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Implementation of machine learning techniques for the quasi real-time blind and electric lighting optimization in a controlled experimental facility

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Abstract Machine Learning techniques have been recently investigated as an alternative to the use of physical simulations, aiming to improve the response time of daylight and electric lighting performance-predictions. In this study, daylight and electric lighting predictor models are derived from daylighting RADIANCE simulations, aiming to provide visual comfort to office room occupants, with a reduced use of electric lighting. The aim is to integrate an intelligent control scheme, that, implemented on a small embedded 32-bit computer (Raspberry Pi), interfaces a KNX system for a quasi-real-time optimization of the building parameters. The present research constitutes a step towards the broader goal of achieving a unified approach, in which the daylight and electric lighting predictor models would be integrated in a Model Predictive Control. A verification of the ML performance is carried-out by comparing the model predictions to data obtained in monitoring sessions in autumn, winter and spring 2020-2021, resulting in an average MAPE of 19.3%.

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1. Introduction
The use of shading and electric lighting automation systems is considered as an energy efficient strategy to optimize the building performance, both for energy savings and an improved occupant's comfort. An adequate regulation of the daylit interior environment implicates an in-sync adjustment of the blinds position according to outdoor sky conditions. The latter should be ideally performed in regards to occupants' comfort and energy performance, using Key Performance Indicators (KPIs) such as the work-plane illuminance (WPI) as well as the daylight glare probability (DGP) [1]. However, the efficiency of an automated control system not only depends on implementing an integrated approach by considering energy and occupants comfort aspects [2], but also in terms of the technical aspects integration. As for instance, the use of HDR imaging techniques has been recently investigated for blinds control [3], [4]. However, its implementation implies the use of invasive devices where privacy and space issues are involved. Such research, preceded the development of a more sophisticated concealed device, featuring a dual function as sky luminance sensor as well as blinds controller [5]. The optimal shading position for daylight provision and glare risk, is determined by performing a lighting simulation according to outdoor sky conditions, its accurate estimation of the indoor WPI, indicates the device's reliability for daylight control [6]. However, due to the time required to perform the lighting computation, the process involved on the blind's adjustment can take up to 10 minutes. The latter, represents a disadvantage for an adequate synchronization of the blinds in regards to outdoor conditions, especially on situations of dynamic sky conditions variations. On the other hand, due to their characteristic noise, a constant adjustment of automatic blind's might cause

distractions or disturb the occupants. In this study, machine learning techniques (ML) based on daylighting RADIANCE simulations [7], are employed as surrogate models to assess the impact of blind positions on WPI and glare on the occupant's eye. A control strategy is implemented in an experimental office setting [8], using a system prototype based on a small embedded 32-bit computer (Raspberry Pi), which interfaces a KNX system to control electric light dimming and blinds position according to current outdoor sky conditions. The strategy presented aims to achieve a quasi-real time optimization of the building parameters, in a time-interval that can be tolerable for the occupants. Hence, a decision could be taken forthwith in the case of glare protection, or every five minutes in the case of daylight sufficiency. This paper further presents a verification of the ML model to predict one specific KPI in a real office setting: the WPI.

