INCORPORATING SIMULATION INTO BUILDING SYSTEMS CONTROL LOGIC

Ardeshir Mahdavi[1] and Bojana Spasojević[2]

[1]Department of Building Physics and Building Ecology
Vienna University of Technology
Vienna, Austria
[2]Department for Building and Environment
Danube University Krems
Krems, Austria

ABSTRACT

We present a prototypically implemented and empirically tested daylight-responsive lighting systems control in buildings that makes use of real-time sensing and lighting simulation. This system can control the position of window blinds and the status of the luminaires. It operates as follows: (1) At regular time intervals, the system considers a set of candidate control states for the subsequent time step; (2) These alternatives are then virtually enacted via lighting simulation. (3) The simulation results are compared and ranked according to the preferences (objective function) specified by the occupants and/or facility manager to identify the candidate control state with the most desirable performance.

KEYWORDS

Simulation, controls, lighting, sky scanning

INTRODUCTION

We present a prototypical implementation of an energy-efficient daylight-responsive lighting systems control in buildings that makes use of real-time sensing and lighting simulation. This system can control the position of window blinds and the status (on/off, dimming level) of the luminaires. It possesses an internal digital representation involving models of the room, the context (sky), and the occupancy. The room model entails information about room geometry, furniture, the location and size of windows, the physical properties of room components (such as reflectance and transmittance), as well as the position of virtual sensors that monitor pertinent performance parameters (such as illuminance levels or glare indices). The room model provides the basis of system's internal representation and is updated dynamically using an optically-based location-sensing system (Icoglu and Mahdavi 2005). The sky model is generated on a real-time basis using calibrated digital photography (Spasojević and Mahdavi 2005). Toward this end, the building's weather station is augmented with a digital camera with a fish-eye converter. From images, the sky luminance model is extracted in terms of distinct luminance values for all sky patches (256 in our current sky luminance distribution template).

In general, the need for a control action arises if a change occurs in one or more of the following:

a) Room configuration (e.g. position of furniture and partition walls);

b) Outdoor daylight (sky) conditions;

c) Occupancy (presence) and/or occupant settings (e.g., preferred illuminance levels, weights in the prescribed objective functions).

To provide and maintain the desired performance under such dynamically changing internal and external conditions, the proposed control system operates as follows (see also Mahdavi et al. 2005):

i) At regular time intervals, the system considers a set of candidate control states (i.e., a set of alternative combinations of the states of control devices such as position of blinds, dimming levels of luminaires) for the subsequent time step;

ii) These alternatives are then virtually enacted via lighting simulation. Thereby, the simulation application uses the aforementioned digital representation of the room, sky, and occupancy toward the prediction of the implications of these alternative control actions, resulting in values for corresponding performance indicators such as task illuminance levels;

iii) These results are compared and ranked according to the preferences (objective function) specified by the occupants and/or facility manager to identify the candidate control state with the most desirable performance;

iv) The system either autonomously instructs the pertinent control device-actuator(s) or informs the user to adjust the control state.

EXPERIMENT

We describe the elements of an actual implementation effort toward a simulation-assisted daylight-responsive illumination control system. As mentioned earlier, the controller must be equipped with dynamic models of room, context (sky), and occupancy. Ideally, all these three models should be self-updating. The manual updating scenario would involve a bottleneck, limiting thus the practical applicability of simulation-based building systems control (Mahdavi 2004).

Test space

As the test space, we selected an office in our Department building at the Vienna University of Technology (Figure 1). This office's two windows are equipped with automatically controllable blinds. Artificial illumination is provided by two free-standing luminaires.

