SIMULATION-BASED INTEGRATION OF CONTEXTUAL FORCES INTO BUILDING SYSTEMS CONTROL

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ABSTRACT

The research on provision of computational support for building performance analysis has traditionally concentrated on the building design phase. However, computational modeling can also effectively apply to the building operation phase. To explore this potential, we consider in this paper simulation-assisted control strategies to integrate contextual forces (specifically daylight) into building control systems.

BACKGROUND

Traditionally, building control systems have operated based on a homeostatic short-term feed back mechanism. For example, thermostatic control of HVAC components involves typical operations (on/off, change in volume and/or temperature of heating/cooling media, etc.) that are essentially guided by temperature sensing in space. More recently, building control systems have become increasingly sophisticated. One of the approaches has been to utilize various methods and tools (including neural nets) to accurately capture the building's dynamic characteristics so as to provide a more reliable basis for the control of its behavior (Curtis 1996, Mistry and Nair 1993, Osman et al. 1996). In this scenario, control options can be improved ("optimized"), as their past impact on the building's dynamic behavior is reflected in the collected information by the sensing system. In this paper we explore how the above intention, namely to capture building's dynamic behavior toward enhanced control strategies, can be supported using advanced computational performance simulation routines. Specifically, we propose the use of generate-and-test as well as bi-directional inference methods to derive preferable control schemes and required values for control variables based on parametric and iterative simulations (Mahdavi 1997).

In order to realize this idea, a conventional building automation system must be supplemented with a multi-aspect virtual model of the building that runs parallel to the building's actual operation. While the real building can "only" react to the actual contextual conditions (e.g. local sky luminance distribution patterns), occupancy interventions, and building control operations, the simulation-based virtual model allows for additional operations: *i)* the virtual model can move backward in time so as to analyze the building's past behavior and/or to calibrate the program toward improved predictive potency; *ii)* the virtual model can move forward in time so as to predict the building's response to alternative control scenarios.

Beyond enhancing the effectiveness of dynamic control systems, the suggested approach may yield additional benefits. These include: *i)* calibration of simulation tools for long-term design and modification feed back; *ii)* prediction of the effects of changes to building hardware and its control systems; *iii)* beta-testing of building control system hardware using simulated data from the virtual building; *iv)* pre-training machine learning systems such as neural networks prior to their field utilization using simulations of building behavior; *v)* re-training of machine learning systems to account for the effects of abrupt modifications to building characteristics (e.g. renovation) using simulation data; *vi)* reduction of the number of sensing units necessary for capturing building's real time operational status.

In this paper, we specifically demonstrate how a lighting simulation tool can be applied to predict light levels as the necessary input information for algorithms towards integrated control of buildings' lighting and energy systems.

APPROACHES

A critical task toward realization of a simulation-assisted building control system lies in the development of a strategy to create a well-defined set of control options that, together with the projected contextual conditions, serve as the basis for comparative and/or parametric simulation runs. The results of these simulations enable the control system to anticipate the impact of control option choice on the values of performance variables. While there may be numerous methods to derive at a structured set of such control options, two principal approaches are briefly described below:

The Generate-and-Test Method (GAT). This method involves the rule-based generation of a finite number of discrete control options. Such options may involve, for example, various positions of a movable external shading device, position of operable windows, or various on/off timing schemes for intermittent heating/cooling. These schemes are then evaluated and ranked (possibly in view of multiple criteria involving power consumption, cost, emissions, visual and thermal comfort, etc.) based on the results of multiple simulation runs.

The Bi-directional Inference Method (BDI). This method involves the explicit definition of control and performance variables (Mahdavi 1993). An example of a control variable would be the position of a moveable external shading and/or light-redirection device, or the deviation of heating/cooling set-point temperature from the space target temperature. Examples of a performance variable are the maintained average illuminance on a task surface, illuminance or luminance distribution uniformity, annual building energy need, the average cumulative deviation of the maintained space temperature from the set-point temperature, or the average cumulative PPD (predicted percentage of thermally dissatisfied people) in a space. Starting from an initial operational state, the bi-directional inference facilitates the derivation of required changes in the control variable(s) based on desired changes in the performance variable(s). This derivation can be accomplished *via* the investigative projection technique (Mahdavi and Berberidou 1995, 1994).

