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An intelligent approach to assessing the effect of building occupancy on building cooling load prediction

Simon S.K. Kwok, Richard K.K. Yuen*, Eric W.M. Lee

Department of Building and Construction, City University of Hong Kong, Tat Chee Avenue, Kowloon Tong, Hong Kong (SAR), PR China

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ABSTRACT

Building cooling load prediction is one of the key factors in the success of energy-saving measures. Many computational models available in the industry have been developed from either forward or inverse modeling approaches. However, these models usually require extensive computer resources and lengthy computation. This paper discusses the use of the multi-layer perceptron (MLP) model, one of the artificial neural network (ANN) models widely adopted in engineering applications, to estimate the cooling load of a building. The training samples used include weather data obtained from the Hong Kong Observatory and building-related data acquired from an existing prestigious commercial building in Hong Kong that houses a mega complex and operates 24 h a day. The paper also discusses the practical difficulties encountered in acquiring building-related data. In contrast to other studies that use ANN models to predict building cooling load, this paper includes the building occupancy rate as one of the input parameters used to determine building cooling load. The results demonstrate that the building occupancy rate plays a critical role in building cooling load prediction and significantly improves predictive accuracy.

1. Introduction

Following the oil embargo of 1973, both the political and scientific communities began to pay more attention to opportunities to improve energy efficiency. Current statistics on energy use in different sectors show that the building sectors use approximately 40% of the world's electricity supply, which is used for heating, air conditioning, ventilation, lighting, and the operation of various types of building services system equipment [1]. The figure is somewhat higher for building services systems operated in tropical or sub-tropical areas, where air conditioning accounts for at least 50% of a building's total energy consumption [2]. The situation is even worse in Hong Kong, as most commercial buildings are fully air-conditioned and mechanically ventilated. As much as 60% of the energy used in Hong Kong's high-rise commercial buildings is powered mechanical ventilation and air-conditioning systems. Therefore, the ways to properly managing the building energy demands retain a lot of research attention, especially in air-conditioning systems.

Energy auditing is generally an effective tool that can assist facility managers in developing energy-saving plans and achieving energy-saving goals [3]. However, energy audits are typically expensive and time-consuming, which discourages building owners and managers from investing both the time and money required for a full energy audit exercise. Researchers have responded by developing inexpensive audit methodologies designed to identify buildings that are likely candidates for energy savings. These methodologies have been made possible by rapid advancements in computer hardware and software developed for building design. Many studies have adopted computer-based simulation models to evaluate building energy consumption levels [3].

Generally, the main stream of energy analysis employs forward approach which the energy predictions are based on a physical description of the building system such as geometry, building construction details, HVAC equipments and operation schedule. Most of the existing detailed energy computer-based simulation tools such as DOE-2, EnergyPlus and BLAST follow the forward modeling approach. However, the process of establishing the simulation model is very time-consuming and resource-intensive, especially for complex mixed-purpose buildings with unregulated operating schedules.

Inverse modeling approach is another method relying on existing building parameters such as energy use, weather or any relevant performance data to identify a set of building parameters such as prediction of cooling load. Typically, regression analyses are employed to estimate the representative parameters for building

* Corresponding author. Tel.: +852 2788 7621; fax: +852 2788 7612.
E-mail address: bckkyuen@cityu.edu.hk (R.K.K. Yuen).

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and/or its systems using measured data. However, the flexibility of inverse models is typically limited by the formulation of the reprehensive building parameters and the accuracy of the building performance data. Another challenge commonly faced is data acquisition, which is the foundation for establishing a viable model. In practice, existing buildings are not all equipped with building automation systems. Simulation projects are often hamstrung by the non-availability of information such as as-built building data, systems specifications, and operating schedules.

Artificial Intelligence (AI) techniques are becoming popularly as an alternative approach to conventional approaches, particularly in inverse modeling approach. An artificial neural network (ANN) can be used to approximate any nonlinear system and has the ability to adapt a complex environment via network training. Free of complex rules and mathematical routines, ANNs learn about the behavior of a complicated multidimensional system. In addition, ANN is fault tolerant, robust and noise immune [4].

Therefore, the unique characteristics of ANN such as adaptability, nonlinearity, arbitrary function mapping ability, make them suitable for forecasting tasks among those AI techniques such as expert systems, genetic algorithms and fuzzy logic and is a good candidate handling the building equipments and occupancy data being inherently noise and incompletion. Furthermore, ANN technology has recently been successfully applied to different areas of the building services engineering sector [5–11].

In this paper, an ANN model is used to simulate the total building cooling load of a prestigious office building in Hong Kong. The real data collected from the building air-conditioning system, together with the hourly weather data obtained from Hong Kong Observatory, are employed as the input parameters of the model, while the total building cooling load is selected as the model output.

2. Employing ANN models for building energy analysis

One of the major concerns of facility managers is how to evaluate and forecast the energy demands of buildings, especially those with air-conditioning systems in which energy demand varies according to changes in external climatic conditions, fluctuations in the occupancy rate over the course of a day, and the internal loads installed in the building [12]. The traditional method used for simulating energy demand in buildings is based on the implementation of building characteristics in more or less ideal physical sub-processes [13]. Although this method provides for a good understanding of the physical environment, it requires a large number of parameters and different degrees of idealization and simplification. Other common modeling techniques based on measured performance data include, for instance, time series analytical and statistical methods. However, these methods ignore the influence from meteorological factors such as temperature and humidity.

Two major approaches are currently used to estimate and analyze energy use in buildings, namely the “forward or classical approach” and the “inverse or data-driven approach.” The forward approach models the design of buildings and HVAC systems and the associated design optimization measures to establish benchmarks used for estimating the energy saving of different proposed retrofitting designs. In contrast to the forward approach, the inverse approach is applicable where the system has already been built and actual performance data are available for model development and/or identification [14].

