A Simplified Open-loop Control Strategy for Integrated Shading and Lighting Systems Using Machine Learning

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Abstract

Conventional integrated shading and lighting systems are usually sensor-dependent, which could entail excessive cost and labor associated with sensor installation, calibration, and maintenance. Advanced systems use daylight modeling to eliminate the use of physical sensors. However, real-time daylight simulation can be computation-heavy, leading to a slow response of the system. This paper proposed a data-driven method for integrated shading and lighting control, employing machine learning models developed from pre-simulated data to predict real-time daylighting and control the blind and lighting accordingly. Verification using climate-based daylight simulation with a case study showed that the method prevented 94.7% of annual glare and reduced lighting use by 64%. The study will contribute to the development of effective daylight-linked control systems for industrial applications.

Key Innovations

- A simplified open-loop control strategy for integrated shading and lighting control is proposed.
- The presented system is effective in preventing glare and reducing lighting energy use without using indoor sensors or intensive real-time daylight simulation.
- The classification algorithm significantly outperformed the regression algorithm for the proposed control method.
- The proposed control method is promising to become an industrial application.

Practical Implications

Classification algorithms are recommended for the proposed control method. Attention should be paid to possible imbalanced class distribution in the dataset for model development and appropriate techniques need to be applied to address the unequal distribution of data.

Introduction

Building shading systems are a promising solution to balance the benefits and drawbacks of daylight ingress in an indoor space. A well-designed and operated shading system is expected to prevent visual discomfort while maximizing daylight and view access under varying weather and sky conditions. Energy use associated with electric lighting can be reduced by integrating the control of the lighting and shading systems. These integrated systems can be divided into manual and automated systems. It is generally agreed that manual shading systems fail to optimize daylight penetration and glare prevention (O'Brien, Kapsis, & Athienitis, 2013). Typically, occupants close the shading devices to avoid visual discomfort and subsequently leave them closed even when there is no glare (Gunay, O'Brien, Beausoleil-Morrison, & Gilani, 2017; O'Brien et al., 2013; Reinhart & Voss, 2003; Van Den Wymelenberg, 2012). In contrast, studies have shown that automated shading systems are capable of effectively optimizing daylight ingress and reducing energy demand (Jain & Garg, 2018; Konstantoglou & Tsangrassoulis, 2016; Tabadkani, Roetzel, Li, & Tsangrassoulis, 2020). Research also suggests that interior automated blinds are more cost-effective than manual blinds over a 30-year time horizon (Al-Masrani & Al-Obaidi, 2019). Hence, integrated automated shading and lighting control have been proposed as a beneficial strategy to improve the indoor visual environment and reduce energy demands (Jain & Garg, 2018).

Automated shading systems can be categorized as open-loop and closed-loop systems (Jain & Garg, 2018). The major difference between the two systems is that the closed-loop system receives feedback while the open-loop system does not. For a typical photometer-dependent system, an open-loop system usually relies on sensors mounted on the external surface of the façade to measure weather and sky conditions while a closed-loop system applies a series of indoor photosensors integrated with dimmers to maintain the desk illuminance at a desirable level. As discussed by Jain and Garg (2018), open-loop systems provide greater flexibility compared to closed-loop systems. Careful sensor calibration is required for closed-loop systems. For instance, the calibration of photosensors in a typical closed-loop system is required for both day and night time (Caicedo, Pandharipande, & Willems, 2014; Park, Choi, Jeong, & Lee, 2011; Peruffo, Pandharipande, Caicedo, & Schenato, 2015). Lee et al. (2017) reported that the complex and expensive calibration required for closed-loop shading systems is challenging for their application in real-life settings (Lee et al., 2017). These systems can be prone to error. There have been studies reporting that closed-loop systems are less effective in reducing energy use compared to open-loop systems (Delvaeye et al., 2016).

