Machine learning techniques for the daylight and electric lighting performance predictions

Chantal Basurto, Oliver Paul, Jérôme H. Kämpf
Idiap Research Institute, 1920 Martigny, Switzerland

Abstract

The use of external blinds is a common strategy for the design of energy efficient buildings, its performance evaluation in this study involves an integrated assessment of daylight, electric lighting and blinds controls. Nowadays, such evaluations are mostly performed with the use of computer simulations, which, due to the complexity of the issue, are still highly demanding in terms of computing time and performance capabilities. In order to improve the response time of daylight and electric lighting performance-predictions, machine learning techniques are employed in this study as surrogate models. The workflow for producing daylight surrogate models from RADIANCE simulations was validated for an individual office room, and the obtained accuracy for predicting daylight performance resulted in 98.91% for work-plane illuminance (WPI) and 99.92% for daylight glare probability (DGP).

Key Innovations

- The study is based on an existing monitored room and its corresponding calibrated virtual model
- The evaluation involves the use of advanced simulation techniques: RADIANCE matrix multiplication methods
- The Machine Learning (ML) models aim to predict external blinds and electric lighting control performance
- The selection of the appropriate ML models involved the analysis of four possible candidates.

Practical Implications

This study implements the performance prediction of daylight and electric lighting, considering occupant's visual comfort and energy savings by the control of exterior horizontal blinds as well as electric lighting. The latter, is achieved at a reduced simulation cost in terms of computing time with a satisfactory prediction accuracy.

Introduction

The use of exterior blinds for solar protection is a common practice in the design of energy efficient buildings. However, due to their multiple effects in different aspects of the building performance, their adequate operation requires to address distinct challenges. An example of such a challenge is achieving a correct balance between an increased daylight admission for the reduction of heating and lighting loads in winter, while minimising the risk of glare for the occupants. Providing an adequate solar protection while achieving a sufficient daylight provision at task area is a similar quest for summer time. The use of blinds and electric lighting controls represents a step forward in achieving an efficient operation of external blinds, since it involves the application of a performance strategy that considers relevant aspects related to their performance. In order to perform an adequate assessment of their impact, the implementation of an integrated evaluation is recommended, where ideally, aspects related to the occupant's comfort as well as to the energy consumption are considered. However, the implementation of such assessment usually signifies a laborious task, since it implies evaluating the effects of multiple blind positions, considering year-round weather conditions. While such an assessment is usually simplified with the use of computer simulations, the tools that are able to perform the most accurate predictions are expensive in terms of computing time as well as post-process evaluation, due to the human-hours invested on the interaction with distinctive tools and interfaces.

As related to this study, the RADIANCE matrix multiplication methods are a validated method for the prediction of daylight (Geisler-Moroder et al., 2017), representing a highly accurate alternative for the prediction of blinds and complex fenestration systems (CFS) performance, as it allows the use of their BSDF data (Andersen and Boer, 2006). However, with such methods, the creation of HDR images for the evaluation of the risk of glare, implies the execution of several steps that signify the generation of thousands of images. If the implementation of climate-based simulations at hourly or shorter time-steps is considered, it implies high costs in terms of computing time and performance, as well as for the procurement of sufficient storage capacity.

Machine Learning techniques have been effectively employed for the prediction of daylight performance in recent years. In most research studies, the main objective has focused on estimating the indoor interior illuminance as an absolute value (Kazanasmaz et al., 2009; Ngarambe et al., 2020), or in the form of performance metrics, such as: Daylight Factor (DF), Daylight Autonomy (DA), Useful Daylight Illuminance (UDI) or Daylight Glare Probability (DGP) (Lorenz et al., 2018; Lorenz and Jabi, 2017; Radziszewski and Waczynska, 2018). The prediction of daylight performance by the use of predictive models is primarily based on the variation of

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two main input parameters: external (climate, temporal settings, exterior obstructions), and internal (building physical features, openings and shading systems, occupancy and sensor data) (Ayoub, 2020). As Ayoub reports, 61% of studies are based on the variation of internal parameters, from which the building physical features (external obstructions, building orientation, building materials), is the most recurrent (30%). While, only 22% have focused on variations relative to the use of shading systems or blinds, and few are found that have considered the use of Artificial neural networks (ANN) for blind control performance predictions (Hu and Olvina, 2011).

