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LIGHTSWITCH-2002: A Model for Manual and Automated Control of Electric Lighting and Blinds

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Abstract

A simulation algorithm is proposed that predicts the lighting energy performance of manually and automatically controlled electric lighting and blind systems in private and two-person offices. Algorithm inputs are annual profiles of user occupancy and work plane illuminances. These two inputs are combined with probabilistic switching patterns, which have been derived from field data, in order to predict the status of the electric lighting and blinds throughout the year. The model features four different user types to mimic variation in control behavior between different occupants.

An example application in a private office with a southern facade yields that –depending on the user type– the electric lighting energy demand for a manually controlled electric lighting and blind system ranges from 10 to 39kWh/m^{2}yr. The predicted mean energy savings of a switch-off occupancy sensor in the example office are 20%. Depending on how reliably occupants switch off a dimmed lighting system, mean electric lighting energy savings due to a daylight-linked photocell control range from 60% to zero.

keywords: lighting controls, daylighting, user behavior models

1. Introduction

According to chapter 27 of the IESNA Lighting Handbook (IESNA, 2000), lighting controls in buildings are installed to provide occupants with "aesthetic and energy management control" over the electric lighting system. Since their first appearance in the 1987 edition of the Application Volume of the Lighting Handbook (IESNA, 1987), lighting controls have been promoted based on the assumption that “local automated control techniques can be more cost effective than the usual reliance on manual operation of lights” (page 27-1 in IESNA, 2000).

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Under what circumstances do lighting controls actually save energy and how much? The Lighting Handbook declares that “it is incumbent on the engineer and lighting designer to be aware of the wide variety of electronic lighting controls available and to correctly apply them to the project at hand”. In order to “correctly” apply these sensors, the handbook proposes a cost analysis by “adding the cost of the control system [including commissioning costs] to the rest of the equipment costs and determining how the controls affect operating costs”. The Handbook acknowledges that “while cost information for lighting controls are easily available, performance information are not as available and may be very site dependant [...] with savings depending on indoor daylight levels, size of space, work schedules and occupant activities as well as occupants’ attitude and training.” Another complicating factor is the uncertainty of “actual blind usage in buildings” (IESNA, 2000). The Lighting Handbook does not further discuss the exact nature of these dependencies so that the lighting designer ultimately has to judge the “correct” lighting system based on personal experience, anecdotal evidence and/or computer-based simulation models*.

Simulation models offer a comparative analysis of the energy performance of different lighting control systems. The energy performance of automated controls is relatively straightforward to model as it is based on deterministic correlations between physical quantities like the illuminance at a photocell and the status of an electric lighting system. The more challenging task is to model a conventional one-level manual switch which constitutes “the most common practice and should function as a reference system, relative to which energy savings of automated lighting controls should be expressed” (IESNA, 2000). Some recent examples of how researchers modeled manual lighting and blind control are summarized in the following:

<u>Electric Lighting:</u> Previous studies that aimed to quantify the energy benefits of photosensor controlled electric lighting systems modeled an ideally commissioned system that exactly “tops up” the daylight to the prescribed minimum illuminance threshold at a work place (Bodart, DeHerde, 2002; Vartiainen, 2001; Herkel, 1997; Erhorn, Kluttig, 1996; Lee, Selkowitz, 1995). The electric lighting energy benefits of the dimmed lighting system were then compared to a non-dimmed system assuming that lighting

* The Lighting Handbook refers to the computer program Controlite 1.0 from Lawrence Berkeley National Laboratories (1985). According to personal communication of the author with the LBNL publication coordinator in March 2002, “Controlite is no longer available and there is nothing newer they can refer to”.

systems are permanently activated during office hours (Lee, Selkowitz, 1995). Bodart and DeHerde (2002) assumed a fixed reduced lighting usage at the extremes of the working day whereas Szerman (1996) used a flat utilization rate of 60% throughout office hours.

Hunt (1980) suggested a prediction method for manual lighting control that is based on field study data. Based on a switch-on probability function for electric lighting and annual frequency distributions of indoor illuminances, he generated mean switch-on probabilities for certain times of a weekday. He assumed that lighting is switched on at the start of a period of occupation, left on throughout the day and switched off at the end. Based on this assumption he derived mean hours of daily usage for the electric lighting at a given work place. Due to the unavailability of applicable field data, Hunt used the same switch-on probability upon arrival as for intermediate switch-on events.

Newsham (1994) used a revised version of Hunt's model to simulate manual lighting control. According to Newsham's model, the electric lighting was switched on in the morning and after lunch if the minimum illuminance level on the work plane lay below 150 lux. Switch-on events during a period of occupation were not considered. The lighting was switched off at the end of the working day.

<u>Blinds:</u> Assumptions made to model the temporary status of a manually operated shading device throughout the year differ drastically between studies. The crudest methods compare the lighting and thermal energy performance of automated lighting and blind systems to a system without any blinds (Bodart and DeHerde, 2002; Ullah, Lefebvre, 2000; Szerman, 1996). This assumption neglects that shading devices are an almost ubiquitous system for office workers to control direct sunlight. More sophisticated approaches assumed that a manually controlled shading device is lowered completely by the occupant during daylight hours when glare is present and fully opened otherwise (Vartiainen E, 2001; Lee, Selkowitz, 1995) . Vartiainen's (2001) glare criteria was the presence of direct sunlight on the building facade. Lee and Selkowitz equalized glare with either the presence of transmitted direct solar radiation above 94.5 Wm^{-2} or a Hopkins glare index above 20. They characterized this manual control strategy as "highly optimistic" as blinds were adjusted by the user on an hourly basis.

Other researchers equalized manual blind usage with protection against overheating. Erhorn and Kluttig (1996) simulated manual blinds as being permanently closed during office hours from May to September. Georg *et al.* (1997) lowered the blinds to satisfy privacy needs when ambient horizontal irradiances were below $10Wm^{-2}$ or to avoid overheating if the mean indoor temperatures over the past 24 hours rose above 25^oC. Goller (1998) assumed that the blinds were manually closed in a non air-conditioned office if glare (irradiance onto facade above $150Wm^{-2}$) or overheating (indoor temperature above 26^oC) appeared. Newsham assumed that blinds were manually opened at the beginning of the working day and fully closed for the remaining of the day if the simulated work space was subject to direct sunlight and the facade irradiance rose above $233Wm^{-2}$ (Newsham, 1994).

All of the above described modeling approaches have in common that they use static thresholds to model occupants interference with their electric lighting or blinds. This approach ignores the essence of Hunt's switch-on probability function, i.e. that while the "use of controls is clearly *influenced* by physical conditions, it tends to be *governed* by a stochastic rather than a precise relationship" (Nicol J F, 2001). The first paper that followed a stochastic approach to manual lighting control was presented in 1995 by Newsham, Mahdavi and Beausoleil-Morrison. The authors developed a model called *Lightswitch* that simulated user occupancy at the work place based on measured field data in an office building in Ottawa, Canada. The resulting user occupancy profiles were then used to estimate the energy benefit of an occupancy sensor. The lighting was constantly activated throughout the day for the manually operated reference lighting system. For the occupancy sensor controlled system the lighting was switched on upon occupant arrival at the work place and switched off whenever the user left the workplace for a time step longer than the delay time of the occupancy sensor.

The present paper proposes a new manual lighting and blind control algorithm that is dynamic *and* stochastic. Dynamic indicates that instead of looking at an average day in a year or month, user occupancy, indoor illuminances and the resulting status of the electric lighting and blinds are considered in 5min time steps throughout the year. Stochastic means that whenever a user is confronted with a control decision i.e. to switch on the lighting or not, a stochastic process is initiated that determines the outcome of the decision. What are the advantages of this new approach over previous approaches?

