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Coupling an artificial neuron network daylighting model and building energy simulation for vacuum photovoltaic glazing

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Abstract

Window plays an essential role in the indoor environment and building energy consumption. As an innovative building integrated photovoltaic (BIPV) window, the vacuum PV glazing was proposed to provide excellent thermal performance and utilise renewable energy. However, the daylighting performance of the vacuum PV glazing and the effect on energy consumption have not been thoroughly investigated. Most whole building energy simulation used the daylighting calculation based on Daylight Factor (DF) method, which fails to address realistic calculation for direct sunlight through complex glazing materials. In this study, a RADIANCE model was developed and validated to adequately represent the daylight behaviour of a vacuum cadmium telluride photovoltaic glazing with a three-layer structure. However, RADIANCE will consume too many computational resources for a whole year simulation. Therefore, an artificial neuron network (ANN) model was trained based on the weather conditions and the RADIANCE simulation results to predict the interior illuminance. Subsequently, a preprocessing coupling method is proposed to determine the lighting consumption of a typical office with the vacuum PV glazing. The performance evaluation of the ANN model indicates that it can predict the illuminance level with higher accuracy than the daylighting calculation methods in EnergyPlus. Therefore, the ANN model can adequately address the complex daylighting response of the vacuum PV glazing. The proposed coupling method showed a more reliable outcome than the simulations sole with EnergyPlus. Furthermore, the computational cost can be reduced dramatically by the ANN daylighting prediction model in comparison with the RADIANCE model. Compared with the lighting consumption determined by the ANN-based coupling method, the two approaches in EnergyPlus, the split-flux method and the DElight method, tend to underestimate the lighting consumption by 5.3% and 9.7%, respectively.

Keywords: Building integrated photovoltaic (BIPV), Vacuum glazing, Semi-transparent photovoltaic, Daylighting model, Building energy model, Artificial neuron networks (ANNs)

1. Introduction

As an essential part of a building envelope, a well-designed window system not only introduces the daylight into an indoor environment for visual comfort but also provides the energy-saving potential as common windows were responsible for 20 - 40% heat gain or heat loss of buildings [1]. In recent years, Building Integrated Photovoltaic (BIPV) systems have attracted increasing attention from researchers and building industry due to its multi-functions for producing renewable energy on-site and being as part of building envelope [2-4]. One of the benefits of BIPV window is that it has a great solar heat gain control ability. However, only a small proportion of the incoming solar energy will be used to generate electricity by the solar cells while most of the remaining energy will be recognized as undesired solar

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heat gain in the cooling season [5]. On the other hand, the heat insulation of the conventional PV glazing is not suitable for the heating-dominated regions [6].

In order to control the solar heat gain and improve the thermal insulation of windows, a novel vacuum PV insulated glass unit was proposed to integrate vacuum glazing and semi-transparent photovoltaic glazing into an insulated glass unit [7, 8]. Many attempts have been made by previous studies to explore the possibility and capability of the combination of the vacuum glazing and PV glazing. The electrical and thermal characterization of the a-Si based vacuum PV glazing with 4-layer structure had been investigated under laboratory condition [9]. The investigation of the overall energy performance of the vacuum PV glazing indicated that this innovative glazing technology could provide a certain amount of energy-saving potential in terms of cooling and heating consumption and overcome the drawback of conventional PV glazing [7, 8]. In this study, a three-layer vacuum PV glazing was proposed to integrate a vacuum glazing into a Cadmium telluride PV glazing with superstrate structure so that it is a highly integrated glass unit which is lighter than the former vacuum PV glazing design with 4-layer structure.

Although previous studies made efforts to investigate the thermal performance of the vacuum PV glazing, the daylighting assessments of this innovative glazing systems were mostly conducted by building energy simulation tools instead of other more advanced daylighting simulation tools. Sun [10] investigated the energy and daylight performance of the CdTe PV glazing for different architecture designs. The annual daylight performance was assessed by RADIANCE, and the energy simulations were conducted by EnergyPlus. However, the daylighting performance of windows is not only related to visual comfort of occupancy but also has a certain amount of effect on energy consumption as the daylighting penetrated through windows could be a substitute for artificial lighting system [11]. Therefore, the daylighting calculation used in the building energy simulation should be able to compute the interior illuminance results with high accuracy to ensure the reliability of lighting consumption calculation.

The building energy simulation tools commonly use Daylight Factor (DF) method to calculate the whole year daylight availability [12]. It is mainly because the DF method can perform a fast calculation based on time steps, whereas using advanced physics-based daylight simulation tools, such as RADIANCE and Daysim, will cost too many computational resources. However, the most vital limitation of DF method is that the reliability of this method will be compromised when addressing daylight calculation under clear sky conditions [13]. The daylight illuminance values predicted by EnergyPlus were very different from the measurement data under real sky conditions while the advanced daylighting simulation tool, RADIANCE, could provide more realistic results [12, 14]. Therefore, the daylighting assessments of complex fenestration systems, such as the vacuum PV glazing, are still an important issue that needs to be conducted by advanced daylight simulation tools.

In recent years, artificial neural networks (ANNs) have been favoured by researchers in the field of building energy analysis [15]. ANNs are trained by a group of historical datasets to learn the relationship between the inputs and outputs. A well-trained ANN model can perform a reliable prediction of the target outputs for a complex, nonlinear system. Benedetti [16] developed an accurate ANN model to predict building energy consumption. Hou and Lian [17] integrated an ANN model and rough sets theory for cooling load prediction. Rizzo and Scelba [18] conducted a novel Maximum Power Point Tracking (MPPT) method for PV systems by using an ANN-based approach. Wong [19] applied an ANN model to estimate building energy consumption of cooling, heating and lighting. Besides the building energy forecasting, ANNs also have the potential to predict interior daylight illuminance. An ANN-based model was developed by Kazansmaz [20] to predict the daylight illuminance in office buildings. Various weather conditions and building parameters are selected as inputs. The sensitivity analysis suggested that the input selection should exclude low relevance variables to improve the prediction capability of the models. Fonseca [21] compared the ANN model with the multivariate linear regression (MLR) to evaluate the impact of daylighting on building energy consumption. The simulations were performed by EnergyPlus coupled with Daysim. It is found that ANN had a better performance than MLR for the function approximation.

The objective of this study is to integrate the advanced daylighting simulation tool, RADIANCE, with the building simulation tool, EnergyPlus, by a novel and reliable approach. In Section 2, the advantage and limitation of EnergyPlus daylighting calculation methods and RADIANCE/DAYSIM are discussed. To overcome the limitation of current daylighting simulation modelling is one of the primary motivation of this study. In Section 3, the structure and optical parameters of the CdTe-based vacuum PV glazing are introduced in detail. In Section 4, the development and validation of RADIANCE models, the training process of the ANN model and the proposed ANN-based coupling method are demonstrated. By utilizing an ANN model for the daylighting prediction, the computation time of the simulation was reduced dramatically. In Section 5, the prediction performance of the ANN model and the energy simulation by the coupling method are discussed. In Section 6, the key findings of this study are summarized. The ANN model can provide reliable performance which represents the real daylight behaviour of the proposed vacuum PV glazing with three-layer structure. A more realistic result in terms of the lighting consumption was determined by the ANN-based coupling method and analyzed by the comparison of EnergyPlus calculations.

2. Daylighting simulation modelling

2.1 EnergyPlus daylighting calculation methods

EnergyPlus is a whole building energy simulation programme which is most commonly used for energy consumption analysis and thermal load simulation [22]. Although EnergyPlus is not a professional daylighting simulation programme, it integrates the daylighting calculation for each thermal balance time step during the daytime to determine the total lighting consumption [23]. The daylighting models of EnergyPlus, which are derived from the daylighting calculation in DOE-2.1E [24], apply Daylight Factor (DF) technique to perform fast daylighting. Daylighting Factor is the most frequently used daylighting assessment metric in building energy simulation software, which is a ratio that represents the available indoor illuminance relative to the outdoor horizontal illuminance. In EnergyPlus, a set of DFs under different sky conditions and sun positions are firstly determined, and then multiplying with the exterior horizontal illuminance of each time step in the daytime to calculate the interior daylighting illuminance at the reference points [25]. Based on the DF method, EnergyPlus provides two different options for daylighting calculation, namely split-flux method and DElight method.

Although the approach of pre-calculating DFs for a limited number of sun positions significantly reduces the computation time for a whole year simulation [26], it is well known that the major limitation of DF is the incapability of the direct sunlight calculation and the internal-reflection calculation which is strongly influenced by building geometry and surface properties [11]. Efforts on the improvement of the daylighting calculation accuracy have been made by introducing the DElight method into EnergyPlus. DElight employs the radiosity method, which is developed based on the algorithm from SUPERLITE [26], instead of the split-flux method to improve the accuracy of inter-reflected illuminance calculation. Radiosity is a scene-dependent algorithm which was adapted from radiation heat transfer mechanism into lighting simulation [27]. Validation studies [24] found that the radiosity algorithm is superior to the split-flux algorithm as the latter one tends to overestimate the inter-reflected daylight at positions very close or far from windows. However, there are several limitations of the DElight method cannot be ignored. The DElight method cannot support dynamic control of fenestration systems and it also cannot calculate the glare index. Ramos and Ghisi [28] conducted a comparison of the daylighting calculation of EnergyPlus and the measured data for the city of Florianópolis in southern Brazil. The results indicated that EnergyPlus produces a greater than 100% overestimation of the external horizontal illuminance for the diffuse and direct illuminance compared with the measurement data. Yi [12] validated a RADIANCE model with real indoor illuminance value of a test room located in Philadelphia, USA and compared the illuminance plots among RADIANCE, Kriging, and EnergyPlus. Comparisons showed that the daylighting calculation results from DElight were remarkably different from the RADIANCE simulation results.

