# A Simulation Study on the Performance of Machine Learning Daylight-Linked Lighting Control Under Urban Topography

**Ernest Kin-wai Tsang – Hong Kong Metropolitan University – ekwtsang@hkmu.edu.hk**
**Emmanuel Imuetinyan Aghimien – Hong Kong Metropolitan University – emmanuel.aghimien@utah.edu**
**Danny Hin-wa Li† – City University of Hong Kong**
**Zhenyu Wang – City University of Hong Kong – zwang598-c@my.cityu.edu.hk**

## Abstract

Daylight-linked lighting control (DLLC) system has been recognized as one of the effective measures for improving indoor illuminance distribution and energy performance. However, the system is often considered ineffective due to poor calibration and commissioning of the system and lack of design guidelines (Bellia et al., 2016). Among different causes, the positions of photosensors play a crucial role in DLLC systems. The position affects the DLLC system in two major aspects. First, the location of the sensor needs to reflect the illuminance level on the working plan level where it would not be affected by a strong source of sunlight. Secondly, under normal circumstances, DLLC is controlled by a single photosensor which leads to over-dimming in the rear part of the room or overprovided electrical lighting at the front part of the room. Traditionally, the use of open-loop and closed-loop controls makes it impossible to change the dimming ratio of artificial lighting due to indoor illuminance distributions and climatic conditions. Hence, an artificial neural network (ANN)-based machine learning (ML) is used to identify the correlation between artificial lighting and photosensors under different operating conditions. This paper focuses on identifying the major input parameters for the ANN model. Findings show that the input parameters (features) have strong correlations with the dimming output. Also, the ANN model performed very well with very small errors in most of the cases.

## 1. Introduction

Tsang et al. (2021) assessed the performances of closed-loop and open-loop DLLC systems under urban topography. Open control system is highly affected by the external lighting environment especially reflected direct sunlight from opposite façade. The view angle of the photosensor is important and a narrower or shielded photosensor is preferred to provide a steadier system performance (Kim & Song, 2007; Do et al., 2023). For a closed-loop lighting control system, installing narrow-view-angle photosensors at the rear part of the room ensures sufficient illuminance of the room and prevents the photosensor from being interfered with by direct or reflected sunlight. Generally, the major focus for closed-loop DLLC and its associated method of testing and commissioning is to ensure the minimum illuminance is achieved in the working zone of the room. Hence, when a photosensor is designed for the rear part of the room to meet the design illuminance values, the front part of the room will always be over lit especially under clear sky conditions. This shortcoming is difficult to eliminate for traditional closed-loop DLLC systems. Hence, machine learning (ML) seems to offer the opportunity of introducing variable lighting output to photosensor signal ratio according to external weather conditions and solar positions. Beccali et al. (2018) suggested that the artificial neural network (ANN), which is the chief ML algorithm (Seyedzadeh et al., 2018), can provide a sensor signal match with a working plane illuminance level. The coefficient of determination achieved using ANN in this study exceeded 0.75. Wagiman et al. (2020) proposed the use of advanced control algorithms such as fuzzy logic to control multiple photosensors and multiple sets of lighting systems. Furthermore, ANN was used to design an adaptive smart indoor lighting control by Seyedolhosseini et al. (2020). This method was asserted to effectively respond to variations in daylight, deal with the non-linearity of lighting systems and reduce power consumption. Similarly, an ANN

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Pernigotto, G., Ballarini, I., Patuzzi, F., Prada, A., Corrado, V., & Gasparella, A. (Eds.). 2025. Building simulation applications BSA 2024. bu,press.
https://doi.org/10.13124/9788860462022

control method for optimizing lighting conditions in an LED-based lighting system was proposed by Mohaghegi et al. (2017). In all these studies, ANN proved to be viable for modelling DLLC systems. Based on the possibilities inherent in the use of ML in previous studies, this paper explored the use of ML in DLLC in urban topography. Specifically, an ANN with four interconnected layers was used in this study. To accomplish this, the best ANN algorithm and training method for DLLC in urban topography was first selected based on simulation methods. Next, the performance of DLLC by ANN were analysed. Lastly, major parameters affecting the performance of DLLC with ANN are discussed.

