AUTOMATED SOLAR SHADING AND OCCUPANT BEHAVIOR

The impact of occupant behavior modeling on the simulation-based performance prediction of automated solar shading systems

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ABSTRACT

When an automated solar shading system is being developed or implemented in a building, simulations are often used to predict the performance of the shading system. In most cases when this is done, occupant behavior is taken into account by using simple schedules, even though it is known that occupant behavior can cause large deviations between the predicted and actual performance. Manual overrides are also almost never taken into account. There are a lot of studies available that focus on developing occupant behavior models, but there is little knowledge available on how to apply them and which models should be used in combination with automated solar shading systems. The main goal of this study is therefore to develop a better understanding of the different ways to represent occupant behavior and of the associated uncertainties when assessing the performance of automated solar shading systems using simulations. The findings of this research can also provide guidance on how to model occupant behavior in combination with automated solar shading systems. The study is divided into three parts: (1) theory, which focuses on choosing the automatic control strategies and occupant behavior models that are used in this study, (2) preparation, which focuses on how to implement different automatic shading control strategies and occupant behavior models with different levels of complexity using simulation software, and (3) case study analysis, which focuses on assessing the performance of different automatic control strategies for solar shading and what the impact of using different types of occupant behavior modeling is. This case study is used to determine when high resolution occupant behavior modeling is required and in which case simple modeling is sufficient. The results show that implementing presence models that provide a slight variation of a simple schedule has almost no impact on the annual performance of the shading system in comparison to just using the schedule. Therefore, it is not worth the effort to implement these type of models. More complex and stochastic presence models can have an impact on the results and can also show the range in performance caused by the difference in behavior between occupants. With simple automatic control strategies, taking into account manual shading overrides can lead to different conclusions regarding absolute performance values when a stochastic presence model is used. With more advanced strategies, it is not needed to include manual overrides as it has almost no impact on the predicted annual performance of the shading system regarding energy demand and visual comfort.
1. INTRODUCTION

In general, people spend almost 90% of their time inside buildings [3], which shows how important it is that the indoor environment of buildings is of high quality. One factor that contributes to a good indoor environment is daylight, as natural light has a beneficial effect on the health, productivity, and safety of building occupants [5]. However, too much daylight can reduce thermal comfort and cause glare. Besides having a healthy indoor environment, energy efficiency is also becoming more and more important during the design and operation of buildings. A system that can influence both of these aspects is solar shading.

The behavior of building occupants can have a large influence on a building’s performance [9]. To reduce the influence of occupants, solar shading can be automated so occupants no longer have to control it manually. Automated solar shading systems can change their state to respond to the outdoor or indoor conditions and to the needs of the building occupants. The two main goals of automated solar shading systems are improving indoor comfort, both thermal and visual comfort, and reducing the energy consumption of a building.

A problem with using fully automated solar shading is that building occupants are not always content with how an automatic system controls the position of the shades. The control strategy of an automatic solar shading system generally responds to a physical quantity, for example solar irradiance, illuminance or temperature. These parameters are measured at a sensor point, which can be placed indoors or outdoors at different locations. It is pretty much impossible to choose the physical quantity, threshold value and sensor location so that every single occupant will always agree with the automatic control strategy, as everybody has his or her own preferences and it is hard to balance conflicting performance aspects. Another downside of fully automated solar shading systems is that occupants want to have the feeling that they can control their indoor environment and adapt it to their needs. This feeling of control also increases their productivity [9]. Therefore, automated solar shading systems often allow occupants to override the automatic control strategy.

During the development of automated solar shading systems or when a certain system is planned to be implemented in a building, simulations are often used as a tool to predict the performance of the shading system. There is a wide variety of published studies on the performance prediction of automated solar shading using simulations, both for internally and externally applied systems. Some use threshold values, like illuminance or irradiance [3,9], while there are also studies available that focus on shading devices that track the position of the sun [7,8]. In the majority of the studies, occupant behavior (OB) is taken into account by using simple schedules, while it is known that occupant behavior can cause large deviations between the performance that is predicted using simulations and the actual performance after realization [10]. Also, manual overrides of the automatic system are almost never taken into account. There are a lot of studies available that focus on developing models for different types of occupant behavior with different levels of complexity [13], but there is little knowledge available on how to apply them and which models should be used in combination with automated solar shading systems. When occupant behavior is not taken into account properly, the building performance can be over- or underestimated. This difference in predicted and actual performance is a problem for the developers of automated solar shading systems, as it can lead to them designing their product based on wrong conclusions, as they assume certain occupant behavior while in reality occupants behave differently. Another problem that can arise is that a certain predicted performance is promised to the clients of the system developer, which cannot be achieved after the system has been realized.

The goal of this study is therefore to develop a better understanding of the different ways that occupant behavior can be represented and of the associated uncertainties when assessing the performance of automated solar shading systems using simulations. As it depends on the research objective which type of occupant behavior models are best used [10], it is investigated in which case it is needed to provide a more realistic representation of occupant behavior and in which case simple models, as are currently being used in studies that assess automated solar shading systems, are sufficient. Different types of occupant behavior are investigated: presence, manual shading control and lighting control. The outcome can be used by automatic shading system developers to optimize the control strategy of their systems and to help them predict their system’s performance more accurately. The findings of this study can also provide guidance on how to model occupant behavior in combination with automated solar shading systems. The study is divided into three main parts: theory, preparation and case study analysis.

The theory phase focuses partly on choosing the different automatic shading control strategies that are used in the case study. It also focuses on choosing occupant behavior models for presence, shading control and lighting control that might be relevant and suitable for this study.

The preparation phase focuses on how to implement the different automatic shading control strategies and occupant behavior models with different levels of complexity using simulation software. The occupant
behavior models are evaluated and the results of this phase are used to determine which models are used in the case study and why. The preparation phase also focuses on how to make sure the performed simulations provide reliable results.

The case study analysis focuses on how increasing occupant behavior modeling complexity influences the predicted performance of an automated solar shading system. An internal roller blinds system, developed by the company Verosol, is used as a case study. The performance of this automated solar shading system, with the different automatic control strategies, is assessed using different occupant behavior modeling resolutions to evaluate the impact on the performance. The results of the case study analysis are used to determine when high resolution occupant behavior modeling is required and in which case simple modeling is sufficient.

**2. METHODOLOGY**

**2.1. Research approach**

Figure 1 shows a schematic overview of the research approach.

The theory phase has two main parts: choosing the automatic control strategies (see section 2.2) and choosing the different occupant behavior models for presence, manual shading control and lighting control (see sections 2.4, 2.5 and 2.6).

The first part of the preparation phase is modeling the case study building (see section 2.3) and modeling the automated shading system, together with the different automatic control strategies. Once the control strategies are implemented, they are verified by analyzing their behavior throughout two typical weeks.

The next part of the preparation phase is modeling and evaluating the different models for presence, manual shading control and lighting control. Based on the degree of variability they give and their applicability in combination with the control strategies and other occupant behavior models, a selection of models is made that are used in the case study.

For presence, a range of different presence models is investigated, from simple deterministic schedules to more complex and stochastic models. Simulations are used to evaluate whether the models provide results that are in line with the expected occupant presence patterns.

The manual shading control models are used to investigate fully manual control and the impact of manual overrides of automated shading. Models with different complexity levels are used, from models with a static threshold to stochastic models. Simulations are used to check whether the behavior resulting from the models is as expected. As the models are also used to determine the impact of manual overrides, it is evaluated whether the environmental parameters...
that determine manual shading interactions reach the level needed for occupants to make changes when the different automatic control strategies are applied.

For lighting control, a model for manual lighting control and a model for automatically controlled lighting are used. This allows the comparison between automated lighting and manually controlled lighting. Simulations are used to evaluate whether the models function as intended.

Another step of the preparation phase is extending the building simulation model with the results from Radiance simulations, as EnergyPlus is known to overestimate indoor illuminance values [11]. Adding Radiance results allows the assessment of both energy performance and visual comfort. Some of the used models also respond to indoor illuminance or irradiance values, which should be predicted better by Radiance. A comparison is made between the results based on EnergyPlus and based on Radiance, to evaluate the impact that using EnergyPlus instead of Radiance can have on the results.

The final step of the preparation phase is related to the use of several stochastic models. With stochastic models, two simulation runs with exactly the same settings can provide different results, because something in the model is determined randomly every time. The amount of runs that is required to get converged results is case dependent [15]. Therefore, a sensitivity analysis is conducted to investigate the sensitivity of this specific case to the number of runs, to find out how many runs are required to provide converged results. The sensitivity is evaluated for all performance indicators, both for the mean and the standard deviation. Based on the results, a number of runs is chosen that is used in case study for all of the combinations that include stochastic models.

After the preparation phase, the building simulation model, including the automatic control strategies and the models for presence, manual shading control and lighting control, is ready for the case study. The case study analysis consists of six parts.

The first part of the case study analysis focuses on a relative performance comparison between the automatic shading control strategies when not taking into account complex occupant behavior modeling. For this part, a set of baseline cases is investigated. Each of the control strategies is combined with the simplest presence model, no manual overrides and automatically dimmed lighting. This way, the impact of occupant behavior on the results is small. The results are compared to a case with the shades always open and one with the shades always closed.

The second part focuses on how manually controlled shading performs in comparison to the automatic control strategies. Different models for manual shading control are used, which also allows the comparison between the different models.

The third part focuses on how using stochastic models for presence with different levels of complexity influences the predicted performance of the automatic control strategies. For this part, modified versions of the baseline cases are used, with only the presence model being changed to different models with higher modeling complexity. This way, the difference in results is only caused by the used presence model.

The fourth part of the case study analysis focuses on how taking into account manual overrides for shading influences the predicted performance of the automatic control strategies. For this part, a different modification is made to the baseline cases. Instead of changing the presence model, different manual shading control models are added to include the effect of manual overrides.

The fifth part focuses on how the automatic control strategies perform when there is manually controlled lighting instead of automatically dimmed lighting. For this part, the only difference with the baseline cases is that the automatically dimmed lighting has been replaced with manual lighting control models.

In the last part, different types of occupant behavior models are combined to investigate the impact on the performance. The combinations of models are chosen based on the results of the previous parts of the case study.

After finishing the study, some conclusions are listed about how occupant behavior can impact the performance prediction of automated solar shading systems when using simulations. These conclusions focus on how to better predict the performance of automated solar shading systems by taking occupant behavior into account and also on how to model occupant behavior in combination with automated solar shading systems.

