Prediction of Electricity Consumption of a HVAC System in a Multi-Complex Building Using Back Propagation and Radial Basis Function Neural Networks

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ABSTRACT

This study examined approaches to predict electricity consumption of a Heating, Ventilation and Air-Conditioning (HVAC) system in a multi-complex building using two neural network models: Back Propagation (BP) and Radial Basis Function (RBF) with input nodes, e.g., temperature, humidity ratio, and wind speed. Predicting HVAC energy consumption of buildings is a crucial part of energy management systems. We used two main neural network models, BP and RBF, to evaluate the prediction performance of electricity consumption of HVAC systems. The BP neural network method exhibited good performance, but it exhibited relatively large fluctuations and slow convergence in the training process. In contrast, RBF exhibited relatively fast learning and reduced computing costs. The HVAC energy consumption rate of working days was higher than that of non-working days. The results indicate that the prediction of HVAC energy consumption using neural networks can effectively control the relationship between the HVAC system and environment conditions.

INTRODUCTION

Heating Ventilation Air-Conditioning (HVAC) systems play a large role in commercial buildings, including office buildings, hotels, and shopping malls, providing a comfortable indoor environment for occupants Bluyssen et al. (2011); (Domjan et al., 2019; Kassai et al., 2016; Melikov, 2016; Sultan, 2007). Such systems account for a large (50%) proportion of energy consumption in buildings (Cholewa et al., 2021; Hou et al., 2006; Kim et al., 2014; Kim et al., 2018; Pérez-Lombard et al., 2008) and around 20 % of total energy consumption (Chua et al., 2013). The performance of HVAC systems is a crucial technology to improve human health and comfort in buildings (Chua et al., 2013; Kassai et al., 2018). Forecasting energy consumption aids in the design of enhanced power and facility management, grid operation and Electrical Energy Storage (EES) (Ye & Kim, 2018). However, studies had not presented how each element such as ambient temperature, humidity ratio, wind speed and working or non-working days in a multi- complex building could affect electricity consumption. This study explored forecasting of energy consumption in a multi-complex building to determine the optimal HVAC system operation in relation to ambient temperature, humidity, wind speed and working or non-working days.

Many studies have used Artificial Neural Network (ANN) methods for predicting building energy consumption, with good accuracy (Bocheng Zhong, 2015; Kim et al., 2019; Lee et al., 2019; Ye & Kim, 2018; Yuan et al., 2018). Modelling with ANN is one of the main algorithms used for forecasting energy consumption in buildings (Ahmad et al., 2016; Azadeh et al., 2008; Ekici & Aksoy, 2009; Kim et al., 2020a, 2020b; Wong et al., 2010) because it can adapt to many irregular rules and neural networks exhibit self-learning (Lek & Guégan, 1999; Ye & Kim, 2018). Compared with statistical and regression methods, ANN methods present better prediction performance (Pombeiro et al., 2017; Sekhar Roy et al., 2018). Ye and Kim (Ye & Kim, 2018)used Levenberg-Marquardt Back Propagation method to predict electricity consumption in a commercial building. Kim et al. (Kim et al., 2019) presented simplified ANN models with sensitivity analysis. And Lee et al. (Lee et al., 2019) suggested a building energy prediction method with training data generation. Yuan et al. used ANN prediction model for a university campus (Yuan et al., 2018), and Biswas et al. (Biswas et al., 2016) showed ANN prediction results in a residential building. And Raza and Khosravi (Raza & Khosravi, 2015) reviewed ANN algorithms for smart grid and buildings.

Back-Propagation (BP) neural networks are widely used to predict energy consumption because they possess several advantages. Such networks combine information storage and process calculations (Jia et al., 2015; Kim et al., 2020a; Xu et al., 2015; You & Cao, 2015; Yu et al., 2008). The storage of training and self-learning is based on the distribution of interconnections between neurons (Ye & Kim, 2018).

Radial Basis Function (RBF) modelling was proposed by Powell in 1981 (Powell, 2015). The algorithm shows a linear combination of functions of input parameters (Buhmann, 2003; Yang et al., 2016). And it has been used in function approximation, energy prediction with time series, and control system. The learning speed of RBF network is usually faster than that of BP networks, and it has no local minima problems (Buhmann, 2003).