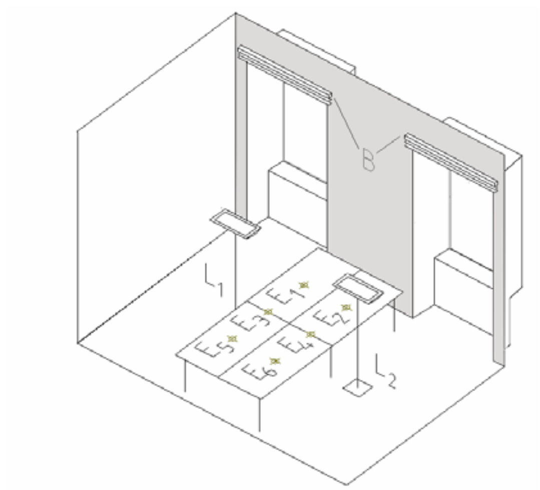

Figure 1 Illustration of the test space (L_1, L_2: Luminaires; B: Blind; E_1 to E_6: virtual illuminance sensors)

Room and occupancy model updating

The room is equipped with a location-sensing system (Icoglu and Mahdavi 2005) which automatically tracks changes in the position of moveable furniture elements (including the aforementioned luminaires). Presence of the people in the room (at the workstations) is monitored with occupancy sensors. User preferences (e.g. desirable illuminance levels, relative weights for objective function) can be communicated to the lighting control application via occupants' and facility manager's computers.

Updating the sky model

Digital images of the sky are continuously taken, analyzed and calibrated real-time to construct the sky model (sky luminance distribution pattern) for the simulation application. The calibration is necessary, as the camera is not a photometric device. It is possible, however, to derive reliable photometric data from properly calibrated digital images (Roy et al. 1998).

Our approach to calibration involves measuring global horizontal illuminance data simultaneously with digital sky imaging. The external illuminance data is obtained from the building's weather station. For each image, the initial estimate of the illuminance resulting from all sky patches on a horizontal surface can be compared to the measured illuminance. The digitally-derived luminance values of the sky patches can be corrected to account for the difference between measured and digitally estimated horizontal illuminance levels. Our previous studies suggest that, for overcast and intermediate sky conditions (without visible sun), this correction may be applied uniformly to all sky patches (Spasojević and Mahdavi 2005). The presence of direct sun, however, necessitates the application of a differential (non-uniform) correction to sky patches. Based on a set of iterations, we devised a simple method for the distribution of this difference across the sky model. Thereby, the difference between measured and calculated global illuminance was assigned to a sky patch where the sun position was detected (Mahdavi et al. 2006).

Control devices and control state space

Three control devices are considered (see Figure 1), namely the two luminaires (L_1, L_2) and the window blinds (B). In the control scenarios considered in this paper, the two blinds are controlled simultaneously. They can be moved up and down, and the slats can be set into horizontal and vertical positions. As a primary indicator of lighting performance, we considered the two mean illuminance levels E_{m1} and E_{m2} (see equations 1 and 2):

$$E_{m1} = (E_1 + E_3 + E_5)/3 \tag{1}$$

$$E_{m2} = (E_2 + E_4 + E_6)/3 \tag{2}$$

Since all these devices affect both E_{m1} and E_{m2}, a central control instance (C) is required to coordinate the three devices toward the most preferable control state (Figure 2).

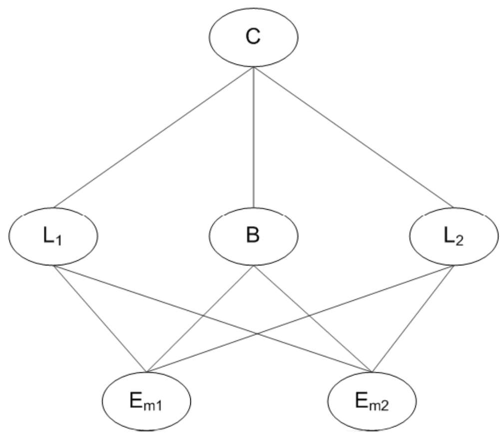

Figure 2 Control system scheme (L_1, L_2: Luminaires; B: Blind; C: Central control instance; E_{m1} and E_{m2}: mean workstation illuminance levels as per equations 1 and 2)

To each device, we allocate a discrete number of possible states. The luminaires can be in any of 10 possible dimming positions (see Table 1). The blinds can be in one of seven possible positions (Figure 3).