## 2. Case Study

### 2.1 Building Model

This study analysed the DLLC system in a typical office in an urban location of Hong Kong. Fig. 1 shows an existing cellular office of 4.55 m (W) × 4.8 m (D) × 3 m (H) employed. The office is equipped with nine recessed LED luminaires. The overall lighting power density was 9.47 W/m$^2$ which is slightly less than the allowable value of the local building energy code (Electrical & Mechanical Services Department, 2021). The working plan illuminance ranged from 320 to 640 lux with an average of 500 lux during night operation while the room setpoint was 500 lux. Usually, those locations with a lower working plane illuminance level are at the corners or closed to walls or windows will not be used for normal office work. The normal operating hours of the office lighting was from 08:00 to 18:00. The minimum lighting output can be reduced to 0% whereas the minimum power consumption was 5%. Also, the power input and lighting output have a linear relationship. While to simulate the effect of reflected sunlight, the north-facing room was chosen for the study.

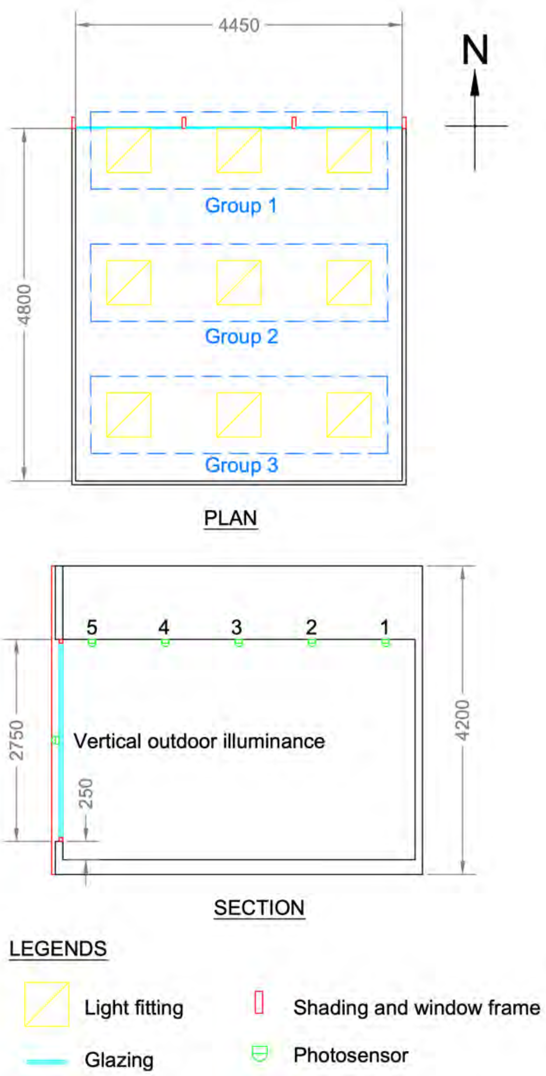


Fig. 1 – The model room used for the simulation

Furthermore, the building had a height of five floors, and the obstruction also had the same height as the office building. The ratio of separation between the two buildings and obstruction height was 1:3 which is the minimum ratio required by the local regulations (Hong Kong Government, 1956). To model the building in heavily obstructed urban topography, a continuous type of obstruction was modelled. As shown in Fig. 2, the office building and obstruction were extended to five times the modelled office's width. Details including fins, mullions and ceiling panels were modelled according to installation details. Finally, the glazing had a visible transmittance of 0.3 while the reflectance for obstructions, ceilings, interior walls, and floors were 0.35, 0.7 0.5 and 0.2, respectively.

