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The technology of sentient buildings

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Invited Paper

Abstract:
Contemporary buildings are expected to meet an extensive set of requirements. They must be conceived, constructed, and operated in a manner that is functionally adequate, environmentally sustainable, occupationally desirable, and economically feasible. Moreover, buildings must increasingly accommodate different user groups, a varied set of activities, and multiple indoor environmental control systems. Accordingly, the optimization of the overall performance of buildings represents a non-trivial task and requires effective and well-tuned technologies. Specifically, the configuration and calibration of environmental control systems in buildings has been shown to be difficult and prone to failures, particularly in large-scale facilities. This paper explores the notion of sentient building technologies and its potential to address certain aspects of indoor environmental control problems in buildings. Specifically, it describes an approach to the integration of simulation-based predictive models in the decision-making repertoire of building control systems.

1. Motivation and Background

Modern buildings are expected to provide optimal indoor conditions for the organizations and people they house. Moreover, they must achieve this in an environmentally sensitive and economically feasible manner. A large number of buildings do not meet such expectations. In fact, the configuration and tuning of the environmental control systems has been repeatedly shown to be a difficult task, particularly in large buildings. A number of reasons may be listed for this circumstance. Both building fabric and building systems can suffer from design flaws due to deficiencies in integration. Often, there is a lack of coordination between the architectural design of building mass, envelope, topology, and orientation on one side and the choice and configuration of building systems on the other side. Environmental and energy systems rarely represent the main concern of the primary designers of buildings. As a result, the detailed design of environmental systems for indoor climate control is frequently referred to experts at later stages of design. Asides from shortcomings in the design and engineering process, there are further problems inherent in the nature of buildings as artifacts. Buildings are complex, in the sense that they must encompass many domains, systems, functions, conditions, and activities. Ideally, multiple systems for heating, cooling, ventilation, air-conditioning, lighting, shading, and security should be integrated and operated in a harmonious fashion. This should be done under changing outdoor (weather) and indoor (occupancy, activity patterns) conditions. Moreover, the design solution for these requirements is typically unique for each new building: every new building instance involves a set of new and unique features (location, site, climate, functions, etc.) requiring customized solutions. A configuration of system solutions that is appropriate for one building does not necessarily work for another one.

Given this context, it is not surprising that the optimization of the state of buildings as complex systems represents a non-trivial challenge. Technically speaking, there is not a simple mapping function from the desired state space of performance conditions in a building back to the state space of multiple building control devices. Classical control rules and algorithms (thermostatic routines, PID functions) do work properly, but only if the control situation is not overtly complex. Otherwise, much postconstruction fine-tuning is required, resulting in considerable time and cost expenditures. This may explain the rather suboptimal performance of environmental systems in many recently completed highrise buildings, even after protracted systems calibration processes.

As in some other areas in which the system complexity is a defining attribute, alternatives to classical (explicit) control methods have been considered also in building industry. Examples are the application of distributed and agent-based control approaches, neural networks and machine learning, and selfadaptive algorithms (see, for example, Guillemin and Morel 2002, Mozer et al. 1997). The specific approach presented in this paper aims at the embodiment of sensor-supported self-representational features in building control logic and the simulation-based use of such representation toward anticipatory evaluation of the consequences of alternative control options. The term "sentient buildings" has been coined to refer to this capacity of self-representation and self-organization (Mahdavi 2004a).

2. Elements of Building Sentience

2.1. Overview

A sentient building (see Figure 1) is defined here as one that:

a- possess a "self-representation", i.e. a representation of its own context, structure, components, systems, and occupancy;
b- can dynamically update (actualize) this self-representation via a network of sensors and supporting computational applications (data-mining, geometric reasoning, etc.);
c- can use this continuously updated self-representation toward regulatory operations (e.g. indoor environmental control, facility management).

Specifically, the executive control application of a sentient building can use simulation to regularly predict the future state of the building as a consequence of alternative control actions. The results of such simulations may be compared on the basis of applicable objective functions to dynamically identify the preferable state of environmental control devices of a building.