Most of the current energy analysis software such as DOE-2.2 [15], TRNSYS [16], BLAST [17], and ENERGYplus [18] adopt the forward dynamic approach, in which energy predictions are based on a physical description of building systems such as their geometry, location, construction details, and HVAC type and operation [19]. The forward dynamic approach usually involves the use of numerical or analytical processes to determine energy transfer among various buildings. The detailed computer programs this approach involves require a high level of expertise and are generally time-consuming and complicated to run. By contrast, in energy analysis tools that use the inverse approach, the model attempts to deduce representative building parameters, such as the building load coefficient (BLC) or the building time constant, using data on existing energy use, weather, and any relevant performance data [19].

As each building reacts differently to external weather influences depending on the construction materials used, internal load from occupants, the provision of heating, ventilation and air-conditioning systems, and building control strategies, forward models cannot easily mimic the building cooling load due to the complex and often unexpected interactions that occur between systems or various modes of heat transfer [14].

Furthermore, steady-state inverse models such as the ANAGRAM and PRISM methods have certain limitations in that they are not capable of analyzing transient effects such as thermal mass effects and seasonal changes in the efficiency of the HVAC system. By contrast, dynamic inverse models including thermal network analysis, Fourier series models, and artificial neural networks are capable of capturing dynamic effects such as building thermal mass dynamics [19].

Artificial neural network (ANN) models, which are dynamic inverse models, have been used for energy analysis because of their ability to learn by example rather than by following programmed rules. ANN does not require explicit relationships between inputs and outputs to be defined in the data set and regression assumptions. Moreover, the ANN adapts itself during a training period, based on examples of similar problems even without a desired solution to each problem. Therefore, once an ANN model has been established, a building professional without knowledge of the physical system or the model itself can easily use it to predict and evaluate a particular building energy performance parameter.

ANN models have been proven to be useful for energy analysis in commercial buildings for the following reasons.

(i) Their predictions enable users to understand how a building should be operated and how this may differ from the way it has been operated in the past or in similar type of buildings. If there is a difference between the actual and ideal or similar scenarios, it can be used as an element of an expert system to produce early diagnoses of building operation problems.
(ii) Prior to an energy retrofit, an ANN model enables the prediction of building energy consumption under present conditions. When this prediction is compared to the measured consumption of the retrofitted building, the difference represents a good estimate of the energy saving attributable to the prospective retrofit. This represents one of the few ways in which actual energy savings can be determined after the pre-retrofit building configuration has ceased to exist.

3. ANN applications in cooling load prediction

A number of researchers and engineers have used ANNs for modeling and predictions in the field of building services engineering. This section discusses some of the recent studies on the application of ANN models to building cooling load prediction.

Yalcintas and Akkurt [20] employed MLP to mimic the total chiller plant power of a 42-storey commercial building in downtown Honolulu, Hawaii. Their independent input variables mainly consisted of climate data, and the model output was chiller plant power consumption [20]. The input parameters used in the MLP model included dry-bulb temperature, wet bulb temperature, dew point temperature, relative humidity percentage, wind speed, and wind direction. The hour of the day was recorded to account for variations in occupancy throughout the day. However, data on hourly power consumption in the chiller plant were not available for every hour of the day. The total number of matching data items was only 121 out of 312 for 13 of the days in the study period.

A further study by Yalcintas and Akkurt [20] developed an ANN model used to predict energy savings delivered by building equipment retrofits. The Levenberg–Marquardt backpropagation algorithm was used in the study and the input layer included the weather variables and the hour of the day. The weather data consisted of dry-bulb temperature, dew point temperature, wind speed, wind direction, air pressure, and visibility. The output was the hourly electricity measurements from the retrofitted equipment. Kreider and Rabl [21] used an ANN model to predict the pre-retrofit energy consumption of a building and compare it with the measured energy consumption of the retrofitted building. The input layer consisted of eight different types of input data including weather factors, ambient dry-bulb temperature, humidity ratio, horizontal insulation, and wind speed; and occupancy-related factors, including hour number (00:00–23:00), a weekday/weekend binary flag (i.e. 0 and 1), chilled water consumption in the past hour, and chilled water consumption in the previous hour.

Yezioro et al. [12] introduced an ANN model that used the Levenberg–Marquardt training algorithm to predict heating/cooling load consumption. The input parameters for the ANN model included hourly weather data such as the outdoor temperature, relative humidity, and set-point temperatures. The occupancy schedule, a key parameter contributing to energy consumption, was used as one of the model's input parameters.

The present study applies an ANN model that uses real measured building data. The measured data were obtained from a prestigious office building in Hong Kong. As there are many international companies with offices in this building that require air conditioning after normal office hours, the building is required to provide 24-h air-conditioning services and be operated 24 h a day, 7 days a week. The fact that the building is in continuous use makes it very complicated to simulate energy consumption via mathematical modeling simulations.

4. ANN model development and training

In general, ANN models employ data-driven, self-adaptive methods, and can be used to perform nonlinear modeling without the need for prior knowledge about the relationship between input and output variables. They have been proven to be universal function approximators [22], and are capable of approximating highly nonlinear system behaviors by constructing behaviors on the basis of historical system data. The most commonly used supervised neural network is MLP. An MLP model can be described as a model consisting of a number of neurons arranged in layers. Each neuron is a multi-input–single-output computational unit. The neurons in one layer are interconnected to the neurons in adjacent layers. This design mimics the learning process of the human brain in that it mimics the relationships between input and output parameters based on historical system data. The MLP model has been applied to a variety of problems, and especially to forecasting because of its inherent and superior input-output mapping capability.

4.1. Model architecture

In this study, the neural network consisting of three layers of neurons which are interconnected to each other as shown in Fig. 1 is employed for Simulation 3.