2.2. Shading system and control strategies
In this study, an automated solar shading system that is developed by the company Verosol is used as case study (figure 2). It is an internal roller blind system with a metalized fabric.

An older control strategy for this system is called PLUG&PLAY [14]. This strategy responds to a facade sensor and automatically lowers the shades to a specific height, that the operator of the building can set, when the irradiance on the facade exceeds 200 W/m². Occupants are also allowed to manually override the system temporarily and they can set the shades to a height of their choice.
A newer control strategy, that is still in development, is called FourC \[15\]. This strategy has a glare safe mode, which lets the shading screen move up and down according to the position of the sun, in order to block direct sunlight from hitting the work plane, while at the same time providing as much view as possible. It also has an overcast sky detection. If the room is occupied and the vertical solar irradiance on the facade is below 120 W/m², the system assumes an overcast sky and the shades are fully raised. The FourC system also has an energy mode that becomes active when the room is unoccupied. In energy mode, the system determines whether the shades are fully lowered or fully raised based whether there is a heating or cooling demand and whether there is a heat gain or loss through the facade. If the indoor temperature is below the average of the heating and cooling setpoint, there is a heating demand. If the indoor temperature is above this value, there is a cooling demand. The heat gain or heat loss through the window is calculated using formula 1.

\[
\text{heat gain} = E_{\text{sun}} + (T_e - T_i) \cdot U \quad (1)
\]

In this formula, \(E_{\text{sun}}\) is the amount of vertical solar irradiance that hits the window, \(T_i\) is the indoor temperature, \(T_e\) is the outdoor temperature and \(U\) is the overall heat transfer coefficient of the window. If the calculated heat gain is positive, there is a heat gain through the facade. If it is negative, there is a heat loss. Table 1 shows whether the shades are raised or lowered depending on these two aspects. Just like with PLUG&PLAY, occupants can manually override the automatic control strategy and set the shades to a height of their choice.

Based on the shading system by Verosol, six different automatic control strategies (figure 3) were created to compare the performance and the robustness to occupant behavior.

Strategies 2 and 3 are based on the PLUG&PLAY system by Verosol. They both have an irradiance sensor on the facade with a threshold of 200 W/m² for lowering the shades and they can only be placed in two positions. The only difference between the strategies is that with strategy 2, the shades are always lowered fully, while with strategy 3, the shades only lower to eye height. This is done to evaluate the impact on the performance when the shading system always provides a view to the outside.

Strategy 1 is the baseline case. The shades only move fully up or fully down and it has an irradiance sensor on the roof instead of the facade. The threshold for lowering the shades is in this case set to 300 W/m². This value was chosen based on a simple comparison study between a roof sensor and a facade sensor with 200 W/m² as threshold, to find a threshold for the roof sensor that corresponds with the 200 W/m² on the facade (see appendix A).
2.3. Building properties
The building model that is used in this study is based on the reference office from Task 56 of the Solar Heating and Cooling Programme of the International Energy Agency [16]. Several modifications were made to the model of Task 56, in order to make the model suitable for this study.

The two-person office (figure 4) is part of a larger office building, with the floor, ceiling and three of the walls connected to other offices. These constructions are assumed adiabatic. The south-facing wall is an external wall and contains one large window, instead of three separate windows as in Task 56. This was done to simplify the model. The window sill has been lowered, because in Task 56 the sill is above 1.2m, meaning it is not possible to have the shades lowered to eye height and still provide a view to the outside, which is needed for control strategy 3. The window is divided in 20 parts. The reason for this is that EnergyPlus does not allow a window construction to be partially shaded. Therefore, the window is divided in separate parts that can be shaded or unshaded individually.

Task 56 describes three different options for the thickness of the insulating material in the external wall and for the window properties, based on three different climate zones. In this study, a climate file of Amsterdam is used, so the set of construction properties from Task 56 for the climate zone of Stuttgart are used, as this climate resembles the Dutch climate the most.

The occupancy schedule from Task 56 is not implemented in the used model, as different models for presence are used instead. The same is true for the lighting schedule. With the exception of the schedules, all other properties for the internal gains due to occupants and lighting are based on Task 56. Internal gains due to appliances are also implemented as in Task 56.

An ideal loads air system is used to keep the indoor temperature between the heating setpoint of 21°C and the cooling setpoint of 25°C. Only during weekends, there is a setback for the heating and cooling setpoints. They are changed to 18°C and 28°C respectively. Ventilation and infiltration rates are set according to Task 56.

Finally, the solar shading system used in Task 56 is not implemented, as the roller blinds system by Verosol is used instead. The properties of the shading material are based on the EnviroScreen [17].

An overview of the model properties can be found in appendix B.

2.4. Presence models
The simplest way to model presence is with a deterministic schedule. With the used schedule, both occupants arrive, have lunch and leave at the same time. This schedule is the same for every weekday throughout the year. During weekends, nobody is present.

The second investigated option to model presence is based on the presence model by Reinhart [18], which is an adapted version of the occupancy model by Newsham [19]. The arrival probabilities in this model are based on the recorded computer network log on times of 240 employees at a single site over 18 days. Temporary absence probabilities are based on data from a second site with around 80 employees. Departure probabilities were chosen based on typical behavior in real buildings. The main difference between the model by Reinhart and the deterministic schedule is that the times of arrival, breaks and departure are determined randomly based on a normal distribution. This randomness is included to take into account that occupants do not always arrive, take breaks and leave at the exact same time. However, the amount of breaks as well as the length of the breaks are determined deterministically in this model.

The second option is based on the model by Wang et al. [20], which is created using occupancy logs obtained from 35 single person offices at a large

![Fig. 4: Modified building geometry](image)
office building with data from a single year. Similar to the model by Reinhart, the model by Wang et al. also determines the times for arrival, breaks and departure randomly. In this model, the lengths of the breaks are also determined randomly based on a normal distribution. The amount of breaks is still determined deterministically.

The model by Page et al. is another option that is used to model presence. This model is based on the inverse function method, which can generate a time series of events from a given probability distribution function. To calibrate and validate the model, data was collected from 20 zones of the LESO-PB building at the EPFL for approximately four years. The model by Page et al. uses a stochastic process based on a probability of presence and a parameter of mobility to determine whether an occupant is present or not and whether a change in presence takes place. For the probability of presence, a schedule is required as input. With the right input schedule, overhours can also be taken into account, which is not the case with the previously discussed options. This model also provides much more varying occupancy patterns, as the arrival time, the amount and length of temporary breaks and the departure time are less fixed as with the other models.

A final option that is used in this study is a presence model with longer periods of absence taken into account. This is included in the model by Page et al. as a separate case.

2.5. Manual shading control models
A schematic overview of the different models for manual shading control that are investigated can be found in appendix C.

The first option for the manual control of shading devices that is investigated is based on the model by Newsham. Only the part about shading control is used from the model, which is based on a field study of a large office building in Japan. With this model, the shades can only be fully lowered or fully raised. The shades are lowered when the transmitted direct solar irradiance exceeds 233 W/m². The shades are only raised at the first arrival of the day. This option does not include a stochastic component.

Another model that is used for the manual control of shading is the model by Reinhart. The manual shading control strategy used in this model is based on the analysis of several different studies that focus on the interaction of people with shading. The model is very similar to Newsham's model. The only difference is that with the model by Reinhart, the shades are lowered when the direct solar irradiance on the work plane exceeds 50 W/m². The shading control part of the model by Reinhart does not include a stochastic component.

A more complex model that is used to model the manual control of shading is the model by Haldi and Robinson, which is based on data from monitoring the manual shading control of six two-person and eight single-person offices of the LESO-PB building for over 6 years. A difference with the models by Newsham and Reinhart is that occupants can also partially shade the window instead of only making full lowering and raising actions. The model determines the shades change probability for lowering and raising actions based on the illuminance on the work plane, the global horizontal illuminance and the currently shaded fraction. Regression parameters that represent the preference of occupants are also included. These regression parameters are different for arrival and intermediate times, as occupants are more likely to make changes at arrival. They are also different for lowering and raising actions and for partial and full lowering/raising actions. The model provides a normal distribution for each of the regression parameters, which indicates the variability between different occupants. After the shades change probability has been calculated, a stochastic process is used to determine whether the change in shading position actually takes place. Once an action takes place, the model calculates what the new height of the shades will be.

These models are intended to be used for manually controlled shading systems. However, they will also be used in this study to model manual overrides of automated shading, as there are no models available with this specific purpose.

2.6. Lighting control models
The first option that is used for the control of lighting is automatic dimming. With this option, electric lighting is used to maintain a horizontal illuminance of at least 500 lux on the work plane. When this value is reached by daylight alone, the electric lighting is turned off. When there is not sufficient daylight available, the electric lighting will be used to reach 500 lux. When nobody is present, the lights are turned off.

The second option is manual lighting control, based on the Lightswitch-2002 model by Reinhart. This model is based on probabilistic behavioral patterns that have been observed in office buildings in Canada, Japan, Germany, the UK and the United States. The model by Reinhart determines the probability for switching on and switching off the lights. The switch on probability is based on the indoor illuminance and is different for arrival and intermediate times. The lights are only switched off when the occupant leaves the room and the switch off probability is based on the amount of unoccupied hours after departure. After the switch on or switch off probability has been calculated, a stochastic process is used to determine whether the action actually takes place. A schematic overview of this model can be found in appendix D.
2.7. Performance indicators
The first performance indicator that is evaluated is the annual primary energy demand. The primary energy demand is investigated for heating, cooling and lighting separately, based on the conversion factors in appendix E. The annual primary energy demands for heating, cooling and lighting are divided by the floor surface area and expressed in kWh/m².

The second performance indicator is spatial daylight autonomy (sDA), which is expressed as the fraction of floor area that receives 300 lux for at least 50% of the occupied hours. To calculate the sDA, a grid of 24 points at work plane height (0.8m) is used. The sDA is expressed as a fraction of the total floor area.

The third performance indicator is related to view to the outside. View is expressed as the fraction of occupied hours that the shades are at least 1.2m above the floor.

The fourth performance indicator is the simplified daylight glare probability (DGPs). This performance indicator is based on vertical eye illuminance (Eᵥ) and is calculated using formula 2.

\[
\text{DGPs} = 6.22 \cdot 10^{-5} \cdot Eᵥ + 0.184 \quad \text{(2)}
\]

Three different viewing directions are used to evaluate glare: directly facing the window (0° viewing direction), facing the window at a 45° angle and facing the wall perpendicular to the window (90° viewing direction).