This study explores the use of Machine Learning Techniques as a surrogate model to improve the response time of daylight and electric lighting performance predictions. In order to achieve an optimal control of blinds and electric lighting, a predictor model is employed to evaluate the impact of a certain blind's position on the work-plane illuminance (WPI), and of glare in the occupant's eye. Simulation cost is a relevant feature of this work, since, due to the longer time that RADIANCE simulations require to complete, the predictor model is rather based on statistical surrogate models such as ANNs. Ubiquity is another feature of this work, since the predictor model is derived from year-round simulations generated by the RADIANCE based matrix multiplication methods, where all possible blinds positions and weather conditions are considered. The ultimate goal is to include the predictor model in a Model Predictive Control (MPC), aiming to obtain a quasi-real-time optimization of the building parameters, to provide visual comfort to the user with less electric lighting.

Methods

Room Description

The evaluated room is located in the first floor of the Idiap Research Institute, in the city of Martigny Switzerland (Lat. 46.10° N, Long. 7.08° E, 471 m above sea level). The building dimensions are approximate 60 m long by 50 m width, with an orientation of 56° due to the South West (Figure 1). The evaluated office room is located on the first floor, it has a rectangular shape with an area of 23 m^2 and dimensions approximately 7.05 m deep by 3.05 m width and 3.06 m height, while the Window to Wall Ratio (WWR) is 60% (Figure 2).

Figure 1. Exterior view of the Idiap Research Institute.

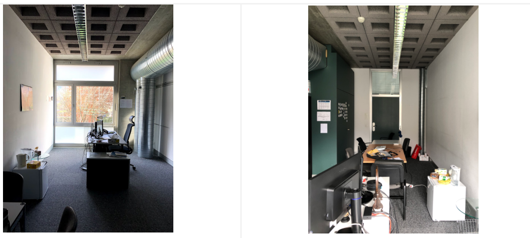

Figure 2. The evaluated office room from the back towards the window (left) and from the window towards the back of the room (right).

In order to create a virtual model that would be later used for the simulations, the photometric properties of surface materials were measured using a Chromameter (Minolta CR-220), which was employed to measure the visual reflectance of walls, ceiling and floor as well as the exterior blinds. The specularity of materials was measured using a glossmeter (Minolta GM-060) characterized at 60° incident angle.

The surfaces reflectance was then determined from the room monitoring: floor grey carpet (8%), concrete ceiling (24%), concrete wall (34%) and white wall (70%). The window is divided in three sections, an upper and lower section with a translucid glass of 31% transmittance, and double clear glazing at the centre unit with 73% transmittance, those were measured with a digital Lux meter (Gossen Mavo-Lux 5032-B). The window is equipped with metal exterior blinds of a halved hexagonal shape with approximate dimensions of 9.0 by 3.0 cm, of a clear grey matte colour and 30% reflectance (Figure 3). In regards of electric lighting, the office room is equipped with three fluorescent tubes of 58 W, which are suspended from the ceiling and placed at the central axis along the room.

As shown in Figure 4, the room geometric features were then reproduced in a virtual model using the program Sketch-up, where the collected data was used to adapt the model characteristics to match as closely as possible to the existing situation.

Virtual Model Calibration

The representativeness of the existing room by the virtual model was assessed by comparing the correspondence of WPI measured on-site with those obtained with the use of RADIANCE simulations. The calibration of the virtual model reported an R^2 of 0.93, which indicated a good correspondence between the monitoring and simulation.

Figure 3. Close view of the exterior blinds with halve hexagonal shape.

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Figure 4. Comparison of a fisheye view image of the existing vs the simulated office room on November 9th at 14:00 pm.

