Simulation-aided development of automated solar shading control strategies using performance mapping and statistical classification

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ABSTRACT
This paper presents a structured, generically applicable, method for using building performance simulation to aid the development of comfort-driven solar shading controls by mapping predicted occupant comfort conditions to sensor measurements. The method uses confusion matrices as a statistical classification approach to facilitate (i) selection of sensor deployment strategies that offer beneficial trade-offs considering multiple performance aspects and (ii) identification of control algorithms that optimise comfort conditions using non-ideal sensors. The support method requires relatively little effort from a developer, only a small number of simulations and fits well within the current practice of shading control development. The method is tested using a sun-tracking control strategy for indoor roller blinds as a case study, which demonstrates that the method can identify high-performance solutions. Finally, generally applicable features of the method are extrapolated from the case study, and alternative applications and the method’s limitations are discussed.

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1. Introduction
Automated solar shading systems are instrumental for improving indoor environmental quality and reducing building energy consumption (Beck and Dolmans 2010; Daum and Morel 2010; Konis and Selkowitz 2017; Kuhn 2017; Lee, DiBartolomeo, and Selkowitz 1998; Shen and Tzempelikos 2012). The performance of solar shading systems, however, greatly depends on how these screens or slats are operated (Correia da Silva, Leal, and Andersen 2015; Daum and Morel 2010; Gunay, O’Brien, and Beausoleil-Morrison 2016; Lee, DiBartolomeo, and Selkowitz 1998; Mahdavi et al. 2008; Shen and Tzempelikos 2012; Tzempelikos and Shen 2013; Yao et al. 2016). Conventional control systems, that are characterized by simple full open and close actions in response to a sensor and a control threshold (Tabadkani et al. 2020), often do not fulfil the comfort requirements of occupants and lead to occupant dissatisfaction (Bian, Leng, and Ma 2018; Meerbeek et al. 2014; Stevens 2001).

Developing control strategies for automated solar shading systems requires making decisions regarding a large number of design parameters involving the control logic, control sensors and the design of the shading device (Kuhn 2017). Additionally, the number of possible sequences of shading system actuations or states defines a vast control space. Leveraging these parameters in the development of comfort-driven control systems is complex because it requires insight into comfort conditions of occupants and trade-offs between conflicting performance aspects (Loonen et al. 2013). Additionally, these aspects are affected by highly dynamic environmental conditions and can interact differently depending on the specific application in terms of, for example, building type, facade properties and interior lay-out (Favoino et al. 2016; Kuhn 2017; Loonen et al. 2013; Loonen et al. 2014; Silva da, Leal, and Andersen 2012).

Shading control strategies rely on sensors to classify indoor comfort conditions and decide upon control actions (Beck and Dolmans 2010; Tabadkani et al. 2020). For instance, vertical outdoor irradiance and indoor convective temperature sensors are commonly used to detect conditions with a risk of glare and thermal discomfort and subsequently close shading devices. Sensors need to be non-intrusive to occupants and are usually placed in non-ideal locations. Therefore, they cannot measure comfort conditions of occupants and building performance indicators directly (Tzempelikos and Shen 2013; Yun et al. 2020). For detecting a risk of daylight glare discomfort, for instance, it is not practically feasible to use the luminance distribution and illuminance at...
the position of occupants as direct control variables and only non-intrusive light sensors can be used. Additionally, it is important that a risk of glare resulting from a control action is predicted beforehand and prevented rather than retroactively corrected. The type of sensor that is used, its position and orientation influence the effectivity of the control strategy in addressing building performance aspects (Tzempelikos and Shen 2013; Yun, Park, and Kim 2017). In the development of a sensor strategy, a trade-off, therefore, must be made between the complexity and costs of the strategy on the one hand, and its positive effects on building performance on the other. An additional consideration is that, whilst control rules can always be easily changed, it is undesirable to change sensing equipment after it has been installed. There is therefore a need for new methods and tools to quantify the effectivity with which different sensor strategies influence whole building performance aspects.

Many studies that develop and test advanced control concepts rely on building performance simulation (BPS) (Atzeri et al. 2018; Coffey 2013; Daum and Morel 2010; Gunay et al. 2014; Huchuk et al. 2016; Seong et al. 2014a; Shen, Hu, and Patel 2014; Shen and Tzempelikos 2012; Tzempelikos and Shen 2013; Wienold 2007; Shen, Hu, and Patel 2014; Yun, Park, and Kim 2017). BPS can provide detailed insight into building performance aspects that are difficult and costly to measure or reproduce in experimental set-ups (de Klijn-Chevalerias et al. 2017). Additionally, with BPS, the effects of advanced control strategies can be evaluated for a large variety of buildings, climates and solar shading types (e.g. blinds, roller shades, shutters). This makes BPS a promising tool for exploring high potential control strategies and identifying risks in the context of automated solar shading (Loonen et al. 2017; Ochoa, Aries, and Hensen 2012). The use of BPS to inform the development of automated solar shading controls is, however, relatively new and there are several issues hindering BPS to be applied effectively in this context.

The development of solar shading controls using BPS currently follows a trial-and-error process where simulations are used to test a preconceived strategy using post hoc analyses (Loonen 2018). Although this process allows a developer to quantify the performance of a control strategy, it gives limited insight into how such a strategy can be improved further. Additionally, the knowledge obtained using this process tends to be case study specific and cannot be easily applied to a different type of solar shading system or a different building. There is therefore a need for generically applicable approaches that structure the use of BPS to identify high-performance solutions in an effective manner.

In recent years, many promising control strategies for solar shading systems have been proposed in scientific publications. There are explicit approaches, that prescribe control actuations under certain conditions. This group includes advanced rule-based control (RBC) algorithms that operate a shading system using knowledge about the sun’s position (Jeong, Choi, and Sung 2016; Koo, Yeo, and Kim 2010; Seong et al. 2014a, 2014b; Tzempelikos and Shen 2013) and proportional control based approaches where the shading system’s position is determined proportional to sensor measurements (Daum and Morel 2010; Kristl et al. 2008; Yun et al. 2020). Other strategies utilize an implicit performance weighing approach, where control actions are selected by comparing the effects that various possible control actions would have on weighted performance indicators. This group includes model predictive control (MPC) strategies, where control responses are optimized using built-in models (Xiong et al. 2019) and pre-defined performance goals (Huchuk et al. 2016; Mahdavi 2001; Mahdavi, Spasojevic, and Brunner 2005; Oldewurtel et al. 2012).

The literature on this topic also includes some generically applicable approaches for developing control strategies using BPS. For example, exhaustive-search simulation studies (Yun, Park, and Kim 2017) and self-learning methods (Gunay et al. 2014) have been applied to relate sensor measurements to performance goals by optimizing control thresholds for simple RBC strategies. This optimization does require, however, exploring a vast space of possible control thresholds. Additionally, the approach remains limited to the constraints of the initially assumed control concept and does not provide the deeper level of understanding that is needed to guide the development of a more advanced control logic. The MPC approach does not have this limitation. Although MPC has been shown to be a promising solution for high-performance building controls (Huchuk et al. 2016; Mahdavi 2001; Mahdavi, Spasojevic, and Brunner 2005; Oldewurtel et al. 2012), it is not commonly applied in practice (Coffey 2013; Piscitelli et al. 2019). A possible explanation can be found in the effort and skill that is required of a developer for every new type of solar shading system or when a system is commissioned into a new building. Potentially, self-learning behaviour can reduce this effort but setting up the model architecture and parametrizing the model remain costly. Additionally, MPC is computationally expensive and complex during operation. Researchers have developed techniques to significantly reduce the computational complexity of MPC by rule-extraction and the mapping of operational conditions to MPC control responses (Coffey 2013; Piscitelli et al. 2019). This process, however, requires more effort from developers and is computationally expensive in the preparation phase. Additionally, a fitness function with relative weights for different performance indicators must be defined beforehand when
applying the MPC to the multi-objective solar shading control problem. This is not easily done based on engineering intuition and tuning these weights towards the desired performance outcomes therefore requires extensive sensitivity analyses (Mahdavi 2001; Oldewurtel et al. 2012).