The last performance indicator is the number of manual interactions with the shading system. This performance indicator is only evaluated for the cases with manually controlled shading and with manual overrides. The number of manual interactions is counted separately for lowering actions and raising actions. It is considered as a comfort indicator, as the amount of manual interactions indicates how often people still have to manually do something to have a comfortable indoor environment.

3. PREPARATION
3.1. Modeling the automatic control strategies
As mentioned, one of the first steps of the preparation phase is modeling the six automatic shading control strategies, which is done using the Energy Management System (EMS) in EnergyPlus. To verify that the strategies are working as intended, a single case, with a simple schedule for presence and no manual overrides taken into account, is simulated and the position of the shades is evaluated in relation to the environmental parameters that are relevant for the different control strategies. This is done for a week in winter and a week in summer (figures 6 through 11).

Strategy 1 uses an irradiance sensor on the roof, so the horizontal irradiance on the roof is used as input for this strategy. During weekdays, the shades are fully lowered if the horizontal solar irradiance on the roof exceeds 300 W/m². Hysteresis is included by setting the threshold for raising to 275 W/m². The shades are fully raised once the solar irradiance on the roof is below this value. During weekends, the shades are modeled to stay raised. Fully lowered means that all 20 window parts are set to shaded and fully raised means that all window parts are set to unshaded. Figure 6 shows the position of the shades in relation to the horizontal solar irradiance on the roof. In winter, the solar irradiance on the roof is low due to the low position of the sun. As a result, the 300 W/m² is not reached and the shades remain raised. In summer, the sun is positioned higher in the sky. Therefore, the threshold is often reached on sunny days, resulting in lowered shades during large parts of the day. Only early in the morning and late in the afternoon, the shades are still raised due to the lower sun position at these times. In the weekends, the shades remain raised. The results show that strategy 1 is functioning as intended.

Control strategy 2 is modeled in almost the exact same way as the first strategy. However, the vertical irradiance on the south facade is now used as input, as strategy 2 uses a facade sensor instead of a roof sensor. The shades are fully lowered if the vertical solar irradiance on the facade exceeds 200 W/m² and they are fully raised when it is below 175 W/m². Figure 6 shows the position of the shades in relation to the vertical solar irradiance on the facade. Unlike with strategy 1, the shades are now lowered during winter days as well. The low position of the sun causes the solar irradiance on the facade to be higher than on the roof. This results in the shades being lowered during winter days. In summer, the opposite is happening, but the irradiance on the roof is still high enough to reach the threshold and therefore the shades are also lowered in summer. These results show that strategy 2 is also functioning as intended.

Strategy 3 is modeled using the same script as strategy 2, but the shades are not fully lowered when the threshold of 200 W/m² is reached. Instead, they are lowered to a position just above eye height, so only the top 15 window parts are shaded and the bottom parts remain unshaded. Figure 8 shows the position of the shades in relation to the vertical solar irradiance on the facade. The results are exactly the same as with strategy 2, but instead of being fully lowered, the shades are now lowered for three quarters. This shows that strategy 3 is functioning as intended.

Strategy 4 is modeled differently than the first three strategies. During weekdays, it is first checked whether the sun is in view, which is the case when the azimuth angle is between 90° and 270°. If this
is not the case, the shades are fully raised. If this is the case, the ‘glare safe height’ is determined (figure 5). This is done based on the solar horizontal profile angle, the distance from the desk to the window and the height of the desk. The reference distance is set to 0.75m, the reference height is set to 0.8m and the solar horizontal profile angle is used as input parameter for this strategy. Due to the division of the window in 20 parts, the exact position of the shades is rounded off to the nearest border below the exact height. The height is always rounded off to the border below, because otherwise the shades would be positioned above the glare safe height. All window parts above the rounded off height are set to shaded and all parts below this height are set to unshaded. Glare safe mode is turned off during weekends and the shades are fully raised. Figure 9 shows the position of the shades in relation to the solar horizontal profile angle. In winter, the sun is positioned very low, resulting in a low solar horizontal profile angle. This results in a very low position of the shades. In the middle of the winter, the shades are fully lowered for almost the entire day, because the sun is always in view between the time it rises and the time it sets. Only in the middle of the afternoon, the shades are raised slightly due to the higher solar horizontal profile angle. In summer, the sun is in view for a smaller part of the day, as it rises in the northeast and sets in the northwest, which are both out of view of the south facade. This results in the shades being fully raised at the start and end of the day, because the sun is always in view between the time it rises and the time it sets. Only in the middle of the afternoon, the solar horizontal profile angle is quite high because the sun is positioned higher in summer. This results in a high position of the shades during the entire day. The results show that glare safe mode is implemented correctly and that control strategy 4 is functioning as intended.

Control strategy 5 starts with checking the occupancy status. If an occupant is present, comfort mode is active and the shades will be positioned at glare safe height, which is modeled similarly as in strategy 4. If there are no people present, energy mode is active, which is modeled based on table 1. To prevent energy mode from turning on during very small periods of absence, a delay is added of 15 minutes after leaving the room before energy mode is activated. Figure 10 shows the position of the shades in relation to the indoor temperature and the heat gain/loss through the facade. The colored background shows that comfort mode is only active during occupied times and that energy mode is active during unoccupied times (nights, mornings, evenings, lunch breaks and weekends). The lunch break has a duration of one hour, so energy mode is active for the last 45 minutes due to the delay. When in comfort mode, the position of the shades is exactly the same as was the case with strategy 4. This is as expected, because the shades are responding to the solar horizontal profile angle when the system is in comfort mode, just like strategy 4. In winter, the indoor temperature is below the average setpoint very often. Only during sunny days it rises above the average setpoint in the middle of the day. At night, there is a heat loss through the facade and therefore the shades are closed. During daytime, there is a heat gain during some days due to solar radiation. On the first two days of the winter week, the indoor temperature is below the average setpoint so heat gain is wanted. Therefore, the shades are raised during the lunch break. On the second following days, there is also a heat gain but the indoor temperature is above the average setpoint. The heat gain is therefore not wanted, so the shades are lowered during the lunch break. On the fifth weekday, there is a heat loss and the indoor temperature is below the average setpoint. Therefore, the shades are lowered during the lunch break. During the weekend, the shades also respond correctly to the indoor temperature and the heat gain/loss. In summer, the shades are raised at night, because the indoor temperature is above the average setpoint so the heat loss is wanted. At the start and end of the day, the shades are lowered because there is already a heat gain that is not wanted. During lunch, the shades are lowered to block the unwanted heat gain. This is also happening during the weekend. The results show that energy mode is implemented correctly and that control strategy 5 is functioning as intended.

Strategy 6 is modeled the same as strategy 5, but with an additional check added to comfort mode. When comfort mode is active, it is checked whether there is an overcast sky based the vertical solar irradiance on the facade. When the facade irradiance is below 120 W/m², the shades are fully raised. Otherwise, the shades are positioned at glare safe height. Figure 11 shows the position of the shades in relation to the vertical solar irradiance on the south facade. With this control strategy, the behavior in energy mode is exactly the same as with strategy 5 (as intended). In comfort mode, the vertical solar irradiance on the facade is important. When it exceeds 120 W/m², the shades behave similar to strategies 4 and 5. This is also as intended, because the system is in glare safe
Fig. 6: Shading position with control strategy 1 in winter (left) and summer (right) *

Fig. 7: Shading position with control strategy 2 in winter (left) and summer (right) *

Fig. 8: Shading position with control strategy 3 in winter (left) and summer (right) *

Fig. 9: Shading position with control strategy 4 in winter (left) and summer (right) *

Fig. 10: Shading position with control strategy 5 in winter (top and bottom left) and summer (top and bottom right) *

Fig. 11: Shading position with control strategy 6 in winter (left) and summer (right) *

* Larger versions of figures 6 through 11 can be found in appendix F.
mode. Every time the system is in comfort mode and the facade irradiance is below 120 W/m², the shades are fully raised. This is exactly how the overcast sky detection is supposed to work. This results in multiple days during both winter and summer with the shades fully raised for large parts of it, which was not the case with strategy 5. Especially in winter this can make a big difference, because the shades would otherwise be fully lowered. These results show that overcast sky detection is implemented correctly and that control strategy 6 is functioning as intended.

Based on the results discussed in this section, it is concluded that all six automatic control strategies are behaving as intended in relation to the environmental parameters that they respond to, meaning the models of the control strategies are verified.

3.2. Modeling presence

The different options to model presence are implemented in EnergyPlus using EMS. The models are simulated and the resulting presence pattern is evaluated. With the exception of the deterministic schedule, all options are based on the EnergyPlus implementation by Gunay et al. [27], but with some modifications.

The first option to model presence is the simple deterministic schedule. The input schedule can be found in appendix G and the resulting presence pattern for an entire week is shown in figure 12.

The schedule that is used as input for the model by Reinhart (see appendix G) is slightly different from the deterministic schedule, as there are two additional coffee breaks. The event times of arrival, breaks and departure are determined randomly at the start of each work day, based on a normal distribution with a standard deviation of 15 minutes. The lunch break always has a length of 1 hour and both coffee breaks have a length of 15 minutes. The event times are determined separately for both occupants, which allows them to arrive, take breaks and leave at different times. Figure 13 shows that this model results in a slightly varying occupancy pattern throughout the week, with both occupants having their own arrival time, lunch breaks and departure time. As a result, the amount of unoccupied periods per day are different throughout the week.

The model by Page et al. requires the probability of presence and the parameter of mobility as input. For the probability of presence, the schedule from modeling guidelines ASHRAE [28] is used (see appendix G). For the parameter of mobility, the value from the study by Gunay et al. is used. Based on these two inputs and the current presence state, it is determined what the probability is that the presence state will be different in the next timestep, so either changing from unoccupied to occupied or the other way around. This probability is then compared to a random number between 0 and 1. If the random number is smaller, the change in presence state takes place. If the random number is larger, the presence state remains the same. It is done separately for both occupants. Figure 15 shows that when the model by Page et al. is implemented as discussed above, it results in unrealistic behavior. Even though the probability of presence late in the evening is very low, there are a lot of days that people arrive late. They also leave again very shortly after they arrive. This behavior often happens multiple times during one evening. The reason is probably the five-minute timesteps that are used for the EnergyPlus
Even though the probability is very low, comparing it to a random number every five minutes results in the occupant actually arriving at some of the timesteps. The high probability of leaving at these times results in the occupant leaving very shortly after arriving. It is very unrealistic that this behavior happens during the majority of the nights throughout the entire year. Therefore, a different approach to modeling the presence model by Page et al. is required.