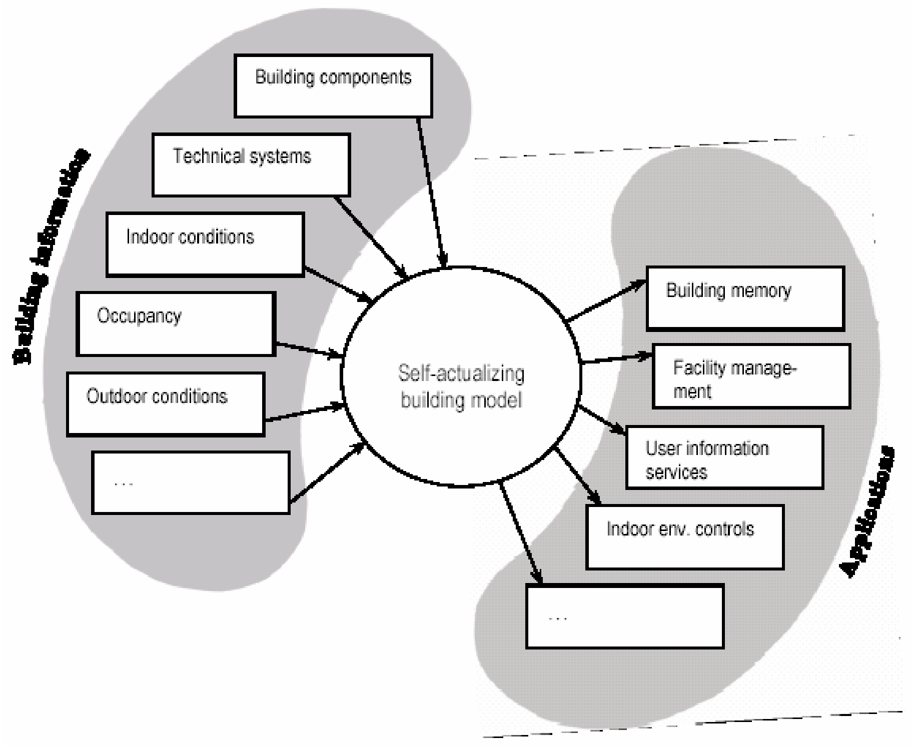


Figure 1: *The "sentient building" scheme*

2.2. Self representation
Much work has been done to develop standard representations (product models) of buildings, involving both semantics (material and component properties) and geometry (IAI 2005, Mahdavi et al. 2002). In principle, a sentient building can make use of schemata encapsulated in such common models as the basis of its representational core. However, next to the representation of the rather static constitutive ingredients of a buildings as considered in common product models, processes (e.g. dynamic changes in the occupancy and in the state of building systems) must be captured in the underlying selfrepresentation of a sentient building (Mahdavi 2004a). Moreover, to be scalable, such combined product-process models should be generated based on transparent and ideally automated computational routines (Mahdavi 2004b).

2.3. Updating the representation
To support the operational processes in sentient buildings, the self-representation needs to be continuously, dynamically, and autonomously updated. This requires a comprehensive sensory infrastructure, which must provide the representation with a real-time flow of information with respect to the changes in the outdoor conditions, indoor climate, occupancy, user actions, device states, room configurations, and object locations (Mahdavi 2004a).

2.4. Using the representation
A continuously updated valid and comprehensive representation can effectively support management, organizational, and control operations in a sentient building. Specifically, such a representation can be used to predict (via building simulation) the future state of a building's indoor climate as a consequence of various control options. Thus, alternative control actions

may be regularly evaluated to identify the most desirable one given an applicable and up-to-date set of objective functions (Mahdavi 2001).

3. A demonstrative implementation

3.1. The basic scenario

To test the sentient buildings idea presented in the previous section, a demonstrative implementation of a simulation-supported building systems control scheme was carried out. Thereby, the following scenario was considered. In a typical double-occupancy office space (see Figures 2 and 3), lighting control systems (electrical lighting, daylight control via window shades) are to be operated based on a simulation-assisted methodology. The objective of the control task is to: *i)* maintain the illuminance levels at the two workstations in this office within a user-specified range; *ii)* minimize the electrical energy consumption for the operation of luminaires. The control decision making process is as follows. At regular time intervals, a number of alternatives for the control device states (i.e. the position of shades and the dimming level of the luminaires) are considered. Using a light simulation application, these alternative states are simulated for the subsequent time interval. The results (illuminance levels at the two reference points in the offices as well as the electrical energy use for luminaires) are evaluated to identify the configuration of device states that yields the most desirable attribute for the performance parameters considered. This configuration of the device states thus identified, can then be realized, either automatically (via instructions to the device actuator), or by the user.

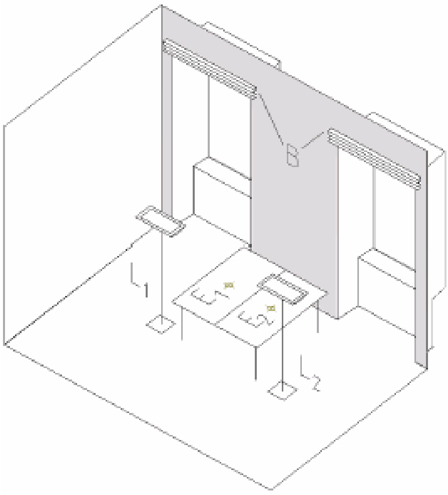


Figure 2: *Schematic illustration of the office space (B: blinds; L_1, L_2: luminaires; E_1, E_2: illuminance sensors)*

