room and simulations indicate that both data sets follow the same trend. However, measured data have greater values compared to simulated data. This offset value changes for different blind setting combinations for window North and West and for different time of the day. Thus, simulated and measured lighting data from 49 tested combinations (7 blinds slat setting times two windows=7^2) including two active windows on north and west sides have been compared together. For linear approximation of the data, least squares method was applied. In other words the square root of the error was minimized:

$$\boldsymbol{Error = y_i - f(x_i) \quad where \quad f(x_i) = ax_i + b} \tag{5}$$

Based on this comparison, an offset value and a gain factor were determined as follows:

$$\begin{aligned}&\textbf{Measured lighting data}\\ &\qquad = \textbf{Offset value} + \textbf{Gain factor}\\ &\qquad \times \textbf{Simulated lighting data}\end{aligned} \tag{6}$$

Where:
Offset value= 125 Lux
Gain factor= 0.28

The regression analysis found the offset value for the all 49 combinations to be 125 lux and the gain factor to be 0.28. The offset value and gain factor bring the two measured and simulated illuminance level curves closer together. However, in some cases, such as 14 pm when North window's blind slats were set on 0° (open) and West window's blind slats were set on 90° (closed), the measured data point to a very high illuminance values caused by direct solar radiation on a specific sensor mote at a specific time of the day, these two curves differ significantly. This is because the lighting software is not able to simulate the exact value of illuminance at these points which could be referred to the difference between actual weather data on April 29th which was partly cloudy and weather file data uploaded and used in the software for sky harbor international airport weather file.

Validation of Developed Prediction Algorithm: The prediction methodology has been implemented on a test room virtual model in order to achieve optimal blind slat settings. Furthermore, the results of simulations were applied on the test room to investigate whether the near-optimal blind slat settings are also optimal in an actual test environment.

The experiment was done on December 3rd from 9am to 2pm with an overcast sky condition. Based on the fitness function with total errors and a weight factor of 0.25, the optimal blind angles settings for two windows on December 3 from 9am to 2pm were conducted. The optimal blind slat angles for two windows in the test room are as assembled in Table 4.

Table 4
Near-Optimal predicted blind slat angles for December 3rd based on developed prediction algorithm.

December 3rd	TE	Ave. Lux*	Window A (North)	Window B (West)
9am	212	136	60	60
10am	200	139	60	45
11am	187	143	60	45
12pm	182	144	60	45
1pm	182	145	60	60
2pm	195	141	60	45

Average lux is the value before applying the 0.28 gain factor and 125 lux offset value.*

The predicted blind slat angles for December 3rd were then applied on the two SmartBlinds inside the test room and the light levels on 9 sensor motes have been recorded, (Table 4). In order to find out if these settings are near-optimal settings in actual test environment, blind slats has been changed in steps of ±15° in upward and downward directions for both windows to compare the average lighting levels with more open and less open blinds in each case. These results are shown in Table 5.

Table 5
The lighting situation inside the test room after applying the optimal blind slat setting and ±15 degree on two windows on December 3rd.

Slat Angle	December 3rd	Ave. Lux*	TE	Window A (North)	Window B (West)
-15°	9am	45	206	75	75
Optimal	9am	142	114	60	60
+15°	9am	106	147	45	45
-15°	10am	60	192	75	60
Optimal	10am	116	155	60	45
+15°	10am	86	177	45	30
-15°	11am	95	153	75	60

Slat Angle	December 3rd	Ave. Lux*	TE	Window A (North)	Window B (West)
Optimal	11am	132	126	60	45
+15º	11am	121	148	45	30
-15º	12pm	108	128	75	60
Optimal	12pm	150	119	60	45
+15º	12pm	140	149	45	30
-15º	1pm	104	158	75	75
Optimal	1pm	201	97	60	60
+15º	1pm	140	125	45	45
-15º	2pm	127	143	75	60
Optimal	2pm	220	104	60	45
+15º	2pm	189	134	45	30

*** After applying the 0.28 gain factor and 125 Lux offset value.*

As shown in Table 5, the average illuminance of 9 sensors in the test room and the total error values which were calculated based on 250 desired lux level, are displayed for December 3rd. The middle values in highlighted cells illustrate the near-optimal predicted angle setting for the blind slats. The other two values display the lighting situation when the slat angle changes 15º upwards and downwards which show the more open and less open blind situations.

According to the average lux levels and total error values listed in the Table 5, the optimal blind slat angle in all cases indicate an average lighting value closer to the desired lighting level and smaller TE values which imply an ideal uniformed lighting situations on the work-plane inside the room.

CONCLUSIONS

This study led us to conclude that the predicted blind settings based on daily and yearly prediction methodologies also predict the near-optimal blind slat settings in similar building spaces. This methodology could be applied as an initial baseline setting for lighting control in buildings during the conceptual design process.

This algorithm provides an initial baseline setting for an integrated control algorithm which will spare us a significant amount of time in fine-tuning the control algorithm in the experimental steps.

The main goal of this research study was to report the results in designing a self-managing algorithm to enhance the capabilities of control systems by almost completely automating their deployment and operation by empowering them to adapt to environmental changes. A future progress would include the development of an adaptive integrated lighting algorithm for an office building that saves significant amount of electrical energy.

REFERENCES

[1] IPCC, Climate Change, Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M, Averyt, K.B., Tignor, M., Miller, H.L., 2007. “The physical science basis. Contribution of the working group I to the fourth assessment report of the intergovernmental panel on climate change. Cambridge: Cambridge University Press; 2007.