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Various open-loop control methods for automated shading have been proposed in the literature. A typical strategy is the cut-off control that adjusts the blind slat angle according to the solar position (Chan & Tzempelikos, 2013). However, it is widely accepted among researchers that this method is not sufficient in preventing glare (Jain & Garg, 2018). There are other simple glare-prevention strategies such as controlling shades based on time, season, and occupancy. However, these methods have the main challenge of not responding to outdoor sky conditions. Another type of open-loop system relies on readings from various sensors. Notably, this method may entail excessive cost and labor for the installation, calibration, maintenance, and replacement of sensors. This shortcoming can be one major obstacle for daylight-linked systems to be applied to buildings (Bellia, Fragliasso, & Stefanizzi, 2016). Additionally, the use of sensors could be limited due to aesthetic considerations in commercial buildings.

With the advancement of simulation and modeling tools, simulation-assisted control is gaining more popularity (Chaiwiwatworakul, Chirarattananon, & Rakkwamsuk, 2009; Chan & Tzempelikos, 2013; Katsifaraki, Bueno, & Kuhn, 2017; van Hoof, Kort, Duijnstee, Rutten, & Hensen, 2010; Xiong & Tzempelikos, 2016). It replaces physical sensors in conventional systems with virtual sensors in a digital model to provide daylight measurements for shading control. With this method, lighting control can be easily integrated into shading control. Jain and Garg (2018) reviewed studies on simulation-assisted open-loop control strategies for shades, blinds, and integrated lighting, concluding that simulation-assisted control with careful calibration is more effective than conventional methods. However, real-time daylight modeling can be computationally intensive and leads to a slow response of the control system. Currently, there is a lack of suitable simulation tools that can be included in the control process. These limitations and obstacles could significantly prevent simulation-assisted control from becoming an industrial application.

As discussed by Jain and Garg (2018), machine learning (ML) can be a promising technique to replace daylight modeling and significantly reduce simulation time. Although ML has been widely applied in studies on architectural design (Ayoub, 2020), a few studies can be found that have used it for building system control, especially integrated shading and lighting control (Jain & Garg, 2018). This paper aims to address this gap by proposing an integrated blind and lighting control strategy based on daylighting predictions using ML models. Specifically, it uses pre-simulated daylight measurements to train ML models that can estimate indoor daylighting and use them for integrated shading and lighting control. It is a simplified method that aims to promote daylight-linked control systems for industrial applications.

Regression algorithms are used in previous studies on estimating daylight measurements using ML while classification and clustering are rarely investigated (Ayoub, 2020). However, as suggested by Ayoub (2020), more research is required to explore the use of these algorithms as they can be useful for glare identification. Therefore, this study also investigates and compares the use of regression algorithm and classification algorithm in the proposed control framework.

Methods

The goal of the proposed control framework is to predict real-time discomfort glare and indoor illuminance using data-driven models developed from pre-simulated data and use the predicted measures to control the shading and lighting system. It aims to prevent discomfort glare and maximize daylight ingress and view access. Discomfort glare is quantified by Daylight Glare Probability (DGP) which is widely used to describe glare from daylight (Wienold & Christoffersen, 2006). Electric lighting is controlled by the average illuminance on the work plane (Katsifaraki et al., 2017). The proposed control framework consists of three steps: daylight simulation, ML model development, and real-time system control. A case study has been presented to demonstrate the application of the proposed control strategy.

Research model

As shown in Figure 1, the research model is a 4.5 m×3.0 m × 2.5 m private office located in Pittsburgh, Pennsylvania, USA (latitude 40.4N, longitude 80W) with an east-facing window (2.6 m×2.1m). It is equipped with an internal automated Venetian blind with slats that can rotate from 0º (fully open) to 90º (fully closed) in 10º increments. Any angle between 0º and 90º refers to the case that the upper side of the slats faces outwards. The slats are flat specular lamellae with a width of 0.05 m and a specularity of 0.8. The spacing between two adjacent slats is also 0.05 m. The horizontal work plane is a 1.6 m ×0.8 m desk at a height of 0.8 m. The occupant's sitting position is marked as the red dot in Figure 1. One LED luminaire is mounted on the ceiling and controlled by an on/off algorithm.