To achieve fast daylighting simulation, the daylighting model carried by EnergyPlus compromises the accuracy of indoor illuminance calculation. However, the reliable simulation of the lighting consumption depends on the accuracy of the daylighting calculation. As the daylighting can be used as the natural lighting resources of the indoor environment, EnergyPlus determines the required electrical lighting energy as a complement to achieve the design illuminance level at the given time step. For a well-designed lighting system, the electric lighting consumption can be saved by controlling the artificial lighting supply when daylighting is available. Therefore, more advanced daylighting simulation programme is required for more reliable results of daylighting illuminance as well as lighting consumption, especially for the applications of novel glazing systems, such as the vacuum PV glazing.

2.2 RADIANCE and Daysim

RADIANCE is an advanced lighting simulation programme which combines a backward ray-tracing algorithm and bidirectional distribution functions. It is originally developed by Ward at Lawrence Berkeley National Laboratory [29]. RADIANCE has the capability to calculate the interior daylighting illuminance, luminance, and glare indices and to visualize the results as colour images or contour plots based on the building geometry, optical properties of the building surfaces, and climatic boundary conditions. The accuracy of the simulation results from RADIANCE has been validated extensively by scale models [30, 31] as well as on-site measurements [12, 32]. Although it is a quite challenge to master RADIANCE due to the lack of a graphical user interface and the complexity of the programme, it is regarded as the most prevailing daylighting modelling and analysis tool by many lighting designers, engineers and researchers. According to the online survey conducted within the daylight simulation community [33], over 50% commonly used daylight simulation programmes were developed based on RADIANCE simulation engine. Comparing with the daylighting calculation from building energy simulation tool, RADIANCE has its advantages in modelling complicated building geometry and complex fenestration systems (CFS) while it must pay the penalty on computational costs [34, 35].

Daysim is a RADIANCE-based dynamic daylight simulation software which combines a daylight coefficient (DC) method with the Perez all-weather sky model to efficiently simulate indoor illuminance and evaluate annual daylight performance by climate-based daylighting metrics, such as daylight autonomy (DA), useful daylight illuminance (UDI) and annual daylight glare probability profiles [36]. Daysim can be used to model various dynamic facades and generate hourly lighting schedules for specific occupancy schedules, dynamic shading systems, complex electric lighting systems controls, and combinations thereof. The lighting schedule can be written as a CSV. file and be imported into EnergyPlus for the simulation of lighting consumption [37]. The validation conducted by Yun and Kim [38] indicated that Daysim predicts more realistic interior illuminance than the split-flux method in EnergyPlus since the daylighting calculation results carried out by EnergyPlus tend to be overestimated compared with the measurement data. Although Daysim uses RADIANCE as the simulation engine, there are still differences in the illuminance results of a specific time between the calculation by Daysim and RADIANCE. The reason is that Daysim adopts DC method to simplify the daylighting simulation of a whole year [39].

From the discussions above, RADIANCE can perform the daylighting simulation with high accuracy; meanwhile, massive computational resources are required. EnergyPlus can deliver the fast daylighting calculation. However, it is quite challenging to address reliable simulation for complex fenestration system in terms of indoor illuminance level and lighting consumption. In this study, RADIANCE is selected to capture the complex daylight behaviour of the vacuum PV glazing. Base on the RADIANCE model, an ANN-based coupling method is proposed to obtain more reliable lighting consumption result than EnergyPlus solely and reduce the computation time of a whole year daylighting simulation.

3. CdTe-based vacuum PV glazing

3.1 Structure of vacuum PV glazing

Fig. 1 shows the cross-section of the proposed vacuum PV glazing with a three-layer structure. A typical CdTe-based PV glazing consists of a stack of thin photovoltaic absorbing layers laminated between a glass coated with transparent conducting oxide (TCO) and another glass sheet as the covering plate. Based on the configuration of the CdTe PV glazing with superstrate structure, the active absorbing layers are deposited on a glass superstrate with TCO coating, and the vacuum PV glazing then is laminated on the back. The evacuated gap of vacuum glazing is only 0.1 mm wide, which is separated by an array of small support pillars. The heat conduction and heat convection can be reduced to a minimum level because of the vacuum space between two glass panes. Therefore, vacuum PV glazing is regarded as one of the best fenestration product in terms of thermal insulation performance.

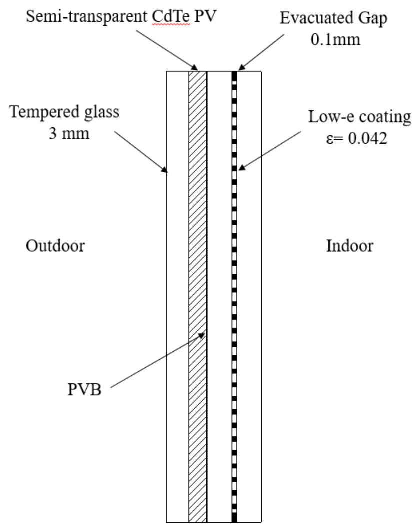


Fig. 1 Structure of the vacuum PV glazing

A small-scale sample of the proposed vacuum PV glazing was made by a solar PV manufacturer named ASP in Hangzhou, China. A vacuum glazing is used as the backside panel of the CdTe PV glazing. The size of the sample is 300 mm * 300 mm, as shown in Fig. 2. It can be seen that the semi-transparent effect allows occupants to have an outside view and admits a certain amount of daylight into the indoor environment. The vacuum PV integral glass unit has a thickness of 14.2 mm, which is thinner than the former vacuum PV glazing with a 4-layer structure [7]. Consequently, the weight of the proposed vacuum PV glazing is lighter.

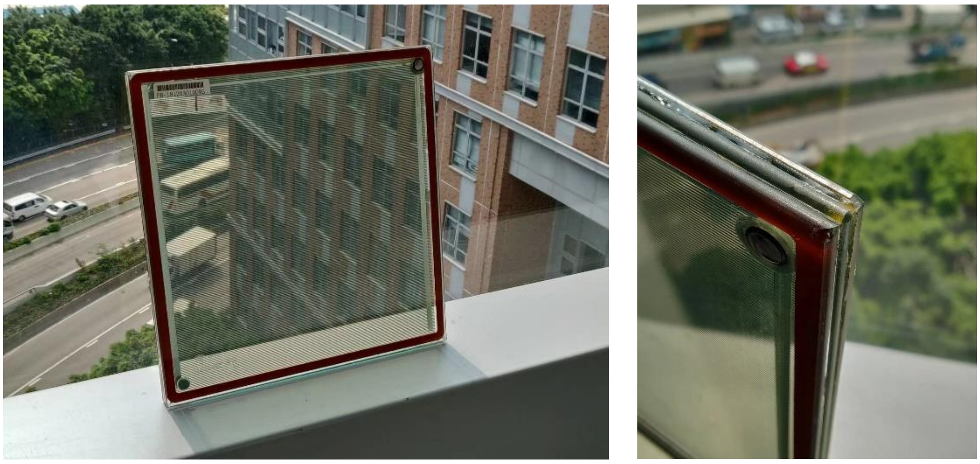


Fig. 2 The pictures of the vacuum PV glazing with three-layer structure

3.2 Optical characteristics measurement

The optical characteristics, as known as the spectral transmittance, reflectance, and absorption of the vacuum PV glazing, were determined by using a UV-VIS-NIR spectrophotometer with the simulated solar spectrum from 300 nm to 2500 nm. The small scale sample of the vacuum PV glazing with the dimension of 300 mm*300 mm was measured in a Hitachi UV-VIS-NIR spectrophotometer equipped with a 150 mm standard integrating sphere. The results of spectral transmittance and reflectance measurements were obtained by averaging the results of three different points of the sample, and the spectral absorption was calculated accordingly. As shown in Fig 3, the average solar transmittance (T), reflectance (R) and absorption (A) for the photovoltaic material of vacuum PV glazing were 6.1%, 14.3%, and 79.6%, respectively. The visible transmittance of the CdTe solar cell was around 18.3%. In the visible range, the highest transmittance was around 600 nm.

The daylight behaviour of the vacuum PV glazing is related to the unique design of the CdTe PV glazing. Although the CdTe solar cell is semi-transparent, the manufacture will use lasers to cut the solar cell into small pieces with a particular PV coverage of the glazing area to increase the transparency of the product. For the vacuum PV glazing sample, the CdTe solar cells are deposited on the glazing as thin liner cells with 50% area coverage of the glazing surface. Subsequently, the vacuum PV glazing has a non-uniform appearance. The optical parameters of the photovoltaic material and glazing are different, which will affect the overall daylight transmittance as the vacuum PV glazing is an integrated glass unit. Therefore, the overall optical properties of the vacuum PV glazing play a pivot role in the daylighting simulation, which need to be determined before the building energy simulation.