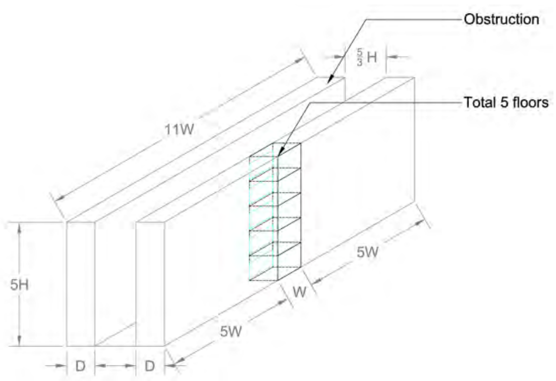


Fig. 2 – External obstruction arrangement to model the urban topography

## 2.2 Daylight-Linked Lighting Control System (DLLC)

A DLLC system aims to maintain the required interior illuminance level and to reduce the reliance on artificial lighting. Hence, by the using DLLC system, the lighting energy consumption can be reduced without affecting indoor occupants. As the purpose of this study is to explore the application of ML in DLLC, there were significant differences in lighting system modelling compared with a previous study (Tsang et al., 2021). Nine luminaires were assigned to three different control groups as shown in Fig. 1. Luminaires under the same group will have identical dimming ratios. Five downward facing photosensors to simulate the actual DLLC setup were installed in the centerline of the ceiling with equal spacing. Three types of photosensors were selected for this study including wide, medium, and narrow spatial sensitivity which has corresponding angles of incidence of 90°, 30° and 15° respectively (DiLaura & IESNA, 2011). In addition, the vertical illuminance on the centre of the window facing external obstruction and sky was also calculated.

# 3. Study Methodologies

This study employed climate-based daylight modelling (CBDM) and measured climatic data to predict natural and artificial illuminance. A tailor-made programme was written to calculate the dimming ratio of each group of lighting. The dimming ratios and other parameters were then used to train the ANN. Then, the abilities of ANN to predict the dimming ratios were analysed. Finally, the trained ANN DLLC system was used to predict the system response and indoor daylighting performance.

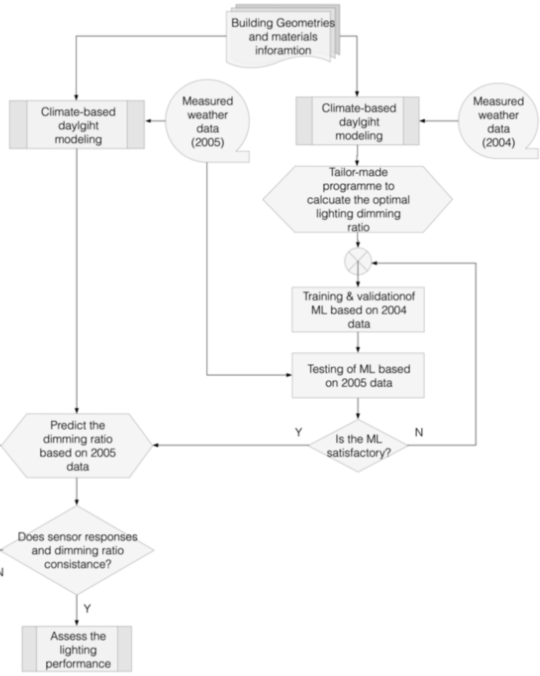


Fig. 3 – Sequence of methodology

## 3.1 Lighting Simulation

### 3.1.1 Simulation package

RADIANCE is a backward ray-tracing program which has been used and tested by some researchers (Li & Tsang, 2005; Mardaljevic, 2000; Reinhart & Walkenhorst, 2001). In this study, version 5.2 was used. A few parameters affecting the accuracy of a computational model are the number of reflections, sampling, and resolution. These settings were considered for controlling these ambient parameters. To ensure the setting can ensure the accuracy of simulation results according to the complexity of the simulation model, a convergence test by tighten the setting until stable results were obtain was carried out. The values of ambient bounce (ab), ambient division (ad), ambient subdivision (as), ambient resolution (ar) and ambient accuracy (aa) were 5, 1024, 512, 1024 and 0.08, respectively.

