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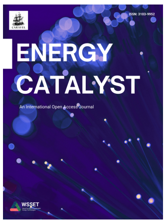

Review article

A Review on Daylighting Prediction by Using Artificial Neural Network Techniques

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ABSTRACT

Daylighting is a key renewable strategy in sustainable building design, reducing energy use while improving visual comfort and productivity. However, predicting daylight performance is complex due to nonlinear interactions among many variables, limiting traditional methods such as physical models, equations, and simulations. Artificial Neural Networks (ANNs) have emerged as an effective alternative. This paper reviews ANN applications in daylight prediction and proposes a framework for algorithm selection, evaluation, and optimization, along with future research directions. The aim is to support more effective use of Artificial Neural Networks in building energy efficiency and luminous environment design. The advantages of using artificial neural networks for daylighting prediction include three aspects: Firstly, the prediction accuracy of ANNs is significantly better than that of traditional empirical models, enabling effective handling of complex nonlinear relationships within daylighting systems. Secondly, ANNs have high computational efficiency, which allows for a rapid real-time response after training, making them suitable for dynamic daylighting control and large-scale design optimization. Finally, the strong coupling capability of ANNs facilitates the integration of multi-dimensional variables including building geometry, meteorological conditions and occupant behaviours, thereby supporting the coordinated optimization of lighting and HVAC systems. In this paper, the state-of-the-art of the application of ANNs in predicting daylighting performance, which covers solar luminance and illuminance, daylighting control scheme and energy saving strategies, is presented. Strengths by using ANNs are highlighted and evaluated. Moreover, the research gaps have been identified and discussed. Further improvement for accuracy of ANNs and its application in daylighting study are suggested.

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1. INTRODUCTION

Artificial lighting consumes around 20% of global generated electricity (Chirarattananon, Chaiwiwatworakul, & Pattanasethanon, 2002). Therefore, exploring novel techniques that could replace artificial lighting has been attracting massive interest in sustainable building designs. Daylighting has been considered as an effective sustainable technique, which has significant potentials to replace artificial lighting,

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leading to vast benefits to view comfort and health of occupants and hence benefits to economy and society as well. Compared to artificial lighting, daylighting can reduce the consumption of electrical energy and hence the greenhouse gas emission produced by the conventional electricity generation. Moreover, according to psychology, occupants prefer daylighting more than artificial lighting due to its vivid colour rendering to offer visual comfort and delightful environment, which promote the productivity and health of occupants (Baker, Fanchiotti, & Steemers, 2013).

The conspicuous contribution of daylighting has been confirmed in a number of literatures. In terms of energy saving, Li and Tsang (Danny H. W. Li & Tsang, 2008) surveyed 35 open layout office buildings in Hong Kong and found that 20-25% of electric lighting energy can be saved with appropriate fenestration and daylighting control. Moreover, McHugh et al. (McHugh, Pande, Ander, & Melnyk, 2004) estimated that around annual 24,000 GWh electric power could be reduced by appropriate photo controls under skylights for 5.388 billion m^2 of commercial floor area in the US. Other researchers revealed that the European Community annual CO_2 emission could be reduced by 223 million tonnes using passive solar design (Alrubaih et al., 2013; Sayigh, 2012). In a cooling-dominant building, using natural lighting could significantly reduce heat dissipation caused by artificial lighting hence reduce the cooling demand (M. Bodart & De Herde, 2002). Furthermore, it has been identified that occupants normally prefer varying levels of natural lighting cycle rather than constant artificial light (Begemann, van den Beld, & Tenner, 1997). The benefits of psychological aspect of natural light have also been demonstrated (A. Nabil, 2005; Boyce, 2010; Hua, Oswald, & Yang, 2011; Veitch & Gifford, 1996).

Daylighting prediction is a key of daylighting design for buildings. It would be ideal to forecast the daylighting performance accurately before a real daylighting design is adopted in light of cost effectiveness. In particular, accurate prediction of daylighting performance can bring dramatic benefits in the cases where expensive and/or innovative technologies or systems are employed (I. L. Wong, 2017). However, accurate daylighting prediction is not an easy task because there are usually a large number of underlying parameters affecting the performance of daylighting. The variables can vary from geographical location, time in a day or a year, local sky conditions and architecture geometries and features. Early work about daylighting prediction employ scale model and mathematic formulae to evaluate the daylight level. In the past decades, computer software has been widely used to simulate the daylighting performance as well. However, due to the varying and non-linear nature of daylighting parameters, the above-mentioned analysis methods considerably rely on long-time measurement or exhaustive data to evaluate the daylighting performance, which are time and labour consuming. Recently, a new and attractive method based on ANNs in predicting daylighting performance has been introduced, which has convincing advantages in solving multi-variables problems (Inchio Lou, 2012).

In the last two decades, ANNs have been applied in various fields of research, for example, heat transfer in nuclear engineering (Cong, Su, Qiu, & Tian, 2013), sizing of solar photovoltaic systems (Mellit, Kalogirou, Hontoria, & Shaari, 2009), refrigeration, air conditioning and heat pump systems (Mohanraj, Jayaraj, & Muraleedharan, 2012), modelling and control of combustion processes (Kalogirou, 2003), modelling of renewable energy systems (Kalogirou, 2001), chemical process control (Hussain, 1999), thermal analysis of heat exchangers (Mohanraj, Jayaraj, & Muraleedharan, 2015), forecasting (Zhang, Eddy Patuwo, & Y. Hu, 1998), and application in the atmospheric sciences (Gardner & Dorling, 1998). In the field of architecture and built environment, ANNs have been used to analysing cooling and heating in buildings, electricity usage, sub-level components operation and optimization, and parameters estimation. Compared to other methods, ANNs can provide speedy, simply and more accurate prediction. Therefore, it would be very useful to present a state-of-the-art of ANNs application in daylighting prediction. It is in this regard this paper is presented.

This paper attempts to review all the possible methods available for daylighting prediction with a special focus on the potential application of ANNs, as shown in Figure 1 (the dashed area is the methods presented in this article). In particular, a discussion will be made to identify potential research gaps. The work builds upon the literature review originally presented in the author's doctoral thesis (Zhang, 2021), which has been revised and updated tor journal publication. This paper is structurally arranged as follows: firstly, various available daylighting prediction methods are summarised and their strengths and weaknesses are discussed; secondly, ANNs predication models in luminance and illuminance, control systems and energy savings are evaluated; thirdly, research gaps are discussed; finally, the conclusions are presented.

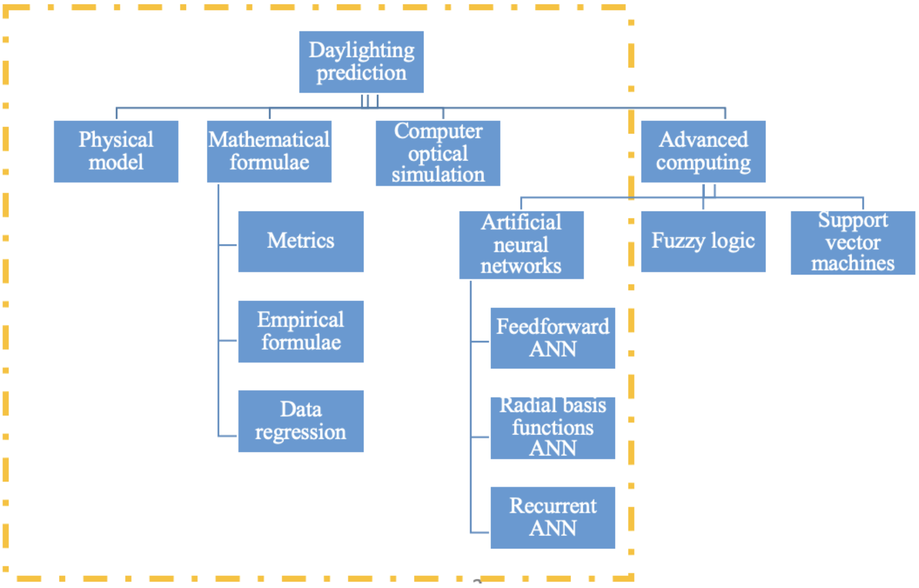


Figure 1. Typical methods for daylighting predictions.

2. DAYLIGHTING PREDICTION METHODS

This section presents an overview of existing daylighting prediction methods including physical model, mathematical formulae, computer simulation and ANNs, followed by discussions on the strength and weakness of each method.

2.1. PHYSICAL MODEL

Physical model has been implemented for centuries to evaluate the illuminance quality in the interior of buildings (Magali Bodart, Deneyer, De Herde, & Wouters, 2007). The models are usually made of card, wood or plastics. The accuracy of evaluation highly depends on measurement position, model geometry and manufacturing details, especially the surfaces reflectance, fenestration and glazing transmittance. The experiment is usually undertaken under the real sky conditions or Commission Internationale de L'Eclairage (CIE) artificial sky.

Littlefair (Littlefair, 2002) proposed a scale model to predict daylight level within an atrium building. It evaluated the performance of an atrium and the illuminance level of neighbouring space. Kim et al. (C.-S. Kim & Chung, 2011) built a 1:20 scale model for measuring indoor illuminance of Seoul Art Museum installed with toplights. With the scale model, the building details, including façade, textures, furniture and inner layout or figures, can be considered. A case study has been done by Aghemo et al (Aghemo, Pellegrino, & LoVerso, 2008) to simulate daylight environment of a high school classroom with various shading system in Italy. By simulating different sky conditions and sun paths, the best shading scheme can be determined. Some rules should be followed in order to get accurate results (Magali Bodart et al., 2007; Littlefair, 2002). General regulations include using original building structure and geometry, preventing light leaking, and choosing the same material property. Further, specialized rules include using appropriate model size and scale varying from 1:500 to 1:1 based on different modelling purpose, the test sensor size and position in the model, etc. The advantage of this method is able to analyse the daylighting performance quantitatively and qualitatively at the same time. Normally, the daylight factor can be measured by photocells and visual impact could be directly presented. However, several studies have revealed that it is difficult to completely match the results from the physical models to those from the actual buildings. Further, it has been found that the daylighting performance in physical models tends to be overvalued. Therefore, using the scaled physical model alone would not be a reliable option.

2.2. MATHEMATICAL FORMULAE

The use of mathematical formulae is another useful method in predicting daylighting performance. This approach may be applied at three different levels, basic metrics, empirical formulae, date regression model.