The layers are classified as input, hidden, and output layers. The nodes in the input layer receive information from external sources, and the neurons in the hidden layers, which act as the computational nodes in the neural network, transmit and transform the information fed from the input layer to the output layer. The output

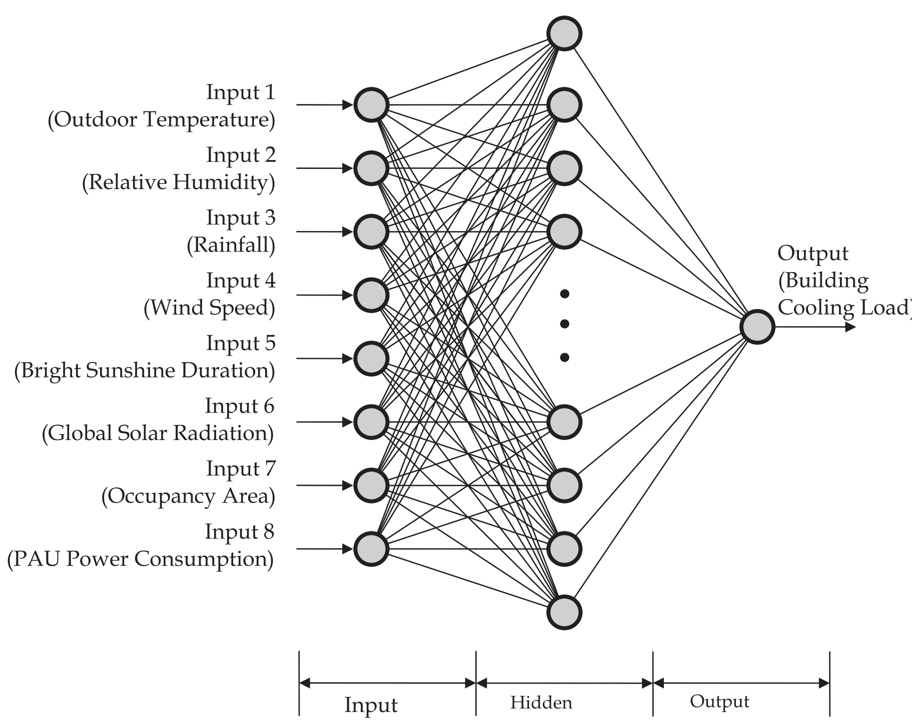

Fig. 1. Architecture of an MLP model uses in the Simulation 3.

layer neurons transmit information out of the network. As an MLP model with one hidden layer and a sufficient number of hidden neurons proven to be a universal function approximator [22], this model is adopted in this study.

4.1.1. Input layer

There are four factors playing a vital part in the cooling loading consumption of a building: i) its physical properties; ii) the equipment installed to maintain the desired internal environment such as ventilation and air-conditioning system; iii) the outdoor environment; and iv) its building occupants such as schedule, activity and behavior. While relatively good progress has been made in simulation of the first three factors, the latter has generally been based on fixed profiles of their occupancy presence and associated implications of their presence [23]. The cooling requirement of a building is governed by complex interactions between the space cooling load and air-handling system, and between the system and the cooling plant. In addition, these interactions are subject to the influences of time-varying parameters such as internal loads, heat gains through the building envelope, occupancy patterns, operating schedules, and external weather conditions. As the first critical factor affecting cooling load, the building physical properties, will not change from time to time. It is assumed to be constant at that particular time and would not be considered as an input in the simulation. The second and fourth factors are attributed to internal load factors, whereas the outdoor environment is represented by six climate parameters including outdoor temperature and relative humidity.

The number of neurons in the input layer is determined by the number of input parameters used. The input parameters are categorized into external load factors and internal load factors, as follows.

a) External Load Factors

External load factors refer to external climate parameters. In this study, the external load factors we use include outdoor temperature, relative humidity, rainfall, wind speed, bright sunshine duration (the total time that the sun intensity exceeds some predetermined threshold of brightness) and global solar radiation. The outdoor temperature, relative humidity, and solar radiation are the key climatic variables affecting building cooling energy, especially in sub-tropical regions [19]. The dry-bulb temperature determines the summer conduction heat gain, while solar radiation humidity duration and the global solar radiation parameter are crucial to the solar heat gain and latent load calculations, respectively. Hence, most of the ANN cooling loading prediction models [1,20,24–27] employ temperature and humidity as two of the input parameters. Other weather data such as rainfall, wind speed, and sunshine duration are also contributive factors to the cooling load simulation. Hourly external weather load parameters including outdoor temperature, relative humidity, rainfall, wind speed, global solar radiation and bright sunshine duration were obtained from the Hong Kong Observatory between August and October of 2008 are adopted in this study.

b) Internal Load Factors

It is common knowledge that the presence and actions of building occupants have a significant impact on the performance of building energy. Energy such as cooling load use in buildings is closely linked to their operational and space characteristics and the behavior of their occupants. The occupant's influence comes from his presence and activities in the building and due to his control actions that aim to improve indoor environmental conditions (thermal, air quality, light, noise [28]. The effects of occupants on a building's energy consumption are varied: people give off heat and "pollutants" (water vapor, odour, CO_2) that add to the buildings internal gains and influence the occupants' comfort [23].

Compared with external climate parameters, it is very difficult to obtain time-varying parameters such as internal loading, operating schedule and occupancy behavior. This is because it is almost impossible to count the number of occupants and to mimic their behavior inside a building at any given time. As a result, the randomness linked to occupants, i.e. the differences in behavior between occupants and the variation in time of each of behavior, plays an even more important part in the discrepancy between the simulated and real performances of buildings [23]. This may be the reason why building occupancy has seldom been adopted as one of the input parameters of the ANN cooling load simulation models [12,14,20,24]. The situation has become even worse if the simulated building is a mega commercial office building with numbers of multi-national enterprises working 24 h for a day and sometimes the work extending across Saturday and Sunday. As providing 24 h for seven days per week air-conditioning load supply is essential for the building, the input parameters with labeled hour number and distinguished weekday and weekend is far from enough to mimic the dynamic change of cooling load.

In this study, we introduce two input parameters to mimic the building occupancy: i) occupancy area (the hourly total occupancy area) and ii) the occupancy rate (the hourly total PAUs power consumption).

(a) The occupancy area

Traditional models usually reflect stationary linear relationships between the load and the fixed schedule in which only the hour of the day, the day of the week and difference labels between weekday and weekend will be labeled.