This paper presents a simulation-based support method for the development of rule-based solar shading control strategies and the optimization of sensor selection, control thresholds and detection algorithms. The support method simplifies the task of developing an advanced control logic by guiding a developer in identifying a set of simple control actions, aimed at balancing trade-offs between a subset of performance aspects under specific representative environmental conditions. These control actions will later form the individual control modes of a multi-mode control strategy. The effects of these control modes on occupant comfort conditions are then graphically mapped to sensor measurements, such that the most beneficial conditions for activating each control mode can be identified. The effectiveness of detection algorithms, sensors and control thresholds are then evaluated using statistical classification techniques and visualized in a confusion matrix. This allows the effectiveness of non-intrusive sensors to be optimized. The graphic nature of this method allows the performance effects of all possible values for a single control threshold to be visualized in a single image using the results of only two full-year simulations. The method builds on, generalizes and structures some of the ad-hoc research tasks observed in literature on advanced solar shading case studies (Chan and Tzempelikos 2013; de Vries, Loonen, and Hensen 2019; Oh, Lee, and Yoon 2012; Shen and Tzempelikos 2017).

The support method gives detailed insight into how control decisions can be used to influence performance trade-offs and offers a structured approach for identifying high-performance solutions inside the design space. The goal of the support method is to assist the development of control solutions that are based on performance goals, yet easily implemented in simple control hardware. An additional requirement being that applying the method to a new case should require little effort from a developer and only a small number of simulations. This feature allows the method to be used to customize a control strategy for a particular building design. This is desirable because the relative weight of evaluation criteria can only be determined in relation to the building context (Kuhn 2017), for example, daylighting performance is more important in a building with small windows.

The support method will be illustrated and tested using a case study that develops a control strategy for an automated indoor roller blind system, with attention for the selection of sensors and control thresholds. The case study is used to show the structured approach and prove that the applied classification and visualization techniques identify high-performance solutions in a practical example. The control strategy was developed in collaboration with industry partners for whom simple control hardware and a limited time investment for each building design project are important considerations.

Section 2 of this paper will give a broad overview of the support method. The support method will be explained in more detail, using the case study, in section 3. The discussion in section 4 will evaluate the efficiency and shortcomings of the support method. Section 5 presents the conclusions of this research. These conclusions extrapolate the generic features and benefits of the support method from the case study and suggest promising future applications.

2. The computational shading control and sensor strategy development method

Figure 1 gives an overview of the proposed support method. A developer starts with five preparatory steps (1.1–1.5). These steps include defining a set of performance aspects, indicators and goals (1.3) that the control strategy will seek to balance. Additionally, the developer defines an initial set of control modes (1.1). In each of these control modes, the shading device is dynamically operated according to a distinct logic that focuses on pursuing a subset of the overall performance goals. The different control modes should vary in terms of how far the shading device is opened and, consequently, in the amount daylight, sunlight and solar radiation that is admitted. The developer then defines several potential sensors alternatives (1.2), that the multi-mode control strategy will use to switch between control modes. Additionally, the developer defines a description of a representative office space (1.4) that is considered representative for the final application of the system. A simulation model is then developed (1.5) to predict the performance of each of the control modes and the corresponding sensor readings for each sensor alternative.

A simulation of a typical year is executed for each of the initial control modes, where the specific control mode is followed continuously (2). These simulations offer the developer a quantification of the overall annual performance of each control mode, the instantaneous performance at each timestep and lists of corresponding simulated sensor readings.

The developer then evaluates, using annual performance indicators, if the individual performance goals
are each met by at least one of the control modes and whether they provide the desired performance trade-offs (3.1). The most promising control modes are now selected and ordered in terms of the amount of solar energy that is admitted, with control mode 1 (CM1) being the most open mode of operation and subsequent control modes.
(CM_2 to CM_n) being more closed. If the initial control modes do not offer the desired performance, new control modes can be added. The developer can find possible improvements by analysing the instantaneous timestep performance of the initial control modes (3.2). If after multiple iterations of testing potential control modes the desired performance goals and trade-offs cannot be achieved, this gives reason to review the feasibility of the initially assumed goals, the proper functioning of the simulation model and the constraints that are posed by the selected dynamic shading system and its physical properties.

In the next step (4), a sensor strategy is developed. This strategy is defined by the detection algorithms, thresholds and sensors that are used to detect the boundaries of conditions where the control system will switch between two adjacent modes of operation. Adjacent here relates to the order in the admittance of solar energy. Each adjacent set of control modes will get a detection algorithm that determines when CM_i leads to poor performance and CM_{i+1} should be activated.

The approach in step 4 is to relate the instantaneous performance, or the performance difference, of two adjacent control modes to sensor readings (4.2) and test detection algorithms using statistical classification techniques. In this research, control decisions are classified in a confusion matrix (4.3) (Fawcett 2006). By relating the decisions of potential detection algorithms to simulated performance predictions, the effectiveness of these algorithms can be evaluated. Potential sensor strategies can be evaluated from a multi-objective perspective by using the confusion matrix method for each performance indicator.

All steps will be graphically illustrated using the case study example. Additionally, a set of indicators that aid the developer in refining detection algorithms will be presented. This set includes indicators that are commonly used in the field of statistical classification as well as quantities developed in this research. The outcome of this process is a multi-mode control strategy, or multiple strategies, with optimised sensors and sensor thresholds. The performance of these strategies is then simulated and compared to a baseline strategy (5).

### 3. Case study: a sun-tracking control strategy for indoor roller blinds

This case study focusses on an automated indoor roller blind system that uses a metal-coated shading fabric with a high solar reflectance and low openness (Table 1). The shade is automated using a silent motor that allows its position to be varied continuously.

| Shadefabric properties | T_vis | R_visfront | T_sol | R_solfront | OF | #front | #back |
|------------------------|-------|------------|-------|------------|----|--------|-------|
| Shade properties        | 0.013 | 0.719      | 0.025 | 0.740      | 0.008 | 0.230  | 0.858 |

#### 3.1. Preparatory steps 1.1–1.5

**3.1.1. Step 1.1: defining a set of initial control modes and a baseline strategy**

In this case study, preventing daylight glare discomfort is the control goal with the highest priority. In this step, a large part of the control space will be excluded based on experience and the body of knowledge on preventing glare with shading devices. By assuming a set of rule-based control modes based on initial analyses in step 3 and optimizing the conditions under which they are activated in step 4, the control space is greatly decreased, and the problem made more manageable.

To maximize the admission of daylight and views, a developer can start with a control mode where the shading system is placed in the most open position. Here, this means fully raising the shade. To minimize cooling energy consumption and glare, a control mode is added where the shading system is placed in the most closed position. In this case, this means fully lowering the shade. An additional control mode is added that balances multiple conflicting performance objectives. Based on a review of literature, a promising sun-tracking algorithm was found (Tzempelikos and Shen 2013). This control logic, titled the solar cut-off logic, balances the goal of limiting daylight glare discomfort with the competing goal of admitting daylight and views to the outdoors. The algorithm controls the roller blind in relation to the sun’s position to block direct sunlight from hitting an occupant’s desk (Figure 2) using Equation (1). The edge of an occupant’s desk is assumed to be at 75 centimetres height and positioned 75 centimetres from the façade. Solar cut-off algorithms can be geometrically defined for most commercially available products (Seong et al. 2014a; Tzempelikos, O’Neill, and Athienitis 2007) and are a good starting point in defining control modes.

\[
sh = \frac{wpd}{\cos(\gamma - 180)} \cdot \tan \alpha + wph, \quad (1)
\]

where wpd is the distance between the edge of the work plane and the façade, wph is the height of the work plane from the floor; sh is the distance between bottom of the shade and the floor (shade height); \(\gamma\) is the solar azimuth in degrees (clockwise from North convention); and \(\alpha\) is the solar altitude in degrees.

Previous research (Atzeri et al. 2018; de Vries, Loonen, and Hensen 2019; Tzempelikos and Shen 2013) showed that the sun-tracking strategy can lead to undesirable degrees of glare and cooling energy consumption.
Figure 2. Parameters and solar position angles used in the solar cut off control logic.

because it causes the shade to be nearly fully raised at mid-day in summer when solar altitude is high. An additional control mode, titled EL, will therefore be included. The EL control mode follows the same sun-tracking behaviour as SC but now the maximum allowable shade height is limited to a seated eye-level height of 1.2 m.

