Applied Energy 87 (2010) 551–557

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Artificial neural networks for energy analysis of office buildings with daylighting

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ARTICLE INFO

Article history:
Received 18 December 2008
Received in revised form 26 March 2009
Accepted 17 June 2009
Available online 14 July 2009

Keywords:
Energy analysis
Artificial neural networks
Daylighting
Office buildings
Optimisation

ABSTRACT

An artificial neural network (ANN) model was developed for office buildings with daylighting for subtropical climates. A total of nine variables were used as the input parameters – four variables were related to the external weather conditions (daily average dry-bulb temperature, daily average wet-bulb temperature, daily global solar radiation and daily average clearness index), four for the building envelope designs (solar aperture, daylight aperture, overhang and side-fins projections), and the last variable was day type (i.e. weekdays, Saturdays and Sundays). There were four nodes at the output layer with the estimated daily electricity use for cooling, heating, electric lighting and total building as the output. Building energy simulation using EnergyPlus was conducted to generate daily building energy use database for the training and testing of ANNs. The Nash–Sutcliffe efficiency coefficient for the ANN modelled cooling, heating, electric lighting and total building electricity use was 0.994, 0.940, 0.993, and 0.996, respectively, indicating excellent predictive power. Error analysis showed that lighting electricity use had the smallest errors, from 0.2% under-estimation to 3.6% over-estimation, with the coefficient of variation of the root mean square error ranging from 3% to 5.6%.

1. Introduction

Recent work by the Inter-governmental Panel on Climate Change (IPCC) has raised public awareness of energy use and the environmental implications [1]. Buildings, energy and the environment are issues facing the building professions, researchers and energy policy makers worldwide, and carbon emissions from the use of energy in buildings was one of the major components in the overall emissions scenarios considered in an IPCC report on mitigation [2]. In Hong Kong, there is a growing concern about energy consumption in buildings, especially office buildings, and its implications for the environment. In 2007, nearly two-thirds of the imported primary energy requirement (mainly coal and oil products, including natural gas) was used for electricity generation [3]. Electricity use in buildings is thus a key energy end-user. Earlier work on the energy use in air-conditioned office buildings in subtropical climates revealed that air-conditioning and electric lighting were the two largest components, accounting for 40–50% and 20–30% electricity consumption, respectively [4,5]. Reductions in lighting energy use have an indirect impact on the HVAC energy requirements. Proper daylighting designs would reduce not only electricity use for artificial lighting but also air-conditioning requirement, especially in cooling-dominated buildings in tropical and subtropical climates [6,7]. The general rule of thumb is to assume that, as a result of the interactions between lighting and HVAC, savings in cooling totally one-third of the savings in electric lighting could be achieved, though full consideration of a balance between beneficial natural light and excessive solar heat is required.

There had been several studies on the energy performance of office buildings in subtropical Hong Kong. These were largely on energy simulations using generic building types [8–10] or energy signatures and energy conservation measures involving energy audits and surveys of existing buildings [4,5,11,12] without daylighting. Earlier work on office buildings with daylighting schemes dealt mainly with monthly and annual energy use characteristics using simulation, sensitivity and regression techniques [13–15]. The regression and time-series models are based on classical statistics/mathematics, and their characteristics are well understood and the estimation process relatively straightforward. These models, however, tend to perform well only for well behaved energy systems. Recent work indicated that artificial neural networks (ANNs) generally work better for buildings with highly non-linear energy use patterns. An ANN energy model can approximate a non-linear relationship between the input variables and the output of a complex system; the main advantage is its self-learning capability [16–18]. In building energy field, ANN method has been adopted for predicting building cooling load [19,20], annual building energy consumption [21] and energy use of building services installations [22–24]. There has been very little work on predicting daily energy consumptions of buildings with daylighting controls using ANN method. This study demonstrates energy saving potentials of daylighting in terms of a number of design variables which will be

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doi:10.1016/j.apenergy.2009.06.028

considered critical at the early design stage for new building development. The primary aim of the present work was, therefore, to develop and evaluate ANNs for predicting daily energy use in fully air-conditioned office buildings with daylighting schemes in subtropical Hong Kong. The scope of work covered (i) generation of daily energy consumption database using building energy simulation, (ii) development of ANNs, and (iii) ANNs model evaluation.