Table 1 Dimming steps and power output

Dimming step	1	2	3	4	5	6	7	8	9	10
Power output [%]	0	20	30	40	50	60	70	80	90	100

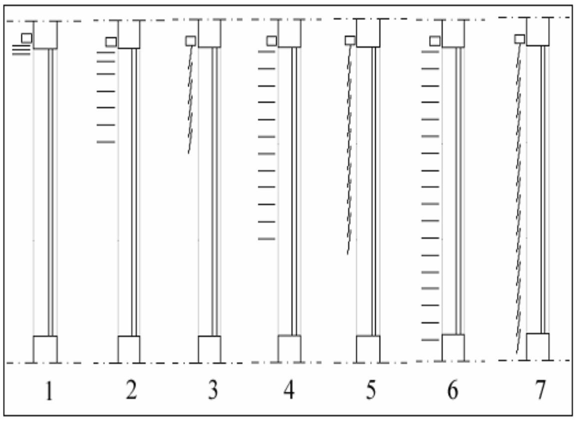

Figure 3 Blind states considered in the experiment

Control objective

Figure 2 illustrates the control system scheme, as relevant to the present test scenario. For these reference points, the simulation program calculates the expected illuminance values as a result of various control device states.

To demonstrate the working of the control system, we consider a simple control scenario involving three objectives:

i) Minimize the deviation of the prevailing values of E_{m1} and E_{m2} from the preferred (user-specified) illuminance levels. The concept of "useful daylight illuminance" (Nabil and Mardaljevic 2005) provided, in this case, the basis for corresponding preference function P_E (see Figure 4);

ii) Minimize electrical energy use. A possible formulation of the corresponding preference function P_L is shown in Figure 5. It is obtained by "inverting" the luminaires' dimming curve (luminous flux as a function of electrical energy input);

iii) Minimize cooling load. A possible corresponding preference function (P_C) for the latter objective is shown in Figure 6. The reasoning behind this formalization is to avoid unnecessary high illuminance levels as they typically involve heat gain, which is undesirable in a building in cooling mode.

The overall behavior of the control system is determined through a utility function (UF). The objective of the control process is to maximize UF. Equation 3 provides an example for such a utility function:

$$UF = w_{E1} \cdot P_{E1} + w_{E2} \cdot P_{E2} + w_C \cdot P_C + w_L \cdot P_L \qquad (3)$$

In this equation P_{E1}, P_{E2}, P_C and P_L are the preferences for illuminance levels (E_1 and E_2), cooling load, and electrical energy consumption (see the illustrative preference functions in Figures 4 to 6). The corresponding weights are represented by w_{E1}, w_{E2}, w_C and w_L.