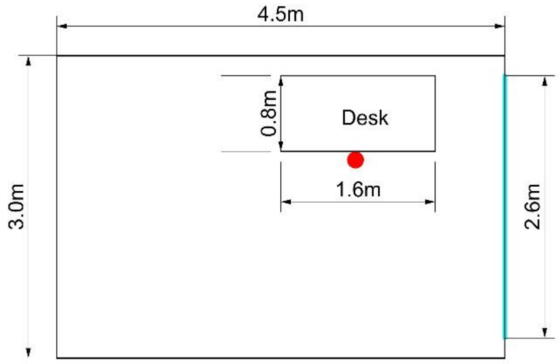

Figure 1: The floor plan of the research model.

A digital fisheye camera is placed at the occupant's sitting position (1.2 m above the floor) to detect time-varying glare. It should be noted that only the regular view direction (parallel to the window) is considered. Daylight simulation is only conducted for occupied hours (8 am to 6 pm). Table 1 summarizes the properties of the materials used in the simulation.

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Table 1: Material properties in the simulation.

Material	Type	Reflectance/ Transmissivity
Ceiling	Opaque	0.7
Wall	Opaque	0.7
Floor	Opaque	0.2
Blind	Metal	0.7
Desk	Opaque	0.5
Window glazing	Transparent	0.87

Daylight modeling

The software Rhinoceros (Rhino) is used to create the office geometry and the daylight modeling tool DIVA is used to perform the simulation. Specifically, DIVA for Rhino is used to conduct annual glare and illuminance simulations. DIVA for Rhino computes annual glare in a simplified way using the enhanced simplified DGP (eDGP) (Wienold, 2009). It separates the computation of the illuminance and luminance contrast and uses a simplified image to derive DGP, thus significantly reducing the computation time. Wienold (2009) suggested that this simplified DGP computation method applies to façade with a specular Venetian blind system. Therefore, it is appropriate to use eDGP in this study as the simulated office is equipped with a specular blind. The simulation parameters used in Radiance are listed in Table 2. Downloaded TMY3 weather file of Pittsburgh airport from the EnergyPlus website is used to run the simulation. Perez all-weather sky model is selected for the modeling to cover all possible sky conditions. The simulations were repeated with varying salt angles from 0º to 90º in 10º increments.

Table 2: Radiance parameters used in the modeling.

Parameter	Value
Direct jitter (-dj)	0
Direct sampling (-ds)	0.2
Direct threshold (-dt)	0
Direct certainty (-dc)	0.25
Direct relays (-dr)	2
Direct pretest (-dp)	512
Specular threshold (-st)	0.85
Ambient bounce (-ab)	3
Ambient accuracy (-aa)	0.1
Ambient resolution (-ar)	300
Ambient divisions (-ad)	1000
Ambient super-sample (-as)	20
Ray reflection limit (-lr)	6
Ray weight limit (-lw)	0.0004

Machine learning model development

In this study, individual ML models are developed for each blind position. In theory, ten models are required as the blind can rotate from 0º to 90º in 10º increments. The development of the ML predictive models follows a standard machine learning process, consisting of four steps: data processing, model selection, model training, and model testing. The machine learning module scikit-learn for Python is used to perform the process.

Figure 2: The workflow for machine learning model development.

1) Data processing

For the classification algorithm, the original output measure needs to be labeled as different categories. In this study, only two categories are considered as summarized in Table 3. It was found that the obtained dataset was imbalanced, especially for the glare dataset, with more cases without glare (labeled as "0") than cases with glare (labeled as "1"). The dataset becomes more imbalanced with a larger slat angle. A classification model developed from such an imbalanced dataset usually performs poorly on the minority class. To overcome this problem, the technique of oversampling the minority class is introduced. With this method, new data points for the minority class can be synthesized from the existing data. As a result, the distribution of the class will become more balanced. This is a data augmentation technique for the minority class that is called the Synthetic Minority Oversampling Technique (SMOTE). In this study, the number of the minority class is increased to that of the majority class after applying the SMOTE. For the regression algorithm, no specific data transformation is conducted.