THE LIGHTING STUDIES

Introduction

In this section, we present illustrative case studies toward exploring the potential for model-based integration of daylighting and electrical lighting consideration in the operation of the environmental control systems of the Intelligent Workplace (IW).

The Test-bed

The studies were performed in the Intelligent Workplace (IW). This is a recently established laboratory at the Carnegie Mellon University campus for demonstration and hands-on study of advanced building systems/technologies and their integration. The western section of a south bay in IW is dedicated to lighting studies (cp. Figure 1). This area is partitioned from the rest of IW using white-colored partitions. About 60% of the external wall of the space consists of glazing. The facade system includes a set of three parallel external moveable louvers which can be used for shading purposes and – to a certain degree – for light redirection purposes. These motorized louvers can be rotated anti-clockwise from a vertical position (P1: 0^o in Figure 1) up to an angle of 105^o (P2 in Figure 1). An array of 12 illuminance sensors is located in the central axis of this space at a height of about 0.8 m above the floor. Illuminance measurements have been performed intermittently in this test space since December 1997. Outdoor light conditions are monitored using a total of 11 illuminance and irradiance sensors that are installed on the daylight monitoring station on the roof of the IW. In terms of electrical lighting, the test space can be illuminated using four luminaires as are depicted in Figure 1. These are indirect-direct luminaires with an asymmetric intensity distribution.

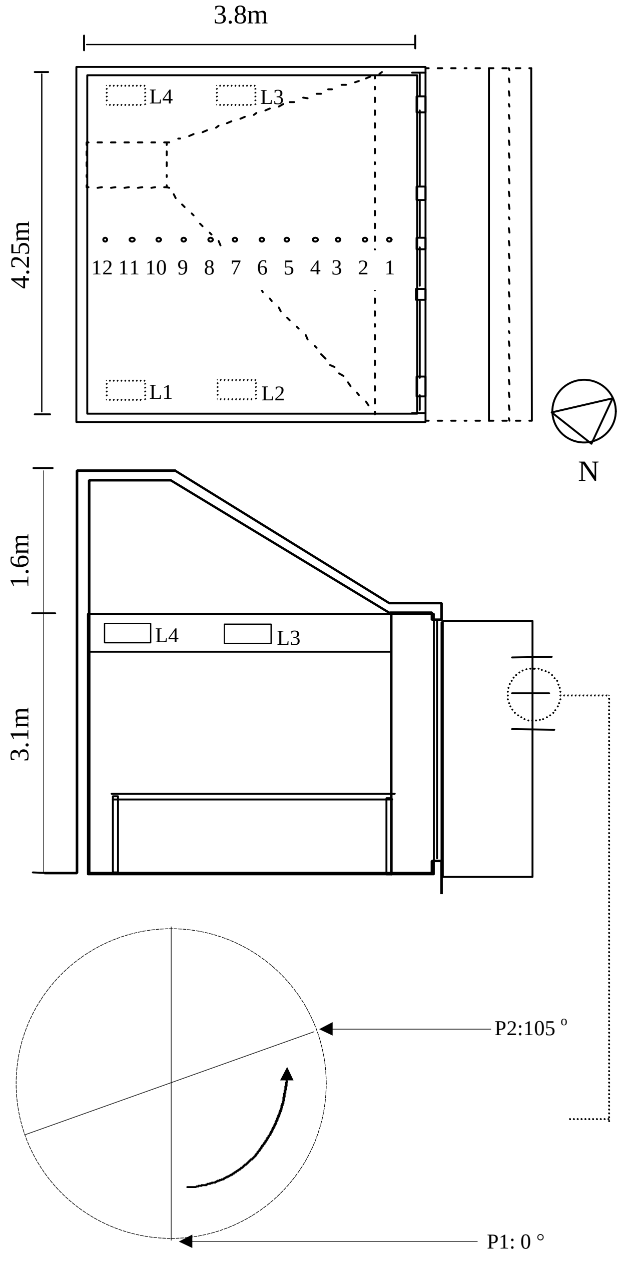

Figure 1. Daylight test bed at IW with the sensor, luminaire, and louver arrangement.