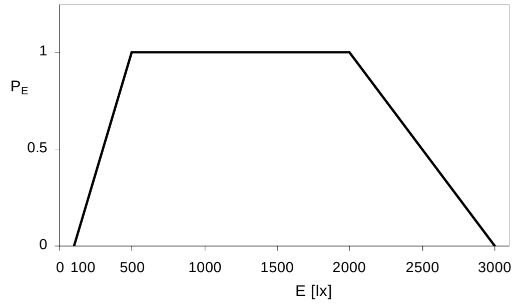

Figure 4: Preference function for task illuminance

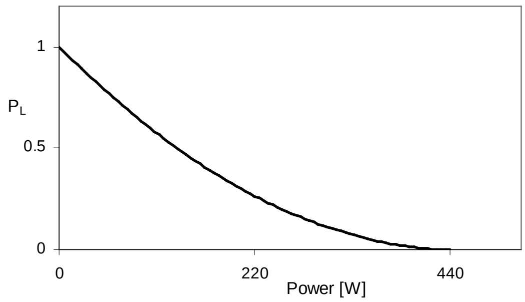

Figure 5: Preference function for electrical power

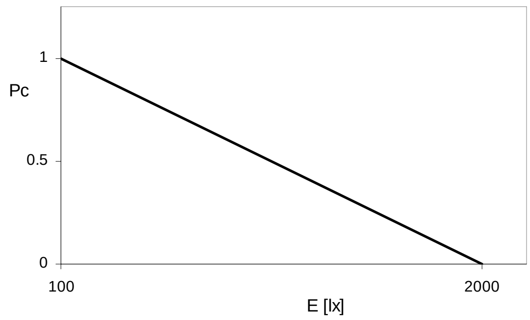

Figure 6: Preference function for cooling

Control process

Consider the following scenario involving a control cycle that is repeated regularly (in this case, every 15 minutes). At the time step t_i, the controller application C goes over a list of candidate states for each device (i.e., L_1, L_2, B) for the time step t_{i+1}. In the present case, four alternative options are considered for each device. These options are: the device's current position, the two neighboring states, and a fourth – randomly chosen – option from the rest of the device's control state space. Thus, the resulting overall option space encompasses a maximum of 64 distinctive control states.

This approach to the selection of the candidate control state space as a sub-region of the entire – theoretically possible – control state space may be characterized as a combination of greedy search and random jumps. It is intended to demonstrate one of the many possibilities to deal with very large search spaces in cases which involve numerous control devices and corresponding device states. From the computational point of view, an exhaustive coverage of such large search spaces may easily become infeasible for real-time applications. In the present case, an exhaustive search for the optimal control state at each time interval would involve 700 options (7 possible blinds positions and 2 luminaires with 10 dimming positions each). An overview of a number of approaches toward efficient operation of model-based control strategies (including search space reduction and accelerated computation via substitution of simulation engines with neural networks) can be found in Mahdavi 2004 and Chang and Mahdavi 2002.

To predict the illuminance levels E_{m1} and E_{m2} at the time t_{i+1} due to these options, the control application uses a combination of functions and simulation. The contribution of the two luminaires can be either calculated using measurement-based functions, or it can be simulated real-time. For the present scenario, which does not involve changes in the room configuration, the contribution of the two luminaires to the illuminance levels E_{m1} and E_{m2} are measured at the outset of the experiment for all dimming steps and stored as functions. However, if some characteristics of the test space would change (e.g., furniture and partitions arrangement, location of luminaires, surface properties), the updated room model could be provided to the lighting simulation application to re-compute illuminance contributions due to electrical lighting for each of luminaire dimming steps.

The contribution of the daylight to indoor illuminance is a function of prevailing sky conditions and the position of the blind and is predicted using numeric simulation. For this purpose, we integrated the lighting simulation program RADIANCE (Ward Larson and Shakespeare 2003) in the control system. Illuminance levels at E_{m1} and E_{m2} are computed at each time step for the aforementioned 64 device state configurations. Note that, currently, the sky model at time t_i is used to predict illuminance levels at time t_{i+1}. In future, we intend to use trend analysis algorithms to obtain a modified version of the sky model at time t_i for computations pertaining to time step t_{i+1}.

Given the obtained values of E_{m1} and E_{m2} as well as electrical energy use (derived based on the identified dimming state of the luminaires), UF values can be derived using Equation 3. Thus, at each time step, the control state with the maximum utility function can be identified for the subsequent time step.

RESULTS

To illustrate the working of the above-described control method, we documented the operation of the system in the course of fifteen days (fourteen days in May and one day in June 2005). In this case the control systems reassessment of the desirable control state occurs regularly every 15 minutes. The following figures illustrate the results of the test operation in terms of system recommendations and its performance. Given this paper's space limitation, figures 7 to 15 exemplify data only for one day, namely May 14^{th}, 2005.

Figure 7 shows the measured external global horizontal illuminance. To allow for an objective evaluation of controller's performance, we measured throughout the experiment the resulting illuminance levels at each time step not only for the system's recommended blind position, but also for the remaining 6 positions. In other words, we obtained measured E_{m1} and E_{m2} values for all possible blind positions at every time step.