But in reality, different areas of an office building may have different operating schedules, especially in those 24 h operated mega office buildings. For example, some local based tenants may open from 9:00 am and close to 7:00 pm (the normal working schedule), while some international firms, especially in those United Stated based multi-national financial firms, and may need working after 8:00 pm and extending until 3:00 am in order to communicate with their headquarters and to deal with the investment business across the borders. Therefore, the hourly change of occupancy area varies after normal working schedule.

In this study, as the building is a mega grade A office building located at the hub center of Hong Kong, its tenants including numbers of multi-national financial companies coming from all over the world. Therefore, to provide 24 h services including access, power supply and air conditioning is essential for the building. In this connection, the occupancy area will still vary after normal working hours (8:00 am to 7:00 pm). The hourly occupancy area would be recorded according to the additional air-conditioning record (after normal working schedule i.e. before 9:00 am and after 7:00 pm) and the percentage of total building occupancy area had been recorded as one of the input parameters to mimic the building occupancy accordingly.

(b) The occupancy rate

The occupancy rate reflects the number of occupants inside a building at any given hour in the day. Manually counting the number of people inside a building is impractical, as it requires a lot of manpower. Although video recordings captured by CCTV cameras placed at all entrances to and exits from a building provide a means of counting the people entering and leaving the building that involves the technique of pattern recognition, the management office of the building observed in this study was unwilling to release video recordings for security reasons. This made collecting data on the hourly occupancy rate for the building impossible.

As an alternative, the occupants' presence of the building can indirectly mimic based on the following processes:

Each human being emits heat and pollutants such as water vapor, carbon dioxide, odour, etc. Therefore, his/her presence directly modifies the indoor environment. Carbon dioxide is a by-product of combustion processes and the metabolism of living organisms. People inhale oxygen and exhale carbon dioxide (CO_2). In a building, the amount of CO_2 exhaled by people is diluted by outside air introduced by mechanical ventilation, air leakage, and open windows (as the case may be). As the audited office buildings are equipped with totally sealed up façade, the mechanical fresh air supply system is provided for diluting and lowering the concentration of the CO_2 to a safe level. In this audited office building, the fresh air is supplied via Primary Air-handling Units (PAU) which employed demand control system using CO_2 concentration level control. The fresh air rate is proportionally controlled by the demand control ventilation system, which measures CO_2 levels at the return air duct of the primary air units (PAUs) serving the building and keeps the CO_2 concentration level below a preset value. CO_2 sensors are adopted to indirectly control the outdoor air quantity supplied to the interior spaces.

Since there are practical problems involved in measuring the fresh air supply rate directly and it is impractical to account for the variable change of CO_2 concentration rate which reflects the change of occupant's density as there may be more than several hundreds of CO_2 sensors installed in the air distribution systems. As an alternative, the occupancy rate of the building was indirectly mimicked based on the total PAU's power. As the total outdoor air quality from the primary air-handling units is regulated by adjusting the fan speed using frequency inverter, this can regulate the fresh air loading on air-conditioning system based on the building occupancy. When the number of occupants increases, the CO_2 concentration level in the air returned to the PAUs increases and the controller proportionally increases the fresh air supply rate accordingly. Thus, the total PAU's power can be used as an indicator of the building occupancy rate.

We recorded the hourly electrical power consumption of the PAUs, which employ variable frequency controls to regulate the demand of fresh air supply rate based on the variable change rate of CO_2 concentration, to mimic the presence of occupants.

The Neuroshell 2 package is used to build, configure and train the network. To analyze the effect of the building occupancy on the ANN model predictions, the three simulations shown in below are developed. The purpose of implementing Simulation 1 is to benchmarking the effect of model without considering any building occupancy factors. In simulation 2, we put the occupancy area data together with external weather factors, whereas both occupancy area and rate factors together with external weather factors were put together to study the influencing of cooling load prediction.

Table 1
Three simulations are carried out with a different number of input parameters. Simulation 1 adopts only the external load factors. Simulation 2 includes the occupancy area factor in the sample inputs, and Simulation 3 includes all external and internal load factors.

Load factors	Input parameters [unit]	Simulation 1	Simulation 2	Simulation 3
External	Outdoor temperature [°C]	✓	✓	✓
	Relative humidity [%]	✓	✓	✓
	Rainfall [mm/h]	✓	✓	✓
	Wind speed [km/h]	✓	✓	✓
	Bright sunshine duration [h]	✓	✓	✓
	Global solar radiation [MJ/m^2]	✓	✓	✓
Internal	Occupancy area [m^2]		✓	✓
	PAU power consumption [kW]			✓

Incorporating the above two internal load parameters and the external climate parameters obtained from Hong Kong Observatory on an hourly basis, three simulations ANN models (models 1, 2 & 3) as shown in Table 1 are developed in the course of this study.

In Simulation 1, only 6 external weather parameters are adopted in the input layer and the total building cooling load is the only output parameter. To reveal the effect of the internal load factors, occupancy area is included as one of the input parameters in Simualtion 2. Moreover, occupancy rate, another parameter representing the internal load, is included in the input variables in Simulation 3.

4.1.2. Hidden layer

The number of hidden neurons for a 3-layer network is estimated by the rule-of-thumb recommended in [29], in which equation (1) is used, where N_h and N_p are the number of hidden neurons and the number of samples, respectively, and N_i and N_o are the number of input and output parameters, respectively.

$$N_h = \frac{N_i + N_o}{2} + \sqrt{N_p} \tag{1}$$

The number of hidden neurons in each of the simulations is determined by rule-of-thumb, as shown in equation (1). A sensitivity test is also carried out to test the validity of the number of hidden neurons determined by observing the change in the prediction error when the number of hidden neurons is varied ± 5 from the number of hidden neurons determined by equation (1).

4.1.3. Output layer

The number of neurons in the output layer of an MLP model is equal to the number of system outputs. Since this study is aimed at predicting the building cooling load in response to internal and external load factors, the output of the MLP model is the building cooling load. Therefore, the output layer of the MLP model has only one neuron representing the output of the prediction (i.e. building cooling load).