The Modeling Tool

The program LUMINA (Mahdavi and Pal 1996) is used for the prediction of light levels in the test space. LUMINA utilizes the three component procedure (i.e. the direct, the externally reflected, and the internally reflected component), to obtain the resultant illuminance distribution in buildings. The direct component is computed by numerical integration of the contributions from all of those discretized patches of the sky dome that are "visible" as viewed from reference receiver points in the space. Either computed or measured irradiance values (both global horizontal and diffuse horizontal irradiance) can be used to generate the sky luminance distribution according to the Perez model (Perez et al. 1993). External obstruction (i.e. light redirection louvers) are treated by the projection of their outline from each reference point on to the sky dome and the replacement of the relative luminance values of the occupied sky patches with those of the obstruction. A radiosity-based approach is adopted for computing the internally reflected component. The results generated by LUMINA have been compared with measurements in different rooms (Mahdavi et al. 1998).

A simple model-based daylight control scenario

As an initial feasibility test of the proposed model-based control approach, we consider the problem of automatically determining the "optimal" louver position among four discrete louver positions, namely 0^o (vertical), 30^o, 60^o, and 90^o (horizontal), toward fulfillment of daylight-related objectives. Consider two illustrative objective functions. The first function aims at minimizing the deviation of the average (daylight-based) illuminance level E_m in the test space from a user-defined target illuminance level E_t (say 500 lx):

$$Minimize(\mid E_t - E_m \mid) \qquad Eq. 1$$

The second objective function aims at maximizing the uniformity of the illuminance distribution in the test space as per the following definition (cp. Mahdavi et al. 1998, 1995):

$$Maximize\ U, \quad where\ \ U = E_m \, . \, (E_m + E_{sd})^{-1} \qquad Eq. 2$$

Here E_m and E_{sd} are the mean and standard deviation of the illuminance levels measured at various locations in the test space.

The model-based louver control scenario in this case follows the GAT approach described above. At time interval t_i, the simulation tool predicts the expected illuminance levels in the space for the time interval t_{i+1} (test space geometry and photometric properties, as well as the outdoor measurements at time interval t_i are used as model input) for the four candidate louver positions. Based on the predefined objective functions, the simulation tool identifies that louver position which is likely to maximize the light distribution uniformity or to minimize the deviation of average illuminance from the target value. To evaluate the performance of this model-based control reasoning, we measured the resulting illuminance levels for the four louver positions and for all selected time intervals during the test period, including a total of 28 time instances. These 28 time instances were selected based on the quality of the measured data and the availability of the measured data for all four louver positions in a particular hour. Besides the classical checks for the quality of measured data, the accuracy of the sky luminance model was also taken into account in the selection of the time instances.

To numerically evaluate the performance of this model-based control approach via a "control quality index", we ranked the resulting (measured) average illuminance and the uniformity according to the degree to which they fulfilled the objective functions. We assigned 100 points to the instances when the model-based recommendation matched the position empirically found to be the best. In those cases where the recommendation was furthest from the optimal position, 0 was assigned. Intermediate cases were evaluated as per the figure 2.