To derive UF (see equation 3), the following weights were used: $w_{E1} = w_{E2} = 0.3$; $w_C = w_L = 0.2$. The resulting recommendations of the control system for dimming positions of the two luminaires and the blind position are shown in Figures 8 and 9 respectively. Figure 10 shows the control system's predictions of the illuminance levels E_{m1} and E_{m2} as a result of the control system's recommended shading and luminaire states. Figure 11 and 12 include comparisons of predicted and measured reference illuminance levels E_{m1} and E_{m2}. Figure 13 shows the electrical power requirement. Figure 14 shows the course of UF throughout the experiment.

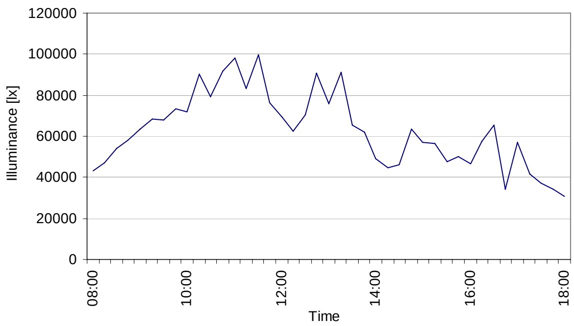

Figure 7 Prevailing external global horizontal illuminance levels in the course of one day