4.2. Network training

Backpropagation [30] (BP) is a traditional training algorithm used for the MLP model. It feeds back the prediction errors from the output layer to the input layer and the weights of the links between the neurons are adjusted according to the BP algorithm. Upon completion of the weight adjustments, a new prediction is carried out to evaluate a new prediction error for the next epoch of weight adjustments. These procedures are repeated numerous times until a satisfactory prediction result is achieved. In this study, the early-stop validation approach is adopted to monitor and stop the BP training. Fig. 2 illustrates the concept of the early-stop training approach.

A total of 1053 samples were collected from August to October 2008 for network training and testing. For model training and evaluating the performance of a trained MLP model, the first 80% of the samples (i.e. those taken from 13-Aug-2008 0:00 to 13-Oct-2008 13:00) are used for network training, while the remaining 20% of the samples (i.e. those taken from 13-Oct-2008 14:00 to 20-Oct-2008 23:00) are hidden during the network training phase and kept in reserve as a testing set to evaluate the performance of the trained network. The 80% of samples used for network training are further divided randomly into proportions of 75% and 25% for the

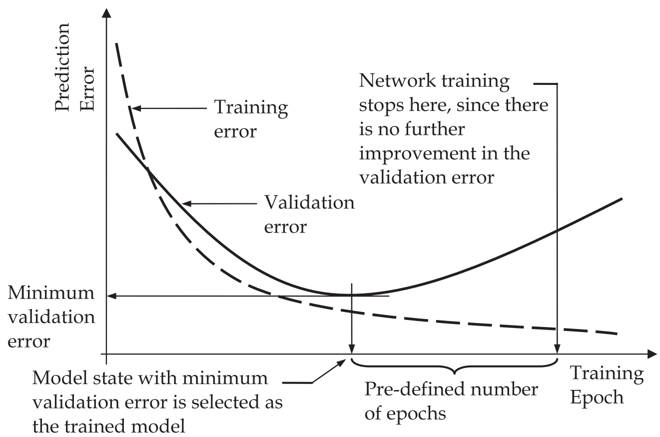

Fig. 2. The early-stop validation approach stops the backpropagation training when there is no further improvement in the validation error over a pre-defined number of epochs after it has reached its minimum level. The intermediate state of the model with the minimum validation error is selected as the trained model.

training samples and validation samples, respectively. The training set is used to train the model with the BP algorithm, while the validation set is used to monitor and stop the BP training using the early-stop validation approach. The testing set does not play a role in the training of the MLP model. Upon completion of the model training, the testing set is used to evaluate the performance of the trained model.

In order to prevent the "overfitted training", the intermediate-state trained model in every training epoch is applied to the validation set to evaluate the prediction error (i.e. the validation error). The network training process is stopped when the validation error reaching the minimum value. Since we have no prior knowledge in the trend of the validation error, "Early-stop" training is adopted. It records the status of the model continuously in the course of training. When there is no reduction in the validation error over a predefined number of epochs (in the paper, the no. of epochs has been selected to be 2000), the model state with the minimum validation error is taken to be the trained model. Fig. 2 illustrates the process of the Early-Stop training.

Upon completion of the network training, the trained MLP is applied to the testing set to evaluate the performance indices by comparing the target values of the testing set and the values predicted by the trained model. The performance indices used in this study are the root-mean-square-percentage-error (RMSPE) and the coefficient of correlation (r), as defined respectively in equations (2) and (3), where N is the total number of samples, and $\{t_i, p_i\}_{i=1}^{N}$ are, respectively, the target values and the predicted values. $\overline{p}$ and $\overline{t}$ are the mean value of the predicted values and the mean value of the target values, respectively.

$$\mathrm{RMSPE} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_i - t_i)^2}}{\overline{p}} \times 100\% \tag{2}$$

$$r = \frac{\sum_{i=1}^{N}(t_i - \overline{t})(p_i - \overline{p})}{\sqrt{\sum_{i=1}^{N}(t_i - \overline{t})^2 \sum_{i=1}^{N}(p_i - \overline{p})^2}} \tag{3}$$

It should be noted that a random process is normally involved in the network training of an MLP model, especially when the available samples are divided into training and validation sets. It is thus not impossible for the random process used to result in 'fortuitous' samples that show the evaluated performance indices are good. Instead of reporting only the best simulation result, a less-prejudice statistical approach is adopted to minimize the effect of randomization. We carried out the network training and performance evaluation process 10 times. The 10 results are statistically analyzed by evaluating the mean of the results and the limits of the 95% confidence intervals. This approach, which differs from that taken in previous studies [20,24], reveals the performance of the ANN model when this less-prejudiced approach is taken, as illustrated in the following Fig. 3.

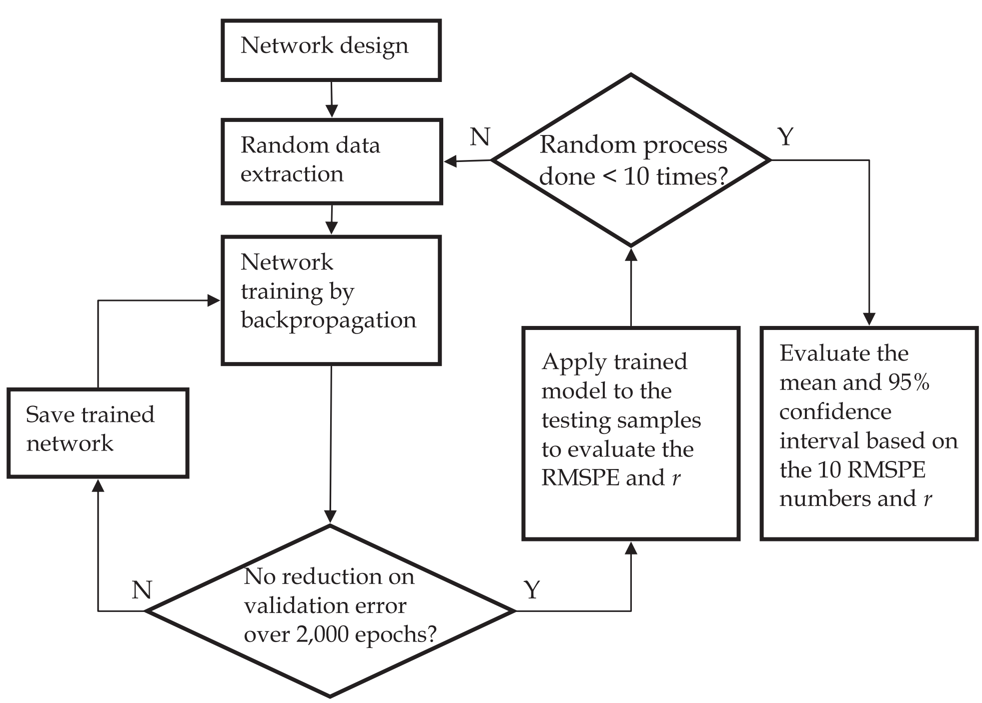

Fig. 3. The training scheme designed to minimize the effect of the random data extraction process.