Daylight factor (DF) is one of the most accepted and basic daylighting performance indicator, as defines below,

$$DFv = \frac{E_{in}}{E_V} = \frac{LT \times A_w}{A_{in} \times (1 - R)} \tag{1}$$

where E_{in} is the average illuminance on all room surfaces, E_V is the vertical illuminance on the window, LT is the light transmittance of glass, A_w is the area of the window, A_{in} is the total area of the indoor surfaces, and R is the area-weighted mean reflectance of all indoor surfaces (Danny H. W. Li & Lam, 2001). DF is the most widely used metrics of daylighting and adopted as a design criteria in relevant industry standards and guides (Kittler, 2007). As the DF is defined for the overcast sky condition, it does not need to consider the building orientation and location, so it is easy to be determined analytically. However, the solar angles and redirection of sunlight are not considered in the formulation of the DF. This often causes problems if the DF metrics is used for prediction under other sky conditions rather than the overcast sky.

The DF value is generally for certain point, to estimate the average illuminance on a working plane. Littlefair (Littlefair, 2002) introduced the concept of average daylight factor (DF_{AV}) and gave an empirical formula,

$$DF_{AV} = \frac{WT\theta}{A(1-R^2)} \tag{2}$$

where W is the glazing area (m^2), T is the transmittance of the glazing and θ is the angle of visible sky at the centre of the window. A is the total area of room surfaces, including roof, floor, walls and windows (m^2). R is the average reflectance of these surfaces. Similar to Eq. (1), this formula for daylight is easy to use but it summarises the overall daylighting performance. Love and Navvab (1994) proposed a new metrics as an indicator of daylighting performance, which is the vertical-to-horizontal illuminance ratio (VH ratio) (Love & Navvab, 1994), that is, the ratio between the illuminance value on a vertical window and outdoors horizontal illuminance value as given by Equation 3. They found that the VH ratio is more stable than the DF under real sky conditions, so more suitable to be used to estimate the illuminance and determine the glare.

$$VH = \frac{E_V}{E_H} \tag{3}$$

Besides these basic formulae, advanced mathematical equations can also be extrapolated based on measurement or theoretical derivation. Kim et al. (S.-Y. Kim & Kim, 2007) used multiple linear regression method to build a mathematical model to forecast the fluctuation of external daylight illuminance. Kazanasmaz (Kazanasmaz, 2013) used the fuzzy logic model to examine the uniformity of daylight illuminance in an office. In recent years, for advanced daylight guide and transmission systems, some mathematical models were put forward to predict the daylighting performance of a system. Su et al. (Su, Khan, Riffat, & Gareth, 2012) proposed a regression model to forecast the output lumen value of a light pipe. Moreover, both (Swift & Smith, 1995) and (Dutton & Shao, 2007) explore the mathematical model to predict the transmission of light pipes.

2.3. COMPUTER OPTICAL SIMULATION

Compared to physical model and mathematical formulae, computer optical simulation combines the benefits of both illuminance calculation and interior visualization (Littlefair, 2002). Moreover, it does not require any physical materials, which is economic, and environment friendly while significantly saves time. Computer simulation can also be much more accurate in certain cases. Radiosity and raytracing are the fundamental methods to calculate illuminance in computer simulation. Radiosity analyses simple surfaces with diffuse element method while raytracing technique deals with complex surfaces with specular reflection (Kazanasmaz, Günaydin, & Binol, 2009). The common computer modelling tools include RADIANCE, LightTools, Photopia, TracePro, EnergyPlus, IES, DAYSIM, Ecotect, Relux, Dialux, Lightsolve, ADELINE, CODYRUN, SkyCalc, Autodesk, SPOT Pro, Lightscape, RadioRay, Microstation, etc.

Those computer software packages have been used extensively in the recent years to predict daylighting performance and evaluate daylighting designs. For instance, Jovanović et al. used DAYSIM to calculate DF, daylight autonomy (DA) and useful daylight illuminance (UDI) (Jovanović, Pejić, Djorić-Veljković, Karamarković, & Djelić, 2014). Li et al. used RADIANCE to simulate the illuminance value in different categories of buildings (Danny H. W. Li & Tsang, 2008). Similar studies could be found in literatures (Apian-Bennewitz, Goller, Herkel, Kovach-Hebling, & Wienold, 1998; C.-S. Kim & Chung, 2011; Krüger & Dorigo, 2008; Lim, Kandar, Ahmad, Ossen, & Abdullah, 2012). Meanwhile, numerical software is also used to guide daylighting design. Andersen et al. employed Lightsolve to simulate the annual daylighting performance, which provided an ideal and reliable design guide for daylighting design in buildings (Andersen, Gagne, & Kleindienst, 2013). Similarly, Gagne et al. used Lightsolve Viewer (LSV) for daylighting design and set up an interactive expert system to explore geometries of daylighting and performance goal in initial design stage (Gagne, Andersen, & Norford, 2011). Kota et al. (Kota, Haberl, Clayton, & Yan, 2014) integrated BIM tool in Revit with Radiance and DAYSIM to simulate the daylighting situation.

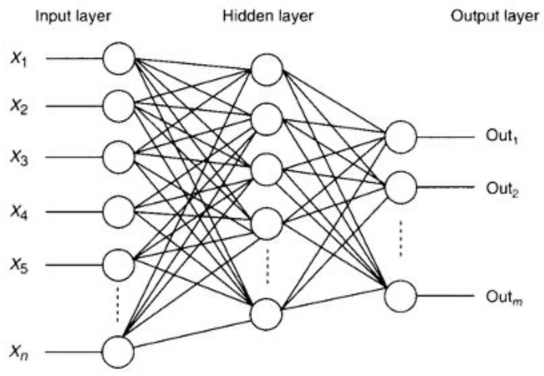
In addition, some studies integrated two or more different types of numerical tools to simulate the daylighting level and predict energy saving. It has been reported in (M. Bodart & De Herde, 2002), which coupled ADELINE to simulate daylighting and TRNSYS to simulate thermal condition and found that 50% to 80% artificial lighting could be reduced by daylighting which can save 40% energy cost. Chen et al. used Ecotect and RADIANCE to simulate the daylighting value and distribution (Chen et al., 2014). Meanwhile, EnergyPlus was used to determine the potential energy saving and some studies can be found in (Arranz, Rodríguez-Ubiñas, Bedoya-Frutos, & Vega-Sánchez, 2014; Galasiu & Atif, 2002; Loutzenhiser, Maxwell, & Manz, 2007; McHugh et al., 2004; Sabry, Sherif, Gadelhak, & Aly, 2014; Tian, Chen, & Chung, 2014).

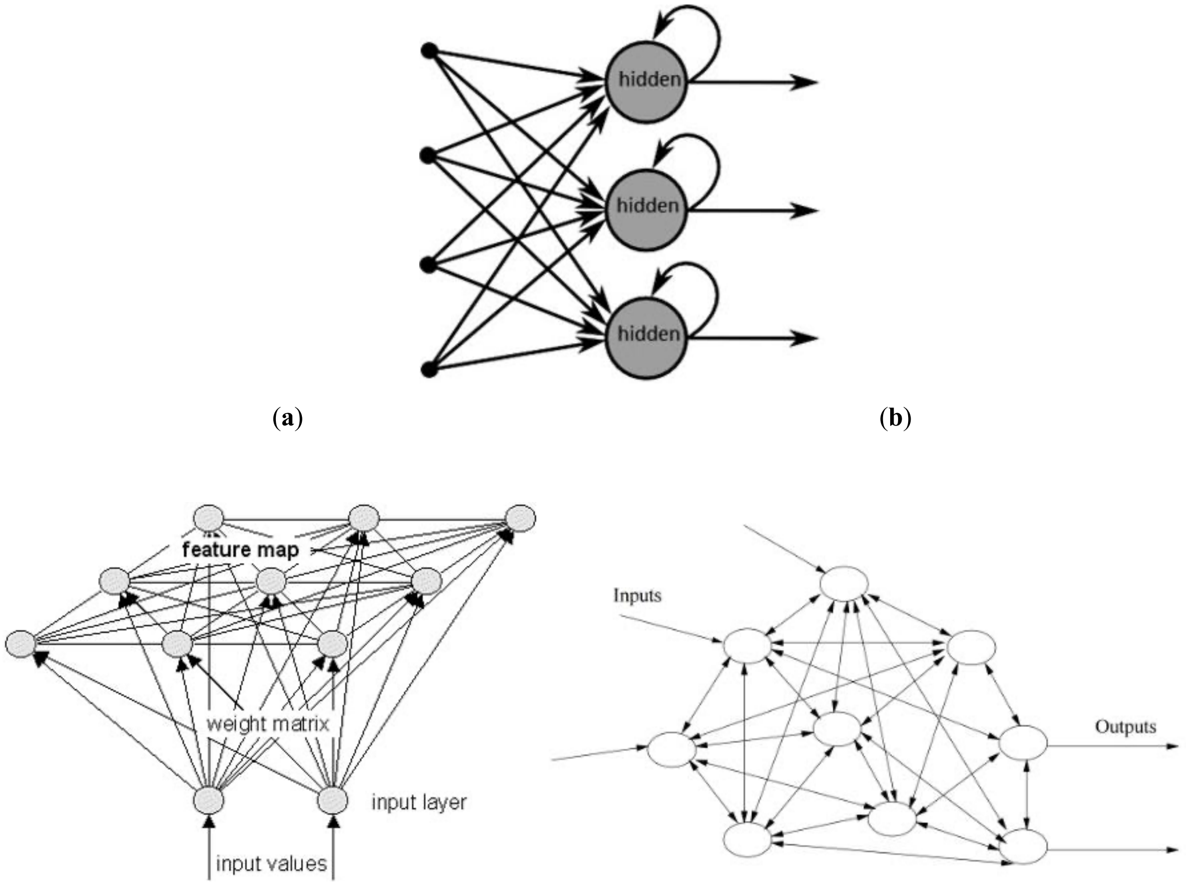
Moreover, simulation techniques have been intensively used in recent years in evaluation of new daylighting systems and technologies. Acosta et al. (Acosta, Navarro, & Sendra, 2013) employed Lightscape to simulate three different shapes of lightscoop skylights in order to choose a proper shape. Dutton et al. (Dutton & Shao, 2007) used Photopia raytracing to predict the lightpipe transmittance. Ullah et al. (Ullah & Shin, 2014) used LightTools and Dialux to simulate inner illuminance quality in multi-floor office buildings with installation of an innovative daylighting system which combines LED light with a highly concentrated optical fibre-based daylighting guide system. Page et al. (Page, Scartezzini, Kaempf, & Morel, 2007) used the raytracing method in RANDIANCE to simulate the visual comfort and performance of an office building installed with electrochromic glazing coupled with an anidolic daylighting system.

2.4. ARTIFICIAL NEURAL NETWORK

Different from conventional computational methods, ANNs simulation does not require building up any physical model. During the past three decades, ANNs has been used as an alternative approach to conventional prediction methods in many research areas. ANNs is a powerful tool in solving complex and non-linear problems in a number of fields by the means of simulation, identification, prediction, optimization, classification and control.