Table 3: Outcome label for the classification algorithm.

DGP	Average Illuminance	Label
> 0.35	> 500 lux	1
<= 0.35	<= 500 lux	0

2) Model selection

- Algorithm selection

Multi-layer feed-forward artificial neural networks (ANNs) are selected to develop the ML predictive models. Specifically, two-layer ANN regression and ANN classification are used to develop the ML models. As reviewed by Ayoub (2020), ANN is the most widely used ML algorithm in existing studies on daylighting prediction. Also, it can solve both regression and classification problems. Therefore, it is selected in this study.

- Model input selection

With the sitting position and view direction of the occupant pre-defined in this study, major factors that influence the daylighting performance include the sky conditions and the solar position. Accordingly, four relevant measures are selected as the model input: direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), solar altitude angle, and solar azimuth angle. These input parameters have been applied in a previous study on illuminance-based blind control (Hu & Olbina, 2011). They are also easy to obtain for real-time control.

3) Model training

- Cross validation

Cross validation is a common model validation technique for assessing how the results of an ML model generalize

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to a new dataset. The procedure for cross validation involves a single parameter called k that refers to the number of groups (or folds) the training dataset is to be randomly split into. k-1 subgroups are used to train the model and the other group is used to validate its performance. This procedure is repeated k times such that each of the k subgroups will be used as the validating dataset once. The average of the selected performance metric across the k processes is used to evaluate the performance of the model. This process is called k-fold cross validation. A typical 10-fold cross-validation is applied in this study.

- Model evaluation metric selection

The performance of a binary ML classification model can be described by the confusion matrix in Table 4. Various performance metrics have been proposed based on the confusion metrics, such as recall and precision. The selection of the evaluation metric depends on the specific problem. In this study, more weight has been placed on the False Negative in glare prediction, i.e., the ML model failing to predict the occurrence of actual glare, than False Positive. Therefore, recall score is selected as the model performance metric for glare classification. In the case of illuminance prediction, the regular accuracy score is used. For regression models, Root Mean Square Error (RMSE) is selected as the model evaluation metric.

Table 4: The confusion matrix for binary classification.

	Predicted = Yes	**Predicted = No**
Actual = Yes	True Positive (TP)	False Negative (FN)
Actual = No	False Positive (FP)	True Negative (TN)

$$Recall = \frac{TP}{TP+FN} \tag{1}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\mathrm{N}}} \tag{3}$$

where y_i is the actual DGP (-) or illuminance (lux), $\hat{y}_i$ is the predicted DGP (-) or illuminance (lux), N is the number of data points.

- Hyperparameter optimization

In machine learning, hyperparameter optimization is the process of choosing the ideal hyperparameter for a learning algorithm. A hyperparameter is a pre-determined parameter that controls the overall learning process of an ML model. A model usually has more than one hyperparameter. In this study, three hyperparameters of the ANN model are selected for the optimization, including learning rate, number of neurons in a given layer, and learning epoch (the number of passes of the entire training dataset the machine learning algorithm has completed). The examined alternatives for each hyperparameter are given in Table 5. A grid search to find the optimal hyperparameter combination is conducted. In total, there are 18 possible combinations.

Table 5: Selected hyperparameters and their examined range.