An extra check is added to the current model. At every timestep in the evening that the probability of presence changes (starting at 18:00), the probability is compared to a random number to determine whether a ‘break’ from the Page et al. model is activated. If the break is active and an occupants leaves, that same occupant does not return any more the same day. By basing it on the probability of presence, there is still a chance that occupants are in the office late in the evening, but it occurs less often. Figure 16 shows that adding this extra check results in a more realistic presence pattern, as there are much less times that occupants are still in the office late in the evening.

For the probability of presence, different input schedules can provide different results. Figure 17 shows that the schedule from ASHRAE has a very different presence pattern compared to measured data for a private office [29]. Especially the peak presence in the middle of the day is very different, as it is almost half of the ASHRAE schedule. Therefore, a separate case is evaluated with the measured schedule for a private office as input for the model by Page et al. Figure 18 shows that this case results in the occupant constantly entering and leaving the room during the entire day, which is caused by the probability of presence being 0.5 for a large part of the day. This behavior is very unrealistic. Therefore, this option is not used in the case study.

The final option to model presence is the model by Page et al. with longer periods of absence taken into account. This option is implemented using the holiday component in EnergyPlus. A holiday of two weeks in winter and a holiday of two months in summer are added to the model. Figure 19 shows the holidays result in no occupants being present during these periods. Choosing different periods of the year for the longer periods of absence will probably provide different results, but the chosen holidays can give an indication whether taking into account longer periods of absence has an impact on the results and how much this impact can be.

Based on the results, five presence models are ready to be used in the case study: a simple deterministic schedule, the model by Reinhart, the model by Wang et al., the model by Page et al. (with extra check) and the model by Page et al. with holidays included.
3.3. Modeling manual shading control

The three options to model manual shading control are implemented using EMS and simulated together with the simple presence schedule. The resulting shading position is evaluated to verify the implemented models. It is also checked what the chance of manual overrides is with each model. The EnergyPlus implementation by Gunay et al. is used for all three options, but some modifications are made.

The first option (based on the model by Newsham) starts with checking the position of the shades at the first arrival of the day. If the shades are not yet fully raised, a manual action takes place and the shades are fully raised, meaning all window parts are set to unshaded. For all timesteps that the room is occupied and the transmitted direct solar irradiance exceeds 233 W/m², the shades are fully lowered, meaning all window parts set to shaded. EnergyPlus only has the total transmitted beam solar irradiance through the entire window as output, so this output is divided by the surface area of the window. Figure 20 shows that the shades are fully lowered when the transmitted direct solar irradiance exceeds 233 W/m². The transmitted direct solar irradiance drops right after the shades are lowered, because the shading screen blocks a large part of the solar irradiance. Once the shading screen is lowered, it remains lowered until the next morning at 8:00, which is the arrival time in simple schedule. These results show that the model by Newsham is functioning as intended.

The second option (based on the model by Reinhart) is modeled very similarly to the previous option. With the model by Reinhart, the shades are only raised at the first arrival of the day, so this part is modeled in the same way as the first option. Lowering the shades is now based on the direct solar irradiance on the work plane instead of the transmitted direct solar irradiance. EnergyPlus does not have this parameter as standard output. There is a workaround to get this parameter, but it is questionable whether EnergyPlus can provide accurate results for indoor irradiance values. Therefore, the results based on Radiance are used instead. In section 3.5, a comparison is made between the results based on EnergyPlus and Radiance. Figure 21 shows the sensor point that is used for determining the horizontal irradiance on the work plane. For all timesteps that the room is occupied and the direct solar irradiance on the work plane exceeds 50 W/m², the shades are fully lowered. Figure 22 shows that the shades are indeed fully lowered when the threshold value of 50 W/m² is exceeded. The direct irradiance on the work plane drops immediately after the shades are lowered, as expected. The shades remain lowered until the morning at 8:00. The results show that the model by Reinhart is also functioning as intended. Comparing the results to the Newsham model already shows that the threshold from the Reinhart model can cause different results than the threshold from the Newsham model, as the shades are lowered for two days with Reinhart and only one day with Newsham.

The third option (based on the model by Haldi and Robinson) is a stochastic model. With this model, the probability of presence is calculated based on a set of regression parameters that represent the preference of users. In order to get an idea of the spread in occupant behavior between different types of occupants, two versions of the model by Haldi and Robinson are used: an active user and a passive user. For the active user, the mean of all regression parameters is taken and the standard deviation is added two times. For the passive user, the standard deviation is subtracted from the mean two times. First it is checked whether an occupant is arriving at the current timestep, because the regression parameters are different for arrival and intermediate times as occupants are more likely to make changes at arrival. Depending on whether it is an arrival or intermediate time, a different set of regression parameters is used to determine the probability of lowering the shades (P) based on formula 3.

\[
\logit(P) = a + b_{Ein} \cdot E_{in} + b_{SF} \cdot SF
\]  

Fig. 21: Sensor point for work plane irradiance/illuminance

Fig. 20: Newsham shading control *

Fig. 22: Reinhart shading control *

* Larger versions of figures 20 and 22 can be found in appendix H.
In this formula, \( E_{\text{in}} \) is the horizontal illuminance at the work plane, \( SF \) is the currently shaded fraction and \( a \), \( b_{E_{\text{in}}} \) and \( b_{SF} \) are the regression parameters. The horizontal work plane illuminance is determined at the sensor point from figure 21, using the results from Radiance simulations. The calculated probability is compared to a random number to determine whether the lowering action takes place or not. If the lowering action takes place, it is determined whether it is a full or partial lowering action. The probability of a full lowering action is determined based on formula 4, which uses the global horizontal illuminance (\( E_{\text{glob,hor}} \)) instead of the work plane illuminance.

\[
\logit(P) = a + b_{E_{\text{glob,hor}}} \cdot E_{\text{glob,hor}} + b_{SF} \cdot SF
\]

(4)

The probability is again compared to a random number to determine whether the full lowering action takes place or not. If the full lowering action does not take place, the new shaded fraction is calculated. Just like with some of the automatic control strategies, the exact position of the shades is rounded off to the nearest border of a window part below the exact height. If, based on the first comparison to a random number, it is determined that a lowering action does not take place at all, it is determined whether a raising action takes place. The same formulas are used to determine the raising probability, and whether it is full or partial, but with different regression parameters. Figure 23 shows the probabilities for lowering and raising actions in relation to the horizontal work plane illuminance. For the current shaded fraction, 0 and 1 are used to calculate the lowering and raising probability respectively. The calculated probabilities show that the active user is more likely to lower or raise the shades than the passive user with the same work plane illuminance. Figure 24 shows the results of a single run with the active and passive user. As the model is stochastic, the results for other runs can be different. The results for both users show that lowering action generally take place when the work plane illuminance is high. Both for the active and passive user, the amount of lowering actions is higher than the amount of raising actions, which corresponds with the probabilities from figure 23. The active user causes more lowering actions than the passive user, but the change in shades position is in most cases smaller. The active user requires a lower work plane illuminance to lower the shades, so therefore the shades are lowered partially more often. The passive user makes less changes, but the change in shades position is larger due to the larger difference in work plane illuminance between two actions. Even though the raising probability is always very low, there are still some raising actions that take place, which is due to the timesteps of five minutes. Because the probability is compared to the random number every five minutes, there will be a raising action every once in a while. This behavior is also visible in figure 24. During long periods with a low work plane illuminance, very little raising actions occur. Unlike for the models by Newsham and Reinhart, it is not possible to say with certainty that the model by Haldi and Robinson is functioning
correctly, because of the stochastic nature of the model. However, the results do show behavior that is expected. Therefore, it is assumed that this model is also functioning as intended.

Based on the results, it can be concluded that the options to model manual shading control are implemented correctly. As these models are also used to model manual overrides taking place with each of the models is evaluated by looking at how often the relevant environmental parameter reaches the required value during occupied hours throughout the year with all six control strategies. The results are shown in figures 25 through 27. Based on these results, it can be determined whether all models should be used in the case study or whether a model will not have an impact because its threshold is never reached.

Figure 25 shows the direct solar irradiance that is transmitted through the window with all six control strategies. The results show that strategy 1 is the only strategy that allows the transmitted direct solar irradiance to exceed 233 W/m² during occupied hours. However, the fraction of occupied hours that it happens is very low (less than 1%). Therefore, implementing the model by Newsham for manual overrides will probably have no effect on the results.

Figure 26 shows the direct solar irradiance on the work plane with all six strategies. The threshold value of 50 W/m² is only reached with strategies 1 and 3, but for a small fraction of the time (1-3%). Implementing the model by Reinhart for manual overrides will therefore probably also have almost no effect on the results. Therefore, implementing both the model by Newsham and the model by Reinhart is probably not worth the effort. To evaluate what the actual impact on the results is, the model by Reinhart is still used in the case study, as this model will probably have the largest impact of the two models. The model by Newsham is not used in the case study.

Figure 27 shows the horizontal illuminance on the work plane with all six strategies. The results show that with each of the strategies, illuminance values are reached that make a lowering action possible with the model by Haldi and Robinson, both for the active and passive user. For each control strategy, there are occupied hours with very low illuminance values, which makes raising actions possible. It is however difficult to say if these actions will actually take place or not, due to the stochastic nature of the model. Based on the results it seems that the model by Haldi and Robinson will probably cause the most manual shading interactions. Therefore, this model will probably also have the biggest impact on the results.

Based on the analysis of the models, three different options are used in the case study: the model by Reinhart, the active user based on the model by Haldi and Robinson and the passive user based on the model by Haldi and Robinson. In the cases were these models are used to model manual overrides of the automatic system, a delay is added of 30 minutes after every manual change before the automatic system starts working again. This is done to prevent the automatic system from undoing every manual change the next timestep.

3.4. Modeling lighting control
The two different options to model lighting control are implemented using EMS and simulated to check whether the models behave as intended.
The first option, the automatic dimming system, is based on the horizontal illuminance at two sensor points (see figure 28), which is determined using the results from Radiance simulations. If the room is occupied, continuous dimming is active. The lighting power dims linearly between 0 W, when 500 lux is available at both sensor points due to daylight, and 294.3 W, when 0 lux is available. If the room is unoccupied, the lights are turned off. A delay of 15 minutes has been implemented to prevent the lights from turning off during very short periods of absence. Figure 29 shows the lighting electric power in relation to the horizontal illuminance due to daylight at both sensor points for a single week. The figure shows that the lights are dimmed between 0 W and the maximum value depending on the available amount of daylight at the two sensor points. Also during unoccupied hours, the lights are turned off. These results show that the automatic dimming system is working as intended. Figure 30 shows the lighting electric power throughout the entire year. The results show that in winter, the maximum power is reached very often, while during summer, the required electric power for lighting is much lower. These results are expected, because in summer, there is more daylight available during occupied hours than in winter.