This study newly proposed a predictive methodology based on two neural networks, BP and RBF algorithms, with input nodes of the surrounding environment e.g., temperature (°C), humidity ratio (g/kg), and wind speed (m/s), which impact HVAC energy consumption of a multi-complex building. In this study, we examined whether either or both of two artificial neural networks were suitable to predict HVAC electricity consumption in a multi-complex building in China and which algorithm was more efficient, in terms of time and accuracy.

METHOD

Back-Propagation neural network

Back Propagation neural networks are widely used neural network models, comprised of a multi-layer feedforward neural network model trained by an error back propagation algorithm. This algorithm is characterized by mapping relationships inside the model with training procedures before calculation, and then it predicts and fits any continuous model function with a specified precision (Hao et al., 2013; Kumar et al., 2013; Yuan et al., 2018). The BP neural network algorithm is generally composed of at least three layers: an input layer, a hidden layer, and an output layer (Liu et al., 2017; You & Cao, 2015). Neurons are inter-connected among layers by numerous functions. By learning a large number of input-output mapping relations, the BP-algorithm utilizes the steepest descent method to continuously adjust the network threshold and weight by means of back propagation (Kuo Lu, 2015; Svozil et al., 1997; Yu et al., 2008). At the same time, the error value of the leading layer of the output layer is estimated by the error value of the output layer, and the error value of the leading layer is deduced by back-propagation of the analogy. Consequently, the estimation error of each layer of the network is determined (Kim et al., 2019; Lee et al., 2019; Ye & Kim, 2018; Yuan et al., 2018). Figure 1 illustrates the structure of BP neural network (Kim et al., 2019; Lee et al., 2019; Ye & Kim, 2018).

Forward-propagation of BP neural network

The output of the hidden layer is expressed by equation (1)

$$O_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - \theta_j\right) \qquad j = 1,2,\ldots,1 \tag{1}$$

The output of the output layer is expressed by equation (2)

$$Y_k = \left(\sum_{j=1}^{l} O_j w_{jk} - d_k\right) \qquad k = 1,2,\ldots,m \tag{2}$$

The error function (Azadeh et al., 2008; Bocheng Zhong, 2015; Xu et al., 2015; Yu et al., 2008) is expressed by equation (3)

$$E_k = \frac{1}{2}\sum_k (H_k - Y_k)^2 \tag{3}$$

In summary, equations (1), (2), and (3) can be derived:

$$E_k = \frac{1}{2}\sum_k \left(H_k - f\left(\sum_{j=1}^{l} w_{jk} f\left(\sum_{i=1}^{n} w_{ij}x_i - \theta_j\right) - d_k\right)\right)^2 \tag{4}$$

The output node and the threshold are derived using the error function (3) as follows:

$$\frac{\partial E_k}{\partial w_{jk}} = -(H_k - Y_k)\cdot f'\left(\sum_{j=1}^{l} O_j w_{jk} - d_k\right)\cdot O_j \tag{5}$$

$$\frac{\partial E_k}{\partial d_k} = (H_k - Y_k)\cdot f'\left(\sum_{j=1}^{l} O_j w_{jk} - d_k\right) \tag{6}$$

The order of the error of the output node is as follows equation (7)

$$\delta_k = (H_k - Y_k)\cdot f'\left(\sum_{j=1}^{l} O_j w_{jk} - d_k\right) \tag{7}$$

Then it can be concluded that

$$\frac{\partial E_k}{\partial w_{jk}} = -\delta_k O_j \tag{8}$$

$$\frac{\partial E_k}{\partial w_{jk}} = -\delta_k O_j \tag{9}$$

The correction formula for the output layer weight and threshold is given by equation (10, 11):

$$w_{jk}(a+1) = w_{jk}(a) + \Delta w_{jk} = w_{jk}(a) + \eta\delta_k O_j \tag{10}$$

$$d_k(a+1) = d_k(a) + \eta\delta_k \tag{11}$$

The correction formula for the hidden layer weight and threshold is as follows equation (12, 13):

$$w_{ij}(a+1) = w_{ij}(a) + \Delta w_{ij} = w_{ij}(a) + \eta\delta_j O_i \tag{12}$$

$$\theta_j(a+1) = \theta_j(a) + \eta\delta_j \tag{13}$$

Where, η is the learning rate of the model.