### 3.1.2 Climate-based daylight modelling

Daylight simulation is time-consuming, and it is impossible to conduct long-term assessments via the traditional step-by-step simulation method. Tregenza and Waters (1983) proposed a daylight coefficients (DC) approach which is a ratio of indoor illuminance level and brightness of the sky patch. By the DC approach, once a set of DC has been determined, it can be used again even if the sky luminance distribution pattern is changed. Mardaljevic (2006) proposed the use of CBDM based on the DC approach and sky luminance distribution model to estimate the indoor illuminance for a typical weather data. In this study, instead of the sky luminance distribution model, the actual sky luminance distribution data based on measurement was used.

#### 3.1.3 Weather data measurement

A measuring station was set up at the City University of Hong Kong to record the solar radiation, illuminance, sky luminance and radiance distribution patterns. Irradiance was measured by Kipp & Zonen CM11 thermopile pyranometers. While the Minolta T-M10 illuminance meters were used to measure the horizontal global and diffuse illuminances. Similarly, EKO MS 300LR was used to measure the sky luminance and radiance distributions. In this study, the meteorological data measured between January 2004 and December 2005 were used in the analysis. Due to the need to remove erroneous measured data, the data quality control test was carried out as described in (Aghimien & Li, 2022). In total, 16,118 and 10,747 sets of valid data for 2004 and 2005, respectively were used.

### 3.2 Determine the Optimal Dimming Ratio

An optimal dimming ratio of artificial lighting provides minimum lighting to maintain the working plane illuminance level to reach the design value or the illuminance values during night conditions. A program was written to tune up the light output until the sample point with the lowest illuminance level reached the setpoint values. The processes were repeated until the illuminance level for all sample points fulfilled the lighting requirement. Then the programme verified if any over lit condition exists. In case of over lit, then the corresponding group of light fitting will tune down. The process was continued until the optimal dimming ratio was reached.

### 3.3 Model Development and Artificial Neural Network (ANN) Description

Before model development, correlation analysis was conducted to determine the data relationship. The 2004 data was used for training and validation using a ratio of 80 to 20% while the 2005 data was used for testing. After splitting, all training and test data were separately scaled using the min-max approach. The technique of separately scaling the data helped to prevent data leakage. Consequently, artificial neural network (ANN) models were developed.

The ANN is the most popular and powerful ML algorithm (Li et al., 2022). Hence, it is regarded as the chief ML algorithm and used in most energy estimations due to its ability to model nonlinear and complex systems (Seyedzadeh et al., 2018). In this study, three supervised ANN models for different spatial sensitivity photosensors (narrow, wide, and medium sensors) were used to predict the dimming ratio of the artificial lighting for the 1st, 3rd and 5th floor, respectively. Hence, nine ANN models were developed in total. The model inputs were vertical illuminance, illuminance levels in photosensor, solar altitude ($\alpha$), solar azimuth ($\phi$), clearness index ($K_t$), diffuse fraction ($K_d$) and Turbidity. The structure of all models is similar. Each model is a feedforward network consisting of 4 interconnected layers (i.e., an input layer, 2 hidden layers and an output layer). For both hidden layers, 63 and 128 hidden neurons were used, respectively while the rectified linear unit (ReLU) activation function was used to address vanish gradient problems. Furthermore, model optimization was done using the Adaptive Moment Estimation (Adam) while "Early stopping" of the training iterations was used in the model development to prevent overfitting.