The second option is manually controlled lighting, based on the model by Reinhart. The EnergyPlus implementation by Gunay et al. is used, but with some modifications. With this model, the probability of switching on or off the lights is determined. The switch-on probability is different for arrival and intermediate times. In case of an arrival, the switch-on probability is determined using figure 31. This figure shows that there are two different types of occupants regarding switching on the lights: occupants that consider the amount of available daylight when they arrive and occupants that do not consider the amount of daylight when they arrive. With the first type of occupant, the amount of illuminance due to daylight at the work plane determines the probability of a switch-on action. The work plane illuminance is based on Radiance simulations. The second type of occupant just turns on the lights every day at arrival. These two types of occupants are modeled separately. For both occupant types, the switch-on probability during intermediate times depends on the work plane illuminance. If the work plane illuminance is below 240 lux, the switch-on probability is 0.02. If the work plane illuminance is equal to or higher than 240 lux, the switch-on probability is 0.005. Once the switch-on probability has been determined, it is compared to a random number to determine whether the action takes place or not. With the model by Reinhart, switch-off actions are modeled to only take place at departure. The switch-off probability depends on the amount of unoccupied hours after departure. The switch-off probability is 0.99 for the final departure of the day and it is determined randomly between 0.09 and 0.31 for all intermediate departures. These values correspond with the switch-off probabilities for unoccupied periods of less than 30 minutes and 30 minutes to an hour, respectively. As it is not always clear at a certain timestep how long the period of absence will last, a random value is chosen. The switch-off probability is again compared to a random number to determine whether the action takes place or not. The switch-off behavior is modeled the same for both types of occupants. Figure 32 shows the lighting electric power throughout the entire year.

* A larger version of figure 29 can be found in appendix I.
both for the occupant that considers the amount of available daylight at arrival and the occupant that does not consider the amount of daylight at arrival. In both cases, the lights are either fully on or fully off, which is as intended. The two users show a clear difference in the yearly pattern. With the user that does not consider daylight at arrival, the lights are turned on every single day. The user that does consider daylight at arrival, turns the lights on more often in winter and not as often in summer. This behavior is expected, because in winter, there is much less daylight available when the occupant arrives at the office than in summer. The different occupants will probably cause very different results when it comes to electricity use for lighting. Both occupants are used in the case study, to get an idea of the spread in performance caused by different types of occupants.

Based on the analysis of the lighting control models, three options are used in the case study: automatic dimming, the user that considers daylight at arrival based on the model by Reinhart and the user that does not consider daylight at arrival based on the model by Reinhart.

3.5. Extending with Radiance simulations
As it is known that EnergyPlus is less accurate in estimating indoor lighting conditions \cite{11}, the building simulation model is extended with results from Radiance simulations. The Radiance simulations are conducted using Rhino, Grasshopper and Honeybee. The geometry of the case study building is modeled using Rhino and linked to Grasshopper using components from Honeybee. The shading device is modeled in a way that it can be positioned at the same positions as in EnergyPlus. The EnergyPlus model has 20 window parts, so the shading device has 21 possible shading heights.

Figure 33 shows the sensor points of the Radiance model. The grid points G1 through G24, which are positioned at work plane height (0.8m), measure horizontal illuminance and are used to determine the spatial daylight autonomy. Sensor points W1 and W2 are also positioned at work plane height. At both points, horizontal illuminance is measured and W1 also measures direct horizontal irradiance. The model by Reinhart for manual shading control uses the direct horizontal irradiance at W1, the model by Haldi and Robinson for manual shading control uses the horizontal illuminance at W1, the model by Reinhart for manual lighting control also uses the horizontal illuminance at W1 and the automatic dimming system uses the illuminance at both W1 and W2. Sensor point E is used to determine the simplified daylight glare probability. This sensor point is positioned at eye height (1.2m) and measures vertical illuminance in three directions.

An annual simulation is conducted for all 21 shading heights and the results for all sensor points are saved as yearly schedules. The schedules are imported in EnergyPlus and an EMS script is used to determine the illuminance or irradiance value at the sensor points at a certain timestep by checking the current position of the shades and taking the value from the schedule that corresponds with that shading position.
In order to check whether it is really necessary to use Radiance instead of only EnergyPlus, a comparison is made between the results from both tools for sensor points W1 and W2. The results are shown in figures 34, 35 and 36.

Figures 34 and 35 show the horizontal illuminance at sensor points W1 and W2 respectively. In both cases, EnergyPlus is overestimating the illuminance level, resulting in higher illuminance levels occurring more often. There are less times that the work plane illuminance is below 500 lux, which means the predicted energy demand for lighting with the automatic dimming system would be lower if only EnergyPlus is used. The manual lighting control model by Reinhart will probably also predict a lower lighting demand. If manual overrides are taken into account, using the model of Haldi and Robinson, the shades will be lowered more often, as the higher illuminance values result in a higher lowering probability. The spatial daylight autonomy and the amount of glare will also be overestimated when EnergyPlus is used.

Figure 36 shows the direct solar irradiance on the work plane in the front of the room, which is used as input for the manual shading control model by Reinhart. EnergyPlus is also overestimating the irradiance values, which will cause more manual overrides to take place.

These results show that it is best to use Radiance instead of EnergyPlus for the prediction of indoor illuminance and irradiance levels.

3.6. Sensitivity analysis of the number of runs

As several stochastic models are used in the case study, the amount of runs for a single case needs to be determined. A sensitivity analysis is used to determine the required number of runs. This analysis is done for the case that is assumed to be most sensitive (see table 2). This case is combined with control strategies 2 and 6, as strategy 2 can be considered representative for the first three strategies and strategy 6 can be considered representative for the last three strategies. For both strategies, five sets of simulations are conducted, each consisting of 200 runs. For each of the sets, the mean and standard deviation are calculated for every performance indicator after 10 runs, after 20 runs, after 30 runs and all the way to 200 runs, with steps of 10. The results for all performance indicators can be found in appendix J.

Figure 37 shows the results for the primary lighting energy demand, which is the most sensitive performance indicator. For the other performance indicators, 10 or 20 runs are already sufficient to get converged results, but for the lighting demand, a higher number is required. After 200 runs it is very clear that strategy 6 is the better performing strategy for this performance indicator, but after only 30 runs, there is still a chance that strategy 2 will come out as the better performing one. This already means that at least 40 runs are required to come to the right conclusion about which strategy performs

<table>
<thead>
<tr>
<th>Table 2: Case for sensitivity analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Presence model</td>
</tr>
<tr>
<td>Manual shading control model</td>
</tr>
<tr>
<td>Lighting control model</td>
</tr>
</tbody>
</table>
best. After 80 runs, the lighting energy demand can be predicted with an accuracy of approximately 5%. This level of accuracy is assumed to be sufficient, so 80 runs is chosen as the required number of runs to get converged results. Therefore, all cases with stochastic models that are part of the case study will be run 80 times.

Fig. 37: Sensitivity to number of runs - primary energy demand for lighting: mean (left) and standard deviation (right)

4. CASE STUDY ANALYSIS

4.1. Overview of the cases

Tables 3 through 7 show the cases with different combinations of models that are investigated in the case study. The cases are divided in five different categories: baseline cases, cases with manually

![Table 3: Baseline cases](image)

<table>
<thead>
<tr>
<th>Automatic control strategy</th>
<th>Presence model</th>
<th>Manual shading control model</th>
<th>Lighting control model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-6</td>
<td>Simple schedule</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>Always open</td>
<td>Simple schedule</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>Always closed</td>
<td>Simple schedule</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
</tbody>
</table>

![Table 4: Manually controlled cases](image)

<table>
<thead>
<tr>
<th>Automatic control strategy</th>
<th>Presence model</th>
<th>Manual shading control model</th>
<th>Lighting control model</th>
</tr>
</thead>
<tbody>
<tr>
<td>none</td>
<td>Simple schedule</td>
<td>Reinhart</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>none</td>
<td>Simple schedule</td>
<td>Haldi and Robinson (active user)</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>none</td>
<td>Simple schedule</td>
<td>Haldi and Robinson (passive user)</td>
<td>Automatic dimming</td>
</tr>
</tbody>
</table>

![Table 5: Presence model cases](image)

<table>
<thead>
<tr>
<th>Automatic control strategy</th>
<th>Presence model</th>
<th>Manual shading control model</th>
<th>Lighting control model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-6</td>
<td>Reinhart</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>1-6</td>
<td>Wang et al.</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>1-6</td>
<td>Page et al. (no holidays)</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>1-6</td>
<td>Page et al. (with holidays)</td>
<td>none</td>
<td>Automatic dimming</td>
</tr>
</tbody>
</table>

![Table 6: Manual override cases](image)

<table>
<thead>
<tr>
<th>Automatic control strategy</th>
<th>Presence model</th>
<th>Manual shading control model</th>
<th>Lighting control model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-6</td>
<td>Simple schedule</td>
<td>Reinhart</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>1-6</td>
<td>Simple schedule</td>
<td>Haldi and Robinson (active user)</td>
<td>Automatic dimming</td>
</tr>
<tr>
<td>1-6</td>
<td>Simple schedule</td>
<td>Haldi and Robinson (passive user)</td>
<td>Automatic dimming</td>
</tr>
</tbody>
</table>

![Table 7: Manual lighting control cases](image)

<table>
<thead>
<tr>
<th>Automatic control strategy</th>
<th>Presence model</th>
<th>Manual shading control model</th>
<th>Lighting control model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-6</td>
<td>Simple schedule</td>
<td>none</td>
<td>Reinhart (considering daylight at arrival)</td>
</tr>
<tr>
<td>1-6</td>
<td>Simple schedule</td>
<td>none</td>
<td>Reinhart (not considering daylight at arrival)</td>
</tr>
</tbody>
</table>
4.2. Comparison of the control strategies

The results of the six baseline cases for primary energy demand, spatial daylight autonomy, view to the outside and glare are shown in figure 38, together with a case with the shades always up and a case with the shades always down. The main question that is answered in this section is:

“How do the automatic control strategies perform relative to each other when not taking into account more complex occupant behavior modeling?”