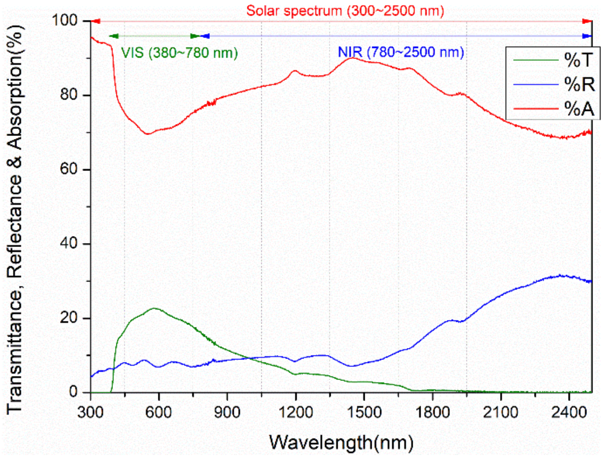


Fig. 3 Optical characteristics of the vacuum PV glazing

4. Methodology

In this paper, a new approach is proposed to combine advanced daylighting simulation model and building simulation model to achieve better energy simulation results for the vacuum PV glazing. The initial daylighting model was conducted by RADIANCE, and the energy simulation model was conducted by EnergyPlus with the same geometry and weather data. Then, the daylighting simulation results of selected time steps were obtained and used to train an ANN model for daylighting prediction. After the daylight illuminance at the reference point for all time steps when the sun is up was predicted by the ANN model, Matlab was used to generate a lighting schedule using the same light control strategy as which used in the EnergyPlus model. EnergyPlus can recognize the hourly lighting schedule to calculate the lighting consumption accordingly. Therefore, EnergyPlus can calculate the lighting consumption with the new lighting schedule based on the ANN prediction which represents the daylighting illuminance simulated by more advanced daylighting model than the daylighting calculation provided by EnergyPlus. The methodology of this study consists of three steps as follows:

1. Daylighting model development and validation: In this stage, the RADIANCE model was compared and validated with mock-up tests conducted in the laboratory. The key parameters of the vacuum PV glazing sample and the simulation parameters of the RADIANCE model have been determined based on the validation.

2. ANN training: The daylight illuminance at the reference point for selected time steps were calculated by the validated RADIANCE model as training target data. The solar-related environmental conditions were collected as input data sets for ANN training.
3. Coupling between ANN daylighting prediction and EnergyPlus: The trained ANN daylighting prediction model was used to predict the illuminance level by daylight. A lighting schedule was generated based on the continuous dimming control strategy as an input file of EnergyPlus. Subsequently, the lighting energy consumption of the room adopted the vacuum PV glazing was obtained based on the coupling between ANN daylighting prediction and EnergyPlus.

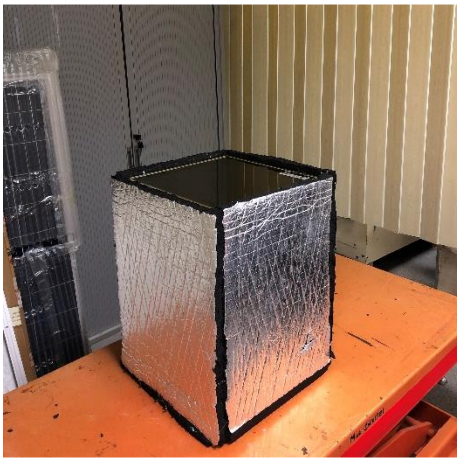
The reliability of this approach depends on three major parts: the validated RADIANCE model, the trained ANN prediction model with high accuracy, and the consistency of the lighting control strategy.

4.1 Daylighting simulation development and validation

In order to develop a reliable daylighting model, which can perform the daylighting calculation of illumination data with high accuracy for the application of the vacuum PV glazing, a set of validation tests were conducted to compare the daylighting calculation results carried out by RADIANCE with the measurement data under the controlled laboratory conditions. After the RADIANCE model had been validated, a daylighting simulation model, which represents the daylight transmittance behaviour of the vacuum PV glazing adopted in a typical small office, can be deployed using the simulation parameters determined by the aforementioned validated model.

This study measures illuminance level (lux) of a scale model mounted with a sample of the novel three-layer vacuum PV glazing. The tests were conducted in the Solar Simulation Lab in the Hong Kong Polytechnic University. As shown in Fig.4, eight Hönle SOL-2000 solar simulator lamps provide steady solar irradiation with uniform distribution as a lighting source in this experiment. The light produced by each Hönle SOL unit is in close proximity to natural sunlight. All SOL units meet the requirements for stationary solar simulators in accordance with International Standard IEC 60904-9 (Photovoltaic devices - Part 9: Solar simulator performance requirements) [40]. The size of the test space is 2.4 m long, 2.35 m wide and 3.6 m high. A test rig was built as a scaled model with the dimension of 300 mm*300 mm*450 mm. The sample of the three-layer vacuum PV glazing, which is a square with the side of 300 mm length, was adopted in this study. The location of the test rig inside the test space was measured by a laser distance meter. An illuminance meter was placed at the center of the bottom in the test rig to measure the illuminance level after the light passing through the vacuum PV glazing sample. The approximate reflectance of the surroundings and floor of the test space and the internal surface of the test rig were measured by a reference reflector. The photometric properties of the test rig and test space are listed in Table 2.

(a) Solar simulator lamps



(b) Test rig

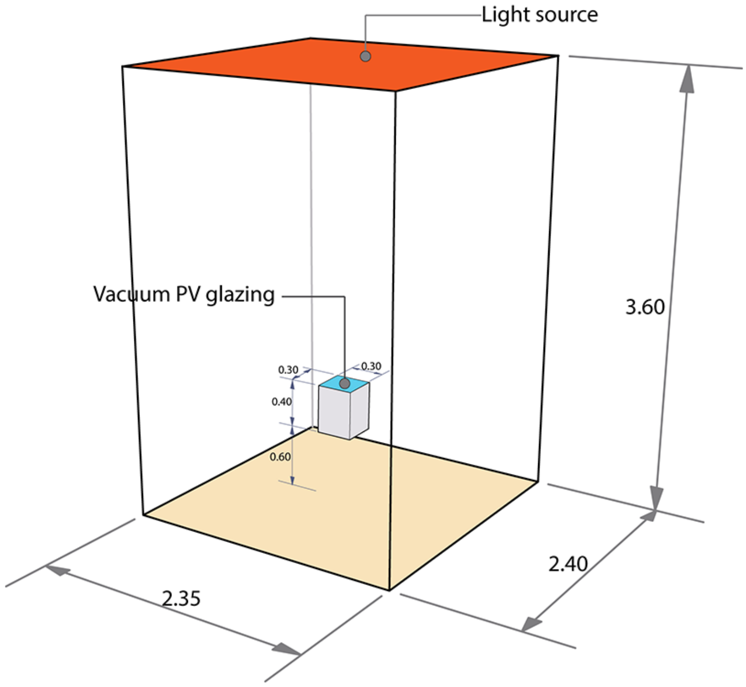
Fig. 4 Validation tests for the daylighting simulations

Table 2 Photometry of materials in the tests

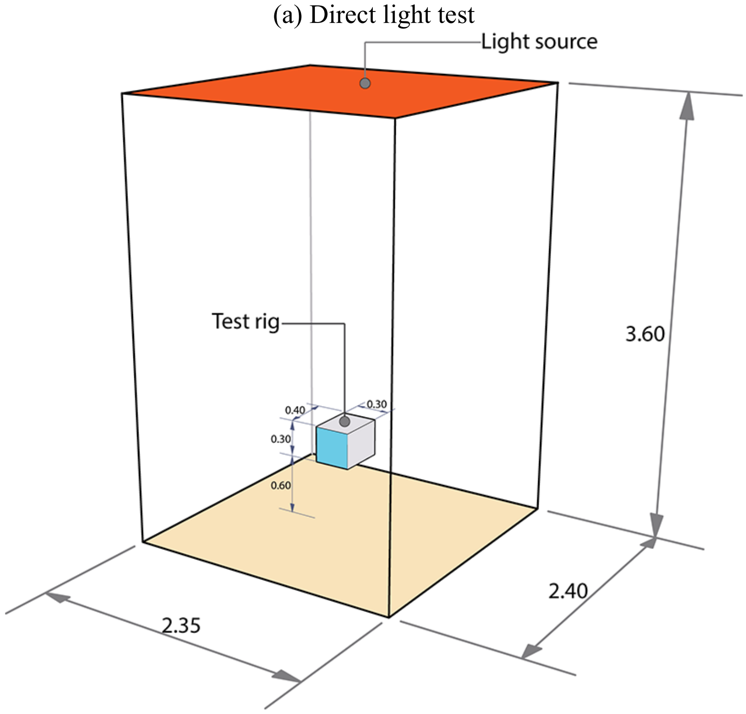
Parameter	Construction	Value
Reflectance	Surroundings	0.598
	Floor	0.196
	Test box interior surface	0.533
Transmittance	Vacuum PV glazing	0.350

Two tests were conducted under different scenarios, which the test rig mounted with the vacuum PV sample were placed horizontally and vertically. In the horizontal position, the vacuum PV glazing mainly received direct light from the solar simulator. And when the vacuum PV glazing was placed vertically, the receiving light was mainly contributed by the diffuse light reflected from surroundings. Therefore, the measurement of both direct and diffuse light can be conducted respectively. The solar simulator performed high light intensity and low light intensity by operating eight lamps and two lamps for both direct light tests and diffuse light tests. For each test, the illuminance at the exterior surface of the vacuum PV glazing was measured by the illuminance meter. Therefore, the same amount of incoming light could be employed for the development of validation daylighting simulation models. The measurement data were used to evaluate the optical characteristics of the vacuum PV glazing and validating the simulation results calculated by the RADIANCE daylighting model.