A conventional control strategy for indoor roller blinds will be used as a benchmark. In this baseline strategy (BL), the roller blind is controlled using an outdoor global vertical irradiance sensor where the shade is either fully raised or lowered in response to a threshold of 200 W/m² (Beck and Dolmans 2010).

3.1.2. Step 1.2: defining potential sensor alternatives

In this study, the focus lies on sensors and algorithms for detecting different ranges in incident solar energy. In literature, a wide variety of sensors are used for this purpose, ranging from outdoor or indoor irradiance and illuminance sensors to glare sensors at the position of an occupant (Silva da, Leal, and Andersen 2012; Yun, Park, and Kim 2017). In this study, three sensors are evaluated: an exterior global horizontal irradiance sensor (E-Igh), an exterior global vertical irradiance sensor (E-Igv), and an indoor vertical illuminance sensor (I-Igv). The placement of these sensors is illustrated in Figure 3. The sensors are set up in an open-loop configuration and are selected because they are non-intrusive to occupants and easily commissioned on-site.

The outdoor irradiance sensors are chosen as this type of sensor is commonly installed for integration in building management systems. The indoor illuminance sensor is positioned in between the glazing and roller blind. This alternative is chosen because it is generally cheaper than the outdoor pyranometers. Additionally, this sensor is expected to better approximate the perception of daylight by occupants as it measures radiation in the visual spectrum, is affected by glazing characteristics, and its vertical position aligns reasonably well with the viewing direction of multiple occupants. Using this selection of sensors, the importance of both the positioning of a sensor and the part of the solar spectrum it measures, will be tested.

3.1.3. Step 1.3: selection of performance aspects and indicators

Explicitly stating performance goals, requirements and priorities beforehand facilitates decision making in the control development process. The performance aspects of interest in this study are daylight quality, visual comfort, view to the outdoors, and energy efficiency.

Spatial daylight autonomy is used as an indicator for daylighting performance, with 300 lux and 50% of occupied hours as cut-off criteria (sDA300/50%). This indicator is defined as the percentage of floor area that receives at least 300 lux for more than 50% of the occupied hours (Illuminating Engineering Society 2012) and has been shown to correlate well with subjective occupant assessments of daylight quality and quantity (Nezamdoost and Van Den Wymelenberg 2017). To be able to evaluate instantaneous daylighting performance, the daylit area fraction D300lx is used. This indicator gives the percentage of floor area that receives at least 300 lux at a point in time.

Visual comfort is operationalized as the lack of visual discomfort and daylight glare probability simplified (DGP) is used as a performance indicator. This metric was empirically derived by Wienold (2009) and relates the probability of the occurrence of glare to vertical illuminance at the eye of the observer. It has been shown that, although DGP can accurately predict glare in instances where occupants are not exposed to direct sunlight and saturation is the dominant mechanism causing
glare (Wienold, Iwata, and Sarey Khanie 2019), the metric performs less well when contrast glare is dominant. In this case study, DGPs is considered sufficiently reliable because the sun-tracking control strategy and low-openness fabric ensure that occupants are not exposed to sunlight.

Seating arrangements closest to the window are the most sensitive to the occurrence of glare (Giovannini et al. 2020). Additionally, the likelihood of glare discomfort is strongly influenced by viewing direction (Bian, Leng, and Ma 2018; Jakubiec and Reinhart 2012). To assess glare probability the two seating positions shown in Figure 2 are assumed. For each seating position, glare is assessed in two viewing directions (Figure 3): one where the occupant is facing a wall, and one where the occupant is facing the window at 45° as recommend in EN 14501 CEN (2017). Annual aggregated performance is quantified using the percentage of occupied hours that a DGPs of 0.40 (disturbing glare) is exceeded. This annual indicator is separately assessed for both viewing directions (DGPs0.4;0deg;exc and DGPs0.4;45deg;exc), where at each timestep the maximum DGPs value of both occupant positions is used. DGPs0.4;0deg;exc thus gives the share of occupied hours that at least one of the two occupants perceives ‘disturbing’ glare if they were facing a wall (Figure 2) whilst DGPs0.4;45deg;exc assumes both occupants are facing the window at 45°. In this case study, DGPs0.4;0deg;exc is considered the most critical as it is representative for instances where the occupants are facing their computer monitors and cannot easily adjust their viewing direction. Disturbing glare in this viewing direction is likely to lead to occupants overruling the automated control system. Therefore, preventing disturbing glare in this viewing direction is stated as a performance goal of the strategy that is going to be developed. DGPs0.4;45deg;exc is considered less critical than DGPs0.4;0deg;exc because the occupants have more freedom to avert from this viewing direction. DGPs0.4;45deg;exc will therefore be treated as a performance indicator that is undesirable, but trade-offs with other aspects, such as daylighting performance, are considered acceptable.

The current state of the knowledge on view quality and quantity does not offer empirically supported performance indicators that are suited for evaluating the effects of dynamic solar shading devices (Hellinga and Hordijk 2014; Heschong 2003; Mardaljevic 2019; Pilechiha et al. 2020; Turan, Reinhart, and Kocher 2019). However, research investigating occupant operation of operable roller shades has shown that users tend to leave the lower portion of a window unshaded to maintain a visual connection with the outdoors (Haldi and Robinson 2010; Konis 2013; Sadeghi et al. 2016). In this study, view of the outdoors is assumed to be only dependent on the position of the shade. It is assessed as the percentage of occupied hours that the shade is positioned above the eye level of a seated occupant (1.2 m). This indicator will be abbreviated as V1.2m;exc.

Energy performance is expressed in terms of primary energy consumption for cooling, heating and lighting and computed from simulated energy demand using
Table 2. Case study details and assumptions.

| Geometry | Dimensions | width: 4.5 m; depth: 6 m; height: 3 m (27 m²) |
|----------|------------|--------------------------------------------|
| Facade orientation | South |
| Window to wall ratio: | 80% |
| Fenestration | Type: Low-E (pos. 3) double glazing with argon cavity filling |
| Glazing: | \( U_{gl} \): 1.2 W/m²K, \( U_{frame} \): 1.5 W/m²K, \( T_{vis} \): 0.82, SHGC: 0.62, CEN |
| Façade | \( R_c = 4.5 \text{ m}^2\text{K}/\text{W} \) |
| Ceiling, walls, floor | Mixed: heavy weight floor/ceiling, lightweight walls |
| Internal gains | People: 3 (variable occupancy), 120 W/pers. |
| Lighting: | Weekdays: 8:00–19:00 (2860 h/year) |
| Equipment: | \( 7.0 \text{ W/m}^2 \) |
| HVAC and settings | Equipment: |
| Infiltration: | ACH: 0.15 |
| Ventilation: | Demand driven, 40 m³/(h × pers.), ACH: 1 (average) |
| Setpoints: | Sensible heat recovery, efficiency: 70% |

Weather

\[ E_{\text{prim}} = \frac{E_{\text{light}}}{\eta_e} + \frac{E_{\text{cool}}}{\eta_e \eta_c \text{COP}_{\text{cool}}} + \frac{E_{\text{heat}}}{\eta_h} \]  

(2)

where \( E_{\text{prim}} \) is the primary energy consumption; \( E_{\text{light}} \) is the lighting energy demand; \( E_{\text{cool}} \) is the cooling energy demand; \( E_{\text{heat}} \) is the heating energy demand; \( \eta_e \) is the site to source primary energy ratio for electricity; \( \eta_c \) is the cooling delivery system efficiency; \( \text{COP}_{\text{cool}} \) is the chiller coefficient of performance, and \( \eta_h \) is the overall heating system efficiency.

3.1.4. Step 1.4: defining a typical application environment

This study uses the reference office building for evaluating building-integrated solar envelope systems, developed within IEA SHC Task 56 (D’Antoni et al. 2019) with some minor adjustments. The details of this office cell and other modelling assumptions are given in Table 2.

3.1.5. Step 1.5: develop a simulation model

To account for the strong dependence of performance on interactions between the thermal and visual domains, this study relies on a co-simulation framework using Radiance (daylighting), EnergyPlus (thermal domain), Matlab (control logic) and BCVTB (information exchange). The Radiance three-phase method is used for daylighting and glare performance assessments as well as the prediction of indoor lighting energy consumption and associated heat gains. This approach has previously been validated for the performance assessment of advanced solar shading systems (McNeil and Lee 2013). BCVTB (Wetter 2011) directs the exchange of information between simulation environments. Matlab is used to describe the behaviour of the shading control logic and compute daylighting conditions and artificial lighting gains using a database with Radiance simulation results.