- An algorithm that mimics individual control decisions should be closer to real behavior than a model that relies on data of cumulated, averaged-out switch-on times in multiple offices.
- As will be shown further below, a first-principles approach is capable of modeling "emergent interactions". An emergent interaction arises when two seemingly independent behavioral patterns lead to an unsuspected effect. In section 3.4 it is shown that a user that controls blinds in a way that maximizes internal illuminance levels due to daylight can actually end up using more electric lighting, than a user that keeps the blinds lowered all the time. The reason for this seeming contradiction is that high internal daylight levels during departure prevent the former user from noticing that a dimmed lighting system is switched on. As a consequence, the lighting is regularly left on outside of regular working hours.
- Yet another benefit of the new model is that it is capable of simulating variations in individual control behavior that have been observed in field studies.

The algorithm is called *Lightswitch-2002*. The name has been chosen to reflect that it has been developed in the same spirit as Newsham's original model, i.e. to predict electric lighting use based on probabilistic behavioral patterns which have *all* been observed in actual office buildings. It is based on a recent review of field data from studies in Canada, Japan, Germany, the UK and the United States (Reinhart and Voss, 2003). The "2002" indicates that the algorithm is expected to evolve over time together with our knowledge in this field. Obviously, this new modeling approach is only as reliable as the underlying behavioral patterns. Lightswitch-2002 can help lighting designers to carry out a comparative energy savings analysis of a range of electric lighting and blind control concepts in private or two-person offices. The algorithm can not be readily transferred to open plan office concepts in which individuals have no perception of personal control over their immediate environment (Bordass *et al*., 1994; Boyce, 1980).

In sections 2 and 3 the algorithm is presented and applied to an example private office with a southern facade orientation. A discussion of the algorithm's validity, relevance and limitations follows in section 4.

2. The Lightswitch-2002 algorithm

2.1 Electric lighting control

Figure 1 shows the basic Lightswitch-2002 approach to determine the electric lighting energy demand in perimeter private/two-person offices. Model inputs are: measured or simulated 5-min annual profiles of user occupancy, and work plane illuminances due to daylight. The latter can nowadays be reliably predicted using dynamic daylight simulation methods (Reinhart, Walkenhorst 2001; Mardaljevic, 2000; Janak M, 1997) that combine a daylight coefficient approach with the Perez (1993) sky model. The simulations for the example application in section 3 have been carried out using the RADIANCE-based (Ward, Shakespeare 1998) daylight simulation method DAYSIM (Reinhart, Walkenhorst 2001). DAYSIM features a stochastic model to simulate 5-min irradiance data series from widely available hourly means (Walkenhorst, Luther, Reinhart, Timmer, 2002). Occupancy at the work place has been simulated using an adapted version of Newsham's (1995) stochastic model. Details of the adapted model can be found under (Reinhart, 2001).

Figure 2 details how the Lightswitch-2002 algorithm processes 5-min occupancy and illuminance input data series. At each time-step the electric lighting and blind status are set according to the outcome of the loop in Figure 2. The gray "set blinds" procedure is described in Figure 4. The occupancy profile determines which switching decision applies. Afterwards a random process is initiated to determine whether the switching decision is followed by a switching event or not. All stochastic processes in Figure 2 are based on field study data. The underlying assumptions of the algorithm are spelled out in Table 1.

2.2 Blind control

Most occupants avoid the presence of direct sunlight at their VDT work place by activating their shading device, i.e. lowering their blinds to block direct sunlight. While this closing criteria for blinds is well established (Bülow-Hübe, 2000; Rea, 1984; Rubin A I, Collins B L, Tibott R L, 1978), it remains unclear whether occupants re-open their blinds on a daily, weekly or even seasonal basis. As for electric lighting, there is a wide individual spread: Rubin (1978) and Foster (2001) reported that blinds were left untouched in single offices for weeks and months. In contrast to this, Lindsay (1993) and Inoue (1988) found that some occupants tended to retract their blinds daily at departure or in the morning upon arrival. These results have been translated into one automated and two manual blind control strategies:

<u>automated blind control:</u> blinds are automatically fully lowered as soon as incoming direct solar irradiance above $50Wm^{-2}$ hits the work place. The slat angle is the smallest of either 0^0 (horizontal), 45^0 or 75^0 (facing out downwards) at which direct sunlight is fully blocked from the work place[**]. The blinds are fully opened otherwise. This is an ideal blind control as the daylight availability is maximized unless the glare criteria is met.

<u>dynamic manual blind control:</u> blinds are manually fully lowered as soon as incoming direct solar irradiance above $50Wm^{-2}$ hits the work place. The slat angle is the smallest of either 0^0, 45^0 or 75^0 (facing out downwards) at which direct sunlight is fully blocked from the work place. The blinds are fully re-opened once a day in the morning upon arrival. This behavior resembles the one identified by Lindsay and Inoue.

<u>static manual blind control:</u> blinds permanently fully lowered (slat angle of 75^0). This scenario describes a user who rarely operates the blinds and mainly uses the window to maintain some visual contact with the outside (Rubin).

Figures 2 and 4 show how the blind control strategies are implemented into Lightswitch-2002. Figure 4 corresponds to the “set blinds” procedure in Figure 2. In case “the blind setting has just changed” (2^{nd} gray field in Figure 2) either the switch-on probabilities from Figure 3(a) or (b) apply. The justification for this toggling between two probability functions is that as soon as the blinds are re-set, the occupant’s attention is drawn towards the lighting situation in the room, i.e. a reassessment of the lighting situation is triggered. Note that a switch-on decision merely determines whether the lighting is switched *on.* In Lightswitch-2002 the lighting can only be switched *off*, if the occupant leaves the office.

[**] Three discrete slat angles have been considered as for each blind setting a new set of daylight coefficients has

2.3 Four User Types

The two switch-on behavioral patterns for the electric lighting (Figure 3(a)) and the two manual blind control scenarios (section 2.2) serve as model inputs to characterize user behavior. These two model inputs lead to four basic user types that mimic the variations in user behavior that has been found in field studies.

2.4 Model Limitations

The model in its present state has some obvious limitations, some of which are acknowledged in the following. The limitations are a result of a lack of quantitative field data.

<u>intermediate switch-off:</u> The scenario that a user returns to the workplace after a temporarily absence and switches *off* the lighting is not covered by the model.

<u>blinds are always fully opened or closed:</u> The model assumes that the users keeps the blinds either fully opened or closed. In reality, some occupants only lower their blinds to a point at which direct glare is avoided.

<u>thermal considerations:</u> The model also ignores any thermally driven mechanisms which might trigger a closing of the blinds to avoid overheating.

<u>privacy issues:</u> Anecdotal evidence suggests that office occupants in densely populated urban settings use their blinds to block the view from the outside to satisfy their privacy needs (Foster, Oreszcyn, 2001). Such privacy needs are not modeled.

<u>seating orientation:</u> The seating orientation of an occupant determines his or her field of view and should therefore influence the usage of lighting and blinds. Due to the absence of conclusive data, the current model considers only horizontal work plane illuminances, i.e. the orientation of the occupant is ignored.

<u>location of control:</u> The frequency with which blind and lighting controls are used depends on the actual location of the control with respect to the occupant’s work place. Occupants are less likely to interrupt their work and use a switch near the entrance than to use a control within easy reach of their work place (Bordass *et al.*, 1994).

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to be simulated. The number of blind positions considered can be increased at will.

3. Example Application

In this section Lightswitch-2002 is used to quantify the electric lighting energy demands in an example private office for a number of lighting and blind controls.