Hyperparameter	**Selected Alternatives**
Learning rate	0.0003, 0.001, 0.01
Layer structure	(32, 16), (32, 8), (16, 8)
Learning epoch	300, 500

Integrated blind and lighting control strategy

Figure 3 illustrates the detailed algorithm for the integrated blind and lighting control. At each time step, the ML predictive models estimate the glare and illuminance with real-time solar irradiance measurements and solar position. The algorithm selects the minimal slat angle that prevents glare to maximize daylight utilization. After the optimal slat angle is determined, the ML model predicts the average work plane illuminance. The light will be switched off if the prediction indicates illuminance is above 500 lux. Otherwise, it will be switched on.

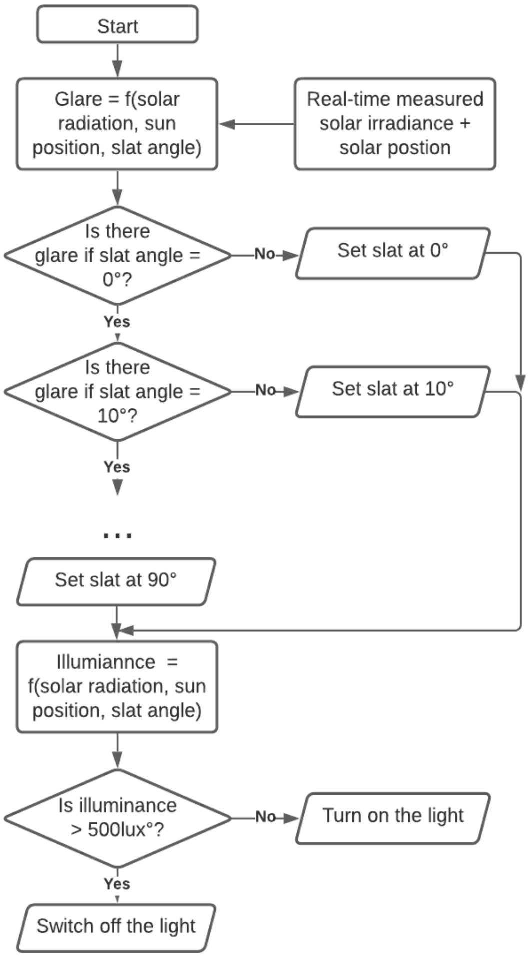

Figure 3: The algorithm for the integrated blind and lighting control.

Performance evaluation of the proposed shading and lighting control strategy

Climate-based daylight simulation is applied to validate the performance of the presented control strategy in preventing glare and reducing lighting use on an annual basis. Specifically, a concept of “on-state-hit” is defined to assess the system’s capability to eliminate glare. It refers to the cases when glare is successfully predicted

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and prevented. The lighting energy savings is quantified by the percentage reduction of hours that require electric lighting compared to a simple on/off control based on office hours.

A historical year's solar irradiance data (the year 2017) obtained from the National Solar Radiation Data Base (NSRDB) is used to conduct the annual glare and illuminance simulation. NSRDB is a publicly open dataset created by the National Renewable Energy Laboratory (NREL). It provides half-hourly and hourly solar irradiance and meteorological data from 1998 to 2019 over the United States at a 4-km horizontal resolution. The data are computed by NREL's Physical Solar Model (PSM) using multi-channel measurements from geostationary satellites. Several studies have validated the NSRDB data using ground-based measurements (Habte, Sengupta, & Lopez, 2017; Sengupta et al., 2018; Yang, 2018). The results show that the data agree with surface observations with acceptable error. The NSRDB irradiance data can be freely accessed via the NSRDB Viewer or through an application programming interface (API). In this study, the hourly solar irradiance data are directly downloaded from the website using the NSRDB Viewer.