The ANNs simulation is a self-learning and self-training platform or programme. According to different network structures, ANNs models can be classified into 4 categories: Feedforward Neural Network, Feedback Neural Network, Self-organizing Map and Random Neural Network (as shown in Figure 2). Most of categories are straightforward applications of optimization theory and statistical estimation (Esen, Ozgen, Esen, & Sengur, 2009). ANNs can model multi-variable problems while extracting the non-linear complex relationships between the variables by means of training data. In the meantime, the performance of ANNs could be evaluated by some routine statistics indexes as shown in Table 1, which represent the accuracy of forecasting. These indexes would be used in section 3 to evaluate the ANN prediction ability.





(**a**) (**b**)

(c) **(d)**

Figure 2. Four categories of ANNs models **(a)** Feedforward Neural Network, **(b)** Feedback Neural Network, **(c)** Self-organizing Map, **(d)** Random neural network. (Agatonovic-Kustrin & Beresford, 2000).

Table 1. Statistics indexes to evaluate ANNs' prediction accuracy (Lewis).

Criteria	**Abbreviation**	**Accuracy preference**
Mean Absolute Error	MAE	value ≤10%, High
Mean Absolute Percentage Error	MAPE	10%≤value≤20%, Good
Mean Squared Error	MSE	20%≤value≤50%, Reasonable
Root Mean Square Error	RMSE	value ≥50%, Inaccurate
Mean Bias Difference	MBD	
Normalised Mean Bias Error	NMBE	
Coefficient of Variation of the RMSE	CVRMSE	
Correlation Coefficient	R	The closer to 1, the more accurate
Squared Correlation Coefficient	R^2	
Nash-Sutcliffe Efficiency Coefficient	NSEC	

Due to different strengths and requirements, different networks could be used in various fields. Almost all relevant researches in literature used the backpropagation (BP) neural network and its variants, which belongs to feedforward neural network category. BP neural network model is illustrated in Figure 3. It is one of the widest applications of ANNs and it is quite convenient and accurate. In fact, it is hard to determine the fastest training algorithm for a given problem. Instead, the most suitable one is always determined by the method of trials and errors. The BP neural network is normally composed of three components (Esen, Inalli, Sengur, & Esen, 2008). These parts usually consist of one input layer, some hidden layers and one output layer, as shown in Figure 3. Within each layer, there are a certain number of neurons. The procedure for developing an ANNs model includes 3 phases including modelling, training and validating. First, modelling involves analysing data, identifying input parameters and selecting network architecture and internal rules. The prepared data can then be trained, for example, by using BP learning algorithm to establish a model. After the training of data and the establishment of the model, it should be validated before application. BP algorithm is a gradient descent method. The principle is that they are processing elements (PEs) and each connection of them has an associate weight. Each time it reduces the total error by changing the weights along its gradient to improve the performance of the network (Nasr et al., 2003). The process of an ANNs simulation starts with weighted summation activation of the neuron through its incoming connections; it is then followed by passing through an activation function and this activated value is the output of the neuron (Kalogirou, 2001). Specifically, training BP model should assign random values to the weight terms (w_{ij}) in all nodes initially. For the output layer for the case of the logistic-sigmoid activation (as shown in Figure 4), the error can be computed as follows:

$$\delta_{pi} = (t_{pi} - \alpha_{pi})\alpha_{pi}(1 - \alpha_{pi}) \tag{4}$$

For a node in a hidden layer:

$$\delta_{pi} = \alpha_{pi}(1 - \alpha_{pi}) \sum k\delta_{pk}w_{kj} \tag{5}$$

where the subscript k is a summation over all nodes in the direction of the output layer. The subscript j is the weight position in each node. Moreover, δ and α for each node are used to calculate an incremental change to each weight via:

$$\Delta w_{ij} = \varepsilon(\delta_{pi} - \alpha_{pj}) + mw_{ij}(old) \tag{6}$$

where ε is the learning rate which determines the size of the weight adjustments during each training iteration and *m* is the momentum factor which is applied to the weight change used in the previous training iteration. The values of ε and *m* are determined prior to the training cycle and controls the speed and stability of the simulation (Kalogirou, 2003).

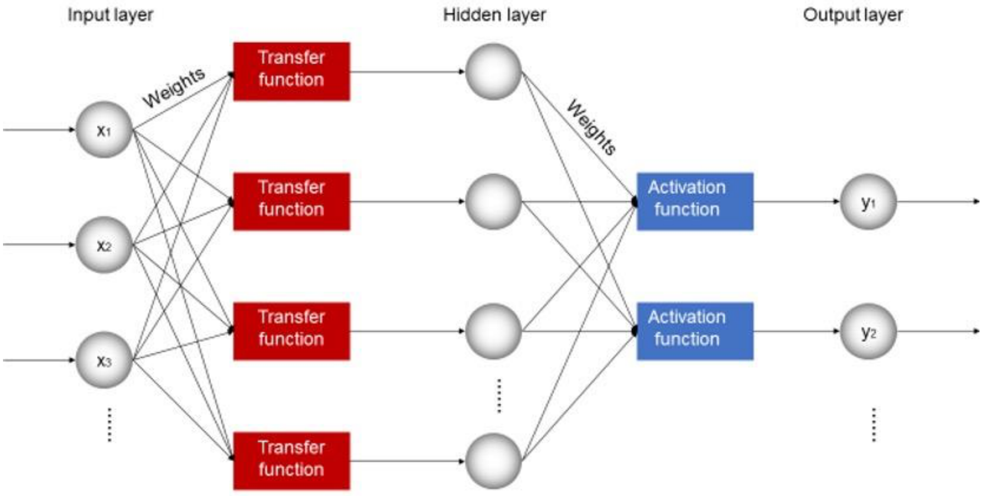


Figure 3. The typical sample of multilayer feedforward neural networks (Katz, Snell, & Merickel, 1992).

In light of non-linear problems, the sigmoid function is the most common logical transfer function in BP algorithm. It includes tansig and logsig algorithms (sometimes purelin algorithm is also used as the transfer function, but it is linear function which is less commonly used) (Hosseini, 2016). They are both an "S" shaped transfer function, logsig ranging from 0 to 1 and tansig ranging from -1 to 1, which can be expressed in Figure 4.

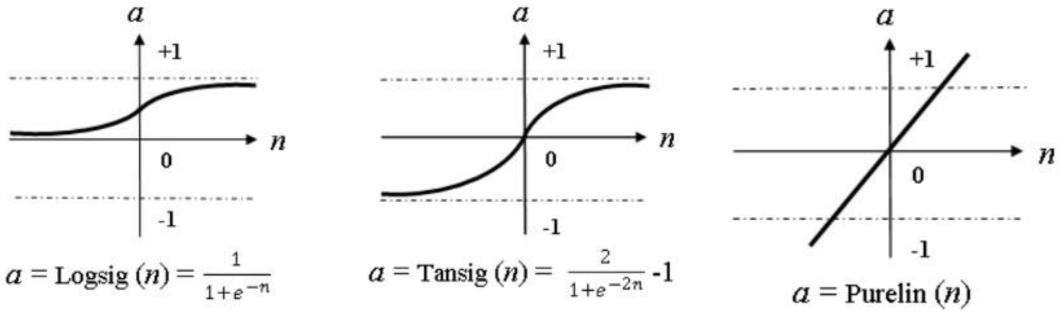


Figure 4. Transfer function used in the neural network (Hosseini, 2016).

Normally, 70% to 90% of dataset is used in training the model and the remaining dataset is used to test and validate the model. Relevant application of ANNs predictions in daylighting would be elaborated in Section 3.

2.5. COMPARISON OF DIFFERENT PREDICTION METHODS IN DAYLIGHTING

These prediction methods all have their advantages and disadvantages in different aspects, while they may also be used together for some specific problems. In this section, the strengths and shortcomings for each prediction method are summarized in Table 2.

Table 2. Summary of typical methods for daylighting prediction.

Methods	Tools	Strengths	Shortcomings
Physical model (Aghemo et al., 2008; Magali Bodart et al., 2007; CIBSE, Nov 2014; Halliday, 2008; C.-S. Kim & Chung, 2011; Littlefair, 2002; Mardaljevic, 2012; Nick Baker, 2013)	Card, wood, plastic etc.	● The daylighting performance is physically visible; ● Building geometrical and façade details could easily be formed; ● It is a cheaper and easier method that many people could use; ● Easier to make and handle.	● Too many rules needed; ● Overestimate daylighting performance; ● Material and labour cost; ● Time consuming
Mathematical formulae (Dutton & Shao, 2007; Kazanasmaz, 2013; S.-Y. Kim & Kim, 2007; Danny H. W. Li & Lam, 2001; Littlefair, 2002; Love & Navvab, 1994; Moon, 1942; Reinhart & Walkenhorst, 2001; Su et al., 2012; Swift & Smith, 1995)	E. g. $DFv = \frac{E_{in}}{E_V} = \frac{LT\times A_W}{A_{in}\times(1-R)}$; $DF_{AV} = \frac{WT\theta}{A(1-R^2)}$; $VH = \frac{E_V}{E_H}$ etc.	● Quickly estimate the daylighting performance; ● No cost in materials; ● Easier and quick to operate for designers.	The accuracy is low, so the results always need to be corrected.
Computer simulation (Acosta et al., 2013; Andersen et al., 2013; Apian-Bennewitz et al., 1998; Arranz et al., 2014; M. Bodart & De Herde, 2002; Chen et al., 2014; Dutton & Shao, 2007; Gagne et al., 2011; Galasiu & Atif, 2002; Jovanović et al., 2014; Kazanasmaz, 2013; Kazanasmaz et al., 2009; C.-S. Kim & Chung, 2011; Kota et al., 2014; Krüger & Dorigo, 2008; Danny H. W. Li & Tsang, 2008; D. H. W. Li, Wong, Tsang, & Cheung, 2006; Lim et al., 2012; Littlefair, 2002; Loutzenhiser et al., 2007; McHugh et al., 2004; Page et al., 2007; Sabry et al., 2014; Tian et al., 2014; Ullah & Shin, 2014)	RADIANCE, LightTools, Photopia, TracePro, EnergyPlus, IES, DAYSIM, Ecotect, Relux, Dialux, Lightsolve, ADELINE, CODYRUN, SkyCalc, Autodesk, SPOT Pro, Lightscape, RadioRay, Microstation, etc.	● Cost effective; ● Complex analysis; ● Deal with a huge number of variables	● Designers need to have strong background; ● Time consuming to build models and simulations with variable parameters; ● Computationally expensive
ANNs	Refer to following Section 3		

3. APPLICATION OF ARTIFICIAL NEURAL NETWORKS TECHNIQUES IN DAYLIGHTING PREDICTION

In this section, the techniques and applications of ANNs as a predication tool in daylighting are critically discussed. It mainly covers luminance and illuminance forecasting, daylighting performance combined with energy saving scheme and control system.