In general, it seems that the results for the total energy demand are quite similar for each of the control strategies. The maximum difference between two strategies is 20 kWh/m². The lighting energy demand shows the biggest differences, so the different shading control strategies seem to have the most impact on lighting energy. The other performance indicators show larger differences between the strategies.

Looking at the energy demand, strategy 1 and 2 perform very similar. Strategy 2 has a slightly higher heating demand due to the use of a facade sensor instead of the roof sensor of strategy 1, which lowers the shades more often in winter, due to the lower sun position, and therefore there is less effective utilization of solar heat gains. It also results in a slightly larger lighting demand. These differences are very small, as the total energy demand has increased with only 5%. The spatial daylight autonomy is lower with strategy 2 and the view to the outside is also a bit lower. However, strategy 2 does result in less perceptible glare. It has the least amount of glare of all strategies.

Strategy 3 shows that only lowering the shades to eye height instead of fully, as in strategy 2, results in a 40% reduction of the lighting energy demand. The impact on heating and cooling is almost zero,
which means that the additional heat gains caused by the shades never going fully down are very small. The sDA has increased from approximately 40% to over 65%. As the shades never go below eye height, there is always a view to the outside. As a result, there is more perceptible glare when facing the window directly or at an angle. When facing the wall, the difference can be neglected.

Strategy 4 results in an energy demand that is approximately 25% higher than the best-performing one (strategy 6), as the shades just follow the position of the sun, even with an overcast sky. The total energy demand is very similar to strategy 2, showing that such a strategy is not very good at reducing the energy demand. The sDA and fraction of occupied hours with view are also quite low as a result of the sun tracking system. The amount of glare is not very different from strategy 3, as the biggest difference, which is caused when directly facing the window, is only 5%.

Strategy 5 shows that energy mode is able to reduce the cooling demand by approximately 15%, as the shades now block unwanted solar heat gains when people are not present. The impact on the heating demand is very small, but there is still a slight reduction. There are no differences between strategy 4 and 5 for the other performance indicators, which makes sense, as the other performance indicators are only evaluated when people are present and energy mode is only active when nobody is present. Strategy 6 shows a decrease in lighting energy demand of approximately 40%, which is caused by the overcast sky detection. This strategy results in the lowest energy demand of all six strategies. The overcast sky detection also results in an increase of the sDA (from 50% to 75%) and the fraction of occupied hours with view (from 55% to 85%). However, it also results in more glare. When facing the window directly or at a 45° angle, there is approximately 10% more perceptible glare. When facing the wall, the increase is only 1%. That this strategy causes more glare, even though it is designed to prevent glare, might be caused by the fact that the shades are up a lot in summer due to the high sun position, exposing the occupant to the brightness of the surroundings and the sky. Another reason might be that using an irradiance sensor on the facade to determine whether there is an overcast sky is not the best solution. Glare is based on indoor illuminance and a sensor based on outdoor irradiance is used to prevent it. It might be better to use an illuminance sensor instead.

Looking at all the different performance indicators, it seems that strategy 3 and 6 are the best performing strategies for most performance indicators. They have the lowest total energy demand, the highest spatial daylight autonomy and they provide the most view to the outside. These strategies are however also the strategies that cause the most perceptible glare, as they are open more often and therefore cause more daylight to enter the room. When facing the wall, the difference in glare with most of the strategies can be neglected.

4.3. Manually controlled shading

The results of the cases with only manually controlled shading are shown in figure 39. The same performance indicators are shown as in the previous section, together with the number of manual interactions with the shading system. For the cases that include stochastic models, the height of the bar indicates the mean of all simulations and the whiskers show the standard deviation. The colored areas in the background indicate the range of the results of the baseline cases (the bottom is the lowest value from strategies 1-6 and the top is the highest value). The main question that is answered in this section is:

“How does a manually controlled shading system perform in comparison to the automatic control strategies?”

Based on the used models, the performance of a manually controlled shading system seems to be quite similar to the automatic control strategies. For most of the performance indicators, the results fall within the range of the baseline cases.

With the model by Reinhart, the cooling demand is slightly higher than with strategy 4, which is the worst performing strategy. The lighting demand however is quite low. Looking at the sDA, this low demand makes sense. The sDA is higher than with any of the automatic control strategies, which explains the higher cooling demand (more solar heat gains) and the reduced lighting demand. The Reinhart model also provides more view than most of the automatic control strategies. Only strategy 3 and 6 provide a view more often. The reason that the sDA is so high but the occupied time with a view is lower, is caused by the fact that with the Reinhart model the shades can only be fully up or down. It apparently also causes more glare, as the results show high DGP values in comparison to the six automatic control strategies, especially when facing away from the window.

The total number of manual interactions with the shading system is quite low when using the Reinhart model (approximately 100 lowering and 100 raising actions), which makes sense, as the shades can only be lowered once a day (or not at all). The shades are only raised at the start of a day, so once they have been lowered they will remain lowered the entire day. The results show that the occupants did not make changes to the shades during approximately 60% of the occupied days.

The results based on the model by Haldi and Robinson show a lower cooling demand but a higher
lighting demand, because with the Reinhart model the shades are either fully up or down, while with the Haldi and Robinson model the window can also be partially shaded. Therefore, there will be more times with the window partially shaded instead of fully unshaded, which reduces the cooling demand and increases the lighting demand. The difference between the active and passive user for heating and cooling is almost zero. The difference among active users or among passive users is also almost zero. For lighting, the difference is slightly larger, both between the active and passive and among active users and passive users. For the other performance indicators, the difference is larger. The active user has a lower sDA, because it is more likely to lower the shades at lower illuminance levels. The difference among active users is only 3%, while the difference among passive users is larger (approximately 12%). This larger difference makes sense, because a passive user makes less changes to the state of the shades and therefore a single change has a larger impact. As a result, the standard deviation for the passive user is larger. Looking at view, the active user performs similar to the Reinhart model. The passive user provides most view as this user is less likely to lower the shades. For glare, there is a bigger difference between the active and passive user. The difference among active users or passive users is still small (approximately 5%). The passive user causes more glare, because this user requires a higher indoor illuminance level before the shades are closed in comparison to the active user. The amount of glare is still less than when the Reinhart model is used, probably due to partial shading instead of the shades being fully open.

The number of manual shading interactions is much higher than when using the Reinhart model, which is caused by the fact that partial blind changes are possible with this model and multiple changes to the shades can be made on the same day. The amount of lowering actions is much larger than the amount of raising action, which is happening because, in the model by Haldi and Robinson, it is included that people are more careful when they lower the shades to still provide a view to the outside. Therefore, they

Fig. 39: Manually controlled cases - (a)+(b) energy demand; (c) sDA; (d) view to outside; (e) DGPs; (f) manual interactions
lower the blinds partially several times. When raising the shades, they tend to raise them fully at once. As expected, the passive user makes less changes to the shades than the active user. However, there are still somewhere between 500 and 1000 manual interactions, depending on whether the user is active or passive. So the similar performance for energy demand, daylight autonomy, view and glare does require quite a large number of manual interactions with the shades, while in the baseline cases there are manual interactions. This large number of manual actions shows a benefit of having automatically controlled shading.

In conclusion, a manually controlled shading system seems to have similar performance to the automatic control strategies. It is however not possible to say that one strategy performs very similar to manual control, as it depends on the performance indicator of interest which control strategy resembles manual control the most. The model by Reinhart probably provides the most unrealistic results, as it only allows the shades to be fully up or down. Especially the results for spatial daylight autonomy, glare and the number of manual interactions are not in line with the model by Haldi and Robinson.

4.4. Influence of presence
The results of the cases with different stochastic models for presence are shown in figure 40. The same performance indicators as for the baseline cases are shown. The solid lines in the background indicate the performance of the baseline cases. The main question that is answered in this section is: “How does using stochastic presence models influence the predicted performance of the automatic control strategies?”

Implementing the models by Reinhart and Wang et al. seems to have almost no effect on any of the performance indicators. The schedule that is used as input for these models is very similar to the schedule that is used for the baseline cases, so it makes sense that the results are similar. Apparently the ‘random’ break times (based on a normal distribution) in the Reinhart model do not impact the overall annual performance of the system. The same can be said for also having the lengths of the breaks determined ‘randomly’, as is the case in the model of Wang et al. As a result, the standard deviation of all performance indicators is close to zero. The results show that these models do not have an added benefit in this case, so it is not worth the effort to implement them.

Implementing the model by Page et al. for presence instead of using the simple schedule does have an impact on the performance for all automatic control strategies. The impact on the heating and cooling energy demand is not very large (difference with baseline cases of approximately 5 kWh/m²). The difference for lighting is quite substantial, as in some cases the mean almost doubles. With the model by Page et al., the lighting demand is larger than with the standard schedule. The main reason is probably that the model by Page et al. also allows people to be present outside of the standard office hours that are included in the simple schedule, meaning overhours are taken into account. It results in people being present at hours without any daylight available, which

![Fig. 40: Presence model cases - (a) energy demand; (b) sDA; (c) view to outside; (d) DGPs](image-url)
causes the larger lighting demand. It also results in the decrease of the sDA with 5-15% for all strategies. The occupied time fraction with perceptible glare has also reduced with approximately 5%. The occupied time fraction with a view to the outside has increased, because the shades will be up at times the sun is not up. In this case, a view is provided, but there is no daylight available. With the model by Page et al., the standard deviation of most performance indicators is quite high, meaning that there is an uncertainty to the actual performance of the system that cannot be neglected. This uncertainty is expected, as not all occupants behave the same. It seems that there is no clear difference in the standard deviation between the six automatic control strategies, meaning that the influence of occupant presence on each of the strategies is similar. However, there is some overlap of the range in performance due to occupant behavior between the different strategies.

Taking into account holidays also has an impact on the results. The energy demand has reduced, which makes sense as the occupants are present less often and therefore less heating, cooling and lighting is required. The amount of glare is very similar for the first three strategies, but is reduced for the last three strategies. This difference is probably caused by the fact that strategies 4, 5 and 6 have the highest amount of glare in summer, which is the time that the large holiday takes place. Both the amount of view and the sDA increase for the first two strategies, while they decrease for the other strategies. The reason might be that the shades are down more often in summer, which is now partially the holiday. The standard deviation for the different performance indicators is similar to the cases without holidays.