### 3.4 Predicting Dimming Ratio by ANN

The lighting performances of the ANN DLLC system were evaluated. Dimming ratios were determined by illuminance level on photosensors and climatic parameters. Afterwards, the total illuminance levels for the working plan and photosensors were updated. Hence, the updated photosensor illuminance became the new input parameters for the ANN DLLC controller. Iteration was continued until the dimming ratio became steady. Then the indoor lighting conditions were assessed according to Bellia and Fragliasso (2017).

## 4. Data Analysis

### 4.1 Features Importance

In the ANN training, input parameters are commonly known as features. Thus, the significance of these features for the 1st, 3rd and 5th floor according to Altmann et al. (2010) is presented in Fig. 4.

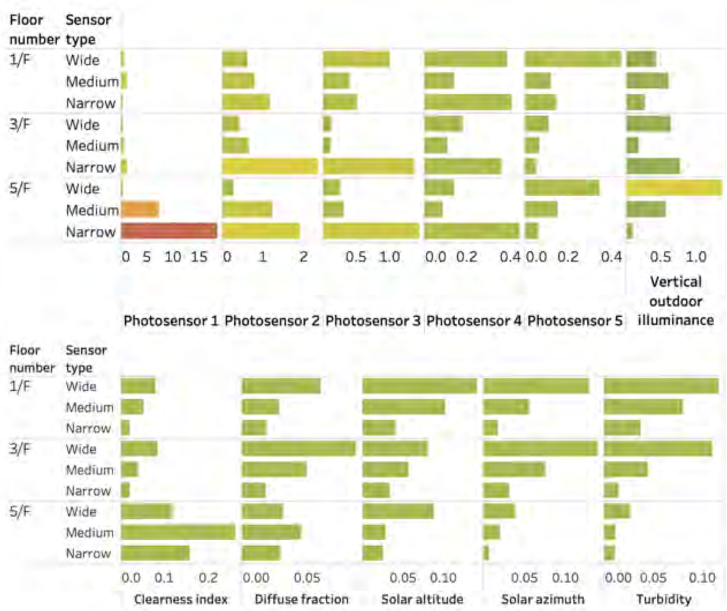

Fig. 4 – Feature importance of dimming ratio

In general, the influence of the illuminance level received from photosensors whether attached to the ceiling or mounted on windows vertically is more important than other climatic parameters.

In this paragraph, the issue related to photosensors is discussed. First, the importance of photosensors located at the rear part of the room (photosensors 1-3) is higher than those located at the front of the room. This may be because the sensor at the front tends to achieve very high illuminance values and hence it is not a good indicator to represent the distribution of indoor illuminance as well as the optimal dimming ratio of the lighting. Second, for less obstructed cases, the importance of the deepest photosensor (photosensor 1) outweighed almost all other parameters. The permutation importance of medium and narrow view angles in that a photosensor can reach 7.26 and 18.38, respectively while other features are only around 2 or less. For an unobstructed indoor environment, the deeper the photosensor the higher is the importance in forming an ANN DLLC system. Third, for photosensors located close to the window, photosensors with a wider view angle have a higher permutation importance. For locations with a heavier obstruction or at the rear part of the room, a narrower field of view for photosensors is much better. Fourth, the importance of outside vertical illuminance is higher than the photosensors close to the window (photosensors 4 & 5) for a less obstructed environment. Using a vertical illuminance sensor can help to improve the performance of a wide-angle sensor.

Under most situations, climatic parameters are less important with a permutation importance less than 0.2. However, based on Fig.4, the importance of the clearness index increases substantially for less obstructed rooms. For less obstructed cases more light flux enters the room from the sky directly so the influence of climatic parameters increases.

### 4.2 Correlations and Errors of ANN Model

To appraise the training for ANN, coefficient of determination ($r^2$), mean bias error (MBE) and root mean square error (RMSE) were reviewed. As pointed out in Section 3.3, the year 2004 was divided into training and validation sets while the year 2005 was used for testing. Fig. 5 shows the $r^2$, MBE and RMSE.