Table 2
The correlation coefficients of the predicted results of Simulation 3 under different numbers of hidden neurons. The number of hidden neurons determined by equation (1) is 30.

No. of hidden neuron	Trial									
	1	2	3	4	5	6	7	8	9	10
25	0.97	0.9737	0.958	0.9714	0.9623	0.9783	0.9806	0.9805	0.978	0.926
26	0.9773	0.9703	0.9724	0.9775	0.9698	0.9784	0.9738	0.9784	0.959	0.9628
27	0.9774	0.9497	0.9743	0.9768	0.9772	0.9755	0.9656	0.9583	0.9589	0.9503
28	0.9788	0.9722	0.9704	0.954	0.9472	0.954	0.9756	0.9653	0.9536	0.9458
29	0.9616	0.9728	0.9692	0.9715	0.9584	0.9624	0.9605	0.9699	0.9712	0.9635
30	0.9584	0.9509	0.9525	0.9399	0.9593	0.9696	0.9634	0.9524	0.9598	0.9548
31	0.971	0.931	0.9683	0.9487	0.9746	0.9758	0.9765	0.9641	0.9643	0.9671
32	0.9773	0.9784	0.9779	0.9776	0.9681	0.9725	0.978	0.9767	0.948	0.9778
33	0.9765	0.9402	0.9681	0.9627	0.9748	0.9681	0.9751	0.9701	0.9749	0.9778
34	0.9678	0.9789	0.9773	0.972	0.977	0.9674	0.9787	0.9783	0.9765	0.9796
35	0.9669	0.9706	0.9590	0.9500	0.9688	0.9701	0.9501	0.9769	0.9770	0.9784

5. Results and discussion

It is known that the cooling load in buildings is affected by many parameters, which can be identified as two important parameters: the outdoor climate and building occupancy. However, the influence of these factors is subject to forecasting type (whether short term or medium/long term), weather zone, building nature (commercial or residential building), building orientation, building occupancy (presence and behavior), operation schedule (fixed schedule or dynamic schedule) etc. In this study, we conducted an energy analysis in one of the tallest office buildings in Hong Kong, a super Grade A office building with usable area more than two million square feet and with a cooling capacity as much as ten thousands cooling ton. It locates at the hub center of Hong Kong (owing to abiding confidential agreement, we cannot disclose the name of the building) with tenants include many multi-national financial companies. The building's standard hours of cooling load supply are 8:00 am to 7:00 pm from Monday to Friday and 8:00 am to 1:00 pm on Saturday. But it is far from satisfying the extensive working nature of those international firms. They have to work after normal office hours, even at mid night at Weekends. In order to fulfill the tenant's abnormal working requirements, the 24 h air conditioning for seven days per week is required for the building. The dynamical change of building occupancy makes it very difficult to forecast the building cooling load by means of employing fix time schedule.

In this study, we had carried out three simulations to analyze the effect of load factors, whereas Simulation 1 employed external weather factor solely and Simulations 2 & 3 used all of the external load factors and internal factors of occupancy area and PAU power consumption respectively. The result of Simulation 1 shows that it is not adequate to employ external weather factors only for implementing a short term load forecasting for such a dynamic load change building. But it does not reflect the insignificant influence of the climate on the load simulation as the external climate factors are only represented as part of the load influencing components.

Internal load factors, such as occupant profile and schedule are other important factors which have vital influence on the cooling load. The dynamically change of building occupancy makes it very difficult to forecast the building cooling load by means of only employing the external climate parameters. The results of simulation 2 & 3 illustrate the importance of employing both internal and external load factors for dynamic cooling load prediction. The best prediction performance to fit to the actual data was obtained by Simulation 3 with which the model included both occupancy area and rate and external weather parameters.

Moreover, a sensitivity study is conducted to justify the number of neurons in the hidden layer of the MLP as determined by equation (1). Simulation 3 is selected for the sensitivity study as a demonstration. The number of hidden neurons in Simulation 3, as determined using equation (1), is 30. In this study, different numbers of hidden neurons ranging from 25 to 35 (i.e. 30 ± 5) are tried to enable the change in network performance to be seen. To analyze the sensitivity statistically, 10 trials are performed for each number of hidden neurons. Table 2 summarizes the results. The minimum and maximum values of the correlation coefficients in Table 2 are 0.9260 and 0.9806, respectively.

The results shown in Table 2 are further analyzed by evaluating the 95% confidence intervals of the 10 trials for each number of hidden neurons by assuming the data are normally distributed. The 95% confidence limits are shown by the error bars in Fig. 4. This figure shows that the confidence intervals under different numbers of hidden neurons overlap with each other. This can be interpreted to mean that the performance of the model does not change significantly when the number of hidden neurons varies between 25 and 35. Therefore, the number of hidden neurons determined in equation (1) is justified statistically and can be adopted throughout the remainder of this study.