These results show that when looking at the annual performance it does not make sense to implement models like the ones from Reinhart and Wang et al. for presence, as these are just slight variations to a simple schedule and therefore the annual mean for all performance indicators is almost the same as with the schedule and the standard deviation is close to zero. However, implementing a more complex and stochastic model like the one by Page et al. shows that presence can have an impact on the performance of automatic control strategies that cannot be neglected. It also shows the range in performance caused by the difference between occupants. Therefore, implementing a complex and stochastic occupant behavior model for presence is worth the additional effort as it provides different results, assuming it can model occupant presence more realistically, meaning the results should better match with the actual performance. The same can be said for taking into account longer periods of absence such as holidays. It would be interesting to also investigate scenarios with holidays during other parts of the year than was done in this study to see how it influences the performance.

Even though stochastic presence modeling impacts the performance of the automatic shading strategies, it does not influence which of the strategies perform best as strategy 3 and 6 still perform better for most performance indicators than the other strategies. So if the objective of a study is to investigate which control strategy is the best performing one, then stochastic presence modeling is not necessary. However, if it is also needed to estimate the actual performance, then stochastic presence modeling can lead to different results.

4.5. Influence of manual overrides

The results of the cases that take into account manual overrides of the automatic control strategies are shown in figure 41. The same performance indicators as for the baseline cases are shown, together with the number of manual shading interactions. The main question that is answered in this section is:

“How does taking into account manual overrides for shading influence the predicted performance of the automatic control strategies?”

Based on the results it can be concluded that taking into account manual overrides for shading based on these models has almost no impact on the annual performance of the automatic control strategies, with the exception of the number of manual interactions. For the first three strategies there is a very small impact on the different performance indicators, which can be neglected in most cases. The standard deviation is also very small. For strategies 4, 5 and 6, the impact is actually zero for all performance indicators, which shows that these strategies are very robust to manual overrides of the automatic system. Therefore, it is probably not worth the additional effort it takes to implement manual override models when assessing these control strategies. The other strategies are also quite robust to manual overrides, but just a bit less as there is still a small difference of approximately 5% when manual overrides are taken into account.

The total number of manual interactions with the shading system for strategies 1, 2 and 3 is actually higher than was the case without an automatic system. This increase is probably caused by the fact that these strategies only have two possible shading positions, while occupants might prefer a position somewhere in between. The delay time of 30 minutes between a manual and automatic change in shading position might also be too short for these strategies. For the other three strategies, the number of lowering actions has decreased. However, strategies 4 and 5 show an increase in raising actions. This increase makes sense as these strategies always follow the position of the sun when people are present, even with an overcast sky, which results in people manually raising the shades due to the low indoor illuminance.
at the work plane. Strategy 6 shows a decrease in both lowering and raising actions in comparison to only manual control, meaning it is actually quite good at predicting a shading position that occupants are content with.

The conclusions mentioned in this section might only be valid when a simple deterministic schedule is used for presence modeling. The used occupancy schedule has a set value of arrival moments during a day that is quite low, while the probability of a manual shading interaction is much larger at arrival than during intermediate times with the model by Haldi and Robinson. More arrival moments can cause more manual shading interactions, which might result in a bigger impact on the performance. Therefore, it also needs to be investigated what the impact of manual overrides is when a stochastic presence model is used (see section 4.7). It does not make sense to do this for the model by Reinhart, as this model is based on a static threshold (50 W/m² on the work plane) and it seems that this threshold is not reached often enough to have a big impact.

4.6. Influence of manual lighting control

The results of the cases with manual lighting control are shown in figure 42. The performance indicators related to visual comfort are not discussed as they are not influenced by changing from automatically to manually controlled lighting. The main question that is answered in this section is:

“How do the automatic control strategies perform when there is manually controlled lighting instead of automatically dimmed lighting?”

The impact on the heating energy demand is again very small and can be neglected. The impact on cooling is larger, as the difference with the baseline case is up to 15 kWh/m². The impact on the lighting demand is much larger than that, as there is a difference of up to 45 kWh/m². Both for cooling and lighting, the energy demand decreases in the case of the occupant that considers the amount of daylight when turning on the lights at arrival. However, the increase in energy demand that is caused by an occupant that does not consider daylight at arrival is

![Graphs showing energy demand, visual comfort, and daylight access for different strategies with and without manual override.](image-url)
much larger. The actual performance will therefore lie somewhere in between these two values, meaning that there is a larger chance that the performance of the automatic shading system is worse without an automatic dimming system present. A note that needs to be made is that even though the energy demand is lower when the occupants are considering daylight at arrival, it probably also means that the illuminance level on the work plane is below 500 lux more often as electric lighting is not always turned on with lower illuminance values. With automatic dimming, the difference between the work plane illuminance due to daylight and 500 lux is compensated for by the lighting system, which is not happening with a manually controlled lighting system. Therefore, the energy demand of the case with occupants that consider daylight at arrival is lower. However, the lower energy demand also means that there is not always sufficient light available at the work plane, so it is not really an advantage to have this reduced energy demand. Based on the results, it can be concluded that the automatic control strategies should probably not be implemented in a building that does not have an automatically dimmed lighting system.

Just like the previous section, these conclusions might also only be valid when a deterministic schedule is used for presence. Presence is used as input for the lighting control model by Reinhart, so using a complex and stochastic presence model, like the one by Page et al., might cause different results. Therefore, a case with stochastic presence and manual lighting also needs to be investigated (see section 4.7).

4.7. Combining different OB models

In sections 4.5 and 4.6 it was discussed that there is also a need to investigate the impact on the performance when combining several of the used occupant behavior models. These cases are shown in table 8. Combined case 1 is related to the impact of manual lighting control and combined case 2 is related to the impact of manual overrides.

The results for the first combined case are shown in figure 44. In this case, the stochastic presence model by Page et al. is combined with the stochastic model for manual lighting control by Reinhart. The only shown performance indicator is the energy demand, as the results for the other performance indicators will not be different from the presence case where the Page et al. model is combined with automatic dimming (section 5.3).

With the stochastic presence model by Page et al., the results are even worse. There is a very large increase in energy demand, especially for lighting, with a manually controlled lighting system instead of an automatically dimmed system. Therefore it is still not recommended to implement these automatic control strategies together with a manually controlled lighting system. However, if it is done and the performance needs to be predicted, then using a stochastic presence model like the one by Page et al. can provide different results than when a simple deterministic schedule is used.

The results for the second combined case are shown in figure 44. In this case, the stochastic presence model by Page et al. is combined with the stochastic

<table>
<thead>
<tr>
<th>Case</th>
<th>Presence model</th>
<th>Manual shading control model</th>
<th>Lighting control model</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>considering daylight</td>
<td>Page et al. (no holidays)</td>
<td>none</td>
</tr>
<tr>
<td></td>
<td>not considering daylight</td>
<td>Page et al. (no holidays)</td>
<td>none</td>
</tr>
<tr>
<td>2</td>
<td>active</td>
<td>Page et al. (no holidays)</td>
<td>Haldi and Robinson (active user)</td>
</tr>
<tr>
<td></td>
<td>passive</td>
<td>Page et al. (no holidays)</td>
<td>Haldi and Robinson (passive user)</td>
</tr>
</tbody>
</table>

Table 8: Combined cases
model for the manual control of shading by Haldi and Robinson, which is used to evaluate the impact of manual overrides. The same performance indicators that were discussed for the cases with manual overrides taken into account are shown here.

As expected, the amount of manual interactions with the shading system has increased in comparison to the case with a deterministic schedule for presence instead of the stochastic model by Page et al. With this last model, the amount of arrivals during a day can be much higher than the set value of the deterministic schedule. The model by Haldi and Robinson results in a higher probability for lowering or raising the shades at arrival times than at intermediate times, so therefore the amount of manual interactions is higher. Now strategy 4, 5 and 6 do no longer result in a lower amount of manual interactions than with a manually controlled shading system, which was the case with the simple schedule for presence. However, this may be caused by the fact that the simple schedule was used as input for the cases with only manual control, instead of the stochastic model by Page et al.

For control strategies 4, 5 and 6, the difference between combined case 1 and the presence model case with the model by Page et al. is very small for all performance indicators related to energy and daylight. This statement is true for both the active and passive user, as these provide almost the same results. These results show that these three strategies are quite robust to manual shading interactions, even when a stochastic model for presence is used. For the first three strategies, the difference is larger and there is also a larger difference between the active and passive user, which was also true for the cases with the simple schedule for presence. Based on the results, it can be concluded that with more simple automatic control strategies like strategies 1, 2 and 3, taking into account manual shading overrides can cause different results, while with more advanced strategies like 4, 5 and 6, it is not needed to include manual overrides as it does not impact the predicted annual performance of the shading system. Only when a study focuses on the number of manual interactions, it is necessary to include a model for manual shading control.

Fig. 44: Combined case 2 - (a) energy demand; (b) sDA; (c) view to outside; (d) DGPs; (e) manual interactions
5. CONCLUSIONS

The goal of this study was to develop a better understanding of the different ways to represent occupant behavior and of the associated uncertainties when assessing the performance of automated solar shading systems using simulations. A case study was used to determine when high resolution occupant behavior modeling is required and in which case simple modeling is sufficient. The outcome of this study can also provide guidance on how to model occupant behavior in combination with automated solar shading systems. Several conclusions could be drawn based on this study:

• Implementing models like the ones from Reinhart and Wang et al. for presence is not worth the effort, as the annual mean for the investigated performance indicators is almost the same as with a simple schedule. The standard deviation is also close to zero. Implementing a stochastic model like the one by Page et al. shows that presence can have an impact on the performance of the automatic control strategies and it also shows the range in performance caused by the difference in behavior between different occupants. Even though stochastic presence modeling impacts the absolute performance of the automatic shading control strategies, there is not a big difference in relative performance between the strategies. So if the absolute performance is of interest and the stochastic presence model provides the expected occupant behavior, then this model should be used.

• With simple automatic shading control strategies like strategies 1, 2 and 3, taking into account manual shading overrides can cause different results. This is however only true when a stochastic presence model like the one by Page et al. is used and not a standard presence schedule. With more advanced strategies like strategies 4, 5 and 6, it is not needed to include manual overrides as it does not impact the predicted annual performance of the shading system. However, if a study focuses on the number of manual interactions, it is of course necessary to include a model for manual shading control.