Data acquisition: simulation methods and key performance indicators (KPI)

As a first step, a database was produced to be employed for the training of the surrogate (or predictor) model. Its input parameters are the weather data (direct and diffuse solar irradiance), hourly sun position (related to the site location), as well as exterior blinds position. The predictor model is derived from year-round simulations, which were carried-out with the use of the RADIANCE matrix multiplication methods (Geisler-Moroder D., 2017). Local weather data such as beam normal and diffuse horizontal irradiance (W/m^2), are required to reproduce the sky luminance distribution in the simulations.

However, since the building is not yet equipped with a local weather station, the simulations were carried out using data obtained from a meteorological station located in the city of Evionnaz at approximately 8 km from the location of the studied room. In order to create the testing cases scenarios, the features of the exterior horizontal blinds were reproduced in a virtual model as well, where eight variants of the blind's positions were created from an open (horizontal, zero tilt) to a closed position (tilt 65°) in steps of 10°. In total, nine feasible positions of the exterior blinds were tested: retracted and deployed considering 8 tilting variants (Table 1).

Table 1. Description of the 'testing cases' that were evaluated in this study.

RC (reference case)	Exterior horizontal blinds							
	Slats horizontal (open)	Tilting variations						'Evb tilt 65°' Slats vertical (closed)
Double glazing translucent and clear.	0°	10°	20°	30°	40°	50°	60°	65°

Their BSDF data (Andersen and Boer, 2006) was generated with the use of the software LBNL-Window v.7.4 (Lawrence Berkeley National Laboratory, 2019)(McNeil, 2015) . With the use of the virtual model, annual WPI at hourly time-steps were estimated at the height of the work plane area corresponding to a 0.6 by 0.6 m surface (0.36 m^2).

Then, the estimation of the risk of glare was based on the use of the DGP index which is based on the vertical eye illuminance, while its criteria its built on the probability of glare disturbance as perceived by the occupants under a certain daylight condition (Wienold, 2009; Wienold and Christoffersen, 2005).

In order to perform such an evaluation, HDR fisheye images of 180° were generated from the occupant's view field (See Figure 5), for every time step using the RADIANCE matrix multiplication methods as well, while the glare prediction was performed with the use of the program *evalglare.* As a result, a vast amount of data was created representing the interior daylight situation in the office room as characterized by the two KPI's (WPI and DGP).

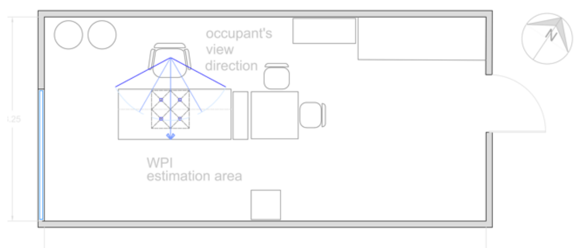

Figure 5. Floor plan view of the analysed room indicating the WPI estimated area and view direction for the HDRI generation.

As a final step, an approximation function was derived from the relationship between data inputs and outputs, represented by the two KPI's for a specific user (as graphically explained in Figure 6). In order to do so, four machine learning models were evaluated and tested to determine the one that: 1) would yield satisfactory accuracy for both WPI and DGP, and 2) that would be more suitable to the problem. The latter is explained in detail in the following section.

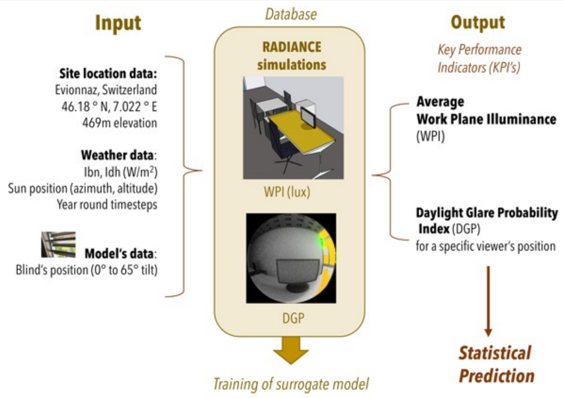

Figure 6. Graphical description of the process involved on the training of the surrogate model, for the daylight performance prediction.