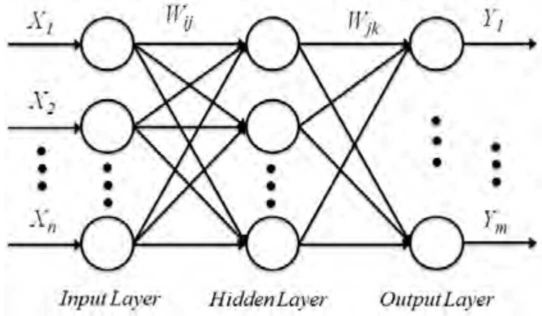

Figure 1 Schematic diagram of a BP neural network structure (Ye & Kim, 2018).

Radial basis Function neural network

An RBF network is very effective when there are many training vectors because the response relies on the

connecting distance of the input values to a fixed point, called the centroid or center (de Leon-Delgado et al., 2018). The main disadvantage of using BP neural network is slow convergence. In contrast, RBF networks exhibit relatively fast learning and achieve good accuracy, thereby reducing computing costs.
The structure of an RBF network is shown in Figure 2.

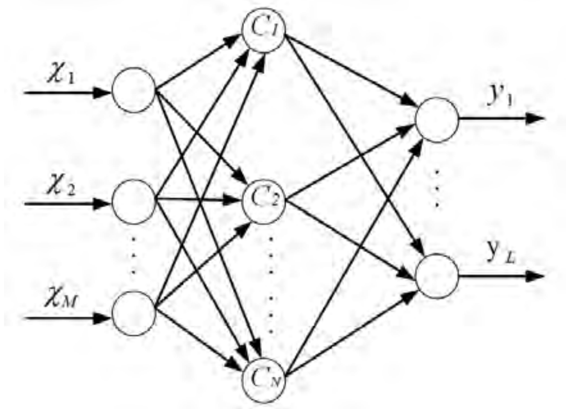

Figure 2 RBF neural network structure diagram.

As shown in Figure 2, an RBF network is composed of three layers. The input layer node is responsible for mapping the input signal to the hidden layer. A linear transformation is implemented between the hidden layer and the output layer. The transformation function of the hidden layer is a radial basis function, most commonly a Gaussian activation function (Buhmann, 2003; de Leon-Delgado et al., 2018).
Gaussian functions are selected for the RBF, and the output of the i neuron in the hidden layer is expressed as

$$u_i(x) = \emptyset\,(\|x - c_i\|) = exp\left[-\frac{\|x-c_i\|}{2\sigma_i^2}\right] \quad (i = 1,2,\cdots,Q) \quad (14)$$

where u_i is the output of the i hidden node, σ_i is the standardized constant of the i hidden node, c_i is the center vector of the Gaussian function of the i hidden node, x is input sample, and Q is the number of hidden layer nodes.
Equation (14) can be used as its conformance with the Gaussian function. After obtaining all outputs of the hidden layer, the final output of an RBF network is calculated as the linear function given in equation (15).
The linear mapping from the hidden layer to the output layer $u_i(x) \rightarrow y_k$ is expressed as

$$\hat{y}(\mathrm{x}) = \beta_0 + \sum_{i=1}^{Q} \beta_k \emptyset\,(\|x - c_i\|) \quad (k = 1,2,\cdots,L) \quad (15)$$

where, the coefficients, β_i for k = 0, 1, 2 ... n, and Q is the number of hidden layer nodes.
For compact matrix notation, equation (15) may be written as

$$y = \emptyset\beta + \epsilon \quad (16)$$

The value $\hat{\beta}$ can be calculated using the Pseudo inverse as follows:

$$\hat{\beta} = (\emptyset^T\emptyset)^{-1}\emptyset^T y \quad (17)$$

The output of an RBF neural network can be finally calculated using the estimated weight.