Figure 3: *Photograph of the office space used as the implementation test bed*

3.2. Product and process models

The product model for the constitutive elements of the space and the process elements for the control task in this case are depicted in Figures 4 and 5 respectively. As it has been demonstrated before (cp. Mahdavi 2004b), a process elements representation such as the one shown in Figure 5 can be generated in an automated fashion once *i)* the control devices (for heating, cooling, shading, ventilation, etc.) are specified; *ii)* the sensors representing the relevant system performance indicators (room temperature, task illuminance, etc.) are specified; and *iii)* the causal connections between devices and sensors are established. Note that Figure 5 represents merely the general hierarchy of the control system ingredients, depicting the relationship between sensors, devices, and decision-making nodes (device controllers and meta-controllers). Device controllers (DCs) represent control logic that can be implemented at the level of individual devices (L_1, L_2, and B in this case). As multiple devices may affect the same sensor (for example electrical light and daylight can contribute to the illuminance level at a certain point in a room), their operation must be coordinated. Such coordinated decision making can be implemented within the so-called meta-controller nodes (M in this case).

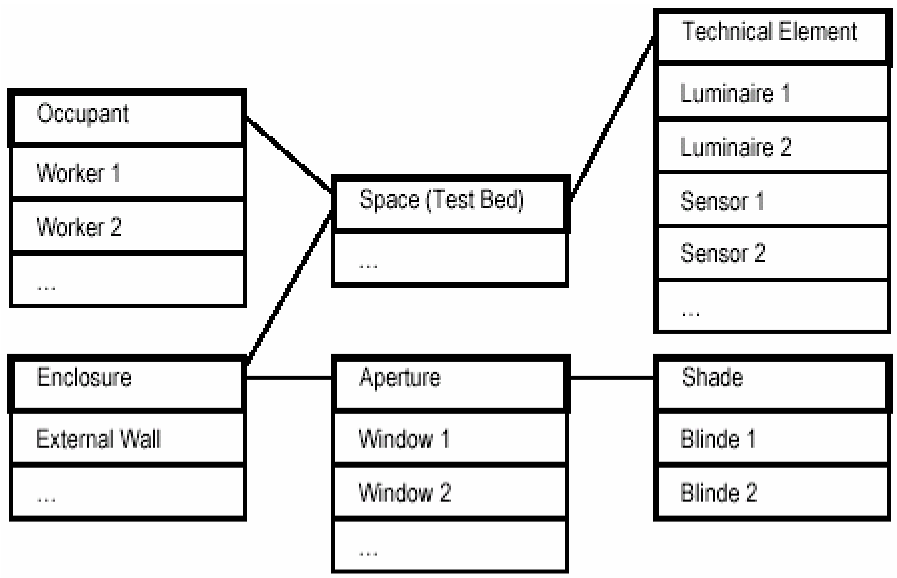


Figure 4: *Product model scheme for the office space used as the implementation test bed*

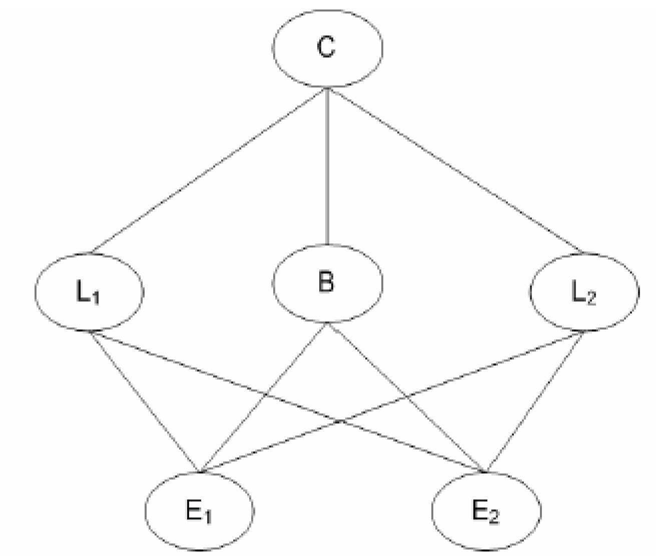


Figure 5: *Control system syntax for the test bed (E_1, E_2: illuminance sensors; B: device-controller for shades, L_1 and L_2: device-controllers for Luminaires; C: Meta-controller)*