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Surrogate Model for the predictions of Daylighting

Machine Learning Models

The "no free lunch theorem", is a common concept in machine learning which states that for any two learning algorithms (considering an infinite set of situations or problems), there are just as many situations where algorithm 1 outperforms algorithm 2, and vice-versa (Wolpert, 2001). Therefore, the suitability of a particular model or architecture to a specific problem should not be assumed without prior experimentation and benchmarking between models (leading to the "almost-no free lunch theorem").

In order to find the most suitable model for the problem described by this study, four diverse statistical and algorithmic approaches were tested. These included: a linear model (which is equivalent to linear regression), a 'multilayer-perceptron neural network' (MLP) and two 'tree-based learning algorithms' – a 'random forest' (Breiman, 2001) and 'gradient boosting machine' (GBM) (Friedman, 2001).

Some of the main features and strengths of these models are explained as following. While linear models are highly interpretable, they show certain performance flaws when the function mapping between the inputs and outputs is not linear. In the context of this study, linear regression is used as a baseline model, providing a performance reference for more complex and computationally expensive algorithms. By establishing such a baseline, one can determine whether increasing modelling complexity is justified given the potential performance gains.

Random forests and GBM algorithms, have empirically shown strong performance on small to medium sized tabular data problems, such as the one formulated in this study. In addition, they are relatively efficient on datasets of this scale and allow for iterative experimentation without the need for large-scale computing resources.

Finally, deep neural networks are considered 'state of the art' across a number of applications. They typically outperform traditional machine learning algorithms when the relationship between input features and target variables is complex, and where the dataset size is very large. The dataset considered in this study may not be of the scale the applications where neural networks are being shown to excel. However, if their suitability is proven with a room characterized by a single window and a desk, then their use would be justified in future work on significantly larger and more complex daylight performance datasets.

Due to the aforementioned reasons, random forest, GBM and MLP algorithms were chosen as suitable candidates to find a function mapping between the input/output data considered in this study. Random forest algorithms were implemented using Python's SKLearn library. The GBM implementation used in this study is XGboost. Both linear regression and MLP models are built using PyTorch version 1.7.0.

Input Features and Data Pre-processing

The features describing the input data used for training the models are summarized in Table 2, while the target variables are described in Table 3.

Table 2. Description of the Input features available for model training.

Name	Type	Description
Blind angle	Integer	Angular position of blinds. Feature takes a discrete choice of values within {0, 10, 20, 30, 40, 50, 50 and 65}.
RC	Boolean	Reference case – true or false. True if data point belongs to reference case with no blinds and clear windows.
Ibn	Float	Normal solar beam radiation measured by weather station. W/m^2.
Idh	Float	Diffuse horizontal solar radiation measured by weather station. W/m^2.
Altitude	Float – angular	Solar inclination in degrees referenced to the horizon - range [0,90].
Azimuth	Float – angular	Solar azimuth in degrees – range [0, 360].

Table 3. Target variables predicted by models tested in this study.

Name	Type	Description
WPI	Float	Work plane illuminance. Float averaged from 4 measurement points.
DGP	Float	Daylight Glare probability. Float representing the glare in eye. Variable has a range of [0.2, 1.0].

It should be noted that, 'altitude' and 'azimuth' are time features which are directly related to the 'time of day' and 'day of year', therefore, for data corresponding to a full calendar, the temporal aspect can be learned from these features alone; hence, date-time specifications are not necessary. Typically, such angular, or cyclic features can pose a challenge for machine learning algorithms, due to difficulties in learning the relation between two given values; as for instance, the fact that 1 and 360 angular values are close to each other.

In order to address this issue, the original 'azimuth' feature was dropped from the dataset and two new features were engineered: Sin azimuth and Cosine azimuth. The exact computation involves taking the sin and cosine of each angle, normalised by the maximum angular value in the feature.

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In order to determine whether such a transformation was indeed useful, a shallow gradient boosting model was trained on a fixed number of boosting rounds on datasets with and without the transformation. The transformed dataset showed a small increase in performance, indicating that such a transformation will indeed increase performance, reduce training time, or both.