2.Methods

2.1 Room Description

The case study is located in the city of Fribourg, Switzerland (Lat. 46.8° N, Long. 7.16° E, 610 m above sea level). It consists of two experimental modules of identical characteristics, with dimensions of 6.23 m long by 3.23 m front, and 3.11 m height each. Both modules count with south and north facing windows, and a proportion window to wall ratio (WWR) of 46% (Figure 1 and 2). The 3D model of the modules in Sketchup format was employed to perform the simulations in which this study is based. The properties of interior materials were measured on-site using special equipment, and were later assigned to the virtual model aiming to achieve the most accurate representation of the existing situation. A Chromameter Minolta CR-2020 was employed to measure the reflectance properties of walls, floor and ceiling, while a glossmeter Minolta GM-060 (characterized at 60° incident angle), was used to measure the specularity of interior materials. The measured surfaces reflectance: floor 16%, white ceiling 80%, white wall at module-R1 (62%), white and light-beige walls at module-R2 (58% and 51% respectively). The glazing transmittance (75%), was determined using a CRI illuminance meter Minolta CL-70F. In regards to the electric lighting, two box-cases containing three ceiling recessed linear LED lamps of 24 W are installed at both sides of each module. The windows are equipped with two distinct horizontal blinds, which properties were also measured using the equipment previously described (Figure 3). Both windows of module-R1 and south of R2, are equipped with curved white venetian blinds of 80 mm width (S-80), and 69% reflectance. The north window of module-R2, is equipped with metallic blinds of a sinuous profile design, 90 mm width and 23% reflectance (L-90). Their geometry was also virtually reproduced in order to generate their BSDF data using the RADIANCE program genBSDF [9].
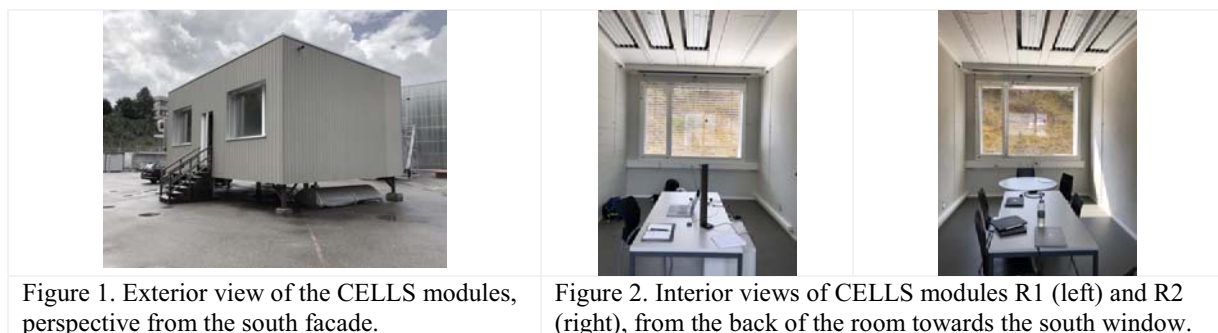

| Figure 1. Exterior view of the CELLS modules, perspective from the south facade. | Figure 2. Interior views of CELLS modules R1 (left) and R2 (right), from the back of the room towards the south window. |

Due to the characteristic dual window opening of the modules, the evaluation included the combination of all possible blind positions at both north and south facades. In order to do that, twelve positions of each blind's variant were created from an open (zero tilt) to a fully closed position (80°). In addition, four reference cases were considered: 1) both windows with blinds fully retracted, 2) both windows with blinds deployed (0° tilt, horizontal position), plus two cases where the north and south blinds are alternatively set in an open or closed position (See Section 2.5).

2.2 On-site monitoring and virtual model calibration

The correspondence between the measured work plane illuminance (WPI), and that obtained by the way of simulations was compared in order to assess the representability of the existing situation by the virtual model (Section 3.1). In order to do that, WPI measurements were obtained using two Hagner detectors (SD2, V-Lambda spectral response)*,* which were placed at the center of the room at 0.80 m height (See Figure 4). Several sets of data were obtained in monitoring sessions carried out in Autumn, Winter and Spring between 2020 and 2021, in both modules. The monitoring process was executed automatically using a KNX system, for which all the different blind combinations were measured in routines that lasted about 10 minutes. In each session, north and south blinds positions were combined, one was set to a fix position while the other was progressively adjusted, from retracted (fully open), to deployed (from 0° tilt to fully closed 80°); while the WPI was simultaneously measured and recorded. The global and diffuse horizontal irradiance (W/m^2), were recorded using a Delta-T, SPN1 pyranometer installed on the top of the facilities, which was later used to reproduce the existing luminous situation in the simulations.
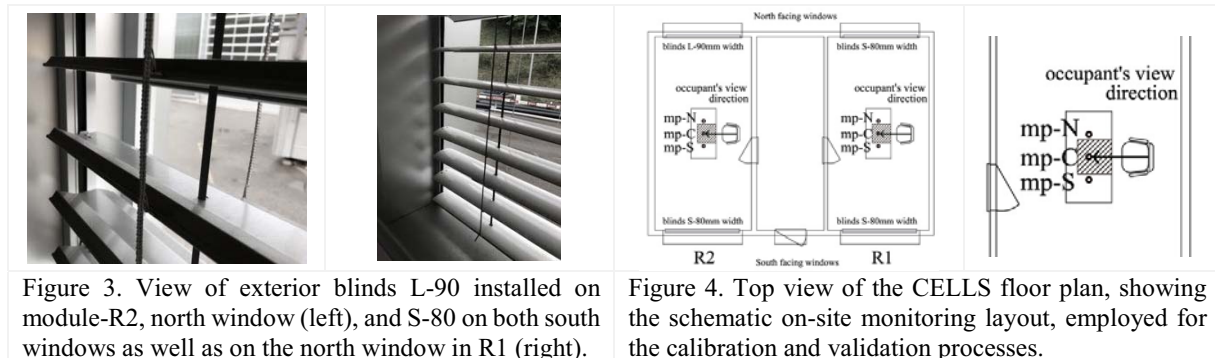

| Figure 3. View of exterior blinds L-90 installed on module-R2, north window (left), and S-80 on both south windows as well as on the north window in R1 (right). | Figure 4. Top view of the CELLS floor plan, showing the schematic on-site monitoring layout, employed for the calibration and validation processes. |