3.1. Luminance and Illuminance Prediction

3.1.1. External luminance prediction

Before designing a daylight dominating building, surveying the daylighting environment to estimate whether enough daylight could be utilized is prime. Janjai et al. have demonstrated that ANNs presented outstanding prediction performance compared with CIE models; meanwhile this study filled the gap with no research employing ANN to predict sky luminance in tropics (Janjai & Plaon, 2011). They chose two cities Nakhon Pathom and Songkhla in Thailand as the measurement locations to obtain the 3-year period (2007-2009) of sky luminance data by utilising EKO sky scanners in monitoring stations. These data according to CIE classification was intentionally selected and grouped into clear, partly cloudy and overcast skies weathers. The study was divided into three stages: first stage, 2007-2008 data from Nakhon Pathom was used to train a new ANN model; second stage, 2009 data of Nakhon Pathom was used to test ANN model and CIE model; finally, data from Songkhla was used to validate the performance of ANN and CIE model.

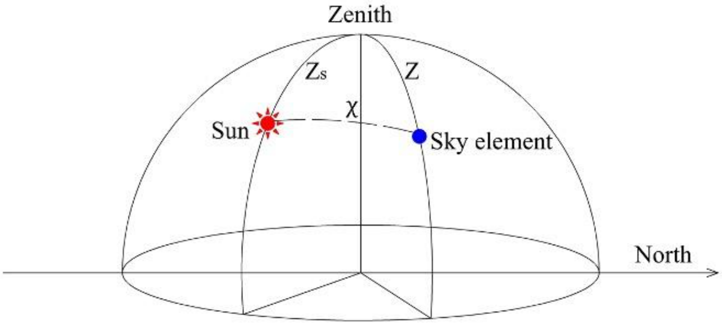


Figure 5. Diagram to explain various zenith angles and the angular distance.

In their ANN modelling, the input parameters include the zenith angle of the sun (Zs), the zenith angle of the sky element (Z) and the angular distance between sun and sky element (χ), as shown in Figure 5, and the sky luminance (L) is the only output. A multi-layer with BP algorithm was used to train the model. RMSE and MBD were chosen to evaluate the deviation between ANNs model and CIE model. The performance values of the ANNs and CIE model are listed in Table 3. It has been proved that the ANNs model performed more accurate analysis than conventional CIE model. In Songkhla, for the case of overcast (CIE 4), the ANN model presented stronger prediction power with RMSE 17.4% and MBD 1.7% compared with CIE 31.8% and -7.3% respectively. Moreover, for clear sky (CIE 13), the RMSE and MBD of ANN model were 31.0% and 3.3% respectively while these for CIE were 37.9% and 3.3%. In terms of partly cloudy (CIE 7, 8, 10) sky, ANN model presented slightly better than CIE model in forecasting sky luminance.

Table 3. The performance of ANN and CIE model for predicting the sky luminance between predicted and measured data in Nakhon Pathom and Songkhla (Janjai & Plaon, 2011).

CIE	**Nakhon Pathom**				**Songkhla**			
	RMSE (%)		**MBD (%)**		**RMSE (%)**		**MBD (%)**	
	ANN	**CIE**	**ANN**	**CIE**	**ANN**	**CIE**	**ANN**	**CIE**
Overcast								
CIE 4	17.4	31.8	1.7	-7.3	17.1	39.6	6.7	0.7
Partly cloudy								
CIE 7	41.9	39.7	-4.3	-5.2	36.3	29.5	4.2	1.7

CIE	**Nakhon Pathom**				**Songkhla**			
	RMSE (%)		**MBD (%)**		**RMSE (%)**		**MBD (%)**	
	ANN	**CIE**	**ANN**	**CIE**	**ANN**	**CIE**	**ANN**	**CIE**
CIE 8	46.3	49.8	-12.4	-12.3	42.2	40.2	-7.1	-6.8
CIE 10	41.2	47.9	2.5	-0.3	35.9	46.7	6.6	2.6
Clear sky								
CIE 13	31.0	37.9	3.3	-7.2	47.7	56.4	-1.3	-9.2

The prediction model of sky luminance, which only considers the solar position but neglects other effects, could cause the deviation of results. Hence, it would be important and versatile to measure the global radiation and develop a "non-local" model to survey the external illuminance. However, because of atmospheric variables, especially turbidity and water vapour, it is difficult to derive a common model, which could possibly consider all affecting components by conventional methods to determine the solar luminous efficacy. López and Gueymard developed a creative ANNs model to predict solar luminous efficacy components under clear sky conditions (López & Gueymard, 2007). In order to determinate the simplest input variables and optimized network architecture, but still keep high prediction accuracy of the model, they tried different combinations of 4 parameters, i.e., solar zenith angle (θ_z), perceptible water (w_p), diffuse fraction (κ) and direct transmittance (κ_b) to obtain direct (K_b), diffuse (K_d) and global (K_g) component of luminous efficacy as the output objectives at the same time. They also tried different network architecture by means of changing the number of neurons in hidden layers (Figure 6).

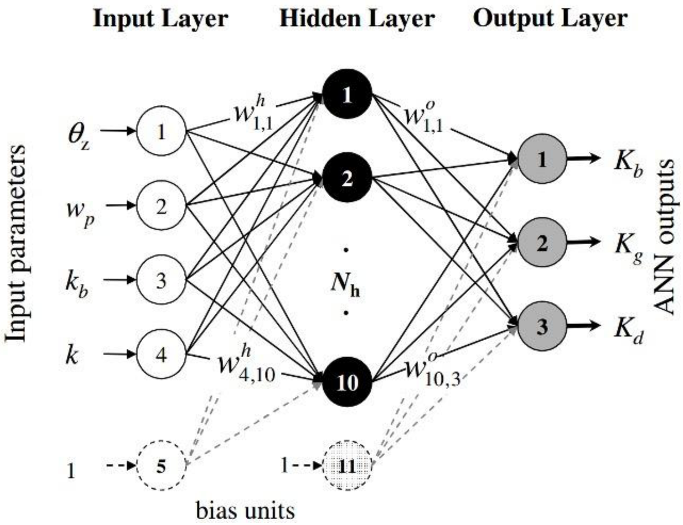


Figure 6. ANN model architecture (López & Gueymard, 2007).

As shown in Table 4, RMSE was used to evaluate the accuracy of the developed ANNs model. All the results showed that RMSE were around 9%, which demonstrated high prediction power. The research found that ANN models could also be used to test the sensibility of each input variable and perceptible water was the important influencing variable. Another interesting finding was whatever the removal of the solar zenith angle did not change the accuracy of prediction. However, removing this parameter means more account number hidden neurons are needed, which can make the model more complex. The study also investigated the impacts of different hidden neurons on the accuracy of the ANNs model. Although 13 hidden neurons slightly improved the prediction power of the ANNs model, it was far too complex and time consuming. Ten neurons were recommended as the proper model architecture for that problem, which has made the error lower than the experimental errors.

Table 4. The RMSE (%) of each ANN configurations (López & Gueymard, 2007).

N_h	**Inputs**								
	$\{\theta_z, w_p, \kappa_b, \kappa\}$			$\{\theta_z, \kappa_b, \kappa\}$			$\{w_p, \kappa_b, \kappa\}$		
	Outputs								
	K_b	K_d	K_g	K_b	K_d	K_g	K_b	K_d	K_g
22	1.4	1.8	1.6	6.4	3.9	4.8	2.0	2.9	2.9
17	1.7	1.9	1.7	6.8	4.0	4.9	2.1	3.0	2.9
13	2.0	2.1	1.8	6.9	4.4	5.2	2.4	3.1	3.0
10	2.1	2.5	2.4	7.4	5.0	6.0	2.7	3.4	3.4
7	3.4	3.1	2.6	7.8	5.0	5.9	3.7	3.7	3.5
5	4.6	4.5	4.1	7.9	5.9	6.3	4.7	4.5	4.1
3	7.4	5.0	5.3	9.2	6.5	6.8	7.6	5.0	5.3

* N_h is the number of hidden neurons in hidden layer.

Similarly, in order to determine natural illumination, Tíba et al. (Tíba & Leal, 2012) tried to calculate the hourly external luminous efficiency through the solar irradiation available. Illuminance measurement is not included in routine meteorological test in Brazil. Because of the lack of these information, an empirical formula was derived by Perez et al. (Perez, Seals, & Michalsky, 1993) to determine the luminous efficiency. This formula created a relationship between illumination and solar irradiation combined with some other meteorological data. Subsequently, in order to develop a model, which could use the global irradiation and routine measured data from meteorological station as input variables, ANN was chosen as the tool to predict the solar luminous efficiency. They chose dew point temperature, rain precipitation, darkness of sky, clearness index of Perez and index of transmittance as the input parameters and only export the hourly luminous efficiency as the output result. A multilayer perceptron (MLP) ANN was chosen to run the simulation (Figure 7). The results were used to compare with Perez model and Robledo model (Perez local calibrated model). Two cities of Recife and Pesqueira were chosen to test the accuracy of ANNs model and the Perez and Robledo model. The compared results were evaluated by the MBD and RMSE which were both lower than 5% as shown in Table 5.

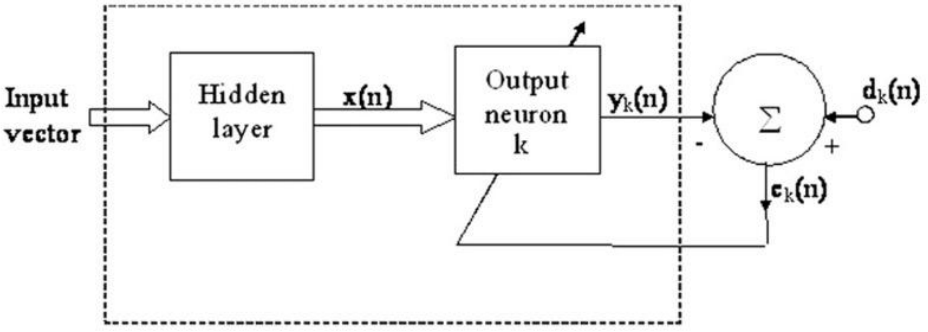


Figure 7. A diagram of MLP ANN model, which has been trained by supervised apprenticeship (Tíba & Leal, 2012).

Table 5. Performance of Perez, ANN, Robledo model (Tíba & Leal, 2012).