[2] Levine, M., Urge-Vorsatz, D., Blok, K., Geng, L., Harvey, D, Lang, S., et al., 2007. “Residential and commercial buildings. Climate change 2007: mitigation. Contribution of working group III to the fourth assessment report of the intergovernmental panel on climate change”. Cambridge University Press; 2007. p. 387e446.

[3] Lam, J.C., Wan, K.K.W., Tsang, C.L., Yang, L., 2008. “Building energy efficiency in different climates”. *Energy Conversion and Management*, 49(8): 2354-2366.

[4] Lee, E. S., Bartolomeo, D. L. D., and Selkowitz, S. E., 1998. “The effect of venetian blinds on daylight photo electric control performance”. Journal of the Illuminating Engineering Society, 28, pp. 3–23.

[5] Choi, A., and Sung, M., 2000. “Development of a daylight responsive dimming system and preliminary evaluation of system performance”. *Building and Environment, **35***, pp. 663–676.

[6] Lee, E. S., and Selkowitz, S. E., 2006. “The New York times headquarters daylighting mockup: monitored performance of the daylighting control system”. *Energy and Buildings, **38***, pp. 914–929.

[7] Beldi, S., and Krarti, M., 2009. “Genetic algorithm based daylight controller”. In Proceedings of the Inaugural USEU-China. Thermophysics Conference UECTC-RE.

[8] Seoa, D., Ihm, P., and Krarti, M., 2011. “Development of an optimal daylighting controller”. *Building and Environment, **46***, pp. 1011–1022.

[9] Li, D., Lam, T., and Wong, S. L., 2006. “Lighting and energy performance for an office using high frequency dimming controls”. *Energy Conversion and Management, **47***(9–10), pp. 1133–1145.

[10] Atif, M. R., and Galasiu, A. D., 2003. “Energy performance of daylight-linked automatic lighting control systems in large atrium spaces: report on two field monitored case studies”. *Energy and Buildings, **35***(5), pp. 441–461.

[11] Bjorn, B., and Eilif, H. H., 1997. “Energy savings in lighting installations by utilizing daylight”. *CADDET energy efficiency newsletter, **1***.

[12] Jonathan, M., Patrick, J. B., and Doug, C. H., 1998. "Ashrae journal". *Energy and Buildings*, ***40***(5), pp. 31–35.

[13] Li, D., L., J. C., 2001. "Evaluation of lighting performance in office buildings with daylighting controls". *Energy and Buildings*, ***33***, pp. 793–803.

[14] Krarti, M., Erickson, P. M., and Hillman, T. C., 2005. "A simplified method to estimate energy savings of artificial lighting use from daylighting". *Building and Environment*, ***40***(6), pp. 747–754.

[15] Kroelinger, M. (2014, April). Implications. InformeDesign. [Online]. Available: http://www.informedesign.org/_news/mar_v03-p.pdf

[16] Daurat, A., Aguirre, A., Foret, J., Gonnet, P., Keromes, A. & Benoit, O., 1993. "Bright light affects alertness and performance rhythms during a 24-h constant routine," in Physiology & Behavior, 53, 929-936.

[17] Leppämäki, S., Partonen, T., Lönnqvist, J., 2002. "Bright-light exposure combined with physical exercise elevates mood," in Journal of Affective Disorders, 72(2), 139-144.

[18] Partonen, T., Lönnqvist, J., 2000. "Bright light improves vitality and alleviates distress in healthy people," in Journal of Affective Disordersf Eastman, 57(3), 55-61.

[19] Eastman, C. I., Martin, S. K., 1999. "How to use light and dark to produce circadian adaptation to night shift work," Annals of Medicine, 31, 87-98.

[20] Knez, I., Kers, C., 2000. "Effects of Indoor Lighting, Gender, and Age on Mood and Cognitive Performance," in Environment and Behavior, 32(6), 817-831.

[21] Burgess, H. J., Sharkey, K. M. & Eastman, C. I., 2002. "Bright light, dark and melatonin can promote circadian adaptation in night shift workers," in Sleep Medicine Reviews, 6(5), 407-420.

[22] Newsham, G. R., 1994. "Manual Control of Window Blinds and Electric Lighting: Implications for Comfort and Energy Consumption," in Indoor and Built Environment, (3) 135–144.

[23] Hopkinson, R.G., Bradley, R.C., 1965. "Glare from very large sources," in Journal of the Illuminating Engineering Society, 55 (5), 288–297.

[24] Sutter, Y., Dumortier, D., Fontoynont, M., 2001. "Prediction of recommended venetian blinds positions to satisfy visual comfort and performance conditions throughout Europe: a case study," in Proceedings of the 9th European Lighting Conference (Lux Europa), Reykjavik, Iceland, pp. 250–254.

[25] Bhavani, R.G., Khan, M.A., 2009. "An intelligent simulation model for blind position control in daylighting schemes in buildings," in Building Simulation, 2, 253-262.

[26] Carvajal, J., Chen, G., Ogmen, H., 2000. "Fuzzy PID controller: design performance evaluation and stability analysis," in Information Science, 123(3), 249–270.

[27] Chang, S., 2000. "A hybrid computational model for building systems control," PhD thesis. Pittsburgh, 2000, PA: Carnegie Mellon University.

[28] Chao, C.T., Teng, C.C., 1997. "A PD-like self-tuning fuzzy controller without steady state error," in Fuzzy Sets and Systems, 87(2), 141–154.

[29] GRAPHISOFT, (2015, January). [Online]. http://www.graphisoft.com/archicad/

[30] RELUX, (2015, January). [Online]. http://www.relux.biz

[31] Karizi, N., 2015. "An Adaptive Intelligent Integrated Lighting Control Approach for High-Performance Office Buildings," PhD thesis. Tempe, 2015, AZ: Arizona State University.