The dataset was split into training, validation and test sets representing splits of 70, 20 and 10% respectively. Since the validation set is used for the validation of hyperparameters and early stopping, its use adds bias to the training process. It is therefore important to create a test set which is held out throughout the training process, representing “unseen data”. Prior to performing such a split, the data was randomly shuffled to ensure that training, validation and test sets remain independent and identically distributed (IID).

Neural networks are highly sensitive to feature scaling. While, scaling or feature normalisation has no impact on the performance of tree-based estimators, all models were trained and evaluated on normalised data for the sake of continuity. In order to avoid data leakage, only training set statistics were used for the normalisation of all three datasets (training, validation and test). Normalisation resulted in all features having a mean of zero, with a standard deviation of one. It should be noted that sin and cosine azimuth features were not normalised, since their values had a range of [-1,1] and hence already a mean value close to zero. Similarly, the categorical RC feature was not normalised.

Hyperparameter Selection

It was observed that all models, in particular, the GBM model, were highly sensitive to hyperparameter tuning - the optimum hyperparameters found for the GBM model yielded a 65% improvement in performance when compared to default parameters. For the random forest and GBM models, the procedure to find optimal hyperparameters was identical.

A search space of all possible hyperparameter candidates was pre-defined, grid search was then used to train and evaluate the models with all possible combinations of these parameters. This procedure involved the use of K-folds cross validation with 5 folds on the training set. K-folds splits the training data into 5 equally sized sections. For fixed hyperameters, 4 of these folds are used to train the model, and the fifth is used to produce an evaluation score. A new set of folds are then used for training and prediction until 5 performance scores are obtained, which are averaged to produce an evaluation score for a given set of hyperameters. This process is repeated in a loop until evaluation scores are obtained for all possible combinations of hyperparameters defined in our search space.

An optimal neural network architecture was also found using K-folds with an optimal learning rate found using learning rate scheduling (Smith, 2017). A summary of the optimal hyperameters for each model used in this study is shown in Table 4. It should be noted that, in the case of the XGboost, multi-output regression is not implemented, therefore, an independent model is trained for each target variable respectively.

Table 4. Summary of hyperparameters chosen for the training of ML models.

Model	Hyperparameters
Neural Network	Number of hidden layers: 2, Number of neurons hidden layer 1: 1000, Number of neurons hidden layer 2: 1000, Optimiser: ‘Adam’, Learning rate: 0.0004, L2 regularisation/weight decay: 0.000008
Random Forest	Number of decision trees: 500, Minimum samples leaf: 1, Minimum samples split: 2
GBM - WTI	Maximum depth per tree: 10, Minimum child weight: 1, Subsample: 0.9, Colsample:1, eta/learning rate: 0.05
GBM - DGP	Maximum depth per tree: 12, Minimum child weight: 1, Subsample: 0.9, Colsample:1, eta/learning rate: 0.03

Model Training and Validation Strategy

For all gradient based models (linear regression, MLP, GBM), mean squared error (MSE) was used as a loss function. The advantage of using MSE is that the function is smooth (differentiable and continuous) with zero gradient where $y == \hat{y}$, which implies small errors are penalised with less magnitude that large errors, often improving convergence when compared to loss functions such as mean absolute error (MAE).

With respect to the random forest model, MSE was used as a metric to find the optimum split threshold for each node in each tree. A disadvantage of MSE is that a single outlier can cause MSE values to swell, making the metric less interpretable. For this reason, the performance of each model is presented and evaluated using MAE. To obtain the accuracy of model predictions for the dedicated task of blinds and electric lighting control, custom metrics were defined for WPI and DGP. These metrics take into account known tolerances in measuring illuminance, and known classifications in daylight glare comfort (Wienold, 2009).

The computation to determine a correct WPI classification is described as follows. If a true value y_i is greater than 300 lx then a prediction is correct if the absolute percentage error between y_i and $\hat{y}_i$ is less than 20%. If the true value y_i is between 100 lx and 300 lx then a prediction is correct if the absolute percentage error between y_i and $\hat{y}_i$ is less than 10%. Below 100 lx, a prediction is correct if the absolute difference between y_i and $\hat{y}_i$ is less than 10 lx. For DGP a prediction is considered correct if both the true value and the prediction fall within the same classification for daylight glare comfort. These classifications are Imperceptible glare: DGP < 35%, Perceptible glare: 35% ≤ DGP < 40%, Disturbing glare: 40% ≤ DGP ≤ 45% and Intolerable glare DGP ≥ 45%.