3.1 Simulation Details

The example office has a southern facade orientation and is located in Toronto, Canada (43.67^{o} N; 79.63^{o} W). The CWEEDS (Environment Canada, 1996) test reference year for 1990 has been used to determine annual indoor illuminance profiles in the office. The facade is unobstructed by neighboring buildings or landscape and the ground albedo is 20%. A facade view and floor plan of the office are shown in Figure 5. The room is 9ft (2.74m) high, 10ft (3.05m) wide and 20ft (6.1m) deep. The ceiling, wall and floor reflectances are 80%, 50% and 20% respectively. The window consists of a double glazing with a low-ε coating and a visual transmittance of 72%.

The simulated work plane is located at 1.5m distance from the facade and has a daylight factor ranging from 11% if the blinds are retracted to 1% if the blinds are lowered with a slat angle of 75^{0}.

The simulated occupancy profile corresponds to a user with working hours from Monday to Friday 8.00 to 18.00 with a one hour lunch break at noon and two 15-min breaks in the morning at 10.00 and the afternoon at 15.00. All arrivals departures and breaks are randomly scheduled in a time interval of ±15min around their official starting times to add realism to the model. The daylight savings time lasts from April1st to October 31st and the total annual hours of occupancy correspond to 2197h. This occupancy profile is higher than a profile one would measure in most real work places as neither holidays, vacation days, sick leaves or business trips have been considered. The mean occupancy probability on a week day is shown in Figure 6(a). The calculated daylight autonomy for the work place, i.e. the percentage of occupied times of the year when a minimum work plane illuminance threshold of 500lux can be maintained by daylight alone, ranges from 89% (blinds always retracted) to 31% (blinds lowered with a 75^{0} slat angle).

The electric lighting system consists of four direct/indirect louvre luminaries with 2 x T5 35W lamps. The resulting installed power for electric lighting without lighting controls is about 15Wm^{-2}.

The shading device is a standard internal venetian blind system. The white slats have a diffuse reflectance of 80%, are spaced 2.1cm apart from each other, are 2.5cm wide and have a radius of 16cm. As stated above, four discrete blind settings have been considered: blinds fully retracted and blinds fully lowered with a slat angle of 0^o, 45^o or 75^o.

3.2 Reference Case: Manual Electric Lighting Control (man)

In the following, Lightswitch-2002 simulations for a manually controlled lighting system (*man*) with an on/off switch near the entrance are presented for the four user types from Table 2. This lighting system serves as a reference against which the energy performance of automated controls are compared further below. As Lightswitch-2002 is based on several stochastic processes, simulation results vary for different realizations. All results presented in this section are the mean of 10 annual simulations.

Figure 6(b) shows the development of the annual mean blind occlusion on a weekday for the three blind control scenarios from section 2.2. The blind occlusion is a single number to characterize the status of a venetian blind system. It is defined as the percentage of a window that is covered by blinds and is independent of the slat angle of the blinds (Rea, 1984). The flat line at 100% corresponds to the static manual blind control (permanently lowered at 75^0). For the dynamic manual blind control the blinds are lowered around 58% outside of regular working hours. In the morning upon first arrival the blinds are opened in the absence of direct sunlight on the work plane and the mean blind occlusion drops to 15%. Throughout the morning as the sun moves around the facade, the blinds are lowered more regularly. The blind occlusion stays constant during lunch break and further rises in the early afternoon. The blind occlusion never falls throughout the day as the blinds are only opened in the morning upon arrival.

In contrast to this, the automated blind control always retracts the blinds during night time. Between 8 and 10AM the blinds are sometimes automatically lowered to avoid direct sunlight. In this time interval the dynamic manual and automated blind controls nearly coincide, as the closing criteria for both controls are identical. After 10AM the two curves divert from each other as the automated blind control retracts the blinds in the absence of direct sunlight on the work place. As a consequence, the mean blind occlusion of the automated blinds never rises above 40%. It drops to zero between 4 and 5PM.

Figure 6(c) shows how the occupancy profiles and blind settings from Figures 6(a) and (b) translate into electric lighting load profiles for the four user types. Users *DiBd* and *DiBs*, who do not consider daylight, keep their lighting activated throughout the day. The load profile for these users is independent of the blind control strategy.

For users *DdBd* and *DdBs*, Lightswitch-2002 yields two very distinct profiles. For the static manual blind control (user *DdBs*) in 60% of all week-days the user decides to switch on the electric lighting upon arrival in the morning. The load profile then slowly rises until the morning break at 10AM when there is a slight chance that the user will switch off the lighting. As the break is only 15min long, the switch-off probability is low (Figure 3(c)). After the break the interior daylighting levels are usually so high (even with the blinds down), that very few switch-on events appear. The load profile falls to 35% during the lunch break and slowly picks up after lunch. The highest load profiles can be found after the afternoon break as falling daylight levels trigger the occupant to switch on the lighting.

The load profile of user *DdBd* has a similar daily pattern as the one of user *DdBs* except that it is shifted down by a constant factor of 40%. The explanation for these dramatic reduction is that in 83% of all arrival times of the year the blinds can be retracted and there is usually sufficient interior daylight for the user keep the lighting off.

The line just below user *DdBd* corresponds to the load profile for users *DdBd* and *DdBs* when the blinds are automatically controlled. It is surprising, that there is no substantial difference between the load profiles for user *DdBd* and automated blinds. The main reason for this is that for both scenarios the blinds are usually fully retracted in the morning upon first arrival. This reveals that the status of the lighting system in the morning has a significant impact on the lighting status for the rest of the day. The investigated office has lots of daylight (i.e. low switch-on probabilities) and short breaks (i.e. low switch-off probabilities) throughout the day. Once the lighting is switched on, the odds are relatively high that it stays on for the remaining of the day.

3.3 Occupancy Sensor

In this section the impact of an occupancy sensor on the electric lighting energy demand in the example office is discussed. Two different occupancy controls are considered:

occ 1: An manually controlled lighting system with a single on/off switch near the entrance and a perfectly located occupancy sensor with a switch-off delay time of 10 minutes. The lighting system can only be activated manually through the switch. It is switched off either manually by the user or automatically by the occupancy sensor once the work place has been deserted for more than 10 minutes. The occupancy sensor requires a standby power of 3W (~$0.2Wm^{-2}$) and is only activated when the lighting system is on[*].

occ 2: An automatically controlled lighting system with an ideally located occupancy sensor with a switch-off delay time of 10 minutes. The occupancy sensor is permanently in standby mode and activates the lighting whenever occupancy is detected. The standby power of the occupancy sensor is 3W (~$0.2Wm^{-2}$).

Figure 7(a) shows the mean daily lighting loads for the *occ 1* scenario for all four users and automated blinds. Users *DiBd* and *DiBs*, who do not consider daylight, again have the highest load profiles throughout the day and the lighting is only switched off temporarily during the three breaks. For users *DdBd* and *DdBs* the load profiles between 8 and 10AM are identical as in the absence of an occupancy sensor. At 10Am the lighting is switched off during the break and –due to the high daylight availability in the office– usually stays off. The figure shows that for the investigated occupancy profile the occupancy sensor plays the role of a “reminder” for the occupant to switch the lighting off during the day. From the viewpoint of the Lightswitch-2002 model, the probability for a switch-off event to take place during a 15min break is 100% for an occupancy sensor compared to 9% for an occupant (Figure 3(c)). For an occupancy profile with extended periods of absence from the work place throughout the day, the sensor would yield even higher savings than the ones shown in Figure 7(a).