To simulate a variable height shading system using the Radiance three-phase method as well as EnergyPlus, the fenestration system needs to be divided into multiple horizontal segments which are either fully shaded or unshaded. To this end, the window is subdivided into 35 horizontally oriented window segments. This modelling resolution was chosen based on a sensitivity analysis presented in de Vries, Loonen and Hensen (de Vries, Loonen, and Hensen 2019).

Hourly weather data for Amsterdam (IWEC) is used in this study. For EnergyPlus, a 5-min time step is chosen, as a sub-hourly resolution helps to increase the reliability of the heat balance algorithms as well as limit the effect of errors deriving from BCVTB’s loosely coupled co-simulation approach. Within Radiance an hourly time step is chosen to describe sky conditions because of the unavailability of sub-hourly weather data and the uncertainties associated with the creation of synthetic sub-hourly data for this location (Walkenhorst et al. 2002) (Table 3).

3.2. Step 2: simulate the performance of each control mode

The performance of the initial control modes is now simulated. In these simulations, the shading system follows one of the envisioned control modes continuously throughout the year. A case is simulated where the shades are always up (AU), one where the system follows the solar cut-off logic (SC), one where the shade is always down (AD) and one where the solar cut-off logic shade height is limited to the seated eye-level (EL).
### Table 3. Simulation parameters and assumptions

|                      | EnergyPlus                        | Radiance                        |
|----------------------|-----------------------------------|---------------------------------|
| **Fenestration**     | Glazing optical properties from IGDB: | BSDF created with LBNL-Window |
|                      | Lay 1: IGDB#1608                  | Lay 1: IGDB#1608                |
|                      | Lay 2: IGDB#11560                 | Lay 2: IGDB#11560               |
| Shade                | anisotropic optical model with properties from CGDB#20032 | Shade: CGDB#20032               |
| **Interior surfaces**| Lambertian reflectors: |                                |
|                      | Ceiling, $r_{vis}$: 0.8, Wall, $r_{vis}$: 0.5 |                                |
|                      | Floor, $r_{vis}$: 0.2              | Sensor grid: $S \times 25$      |
|                      | $V_{\text{contr}}$: $- ab_{12} - \text{ad}_{5} 2 \times 10^{-6}$ |                                |
|                      | $D_{\text{contr}}$: $- ab_{2} - \text{ad}_{10} 3 - \text{lw}_{5} 5 \times 10^{-4} - c_{3000}$ |                                |
|                      | $s$ and D sky resolution: MF3      |                                |
| **Simulation settings** | Idealised HVAC system: unlimited capacity and ideal response | hourly time step |
|                      | $5 \text{ min. time step}$        |                                |

Figure 4. Summary of whole building performance for each control mode and the baseline strategy. BL: Baseline, AU: Always up, SC: Solar cut-off, EL: Solar cut-off with maximum height at eye level, AD: Always down.

### 3.3. Step 3: evaluate the performance of each control mode

Figure 4 shows the performance of each of the cases in relation to the baseline. Here, the performance indicators are reformulated such that the most desirable situation is reached if all performance indicators are as low as possible. View and glare performance is shown as the share of occupied hours that their required criterion was not met. Daylighting performance is presented as the complementary percentage to $sDA_{300/50}$: the floor area that does not receive at least 300 lux for 50% of occupied time.

The graph shows that each of the control modes successfully addresses a single performance aspect but performs badly on the other aspects. As expected, the AU case offers the best $sDA_{300/50}$ and $V_{1.2;vexc}$ but performs less well than the BL in terms of $DGP_{0.4;45\deg;vexc}$ and $E_{\text{prim}}$. The SC case offers a more beneficial trade-off between the different performance aspects. Compared to the BL strategy it offers superior $sDA_{300/50}$ and a slight improvement in $E_{\text{prim}}$ which can be attributed to reductions in lighting energy consumption. The SC logic performs similar to the BL strategy in terms of the other indicators, and does not satisfy the defined requirement of 0% $DGP_{0.4;45\deg;vexc}$.

The EL logic does fulfill the 0% $DGP_{0.4;0\deg;vexc}$ requirement and greatly reduces $DGP_{0.4;45\deg;vexc}$. With regards to daylighting and energy performance the EL strategy performance similar to the BL. The AD case fully eliminates disturbing glare in both viewing directions but performs very badly in all other performance indicators.

These results suggest that combining the AU, SC and EL control logics into a multi-mode control strategy could provide a strategy that performs significantly better than the baseline. In this multi-mode control strategy, the SC control mode would be activated under conditions where the AU mode leads to glare or an unacceptable amount of cooling energy consumption. Likewise, the EL strategy would be activated when excessive admission of solar energy in the SC mode would cause undesired performance. The AD case does not appear to offer any additional beneficial performance trade-offs in relation to the other cases and it will therefore not be considered as a potential control mode for the multi-mode strategy.

The development of more refined control actions can be supported by analysing the instantaneous timestep performance of the initially simulated cases (step 3.2). In this research, for instance, the EL strategy was added after analysing the contour plots in Appendix A. These
plots show the timestep performance of the SC strategy and indicate that the EL strategy leads to excessive cooling energy consumption and glare when the shade is positioned very high at mid-day in summer.

The three most promising cases (AU, SC, EL) have now been identified. In Figure 4 these cases are ordered and numbered in terms of the amount of solar energy that they admit. As control modes in a multi-mode strategy, they will be respectively referred to as CM1AU, CM2SC and CM3EL.

The analyses of the different cases in step 3 can also be used to verify the proper functioning of the simulation model. The results in Figure 4 show that as less solar energy is admitted, sDA300/50, lighting and cooling energy consumption decrease whilst heating energy consumption and DGP0.4; exc rise. Additionally, analysing timestep (Appendix A) or monthly (Appendix C) aggregated simulation outputs can assist the modeller in verifying the simulation model.

### 3.4. Sensor strategy optimization: mapping of performance effects to sensor measurements and statistical classification of detection algorithms

The goal of this step is to develop a sensor strategy that identifies the most ideal conditions to activate each control mode. In the case study, two detection algorithms will have to be defined: one for activating CM2SC and one for activating CM3EL. The CM2SC detection algorithm determines when the system will switch between the CM1AU and the CM2SC control modes. To develop this algorithm, instantaneous performance results from the AU and SC cases are related to the simulated sensor measurements and the effectivity of potential detections algorithms, and sensors, is evaluated using confusion matrices. The same approach is used to develop the CM3EL detection algorithm that determines when the system switches between CM2SC and CM3EL.

#### 3.4.1. The confusion matrix approach: a detection algorithm for switching between the CM1AU and the CM2SC control mode

Figure 5 illustrates how the confusion matrix approach works using the CM2SC detection algorithm and the I-Eg sensor as an example. Simulated glare performance (DGP0.4;0deg and DGP0.4;45deg) from the AU case is plotted in relation to the I-Eg sensor measurements. Figures 6 and 7 show the same simulation results (DGP0.4;45deg in relation to I-Eg) but underline the generic features of the approach and clarify the steps involved in making the confusion matrix. Earlier, we have defined DGP ≥ 0.4 as a criterion for undesired glare performance. Here, we will take a conservative approach and focus on preventing glare in the 45-degree viewing direction (coloured circles in Figure 5). Using the performance criterion, each instance is tested for the condition DGP45deg ≥ 0.4 classifying them into ‘positives’ (P) or ‘negatives’ (N), where positive stand for the occurrence of glare. This classification is called the true performance classification (PCtrue). In the images, it is represented by a horizontal line (Figure 6).