2. Generation of building energy consumption database

Building energy simulation was conducted to generate daily building energy use database for the subsequent training and testing of ANNs. The simulation tool employed was the EnergyPlus building energy simulation program [25,26], which was built on the strengths of two widely used programs, namely BLAST [27] and DOE-2 [28]. For daylighting analysis, improvements made to EnergyPlus include interior inter-reflection calculation algorithm, reflection from neighbouring buildings and handling of complex fenestration systems. The software has good back-up supports and is one of the simulation programs recommended in the local performance-based building energy code for building energy analysis [29]. For daylighting and energy analysis, the package has been tested and validated with other simulation tools [30] and experimental data [31,32]. The success of a daylighting scheme depends very much on a good understanding of the dynamic interactions between the external climates, indoor design conditions, the building envelope and the building services installations. Detailed building energy simulation programs incorporate sets of mathematical models that seek to explain quantitatively how each component of a building behaves under given circumstances. Two major sets of inputs were developed for the simulation – hourly weather database and generic office building designs.

2.1. Generic reference building

A generic office building was developed to serve as a baseline reference for comparison and evaluation. The generic building incorporated most of the design features common in local office buildings. Details can be found in Ref. [15]. Briefly, the base-case building was a square (35 m × 35 m) 40-storey office block with curtain wall designs and a centralized heating, ventilation and air-conditioning (HVAC) system. The floor-to-floor and window heights were 3.5 m and 1.5 m, respectively. This represented a window-to-wall ratio (WWR) of 43%. Glazing was single reflective glass with a shading coefficient (SC) and a light transmittance (LT) of 0.4 and 0.3, respectively. The *U*-values for the roof, external walls and windows were 0.46, 1.95 and 5.1 W/m^2 °C, respectively. The air-conditioning plant was a variable-air-volume system with a temperature set point of 24 °C in summer and 21 °C in winter. The chillers were of a packaged air-cooled hermetic reciprocating type with a coefficient of performance of 2.8. Table 1 shows a summary of the key design parameters. The indoor designed illuminance was 500 lux with an installed lighting power density of 20 W/m^2. To avoid the likely problems of glare, excessive brightness ratio and thermal discomfort, internal shading devices were used in the perimeter zones. It was assumed that these devices would be operated when the discomfort glare index at the reference point was more than 22 or the total solar irradiance incident on the windows exceeded 200 W/m^2, the threshold beyond which direct sunlight might cause glare and other undesirable visual effects. The internal shading devices reduced the SC and LT of the glazing system by 75% and 60%, respectively. For daylighting simulation, top-up controls were used for regulating the electric lighting installed at the four perimeter zones in response to the amounts of daylight available. Daylight levels were determined at a reference point in each perimeter office at a working plane of 0.75 m above the finished floor level and at a depth of 2.5 m centred with respect to the windows.

Table 1
Brief description of base-case office building.

Location	Hong Kong (latitude 22.3°N, longitude 114.2°E)
Building type and storeys	Office building, 40 storeys above ground
Floor areas	Total gross floor area = 49,000m^2 Air-conditioned area = 41,160m^2
Dimensions and heights	35 m × 35 m (square); floor-to-floor = 3.5 m; window height = 1.5 m; window-to-wall ratio = 0.43
Constructions of building envelope	(a) External walls (spandrel portion of curtain wall) – 6 mm glass + 25 mm airspace + 19 mm plywood + wall paper (*U*-value = 1.95 W/m^2 °C) (b) Roof – 13 mm slag + 10 mm roof build-up + 50 mm roof insulation + 200 mm n.w. concrete + ceiling void + 19 mm ceiling panel (*U*-value = 0.46 W/m^2 °C) (c) Windows – 6 mm reflective single glazing (SC = 0.4, LT = 0.3, *U*-value = 5.1 W/m^2 °C)
Operating hours	Monday to Friday: 08:00–18:00; Saturday: 08:00–13:00; Sunday closed
HVAC design parameters	Occupancy density = 8 m^2/person Lighting load = 20 W/m^2; equipment load = 18 W/m^2 Infiltration = 0.6 air change per hour during fans OFF Space design temperature = 24 °C

2.2. Weather file

The EnergyPlus package uses 8760 hourly records of measured weather data to analyse the building energy performance including lighting, heating and cooling loads and the corresponding energy use. Weather conditions, however, vary from one year to another. It is crucial to develop a weather database, which is typical or representative of a particular geographic area so that different schemes may be readily compared. Based on 27-year long-term (1979–2005) measured weather data, a typical meteorological year (TMY) representing the prevailing local climatic conditions with respect to building energy performance analysis was developed [33]. This was a weather file containing 8760 hourly records of dry-bulb temperature, relative humidity, solar radiation, illuminance and wind speed and wind direction. The direct and diffuse components of solar radiation were determined from the corresponding global solar radiation [34] and the daylight availability (i.e. outdoor illuminance) from the luminous efficacy model developed for Hong Kong [35].