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For the MLP model, the validation set was used for early stopping to avoid overfitting. Training was ended when the validation loss failed to improve after 6 epochs. Similarly, for GBM models, boosting rounds were increased until validation loss failed to improve after 10 rounds. The test set was held out throughout the entire process, and used to evaluate performance after training. Feature normalization was reversed before computing the evaluation statistics presented later in this paper.

Electric Lighting Performance Prediction

The purpose of this study is to rely on a unified energy efficient scheme, therefore the use of a dimming system is considered in order to achieve a reduction of the electric lighting consumption in the office room. Therefore, the electric lighting dimming position would be estimated as a compensation of the WPI provided by daylight, using a minimum threshold of 300 lx at every time step. In order to do this, two possible forthcoming approaches are being considered: 1) The estimation of the electric lighting power is first obtained with the use of a simple polynomial regression based on measured illuminance, then the compensation of WPI to reach 300 lx will be determined from the daylight predictor model. 2) The estimation of electric lighting to achieve 300 lx of WPI will be estimated as a result of real-time monitoring with the use of a Lux-meter installed on the office occupant's desk.

Results and Discussion

The MSE, MAE and accuracy for each model for a single room at Idiap is summarized in Table 5. It was observed, that the two 'tree-based learning algorithms', the 'Random Forest' (RF) and the 'Gradient Boosting Machine' (GBM), were the ones that achieved a highest accuracy prediction compared to the other models tested in this study. From those, the GBM achieved the highest degree of accuracy with both predictions of the performance indicators, WPI and DGP slightly below 100%. The 'RF' and 'multi-layer perceptron neural network' (MLP), both achieved an accuracy close to 100% for DGP and 97% and 96% respectively for WPI.

In the case of the 'Linear model', the results for WPI were far below of what would be considered a good candidate, however, such a model may be suitable for the classification of glare comfort levels.

Whilst the MLP model was outperformed by the tree-based models in terms of both accuracy and MAE, it should be noted that in some cases, the MLP model yielded a lower MSE score than the tree-based models. Since MSE is more susceptible to outliers than MAE, this implies that the MLP model may have a greater capacity to generalize to outliers in the dataset than the tree-based models. This has significant implications for further work and model choice when the complexity of the problem is scaled.

For the GBM model, the discrepancies between the predictions and the true values were analysed in order to assess their meaningfulness for the objective of our application (blinds and electric lighting control). In the case of DGP, 6 out of 7884 predictions in the test set were misclassified, as illustrated in Figure 7. First, the entire test set of ML model predictions vs the true values is shown in the segment 'a' of the graph, in which, a single false prediction is highlighted in red. The false prediction is then displayed in a 24 hours' time-sequence where the extent of the inaccuracy of 'prediction vs the true value' is shown in detail (segment 'b'). In this particular case, the graph illustrates in segment "c top" the glare situation on August 28th at 14:00 with the blinds in a retracted position. The HDR image shows the spread of the glare source from the occupant's point of view. For that specific time a DGP of 0.36 was obtained from the RADIANCE simulations, while the ML model resulted in an underpredicted value of 0.32. The colour in the picture illustrates the large extent of the glare source, which is due to the contrast between the window and the background area. The *evalglare* reports an average luminance of 1080 cd/m^2 and a solid angle of 1.3 sr, indicating a very large source of glare with a luminance of about 4 times the luminance of the computer screen. This situation may slightly be uncomfortable for the user according to the average population used in the study to build the DGP categories.

Table 5. Summary of results for validation and test sets.