3.3. Updating the model

3.3.1. Overview

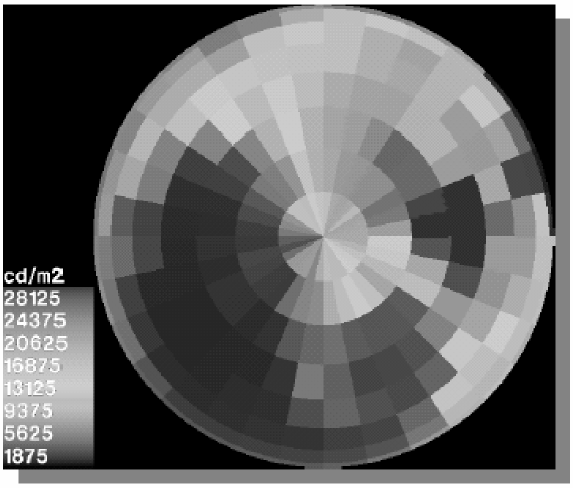
As argued before, to achieve the sentient buildings functionality, it is necessary that the building's selfrepresentation is autonomously updated. Otherwise, the overhead associated with manual actualization of model state would be infeasible. As such, a comprehensive building representation must contain a wide range of information including outdoor conditions, indoor climate, state space of control devices, location of moveable room objects, physical properties of room elements, occupancy, user preferences and control actions, utility rates, etc. To continuously collect this information, a manifold sensing infrastructure would be required. As the overall concept for the configuration of such a sensory infrastructure has been discussed elsewhere (see, for example, Mahdavi 2004a), only a few illustrative instances of automated model self-actualization are discussed below. Section 3.3.2. deals with automated real-time scanning of sky luminance distribution, as this information is required for the dependable simulation of daylight distribution inside the building (Spasojevic and Mahdavi 2005). Section 3.3.3. briefly describes a location-sensing solution to identify changes in the configuration of rooms (e.g. mobile partition walls) and positions of objects (such as furniture elements) in rooms.

3.3.2. Updating the context

Reliable prediction of daylight availability in indoor environments via computational simulation requires reasonably detailed and accurate sky luminance models. As past research has demonstrated (Roy et al. 1998), relatively low-cost sky luminance mapping via digital imaging could provide an efficient means to collect information on sky luminance distribution patterns on a more pervasive basis. To examine the reliability of this approach, a digital camera, equipped with a fisheye converter and pointing toward the sky zenith, was placed on the roof of a building that houses the implementation test bed. Sky images were collected under varying sky conditions. Simultaneously, the luminance due to sky was measured using a photometric sky monitoring device. Additionally, the horizontal illuminance due to the entire sky dome was measured using a precision illuminance meter. To further calibrate the process, a correction factor was applied to the digitally gained luminance values. Figure 6 provides an example of sky luminance data gained from digital images. This correction factor was derived as the ratio of the optically measured horizontal illuminance due to the entire sky dome to the horizontal illuminance of the sky as derived from digital images. Figure 7 shows the relationship between photometrically obtained (vertical axis) and the corrected camera-based luminance values (horizontal axis). The correlation coefficient (r^2) of the corresponding linear regression amounts to 0.83.

3.3.3. Updating the room model

Location sensing (tracking the position and orientation of objects in rooms) can be applied to construct and continuously update models of buildings as dynamic environments. As buildings and rooms are not static entities but change in multiple ways over time, the ability to automatically track such changes is necessary for the viability of sentient building models and the requirements of simulation-based building control applications. The location sensing system deployed for the present implementation uses a vision-based technology and scans scenes for distinctive optical markers. It exploits a combination of cameras and visual markers (low-cost black-andwhite tags). Using optimized image processing methods, it obtains in real-time the identification and location (both position and orientation data) of an object to which the visual tag is attached (Icoglu and Mahdavi 2004). The overall system architecture is schematically depicted in Figure 8.



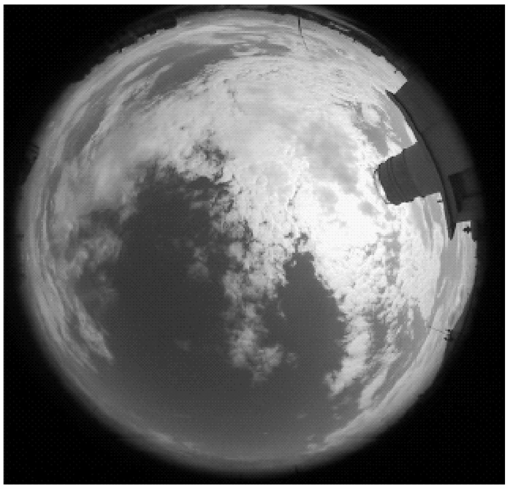


Figure 6: *Example of sky luminance distribution (left) derived from digital photography (right)*