2.3. Parametric building energy simulation

It is essential to understand the basic principles and to quantify with reasons, the relative importance and impact of input parameters to the output results selected. When performing building energy simulations, changes in energy use from certain input variables are more significant than others. Such selected inputs should, therefore, be given particular attention during modelling. Also, high-sensitivity elements are important from both technical and economic point of view and should be considered with utmost care if optimisation of the system performance is to be achieved. Our earlier work on regression and sensitivity analysis indicated that key building envelop design parameters affecting energy use were WWR, LT, SC and external shading devices (i.e. overhangs (OV) and side-fins (SF)) [15]. These five building envelope design parameters were considered in this study, and perturbations were introduced by changing systematically a range of different values to each of the input parameters, one at a time. A specific glazing has a unique set of values for LT and SC. Variations in LT and SC were, therefore, considered concurrently, and the combinations

Table 2
Summary of input values for parametric analysis.

Input parameter	Base-case value	Number of perturbation	Range
WWR	0.43	7	0.1–0.7
LT/SC	0.3/0.4	7	0.2–0.9/0.3–0.95
OV	0	8	0.1–0.8
SF	0	8	0.1–0.8

of LT and SC were selected from the built-in material library of EnergyPlus. A total of seven perturbations were made to WWR and LT/SC, and eight to OV and SF. Altogether 31 simulation runs were conducted, and the ranges of the parameters were kept within those found in a survey of local office buildings [36]. Table 2 shows the input values for the parametric analysis. Daily values of four major computed energy consumption data were analysed, namely cooling, heating, electric lighting and total building. These daily energy use data formed the basis for the training and testing of the ANNs.

3. Development of ANNs models

Artificial neural networks (ANNs) are information processing systems that are non-algorithmic, non-digital, and intensely parallel [37]. They learn the relationship between the input and output variables by studying previously recorded data. An ANN resembles the biological neural system, composed by layers of parallel elemental units, called neurons. The neurons are connected by a large number of weighted links, over which signals or information can pass. Basically a neuron receives inputs over its incoming connections, combines the inputs, performs generally a non-linear operation, and then outputs the final results. For the present study, a software package "NeuroShell 2" [38] was used to train and develop the ANNs for building energy use estimation. Similar technique was applied to solar radiation modelling work [39]. Briefly, the neural network adopted was a feed-forward multi-layer perceptron (MLP), which is among the most commonly used neural networks that learn from examples. A schematic diagram of the basic architecture is shown in Fig. 1. It had three layers – the input, hidden and output layers. Each layer was interconnected together by the connection strengths called weights. A total of nine variables were used as the input parameters for the input nodes of the input layer. Four variables were related to the external weather conditions (daily average dry-bulb temperature, daily average wet-bulb temperature, daily global solar radiation and daily average clearness index). The key to any successful daylighting scheme in cooling-dominated office buildings in subtropical or tropical climates is a proper balance beneficial natural daylight and excessive solar heat gain. In general, solar aperture (SA = WWR $\times$ SC) and daylight aperture (DA = WWR $\times$ LT) are parameters often used in solar heat and daylighting analysis [40]. Therefore, two variables SA and DA (instead of WWR, SC and LT) together with overhang and side-fins projections were used to account for the building envelope designs. The last variable was day type (i.e. weekdays, Saturdays and Sundays). There were four nodes at the output layer with the estimated daily electricity use for cooling, heating, electric lighting and total building as the output. The transfer function adopted for the neurons was a logistic sigmoid function $f(z_i)$, where z_i was the weighted sum of the inputs. Thus:

$$f(z_i) = \frac{1}{1 + e^{-Z_i}} \tag{1}$$

$$z_i = \sum_{j=1}^{6} w_{ij} x_j + \beta_i \tag{2}$$

where x_j is the incoming signal from the jth neuron (at the input layer), w_{ij} the weight on the connection directed from neuron j to neuron i (at the hidden layer) and β_i the bias of neuron i. Neural networks learn to solve a problem rather than being programmed to do so. Learning is achieved through training. In other words, training is the procedure by which the networks learn, and learning is thus the