As mentioned above, RADIANCE is a backward ray-tracing tool with a high accuracy, which is widely used for the analysis and visualization of lighting. In this study, the 3-dimensional models based on the geometry of the test space and test rig was built up using Rhino 6 [41]. Currently, Rhino 6 includes Grasshopper [42] which is a graphical algorithm editor that can be performed as a platform to utilize various functional plugins, such as Ladybug and Honeybee. Ladybug and Honeybee are capable of importing weather data and utilizing RADIANCE and Daysim as engines to conduct daylighting simulation associated with the 3-D model developed by Rhino 6. Furthermore, the simulation results can be visualized in Rhino/Grasshopper environment. In order to validate the direct light test and diffuse light test, two RADIANCE models were reproduced based on the geometry and photometry of the test rig and test space, and the position of the test rig accordingly as shown in Fig. 5.



(a) Direct light test



(b) Diffuse light test

Fig. 5 The RADIANCE models for (a) direct light test and (b) diffuse light test

In the validation stage, the RADIANCE models generated a uniform CIE standard sky [43] based on illuminance value. The illuminance value of the sky condition was set corresponding to the measurement data to ensure the simulated incoming light of the test rig identical to the test conditions. As listed in Table 3, the following simulation parameters were adopted in the RADIANCE daylighting models to improve the accuracy of the calculated illuminance results.

Table 3 Details of RADIANCE simulation parameters

Ambient bounces	Ambient accuracy	Ambient divisions	Ambient resolution	ambient super-samples	Direct threshold	Direct sampling
3	0.1	4096	128	4096	0.15	0.05

Fig. 6 shows the actual measurement data and the simulation results under different test scenarios and lighting conditions. There are in total 4 combinations of test scenarios and lighting conditions, which are the direct light test with 8 lamps, the direct light test with 2 lamps, the diffuse light test with 8 lamps, and the diffuse light test with 2 lamps. It can be found that, for the direct light tests, the differences between the simulation results and the measurement data were within ±105.1 lux. The relative divergences were lower than 1.6%. The comparison of the illuminance values for the diffuse light tests also shows the insignificant discrepancies between the results from the simulations and measurements.

The simulation results were closely matched the measurement data as the difference is +4.9 lux for the high light intensity and +6.1 lux for the low light intensity. The relative divergences of illuminance were within 0.3% - 1.5%. Therefore, the comparison between the measurements and simulations indicates that the RADIANCE model has the ability to simulate proper sky conditions, direct and diffuse light passing through the vacuum PV glazing, and internal reflected component to determine the illuminance map under given lighting conditions.

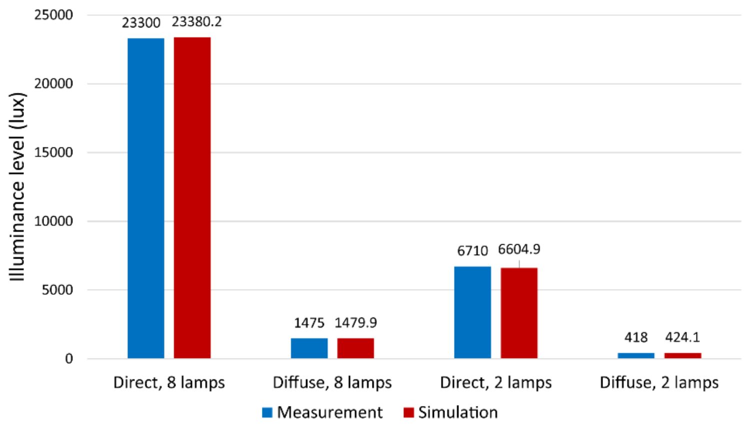


Fig. 6 Illuminance for the direct light tests and diffuse light tests

Based on the validated RADIANCE model, a daylighting model was developed to represent the behaviour of daylight for a typical small office with the vacuum PV glazing. The 3D model was built in Rhinos 6 as shown in Fig. 7. A small office, which is 2.3 m wide, 3.0 m deep and 2.5 m high, was developed and installed a south-oriented window which is a vacuum PV insulated glass unit with the dimension of 2.1 m * 1.8 m. Besides the geometry and material properties of the building envelope, other essential inputs for the daylighting model are the sky conditions. In this study, RADIANCE engine generated the climate-based sky by using Ladybug component to import the weather data of Hong Kong into the simulation model. Perez All-Weather Sky Model [44] was adopted to determine the relative luminance distribution of the sky dome based on the given weather file. The simulation parameters of the daylighting model and the optical parameters of the vacuum PV glazing were employed in accordance with the validation models. Therefore, for any given time, the RADIANCE daylighting model is capable of simulating proper sky conditions, direct and diffuse daylight passing through the vacuum PV glazing, and the internal reflected component of interior illuminance to determine the indoor illuminance and visualize the results as colour maps. In summary, the key aspects of the RADIANCE daylighting model are listed in Table 4.

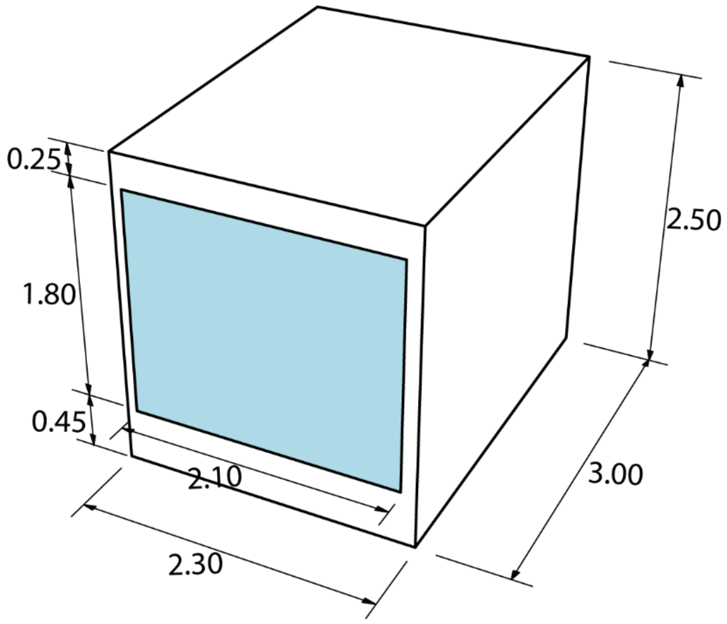


Fig. 7 The RADIANCE daylighting model of a typical office

Table 4 Key aspects of the RADIANCE daylighting model

Key aspects	
Sky model	Perez All-Weather Sky Model
Glazing type	Vacuum PV glazing, transmittance: 0.35
Window size	2.1 m * 1.8 m
Building location	Hong Kong
Building orientation	South
Room dimensions	2.3 m * 3.0 m * 2.5 m
Interior surface properties	Ceiling, reflectance: 0.80 Wall, reflectance: 0.42 Floor, reflectance: 0.32

4.2 ANN-based daylighting prediction

In the previous section, the RADIANCE model was developed to represent the daylight behaviour of the vacuum PV glazing. It is found that it took around 132 seconds on average for the RADIANCE simulation of a single time step. With respect to a whole year daylighting simulation, which includes in total 4379 daytime hours in Hong Kong, it requires 160 hours by using RADIANCE. As a data-driven prediction model, ANN is recognized as a successful approach in the application area of function approximation [45]. Therefore, ANN was utilized in this study to learn the relationship between multiple inputs and a single output, which is the illuminance value at a certain point. Only a few of RADIANCE simulations for selected time steps were required to obtain the training datasets for the ANN model. A well-trained ANN model is able to predict the illuminance results with high accuracy. Hence, the utilization of ANN is the most promising method to reduce computation time as regards daylighting prediction.

In ANN modelling, the selection of the input parameters is critical for the prediction accuracy. The inputs must be closely related to interior daylighting illuminance. Kazanasmaz [20] developed an ANN daylighting prediction model which has 13 input variables. However, the sensitivity analysis indicated that outdoor temperature and UV index are least effective parameters. The finding suggests that the models' prediction ability may improve by excluding low relevance parameters. In this respect, five environmental parameters, which are direct normal radiation, diffuse horizontal radiation, sun altitude, sun azimuth, and sky cover, were selected as the input variables of the ANN prediction model. Those parameters can be acquired from the weather file as individual value of each hour among all 8760 hours. The direct normal radiation and diffuse horizontal radiation indicate solar intensity. The sun altitude and sun azimuth determine the sun position and the angle that the sunlight reaches the window. The sky cover is the amount of opaque cloud, in tenth, covering the sky.

As shown in Fig. 8, the process of ANN-based daylighting prediction was comprised of three main stages - preparation, daylighting simulation, and ANN model training and evaluation. In the preparation stage, weather file and boundary conditions, such as the building geometry and the key parameters of the building envelope, were deployed to develop the RADIANCE daylight simulation model. Matlab was used to generate a set of time steps for the daylighting simulation. A total of 364 time steps, which are 9:00 am, 12:00 pm, 14:00 pm and 16:00 pm every four days from January 1st to December 27st, were selected to represent the typical hours of morning, noon and afternoon through the whole year. As only 364 datasets are required for the ANN model instead of in total 4379 time steps, the computation time can be dramatically reduced by using only 8.3% of simulation time. The second stage is to run the daylighting simulation by the developed RADIANCE daylighting model for the given conditions. For each time step, an illuminance map at the working plane (0.8 m above the floor) was calculated by RADIANCE and the illuminance value at the reference point was collected by Matlab as the training target for the next step. The reference point is 1.35 m away from the window, 1.15 m away from each side of the wall, and 0.8 m above the floor. It is identified as the location of the sensor which was used to operate the lighting control system. Meanwhile, direct normal radiation, diffuse horizontal radiation, sun altitude, sun azimuth and sky cover of each selected time step were obtained from the weather file as the training input variables for further ANN model training.