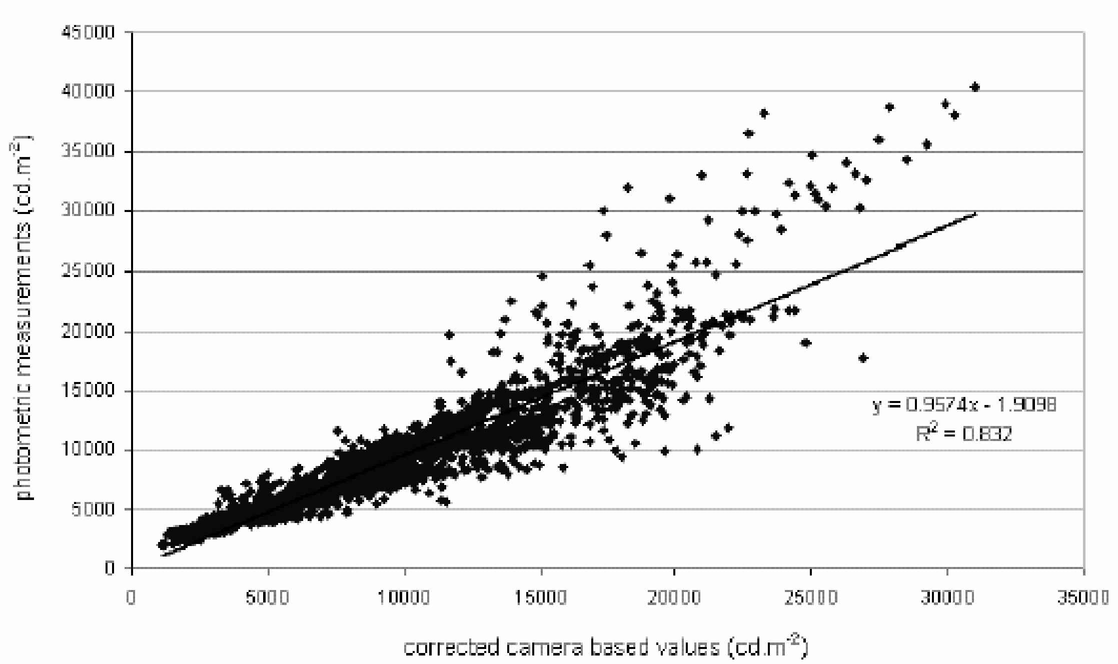


Figure 7: *Photometrically obtained versus camera-based luminance values*

Network cameras (netcams) are used as visual sensors, augmented with pan-tilt units that increase the range of these devices. Netcams are specifically designed for built environments and make use of the existing network installation. The system is designed as a distributed framework, whereby hardware and software components are tied together via Internet. Netcams and pan-tilts constitute the hardware part of the system whereas Processing Units (PUs) form the distributed software components. PUs are programs that extract the context information by using optimized image processing and computer vision methods. They are the consumers of the hardware resources. PUs, implemented on different computers scattered across the facility, convey the location data to the central Application Server where incoming pieces of information are combined, stored in the system database, and displayed to the operator. An additional function of the Application Server is to control the status of the components and dynamically assign active netcams to active PUs in such a manner that the workload is constantly balanced within the system. This arrangement provides a self-organizing capability and minimizes operator overhead. The resulting flexible and adaptive structure offers a suitable response to the requirements of control applications for sentient buildings.

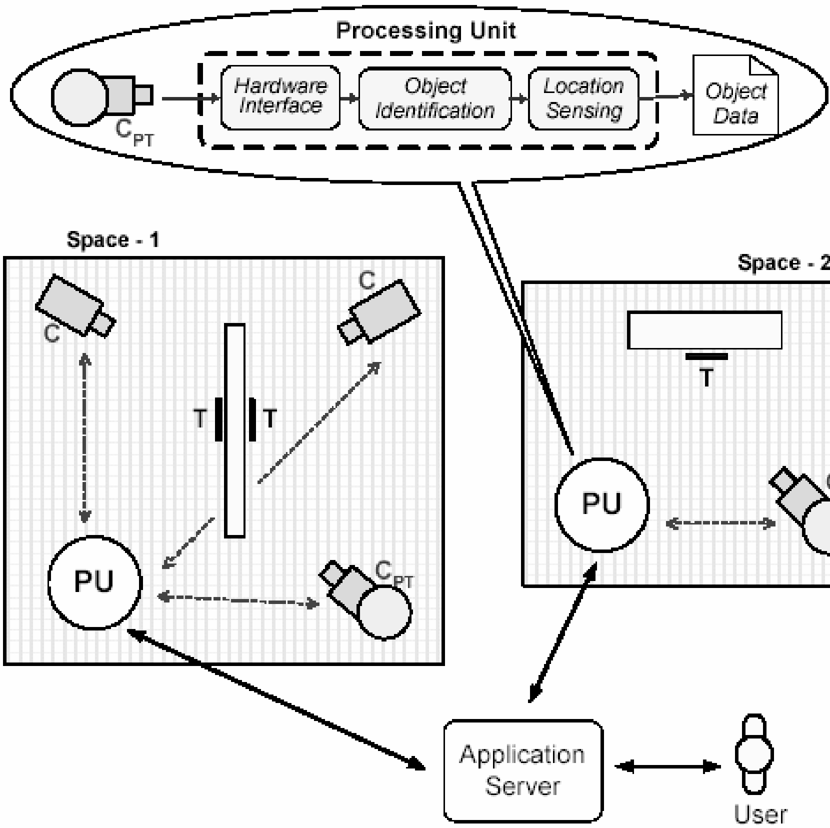


Figure 8: *Schematic illustration of the overall structure of a location sensing system for sentient buildings (C: network camera; CPT network pan-tilt camera unit; T: optical tag; PU processing unit)*