The performance indices (i.e. r and RMSPE) for the simulations are evaluated through 10 trials in which different random data

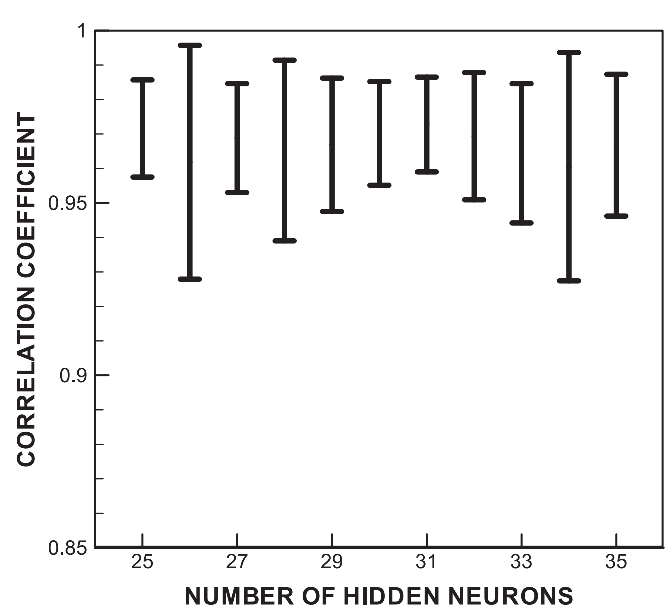

Fig. 4. Confidence intervals for the correlation coefficient of the trials for each number of hidden neurons.

Table 3
Performance indices for the 10 trials of each simulation.

Trial	Performance indices					
	Simulation 1		Simulation 2		Simulation 3	
	r	RMSPE	*r*	RMSPE	*r*	RMSPE
1	0.5551	46.86%	0.7357	43.46%	0.9778	13.53%
2	0.5457	45.81%	0.9038	24.89%	0.9783	13.32%
3	0.5322	52.36%	0.7821	48.81%	0.9583	16.39%
4	0.5816	51.33%	0.8665	29.21%	0.9652	14.49%
5	0.5735	49.45%	0.9090	36.68%	0.9699	15.40%
6	0.4702	66.55%	0.9128	23.54%	0.9783	13.41%
7	0.5702	50.80%	0.8356	33.79%	0.9641	15.18%
8	0.5407	55.04%	0.8267	35.68%	0.9759	13.24%
9	0.5962	47.20%	0.9065	25.26%	0.9701	13.94%
10	0.5502	45.29%	0.8853	29.42%	0.9778	13.53%
Upper limit of the 95% confidence interval	0.6197	63.35%	0.9752	49.38%	0.9856	16.36%
Lower limit of the 95% confidence interval	0.4834	38.78%	0.7376	16.77%	0.9575	12.12%

extraction methods are used for each of the simulations. The evaluated performance indices (i.e. *r* and RMSPE) for each trial are presented in Table 3 which is graphically presented in Fig. 5.

It shows that, with respect to the coefficient of correlation, the 95% confidence intervals of Simulation 2&3 are higher than that of Simulation 1 with no overlapping. The figure also shows that, with respect to RMSPE, the 95% confidence interval of Simulation 2 overlaps with that of Simulation 1 but that of Simulation 3 is lower than that of Simulation 1 without overlapping. It concludes that the ANN prediction can be significantly improved by taking both of the occupancy area and occupancy rate into consideration. Fig. 6 shows the typical prediction results from Simulations 1, 2 and 3 of which Simulation 3 achieves the best fit to the actual data

In this study, short term cooling load forecast for a mega office building with more than 2 million square feet grade A office area and with a capacity of more than ten thousand AC cooling Ton was conducted.

As weather conditions influence the cooling load greatly, usually larger cooling load occurs between June and October in sub-tropical climate zones like Hong Kong. However, external weather

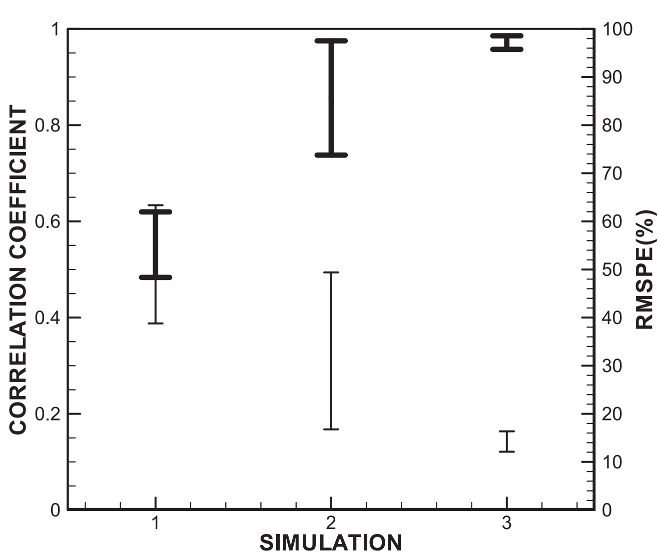

Fig. 5. The 95% confidence intervals for the correlation coefficients and RMSPEs of Simulations 1, 2 and 3. The bold lines represent the correlation coefficients, while the thin lines represent the RMSPEs.

factor is not the only factor affecting the cooling load. Internal load factors, such as occupant profile and schedule are other important factors which have vital influence on the cooling load.

In this study, two parameters were introduced to mimic the occupant's presence. The first one is the occupancy area and the second is occupancy rate. Usually, most of the simulation models will imply fixed working schedule to represent the building occupancy profile. In reality, the building occupancy profile will vary after normal fixed schedule because of the need to do overtime work for some of the tenants especially for those international firms. Moreover, there are some firms which operate five days a week, whereas there are some firms that operate six days or even seven days a week. As a result, the building occupancy profile will dynamically change after fixed working schedule, particular at weekends. As such, we summarized the hourly record of overtime requirements for the whole building. There will be hundreds of requests for overtime work in an hour sometimes. It is commonly known that the more the working areas occupy, the more the energy consumes.

The dynamically changed occupancy area is taken as one of the input parameters together with other 6 external weather factors to mimic the cooling load in Simulation 2 with details as shown in Table 1. The simulation results show that the performance of simulation has been significantly improved.