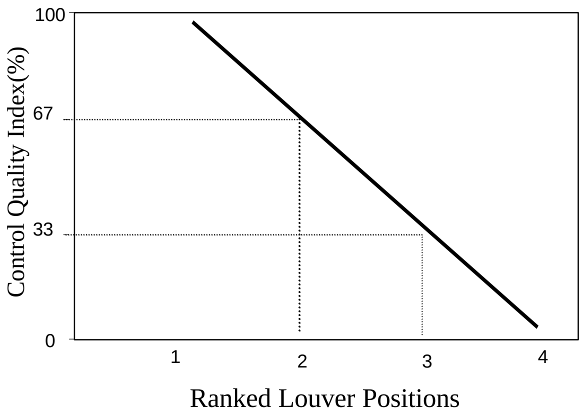

Figure 2. Mapping between ranked louver positions and control quality index

These results (Tables 1 and 2) demonstrate an encouraging potential for the feasibility of the proposed approach. The better performance in the case of the uniformity indicator is due to the "relative" nature of this indicator, which, in contrast to the illuminance, is less affected by the absolute errors in the predictions of the simulation model.

Table 1. Evaluation of daylight control experiment for the test period

	Illuminance	Uniformity
Control Quality Index	73.8	98.9

Table 2. Performance of the model-based daylight control strategy expressed as the percentage of all instances with a specific control quality index for both uniformity and illuminance

Control Quality Index	Percentage of total instances	
	Uniformity	Illuminance
100	96	61
67	4	11
33	-	17
0	-	11

Daylight-based dimming of the electrical light

The previous section illustrated the strategy to select a preferable louver position toward improving the daylight availability and distribution in the test space. In this section, we consider the problem of daylight-based dimming of the electrical lights via a model-based control strategy. The objective of this control strategy is to arrive at a configuration of daylighting and electrical lighting settings that would accommodate the desired value of one or more performance variables. As indicated before, the daylighting settings (the values of the daylighting control variables) are expressed in terms of the position of the external light re-direction louvers. The electrical lighting settings (the values of the electrical lighting control variables) are expressed in terms of the dimming level of the luminaires in the space. For example, each of the four luminaires in the test space can be at one of ten possible power level states.

An attractive feature of a model-based control strategy is the diversity of the performance variables that can be considered. Furthermore, these performance variables need not be limited to strictly visual criteria (such as illuminance levels), but also address multiple performance criteria (such as energy use and thermal comfort). Currently, the light modeling tool predicts the values of the following performance variables: average illuminance on any actual or virtual plane in the space, uniformity of illuminance distribution on any plane in the space (U_E, cp. Mahdavi 1998), Glare due to daylight (DGI, cp. Hopkinson 1971), Glare due to electrical light (CGI, cp. Einhorn 1979), solar gain (Q), and electrical power consumption (P). The glare on the CRT (G_{CRT}) is also considered and is taken as the ratio of the luminance of the screen to the background luminance. User's preference for the desired attributes of such performance variables may be expressed to the control system by graphic means. Illustrative examples of preference functions for the performance variable attributes are given in figure 3.

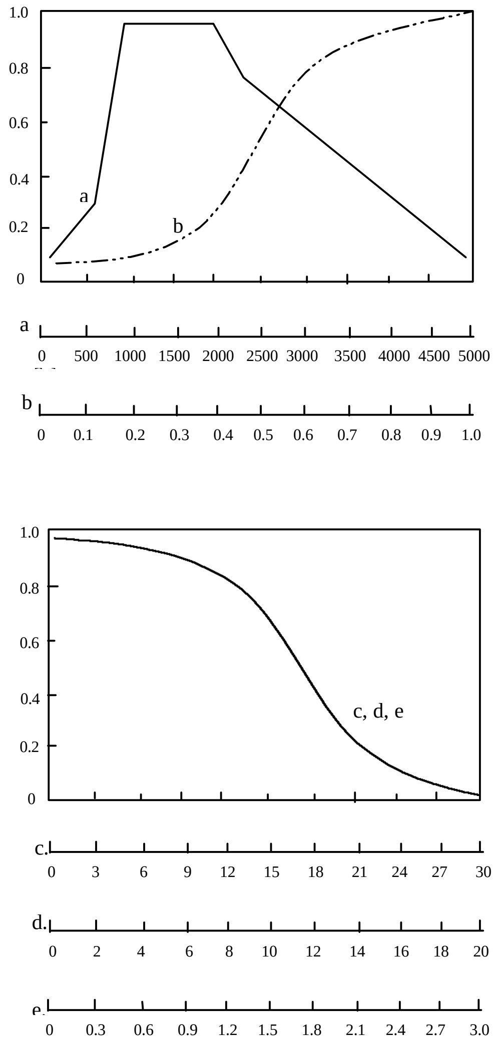

Figure 3. Illustrative preference functions for selected performance variable attributes (a: Average illuminance in lx. b: Uniformity c: DGI d: CGI e: G_{CRT})