[*] Technical note: As a real-world occupancy sensor can at times miss the presence of a user, a safety feature would be to leave the sensor activated and ready to switch the lighting back on for 1 minute after it has switched off the lighting. This way an “overlooked” user only has to wave instead of having to stumble to the switch near the office entrance in the dark.

For an occupancy sensor that switches the lighting on *and* off, the sensor mimics the behavior of users *DiBd* and *DiBs*. Therefore, all load profiles in Figure 7(b) correspond to the load profile of these two users in Figure 7(a). As the sensor is permanently activated, its annual standby power is 1.3 kWh/m^{-2}yr. This additional energy demand further reduces the energy performance of such a lighting control system. A comparison of the load profile of user *DdBd* and *DdBs* in Figures 6(c) and 7(b) shows that an on/off occupancy sensor can actual increase the energy demand compared to a conventional on/off switch for users that tend to work by daylight alone.

3.4 Dimmed Lighting

In this section the saving potential of a dimmed, photocell-controlled lighting system is investigated. One complication for modeling a dimmed lighting system is that results from field studies are still incomplete. Figure 3(c) shows that the switch-off probability for an indirect dimmed lighting system lies below the one with no controls. In the original paper in which the figure was derived, the authors presumed, that the switching behaviors for dimmed and undimmed lighting systems might differ because occupants sometimes do not notice during departure that their dimmed lighting system is activated (Reinhart and Voss, 2003). This misapprehension can only happen in the presence of daylight in the space. Therefore, Lightswitch-2002 models direct and indirect dimmed lighting systems as follows:

- For an <u>indirect</u> lighting system, the switch-off probabilities toggles between “no-controls” and “indirect dimmed lighting” depending on the presence of daylight at a given time step.
- For a <u>direct</u> lighting system, the chance of the user noticing that the lighting is activated is higher that for the indirect system. Therefore, the reduced switch-off probability from Figure 3(c) is applied, if the minimum work plane illuminance due to daylight lies above 375lux. The “no control” switch-off probability is used for all other time steps.

Figure 8(a) and 8(b) show the daily mean load profiles for an indirect and a direct dimmed lighting system for all four user types. The lighting system is manually activated via an on/off switch near the office entrance. When activated, the ideally commissioned photocell exactly “tops up” the daylight with electric lighting until a minimum illuminance of 500lux is maintained throughout the work plane. The photocell is mounted above the work place facing downwards. The inset in Figure 8(a) shows a fisheye view of the work place as “seen” by the photocell. At a minimum lighting output of 1% the system consumes 8% of its full electric power (Figure 27-15 in the IESNA Handbook). 25% of the installed electric lighting power stem from the electronic ballasts (SIA, 1995). Therefore, the energy savings due to dimming do only effect the remaining 75% of the lighting system, i.e. 11.25 W/m^2. The electronic ballast has no standby demand when the lighting system is switched off.

Figure 8(a) shows that during occupied hours the photocell control significantly reduces daily load profiles of the indirect lighting system for *all* four user types. The “rub” is that the reduced switch-off probability leads to an appreciable number of times per year when the occupants leave their lighting on after working hours. As a consequence, even though the daily loads are greatly reduced, total annual lighting demands are comparable to the reference case.

If the investigated dimmed lighting system is direct, the occupants stands a higher chance to notice if the lighting is switch on during departure. Figure 8(b) reveals that for a lighting system with such a user response the load profiles are reduced during the day as well as during the night. An exception is user *DiBd*. This user always activates the lighting during the day but actively uses the blinds. As a consequence, the daylight levels tend to be high in the user’s office during departure, i.e. the dimmed lighting tends to be left on. This leads to the peculiar effect that an oversupply of daylight in the late afternoon has a negative effect on the electric lighting load profile.

3.5 Electric Lighting Energy Performance

How can all of these information help a designer to choose an adequate lighting system for the investigated office? Figures 6 to 8 show that the actual electric lighting energy demand in an office is closely entangled with the occupant’s user type. For a single office, it is of course impossible (and undesirable) to predict the user type of the occupant. In this case the designer should work with the highest energy demand of the four users.

If on the other hand the private office is one of many identical offices in a large building, the average energy demand for this *ensemble* of offices is the design criteria of interest and the relevant question becomes: What is the frequency distribution of the four user types in the building?

Unfortunately, there is no data currently available to meaningfully answer this question. A straightforward engineering approach is to assign equal frequencies to all four user types. This approach is not supported by the few field study results that are available and that rather suggest that user behavior is polarized in different buildings (Reinhart and Voss, 2003). Nevertheless, in the absence of a better solution, the approach of equal frequencies will be used in the following to compare the electric lighting energy performance of the above described five lighting scenarios.

Figure 9 summarizes the annual electric lighting energy demands in a building with a number of identical offices and occupancy profiles for the five investigated lighting control systems with manual and automated blinds. The example office corresponds to the one described in section 3.1. The reader should note, that the results presented in Figure 9 highly depend on the location, office geometry and user occupancy profile chosen as simulation inputs. They cannot be generalized for arbitrary office settings! The gray bars indicate the range of possible energy demands for each particular lighting system for the four user types. The solid line connects the mean annual electric lighting energy demands for the lighting scenarios assuming that all four user types appear with equal frequencies. The reference system with manually controlled blinds and lighting has a mean annual electric lighting energy demand of:

$$25\%(9.6+38.9+21.3+38.9)\frac{\mathrm{kWh}}{\mathrm{m^2yr}}=27.2\frac{\mathrm{kWh}}{\mathrm{m^2yr}} \qquad \text{(equ. 1)}$$

Systems for which the solid black line lies below this reference energy can be expected to save energy in the example office building while the others are likely to use more.

An energy-efficient occupancy sensor (*occ 1*) will on average save about 20% in the example office building. This number is comparable to field study results by Jennings *et al.* (1999) in private offices. As mentioned above, these savings largely depend on the occupancy profiles at the work place. An occupancy control that always activates the electric lighting during occupancy (*occ 2*) prevents users to work by daylight alone. As a consequence, energy savings, that a considerable proportion of occupants would otherwise recuperate with a simple manual control, are lost through such a control system. This type of occupancy control should be restricted to aisles, lavatories and other unassigned areas where occupants do not tend to use manual controls (Bordass *et al.,* 1994; IESNA, 2000).

While a photocell controlled lighting system has an enormous savings potential (59% for *direct dimmed*), the difference between the two investigated dimmed lighting systems reveals that these savings can reduce to virtually nothing (1% for *indirect dimmed*) if the lighting is not regularly switched off outside of regular working hours. This finding provides yet another reason why some installed dimmed lighting systems do not perform as expected (Floyd, Parker, 1995).

Another lesson to be learnt from Figure 9 is that dimmed lighting systems need to feature a mechanism that ensures that the system is switched off at the end of the working day i.e. “manual on...manual and auto off” (Bordass *et al.,* 1994). This can be achieved either by a combination with an occupancy sensor or by sending a switch off signal to the whole building after working hours.

The two investigated dimmed lighting systems were assumed to be ideally commissioned. The performance of real world photocells depends on their location, angular sensitivity and how well their response function is calibrated. These aspects will be implemented in future simulations to provide more realistic performance predictions of a dimmed lighting system. A promising approach to accurately model photocell sensor response using RADIANCE has recently been proposed by Ehrlich *et al.* (2002).

Despite of the variety of challenges associated with installing a successful photocell controlled lighting system (Love, 1995), it should be pointed out that scenario *direct dimmed* is the only one that significantly improves the internal load profile for *all* four user types (Figure 9). This information is useful if internal loads have to be kept low.