2.3 Data acquisition: simulation methods and key performance indicators (KPIs)

A database was first produced for the training of the predictor model, for which two KPI's were considered in order to assess the daylight performance inside the modules. First, the WPI, was obtained as a base for the estimation of the electric lighting requirements, which would be compensated from the daylight provision using a minimum threshold of 300 lx. The predictor model is derived from year-round simulations obtained with the use of the RADIANCE matrix multiplication methods [10]. In order to do that, measurement points were placed at the height of a table desk (0.80 m), covering an area of 36 dm^2 (0.6 by 0.6 m), corresponding to the occupant's working area. Then the estimation of the risk of glare was based on the daylight glare probability index (DGP), which indicates the probability that the room occupants would experience discomfort glare situations issued from daylight [1]. In order to do that, HDR 180° fisheye images were generated in a straight view direction from the sitting position of the occupant (Figure 4), while the glare prediction was obtained using the RADIANCE program *evalglare*. The main simulation parameters are: -ab 6, -ad 16384, -lw 1e-4; -pj 0.7, -dc 1, -dt 0, -st 1, -ss 0. The definition of the sky model was generated according to the Reinhart sky subdivision in 5185 sky patches (MF:6).

2.4 Machine Learning models for the daylighting performance prediction

Following a previous study [7], where four diverse statistical and algorithmic approaches were tested in order to find the most suitable model for a similar case study, 'gradient boosting machine' was chosen as function approximator. As the XGBoost, implementation of gradient boosting used in the previous study resulted in an excessive RAM usage for a Raspberry Pi, a lighter implementation, namely LightGBM [11], was used instead. Two models – one for WPI and one for DGP - were created using the same workflow. The model's inputs were equivalent to those used in the previous work: blind angle given in degrees, solar radiation data in W/m^2, altitude, Sin and Cosine azimuth of the sun position; and Boolean values to indicate blinds deployment. The models were trained on 95% of the data, while the remaining 5% was held out as a test set. In order to find the best hyperparameters, an adapted version of stratified K-fold was used, where

the target values were grouped in 20 bins – a number chosen according to Sturge's rule [12]. The list of hyperparameters is given as follows, with the values ordered as WPI and DGP for module-R1, and WPI and DGP for module-R2: maximum depth of {10, 12, -1 (no limit), 11}; number of leaves of {60, 90, 140, 50}; learning rate of {0.09, 0.06, 0.06, 0.09}. In all the models, the minimum data in leaf was set to 20, and bagging and feature fractions to 1. With regards to module-R1 and R2, the WPI models had a mean absolute error (MAE) on the test set of 2.28 lx and 1.60 lx respectively, while the MAEs of the DGP models were 0.00058 and 0.00067. In all considered cases, the R^2 was 0.99.

2.4.1 Electric Lighting performance prediction. A dimming system is employed in this study aiming to achieve a reduction of the electric lighting consumption in the modules. The dimming position was estimated as a compensation of the WPI provided by the daylight, using a minimum threshold of 300 lx. The estimation of the electric lighting was based on on-site illuminance measurements obtained in module-R1 in dark outdoor conditions (illuminance with electric lights off $\approx$ 0 lx), using three photometric sensors placed on a desk (Figure 4). Then the prediction of the electric lighting power for a certain dimming position was obtained using a simple polynomial regression based on the measured illuminance. The necessary electric light compensation of WPI to reach 300 lx is determined from the daylight predictor model.