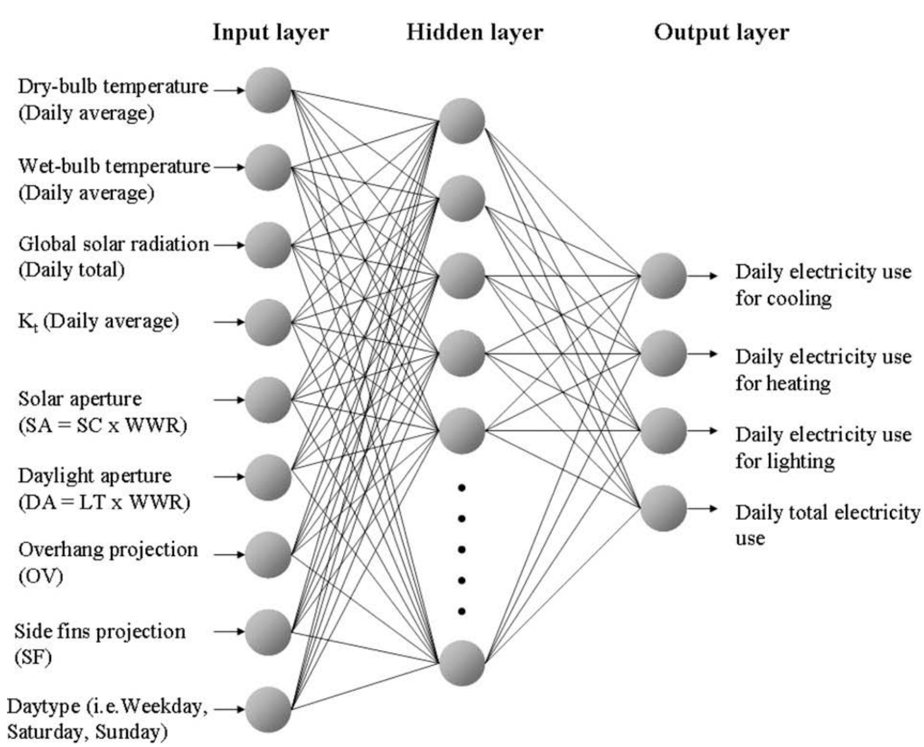

Fig. 1. Topology of the multi-layer perceptron (MLP) artificial neural network (ANN).

end results. The methodology used was the most common one – supervised training, in which simulated daily electricity consumption data were given and the network learned by comparing the energy data from simulation with the estimated output. The difference (i.e. an error) propagated backward (using back-propagation training algorithm) from the output layer, via the hidden layer, back to the input layer, and the weights on the interconnections between the neurons were updated as the error back-propagated. A multi-layer network can mathematically approximate any continuous multivariate function to any degree of accuracy, provided that sufficiently many hidden neurons are available. Thus, instead of learning and generalising the basic structure of the data, it may learn irrelevant details of individual cases. In this study, 70% and 30% of the data were used for training and testing, respectively. Training and testing of the network continued until no improvement in the output was achieved (i.e. minimum error) after a predetermined number of epochs.

4. ANN model evaluation and error analysis

The Nash–Sutcliffe efficiency coefficient (NSEC) [41] was adopted by the ANN tool "NeuroShell 2" as a measure of the predictive power of the ANN model developed, defined as follows:

$$\mathrm{NSEC} = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{y}_i)^2} \tag{3}$$

where x_i = ANN modelled daily electricity consumption (kW h), y_i = EnergyPlus simulated daily electricity consumption (kW h), $\bar{y}_i$= EnergyPlus simulated daily mean electricity consumption (kW h), n = total number of data used in the ANN training and testing (i.e. 31×365).

Conceptually, NSEC is similar to the coefficient of determination (R^2) used to assess the strength of correlation in regression analysis. NSEC can range from $-\infty$ to 1. An NSEC of 1 corresponds to a perfect match of the predicted and measured data, and zero indicates that the model predictions are as accurate as the mean of the measured data. A negative NSEC occurs when the measured mean is a better predictor than the model. Essentially, the closer the model efficiency is to 1, the more accurate the model is. NSEC for the ANN modelled cooling, heating, electric lighting and total building electricity use was 0.994, 0.940, 0.993, and 0.996, respectively, indicating excellent predictive power. The relatively small NSEC for heating electricity use was probably due to the insignificant heating requirements during the short and mild winters in subtropical climates.