Results

Comparison between the TMY weather and the historical weather

Figure 4 shows the boxplots of the DNI and DHI extracted from the TMY weather and actual weather. Overall, the actual weather seems to have higher DNI and lower DHI compared to the TMY weather, indicating that there might be more clear days. To further compare the two weather profiles, a detailed analysis of the sky condition was performed according to a model developed by a few researchers (Fakra, Boyer, Miranville, & Bigot, 2011). They proposed the concept of sky ratio. As indicated in Equation (4), this measure can be computed with DHI and Global Horizontal Irradiance (GHI). Using the threshold for sky ratio and the sky condition categories presented by Motamed et al. (2020), the sky conditions with the two weather files can be described (Motamed, Bueno, Deschamps, Kuhn, & Scartezzini, 2020). As shown in Figure 5, the actual weather has more clear days and fewer cloudy days compared to the TMY weather. The result further supports that the two weather profiles are different.

$$Sky\ ratio = \frac{DHI}{GHI} \tag{4}$$

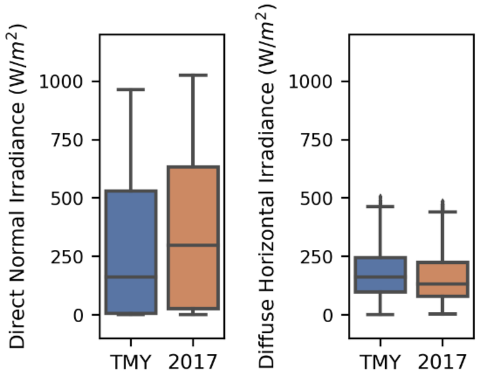

Figure 4: Boxplots of the solar irradiance with the TMY weather and the historical year weather.

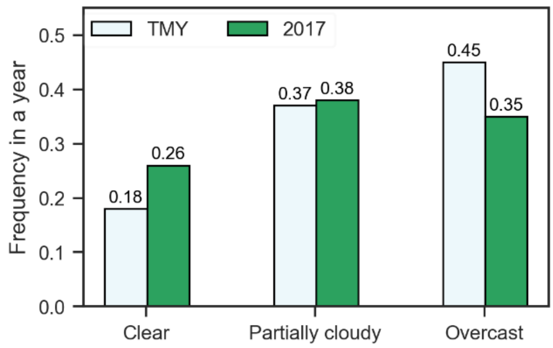

Figure 5: Distribution of the sky conditions of the two weather files.

Performance of the regression model and the classification model

1) Glare prediction

The annual glare simulation with TMY weather indicated that there was only one sample that was classified as "1" (with glare) in the training dataset when the slat was rotated to 70º. If the slat was rotated to 80º, there were no cases with glare. Such datasets cannot be used to train an ML model and therefore were excluded from the model development. It is therefore assumed that glare could be fully avoided with a slat angle of 70º and the slats would not be rotated to a position beyond this angle. As a result, a total of 7 predictive models were trained for the classification algorithm and 8 models were developed for the regression algorithm (including the 70º model). The RMSE of the regression model for each slat angle is shown in Figure 6. Note that RMSE varied from 0.05 to 0.15, decreasing with the increase of blind slat angle. The decreasing pattern was due to the reduced DGP values for larger slat angles. It should be highlighted that for slat angles of 0º and 10º RMSE was above 0.15, which was not satisfying considering the small varying range of DGP (0-1). The models might misclassify the glare conditions and fail to predict actual glare, leading to the occurrence of glare when the presented control strategy is applied.

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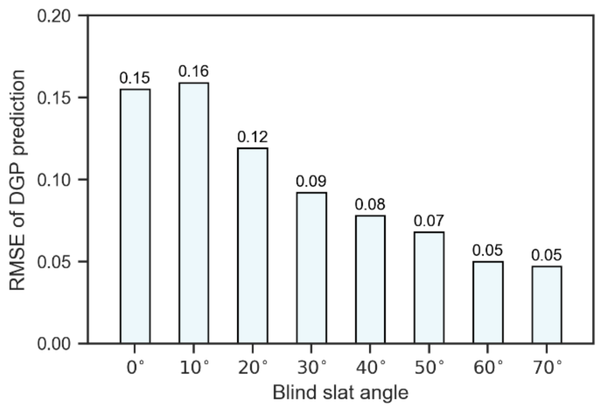

Figure 6: RMSE of DGP prediction with ANN regression algorithm.