The goal of the sensor strategy is to predict this performance classification using a detection algorithm and sensor measurements S creating a PDetected that separates all instances into predicted P and N classes. An ideal sensor strategy (Figure 6) would be one that always classifies performance conditions correctly (PCtrue = PCdetected). Actual sensor strategies are generally less effective and will classify some instances incorrectly. The effectivity of a sensor strategy can be evaluated by relating the detected classification to the true classification and binning all instances in one of the four cells of a confusion matrix. Figures 5 and 7 illustrate this graphically. Here, a potential detection algorithm that uses a single sensor threshold of 3700 lux is used, and PDdetected can be represented by a vertical line. The two lines now graphically define a confusion matrix where all instances are contained within one of four quadrants:
Figure 6. Actual performance classification of instantaneous performance of CM1 based on a performance criterion. Sensor: I-Eg:V, Performance indicator: DGP45deg

- The true positives (TP): the sensor algorithm correctly detected glare in CM1AU. CM2SC is activated to prevent glare.
- The true negatives (TN): the sensor algorithm correctly detected no glare in CM1AU. CM1AU is activated to maximize the admission of daylight and views.
- The false positives (FP): the sensor algorithm wrongly detected glare in CM1AU. CM2SC is activated and the shade is lowered further than what would be necessary to prevent glare.
- The false negatives (FN): the sensor algorithm wrongly detected no glare in CM1AU. CM1AU is activated and this causes occupants to be exposed to glare.

The effectivity of different sensor strategies can be quantified by looking at the share of occupied hours that are contained in each confusion matrix region. The share of all positives that were detected by the sensor strategy, or true positive rate (TPR), gives an idea of how well the strategy detects conditions where the occupants perceive glare. Here, a TPR of a 100% means that all instances with disturbing glare where detected. The ‘accuracy’ (ACC) quantifies the frequency of the system making correct performance classifications and is defined as the ratio between the number of instances contained in the ‘true’ regions to the number of total instances. In this example, a greater ACC indicates better performance trade-offs between daylighting performance and visual comfort. The 3700-lux threshold that is evaluated in the confusion matrix in Figure 5 is defined such that false negatives, where activating CM1:AU would cause glare in the 45-deg viewing direction, never occur. The accuracy of this strategy is not ideal (89%) due to a substantial number of false positives (11%) that lead to an unnecessary decline in daylighting and view performance.

ACC and TPR only quantify the frequency of false control decisions but not the severity of the effects on other performance aspects. The impact of false control decisions can be large or small, however, depending on environmental conditions. More detailed insight into performance trade-offs can be obtained by looking at the effects of false control decisions on daylighting performance. To quantify these effects, the instantaneous difference in $D_{1;3000x}$ between the SC and AU cases is computed for each timestep (Equation (3)). This performance difference ($\Delta D_{T;3000x:SC;AU}$) is visualized in Figure 5 using the gradient colour scale of the 45-degree viewing angle. The dark blue colour of the instances contained in the FP
Figure 7. Performance classification by a simple detection algorithm (if \( S > 3700 \) then: positive) and evaluation of its effectivity using a confusion matrix. Sensor: I-Eg,v, Performance indicator: DGP_{45deg}

region indicates that these instances will have a particularly strong negative effect on daylighting performance.

\[
\Delta D_{t;300lx;SC;1AU} = D_{t;300lx;SC} - D_{t;300lx;AU}
\]

where \( D_{t;300lx;SC} \) is the percentage of floor area that receives more than 300 lux, at time step \( t \), for the SC case; \( D_{t;300lx;AU} \) is the percentage of floor area that receives more than 300 lux, at time step \( t \), for the AU case; \( D_{t;300lx;2SC;1AU} \) is the change in instantaneous daylighting performance when switching from CM_{1;AU} to CM_{2;SC}.

Table 4 summarizes the effectivity scores (TPR:100% and ACC:98%) associated to the 3700-lux threshold along with the resulting overall daylighting performance (sDA_{actual}: 74%) if this detection algorithm would be implemented in a two-mode strategy (CM_{1;AU} + CM_{2;SC}). In addition, the table shows the ideal daylighting performance that could be achieved (sDA_{ideal}: 100%) with a two-mode strategy if the detection algorithm would make no false classifications (PC_{detected} = PC_{true}). Together, the collection of indicators quantify how well the detection algorithm can isolate instances with undesired performance, what the effects are of wrong control decisions, and what could be gained by improving the algorithm further. By comparing sDA_{actual} to sDA_{ideal} it becomes clear that, although sDA_{actual} is significantly better than that of the BL (sDA:22%), there is still a lot of room for further improvement.

Figure 5 suggests that a better trade-off between glare and daylighting performance can be obtained by moving the threshold closer to the point where the linear regression line of the scatter plot intersects the 0.4 DGP disturbing glare line. This approach is illustrated with the second cross. Here, the choice is made to accept that 3% of all DGP_{0.4;45deg} exceedance goes undetected (TPR: 97% and 2% FN) by using a control threshold of 6400 lux. The graph shows that this reduces the occurrence of FP to 0%. Table 4 summarises the positive effects of changing the detection threshold, where sDA_{actual} increases to 100%, matching sDA_{ideal}. Note that, although DGP_{0.4;45deg} increases, the more critical DGP_{0.4;0deg} indicator remains almost unchanged. This means that the disturbing visual discomfort that is introduced by this new threshold, could be mitigated by a change in the viewing direction of the occupant. In this case study, this
Table 4. Summary of the effectivity of tested sensors, thresholds and detection algorithms for switching between the CM1AU and CM2SC control modes.

| Threshold based on: | Sensor: | Exterior horizontal irradiance | Exterior vertical irradiance | Interior vertical illuminance |
|---------------------|---------|---------------------------------|-----------------------------|-------------------------------|
|                     | 30 W/m² | 50 W/m²                         | 3700 lux                     |
|                     | Glare:  | TPR: 100% ACC: 78% TPR: 100% ACC: 91% TPR: 100% ACC: 89% |
|                     | DGPS  | DGPS 31% DGPS 7% DGPS 31% DGPS 7% DGPS 31% DGPS 7% |
|                     | sDA:   | Actual: 69% Ideal: 100% Actual: 78% Ideal: 100% Ideal: 100% |
|                     | Eprim; | kWh/m² Negative Positive Negative Positive Negative Positive |
|                     | 0.0450deg >= 0.4 | ΣTN: 1.1 ΣTP: 10.6 ΣTN: 4.7 ΣTP: 7.0 ΣTN: 4.5 ΣTP: 7.2 |
|                     |         | ΣFN: -0.5 ΣTP: -8.7 ΣFN: -0.9 ΣTP: -8.3 ΣFN: -0.7 ΣTP: -8.4 |
|                     |         | totTN: 0.7 totTP: 1.9 totTN: 3.8 totTP: -1.3 totTN: 3.8 totTP: -1.3 |
| Saved:              | Actual: 0.7 Ideal: 11.7 Actual: 3.8 Ideal: 11.7 Ideal: 3.8 Ideal: 11.7 |

| Threshold based on: | Sensor: | Exterior horizontal irradiance | Exterior vertical irradiance | Interior vertical illuminance |
|---------------------|---------|---------------------------------|-----------------------------|-------------------------------|
|                     | 80 W/m² | 80 W/m²                         | 6400 lux                     |
|                     | Glare:  | TPR: 97% ACC: 87% TPR: 97% ACC: 97% TPR: 97% ACC: 98% |
|                     | DGPS  | 0.0450deg 33% DGPS 0.0450deg 8% DGPS 0.0450deg 7% DGPS 0.0450deg 8% |
|                     | sDA:   | Actual: 83% Ideal: 100% Actual: 99% Ideal: 100% Actual: 100% |
|                     | Eprim; | kWh/m² Negative Positive Negative Positive Negative Positive |
|                     | 0.0450deg >= 0.4 | ΣTN: 5.5 ΣTP: 6.2 ΣTN: 7.2 ΣTP: 4.5 ΣTN: 7.9 ΣTP: 3.8 |
|                     |         | ΣFN: -0.7 ΣTP: -8.5 ΣFN: -1.2 ΣTP: -8.0 ΣFN: -1.1 ΣTP: -8.1 |
|                     |         | totTN: 4.8 totTP: -2.3 totTN: 6.0 totTP: -3.5 totTN: 6.8 totTP: -4.3 |
| Saved:              | Actual: 4.8 Ideal: 11.7 Actual: 6.0 Ideal: 11.7 Ideal: 6.8 Ideal: 11.7 |

is considered an acceptable trade-off for improving daylighting performance.