Location	**RMSE (%)**			**MBD (%)**		
	Perez	**ANN**	**Robledo**	**Perez**	**ANN**	**Robledo**
Pesqueira	3.7	3.6	7.2	-0.2	4.1	0.7
Recife	8.5	5.8	5.3	1.3	5.7	0.2

Pattanasethanon et al. (Pattanasethanon, Lertsatitthanakorn, Atthajariyakul, & Soponronnarit, 2008) compared the performance of an empirical sine model, a novel sine model and an ANN model to forecast the horizontal plane solar illuminance of all sky types at Mahasarakham in Thailand. Frequently used BP algorithm was used to training the ANN model. One-year data of solar altitude angle and the clearness index (ε)/sky ratio (SR) were chosen as the input data while global illuminance, global irradiance and diffuse irradiance on horizontal plane are the output targets. The RMSE, MBD and R^2 were used to evaluate the forecast ability simultaneously. Subsequently, the next half year data was used to test the ANN model. The prediction power was summarised in Table 6.

Table 6. Summary of prediction power of Sine, Novel sine and ANN model to illuminance (Pattanasethanon et al., 2008).

Sky condition	**Model (%)**	**Global illuminance**			**Global irradiance**			**Diffuse irradiance**		
		Sine	**Novel sine**	**ANN**	**Sine**	**Novel sine**	**ANN**	**Sine**	**Novel sine**	**ANN**
SR	MBD	11.6	10.8	0.08	12.8	12.5	3.00	12.2	12.7	7.64
	RMSE	12.5	14.8	10.8	19.3	23.3	15.93	15.5	19.92	8.78
	R^2	0.96	0.95	0.98	0.91	0.89	0.92	0.96	0.95	0.98
ε	MBD	3.8	4.5	3.7	3.93	4.50	3.79	4.46	5.50	4.33
	RMSE	4.5	11.8	3.8	15.7	19.50	14.52	16	20.45	9.08
	R^2	0.96	0.95	0.98	0.92	0.91	0.93	0.96	0.95	0.98

3.1.2. INTERNAL ILLUMINANCE PREDICTION

The ultimate goal of predicting external solar illuminance availability is to evaluate if there is enough daylight in interior space and the appropriate daylighting scheme to be used. Navada et al. (Sandhyalaxmi G Navada, 2016) developed 2 ANN models to predict the external and internal illuminance respectively. There were two different approaches demonstrated in this study. One is developing the ANN prediction model by using measured interior illuminance data which is similar to most other researches; and the other is utilizing Perez model (Perez et al., 1993) to convert obtained meteorological data to interior illuminance and then establishing the ANNs model. In Navada's model, a top floor room with dimension of 3.75 m × 3.75 m × 2.35 m and two blinded windows was built (Figure 8).

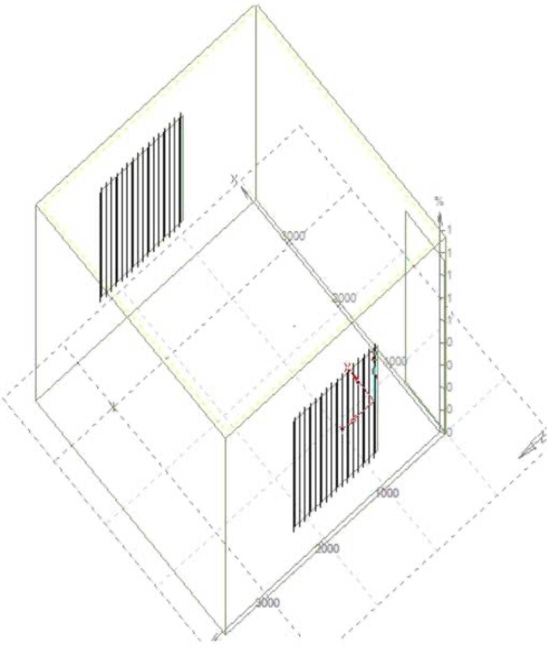


Figure 8. The sketch model of simulation room (Sandhyalaxmi G Navada, 2016).

The internal illuminance was measured at different blind positions at 0.8 m above the floor. The time series was from 9 am to 5 pm and the blind position changed from 0^{o} to 90^{o} (blind closed) with the increment of 15°. BP algorithm was employed as the learning algorithm. Two input variables were P (blind position) and T (times), while illuminance was the only output. The error of ANN prediction was always below 5%, which means ANN is a strong prediction tool. In the other meteorological method, 2009-2011 hourly solar irradiance from National Renewable Energy Laboratory (NREL) was converted to the outside illuminance by Perez model. Subsequently, according to the known luminance distribution and DF definition (i.e., Equation 1), the interior illuminance was calculated. The next will be the same to the first method, which used 2009-2010 data for training and 2011 data for validation of the ANNs model. The correlation coefficient R was around 0.97 for the ANNs prediction, which is generally good. Moreover, this study compared the performance of various prediction models, which is in order to obtain the most accurate results. The compared results are shown in Table 7.

Table 7. Compared results of various prediction methods (Sandhyalaxmi G Navada, 2016).

Time	% Error Forecast method	Time series prediction	Nero excel predictor	Matlab code	Nntool
09:00	24.81	-0.70	0.43	2.15	2.54
09:30	34.86	-0.98	2.68	20.42	2.05
10:00	36.14	-4.03	-0.15	-1.05	-0.93
10:30	-28.43	-1.68	3.31	2.80	-4.98
11:00	-50.32	-6.34	5.91	3.77	1.89
11:30	-69.24	-6.28	3.58	3.68	5.24
12:00	-82.10	-7.46	-0.11	1.83	1.97
12:30	-90.28	-9.02	-2.73	1.06	-0.94
13:00	-86.47	0.07	1.98	3.53	4.23
13:30	-84.71	-3.70	0.26	0.29	1.89
14:00	-75.87	-2.07	2.94	2.18	3.71
14:30	-58.32	-2.05	5.20	2.99	1.13
15:00	-44.41	-1.93	5.47	3.57	-2.21
15:30	42.21	-4.57	-0.67	1.81	-0.19
16:00	42.20	-4.48	-0.28	0.15	-0.01
16:30	50.43	-0.14	4.84	4.45	7.37
17:00	-9.18	-4.04	-2.26	0.56	-1.04

Kazanasmaz et al. (Kazanasmaz et al., 2009) developed a more detailed model. This model considered comprehensive parameters, which may affect the illuminance level inside office buildings. The building was located in the Faculty of Architecture of the Izmir Institute of Technology in Izmir, Turkey. It is a 2-story building and both the ground floor and first floor were surveyed in this research. PeakTech lightmeter was used to measure the illuminance value of every point, which 0.5 m away from the boundary and 0.7 m high from the floor. The ANNs model consisted of three layers with 13 input and 1 output variables. Three categories data were chosen as input variables: 6 building parameters (orientation, geometry, windows amount, distance to windows, floor character, sensors' position), 2 time variables (date, hour) and 5 weather variables (solar radiation, UV index, UV dose, temperature, humidity) (Figure 9). The only one output was again the illuminance. In the simulation, 80% of the input data was used to train the model and 20% was used to validate. BP was still utilised as the learning algorithm. The innovation of this model was the use of the Excel spreadsheet. defined by Hegazy and Ayed (Tarek Hegazy, 1998), to optimize the weights in the ANNs structure. It presented the template of the hidden layer in the ANNs model. The model first set 5 or 6 neurons in hidden layers, which resulted in errors of 35.87% and 20.62% respectively. The number of neurons was then increased to 7, 8, 9 and 11 whilst it was found all had 2.20% error. Hence, 7 neurons were the chosen as the best number for the network construction. The forecasting precision is around 98%, which is quite satisfactory. For the sake of simplifying the model, sensitivity analysis was then carried out to identify the most sensible input parameters. It was found that hour, windows' number, orientation and measurement point were the most sensible parameters whilst room geometry, temperature and UV were not. However, neglecting the less sensible parameters would not be a wise decision since it could reduce the accuracy of the ANNs model.

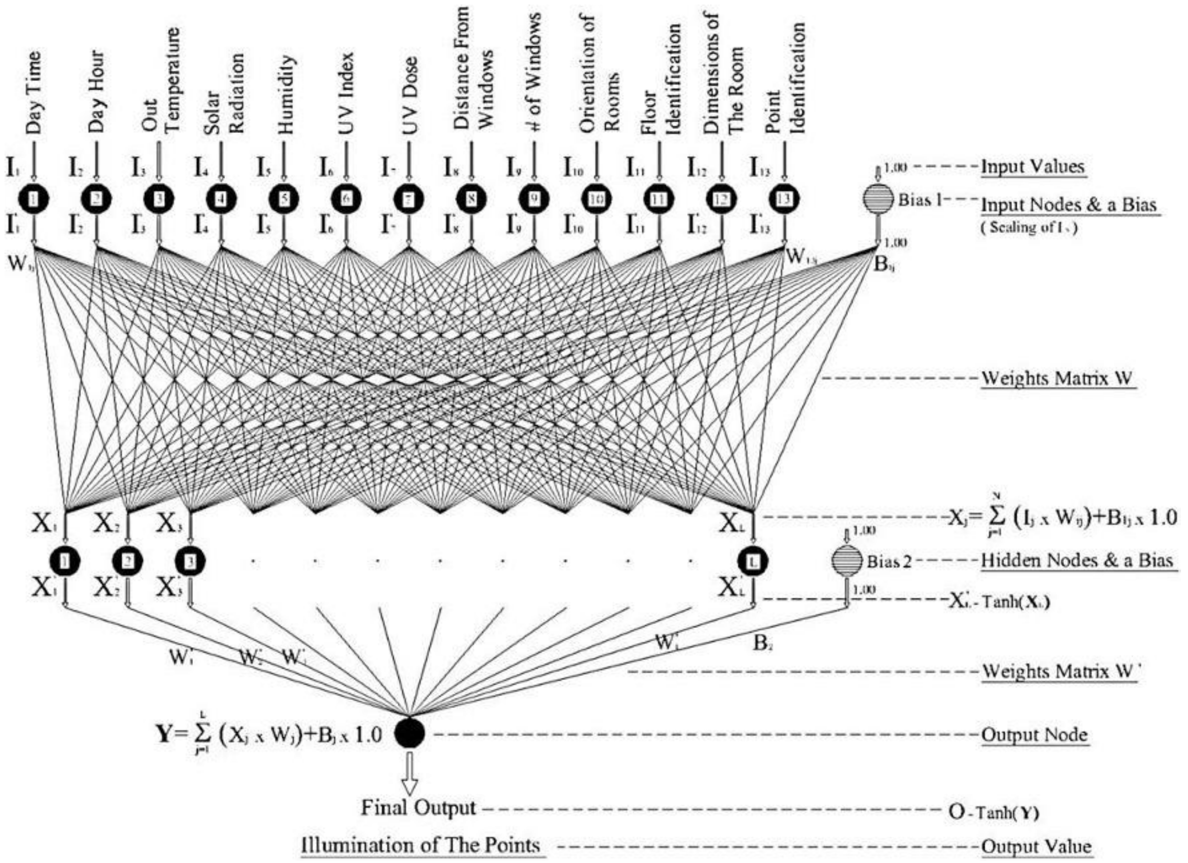


Figure 9. A graphic of the best performance ANN architecture (Kazanasmaz et al., 2009).