2.5 Implementation of an intelligent control system

Aiming to provide an adequate interior visual environment with a reduced lighting energy consumption, an intelligent lighting control strategy is implemented in the office setting, which scheme is shown in Figure 5. The daylight and electric lighting predictor models are used to optimize the room settings (blind position and electric lighting intensity), by a continuous estimation of the KPIs (WPI and DGP), based on monitored sky conditions. New specifications of the room settings are then provided, which are physically applied to the office environment through a KNX system. Such process is run on a small embedded 32-bit computer (Raspberry Pi 3B), in order to reduce the amount of energy required to optimize the room setup. The strategy of the optimization process consists on maintaining an adequate visual comfort with a reduced risk of glare for the occupants (<= 0.35 DGP, 'imperceptible')[1], while maximizing the daylight provision indoors. If the WPI resulting from such optimization is still lower than the established 300 lx threshold, the latter would be achieved by the compensation from electric lighting. The electric lighting predictor model is then employed to find the minimum intensity of electric lighting required to reach the illuminance threshold. The blinds position would be instantaneously adjusted, only when necessary to prevent the DGP from exceeding the 0.35 limit, otherwise a time interval of five minutes is considered between every adjustment. Such interval represents a balance choice for blinds operation in office environments, in order to achieve an efficient performance as well as to avoid the blinds constant movement which could cause distraction to the occupants. In the schema describing the control strategy (Figure 5), the denotation **BN** and **BS** refers to
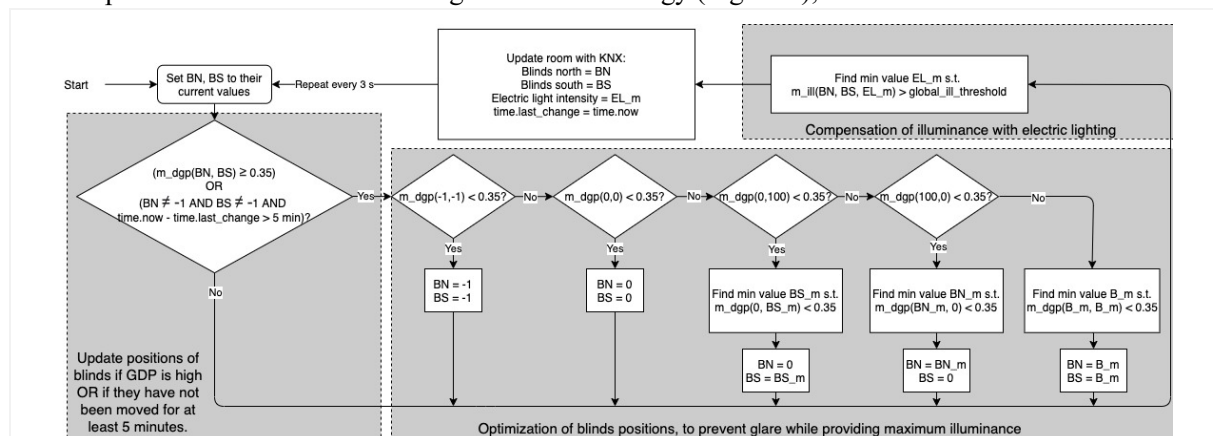

Figure 5. Intelligent control scheme for a quasi-real time optimization of building parameters to achieve visual comfort and a reduced use of electric lighting.

a deployed position of north and south blinds respectively. The '0' value represents the minimum tilt angle of the slats (horizontal position, 0°), while a value of 100 indicates the maximum (fully closed, approximately 80° from horizontal position), a value of -1 indicates the blinds completely retracted (fully open). The **m_dgp (BN, BS),** indicates the implementation of the predictor model to compute the DGP based on the opening angle of north and south blinds (BN, BS), as well as on the sky conditions obtained from the SPN1 pyranometer. Then, **m_ill (BN, BS, EL)** computes the WPI based on the positioning of the blinds (BN and BS), as well as on the intensity of the 'electric lighting' (EL). Due to the unavailability of appropriate equipment to verify the glare KPI (a.k.a. the DGP), this paper focuses on the verification of ML predictions vs on-site measurements for WPI. DGP verification is considered as future work.

3. Results and Discussion

3.1 Virtual Model calibration: on-site monitoring vs RADIANCE simulations

As described in Section 2.2, the representability of the existing situation by the virtual model was assessed by comparing monitored and simulated WPI. A resulting R^2 of 0.96 was reported for both modules R1 and R2. Regarding the inaccuracy's analysis, a MAE of 19 lx and MAPE of 24% was reported for module-R1, as well as a MAE of 64 lx and 23% MAPE for module-R2.

3.2 Machine Learning model verification: on-site monitoring vs ML prediction

In a second step, the monitored WPI obtained during the sessions described in Section 2.2 were compared to ML predictions generated for the exact date and blind conditions as the monitored ones. As a result, a MAE of 35 lx, and 44% MAPE was reported for module-R1; while for module-R2, 142 lx and 41% was reported for MAE and MAPE respectively.