Figure 7 displays the recall score for glare prediction with the ANN classification algorithm. Overall, the models had a high recall score for slat angles below 50º, all above 0.95. The performance of the 60º model was quite low (0.42), which was due to the imbalanced distribution of the training dataset. There were only 11 data points that were classified with glare. Applying the SMOTE technique was not helpful in this case. However, it was expected that the performance of the control strategy would not be significantly impacted as there would not be many glare cases when the blind was rotated 60º.

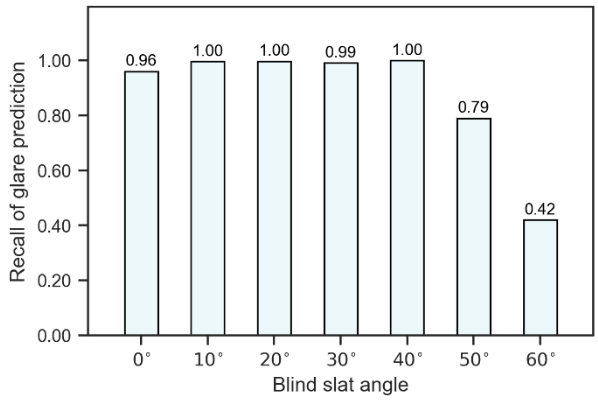

Figure 7: Recall of DGP prediction with ANN classification algorithm.

2) Illuminance prediction

The RMSE of each regression model for average illuminance prediction is shown in Figure 8. Overall, the RMSE for illuminance was large, ranging from 89.09 lux to 1055.32 lux. It exhibited a similar trend in the DGP prediction, decreasing as the slat angle increased. Similar to DGP prediction, this decrease was due to the lower illuminance at higher slat angles. Overall, the prediction appears to be unsuccessful. Another explanation of the large RMSE is that average illuminance over the entire work plane was used as the outcome variable instead of the illuminance at a reference point. As horizontal illuminance is location-dependent, the prediction should be more accurate if the illuminance at one point is used as the outcome measure.

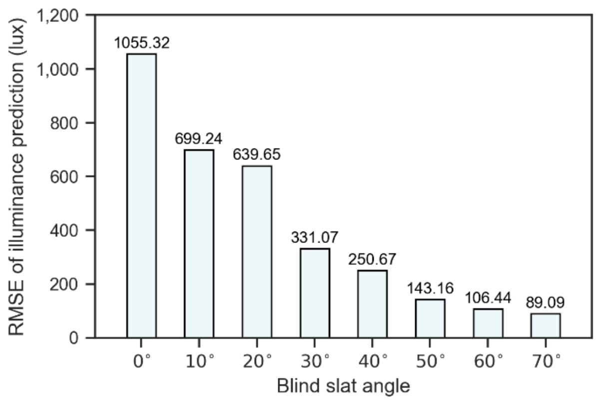

Figure 8: RMSE of illuminance prediction with ANN regression algorithm.

The accuracy for illuminance classification is provided in Figure 9. It is found that the accuracy for each of the predictive models was close, varying from 0.90 to 0.94. Generally, all classification models had high accuracy, suggesting a satisfying predicting capability.

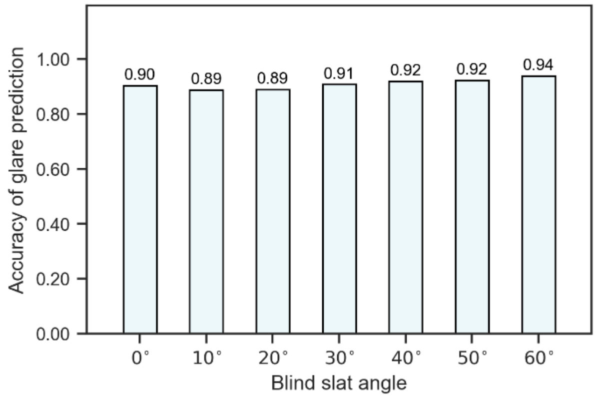

Figure 9: Accuracy of illuminance prediction with ANN classification algorithm.