3.2. *PREDICTION OF ENERGY SAVING DUE TO DAYLIGHTING*

One of the criteria to assess the daylighting design is based on how much energy could be saved. Fonseca et al. (Fonseca, Didoné, & Pereira, 2013) compared ANNs modelling and multivariate linear regression (MLR) in predicting energy saving by employing daylighting. The office simulated was located in Florianopolis climate in Brazil. The data was from 216 parameter groups in 3 types with different room depth (Figure 10). Cross-validation (Figure 11) was used to train and validate the ANN model due to limited data. The data was simulated by EnergyPlus (energy) and Daysim/RADIANCE (lighting). The ANN network architecture here adopted 6 input variables, 1 hidden layer with 10 nodes and 1 output variable structure. The 6 input parameters include quantitative variables (room depth, room orientation, solar heat gain coefficient, and window-to-wall ratio) and qualitative variables (vertical and horizontal shading coefficient). 90% of parameter groups to train the ANNs model while the rest 10% were for validation. Multifold cross-validation presents an excellent performance to solve the issue of limited data sets. From the comparison of their coefficients of determination, that is, $R^2 = 0.9867$ for ANN and 0.8028 for MLR, it is clear that ANN can provide much more accurate prediction of daylighting energy saving.

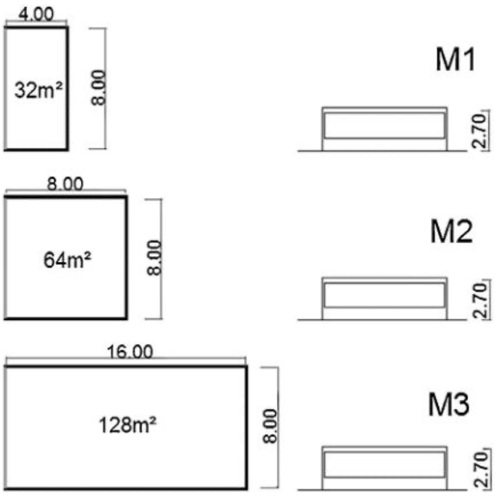


Figure 10. Scheme of geometries of test room (Fonseca et al., 2013).

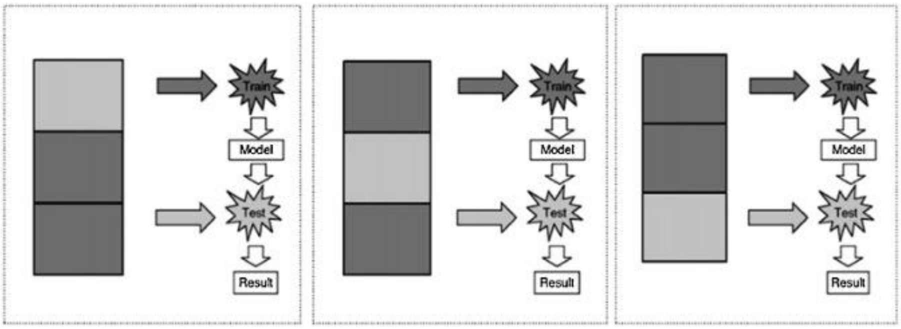


Figure 11. A sample diagram of cross-validation method (Fonseca et al., 2013).

Electric lighting consumes about 20%~30% of office building electricity (de Bakker, Aries, Kort, & Rosemann, 2017). Proper lighting design with utilization of daylighting can directly reduce the lighting energy consumption and also indirectly reduce air conditioning energy consumption which would be used to neutralize the heat released by artificial lighting. Wong et al. (S. L. Wong, Wan, & Lam, 2010) used ANNs modelling to develop the daylighting design for an office building in subtropical zone. The daily electricity consumption for cooling, heating, artificial lighting, etc. was the output of the ANNs model (Figure 12). In this study, EnergyPlus simulations were first run followed by ANNs modelling – 70% and 30% of the data obtained from EnergyPlus was used to train and validate the ANNs model, respectively. Different from other researches, a commercial software named NeuroShell 2 was chosen as the prediction tool. A new coefficient Nash-Sutcliffe efficiency coefficient (NSEC) which can be expressed as in Equation 7, which is similar to the R^2 and was adopted to access the accuracy of the model.

$$NSEC = 1 - \frac{\sum_{i=1}^{n}(x_{i-}y_i)^2}{\sum_{i=1}^{n}(x_i\bar{y_i})^2} \tag{7}$$

where x_i is the daily electricity consumption obtained in ANNs, y_i and $\bar{y_i}$ are the daily electricity consumption and the mean electricity consumption respectively simulated in EnergyPlus, n is the total number of data used in ANNs training and testing. NSEC was introduced to evaluate the model performance, which were 0.994, 0.940, 0.993 and 0.996 respectively. Logistic sigmoid was chosen as the active function. 3 groups of random input data generated by using Monte Carlo methods were employed to assess the accuracy of ANNs model. Statistical analysis involved MBD, RMSE, NMBE and CVRMSE. It was concluded that ANNs could well describe the non-linear relationship between input and output variables; it is especially useful at mass end use situations (e.g., cooling in summer and heating in winter). Moreover, ANNs model can optimize design parameters without carrying out experiments and avoid considerable time consuming. In order to get the relative minimum consumption of the total electricity, different combinations of input parameters were put into the ANNs model to predict the total electricity consumption value. The minimum energy consumption value can be obtained from the ANNs model in a mesh graphic (Figure 13) and the corresponding best input parameters for best design can also be determined.

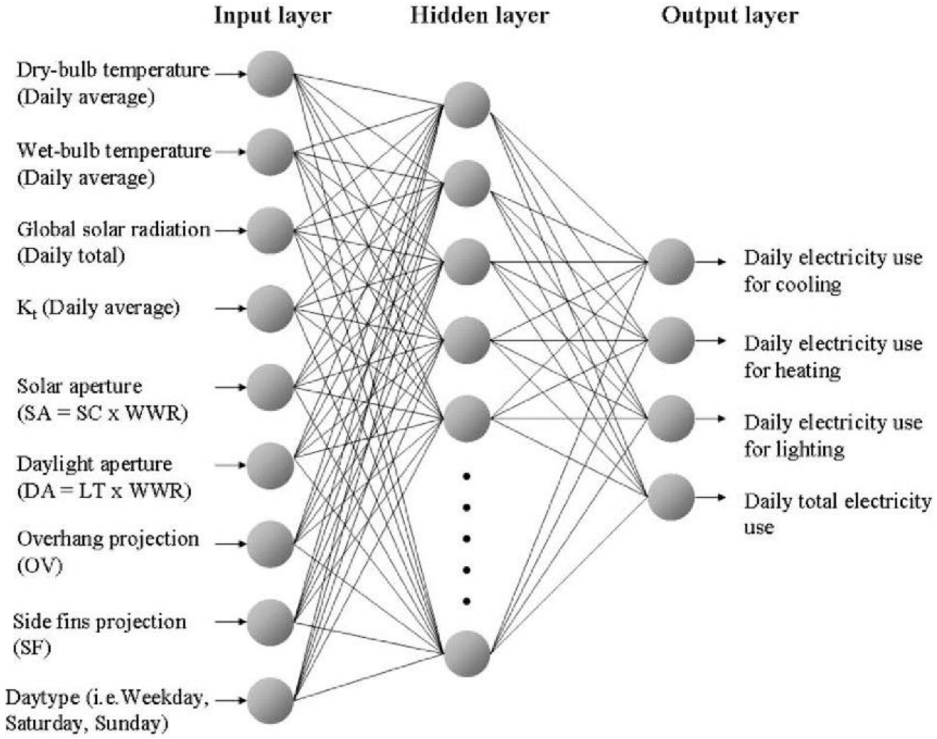


Figure 12. The multi-layer perceptron (MLP) ANN structure (S. L. Wong et al., 2010).

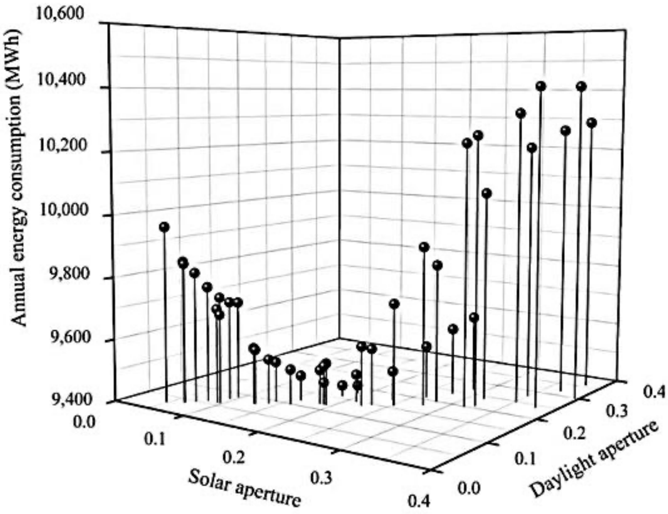


Figure 13. A demonstration of optimization using ANN model to determine proper design parameters in application (S. L. Wong et al., 2010).

According to (Dounis & Caraiscos, 2009), if daylighting and HVAC (heating, ventilating and air conditioning) system are separately considered, it often causes conflicts between energy efficiency and environmental comfort. Hence, to set up an integrated control process, which could simultaneously satisfy all requirements as mentioned above, is essential. Due to the complex geometrical conditions and complex operations, ANNs would be an ideal option. Daylighting integrated with HVAC system is a nonlinear problem. The integrated daylighting and HVAC (IDHAVC) model (as shown in Figure 14) was set by Kim et al. (W. Kim, Jeon, & Kim, 2016) to predict the building energy performance. It was an integrated meta-model (Figure 15), which included regression models (indoor artificial illuminance model, lighting energy consumption model) and ANN models (temperature, indoor daylighting illuminance, total energy consumption). The building was located in Seoul, Korea and ANN were trained with data generated from EnergyPlus for three months. The ANNs model consisted of 4 variables for indoor daylighting illuminance and 11 variables for temperature and total energy consumption respectively. Levenberg-Marquardt (LM) algorithm was adopted to train the ANNs model. The number of hidden layers were fixed at three and the neurons in each hidden layers were optimized by Genetic Algorithm (GA). 70% of the data generated by EnergyPlus were used to train the model, 15% were used to test and the rest 15% for validation to avoid overfitting. The prediction accuracy is measured through R^2 which is bigger than 0.98. This optimization model was achieved via minimizing energy consumption but still keeping the same thermal and visual comforts of occupants. It was shown that 13.7% energy could be saved compared with original model.