$$\hat{y} = \emptyset\hat{\beta} \quad (18)$$

Overview of energy consumption in a multi-complex building: A case study

This study used electricity consumption data (March to May) for a multi-complex in Nanjing, China, to validate the prediction model and algorithms. The building occupies 370,000 square meters and has 33 floors, with a total height of 150 meters. Thus, it exhibited a high-energy consumption. The building is classified into several areas. The first to fifth floors are for shopping malls, the sixth to 22nd floors are for office space, the 23rd to 33rd floors are for hotel and living areas, and there are also functional spaces distributed throughout the building housing mechanical or electrical systems.
The specific proportions of each class of use are summarized in Figure 3. Shopping malls account for 30% of the total building area, comprehensive office areas account for 35%, hotel areas account for about 19% of the total building area. The remaining 4% is for other purposes in the building.

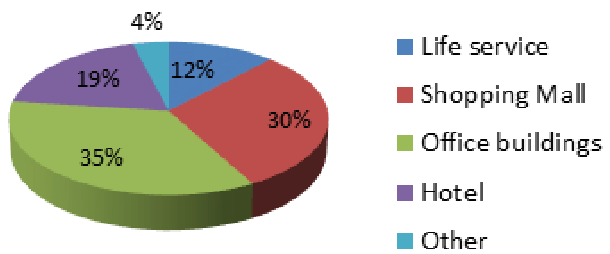

Figure 3 Proportions of the building areas

Energy consumption in hotel areas account for 32% of the total energy consumption and shopping malls and office areas account for 22% and 19% of total energy consumption, respectively shown at figure. 4. Living service areas account for about 14% of total energy consumption.

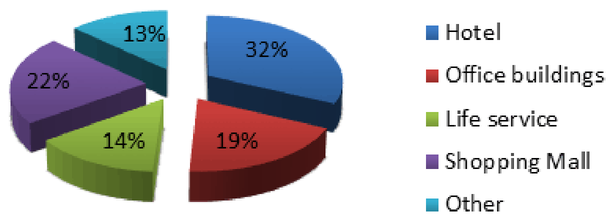

Figure 4 Proportions of the building energy consumption ratio

Figure 5 presents the monthly total electricity energy consumption in the building based on measured value using a comprehensive electricity monitoring system. The electricity consumption rate on May was higher than that of March and April.

HVAC system composition

The centralized all-air HVAC system is mainly composed of an air handling unit, controller, frequency converter, air ducts, fans, temperature sensors, and terminal devices. The system controls the variable air volume based on the set temperature of different rooms. First, the system calculates the volume of air required to maintain the desired temperature of halls and each room, based on the occupants' thermal comfort, and adjusts the frequency converter. The air condition system in the building utilizes a typical centralized system.

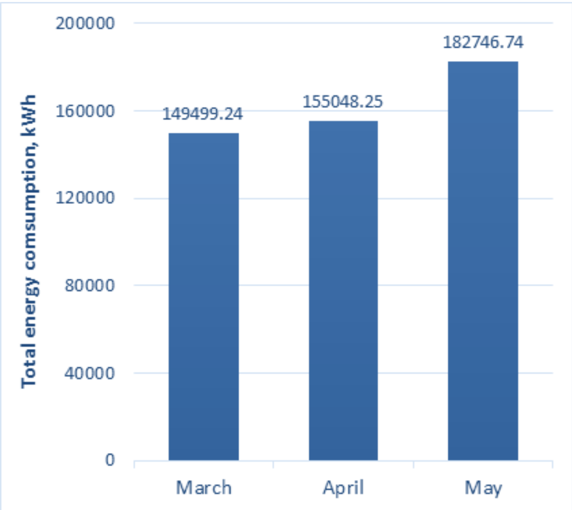

Figure 5 Monthly total energy consumption.