The confusion matrix approach can also be used to assess how well the detection algorithm identifies instances where switching from the CM1AU to CM2SC would improve energy performance. This process is visualized in Figure 8. In this case, control decisions are evaluated as if the only goal of the control is to minimize energy consumption. The effects of switching between the two control modes is quantified using the difference in instantaneous primary energy consumption for heating, cooling and lighting \( \Delta E_{\text{prim}} \) between the AU and SC cases (Equation (4)).

\[
\Delta E_{\text{prim};2SC};1AU = E_{\text{prim};SC} - E_{\text{prim};AU}
\]  

where \( E_{\text{prim};SC} \) is the instantaneous primary energy consumption for heating, cooling and lighting, at time step \( t \), for strategy SC; \( E_{\text{prim};AU} \) is the instantaneous primary energy consumption for heating, cooling and lighting, at time step \( t \), for strategy AU.

Instances where activating CM2SC saves energy are now labelled as ‘positives’ and the PCtrue is based on the performance criterion \( \Delta E_{\text{prim}} < 0 \). This criterion is represented in the graph by the horizontal line at \( \Delta E_{\text{prim}} = 0 \). The graph is used to evaluate the effectivity of the previously defined 6400-lux threshold from an energy perspective. This detection algorithm is again represented by a vertical line that defines PCdetected and the two lines delineate the regions of the confusion matrix. The colour scale is used to visualize \( \Delta D_{13000k2SC;1AU} \) and highlights the relationship between energy and daylighting performance. To obtain a quantification of the total effects of the wrong and correct control decisions, the \( \Delta E_{\text{prim}} \) of all instances contained within each of the four regions of the confusion matrix are summed. The four regions, denoted with the subscript \( e \), can be interpreted as follows:

- The true positives \( \text{TP}_e \): the sensor algorithm activates CM2SC. This reduces \( E_{\text{prim}} \) compared to activating CM1AU. A negative value for \( \sum \text{TP}_e \) quantifies this reduction.
- The true negatives \( \text{TN}_e \): the sensor algorithm activates CM1AU. This reduces \( E_{\text{prim}} \) compared to activating CM2SC. A positive value for \( \sum \text{TN}_e \) quantifies this reduction.
- The false positives \( \text{FP}_e \): the sensor algorithm activates CM2SC. This increases \( E_{\text{prim}} \) compared to activating CM1AU. A positive value for \( \sum \text{FP}_e \) quantifies this increase.
- The false negatives \( \text{FN}_e \): the sensor algorithm activates CM1AU. This increases \( E_{\text{prim}} \) compared to activating CM2SC. A negative value for \( \sum \text{FN}_e \) quantifies this increase.

The sums of two of the four matrix cells can be used to assess the effects that potential detection algorithms would have in a two-mode strategy (CM1AU + CM2SC) compared to the initial AU or SC cases. By summing all the detected ‘negatives’ \( \text{tot} \text{TN}_e \) the effects can be compared in relation to the SC case and by summing all
the detected ‘positives’ (totPe) the effects can be compared in relation to the AU case. The 6400-lux threshold CM1;AU;2;SC solution has a $E_{\text{prim}}$ that is 6.8 kWh/m$^2$ (totNe = TNe + FNe) lower than that of the SC case. This net effect is a consequence of the instances where raising the shade saved energy (TNe: 7.9 kWh/m$^2$) and the instances where doing so would lead to more energy consumption (FNe: –1.1 kWh/m$^2$). For the initial 3700-lux threshold, the reduction in $E_{\text{prim}}$ compared to SC is only 3.8 kWh/m$^2$ (Table 4). This shows that the 6400-lux threshold is also more beneficial in terms of energy performance.

The four regions also allow the performance of a detection algorithm to be benchmarked against an ideal sensor strategy that always activates the CM with the lowest $E_{\text{prim}}$ (PCdetected = PCtrue). With an ideal strategy $E_{\text{prim}}$ would be 11.7 kWh/m$^2$ (TNe + FP) lower than that of the SC case. This means that 58% of the $E_{\text{prim}}$ reduction that could potentially be achieved by optimizing the detection algorithm has been realized with the 6400-lux algorithm. To facilitate these comparisons, the totNe score that is obtained by each sensor strategy is summarized under the header ‘actual’ next to the ‘ideal’ score.

Using these graphs and Table 4, some observations can be made. Figure 8 suggests that raising the shade fully saves energy in almost all instances where doing so would improve indoor daylighting conditions. In almost all instances where raising the shade would not cause such an improvement, the increase in solar heat gains would lead to an increase in total primary energy consumption. In this case, there appears to be little conflict between the goal of improving daylighting performance and the goal of improving energy performance.

The indicators in Table 4 show that compared to the original, 3700-lux threshold, the 6400-lux threshold offers more beneficial performance trade-offs between visual comfort and the other performance aspects. With this approach, both daylighting and energy performance come quite close to the ideal performance that is achievable using the selected control actuations. This suggests that there is little need for testing more complex detection algorithms.

To also be able to compare the effectivity of different sensors, control thresholds where determined for each type of sensor using both the 0% and the 2% DGPs $0.4;45\deg$ exceedance approaches. In Table 4, these thresholds are summarized along with the corresponding effectivity of each sensor strategy. The variation in daylighting and energy performance amongst the sensors shows that they vary in the effectivity with which they can classify instances with glare. It can be concluded that the E-Ig+h sensor is less effective in classifying glare than the other sensors. Meeting the visual comfort requirement with this sensor leads to a 2 kWh/m$^2$ higher $E_{\text{prim}}$ and a 17% lower sDA$300lx;50\%$ than with the other sensors. Although the differences between the E-Iv and the I-Eg+h are less pronounced, the I-Eg+h sensor does perform better in terms of both daylighting (1%) and energy consumption (0.8 kWh/m$^2$).

### 3.4.2. A detection algorithm for switching between the CM$_{2SC}$ and the CM$_{3EL}$ control modes

In determining the detection algorithm for switching between CM$_{2SC}$ and CM$_{3EL}$, the goal of prohibiting glare discomfort is again given priority. Measurements from the three sensors are used to detect when CM$_{2SC}$ leads to glare and decide that CM$_{3EL}$ should be activated. Figure 9 shows simulated glare performance in relation to sensor measurements from the SC case. Here, two sensor
types are shown to illustrate the differences in the effectiveness with which the sensors classify visual discomfort. A and B show results for the I-E_{g,v} sensor. C and D show results for the E-I_{g,h} sensor. The colour scale is again used to plot instantaneous effects on daylighting performance ($\Delta D_{t;300x3EL2SC}$) of switching between the two control modes (Equation 5).

$$\Delta D_{t;300x3EL2SC} = D_{t;300xEL} - D_{t;300xSC}$$

where $D_{t;300xEL}$ is the percentage of floor area that receives more than 300 lux, at time step $t$, for the EL case; $D_{t;300xSC}$ is the percentage of floor area that receives more than 300 lux, at time step $t$, for the SC case; $D_{t;300x3EL2SC}$ is the change in instantaneous daylighting performance when switching from CM2;SC to CM3;EL.

The top graphs (A and C) show a detection algorithm where the control threshold is chosen such that disturbing glare is always prevented for the view facing the wall (0% FN). The relationship between glare probability and sensor measurements is less linear than in the previous example. As a result, there are many instances (35%) contained within the FP region. These instances have a strong negative effect on daylighting performance as can be seen from their negative $\Delta D_{t;300x3EL2SC}$ values and the performance that is achieved compared to the ideal (Table 5).