To quantitatively evaluate the performance of the ANN model (i.e. determining the differences between energy consumption from simulation and ANN model), an independent set of simulation results was used. Three simulation runs were conducted. A random numerical experiment was carried out to generate three sets of input building envelope design parameters for the simulation exercise. A set of random numbers is a set of number for which knowledge of any subset of the numbers will not tell people with certainty the value of the next one sampled from the set. The methods using random experiments are also called Monte Carlo methods, and the procedures which produce the random quantities are called random number generators (RNGs) [42]. The pseudo-random number generator using three simple multiplicative congruential generators developed by Wichmann and Hill [43] was adopted for this study, and executed through Microsoft's Excel Spreadsheet [44]. The five input parameters were generated within the same ranges as those used in the parametric building energy simulation shown in Table 2. These three sets of randomly generated input variables represented three different designs independent of those used in the development of the ANN model. Fig. 2 shows a comparison between the ANN modelled and simulated daily (weekday) electricity consumption for Case 1. EnergyPlus assumed 1st of January was a Sunday. There were, therefore, 260 weekdays. It can be seen that the ANN modelled daily profiles tend

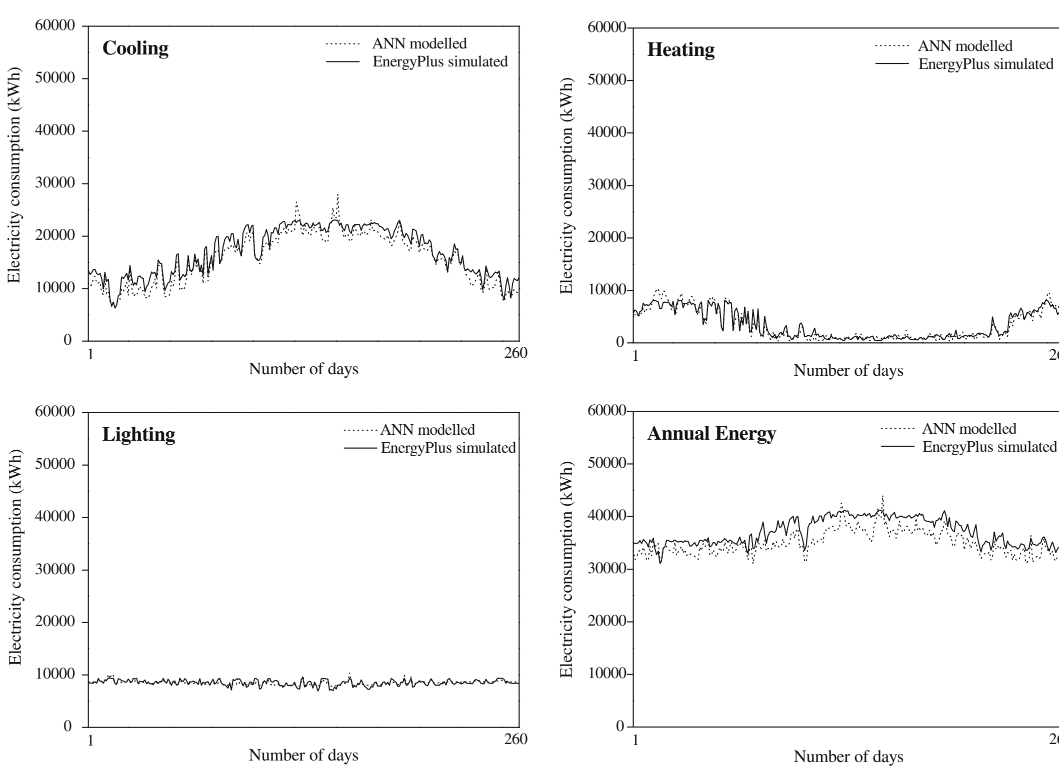

Fig. 2. Comparison of ANN modelled and Energy Plus simulated daily electricity consumption (weekdays).

to follow the corresponding simulated ones quite closely. Distinct seasonal variations in electricity use for cooling (peaks during summer months) and heating (peaks in winter) can be observed. Electric lighting electricity consumption tends to slightly lower in June and July, probably due to the longer day length and hence more daylight availability. Again, heating tends to have the largest deviations. Statistical analysis involving mean bias error (MBE) and root mean square error (RMSE) was conducted for each of the three simulated results. These statistics were determined as follows:

$$\mathrm{MBE} = \frac{\sum_{i=1}^{365}(x_i - y_i)}{365} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{365}(x_i - y_i)^2}{365}} \tag{5}$$