For most of the training and validation sets, the $r^2$ was around 90% or higher. The features (lighting level received by photosensors and climatic parameters) have a strong correlation with the lighting dimming ratio. As expected, the test set data shows a poor correlation compared with training and validation sets. Most of the $r^2$ are under 0.9 while some of them can be as low as 0.74. The photosensors with a wider field of view have a lower correlation. Among all floors, the 3rd floor has the lowest $r^2$. For the wide-angle photosensors, the lighting group 1 has the worst performance. It might be due to a lower dimming ratio and very high illuminance level received by photosensors which resulted in a lower correlation.

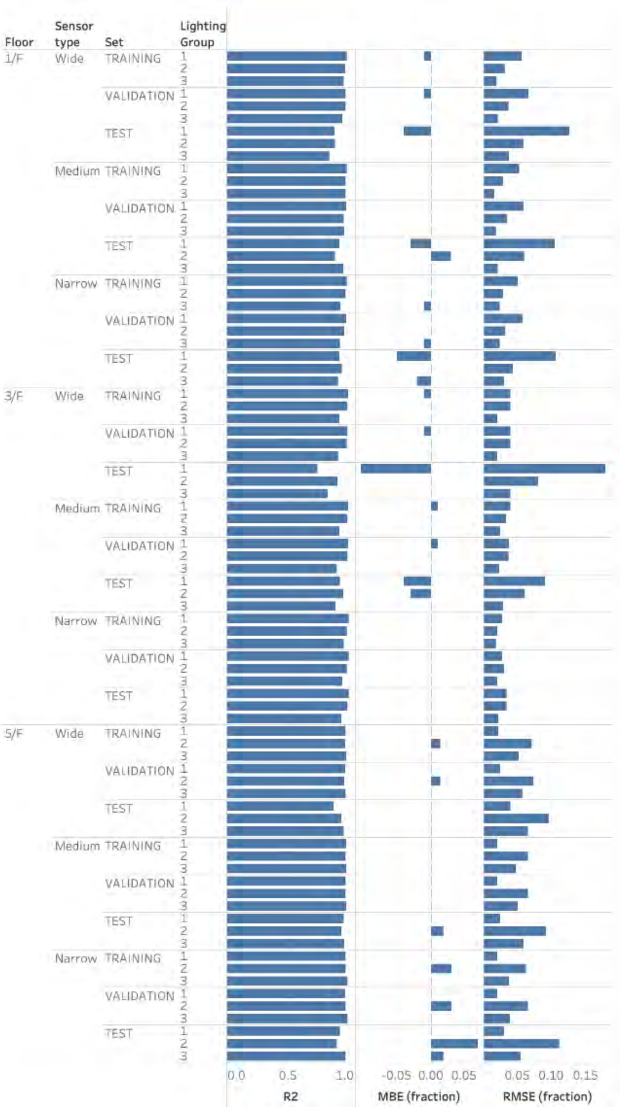


Fig. 5 – $r^2$, MBE and RMSE for ANN model

In terms of error, the behaviours are similar to the $r^2$. In general, the ANN model tends to slightly underestimate the dimming ratio of lighting for moderate or heavily obstructed scenarios (3rd and 1st floors) whereas it overestimates the dimming ratio for the less obstructed cases (5th floor). For the lowest floor, most of the MBEs are low. The highest MBE occurred in lighting group 1 (closest to the window) with only about -0.05 and the corresponding RMSE is 0.126, i.e. on average about 5% deviated from the optimal setting. On the topmost floor, the MBE can reach 0.07 and this occurred in the lighting group 2 with narrow spatial sensitivity photosensor. The largest MBE and RMSE were found on the 3rd floor with wide-view-angle photosensor. The first group of lighting reached an MBE of -0.104 and RMSE of 0.18. Even though several points have very large relative errors, most of the points can provide satisfactory performance.