Model / target	Validation MAE	Test MAE	Validation MSE	Test MSE	Validation accuracy	Test accuracy
Linear - WPI	98.43	98.77	79930.37	89887.85	11.53 %	11.73 %
Linear - DGP	0.0354	0.0353	0.0021	0.0021	99.87 %	99.85 %
MLP - WPI	7.12	7.16	1101.94	1281.51	95.61 %	95.41 %
MLP - DGP	0.00358	0.00357	0.000123	0.000122	99.87 %	99.91 %
RF - WPI	5.61	5.59	1493.19	1691.98	96.77 %	96.78 %
RF - DGP	0.00254	0.00258	0.000110	0.000120	99.89 %	99.92 %
GBM - WPI	4.19	3.99	1164.09	1021.63	98.67 %	98.91 %
GBM - DGP	0.00229	0.00229	0.000109	0.000104	99.91 %	99.92 %

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However, depending on the individual, itself, it may be perfectly tolerated, showing the importance of a user feed-back loop in the automation to minimize the unwanted glary situations. The distribution and frequency of the DGP false predictions with respect to time is shown in the histogram (Fig. 7c-below). It shows, that all the false predictions occur in the afternoon from 12:00 to 14:00, while most of them take place at the latter hour, all showing an under prediction of the ML model vs the true value. This would signify that during those rare moments, the blinds would be kept in a retracted (fully open) position leading to a higher risk of glare for the average occupant.

In the case of WPI, 71 out of 7884 predictions were labelled as misplaced within a range equal or below 300 lx. This range is of specific interest for our application as we target to complement daylight with electric lighting to always keep a minimum of 300 lx as a spatial average on the work-plane satisfying the norms. The WPI analysis is shown in Figure 8, where the entire set of predictions is shown as scatter plot (segment ‘a’), while the illuminance threshold representing the relevant range for our application [0, 300 lx] is shown in a zoomed display. The focus of a single false prediction corresponding to a zero tilt blinds position in March 23th at 16:00 is shown in a 24 hours’ time-sequence (b). It indicates for that case an overprediction of the ML model vs the RADIANCE simulation, since the true value averages 102 lx while the ML model estimated 200 lx. This overprediction of daylight provision would lead to an underprediction of electric lighting needs, which might result in a deficit of 98 lx on the work plane. Again, we count on user-feedback to further investigate if this is a major drawback of our surrogate model in which case we need to improve it further. The distribution and frequency of the false WPI predictions is shown in a histogram on the segment ‘c’ of the graph, showing that most of the predictions labelled as wrong are found in the afternoon about 16:00. From those, about ten were located outside working hours, making them irrelevant for the purposes of our study. Regarding the proportion of false predictions, the analysis showed that 63% of the time the ML model produced overpredicted values (like in our illustrated example), while 37% were underpredictions. Underpredictions would signify a waste of electricity for lighting, however insignificant on the final energy balance due to their low occurrences.