The electric lighting energy savings resulting from installing an automated blind control (Figure 9) are rather sobering for the example office due to a number of reasons. The investigated work place receives an abundance of daylight throughout most of the year even when the blinds are lowered with a 75^0 slat angle. The choice of a slat angle of 75^0 for the static manual blind control has been driven by finding a blind position that blocks direct sunlight all year round but still allows the occupant to “peek out”. Slight changes to this angle would have a dramatic effect on indoor daylight levels.

It also needs to be stressed that these simulations only took electric lighting energy into account while total energy balances, which also consider heating and cooling loads, would be necessary to paint a more holistic picture of the energy performance of an automated blind control.

A final aspect concerns the frequency distribution of the four user types. Out of the four users only user *DdBs* effectively benefits from an automated blind system. User *DdBd* and *DiBd* always retract their blinds early in the morning when it is decided whether the lighting is activated or not and user *DiBs* ignores indoor daylight levels anyhow. This means that the electric lighting energy demand of only 25% of all occupants is affected by the automated blinds. This is a finding that certainly requires further validation[*].

4. Discussion and Conclusion

In the following the originality, relevance, limitations and availability of the Lightswitch-2002 model are discussed, and unresolved issues are addressed.

<u>originality:</u> The decisive innovation of Lightswitch-2002 over former models is that each manual switching decision has a probability function assigned to it and a random process decides whether a switching event takes place or not. The capability to carefully model the switching and energy characteristics of an automated control helps to identify under what circumstances the control leads to energy savings and how big these savings are. The four user behavioral types that are currently implemented in Lightswitch-2002 mimic the individual spread between different occupants that has been found in real buildings. This informs a designer how robust a lighting concept in a particular building is towards "unexpected" usage.

<u>relevance:</u> The example application of the model for a daylit office with a southern facade indicates that annual electric lighting energy demands for a manually controlled lighting and blind system may vary between 10 and 39kWh/m^{2}yr for different user types. The combination of these user-specific energy demands with frequency distributions for the different users offers some guidance as to how much energy savings can be expected from a particular control strategy in a particular building. The

[*] It is questionable how many individuals are in fact diligently changing their blinds on a daily basis while not

predicted mean energy savings of 20% for an energy-efficient occupancy sensor in the example office agree well with field measurements in an office building in California (Jennings *et al.*,1999).

limitations: A number of technical limitations of the model concerning intermediate switch-off, thermal considerations, privacy issues, seating orientation and the location of controls are mentioned in section 2.4. A conceptual limitation of the model is that it is purely descriptive, i.e. it predicts how occupants might interact with a lighting system without providing any information on user satisfaction or acceptance.

availability: The Lightswitch-2002 algorithm has been integrated into the online design support tool Lightswitch Wizard (www.buildwiz.com) as well as the expert daylighting analysis software DAYSIM (www.daysim.com).

4.1 Unresolved Issues

model validation: Even though the Lightswitch-2002 algorithm is based on scientifically sound methods, it is still of "preliminary" nature as are the underlying behavioral patterns. Both will need to be refined in the future as behavioral research on manual lighting control advances[*]. The example application of the model has revealed that two quantities require future attention: Events that trigger that blinds are retracted or lighting is switched *off* and the frequency distribution of different user types in various buildings.

total energy demand: The relevance of the model results will be limited as long as they are restricted to electric lighting energy demands. Therefore, the Lightwitch-2002 algorithm is presently integrated into the whole building energy simulation program ESP-R so that the overall energy performance of different lighting and blind control strategies can be holistically assessed (Bourgeois *et al.*, 2004).

stochastic effects: The model is based on numerous stochastic processes that influence the final outcome of a simulation. A future study will test how sensitive simulation results are with respect to these stochastic effects.

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paying any attention to indoor daylight levels when it comes to switching on their lighting (user *DiBd*).

[*] One possible platform for these validation will be through the field studies that are carried out in the context of IEA Task 31 *"Daylighting Buildings in the 21st century" (*http://www.iea-shc.org/task31/index.html)

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Table and Figure Captions

Table 1. Underlying assumptions of the Lightswitch-2002 algorithm. Further details are provided in Reinhart and Voss (2003).

Table 2. Lightswitch-2002 accounts for four different user types.

Figure 1. Basic approach of the Lightswitch-2002 model.

Figure 2: The Lightswitch-2002 algorithm for electric lighting and blinds. The "set blinds" procedure is described in Figure 3.

Figure. 3 (a): Measured switch-on probability function upon arrival. Hunt's (1979) original function (solid line) describes the average switching behavior of a group of users. The dotted line models the switching behavior of a user that keeps the electric lighting activated throughout the working day. (b) *Intermediate* or *within-day* switch-on probability for electric lighting (Reinhart and Voss, 2003).(c) Measured switch-off probabilities for different times of user absence for a lighting system without controls, with an occupancy sensor (Pigg *et al.*, 1996) and for a dimmed, indirect lighting system (Reinhart and Voss, 2003).

Figure 4: Control algorithms for manually controlled and automated blinds. In the event of *close blinds,* the blinds are fully lowered and the smallest slat angles out 0^0, 45^0 and 75^0 is chosen under which direct sunlight is fully blocked.

Figure 5: (a)Facade view and (b) top view of the example office with the work place.

Figure 6: Weekday profile of the (a) annual mean occupancy probability, (b) blind occlusion, and (c) electric lighting load in the example office.

Figure 7: Weekday profile of the annual mean electric lighting load in the example office for (a) an energy-efficient and (b) an on/off occupancy sensor.

Figure 8: Weekday profile of the annual mean electric lighting load in the example office for (a) an indirect and (b) a direct photocell-controlled dimmed lighting systems.

Figure 9: Predictions of the annual electric energy demand in the example office for five different lighting scenarios combined with manually controlled and automated blinds. The gray bars indicate the range of simulation results for the four different user types.

Table 1.

(i)	Even though occupants behave *differently*, they use their lighting and blind controls *consciously* and *consistently.*
(ii)	Manual lighting control mainly coincides with the occupant's arrival at or departure from the work place. Some individuals always activate their lighting throughout the whole working day independently of prevailing daylight levels (behavior *user does not consider daylight* in Figure 3(a)). Others only switch on their electric lighting when indoor illuminance levels due to daylight are low (*user considers daylight* in Figure 3(a)). For the latter user type the switch–on probability for electric lighting tends to be correlated to minimum indoor illuminance levels at the work plane upon arrival (Hunt 1979; Love 1998) .
(iii)	*Intermediat*e or *within-day* switch-on events of the electric lighting are related to minimum work plane illuminances as shown in Figure 3(b). The switch-on probability rises from 0.5% to 2% per 5-minute time step for minimum work plane illuminances below some 250 lux. This level resemble the illuminances at which subjects in a laboratory study tended to reset their electric lighting levels that were slowly falling over time (Newsham *et al.*, 2002). As users cannot work in the dark, the intermediate switch-on probability from has been modified and set to unity for vanishing indoor illuminances due to daylight. This plausible modification to the intermediate switch-on function will need to be refined/validated as more field data will become available.
(iv)	The length of absence from the work place strongly correlates with the probability that the electric lighting is manually switched off. It has been found that the presence of automated lighting controls influences the behavior of some people (Pigg *et al.*, 1996). People in private offices with occupancy control were found to be less likely to turn off their lights upon temporary departure than people without sensors. Similarly, switch-off probabilities were found to be lower for a dimmed, purely indirect lighting system that for an undimmed system. These effects are summarized in Figure 3(c).