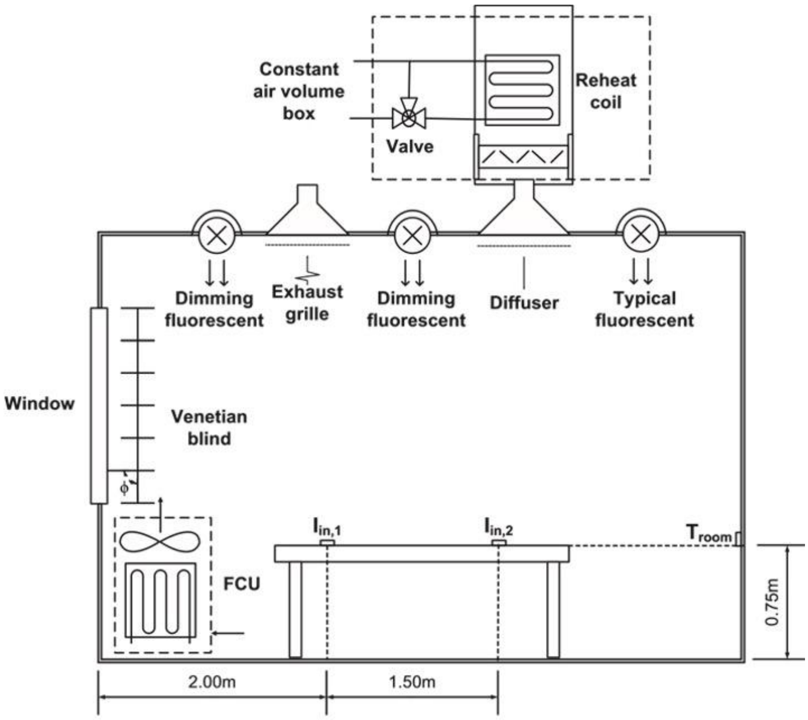


Figure 14. The schematic of the IDHVAC system (W. Kim et al., 2016).

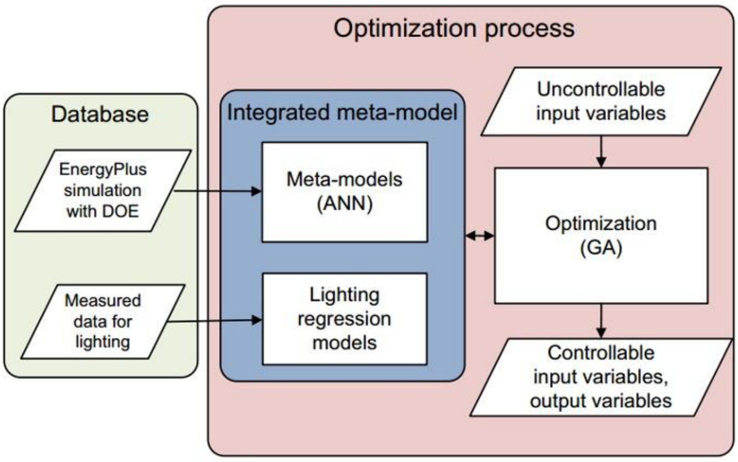


Figure 15. Flow chart of the IDHVAC system optimization (W. Kim et al., 2016).

3.3. DAYLIGHTING CONTROLS

Excessive daylighting could cause overheating problem in buildings, which increases the consumption of cooling energy. It is essential, in daylighting design, to estimate the daylighting control system to avoid unwanted sun light and thermal discomfort. According to different strategies for the control of lighting systems, daylight-linked lighting controls can be divided into daylight-linked switching and daylight-linked dimming

(Danny H. W. Li, Cheung, Wong, & Lam, 2010). Daylight-linked switching can control the light by switching between ‘On’ and ‘Off’ states based on available daylight. There may also be multi-level switching. For instance, based on the level of available daylight in a particular control zone, 33%, 50%, and 66% of light in the zone may be switched off. Dimming system controls the lamp outputs continuously using dimmable electronic ballasts. Dimming requires dimmable ballasts to maintain the illuminance level of the lamps, so it is more expensive than switching system. However, integrating energy efficient lamps with lighting control can significantly reduce electrical energy consumption (Lam, 2003) and also improve vision efficiency (Öztürk, 2008). Adding lighting control system is widely common strategies in retrofitting project of lighting. Based on simulation studies, which predict the effect of retrofitting investment save the unexpected money and time. However, traditional simulations need a large number of data and a lot of time. ANN as a surrogate model was developed by Hu et al. to simulate lighting retrofitting in a building located in Chicago (Hu, Shen, & Gu, 2015). It successfully solves the issue of time wasting and uncertainty retrofitting parameters. This model could predict the lighting and HVAC energy consumption under different combinations of lamp types, control strategies, weather conditions and occupants’ pattern. This created model could save a large number of repeating modelling runs. Surrogate modelling (SUMO) toolbox was firstly introduced into ANNs modelling. Weather condition, LED wattage and occupancy level and control strategies were all considered as input parameters in the modelling. The results of the ANNs modelling showed a reliable relationship between the input building parameters and the output lighting energy consumption. Meanwhile, it has shown that the minimum lighting electricity energy consumption could be achieved by using occupancy plus daylighting control replacing exciting manual control and change the T12 lamp to LED lamp. Another advantage of this model is the HVAC energy consumption could be obtained at the same time, which has 98% precision and considerably saves time.

Venetian blinds is another form of daylighting control, which can significantly control direct solar radiation and glare as well as overheating. Based on ANNs modelling, an illuminance-based slat angle selection (ISAS) model was developed to predict the optimum slat angles of split blinds to achieve the required illuminance (Hu & Olbina, 2011). The input variables were the horizontal illuminance and the sun angle while the output was the illuminance level at a sensor point. The automated split-controlled blinds divided the whole blinds into three equal parts from the top to the bottom (Figure 16). EnergyPlus was employed to simulate the working plane illuminance at the sensors’ positions in an office located in Gainesville, Florida, USA. The illuminance data obtained from the EnergyPlus simulation, combined with weather parameters, were used to train the ANNs model which was subsequently validated. Once the ANNs model was established, the illuminance predicted by the ANNs model was employed to optimise the slats angle and to find the optimum value. Similar to most other researches, a multi-layer feedforward ANNs model with BP learning algorithm was derived. Illuminance at sensor points located at 3 positions of the blind, i.e., top, middle and bottom, were predicted. It was shown that the model prediction performance in terms of comparison between the prediction illuminance and measured value could reach 94.7%, this demonstrated high accuracy in forecasting illuminance level in sensor point. Then the illuminance forecasted by ANNs were input to a mathematical model to optimize the slat angles of blind to achieve the aim of daylighting control (the process is shown in Figure 17). Another advantage of ANNs model is that it could solve the real-time blind control problems. Since the external illuminance data could directly feed in the ANN model and determine the optimum slat angle of blinds, this really solves the difficulties in controlling the daylight in real conditions as a result of the dynamical change nature of solar irradiation.

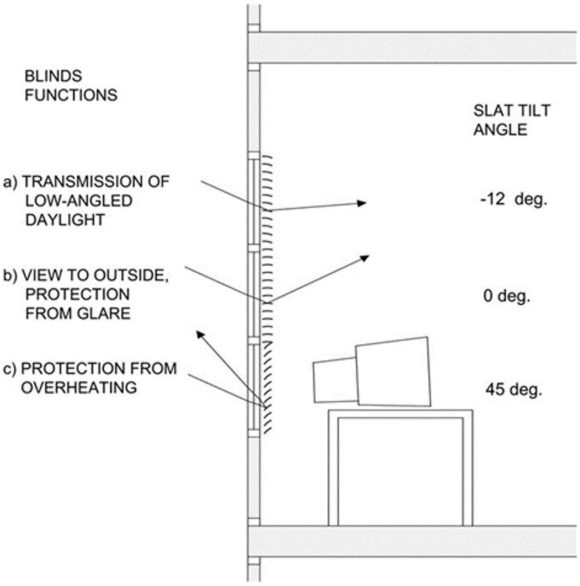


Figure 16. The diagram of automated split-controlled blinds (Hu & Olbina, 2011).

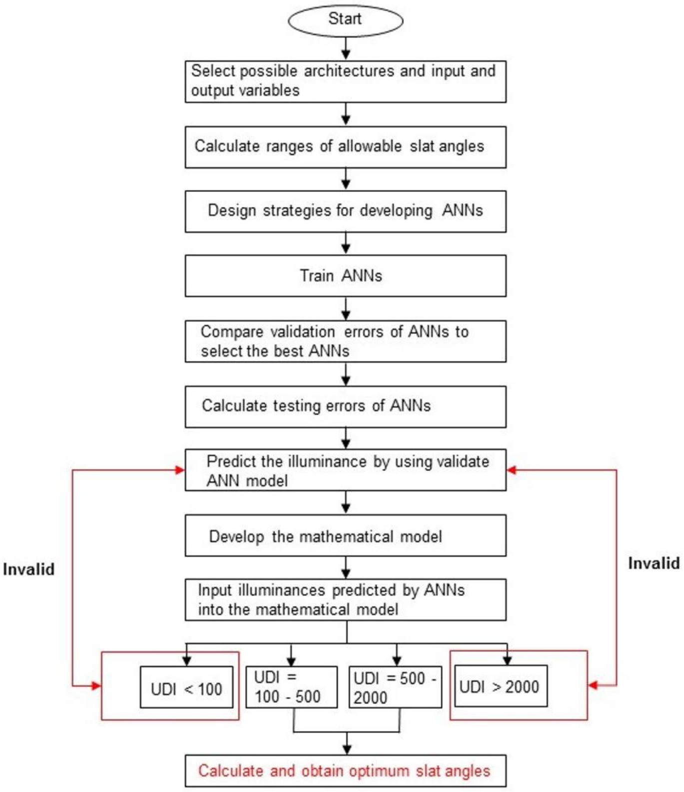


Figure 17. The flow chart of ANNs application in daylighting control of blind (Hu & Olbina, 2011). *The UDI is the abbreviation of useful daylight illuminance and its unit is lux.

Almost all articles in daylighting prediction by ANNs modeling are searched and reviewed. A summary of ANNs application in predicting daylighting with detailed input and output parameters is presented in Table 8.

Table 8. Summary of ANN applied to predict daylighting in literatures.