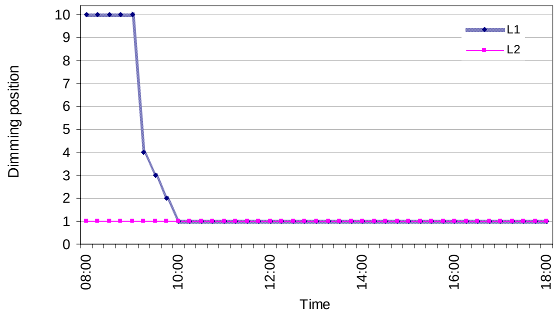

Figure 8 System's recommendations for the luminaires' dimming positions

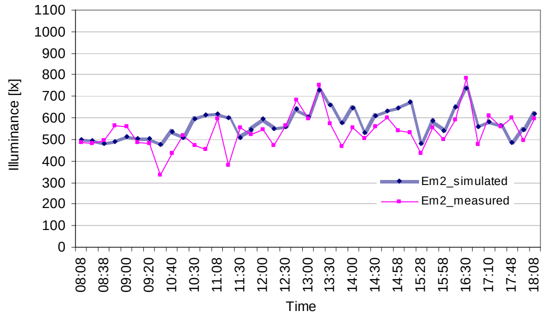

Figure 12 Predicted versus measured task illuminance level E_{m2}

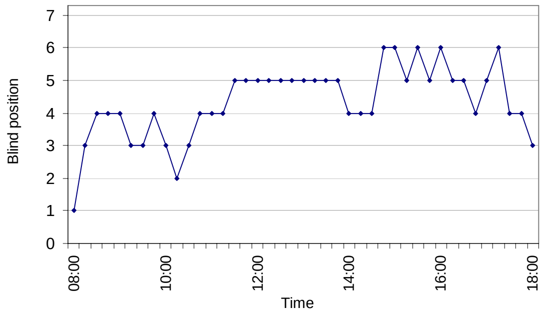

Figure 9 System's recommendations for the blind positions

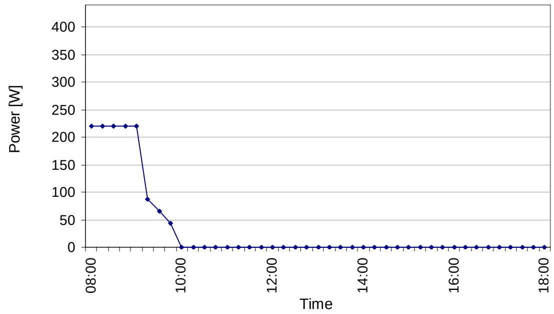

Figure 13 Electrical power requirement as the result of system's operation

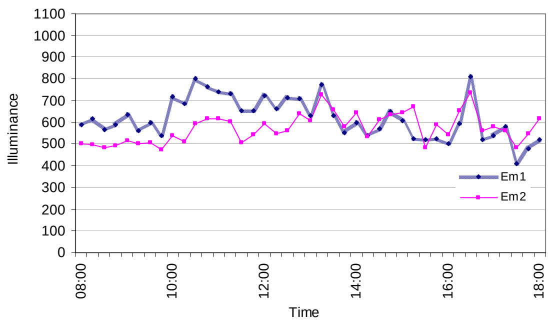

Figure 10 Task illuminance levels (E_{m1} and E_{m2}) as the result of system's operation

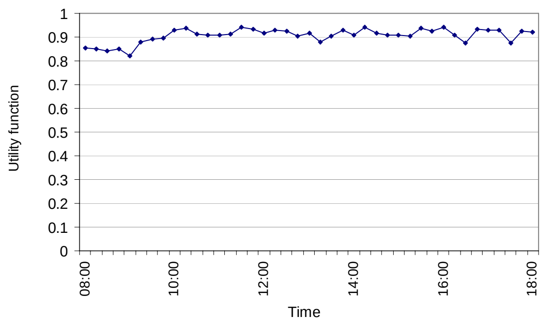

Figure 14 Utility function (UF) values resulting from system's operation

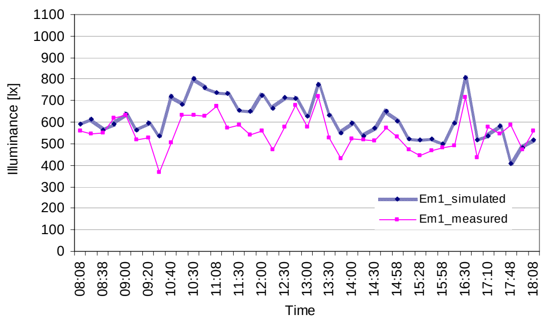

Figure 11 Predicted versus measured task illuminance level E_{m1}

Figures 11 and 12 display a relatively good match between control systems predictions and actually achieved illuminance levels in the test room for the selected day. A more comprehensive evaluation of the system's performance over the entire duration of the experiment requires, however, a more in-depth analysis of the respective data. As mentioned before, the controller application considers at each time interval (i.e. every 15 minutes) 64 combinations of the control device states. An exhaustive search for the optimal control state at each time interval would involve, however, 700 options (7 possible blinds positions and 2 luminaires with 10 dimming positions each). Since we obtained measured illuminance levels (E_{m1}, E_{m2}) for every interval and every possible blind position over the test period, we can objectively rank the performance of all 700 configurations at each time interval based on their corresponding utility function values (note that the contributions of the luminaires to E_{m1} and E_{m2} levels showed experimentally to be largely independent of blind positions and were thus computed here solely based on the respective dimming positions). This availability of measured data for the entire search space at each time interval allows for an objective evaluation of the performance of the control method.

Thus, we posed the following question: What was the objective rank of the control system's recommended control state amongst all 700 possible control states? Figure 15 illustrates the results in terms of a relative frequency graph (for a total of 590 intervals over the test period). It suggests that for approximately 74% of all intervals, the control state recommended by the controller was amongst the top 5% of all possible options. In more than 80% of the time, the controller's recommendation was amongst the top 10% list of objectively ranked control states. Only less than 6% of the controller's recommendations fall outside the top 25% control options. We consider this level of performance quite promising, given the large list of potential sources of error in the processes involved (e.g., sky scanning, image calibration, lighting simulation, indoor measurements).