Simulation of BP and RBF neural network model

For the present study, 92 days (March – May 2014) of measured electricity consumption data of the HVAC system of a multi-complex building were used to validate the models.
The input and output were defined to design the network models in the form of vectors. Input nodes that could affect actual electricity consumption of the HVAC system were selected, and included temperature (°C), humidity ratio (g/kg), wind speed (m/s) and whether each day was either a working or non-working day (on or off). To evaluate predictive performance, of electricity consumption for working or non-working days, the simulation modelling was categorized into three parts. First, we used data from 80 days to train the neural networks, and then predicted data for the remaining 12 days, including both working and non-working days. Second, the predicted values were selected for only 6 working days. Finally, the predicted data were selected for only 6 non-working days. Combined with the selection of electricity consumption factors, the temperature, humidity, wind speed and working or non-working days were input as vectors to the network model. Similarly, the corresponding electricity consumption for the HVAC system were also designed as an output vector. Input and input necklaces in the network model were then changed to

$$X = \begin{bmatrix} T_1 & A_1 & B_1 & C_1 \\ T_1 & A_2 & B_2 & C_2 \\ \vdots & \vdots & \vdots & \vdots \\ T_P & A_P & B_P & C_P \end{bmatrix} \tag{19}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_P \end{bmatrix} \tag{20}$$

Where T is dry bulb temperature (°C), A: humidity ratio (g/kg), B is wind speed (m/s), C is working day (on/off), y is electricity consumption (kWh), and p is sample data quantity.
Combined with the model structure of the neural networks, the four main influencing factors defined above were selected as the input to the energy consumption model, and the building's energy consumption was taken as the output, as shown in Figure 6 below.

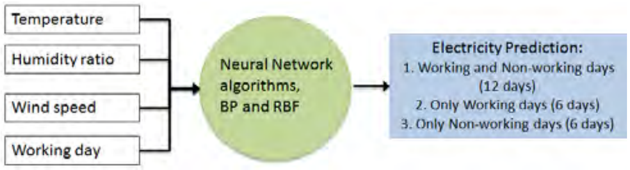

Figure 6 Prediction models to design input and output factors.

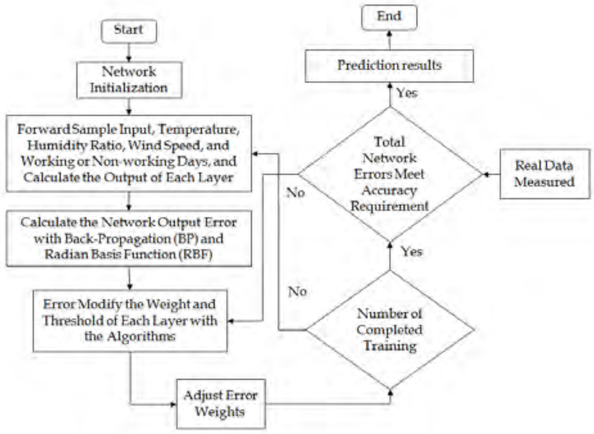

Figure 7 Algorithm flow chart of training process for BP and RBF neural network.

The network algorithm process is shown in Figure 7. Both BP and RBF neural networks are nonlinear, multilayer, forward networks. In the algorithm, the flow uses continuous approximation to reduce the error term. The BP neural network approximates the minimum error by constantly adjusting the weight of neurons. The method is usually a gradient descent. The RBF algorithm uses a feedforward neural network, which does not approximate the minimum error by constantly adjusting the weight value. Rather, it uses the excitation function of the RBF neural network, which is a Gaussian function, to reduce error rates (Buhmann, 2003; de Leon-Delgado et al., 2018; Yang et al., 2016). Gaussian functions obtain the weighting by

the distance between the input and the center point of the function (Yang et al., 2016).
In the training of artificial neural networks, because the influencing factors and scale of units differ, the vector magnitude of each data sample could affect the predicted results. To minimize the impact of different types of factors on the magnitude of data, the data samples were normalized between 0 and 1 (Hao et al., 2013). The current study used the commonly used formula (21) for normalization:

$$X = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (21)$$

Where: X is normalized data, x is each sample data, x_{min} is the minimum value of the sample data, x_{max} is the maximum value of the sample data.
To define accuracy of simulation results, the root mean squared error (RMSE) of actual and predicted values was used (Kuo Lu, 2015; Ye & Kim, 2018). The BP and RBF neural networks also used the mean squared error function during training to evaluate the accuracy of predicted values. Lower value of RMSE means good accuracy and stability of the modelling. The formula used to compute the RMSE is as follows [22]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{actual,i} - X_{predicted,i}\right)^2}{n}} \quad (22)$$