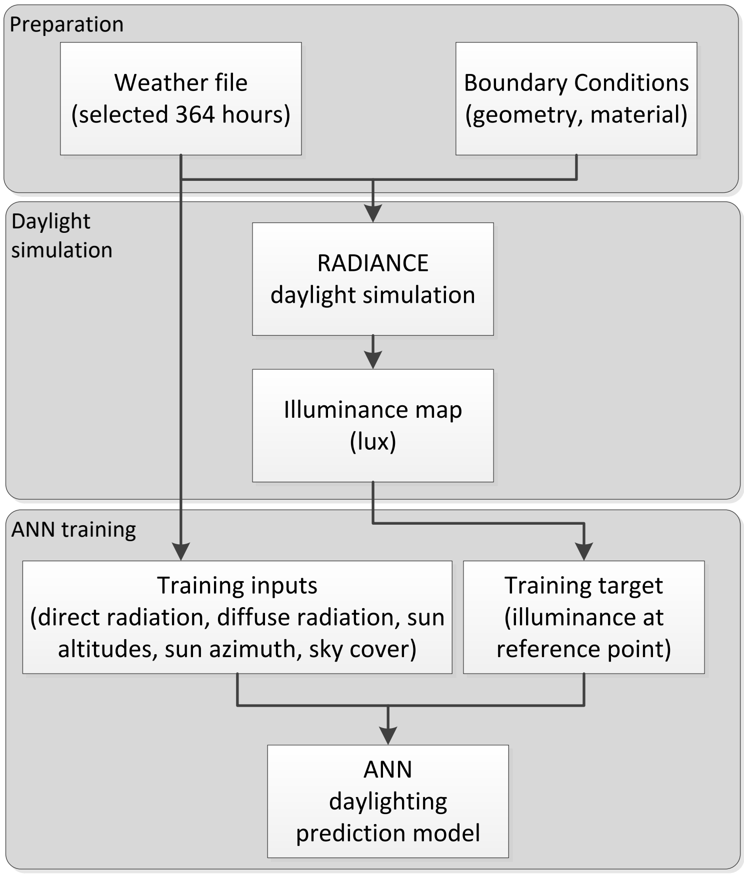


Fig. 8 Process for the development of the ANN daylighting prediction model

In the training stage, Matlab neural network toolbox was used to build up the ANN prediction model. As shown in Fig. 9, a three-layer feed-forward neural network was developed by adopting backpropagation algorithms. The input layer consists of 5 neurons in accordance with the 5 input variables. The middle layers consist of two hidden layers with 20 neurons and 10 neurons, respectively. Each neuron has a weight and a bias to form the output by multiplying the inputs with the weight and then adding the bias. The output is passed through a transfer function to become the input for the next layer. Hyperbolic tangent sigmoid (TANSIG) transfer function was adopted in both hidden layers. Levenberg-Marquardt algorithm was used as the training function to minimize the error between the output and target by back-propagating the adjustment to the weights and biases of neurons in the hidden layers and the output layer. In the output layer, there is a single neuron to represent the output variable which is the illuminance value at the reference point.

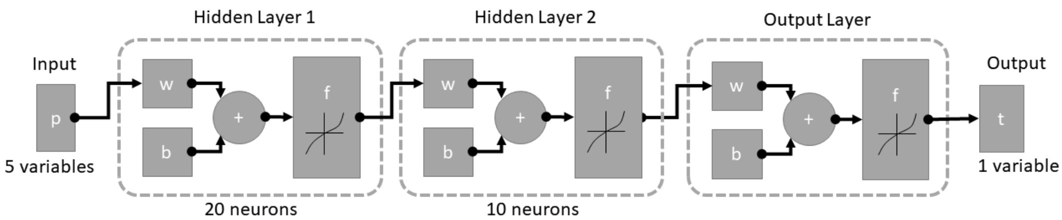


Fig. 9 Structure of the ANN model

For the first step of the training process, the datasets of input and target variables were normalized by scaling minimum and maximum values into the range of 0 to 1. The value range of the inputs and outputs were shown in Table 5. After the training datasets were determined, the ANN prediction model was using 70% of data for training, 15% of data for validation and 15% of data for testing. Mean squared error (MSE) is used as the performance function to evaluate the network's performance according to the average squared difference between outputs and the targets. When the training data were presented to the network, the weight and bias of each neuron of the hidden layer and output layer were updated according to the partial derivative of the error. The validation data are used to measure the performance of the network by calculating the MSE. In the validation stage, an increase in the MSE will be considered as a failure of the validation check. The performance goal was set at 10^{-5} and the minimum performance gradient was set at 10^{-7}. The maximum validation failures number was set at 10. When training is sufficient, the performance goal or the minimum performance gradient should be achieved before the maximum validation failures occur. The testing data are used to provide an independent evaluation of the network performance after training. Fig. 10 shows the regression analysis for the ANN training, validation and testing. It can be seen that the outputs of the testing data were well fitted with the targets. The details of the trained ANN model performance is shown in Table 6.

Table 5 Summary of input and output variables for ANN training

Parameters	Data for ANN training	
	Minimum	Maximum
Direct normal radiation (Wh/m^2)	0	780
Diffuse horizontal radiation (Wh/m^2)	5	402
Sun altitude	1.38°	84.01°
Sun azimuth	70.90°	294.82°
Sky cover	0	10
Illuminance value (lux)	26.17	19120.06

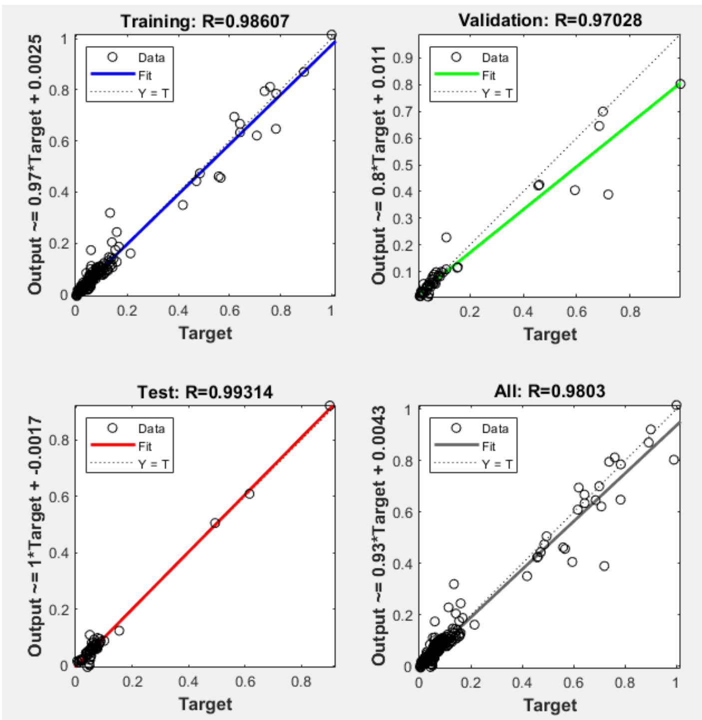


Fig. 10 Regression analysis for the trained ANN model

Table 6 Details of the trained ANN model performance

Data	Samples	MSE	R
Training	254	$6.49*10^{-4}$	0.986
Validation	55	$3.77*10^{-3}$	0.970
Testing	55	$3.14*10^{-4}$	0.993

4.3 Coupling between the ANN-based daylight model and building energy model

For the purpose of developing the coupling between the ANN-based daylighting model and the building energy model, an energy simulation model was constructed in EnergyPlus with the same geometry of the RADIANCE daylighting model. A mock-up model was developed to represent a typical small office located in Hong Kong. The south-orientated wall which mounted the proposed vacuum PV glazing is the only external wall in this model. The ceiling, floor, and other wall are considered as internal wall within air-conditioned space. The key properties of each building surface were set as the same as the RADIANCE model. The referent point for daylighting calculation in EnergyPlus was located at the same location, which is 1.35 m away from the window, in the daylighting model. EnergyPlus also uses Perez All-Weather Sky Model [44] to calculate the sky conditions based on the weather data of Hong Kong. The consistency of the geometry, the boundary conditions and the sky conditions in both the EnergyPlus model and the RADIANCE model is the foundation for implementing the coupling between advanced daylight prediction and building energy simulation. In order to fully utilize the available daylighting to reduce lighting consumption, a continuously-dimmable control system was used in EnergyPlus. Consequently, the divergence of the daylighting calculation conducted by EnergyPlus and the coupling method based on the ANN-based prediction model can be fully demonstrated.