The occurrence of glare in the SC case can be attributed to a large fraction of the window being exposed at high solar altitude giving occupants a large view of the sky. This situation can lead to glare at instances with high luminance sky conditions. A detection algorithm based on both illuminance and the amount of window area that is visible to the occupant, therefore, seems like a promising direction for further improvement. Figures C and D illustrate this approach. Here the illuminance, or irradiance, measured by the sensors is multiplied by the unshaded height of the window. The relationship between DGPs and these manipulated sensor measurements are more linear than in the cases using the unmanipulated sensor measurements. Consequently, the performance trade-offs that can be achieved are more beneficial as can be seen by the improvement in the effectivity indices shown in Table 5.
Table 5. Summary of the effectivity of tested sensors, thresholds and detection algorithms for switching between the CM2; SC and CM3; EL control modes.

| Threshold based on: | Exterior horizontal irradiance sensor | Exterior vertical irradiance sensor | Interior vertical illuminance sensor |
|---------------------|---------------------------------------|-----------------------------------|-------------------------------------|
|                     | 310 W/m² | 150 W/m² | 12000 lux |
| Glare: TPR: | 100% | 77% | 100% | 64% | 100% | 64% |
| ACC: | 100% | 77% | 100% | 64% | 100% | 64% |
| DGP0.45deg >= 0.40 | DGP0.45deg | 0% | DGP0.45deg | 0% | DGP0.45deg | 0% |
| sDA: | Actual: 57% | Ideal: 69% | Actual: 55% | Ideal: 69% | Actual: 53% | Ideal: 69% |
| Eprim: kWh/m² | Negative | Positive | Negative | Positive | Negative | Positive |
| TN: | 7.2 | FP: | 1.6 | TN: | 7.1 | FP: | 1.7 |
| FN: | 0.0 | TP: | -1.1 | FN: | 0.0 | TP: | -1.1 |
| totTN: | 7.2 | totTP: | -1.1 | totTN: | 7.1 | totTP: | 0.6 |
| Saved: | Actual: | 1.1 | Actual: | -0.6 | Actual: | 1.1 | Actual: | -0.6 |

For assessing the effects of the different detection algorithms on energy performance, Equation (6) is used.

\[ \Delta E_{\text{det},3EL;SC} = E_{\text{det},SC} - E_{\text{det},EL} \]  

where \( E_{\text{det},EL} \) is the instantaneous primary energy consumption for heating, cooling and lighting, at time step \( t \), for strategy EL and \( E_{\text{det},SC} \) is the instantaneous primary energy consumption for heating, cooling and lighting, at time step \( t \), for strategy SC.

The energy and daylighting scores of the different sensors shown in Table 5 show that the I-Eg;v sensor identifies visual discomfort most effectively. The differences between the sensors are less pronounced here than in the previous case with CM1; AU and CM2; SC. By comparing the scores of the two approaches for switching between CM2; SC and CM3; EL, it becomes clear that the most beneficial performance trade-offs can be achieved when sensor measurements are multiplied by the unshaded height of the window. Although there is some room for additional improvement, the achieved daylighting performance is reasonably close to the ideal. The graphs suggest that further improvements could be found by reducing the amount, or the negative effects, of the FP’s shown in Figure 9. The amount of FP’s can be reduced by improving the detection approach. Reducing the negative effects can be done by adjusting control response.

3.5. Step 5: simulate the performance of the developed multi-mode control strategies

A multi-mode control strategy with optimized detection algorithms has now been developed. The previous steps have focussed on evaluating and improving the performance of the individual detection and actuation algorithms. In this step, the performance of the complete multi-mode control strategy is assessed and compared to the baseline strategy. To evaluate if the confusion matrix method ranks the different sensors correctly, all sensors are included in this comparison. Only the best performing detection algorithms from the previous section are now evaluated. CM2; SC is activated using the 2% allowed DGPs0.4;45deg exceedance sensor threshold and the algorithm where the sensor measurements are multiplied by the unshaded height is used to activate CM3; EL.

Figure 11 presents a summary of whole building performance for the developed control strategies and sensor alternatives. The performance indicators are defined as in Figure 4 where the goal is to get each indicator as low as possible.
Figure 10. Evaluation of the effectiveness of sensor strategy in addressing energy performance. Vertical axis: difference in instantaneous primary energy consumption of SC and EL strategies. Colour: difference in instantaneous daylighting performance of SC and EL strategies.

...possible. To also evaluate the benefits of the individual control modes and detection algorithms, scenarios that include only two of the three proposed control modes are included for each sensor alternative.

For all sensor types, we see a similar pattern in performance improvements. Compared to the SC only strategy, fully raising the shade in the two-mode CM1AU2SC strategies improve daylighting (by 16–32% sDA300lx;50%) and energy performance (by 6–11%) as well as the time with a view to the outdoors (by 24–27%) without causing a significant change in visual discomfort. The improvements in energy performance can be attributed to reductions in lighting energy consumption as well as to slight improvements in cooling energy consumption due to reduced lighting gains. The CM3EL improves overall energy performance and reduces the time that the visual discomfort criterion is met to 0% (a 7% reduction) for the 0-degree viewing direction. These improvements do have a negative effect on daylighting performance (8–12% relative reduction in sDA300lx;50%). Compared to the SC only alternative, implementation of both the CM1AU and CM3EL control modes has a beneficial effect on all performance aspects. The only exception to this is the alternative using a horizontal irradiance sensor, where there is no improvement in daylighting performance.

Overall, substantial differences can be observed between the three sensors, where the indoor illuminance sensor stands out as the best performing alternative for all performance indicators. Compared to the worst performing alternative, the horizontal exterior irradiance sensor (E-Igh CM1AU2SC3EL), the illuminance sensor (I-Ev CM1AU2SC3EL) offers a 3% lower $E_{\text{prim}}$, a 9% higher sDA300lx;50%, 3% reduction in DGP$s_{0.4;45\text{deg}}$ exceedance and 3% more $V_{1.2\text{m};\text{exc}}$. The large differences in daylighting performance between these two sensors can mainly be explained by the horizontal irradiance sensor’s poor performance when it comes to detecting low-light conditions. This is not surprising as this threshold marks the lower boundary of conditions characterized as being partly cloudy or slightly overcast. Under such conditions, the contribution of the direct component will start becoming more significant in the overall sensor measurements and a vertically oriented sensor is better equipped to identify such instances.

Amongst the investigated alternatives I-Ev-CM1AU2SC3EL strategy offers the best trade-off in performance aspects. Compared to the conventional BL strategy it offers significant improvements for all indicators: 14% reduction in $E_{\text{prim}}$, a 56% higher sDA300lx;50%, 21% more $V_{1.2\text{m};\text{exc}}$ and 15% reduction in DGP$s_{0.4;45\text{deg}}$ exceedance. Additionally, the I-Ev-CM1AU2SC3EL strategy can mitigate disturbing glare in the most critical viewing direction completely.

4. Discussion

This section evaluates the efficiency and limitations of the support method using the results of the case study. Additionally, this section discusses how the method can be used to customize controls for specific building applications.

In the confusion matrix method, instantaneous performance results of two separate simulations are used to identify ideal circumstances for switching between adjacent control modes. This approach has the limitation that it only quantifies the immediate performance effects of control actions. In assessing energy performance effects, this does not accurately describe the transient effects of shade actuations, and the admission of solar energy, on energy performance. This causes an error in the estimated energy reductions that are used to assess the individual control improvements. To explore the extent
Figure 11. Summary of whole building performance predicted using simulations of the multi-mode SCmm strategy in combination with different sensors. Performance indices defined as in Figure 4.

to which this limitation influences the conclusions of the confusion matrix evaluations, the energy reductions that were estimated using this method are compared to the results from the multi-mode simulations (step 9). If we compare the energy performance results shown in Figure 11 to the estimated energy performance improvements, obtained by summing instantaneous $E_{prim}$ in the confusion matrix quadrants (Tables 4 and 5), it can be seen that both evaluations lead to the same ranking of options for all sensors, detection algorithms and control mode alternatives. From this, it can be concluded that the confusion matrix approach can reliably rank amongst alternatives and identify high performing solutions.

Although the relative hierarchy of the different options is predicted correctly, the predicted energy savings are less accurate. The summation of confusion matrix quadrants suggests that the CM$_{1;AU,2;SC}$ strategy would have a 6.8 kWh/m$^2$ lower $E_{prim}$ than the SC only strategy (Table 4) whereas the results from step 9 show this reduction to be 8.5 kWh/m$^2$ (Figure 11). The CM$_{2;SC,3;EL}$ strategy is estimated to lead to a 0.3 kWh/m$^2$ reduction in $E_{prim}$ relative to SC whereas Figure 11 shows that this difference should be 3.2 kWh/m$^2$. Overall, the conclusions drawn from the multi-mode simulation study are in line with those based on the confusion matrix method. There are some discrepancies in predicted energy savings in absolute terms, but it is not the goal of the method to give an exact prediction of potential energy savings. Rather, the goal is to be able to rank the relative merits of different options and identify high performing solutions. This comparison showed that the confusion matrix method can meet this goal in a reliable way using only a very limited number of simulations.