Comparison between the performance of the proposed control strategy based on the regression model and the classification model

Figure 10 illustrates the comparison between the proposed integrated shading and lighting control strategy using the regression and classification algorithm. Notably, the ANN classification model-based control achieved a high percentage of "on-state-hit" (94.7%) while the regression-based control only prevented 61.2% of the annual glare. Both regression- and classification-based control reduced lighting use by approximately 64%, exhibiting negligible difference. Considering the overall performance, the classification algorithm outperformed the regression algorithm and should be used for the presented control strategy.

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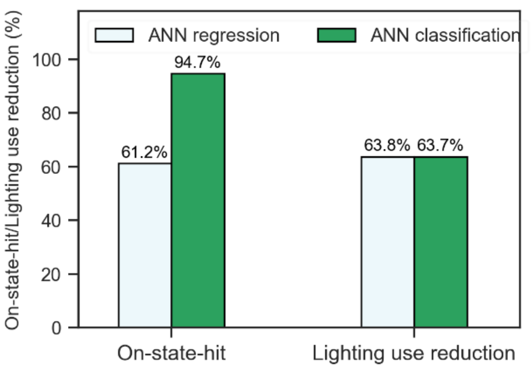

Figure 10: Percentage "on-state-hit" and lighting use reduction of the proposed control strategy based on ANN regression and classification.

Discussion

The presented control strategy in this paper can eliminate indoor sensors that are used in conventional open-loop systems. It also avoids intensive real-time daylight modeling that is required by advanced model predictive control. It makes use of pre-simulated data rather than physically measured data to derive machine learning predictive models for real-time control. Therefore, it is promising to become an industrial application, contributing to the development of effective daylight-linked control systems for real-life applications.

Despite the strengths, the study has several limitations. The main limitation is that the presented control strategy was not physically verified. Instead, climate-based daylight simulation was used to demonstrate the use of the presented control method, and a control interval of one hour was considered. This time interval will be too long for real-time control. In physical validation, the first step is to obtain a well-calibrated daylight model. Annual daylight simulation with the shading device at selected positions will be conducted and the result will be used to train machine learning predictive models. Solar irradiance will be collected in real-time using pyranometers on the rooftop of the building and used to feed the data-driven models for daylighting prediction. The control algorithm selects the shade position that prevents glare while maximizing daylight ingress and determine if the lighting needs to be switched on. The control interval should be determined according to multiple considerations. For instance, a time lag for operation for motor-driven blinds should be considered. Frequent shading operations could disrupt or disturb occupants and shorten the lifespan of the motor, which should be avoided. Pre-experimentation and communication with the occupants are required to establish an appropriate control interval. Other challenges include how to apply the control method for shading control in open-plan offices and how to include occupants in the control loop to increase user satisfaction. Future studies are required to address these challenges.

Conclusion

This paper proposed a simplified open-loop control method for integrated blind and lighting systems. The presented method makes use of machine learning models developed from daylight simulation data to predict real-time glare and work plane illuminance. The blind and lighting are controlled based on the prediction to eliminate glare and maximize daylight ingress. The application of the proposed control strategy was demonstrated with a case study. ANN classification and regression algorithm were used to develop the ML predictive models and their performance was compared. Climate-based daylight simulation was used to verify the performance of the presented control strategy in glare prevention and lighting energy saving. It was found that 94.7% of annual glare was prevented with the classification models while 61.2% was avoided with the regression models. Both algorithms resulted in reduced lighting use by approximately 64%. The result suggests that the classification algorithm outperforms the regression algorithm and is recommended for the proposed control framework. Future experimental studies are required to further verify the findings from this study.

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