RESULT

This study used BP and RBF neural network models to forecast the electricity consumption profile of a HVAC system for a multi-complex building located in Nanjing, China. In the case study, the two models were trained on measured data for 92 days of local weather variables: temperature (° C), humidity ratio (g/kg), wind speed (m/s), and working status (0 or 1). The neural network training data comprised results for 80 days and the electricity consumption were forecast for the remaining 12 days using BP and RBF neural networks. This study examined the accuracy and error rates of the two neural network models and investigated how working or non-working day significantly impact the accuracy and error rate of predictions of the HVAC electricity consumption. The results are presented in Figures 8-13.
Both BP and RBF model outputs were in close agreement with observations of energy use. However, the RBF curve differed more from real values than the BP curve. In general, the results obtained using the BP algorithm matched field data better than the RBF model.
Figure 9 presents comparisons of relative error rates for the BP and RBF neural networks. The relative error rate represents the ratio of the absolute error rate relative to the observed rate of energy consumption and larger error rates indicate a lower accuracy of predicted values. The error rate for the BP neural network was relatively stable and lower than that of the RBF neural networks. The maximum error rate of the BP neural network was 14.50% and the minimum was 1.07%. Similarly, the maximum error rate of the RBF neural network model prediction was 21.04% and the minimum was 0.48%. The mean relative error and the RMSE results are shown in Table 2. The mean relative error for the RBF neural network was 8.95%, which was larger than the mean relative error (7.71%) for the BP neural network. The RMSE was 724.97 for the RBF neural network and 543.32 for the BP neural network. Therefore, the BP neural network produced more accurate and stable predictions than the RBF neural network.

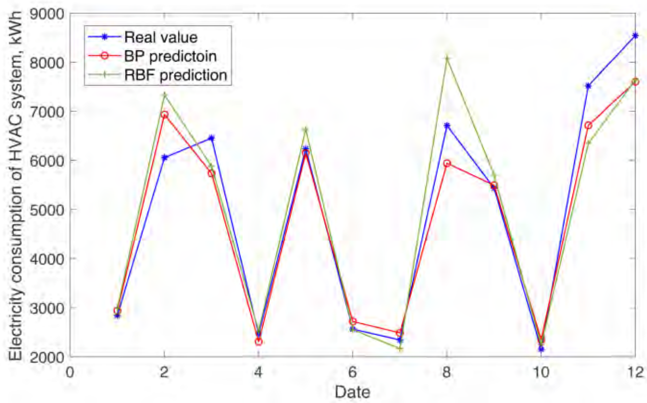

Figure 8 Comparison of the predicted electricity consumption rates from BP and RBF neural networks and the actual values.

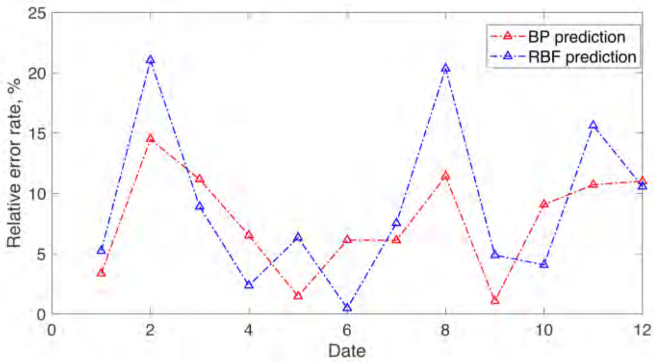

Figure 9 Comparison of the relative errors for BP and BBF.

In this study, HVAC energy consumption on both working and non-working days was predicted. However, in Figures 10-13, the difference between working and non-working day could not be clearly discerned. Therefore, this study predicted HVAC energy consumption rate in two additional scenarios: 6 working and 6 non-working days.