• When modeling presence, it should be clear what the intended use of the model is, as this influences whether certain models can be used or not. For example, the presence model by Page et al. in combination with the measured input schedule for a private office resulted in a very unrealistic occupancy pattern with people constantly entering and leaving the office. Looking at the overall hours of presence, it is probably in line with the input schedule. However, the amount of arrival times were relevant in this study, as some of the used models for manual shading control and lighting control provide different occupant behavior at arrival times. Therefore, this option to model presence was not suitable for this study.

• When the impact of manual overrides is of interest, it should first be checked how often the threshold is reached before the model is implemented. This can save on time and effort, because models that will not have an impact do not need to be implemented at all. The model by Newsham was not suitable for the case that was investigated in this study, as the threshold used by this model was almost never reached due to the automated shading system.

• If indoor lighting conditions like illuminance or irradiance levels are required, either to evaluate indoor comfort or as input for parts of the building simulation model, it is best to use results from Radiance simulations. The results showed that EnergyPlus seems to overestimate illuminance and irradiance values inside the room, which can cause the model to behave very differently than if Radiance results are used.

• The sensitivity analysis showed that the number of simulation runs can have a large impact on the results when stochastic models are used. If the number of runs is chosen too low, a study can lead to completely wrong conclusions. In this case for example, control strategy 2 could perform better than strategy 6 regarding lighting demand after only 10 runs, while after more runs it is clear that strategy 6 is the better performing strategy on this area. This shows how important it is to choose a number of runs that is high enough

There are also some conclusions that can be drawn related to this specific case:

• Without taking into account complex occupant behavior modeling, it seems that the results for the total energy demand are quite similar for each of the investigated control strategies. The other performance indicators show larger differences between the control strategies. The strategies with the lowest total energy demand, highest spatial daylight autonomy and most view to the outside also cause the most perceptible glare, as the shades are open more often an therefore more daylight is allowed to enter the room. However, the amount of glare when facing the wall is very similar for each control strategy.

• The performance of manually controlled shading seems to fall within the range of variability of the performance of the investigated automatic control strategies. Depending on the performance indicator of interest, it is different which control strategy resembles manual control the most.

• It is not recommended to implement the investigated automatic control strategies together with a manually controlled lighting system, as it results in a large increase in energy demand. However, if it is done and the performance needs to be predicted, then a
stochastic presence model like the one by Page et al. should be used.

The study also has some limitations related to the case study analysis and the used models. The limitations and some suggestions for future work are listed below:

• In this study, different occupant behavior models are used. These models are based on observational studies in different buildings. It is not verified whether the models are also suitable for the specific case that is investigated in this study. The assumption is made that they can be used for this case. Also, it is assumed that the different models are compatible with each other and that they can be combined, which is also not verified. In order to combine them, modifications had to be made to some of the models, which might also impact the resulting occupant behavior. The observational studies that the models are based on did not always take place in two-person offices, while in this study it is assumed that all models can be used for a case with a two-person office.

• All results provided in this study are for a specific case: an office with certain construction properties and a large south-facing window, which is situated in the Netherlands. Different construction properties might cause different results, as the relative impact of occupant behavior can vary for different building types. Investigating different orientations of the window (for example east or west) might lead to different results. Depending on the orientation, the window is exposed to the sun during different parts of the day. Certain occupant behavior models can therefore have a smaller or larger impact on the performance of the shading system. It would also be interesting to investigate different climates, but this depends on the market of the specific shading system that is investigated.

• The used presence models are all based on a certain input schedule. The input schedule of the deterministic schedule, the model by Reinhart and the model by Wang et al. are very similar, while the input schedule of the model by Page et al. is different. The results of this last model are also deviating the most from the baseline cases. It is assumed that this is due to the stochastic nature of the model, but it could also mainly be caused by the used input schedule. It would be interesting to also investigate a case with the input schedule that is used for the model by Page et al. as a deterministic presence schedule. The results can then be compared to the results from this study, to see whether the difference in performance is caused by the input schedule, the stochastic nature of the model or a combination of both.

• Longer periods of absence are in this study modeled as two specific holidays. The resulting difference in performance is therefore related to this specific case. It would be interesting to investigate scenarios with holidays during other parts of the year. It could also be interesting to determine the longer periods of absence using a stochastic model, meaning the time a holiday takes place and the duration of the holiday are determined randomly for each simulation run.

• The models of manual shading control are also used to evaluate manual overrides of an automatic system, while these models are not made for this purpose. It is assumed that they can be used to model manual overrides, but this has not been verified.

• The impact of different occupant behavior models on the performance of the automated solar shading system is evaluated on an annual basis. This makes it possible to quickly see the overall impact of specific models, but there is also a lot of information lost by just looking at annual values. It could be interesting to also study different parameters like the behavior of the shades, presence and lighting on a daily basis and see how the different occupant behavior models influence or are influenced by the shading system. These result can provide more insight in how everything is functioning and what is actually happening, which can be used by the developer of the shading system to improve the product.

6. REFERENCES


7. APPENDICES

A. Comparison roof and facade sensor

A comparison is made for the Dutch climate between an irradiance sensor on the roof and a sensor on the south-facing facade.

All hourly data points from the climate file of Amsterdam that have a vertical solar irradiance between 180 and 220 W/m² are extracted and the horizontal solar irradiance for all these data points is evaluated (figure A1). The average horizontal irradiance for the relevant data points is 300 W/m², so this value is chosen as threshold for the horizontal irradiance sensor.

The vertical irradiance threshold of 200 W/m² is compared to the horizontal irradiance threshold of 300 W/m² for an entire year (figure A2). Table A1 contains the explanation of the colored areas. This shows that the two different thresholds cause a similar effect for a large amount of the data points.

Table A1: Explanation colored areas figure A2

<table>
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<tr>
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<th>Vertical threshold</th>
<th>Horizontal threshold</th>
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<tbody>
<tr>
<td>1</td>
<td>shades up</td>
<td>shades up</td>
</tr>
<tr>
<td>2</td>
<td>shades down</td>
<td>shades down</td>
</tr>
<tr>
<td>3</td>
<td>shades up</td>
<td>shades down</td>
</tr>
<tr>
<td>4</td>
<td>shades down</td>
<td>shades up</td>
</tr>
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Fig. A1: Data points with vertical irradiance of 180-220 W/m²

Fig. A2: Comparison horizontal and vertical threshold
### B. Model properties

#### Table B1: External wall properties

<table>
<thead>
<tr>
<th>Materials</th>
<th>Thickness (m)</th>
<th>Thermal conductivity (W/mK)</th>
<th>Density (kg/m³)</th>
<th>Specific heat (J/kgK)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
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<td>Mineral wool</td>
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<tr>
<td>Aluminum</td>
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<td>860</td>
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#### Table B2: Interior wall properties

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<th>Density (kg/m³)</th>
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#### Table B3: Floor properties

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<th>Materials</th>
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<th>Specific heat (J/kgK)</th>
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#### Table B4: Ceiling properties

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<th>Density (kg/m³)</th>
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</tbody>
</table>

#### Table B5: Window frame properties

<table>
<thead>
<tr>
<th>Materials</th>
<th>Thickness (m)</th>
<th>Thermal conductivity (W/mK)</th>
<th>Density (kg/m³)</th>
<th>Specific heat (J/kgK)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aluminum</td>
<td>0.01</td>
<td>0.01477</td>
<td>2700</td>
<td>860</td>
</tr>
</tbody>
</table>

#### Table B6: Window properties

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Glass</td>
<td>0.006</td>
<td>0.9</td>
<td>0.6</td>
<td>0.17</td>
<td>0.84</td>
<td>0.055</td>
</tr>
<tr>
<td>Argon</td>
<td>0.013</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Glass</td>
<td>0.006</td>
<td>0.9</td>
<td>0.755</td>
<td>0.071</td>
<td>0.881</td>
<td>0.08</td>
</tr>
</tbody>
</table>

#### Table B7: Shading screen properties

<table>
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</thead>
<tbody>
<tr>
<td>EnviroScreen</td>
<td>0.0004</td>
<td>0.2</td>
<td>0.078</td>
<td>0.648</td>
<td>0.077</td>
<td>0.632</td>
</tr>
</tbody>
</table>
C. Manual shading control models

![Diagram C1: Model by Newsham (1994)]

![Diagram C2: Model by Reinhart (2004)]

![Diagram C3: Model by Haldi and Robinson (2010)]
D. Manual lighting control model

Fig. D1: Model by Reinhart (2004)
E. Conversion factors for primary energy

\[
\begin{align*}
\text{COP} & = 3.00^{[24,25]} \\
\eta_{\text{heating}} & = 0.95^{[24]} \\
\eta_{\text{cooling}} & = 0.70^{[24,25]} \\
\eta_{\text{electrical}} & = 0.39^{[24,25]}
\end{align*}
\]
F. Shading position with the control strategies

**Fig. F1:** Shading position with control strategy 1 in winter (top) and summer (bottom)

**Fig. F2:** Shading position with control strategy 2 in winter (top) and summer (bottom)
Fig. F3: Shading position with control strategy 3 in winter (top) and summer (bottom)

Fig. F4: Shading position with control strategy 4 in winter (top) and summer (bottom)
Fig. F5: Shading position with control strategy 5 in winter (top two) and summer (bottom two)
Fig. F6: Shading position with control strategy 6 in winter (top) and summer (bottom)
G. Input schedules of presence models

Fig. G1: Simple deterministic presence schedule

Fig. G2: Schedule for Reinhart presence model

Fig. G3: Schedule for Wang et al. presence model

Fig. G4: Schedule for Page et al. presence model
H. Shading position with manual shading control

Fig. H1: Shading position with the Newsham shading control model

Fig. H2: Shading position with the Reinhart shading control model

Fig. H3: Shading position with the Haldi and Robinson shading control model: active user (top) and passive user (bottom)
I. Automatic dimming of lighting

![Graph showing automatic dimming of lighting](image)

*Fig. I1: Automatic dimming of the lighting*
J. Sensitivity analysis results

Fig. J1: Sensitivity to number of runs - primary energy demand for heating: mean (left) and standard deviation (right)

Fig. J2: Sensitivity to number of runs - primary energy demand for cooling: mean (left) and standard deviation (right)

Fig. J3: Sensitivity to number of runs - primary energy demand for lighting: mean (left) and standard deviation (right)

Fig. J4: Sensitivity to number of runs - spatial daylight autonomy: mean (left) and standard deviation (right)
Fig. J5: Sensitivity to number of runs - occupied fraction with view: mean (left) and standard deviation (right)

Fig. J6: Sensitivity to number of runs - simplified daylight glare probability: mean (left) and standard deviation (right)