These preference functions provide the basis for the derivation of objective functions toward the evaluation of control options. An objective function may be based on a single performance indicator, or on a weighted aggregate of two or more performance indicators. An example of such a function U is given in equation 3. Needless to say, such weightings involve subjective and contextual considerations and may not be standardized. Rather, preference functions and the weighting mechanism are intended to provide the user of the system with an explorative environment for the study of the relative implications of the impact of various performance indicators in view of preferable control strategies.

Maximize U,

Where

$$U = w_{Em} \cdot P_{Em} + w_U \cdot P_U + w_{DGI} \cdot P_{DGI} + w_{CGI} \cdot P_{CGI} + w_{GCRT} \cdot P_{GCRT} + w_Q \cdot P_Q + w_P \cdot P_P \qquad \textit{Eq. 3}$$

w_{Em} = *Weight for average illuminance*
w_U = *Weight for uniformity*
w_{DGI} = *Weight for DGI*
w_{CGI} = *Weight for CGI*
w_{GCRT} = *Weight for glare on CRT*
w_Q = *Weight for solar gain*
w_P = *Weight for power consumption*
P_{Em} = *Preference index for average illuminance*
P_U = *Preference index for uniformity*
P_{DGI} = *Preference index for DGI*
P_{CGI} = *Preference index for CGI*
P_{GCRT} = *Preference index for glare on CRT*
P_Q = *Preference index for solar gain*
P_p = *Preference index for power consumption*

To generate control schemes, two options have been implemented.

First Control Scenario: The first option involves the simultaneous assessment of various combinations of the values of the daylighting and electrical lighting control variables. This strategy requires, due to the potentially unmanageable size of the resulting control state space, a reduction of the possible number of states. This is achieved, in the present case, by dimming the four space luminaires in terms of two coupled pairs. Moreover, at each time step, only three dimming states are considered for each pair, namely the status quo, the immediate higher state, and the immediate lower state. Let L be the number of luminaires (or luminaire groups) and D the number of dimming states considered for each luminaire. The total number of possible combinations n is then given by equation 4.

$$n = D^L \qquad \textit{Eq. 4}$$

For example, if we assume that L = 2 and D = 3, nine possible electrical lighting control states will result. Assuming three daylight control states (three louver positions), a total of 27 simulation runs would be necessary at each time step.

The concurrent assessment of daylight and electrical light options allow for the real-time incorporation of changes in room and aperture configuration, as well as flexibility in the definition of the relevant parameter for performance variables (such as the position of observer, etc.). However, the limitation of possible dimming options at each time step to the immediate adjacent positions may result in the inability of the search process to transcend local minima and/or maxima.

Second Control Scenario: The second implemented control option involves a sequential approach. First, the preferable louver position is derived based on the methodology described in the previous section. The result is then combined with a preprocessed matrix of various luminaire power levels. This matrix can be computed ahead of the real-time control operation based on the assumption that the incident electrically generated light at any point in the space may be calculated by the addition of individual contributions of each luminaire. This matrix need only be re-generated if there is a change either in the configuration of interior space or in the number, type, or position of the luminaires. The advantage of this approach is the possibility to extend the searchable area in the control state space. The typical time interval between two actuation events (e.g. change of louver position and/or change of the dimming level of a luminaire) is generally sufficient to allow for the simulation of a larger number of louver positions. Combining the results of the selected louver settings with the matrix of electrical lighting states does not require real-time simulation and is thus highly efficient from the view point of computational time. As a result, a larger number of dimming options may be considered and evaluated toward the selection of the preferable combined daylighting and electrical lighting settings.