The hardware-software configuration described above was selected given the current state of technology in the domain of optically-based location sensing. It enabled us to provide a proof of concept for the proposed location-sensing strategy for sentient building applications. However, for a scalable and wide-spread use in actual buildings, efforts are needed to make the system more compact and more cost-effective. Toward this end, the author has proposed the application of compact low-cost network cameras equipped with fish-eyes. This would allow us to replace the rather large and expensive pan-tilt cameral units with smaller cameras, while maintaining the benefit of wide angles needed to efficiently capture indoor spaces. This hardware solution will be accompanied by the development of geometric algorithms to translate fish-eye-based spherical projections into orthogonal projections typical for architectural spaces. The methods already developed for tag recognition (together with the determination of position and orientation) can be thus incorporated within this new framework. Small network cameras equipped with fisheyes cannot only provide information toward location sensing, but also provide information on luminance distribution in interior spaces. Using an analogous strategy for sky scanning (cp. section 3.3.2.), such cameras may be supplemented with an illuminance meter, thus facilitating the photometric calibration of photographic images toward the determination of luminance distribution across room surfaces as well as changes in room surface reflectance coefficients. Such a system should be also capable of detecting occupants' movements.

3.4. Control state space

The control state space of a building encompasses, by definition, the sum of all possible (and practically relevant) positions of the building's control devices. A control state space for a building's systems has as many dimensions as there are individually controllable devices. Each dimension holds the range of values that the position of a device may have. In the most simple case, the dimension of a device may be construed as accommodating just two values, namely on and off. The control state space of a building may thus include a theoretically infinite number of members, particularly in case of continuously variable controller positions. To make this space manageable, first a discretization of device positions is required. In the present case, the shading system states (for the automated daylight control scenario) were discretized into seven distinct positions (see Figure 9). As to the control state space of the electrical lighting in the test bed, 10 discrete dimming positions were assumed for each luminaire (see Table 1).

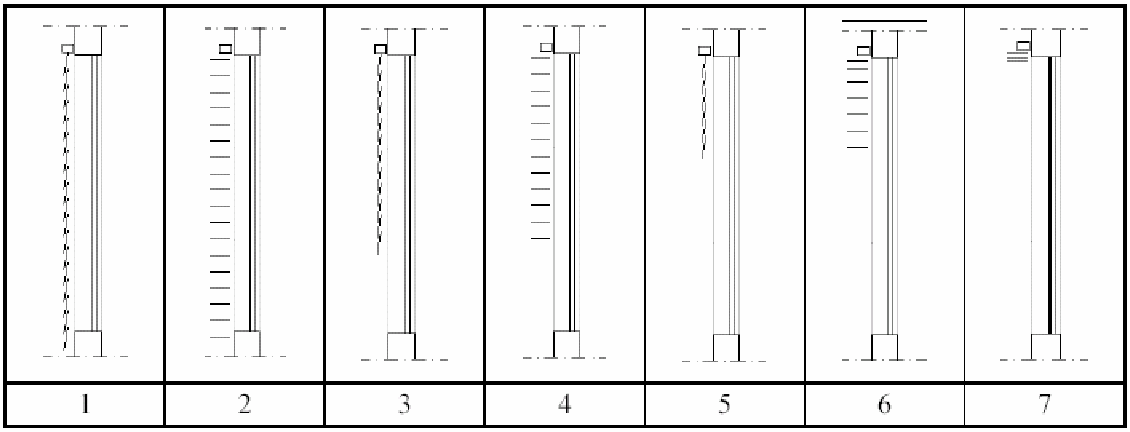


Figure 9: *Control state space of the shading device in the test bed*

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

Table 1: *Control state space of the electrical lighting devices in the test bed*

3.5. Control Objectives

For the purposes of the present illustration, the objective of the control task was to maximize the value of a weighted utility function comprising both the illuminance levels at the two workstations and the electrical energy consumption. Equation 1 provides an example for such a utility function:

$$UF = w_{E1} \cdot P_{E1} + w_{E2} \cdot P_{E2} + w_L \cdot P_L \qquad (1)$$

In this equation P_{E1}, P_{E2}, and P_L stand for the preferences for illuminance levels (E_1 and E_2) and electrical energy consumption. The corresponding weights are represented by w_{E1}, w_{E2}, and w_L.

Figures 10 and 11 depict illustrative preference functions as adapted for the implementation. Note that the users can change, at any time, their preference settings for illuminance levels. Likewise, the preference function for electrical energy use as well as the relative weighting of illuminance versus energy consumption can be modified dynamically. Last but not least, the user can also override system's control instructions and control shades and luminaires manually.