Furthermore, the effects of occupant's presence on a building's energy consumption vary: people give off heat and pollutants that add to the building's internal gains and then require more cooling load. As the occupancy area could not mimic the occupant's presence, we introduce another input parameter, the occupancy rate. The occupancy rate is input as the total energy of primary air units (PAUs) with which the output of fresh air rate is subject to the measured CO_2 level. When the numbers of occupants increase, the CO_2 concentration level will increase and will lead to the increase of fresh air supply rate accordingly. As such, the total energy to supply fresh air can mimic the presence of occupant at the particular time. The detail of simulation is demonstrated in Simulation 3 of Table 1. The result in Table 3 demonstrates a significant improvement comparing with Simulation 2.

In view of the above, if it is only to employ one of the two critical load factors (either external or internal load factors) to simulate the building cooling load, it will inevitably lead to unsatisfactory result. This is the reason why the result of Simulation 1, which employed external weather factors only, shows less influence. However, if we employ external weather and internal occupancy factors, the simulation results (Simulation 2 & 3) are more satisfactory.

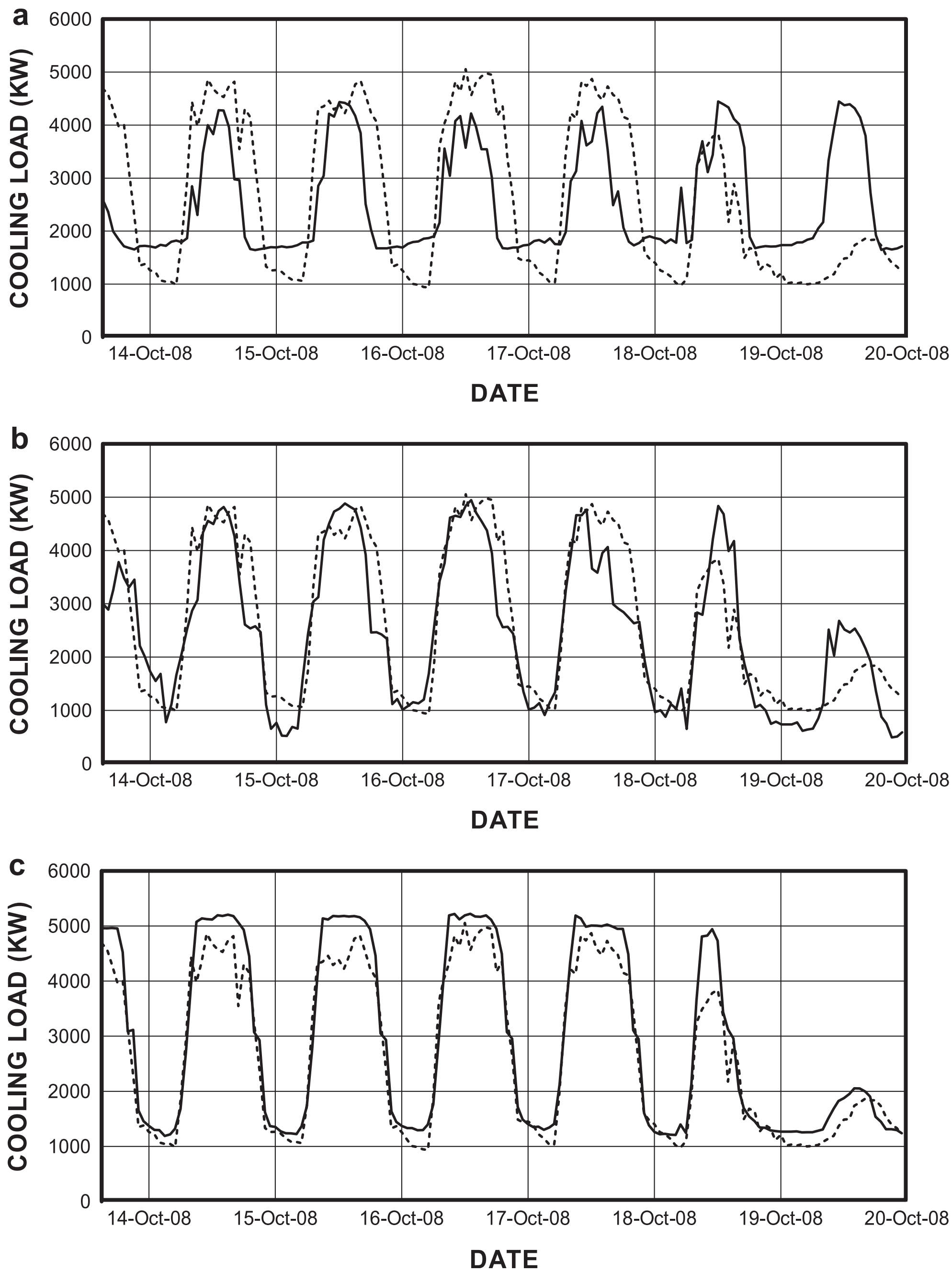

Fig. 6. Typical results for (a) Simulation 1; (b) Simulation-2; and (c) Simulation 3. The solid line represents the predicted cooling load and the dashed line represents the actual cooling load.

6. Conclusions

This study investigates the modeling of building cooling load through an intelligent approach that takes into account the building occupancy rate, a factor disregarded in previous studies. The difficulties encountered in obtaining building occupancy data and the alternative ways in which such data can be collected. The ANN-based MLP model is incorporated into the intelligent modeling approach we propose. The number of hidden neurons adopted in the MLP model is determined by using the rule-of-thumb in equation (1). A sensitivity test demonstrates that the performance of the MLP model is insensitive to the number of hidden neurons, which varies ±5 neurons from the number determined by the rule-of-thumb. A statistical approach is used to minimize the effects induced by the random data extraction method employed for network training and testing. The performance indices (i.e. *r* and RMSPE) are represented by the upper and lower limits of the 95% confidence interval obtained from a series of trials. The results of the simulations carried out in this study reveal that the use of building occupancy data can significantly improve the accuracy of MLP model predictions. This research clearly demonstrates the importance of the occupancy data in the building cooling load prediction by ANN.

In further research designed to build on the findings of this study, consideration should be given to increasing the level of accuracy via looking for the parameters which could not only simulate the occupant presence but also reflect their behaviors in the building.

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