## 4.3 Lighting System Performance

The performance of the ANN DLLC system was examined according to Bellia and Fragliasso (2017). Intrinsic light excess (ILE) is the light that exceeds design values which cannot be avoided unless there are changes in the lighting system configuration. Light deficit (LD) is the lighting provided less than the requirement and light waste (LW) is lighting supplied more than an ideal system. The summary of ANN DLLC system performance with different types of photosensors and locations is tabulated in Table 1.

Table 1 – Lighting performance of ANN DLLC system with different spatial sensitivity photosensors

| | Spatial sensitivity | | |
|---|---|---|---|
| | **Wide** | **Medium** | **Narrow** |
| *1/F (ILE% = 0.06%)* | | | |
| LD (%) | **4.22** | **5.89** | 24.1 |
| LW (%) | **6.61** | **4.13** | 1.77 |
| *3/F (ILE% = 0.11%)* | | | |
| LD (%) | 8.69 | 10.31 | 16.31 |
| LW (%) | **5.21** | **4.45** | **2.88** |
| *5/F (ILE% = 0.78%)* | | | |
| LD (%) | 43.91 | 35.45 | 24.76 |
| LW (%) | **0.66** | **2.21** | 12.02 |

Each ideal ANN DLLC system has been calibrated carefully. The lighting was divided into three different groups, and each can be controlled individually. The lighting level is close to setpoint and hence a very low ILE was recorded for all the floors. As the floor level increased, the variation of natural lighting inside the room increased and hence there was a slight increase in the ILE.

The LD and LW for the topmost floor (5th floor) were very large. This is because daylight can provide sufficient lighting for most of the cases, hence, the total light requirement (LR) is reduced. As the denominator (i.e. LR) of LD and LW dropped, the percentage increased. In contrast to the correlation study, the wide and medium spatial sensitivity photosensors provided better LD and LW under moderately and heavily obstructed room while a narrower photosensor increases the LD. However, for the topmost floor, a photosensor with narrow spatial sensitivity can reduce the LD. This may be due to large illuminance level variations on the working plan level, and it is required to reduce the view angle to ensure sufficient illuminance level for underlit locations. Similar observations can be found in closed-loop control (Kim and Song, 2007; Do et al., 2023).

## 5. Conclusion

The feasibility of using multi-photosensor and multi-lighting controllers by the ANN system has been covered in this study via simulation techniques. CBDM and measured sky luminance distribution patterns were used to model the indoor illuminance levels which covered most of the weather conditions. Based on the importance study, it is noted that the photosensor located at the rear of the room is more important than other parameters. For less obstructed cases, outdoor vertical illuminance is also one of the key features. Except for the topmost floor, climatic parameters are not so important as under heavily obstructed cases, the light flux received by photosensors may also be able to reflect the climatic parameters to a certain extent. As more sky can be "seen" by the indoor working plan, $K_t$ becomes more important. To evaluate the ANN's ability to predict the optimal dimming ratio of lighting, correlation and error analysis were conducted. In most cases, $r^2$ of 0.9 or above were achieved. Major errors were found in the topmost floor, or the points closed to windows. It is believed that these variations are due to strong daylight in these cases. The ANN DLLC system performances were also analysed and it performed very well. For wide or medium photosensors, the LD and LW can be lower than 10% under moderately or heavily obstructed cases. For the topmost floor, the percentage error is larger. However, it may only be because the lighting required is very small and resulted in a larger relative error. This study can be used to set design guidelines on selecting the location of photosensors. This is not applicable to the ANN controller; it is also applied to other type of DLLC system. More should be conducted based on this approach to generalise the best practices which allow better calibration of DLLC system during testing and commissioning processes. The applications of ANN DLLC should be further compared with traditional controllers such as closed-loop controllers. Hence, further work is needed.

## Acknowledgement

Work described was fully supported by a Faculty Development Scheme from the Research Grant Council of HKSAR [Project no. UGC/FDS16/E03/20].

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