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Table 2.

user *DdBd*[&]	The user controls the lighting system with sensitivity to ambient daylight conditions and uses the blinds on a daily basis
user *DiBd*	The user controls the lighting system independent of ambient daylight conditions and uses the blinds on a daily basis
user *DdBs*	The user controls the lighting system with sensitivity to ambient daylight conditions and keeps the blinds permanently lowered with a slat angle of 75^0.
user *DiBs*	The user controls the lighting system independent of ambient daylight conditions and keeps the blinds permanently lowered with a slat angle of 75^0.

[&])Dd: Daylight dependant lighting use; Di: Daylight independent lighting use; Bs: Blinds static: Bd: Blinds dynamic.

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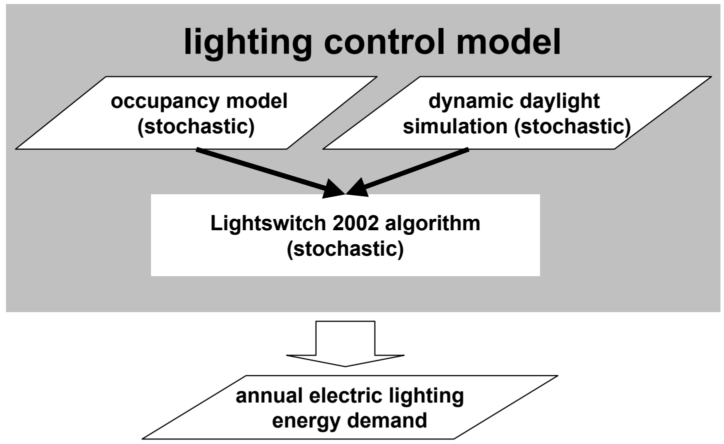
Figure 1:



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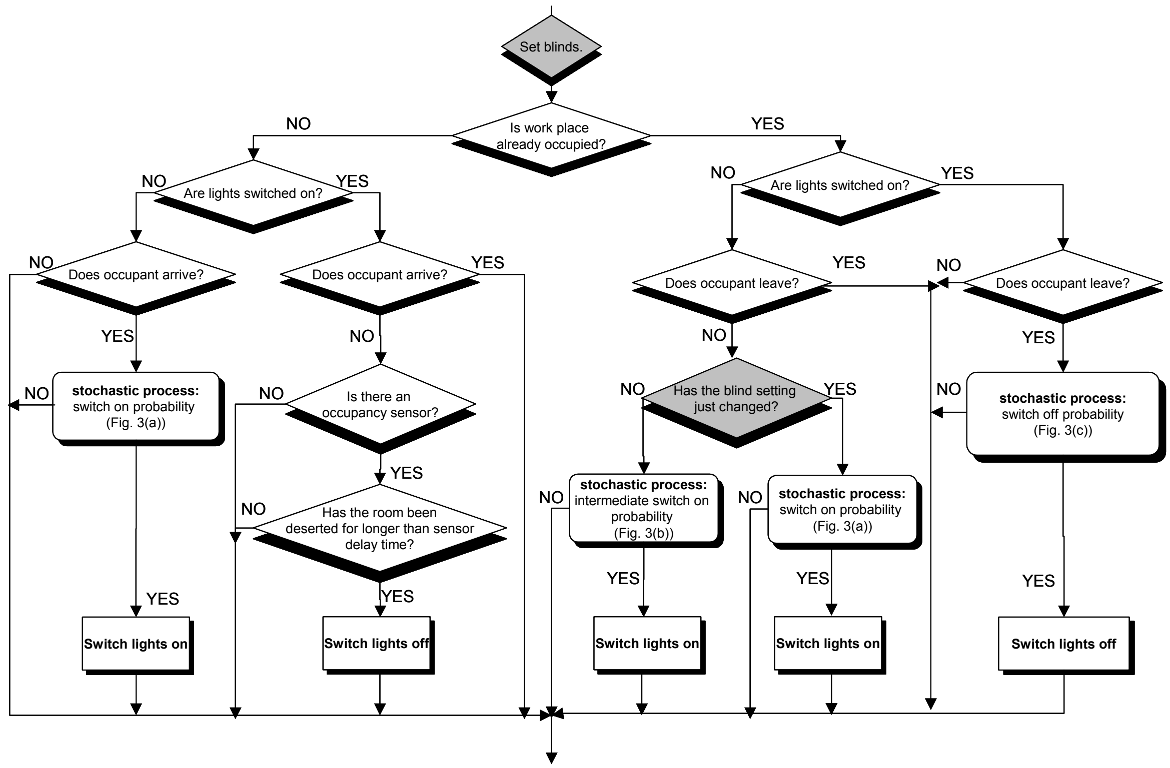
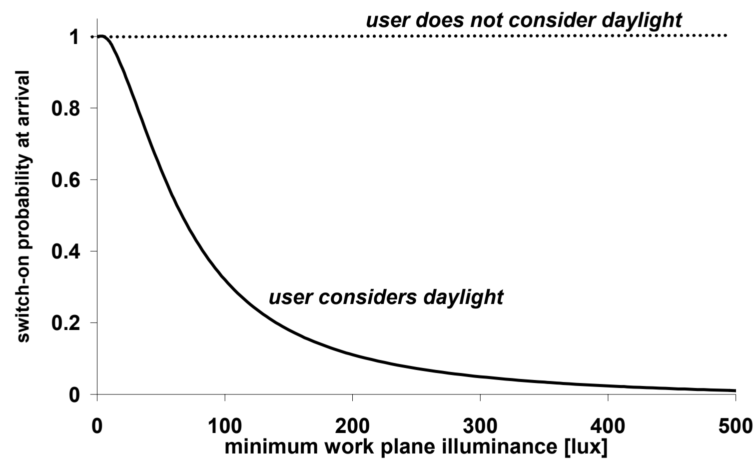


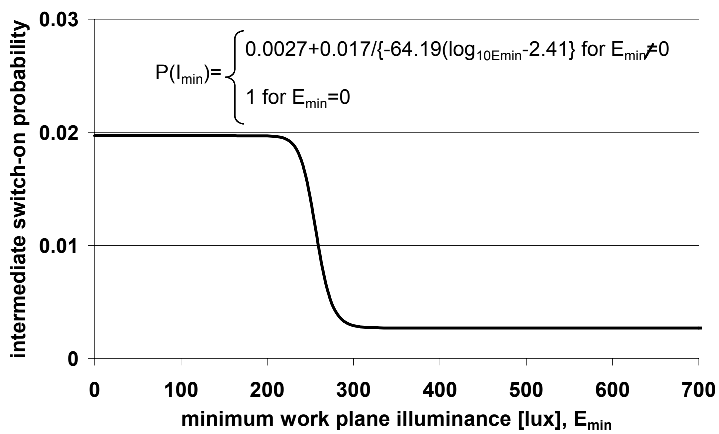
Figure 2:

Figure. 3

(a)


user does not consider daylight
user considers daylight
switch-on probability at arrival
1
0.8
0.6
0.4
0.2
0
0
100
200
300
400
500
minimum work plane illuminance [lux]

(b)


P(Imin)=
0.0027+0.017/{-64.19(log10Emin-2.41} for Emin≠0
1 for Emin=0
intermediate switch-on probability
0.03
0.02
0.01
0
0
100
200
300
400
500
600
700
minimum work plane illuminance [lux], Emin

(c)