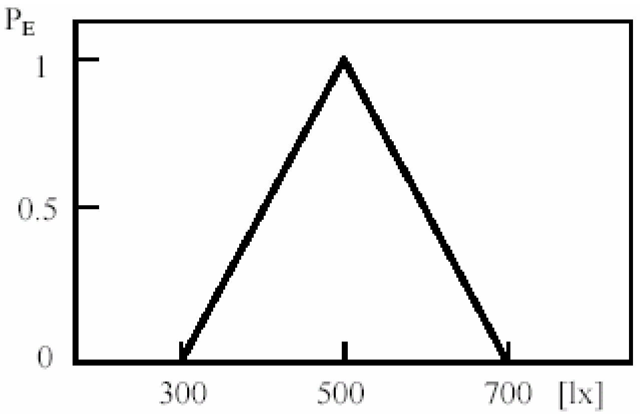


Figure 10: *An illustrative preference function for task illuminance*

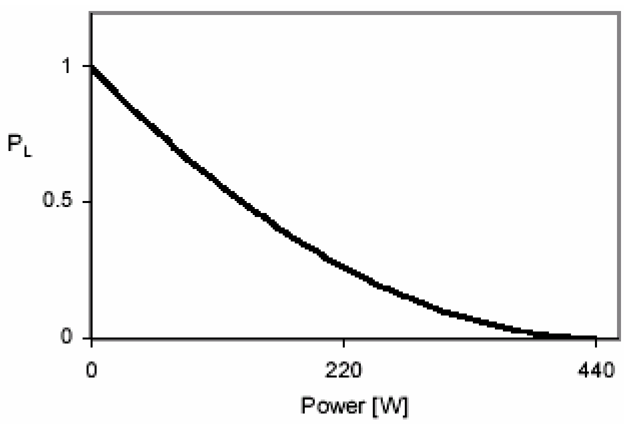


Figure 11: *An illustrative preference function for electrical power for luminaires*

3.5. Control process

At time interval ti, the system moves to identify the most desirable control state at time ti+1. As combinations of possible device positions cannot be evaluated exhaustively, a subset of candidate options must be identified. There are different ways to reduce the size of the candidate control state space. In the present case, a combination of "greedy search" and "stochastic jumps" is applied. Specifically, at each time interval, each device (i.e. L_1, L_2, B) submits to the control application C a list of candidate device states (see Figure 5). In the present case, each device submits four alternative options. These options are: the device's current position, the two neighboring device states, and a fourth – randomly selected – option from the rest of the device's control state space. The control application considers the resulting overall option space involving a maximum of 64 combined options. To predict the illuminance levels at E_1 and E_2 due to these options, the lighting simulation application LUMINA is used (Pal and Mahdavi 1999). The simulation application is provided with the actualized room and sky luminance distribution models. Based on this information and the associated electrical energy consumption data, the utility function values are derived using equation 1. Thus, the control state with the maximum utility function can be identified at each time step.

3.6. Illustrative results

To illustrate the control process, the operation of the system in the course of a day was documented. The external global horizontal illuminance level for this day is shown in Figure 12. The following weight assumptions for Eq. 1

were applied: $w_{E1} = w_{E2} = 0.4$; $w_L = 0.2$. Figures 13 and 14 show the recommendations of the control application for dimming positions of the two luminaires and the blind position. Figures 15 to 17 illustrate the resulting illuminance levels at E_1 and E_2, the electrical energy power requirement, and the utility function.