Fig. 11 shows the process for coupling the ANN-based daylighting prediction model with the whole building energy model. Firstly, the required inputs for the ANN model is obtained from the weather file of Hong Kong. The required inputs include the direct normal radiation, diffuse horizontal radiation, sun altitude, sun azimuth and sky cover for each time step when the sun is up. For the weather condition in Hong Kong, there are in total 4379 hours defined as daytime where the direct normal radiation and the diffuse horizontal radiation are above zero. The second step is to obtain the predicted results from the trained ANN model. The input variables are normalized by the same setting in the training process. Then the trained ANN model can use the normalized inputs to predict the outputs accordingly. After the denormalization of the outputs, the illuminance values at the reference point of all the time steps when daylight penetrates into indoor space are determined. The next step is to use Matlab to generate the lighting schedule based on the lighting control strategy and the occupancy schedule used in the EnergyPlus model. In EnergyPlus, Schedule: File can be used to read in hourly or sub-hourly schedules computed by other software or developed in a spreadsheet. As a result, the daylight illuminance results of the ANN prediction model can be used in the EnergyPlus model to determine the lighting consumption of a whole year.

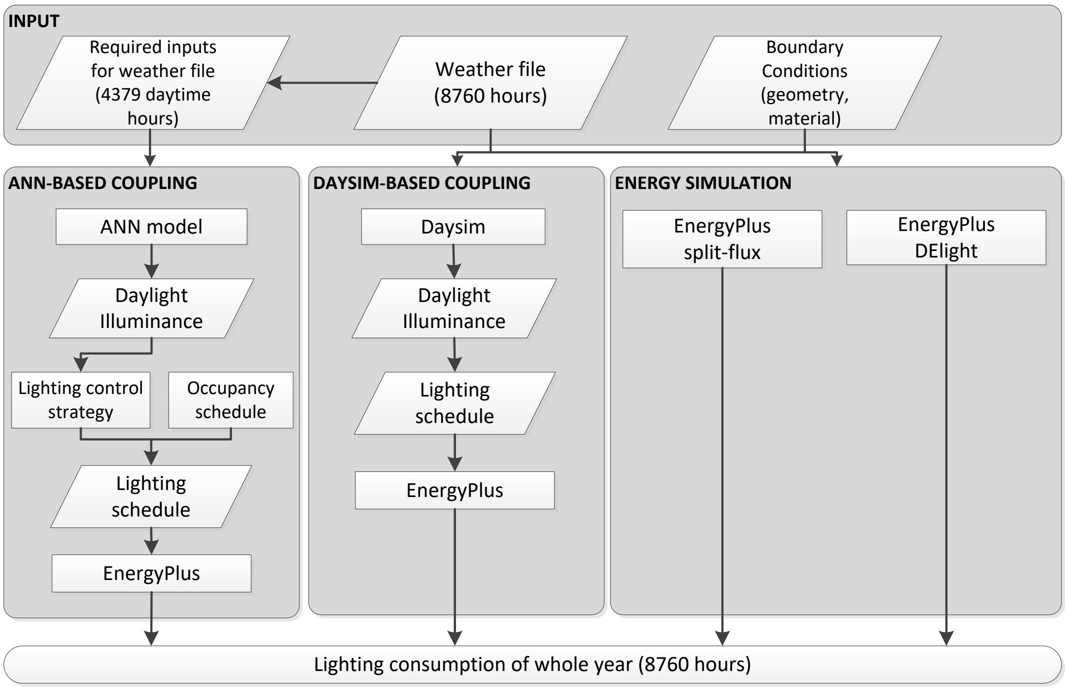


Fig. 11 Overall process of the coupling method

For the coupling method, one important issue is that the lighting control strategy must be consistence with the one adopted in the EnergyPlus building energy model when determining the lighting schedule using the predicting result by the ANN-based daylighting prediction model. In EnergyPlus, the lighting control system simulation will be carried out once the daylighting illuminance level at the reference point has been determined. The fractional electric lighting output, f_L, is defined as the portion of the illumination needed from the artificial lighting system to meet the illuminance set point at the reference point. It can be calculated by:

$$f_L = \max\left[0, \frac{I_{set} - I_d}{I_{set}}\right] \tag{1}$$

where I_{set} is the illuminance set point which equals to 300 lux and I_d is the daylight illuminance at the reference point. It is assumed that the lighting system can produce the illuminance set point at the reference point when it is operated at maximum power.

In terms of the calculation of the lighting consumption, the fraction of electric input power of the lighting system, f_P, is subsequently determined corresponding to f_L by following equations:

$$f_P = \begin{cases} f_{P,\min} & f_L \le f_{L,\min} \\ \dfrac{f_L + (1 - f_L) f_{P,\min} - f_{L,\min}}{1 - f_{L,\min}} & f_{L,\min} < f_L \le 1 \end{cases} \tag{2}$$

For the continuous dimming control strategy, it is assumed that when lighting is needed in the daytime, f_P is constant and equal to $f_{P,min}$ for $f_L \le f_{L,min}$ and that f_P increases linearly from $f_{P,min}$ to 1.0 as f_L increases from $f_{L,min}$ to 1.0. In EnergyPlus, the default setting for $f_{p,min}$ is 0.3, and $f_{L,min}$ is 0.2. Here, $f_{p,min}$ and $f_{L,min}$ are set to be 0. Therefore, if the daylight illuminance exceeds the set point, f_L will be equal to 0, which means no artificial lighting is required. By this continuous dimming control strategy, the lighting system is operated to be highly sensitive to the variation of the available indoor daylighting to maximum the energy-saving potential.

The overall approach of the coupling method between the ANN-based daylighting prediction model and the building energy model is carried out by replacing the lighting schedule in EnergyPlus. Based on the daylighting prediction results and lighting control strategy, the lighting schedule can be generated accordingly. Therefore, this coupling mechanism is regarded as preprocessing coupling. As shown in Fig. 11, the lighting schedule generated by the Daysim daylighting simulation model were also imported into EnergyPlus for the calculation of lighting consumption. The lighting consumptions of a whole year based on two daylighting calculation approaches within the energy simulation tool, namely, the DElight method and the split-flux method, were also calculated. The comparison of monthly or annual lighting consumptions carried out by ANN-based coupling, Daysim-based coupling and EnergyPlus simulations were conducted to investigate the influence of the daylighting prediction by different approaches on the lighting consumption.

5. Result and discussion

5.1 ANN model performance evaluation

From the results of the validation experiments in the previous section, the RADIANCE model can be used to simulate the daylight behaviour of the vacuum PV glazing with very high accuracy. Furthermore, the ANN-based daylighting prediction model has been trained based on the simulation result of the RADIANCE model for the selected time steps. The error analysis of the trained ANN model indicates that the comparison between the ANN prediction model and the RADIANCE model were within an acceptable error range. Based on the previous findings, this section conducted an evaluation on the ANN model performance under 4 different scenarios, which are cloudy sky condition in summer, clear sky condition in summer, cloudy sky condition in winter, and clear sky condition in winter. The comparisons of the illuminance values also include the daylighting simulation by Daysim and the daylighting calculation carried out by EnergyPlus with two different approaches, namely, split-flux method and DElight method.

Based on the detailed weather conditions in Hong Kong, June 23rd and June 28th were selected to represent the summertime near the summer solstice (June 21st) with the cloudy sky condition and the clear sky condition, respectively. December 12th and December 22nd were selected as winter days around the winter solstice (December 21st) with the cloudy sky condition and the clear sky condition, respectively. The summer solstice is the day with the longest period of daylight when the sun reaches its highest position in the sky. On the contrary, during the winter solstice, the daily maximum elevation of the sun is at the lowest level while the daytime period is the shortest of a whole year. Therefore, for the cases in Hong Kong, the south-orientated window will receive approximately the minimum amount of direct daylight in the selected summer days and the maximum amount of direct daylight in the selected winter days.

Fig. 12 shows the predicted illuminance level by the trained ANN model as well as the daylighting calculation results carried out by RADIANCE, Daysim, DElight method and split-flux method for the selected summer days from 7:00 am to 19:00 pm. Comparing with the RADIANCE results, the ANN prediction results of illuminance were slightly less for both cloudy sky condition and clear sky condition.

Daysim predicted the illuminance value much less than which of the RADIANCE model. In contrast, the two approaches by EnergyPlus tended to overestimate the illuminance level, especially for the DElight method. The average illuminances determined by RADIANCE were 714.2 lux for the cloudy day and 760.9 lux for the sunny day, while the average illuminances predicted by the ANN model were 706.2 lux and 737.5 lux, respectively. It worth noting that the daylighting calculations by the split-flux method were also close to the RADIANCE results, which the difference on the average illuminance values were +8.7 lux and +65.4 lux for cloudy condition and sunny condition, respectively.