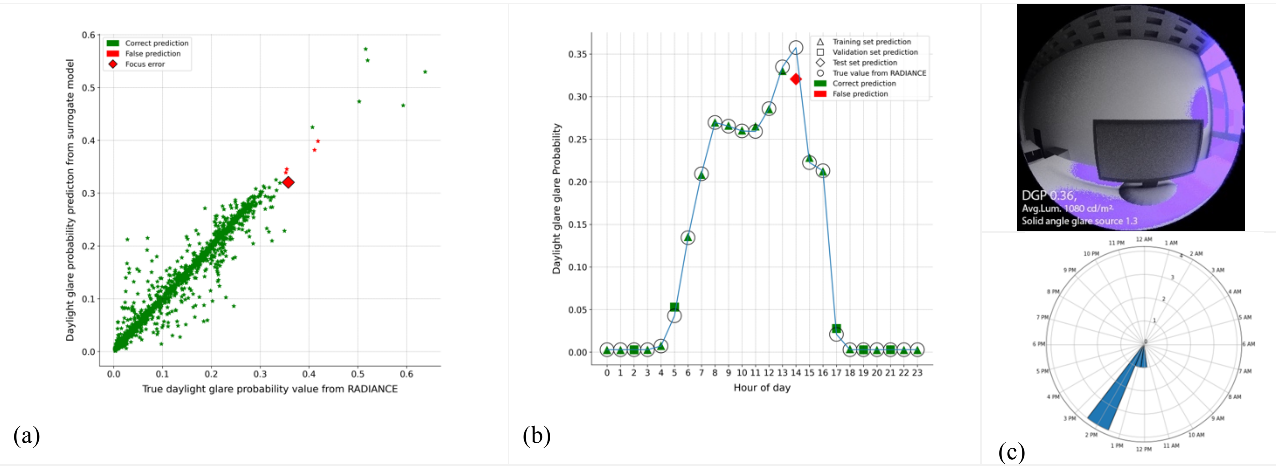

Figure 7. Scatter plot of ML model predictions against true values for glare probability (a), the false prediction highlighted in red displayed in a 24 hours’ time-sequence (b). The HDR image illustrating the false prediction glare situation (c-above), and the histogram showing the frequency of the false DGP predictions (c-below).

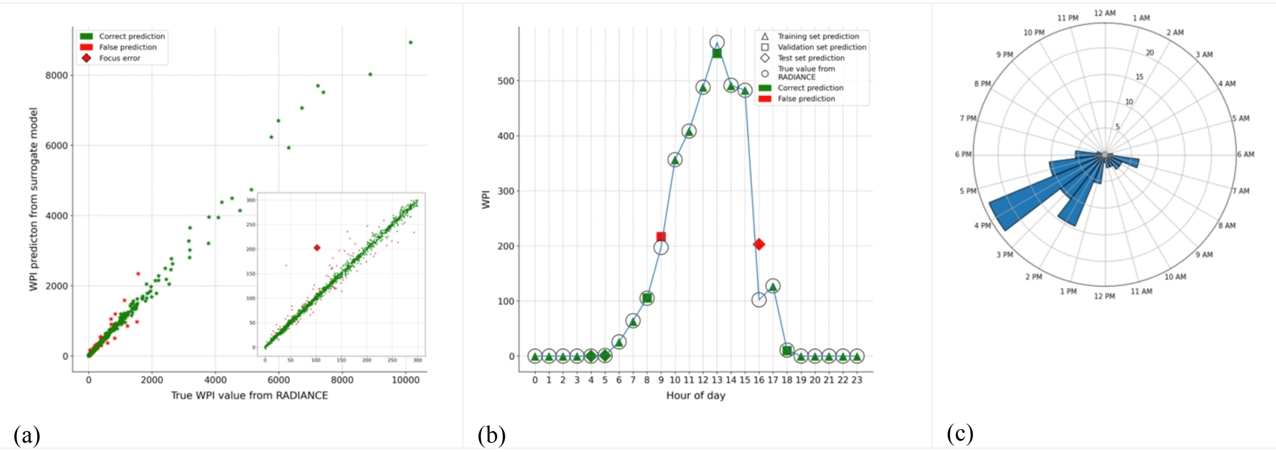

Figure 8. Scatter plot of ML model predictions against true values for WPI (a), the false prediction highlighted in red displayed in a 24 hours’ time sequence (b), the histogram showing the frequency of the false predictions (c).

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Conclusions

This study aimed to investigate the impact of external blinds on the occupant's visual comfort as well as on the energy use for electric lighting. The main objective was to improve the response time of daylight performance predictions by the use of ML. Different algorithms were explored as an alternative to computer simulations for daylight prediction, which are commonly very expensive in terms of computing time and performance capabilities.

The results showed, that all the 'non-linear models' explored in this study are able to estimate WPI and DGP to a satisfactory degree of accuracy, implying that such models could provide an alternative to offline physically based simulations. The GBM models showed to be the most reliable option since the test accuracy for DGP and WPI was the closest to 100%.

In this study, the use of ML techniques has proved to be a solid alternative for the prediction of daylight performance at a low-cost computing expense. Its use can be confidently implemented for quasi real-time embedded low-power blind control systems, aiming to achieve a bifold performance for glare reduction and a satisfactory daylight distribution indoors. Further work will explore the robustness and performance of the developed models with the feed-back of users in an increasing complexity of environments, such as, indoor spaces with multiple occupant positions and/or multiple windows or façade orientations.

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