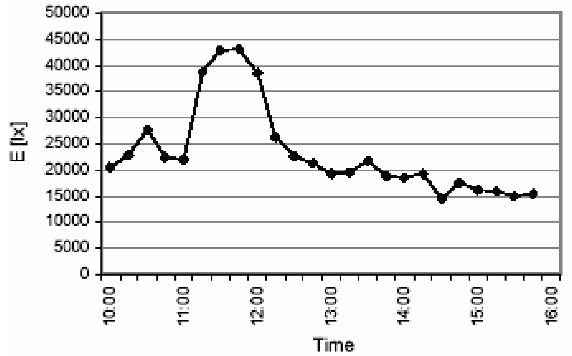


Figure 12: *Measured external global horizontal illuminance for the test day*

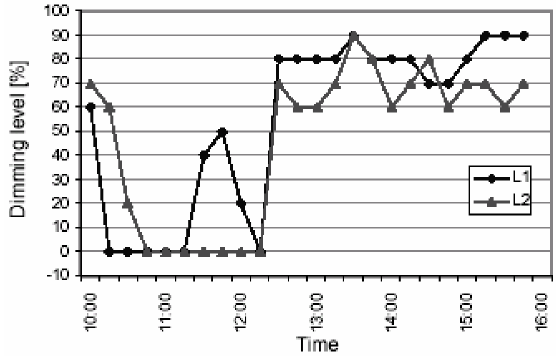


Figure 13: *Control system recommendations for the luminaire dimming positions*

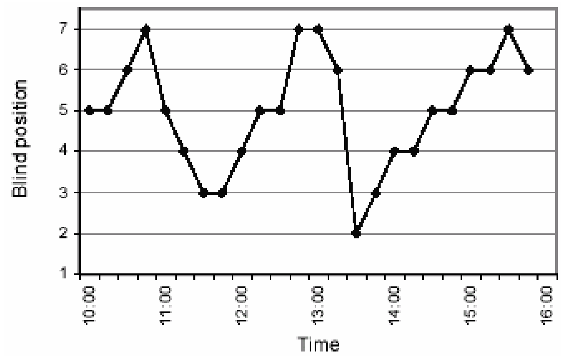


Figure 14: *Control system recommendations for the blind position (cp. Figure 9)*

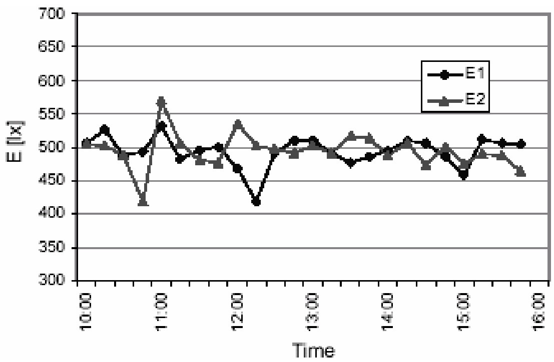


Figure 15: *Resulting illuminance levels for E_1 and E_2*

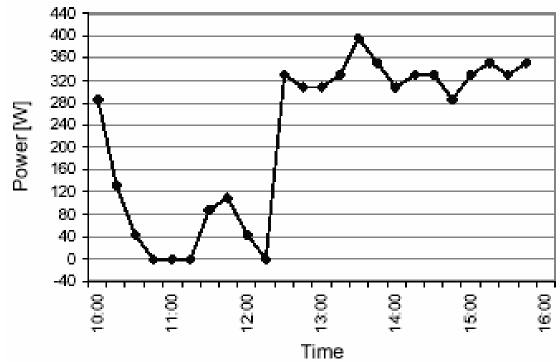


Figure 16: *Resulting power values*

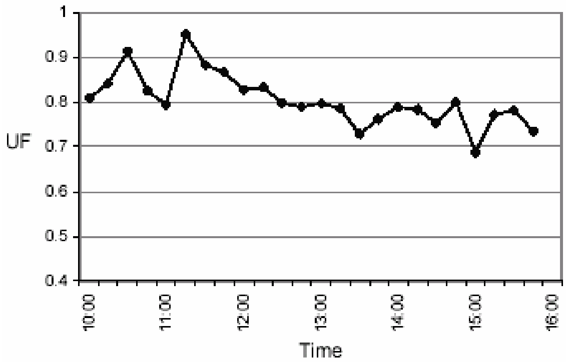


Figure 17: *Resulting utility function values*

4. Conclusion

The concept and a prototypical implementation of a simulation-assisted systems control in buildings were presented, using a lighting control scenario. It was demonstrated, how the overall framework of sentient building technologies allows, in principle, to incorporate simulation-based predictive models as an integral component of the control logic repertoire for building systems. In order to develop the proposed concepts and techniques into technically mature and commercially viable solutions, substantial additional research and implementation work is needed. Specifically, ongoing research aims to address a number of open issues:

i. The implementation presented in this paper must be considerably extended to cover the integration of multiple building systems (heating, cooling, ventilation, lighting);

ii. The scalability of the system and its self-updating capability must be improved to accommodate larger building objects with multiple sections, floors, rooms, workstations, and associated control devices;

iii. The location-sensing system prototype needs to be made lighter, more cost-effective, and more robust. Moreover, it must be augmented to capture occupancy movements and changes in reflective properties of room surfaces and objects. Specifically, the deployment of compact network cameras equipped with fish-eyes will be explored to provide a costeffective and scalable solution not only for location-sensing, but also for the detection of luminance distribution and reflectance changes (across interior room surfaces) as well as occupants' movements;

iv. Efficient geometric reasoning algorithms must be developed to reconstruct building geometry models autonomously based on sensor-driven input (Suter et al. 2005), for example after modification and renovation activities;

v. To deal with the computational (simulation) loads due to the growth in size of the control state space in large buildings, more efficient methods, algorithms, and filters are needed (Mahdavi 2004a);

vi. Finally, a comprehensive sensory infrastructure that continuously updates a building's selfrepresentation must be secured against potential misuse. Real or imagined potential for such misuse can easily lead the occupants of a sentient building to perceive its informational infrastructure as intrusive and alarming. The associated social and psychological implications of this possibility must be studied carefully to arrive at admissible and acceptable solutions for sentient building technologies.

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