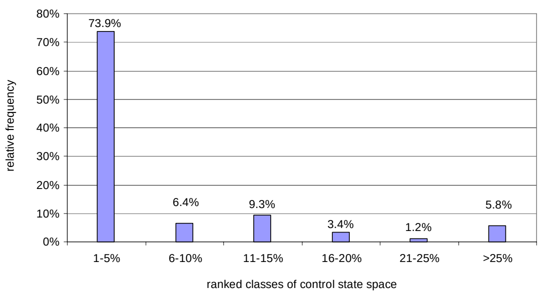

Figure 15 Ranking of the system's recommendation amongst all possible control options over the experiment period of 15 days, expressed in terms of relative frequency distribution

CONCLUSION

We described the architecture and a prototypical implementation of a simulation-assisted illumination systems control in buildings. Experiences to date with the performance of the simulation-based controller are promising. Developed to its full potential, the proposed system could offer a number of advantages:

i) Given the role of virtual sensors, the reliance on physical sensors for performance monitoring could be reduced, resulting in a more efficient sensory infrastructure;

ii) Physical sensors can typically monitor only limited kinds of performance indicators (e.g., illuminance in case of lighting controls). Using virtual sensors, more elaborate performance indicators (such as glare indices) could be considered;

iii) In a model-based control system, changes in rooms (e.g., remodeling, retrofit) could be digitally reflected in the building model, thus reducing the need for extensive reconfigurations of physical sensory components;

iv) In model-based controls integration of multiple systems (heating, cooling, ventilation, lighting, etc.) could be achieved in a more transparent fashion, resulting in comprehensive performance specification and monitoring.

Work is under way to extend the methodology towards the integrated control of buildings lighting and thermal systems. Moreover, the scalability of the system and its self-updating capability is to be improved via further implementation efforts involving larger objects and multiple environmental systems.

ACKNOWLEDGMENT

The research presented in this paper has been carried out at the Department of Building Physics and Building Ecology of Vienna University of Technology. It was supported, in part, by grants from the Austrian Science Foundation (FWF), project numbers P15998-N07 and L219-N07. Members of the research team include, besides the authors, K. Brunner, S. Dervishi, O. Icoglu, S. Leal, J. Lechleitner, S. Metzger, and G. Suter.

REFERENCES

Chang S. and Mahdavi A. 2002. “A hybrid system for daylight responsive lighting control”, Journal of the Illuminating Engineering Society, Vol 31, pp 147 - 157.

Icoglu O. and Mahdavi A. 2005. “A vision-based sensing system for sentient building models”, Proceedings of CIB W78 22nd Conference on Information Technology in Construction, ISBN: 3-86005-478-3, CIB Publication No. 304, p. 559-566.

Mahdavi A. 2004. “Self-organizing models for sentient buildings”, Advanced Building Simulation, Spon Press, ISBN 0-415-32122-9, pp 159-188.

Mahdavi A, Spasojević B, Brunner K.A. 2005. “Elements of a simulation-assisted daylight-responsive illumination systems control in buildings”, Proceedings of the 9th International Building Performance Simulation Association Conference, Montreal, Canada, Vol. 2, pp. 693-699.

Mahdavi A, Tsiopoulou C, and Spasojević B. 2006. "Generation of detailed sky luminance maps via calibrated digital imaging" in BauSIM2006 (IBPSA) "Energieeffizienz von Gebäuden und Behaglichkeit in Räumen", R. Koenigsdorff, C.

van Treeck (ed.), Eigenverlag TU München, München, ISBN 3-00-019823-7, pp 135 - 137.

Nabil A. and Mardaljevic J. 2005. "Useful daylight illuminance: a new paradigm for assessing daylight in buildings", Lighting Research Technology, Vol 37, pp 41-57.

Roy G.G, Hayman S, Julian W. 1998. "Sky Modeling from Digital Imagery", ARC Project A89530177, Final Report. The University of Sydney, Murdoch University, Australia, 72 pages.

Spasojević B. and Mahdavi A. 2005. "Sky luminance mapping for computational daylight modeling", Proceedings of the 9th international Building Performance Simulation Association Conference, Montreal, Canada, Vol 3, pp 1163-1169.

Ward Larson G. and Shakespeare R. 2003. "Rendering with Radiance. The Art and Science of Lighting Visualization", Revised Edition, Space and Davis, CA, USA.