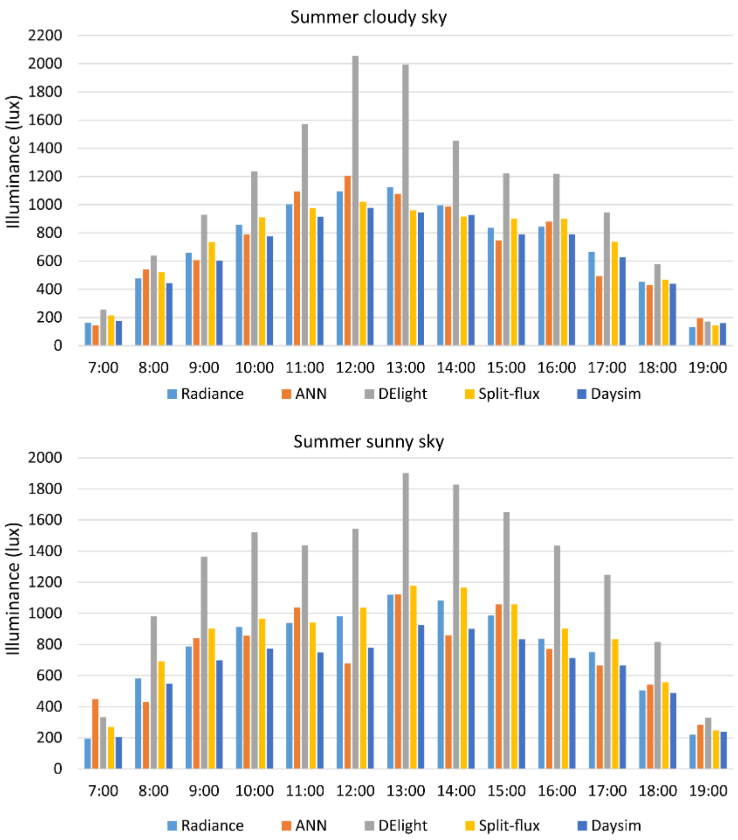


Fig. 12 Illuminance level under sunny and cloudy sky conditions for summer cases

As shown in Fig. 13, for the selected winter days, results from the ANN model were closely matched with the results from the RADIANCE model. For the cloudy day in winter, the average illuminance by RADIANCE was 489.5 lux while it is 487.1 lux by the ANN model prediction. For the sunny day in winter, the average illuminance values were 5762.3 lux and 5718.0 lux determined by the RADIANCE model and the ANN model respectively. The difference between the results by the RADIANCE model and the other daylighting calculation methods varied from +58.2 lux by Daysim to +92.3 lux by the split-flux method on a cloudy day, and from -511.5 lux by DElight to +598.7 lux by Daysim on a sunny day. On the selected sunny day in winter (December 22nd), it can be found that DElight method tended to overestimate the illuminance level from 8:00 am to 10:00 am and 15:00 pm to 17:00 pm, and underestimate the illuminance level from 11:00 am to 14:00 pm when the low angle sunlight penetrated directly to indoor. The results were in line with the limitation of the DF method, which it is incapable of predicting the daylighting when the direct sunlight dominated.

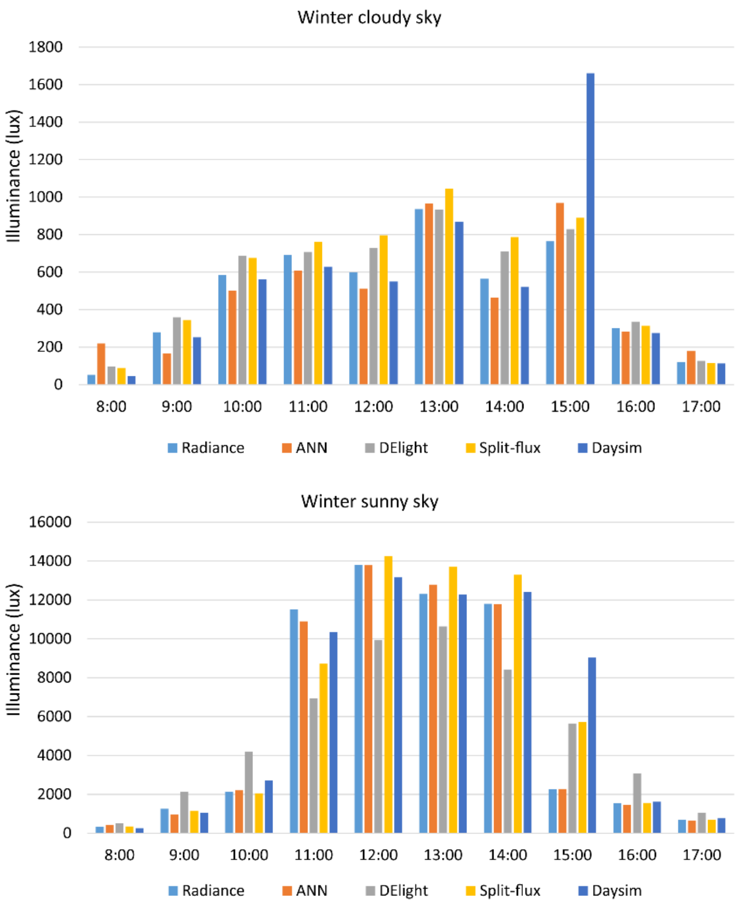


Fig. 13 Illuminance level under sunny and cloudy sky conditions for winter cases

To conduct the performance evaluation more rigorously, the mean bias error (MBE) and the coefficient of variation of root mean square error (CvRMSE), with respect to the RADIANCE results, were calculated for all 4 cases. The equations to calculate MBE and CvRMSE are as follows:

$$MBE(\%) = \frac{\sum_{i=1}^{N}(P_i - R_i)}{\sum_{i=1}^{N} R_i} \tag{3}$$

$$CvRMSE(\%) = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - R_i)^2}}{\frac{1}{N}\sum_{i=1}^{N} R_i} \tag{4}$$

where N is the number of data, P_i is the predicted illuminance value from the ANN model, EnergyPlus or Daysim, R_i is the RADIANCE value.

The MBE and CvRMSE are statistical metrics used to quantify the consistency or divergence between two data series. The RADIANCE simulation results were set as the baseline data in the calculation of MBE and CvRMSE. The MBE can provide an indication of the overall tendency of prediction values relative to the baseline values to be higher or lower. The CvRMSE normalises the root mean square errors with the mean of the baseline values to compare the “fitness” of different models. According to ASHRAE Guideline 14, the model is considered as a model with high accuracy if the value of the MBE and the

CvRMSE not exceed 10% and 30%, respectively.

Table 7 shows the MBE and CvRMSE of the ANN model, DElight method, split-flux method, and Daysim. The overall MBE of the ANN model is -1.08% and the CvRMSE is 9.01%, which is the smallest among all daylighting simulation models. This suggests that the ANN predictions were much closer to RADIANCE than EnergyPlus as well as Daysim.

Table 7. MBE and CvRMSE of different daylighting simulation models

Sky condition		ANN	DElight	Split-flux	Daysim
Summer cloudy sky	MBE	-1.22%	53.39%	1.11%	-7.92%
	CvRMSE	10.83%	65.48%	9.90%	10.77%
Summer clear sky	MBE	-3.08%	65.66%	8.59%	-13.97%
	CvRMSE	18.87%	70.79%	9.40%	17.20%
Winter cloudy sky	MBE	-0.48%	12.63%	18.85%	11.90%
	CvRMSE	22.25%	16.08%	23.68%	58.42%
Winter clear sky	MBE	-0.77%	-8.88%	6.63%	10.39%
	CvRMSE	4.64%	45.61%	26.92%	38.15%
Overall	MBE	-1.08%	8.52%	6.97%	5.45%
	CvRMSE	9.01%	72.26%	40.95%	58.37%

Fig. 14 shows how the predicted illuminance carried out by the ANN model, EnergyPlus or Daysim differ from the RADIANCE results for all selected cases. When the difference is closer to the zero, it suggests that the prediction is closer to the RADIANCE simulation. It can be found that the ANN model demonstrates the best prediction performance than other daylighting models as the variations of the ANN model were the slightest. For the cases of summer days and the winter cloudy day, DElight generally predicted the illuminance higher than the RADIANCE results while Daysim generally predicted the illuminance lower than the RADIANCE results. On the winter sunny day, all the daylighting simulations show a relatively greater difference. The reason is that the window was receiving direct sunlight in most hours of that day when the selected day is near the winter solstice. However, the difference between RADIANCE and the ANN model is much smaller than the difference between RADIANCE and other daylighting simulations. Therefore, the prediction illuminance by the ANN model is considered as more realistic results than the prediction by EnergyPlus and Daysim in all test scenarios.

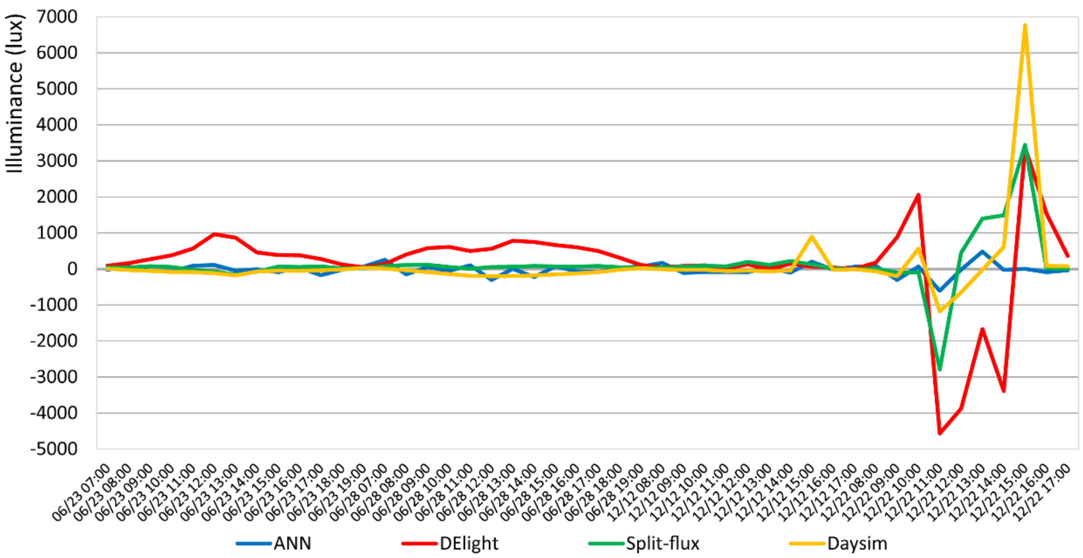


Fig. 14 Illuminance difference between RADIANCE and other daylighting models

The relative error of the result of each time step was determined by the illuminance percentage error (IPE) [46] according to the equation as follow:

$$IPE = \frac{|P(i) - R(i)|}{R(i)} \tag{3}$$

As shown in Fig. 15, 69.6% IPEs of the ANN prediction model are less than 15%. Only a few IPE are above 30%. Therefore, the ANN model can predict the illuminance value in an acceptable range compared with the RADIANCE model. It is noteworthy that there are two IPEs of the ANN model were over 100%. On June 28th at 7:00 am, the IPE is 132.1% while on December 12th at 8:00 am, the IPE is 318.5%. Those results indicate that the trained ANN model may show uncertainty when the sun has just risen up and the solar intensity is quite small. The percentage of all cases which the IPEs of different approaches fell in the particular range of errors were listed in Table 8.