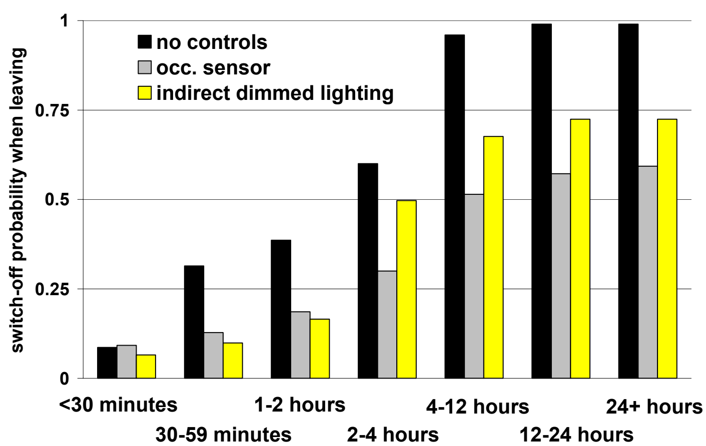

no controls
occ. sensor
indirect dimmed lighting
switch-off probability when leaving
1
0.75
0.5
0.25
0
<30 minutes
30-59 minutes
1-2 hours
2-4 hours
4-12 hours
12-24 hours
24+ hours

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Figure 4:

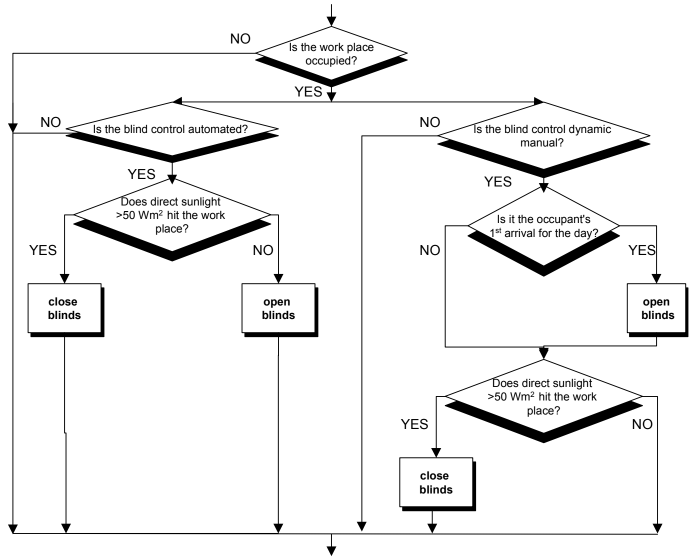


Figure 5:

(a) (b)

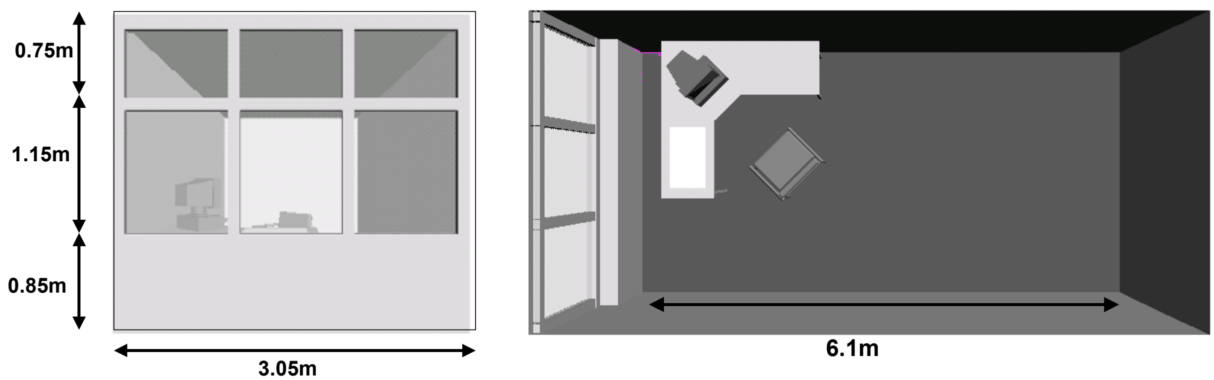
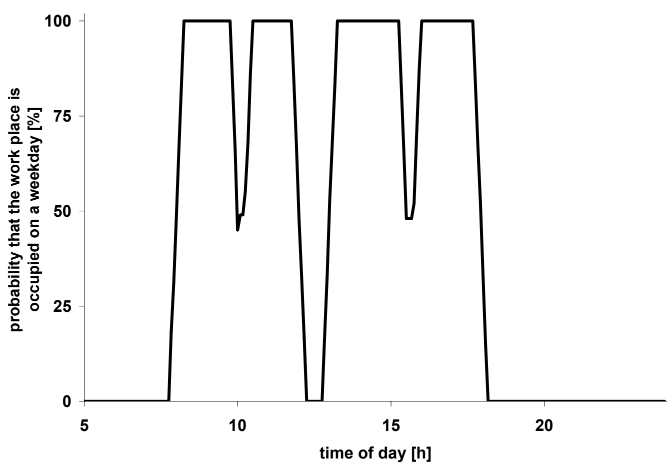
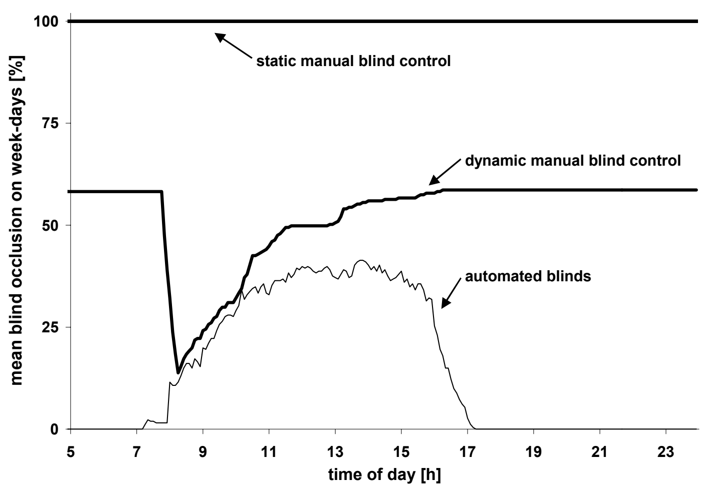


Figure 6.
(a)


probability that the work place is occupied on a weekday [%]
100
75
50
25
0
5
10
15
20
time of day [h]

(b)


mean blind occlusion on week-days [%]
100
75
50
25
0
static manual blind control
dynamic manual blind control
automated blinds
5
7
9
11
13
15
17
19
21
23
time of day [h]

(c)

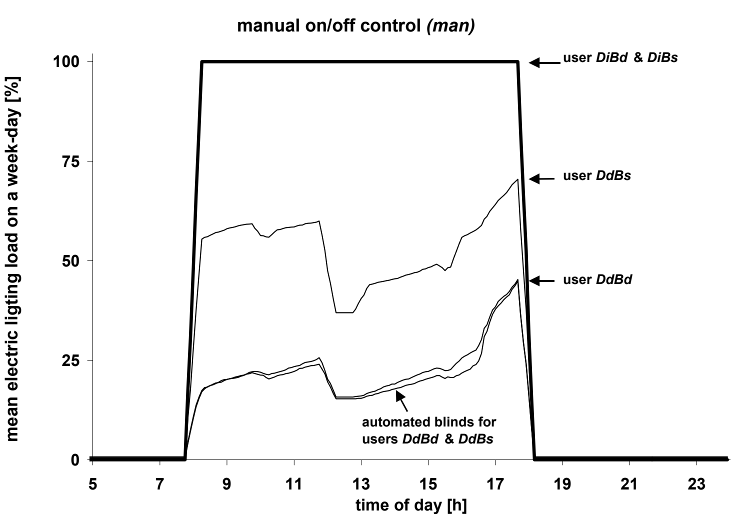

manual on/off control *(man)*
mean electric ligting load on a week-day [%]
100
75
50
25
0
user *DiBd* & *DiBs*
user *DdBs*
user *DdBd*
automated blinds for
users *DdBd* & *DdBs*
5
7
9
11
13
15
17
19
21
23
time of day [h]