The mean bias error provides information on the long-term performance of the ANN model. A positive MBE indicates that the ANN modelled annual electricity consumption is higher than the EnergyPlus simulated value vice versa. It is worth noting that over-estimation in an individual observation can be offset by under-estimation in a separate observation. The RMSE is a measure of how close the ANN predicted daily profile is to the one based on simulated results. Normalised mean bias error (NMBE) and coefficient of variation of the root mean square error (CVRMSE) were also determined by dividing the MBE and RMSE by their respective daily mean simulated electricity consumption. Table 3 shows a summary of the error analysis of the three independent design cases. Lighting electricity use shows the smallest errors, from 0.2% under-estimation in Case 1 to 3.6% over-estimation in Case 2 and the CVRMSE ranging from 3% to 5.6%. There is no clear pattern showing whether the ANN model tends to either over- or under-estimate. Heating has the largest errors with a CVRMSE range of 26.9–45.5%. To ascertain whether the ANN model could perform better for cooling in the summer (June–August) and heating during winter months (December, January and February), seasonal MBE and RMSE were also considered. Table 4 compares the annual and seasonal error analysis of cooling and heating electricity consumption for the three cases. It can be seen that the errors are greatly reduced except NMBE for Case 1. This suggests that the ANN model tends have more accurate predictions of electricity use for periods during which a particular end-use exhibits substantial demand (i.e. summer cooling and winter heating).

Furthermore, the predicted annual electricity use of the three cases was compared against our previous developed multiple regression model for building energy and daylighting analysis [15]. Fig. 3 shows the relative error of predicted annual electricity consumptions using the ANN model and the correlation method for the three cases. It can be seen that relative errors of the three cases using correlation model and ANN model range from −3.8% to 5.8% and 5.6% to 8.2%, respectively. The results indicate that the correlation model performs slightly better than the ANN model for annual energy prediction. Nevertheless, this study implies that the ANN model is established well to describe the complex non-linear relationship between the building energy consumptions and the selected variables (building design and meteorological parameters), particularly for prediction of daily energy consumptions.

5. Optimisation

One of the applications of an ANN model is to conduct optimisation of certain design variables without the laborious and time-

Table 3
Summary of error analysis of the three independent design cases.

		Case 1	Case 2	Case 3
WWR		0.38	0.52	0.66
SC		0.92	0.63	0.33
LT		0.80	0.39	0.21
OV		0.32	0.49	0.13
SF		0.21	0.14	0.65
Cooling	MBE (kW h)	940	428	788
	NMBE (%)	7.7	3.6	7.4
	RMSE (kW h)	1410	725	1107
	CVRMSE (%)	11.5	6.1	10.3
Heating	MBE (kW h)	−18	−87	372
	NMBE (%)	−0.7	−3.5	27.9
	RMSE (kW h)	785	665	607
	CVRMSE (%)	29.8	26.9	45.5
Lighting	MBE (kW h)	−13	256	49
	NMBE (%)	−0.2	3.6	0.7
	RMSE (kW h)	356	396	224
	CVRMSE (%)	5.0	5.6	3.0
Total	MBE (kW h)	1559	2083	2090
	NMBE (%)	5.6	7.6	8.2
	RMSE (kW h)	2118	2578	2904
	CVRMSE (%)	7.6	9.4	11.4

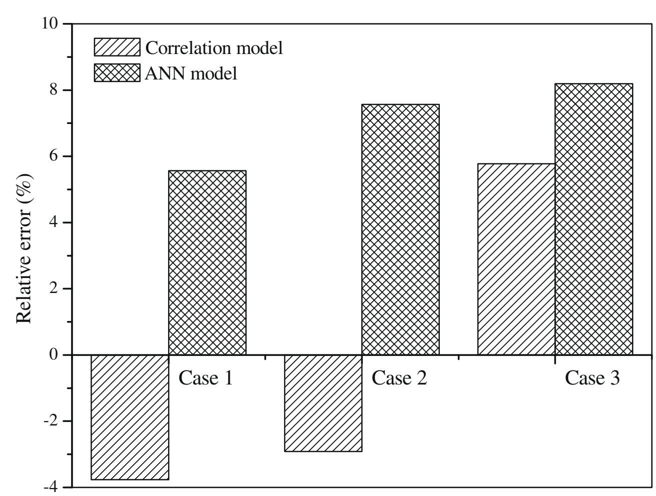

Fig. 3. Relative error of predicted annual energy consumption for the three cases.