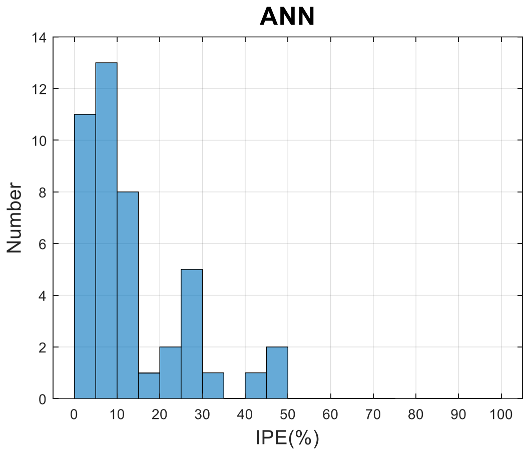


Fig. 15 Distribution of the illuminance percentage error of the ANN model

Table 8. Distribution of the illuminance percentage error (IPE)

	0-5%	5-10%	10-15%	15-20%	20-25%	25-30%	30-35%	35-40%	40-45%	45-50%	>50%
ANN	23.9%	28.3%	17.4%	2.2%	4.3%	10.9%	2.2%	0.0%	2.2%	4.3%	4.3%
DElight	6.5%	2.2%	4.3%	2.2%	2.2%	10.9%	4.3%	2.2%	8.7%	4.3%	52.2%
Split-flux	21.7%	28.3%	26.1%	6.5%	4.3%	0.0%	4.3%	4.3%	0.0%	0.0%	4.3%
Daysim	10.9%	45.7%	15.2%	13.0%	8.7%	2.2%	0.0%	0.0%	0.0%	0.0%	4.3%

5.2 Energy simulation by using the coupling method

In the previous section, the ANN performance evaluation indicates that the ANN-based daylighting model can be used to represent the daylight behaviour of the vacuum PV glazing with more reliable prediction than DElight method and split-flux method in EnergyPlus. Because of the consistency of the lighting control strategy of the coupling method, the predicting daylight illuminance for all time steps when the sun is up can be used to substitute the daylighting calculation by EnergyPlus. Therefore, the lighting consumption calculation for the small office adopted the vacuum PV glazing can obtain more realistic results by implementing the coupling between the ANN daylighting prediction model and EnergyPlus. This section compared the lighting consumption determined by the ANN-based coupling method, EnergyPlus, and Daysim-based coupling method following the process illustrated in Fig. 11.

Fig. 16 shows the monthly lighting consumptions conducted by different approaches. It can be seen that the calculation of the lighting consumption by two different methods in EnergyPlus shows the same trend through a whole year. The monthly lighting consumption from the split-flux method are larger than which from the DElight method. For most months, the results from the ANN model are larger than the results from EnergyPlus. The monthly lighting consumptions determined by the coupling between Daysim and EnergyPlus are in close proximity to the results from split-flux method from February to November. The annual lighting consumption by the ANN model is 82.9 kWh, while the lighting consumption is 9.7% less by using the DElight method, and 5.3% less by the split-flux method. The Daysim-based coupling calculates 79.3 kWh of the lighting consumption, which is 4.4 % less than which of the energy simulation using the ANN-based daylighting prediction.

From the comparison of different daylighting simulations in the previous section, the overall MBE of the ANN model, Delight method, split-flux method and Daysim is -1.08%, 8.52%, 6.97% and 5.45%, respectively. The larger positive MBE suggests that the larger overestimation on the illuminance value by daylighting simulation. Consequently, the lighting consumption results determined by EnergyPlus and Daysim-based coupling are underestimated. The results of lighting consumption based on different approaches indicate how the daylighting prediction affects the calculation of the lighting consumption for the application of the vacuum PV glazing. The coupling between the ANN-based daylighting prediction model and the building energy simulation model enhanced the reliability of the energy simulation in terms of the lighting consumption by performing high accurate daylighting prediction.

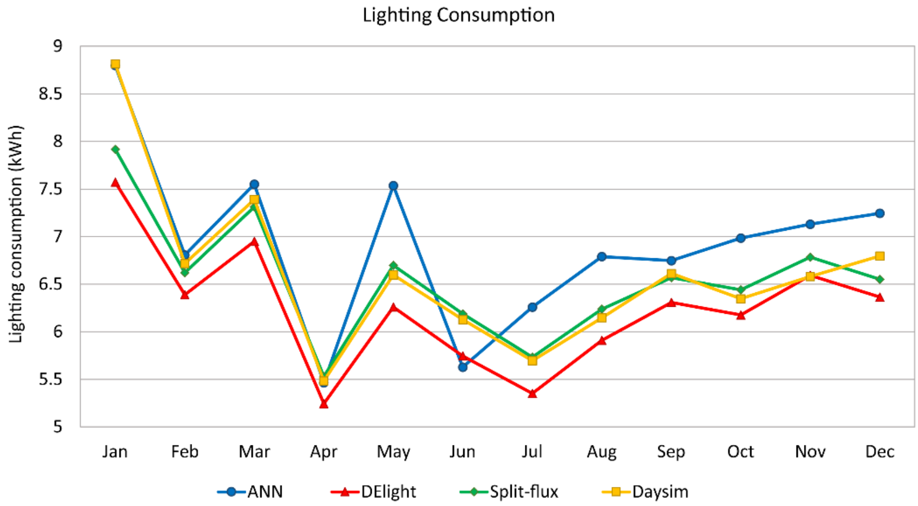


Fig. 16 Monthly lighting consumption based on ANN prediction, EnergyPlus, and Daysim

6. Conclusions

In this study, an artificial neuron network (ANN) coupling method was developed to integrate the advanced daylighting prediction model into the building simulation model to investigate how the complex daylight behaviour of the three-layer vacuum cadmium telluride photovoltaic glazing affects the lighting consumption. The primary conclusions of this study are as follows:

1. The validated RADIANCE model can be used to simulate the direct and diffuse light passing through the vacuum PV glazing under given lighting. The validation results of the relative divergences of illuminance between the simulations and measurements were within 0.3% - 1.5%. This method can also be used on other advanced PV glazings for further daylight simulation instead of the measurements by

spectrophotometer. However, massive computation time is required for a whole year simulation by RADIANCE. For each time step, it consumed 132 seconds on average. Therefore, it is inefficient to couple the RADIANCE model with building energy simulation directly.

2. The ANN daylighting prediction model reduces the computation cost dramatically. The training process only required 364 datasets as the typical daytime hours through a whole year instead of in total 4379 time steps when the sun is up in Hong Kong. The computation time of the daylighting simulation can be significantly reduced by using only 8.3% of simulation time.

3. The well-trained ANN model predicts the illuminance values with high accuracy and stability compared with the daylighting calculation methods in EnergyPlus. For the prediction performance of the ANN model, the overall mean bias error (MBE) is -1.08% and the coefficient of variation of root mean square error (CvRMSE) is 9.01% while most of the illuminance percentage errors are within 15%. Whereas, the daylighting calculations in EnergyPlus generally predict the illuminance with larger value than the RADIANCE simulation results. Consequently, the lighting consumption calculation based on the ANN-based coupling method will obtain more realistic results than other methods.

4. The comparison of the lighting consumption based on different approaches indicates that EnergyPlus tends to underestimate the lighting consumption compared with the ANN-based coupling method. The lighting consumption is 9.7% and 5.3% less by using the DElight method and split-flux method, respectively.

This paper demonstrated the strength of the integration of the ANN prediction model with energy simulation tools. For the application of complex glazing systems, such as the three-layer vacuum PV glazing, the well-trained ANN model can provide more reliable daylighting prediction than the available methods by EnergyPlus and also save the computational cost compared with the physical-based daylighting simulation by RADIANCE. It is also found that the prediction error of a specific time step may be relatively large when the inputs are from extreme weather conditions. For future work, a sensitivity analysis can be applied to investigate the influence of the selection of the inputs. Moreover, the potential of the ANN model can be enhanced by developing an adaptive ANN model which can be used in different locations with different climate conditions and dynamic coupling the ANN model with the whole building energy simulation tool. This method can be used to further investigate the correlation between the daylighting performance of the vacuum PV glazing and different locations with different climates.

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