3.3 Machine Learning model verification: on-site monitoring vs ML prediction

The performance of the LightGBM was assessed by comparing the WPI model estimations with monitored data obtained for this specific purpose in two new sessions in Spring 2021. In such case, a MAE of 36 lx and MAPE of 19.28% was reported for module-R1, while 97 lx and 19.4% respectively, were reported for module-R2. An illustration of the discrepancies between the WPI model predictions and the true values is shown in Figure 6. The entire data set is shown as a heatmap (Figure 6 left), showing the absolute percentage error as a function of blinds positions and time of day. Interestingly, regular patterns for cases with increased errors appear, from which four selected situations are highlighted in red. In cases 1 and 4, which correspond to the relevant range of 300 lx for our application, an average underprediction of 54% by the ML model was observed, which would signify an overestimation of the electric lighting needs, resulting in less energy savings. In case 2, for a true value of 2730 lx the ML model overpredicts by 109%, while in case 3 for a
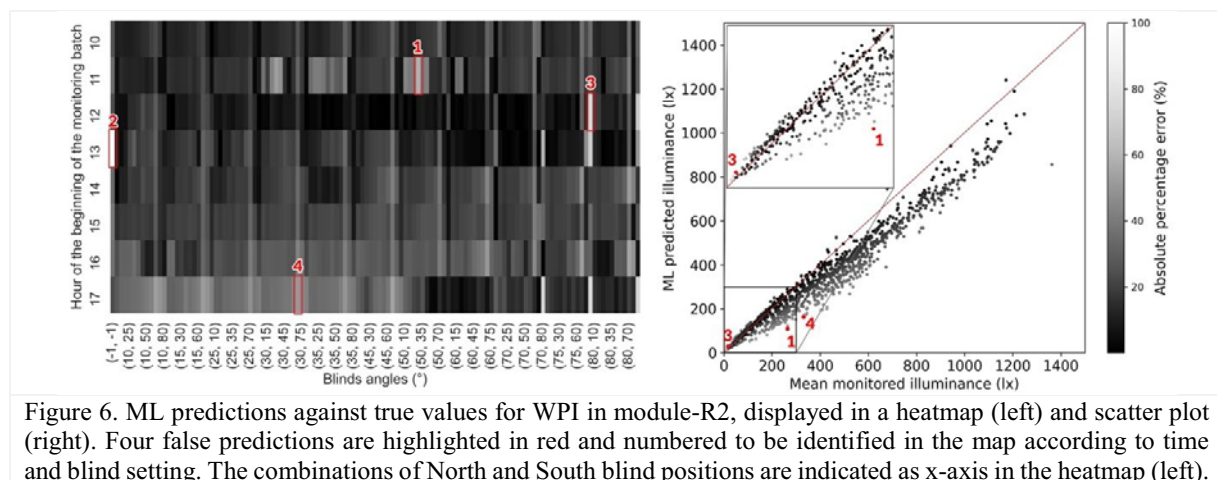

Figure 6. ML predictions against true values for WPI in module-R2, displayed in a heatmap (left) and scatter plot (right). Four false predictions are highlighted in red and numbered to be identified in the map according to time and blind setting. The combinations of North and South blind positions are indicated as x-axis in the heatmap (left).

true value below 20 lx, it overpredicts by 75%. In both cases 2 and 3, the errors are not impacting the outcomes of our algorithm regarding both the visual comfort and the required illuminance on the workplane. A limited portion of the data set below 1500 lx is shown as a scatter plot (Figure 6 right), while the illuminance threshold representing the relevant range for our application (300 lx) is shown in a zoomed display. We notice that in both scatter plots, an underprediction of the ML model can be observed for close to 100% of the dataset analyzed in this study. The overpredictions on the relevant range, correspond to an average of 10 lx, which is negligible. The latter would signify a small increase on energy consumption, yet, not having an impact on visual comfort, as the requirements of the norms for minimum WPI can always be guaranteed.

4. Conclusions

In this study, Machine Learning techniques were employed as surrogate models in order to achieve a quasi-real time optimization of the building parameters. A control strategy was implemented in a small embedded 32-bit computer that interfaces a KNX system to control blinds and electric lighting according to outdoor sky conditions. The ML model performance was assessed by comparing the WPI predictions with on-site measurements obtained in different monitoring sessions. The results report an average MAPE of 19.3%, indicating that the selected model LightGBM can estimate WPI to a satisfactory level of accuracy for our application. Therefore, daylight and electric lighting predictor models can be confidently employed in real environments, selecting the best blinds and dimming lighting settings to provide visual comfort with a reasonable reduction in the use of electric lighting while guaranteeing satisfaction of illuminance norms.

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