Table 4
Comparison between annual and seasonal error analysis of cooling and heating electricity use.

	Cooling				Heating			
	NMBE (%)		CVRMSE (%)		NMBE (%)		CVRMSE (%)	
	Annual	Seasonal (June–August)	Annual	Seasonal (June–August)	Annual	Seasonal (December–February)	Annual	Seasonal (December–February)
Case 1	7.7	1.1	11.5	4.3	−0.7	−1.6	29.8	9.9
Case 2	3.6	1	6.1	2.6	−3.5	−0.6	26.9	7.4
Case 3	7.4	0.8	10.3	3	27.9	4.5	45.5	14.5

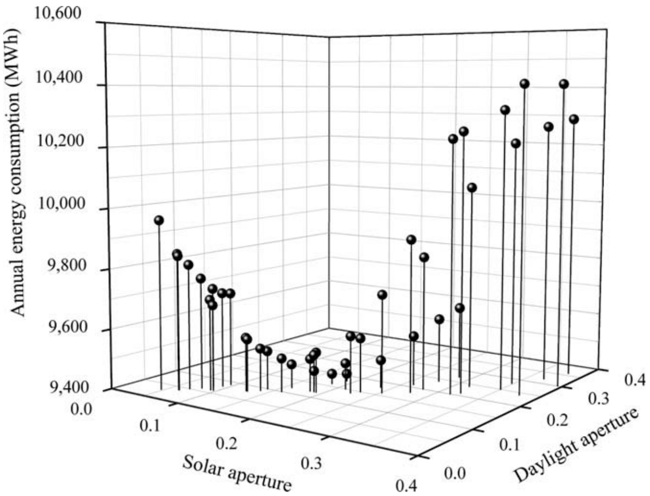

Fig. 4. Annual total building electricity use for different solar and daylight apertures.

consuming exercise of numerous full hourly simulations [18,45]. To demonstrate this, different combinations of WWR, SC and LT (hence different SA and DA) were inputted into the ANN and the corresponding predicted electricity consumption data were analysed. Again, the input design parameters were randomly generated. SA varied from 0.046 to 0.395 and DA from 0.03 to 0.36 (corresponding to 0.1–0.9 for WWR, 0.32–0.95 for SC and 0.2–0.8 for LT). Altogether 41 combinations of SA and DA were considered. Fig. 4 shows the total electricity consumption for the 41 combinations of SA and DA. The optimum designs (i.e. the lowest electricity consumption) are just over 9.4 GW h, corresponding to the region around 0.19 SA and 0.16 DA.

6. Conclusions

An ANN model was developed for office buildings with daylighting for subtropical climates. A total of nine variables were used as the input parameters – four variables were related to the external weather conditions (daily average dry-bulb temperature, daily average wet-bulb temperature, daily global solar radiation and daily average clearness index), four for the building envelope designs (solar aperture, daylight aperture, overhang and side-fins projections), and the last variable was day type (i.e. weekdays, Saturdays and Sundays). There were four nodes at the output layer with the estimated daily electricity use for cooling, heating, electric lighting and total building as the output. The Nash–Sutcliffe efficiency coefficient (NSEC) for the ANN modelled cooling, heating, electric lighting and total building electricity use was 0.994, 0.940, 0.993, and 0.996, respectively, indicating excellent predictive power. The relatively small NSEC for heating electricity use was probably due to the insignificant heating requirements during the short and mild winters in subtropical climates. Error analysis of three independent design cases showed that lighting electricity use had the smallest errors, from 0.2% under-estimation to 3.6% over-estimation, with the coefficient of variation of the root mean square error (CVRMSE) ranging from 3% to 5.6%. There was no clear pattern showing whether the ANN model tended to either over- or under-estimate. Comparisons between the annual and seasonal error analysis of cooling and heating electricity consumption suggested that the ANN model tended have more accurate predictions of electricity use for periods during which a particular end-use exhibited substantial demand (i.e. summer cooling and winter heating).

Acknowledgements

T.N.T. Lam and K.K.W. Wan were supported by City University of Hong Kong Studentship. Weather data were obtained from the Hong Kong Observatory of the Hong Kong SAR.

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