Literatures	**ANNs models**	**Input variables**	**Output variables**	**Accuracy**
External luminance prediction				
Janjai et al. (Janjai & Plaon, 2011)	BP	● Solar zenith angle; ● Zenith angle of the sky element;	Sky luminance	Table 3

Literatures	**ANNs models**	**Input variables**	**Output variables**	**Accuracy**
		● Angular distance between the sky element and the sun		
López et al. (López & Gueymard, 2007)	BP	● Solar zenith angle; ● Perceptible water; ● Diffuse fraction; ● Direct transmittance	● Direct component of luminous efficacy; ● Diffuse component of luminous efficacy; ● Global component of luminous efficacy	Table 4
Tíba et al. (Tíba & Leal, 2012)	MLP	● Dew point temperature; ● Rain precipitation; ● Darkness of sky; ● Clearness index of Perez; ● Index of transmittance	Hourly luminous efficiency	Table 5
Pattanasethanon et al. (Pattanasethanon et al., 2008)	BP	● Solar altitude angle; ● Clearness index/sky ratio	● Global illuminance; ● Global irradiance; ● Diffuse irradiance	Table 6
Internal illuminance prediction				
Navada et al. (Sandhyalaxmi G Navada, 2016)	BP	● Blind position; ● Times	Illuminance	Table 7
Kazanasmaz et al. (Kazanasmaz et al., 2009)	BP	● Orientation; ● Geometry; ● Windows amount; ● Distance to windows; ● Floor character, ● Sensors' position; ● Date; ● Hour; ● Solar radiation; ● UV index; ● UV dose; ● Temperature; ● Humidity	Illuminance	Precision = 98%
Prediction of energy saving due to daylighting				
Fonseca et al. (Fonseca et al., 2013)	MLP	● Humidity ● Room depth; ● Room orientation; ● Solar heat gain coefficient; ● Window to wall ratio; ● Vertical shading coefficient; ● Horizontal shading coefficient	Final electric energy consumption	$R^2 = 0.9867$
Wong et al. (S. L. Wong et al., 2010)	BP	● Dry-bulb temperature (Daily average); ● Wet-bulb temperature (Daily average); ● Global solar radiation (Daily total); ● Daily average clearness index; ● Solar aperture; ● Daylight aperture; ● Overhang projection;	● Daily electricity use for cooling; ● Daily electricity use for heating; ● Daily electricity use for lighting; ● Daily total electricity use	● NSEC = 0.994 ● NSEC = 0.940 ● NSEC = 0.993 ● NSEC = 0.996

Literatures	ANNs models	Input variables	Output variables	Accuracy
		● Side fins projection; ● Daytype		
Kim et al. (W. Kim et al., 2016)	LM	● Slat angle; ● Outdoor air ratio; ● Lighting energy consumption; ● Setpoint temperature; ● Air handling unit schedule (on/off); ● Flow rate; ● Outdoor air temperature; ● Previous time step room temperature; ● Outdoor illuminance; ● Azimuth angle	● Room temperature ● Total energy consumption ● Indoor daylight illuminance	$R^2 > 0.98$
Daylighting controls				
Hu et al. (Hu et al., 2015)	SUMO	● Weather condition (overcast, medium, clear); ● LED input wattage; ● Occupancy level (low, medium, high)	Energy consumption	Precision = 98%
Hu et al. (Hu & Olbina, 2011)	MLP	● Solar altitude angle; ● Solar azimuth angle; ● Global horizontal illuminance; ● Diffuse horizontal illuminance; ● Slat angle; ● Global horizontal radiation; ● Dry blub temperature; ● Zenith luminance; ● Relative humidity; ● Horizontal infrared radiation intensity from sky	Illuminance at 3 sensor points of the blind (top, middle, bottom)	Precision = 94.7%

Table 9 summarizes the strengths and weaknesses of ANNs across seven domains, including prediction performance, computational efficiency, variable handling and so forth. The strengths of each domain are highlighted, such as high accuracy, rapid computational speed, strong multivariable coupling capability, while the weaknesses include limited interpretability, lack of theoretical guidance for architectural design, and insufficient exploration of advanced algorithms, among other issues. This comparative overview serves as a guide for understanding the trade-offs involved in deploying ANNs, depending on whether the focus is on predictive accuracy, computational speed, system integration, or real-time control capability.

Table 9. Summary of strengths and weaknesses of ANNs in seven domains.

Domain	Strengths	Weaknesses
Prediction performance	Achieves high accuracy, outperforming traditional empirical models and Multiple Linear Regression (MLR), and effectively handles complex non-linear relationships.	The “Black Box” nature results in limited interpretability, making it difficult to understand the physical relationships between inputs and outputs. This also leads to poor generalization.
Computational efficiency	Offers high computational efficiency, enabling rapid, real-time responses, that are suitable for dynamic daylighting control and large-scale design optimization.	Performance is highly dependent on the quality and quantity of training data. Inadequate data splitting or noisy data can lead to poor predictions and overfitting.

Domain	**Strengths**	**Weaknesses**
Variable handling	Demonstrates a strong coupling capability, easily integrating multi-dimensional variables (e.g., building geometry, weather, occupant behaviour), thereby supporting coordinated optimization with HVAC systems.	The selection of an optimal network architecture (number of hidden layers and neurons) lacks theoretical guidance and often relies on time-consuming trial and error.
Application scenarios	Has versatile applications, including luminance/illuminance prediction, energy savings forecasting, and daylighting control systems (e.g., blind angle optimization).	The vast majority of studies use the basic backpropagation (BP) algorithm, with insufficient exploration of more advanced variants (e.g., Levenberg-Marquardt (LM), conjugate gradient) to improve training speed and stability.
Generalization ability	Excellent at modelling non-linear relationships and particularly useful for predicting end-use consumption (e.g., cooling, heating) and optimizing design parameters without physical experiments.	The prediction performance of a model depends on the training data. It becomes ineffective when the data do not cover the entire operating range of the system.
System integration	Effectively resolves conflicts between energy efficiency and occupant comfort by enabling integrated control of lighting and HVAC systems.	There is a lack of geometric generalization. Research on integrating geometric parameters into general models remains insufficient. Most ANNs are trained for specific configurations, making them difficult to apply directly to new buildings.
Real-time control	Solves real-time control problems (e.g., automated blinds) by processing dynamic external data (e.g., solar position, illuminance) to determine optimal settings instantly.	There is no clear justification for the common practice of using three years of data for training; the optimal time scale for input data remains unstandardized.

4. DISCUSSION ON RESEARCH GAPS

ANNs has been proved a useful and powerful numerical tool for predicting daylighting performance and optimizing daylighting design. However, according to the comprehensive review, there are still research gaps, which hinder the widespread application of ANNs in daylighting prediction and optimization. In this section, these gaps and problems are summarized and analysed.

1. Almost all ANNs models in literature used BP algorithm as the training method. However, some improvements have recently been made for the BP algorithm. For instance, advanced techniques such as adding momentum and adaptive learning rate, as well as using more effective optimization algorithm, e.g., conjugate gradient method, LM method etc., should be explored.
2. Most literature in this topic chose three years data for the input parameters; however, no evidence has been available as why three years is better. Some justification should be provided or some other time scales may be adopted.
3. In ANNs training procedure, if too large capacity or too many iterations were selected, over training would happen. Prior to running ANNs simulation, considerable high precision or large number of training cycles should always set as priority to define when to stop the training process. However, due to unavoidable uncertainty, some training data obtained from experiments or elsewhere could sometimes be erroneous. Hence, over high precision can also cause over fitting and reduce the prediction accuracy. In order to overcome this problem, the number of training cycles and input data need to be optimized.
4. Since the data used to train ANNs model sometimes cannot cover the entire range of the data, the extrapolation can become ineffective. When preparing the input data for training ANNs model, the maximum and minimum values should be selected from all the proposed data. Empirical correlations can be applied to some training samples and the selected training data shall be able to represent the entire operating range of the system in order to reduce the extrapolation errors.
5. Decision on the number of the hidden layers is dependent on empirical trials. Effective methods need

to be developed to find out the appropriate number. So far, the number of neurons in hidden layers can be calculated as follows (Kalogirou & Bojic, 2000),

$$L = \sqrt{m + n} + a,\ a \in [1,10] \tag{8}$$

where L is the number of neurons in hidden layers, m is the number of neurons in input layer, n is the number of neurons in output layer, and a is an adapting variable, which range from 1 to 10.

6. Most of the hidden layers tend to be one hidden layer. In fact, two or more hidden layers help return more accuracy. However, more hidden layers cost more time and make the system complex. Therefore, the balance of accuracy and time cost is a key problem. The Bayesian approach can offer selection of optimum number of hidden layers. In addition, under what circumstances a second hidden layer should be chosen needs to be discussed in future research.
7. Not many researchers in this field have considered the input parameters with respect to the output parameters. In fact, sensibility test should be undertaken to determine the input parameters in order to remove the irrelative parameters and keep the model as accurate as possible.
8. For luminance and illuminance, one of the most important factors is local climate. For indoor daylighting level, the sun position is a crucial parameter. These parameters should be considered into the ANNs modelling.
9. The initial dataset should remove noise before being used. For instance, GA could be used to optimize the input dataset such as variable extraction and selection on measured data.
10. The outputs of neural networks may not be exactly what expected. The outputs could be corrected by post-processing results, such as fuzzy logic.
11. ANNs model is a strong simulation tool to solve the problems with large number of input variables data. The input data can be split into training data, testing data and validation data. Improper data splitting can lead to a poor prediction. More quantitative guidance on the data selection is one of the keys to successful ANNs simulation in daylighting performance and optimization.
12. There is a lack of research on the integration of geometric parameters into general multi-nonlinear regression (MNLR) models. Artificial Neural Networks (ANNs) have demonstrated strong capabilities in handling complex nonlinear relationships in the prediction of daylight performance. However, most existing studies focus on achieving high prediction accuracy through ANN models themselves. Their “black box” nature limits their interpretability and generalization ability. Specifically, geometric parameters, including room depth, window-to-wall ratio, and shading device dimensions, have been demonstrated to be key factors affecting indoor daylight performance. However, most ANN models are trained for specific building geometric configurations. This makes it difficult to directly apply such models to new buildings. Future research should systematically explore the nonlinear relationships between geometric parameters and daylight performance and produce a general multi-nonlinear regression (MNLR) equation. Such an equation would be easier for architects and engineers to apply rapidly in the early design stage, without the need for specialized software.

5. CONCLUSIONS

This paper has presented a literature review on the research work in daylighting prediction and optimization by using ANNs approach. In the review, the luminance and illuminance prediction, daylighting control and energy saving with daylighting have been extensively discussed. The existing work can be useful for building professionals and researchers to estimate the availability and suitability of ANNs in predicting daylighting performance. Moreover, the research gaps currently hindering the widespread and effective application of ANNs in daylighting prediction and optimization have been explored and presented. The findings could help architects and practising engineers adopt proper daylighting design schemes and evaluation methods, and therefore promote sustainable developments in architectural buildings.

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AUTHOR CONTRIBUTIONS

Li Zhang: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Yuehong Su**: Supervision, Resources, Writing – review & editing.

COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA ACCESSIBILITY

The authors do not have permission to share data.

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