A Demonstrative Example: An actual lighting control experiment has been performed at IW to illustrate the latter scenario. The following steps were taken:

1. Outdoor light conditions, the current louver position, luminaire power levels, and the current time were identified (Table 3).

2. Simulations were done for each of the eight louver positions based on the input data. Calculated performance indices for each louver position were further processed to generate the utility value (U) based on the defined preference indices and corresponding weights (Table 4), then the louver position that maximizes utility was selected (105 degrees).

3. Another round of simulations for the chosen louver position was performed to generate intermediate data enabling glare indices calculations when the selected louver position is combined with various sets of luminaire power level configurations. Some of those glare component parameters being calculated (daylight component) were background luminance, luminance of each window patch for DGI calculation, direct and indirect illuminance on the vertical surface of the eye for CGI calculation, as well as the luminance on the computer screen for G_{CRT} calculation.

4. For each luminaire, 5 steps of candidate power levels (with two steps below and two steps above the current power level) were identified. Then, from the lookup table, all 625 (i.e., 5^4) such combinations were scanned to identify the corresponding illuminance distribution and power consumption along with the glare component parameters (electrical light component) for CGI and G_{CRT} calculations.

5. Final values of glare indices were generated by synthetically combining the glare component parameters - both daylight component and electrical light component - calculated in step 3 and 4 for each louver-luminaire set. This is possible since the pre-calculated glare component parameters are additive in generating the final glare indices. The louver position and luminaire power levels for the preferable control state were identified by selecting the one option out of all 625 sets of louver-luminaire control options which maximizes the utility value (Table 5). Finally, analog control signals were sent to the louver controller and luminaire ballasts to update the control state.

Table 3. Initial state as inputs to simulation (L1, L2, etc. are current luminaire input power levels)

Year	Mth.	Day	Hr.	I_{global} [W/m^2]	$I_{diffuse}$ [W/m^2]	E_{global} [lx]	θ_n (lvr) [degree]	L1 [%]	L2 [%]	L3 [%]	L4 [%]
1998	5	12	15	343	277	39,582	30	50	40	40	50

Table 4. Performance indices and the utility values for each optional louver position (weight factors : w_{Em}= 0.45, w_{UE} = 0.2, w_{DGI} = 0.05, w_{CGI} = 0.03, w_{GCRT} = 0.1, w_Q = 0.12, and w_P = 0.05)

θ_{n+1} (lvr) [degree]	E_m [lx]	U_E	DGI	CGI	G_{CRT}	Q [W]	P [W]	*U*
0	291	0.849	4.31	0	0.744	4.29	0	0.623
15	249	0.856	4.14	0	0.752	3.84	0	0.593
30	251	0.855	4.28	0	0.749	3.59	0	0.594
45	263	0.870	4.39	0	0.742	3.54	0	0.606
60	280	0.859	5.56	0	0.739	3.46	0	0.617
75	310	0.430	5.81	0	0.731	3.57	0	0.665
90	331	0.840	5.98	0	0.707	3.90	0	0.665
105	337	0.841	6.00	0	0.747	4.47	0	0.670

Table 5. Selected control option with the corresponding performance indices and utility

θ_{n+1} (lvr) [degree]	L1 [%]	L2 [%]	L3 [%]	L4 [%]	E_m [lx]	U_E	DGI	CGI	G_{CRT}	Q [W]	P [W]	*U*
105	30	20	20	30	698	0.913	3.93	0	0.561	4.47	58	0.917

CONCLUDING REMARKS

We have illustrated how computational modeling may be applied to enrich the informational repertoire of systems control operations for lighting. Beyond mere reactive operations based on environmental sensing, model-based building control allows for proactive evaluation of a richer set of control options. A highly attractive feature of this model-based strategy lies in its potential for a transparent and high-level integration of multiple control agenda. Thus, complex control strategies may be formulated to simultaneously address economical and ecological considerations in providing appropriate levels of building performance.

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