The presented correlations between sensor measurements and performance effects depend on building design characteristics, occupant positions and contextual factors such as climate. Ideally, the proposed method is used to optimize control thresholds for specific building applications. To illustrate this, the support method was applied for three different buildings, varying in terms of their fenestration design and window-to-wall ratios (WWR: 40%, 60% and 80%). This additional study, shown in Appendix B, is not discussed in detail but the main conclusions can be summarized as follows. The scatter plots in Figure 14 show how the correlation between sensor measurements and glare and energy performance changes with the varying WWR. The graph shows that only the 40% WWR case leads to different conclusions regarding the control thresholds that are needed to satisfy required comfort conditions.

5. Concluding remarks

This research presented a method that structures the use of BPS to support the development of comfort-driven control strategies for automated solar shading systems. The method is proposed as an alternative for the, often ad-hoc, approach that characterizes the current use of BPS in this field. The method was illustrated and tested using an automated indoor roller blind system as a case study where the structured method was used to guide the development of a multi-mode sun-tracking control strategy. Confusion matrices were used as a tool to assess the effectivity of control decisions and optimize the sensor strategy that is used to switch between control modes.

A series of scatter plots, relating sensor measurements to performance effects, combined with confusion
matrices and a set of associated indicators were introduced to navigate the control space. These tools help quantify performance trade-offs and guide decision making in developing a sensor strategy. The mapping of sensor measurements to performance effects allows performance criteria to be directly translated to control thresholds. The visualization of this mapping in a set of scatter plots allowed the effects of moving control thresholds to be visualized in a single image and optimal control thresholds to be identified. The graphic nature of this mapping allows developers to investigate the performance effects of changing the relative weight of evaluation criteria without having to run additional simulations. Additionally, the plots visually support the developer in extracting detection algorithms from simulation data. Using the confusion matrix as a control decision classification tool, the performance of an existing concept could be analysed in a way that illustrated the constraints of a detection algorithm in relation to a more ideal unconstrained case. Being able to benchmark a potential concept in relation to an ideal control concept allows developers to weigh the costs of increasing control and sensor strategy complexity to potential gains in choosing research and development directions.

The most promising alternative that was identified in the case study, the SCmm-CM1AU2SC3EL multi-mode strategy using an indoor illuminance sensor, offers a reduction of 14% in $E_{\text{prim}}$, 56% more sDA300lx;50%, and 8–15% reduction in DGPs0.4 exceedance in relation to the conventional baseline solution (Figure 11). This shows that the support method can identify high-performance control rules, detection algorithms, thresholds and sensors using only a limited number of simulations. In this paper, many simulation results were presented to illustrate and test the proposed method. For identifying the best performing SCmm-CM1AU2SC3EL alternative and comparing it against a baseline, only five simulations would have to be executed in practice.

The method was tested on three building designs with varying fenestration designs and offered significant performance improvements over the baseline strategies in all cases. The results showed that the performance improvements were largest when control thresholds were customized to the specific building application. By making scatter plots for multiple representative building applications, like in Figure 14, developers can also obtain insight and intuition into how the mapping of sensor measurements and performance effects are influenced by different building characteristics and adjust control thresholds on the basis of this insight.

The case study focussed on using single control thresholds for switching between control modes and only a single radiation sensor was used to inform the system in each alternative. Additionally, the actuation algorithms were intentionally kept simple and the study investigated a roller blind system with a limited degree of control freedom. It should be noted that the presented algorithms and sensor combinations are not part of the support method. The extent, however, to which the proposed method preserves its advantages when applied to systems with more control freedom should be tested in future research.

A few applications of the method, that go beyond the current case study, are recommended for further research. The performance mapping approach is not limited to using a single sensor and for developing detection algorithms based on multiple sensors, multi-dimensional plots can be used. Additionally, multiple performance criteria can be used with the confusion matrix method to identify threshold ranges that relate to different degrees of occupant sensitivities and comfort preferences. The ‘disturbing’ and ‘perceptible’ glare criteria can be used, for instance, to define the upper and lower boundaries of a threshold range that can be adjusted by users.

Different statistical classification techniques could be used as an alternative, or in addition to, the confusion matrices presented in this research. The confusion matrix approach has the advantage that different weights can be assigned to different types of false control decisions (e.g. causing glare is worse than decreasing the admission of daylight). A disadvantage of the current approach is that sensors are evaluated using specific control thresholds. For assessing sensors in a way that is not tied to a specific control threshold a ROC-curve could be used. The performance mapping approach also offers the possibility to develop detection algorithms based on machine learning techniques (Gunay et al. 2014). The PCtrue and sensor measurements from the simulation results can be used in step 4 to train a classification tree or support vector machine, where, for example, the sensor measurements and solar position are used as predictors. This application could also provide opportunities to include user overrides, measured during control operation (Sadeghi et al. 2016), in the training data at a later stage.

In the support method, the control space of possible control actuations is constrained to a select number of control modes that are selected based on engineering knowledge and structured analyses. Hereby the control space is made smaller and more manageable. A disadvantage of this constraint is that, although the method leads to high-performance outcomes, ideal performance cannot be guaranteed. The support method is, however, also suited for developing actuation algorithms that exploit a larger part of the control space by using a proportional control approach (Shen and Tzempelikos 2017). To
illustrate this point, Figure 9(B) illustrates how this could be approached in the case study. The graph indicates a slope that can be used in the CM3:EL mode to define the maximum shade height proportionally to sensor measurements, as an alternative to using seated eye level. Another possible application would be to discretize the control space and treat every shading system state as if it were a separate control mode. The mapping of sensor measurement to performance effects requires that distinct simulation alternatives are used but potentially a large number of control modes can be used. In the case study, this would mean using annual simulations of discrete shade height positions in step 2 and 3. In this application, the error in the assessment of instantaneous energy performance effects would have to be carefully assessed.

6. Data availability

The simulation toolchain and analyses functions that were developed for this study is publicly accessible and can be found in the following repository: https://gitlab.tue.nl/bp-tue/solarshading.

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Nomenclature

RBC Rule base control
MPC Model predictive control
BPS building performance simulation
wpd Wor kplane distance
sh shade height
α solar altitude [°]
wph Work plane height
γ solar azimuth [°]
E-I_v outdoor global vertical irradiance sensor
E-I_g,h outdoor global vertical irradiance sensor
I-E_g,v indoor vertical illuminance sensor
sDA300/50% Spatial daylight autonomy 300 lux 50% of time
DGPs daylight glare probability simplified

DGPs_{0.4,45deg,exc} DGPS 0.4 exceedance for the 45° viewing direction
V_{1.2m,exc} Share of occupied hours that sh ≥ 1.2 meters
E_{prim.} Primary energy consumption for heating, cooling and lighting
η_s Site to source primary energy ratio for electricity
η_c Cooling delivery system efficiency
η_h Overall heating system efficiency
IWEC International Weather for Energy Calculations

BCVTB Building controls virtual testbed
IGDB International glazing database
CGDB Complex glazing database
AU Always up control logic
SC Solar cut-off control logic
AD Always down control logic
EL Eye-level control logic
CM1AU Control mode nr. 1 following the AU logic as part of a multi-mode strategy
CM1AU;2SC A multi-mode control strategy with two control modes
PC_{true} True performance classification
PC_{detected} Detected performance classification
P and N ‘Positive’ and ‘negative’ classifications by the detection algorithm
TP True positive Condition: PC_{true} = P and PC_{detected} = P
TN True negative Condition: PC_{true} = N and PC_{detected} = N
FP False positive Condition: PC_{true} = N and PC_{detected} = P
FN False negative Condition: PC_{true} = P and PC_{detected} = N

sDA_{ideal} sDA that of a two-mode control strategy assuming an ideal detection algorithm
sDA_{actual} sDA that of a two-mode control strategy using the investigated detection algorithm

ΔD_{t;300lx;2CM;1CM} Difference in instantaneous daylighting performance of two simulated control modes
ΔE_{prim;2CM;1CM} Difference in instantaneous primary energy consumption of two simulated control modes

∑TNe Sum of all ΔE_{prim} contained in the true negative region
TN_e + FP_e TN_e + FP_e

WWR Window-to-wall ratio
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