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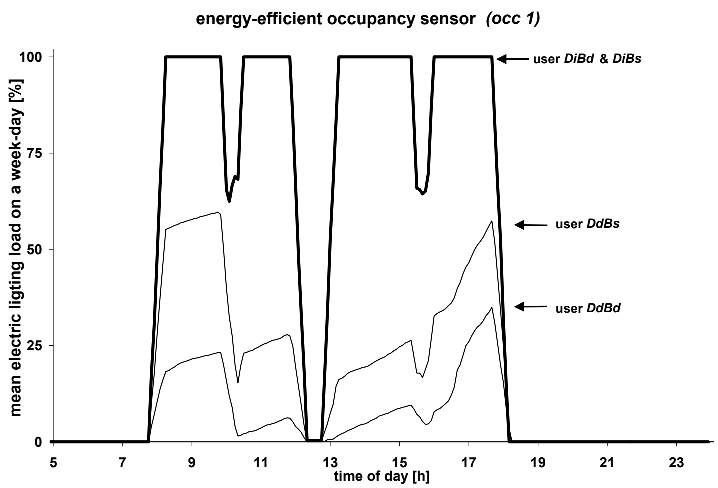
Figure 7:

(a)



(b)

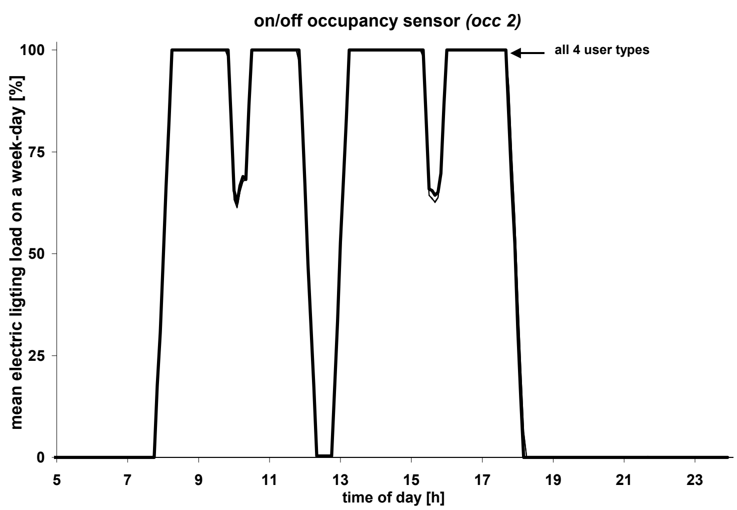


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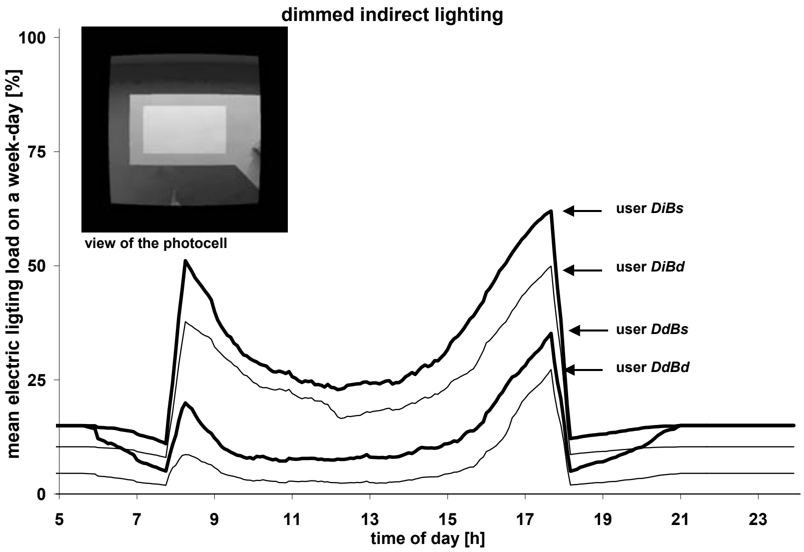
Figure 8:

(a)



(b)

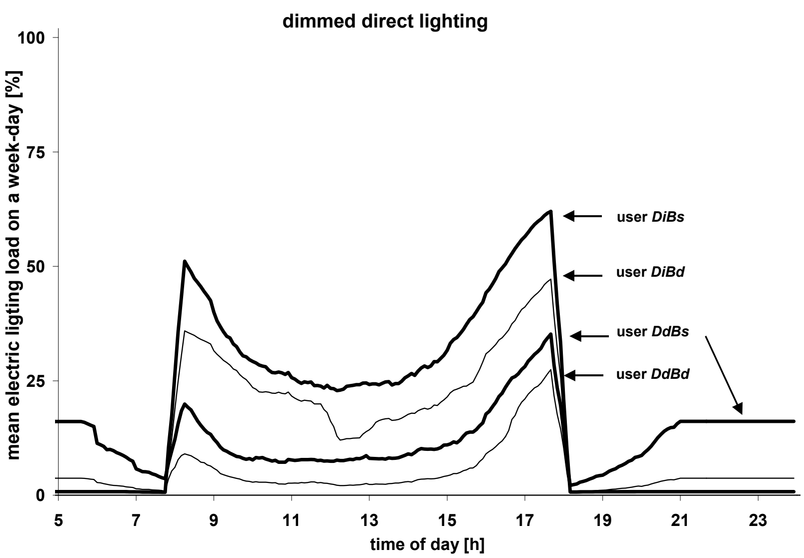
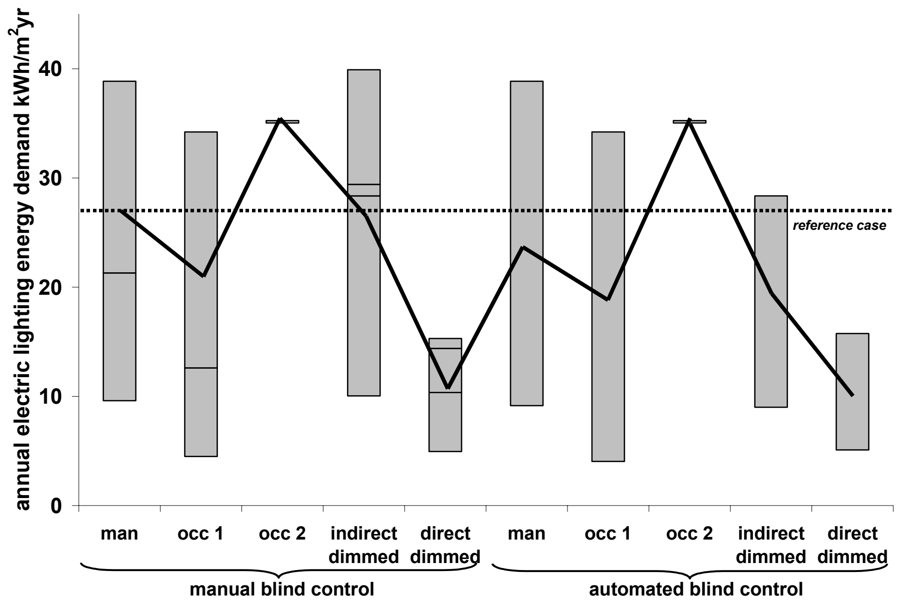


Figure 9:


annual electric lighting energy demand kWh/m²yr
0
10
20
30
40
reference case
man
occ 1
occ 2
indirect dimmed
direct dimmed
man
occ 1
occ 2
indirect dimmed
direct dimmed
manual blind control
automated blind control