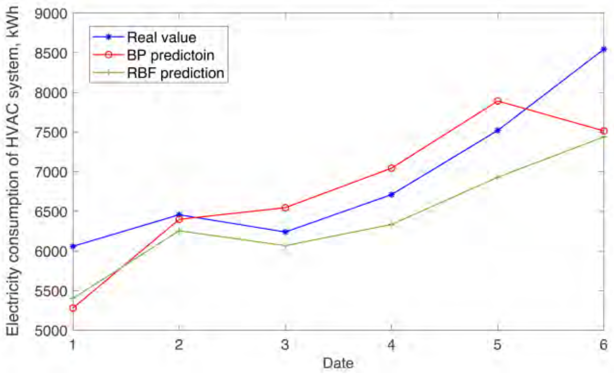

Figure 10 Comparison of the predicted electricity consumption rates obtained with BP and RBF, and the actual values on 6 working days.

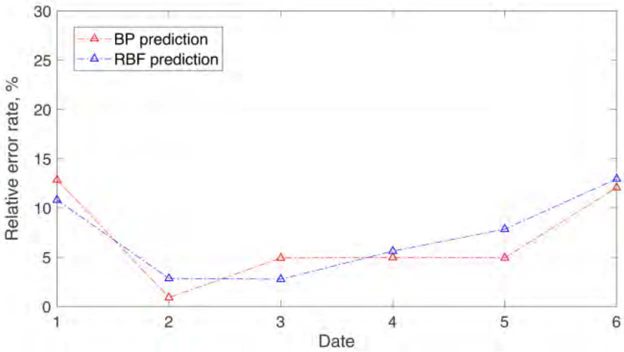

Figure 11 Comparison of the relative error for BP and BBF on 6 working days.

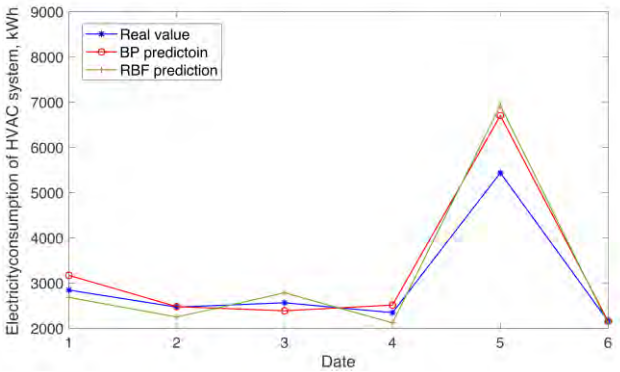

Figure 12 Comparison of the predicted electricity consumption rates obtained with BP and RBF, and the actual values on 6 non-working days.

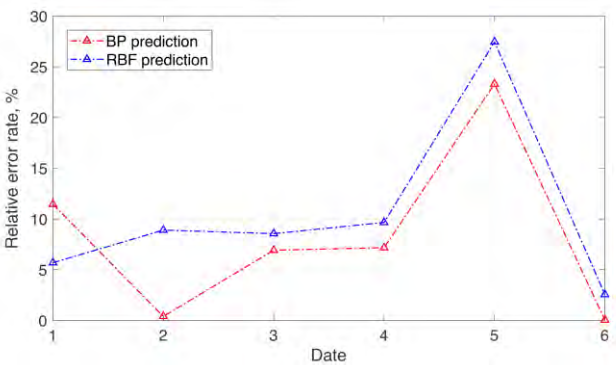

Figure 13 Comparison of the relative error for BP and BBF on 6 non-working days.

Figures 10-13 compare the performance of BP and RBF neural networks with HVAC electricity consumption measured for 6 working days and 6 non-working days. As shown in Figures 10, and 12, overall HVAC energy consumption on working days were much higher than those in non-working days. Occupancy ratio, facility management plan, and plug load data are likely to have affected actual HVAC electricity consumption rates and explain these differences between working and non-working days. The error rates were lower and more stable for the BP neural network than RBF modelling for both working and non-working days. When temperature and humidity ratios increased, actual electricity consumption values also increased. Thus, the ratio of temperature to humidity was highly correlated with electricity consumption, but wind speed was not strongly correlated. Hence, input combinations of temperature and humidity ratios exerted a strong influence on HVAC electricity consumption. The error rates of the BP neural network results were 6.77% and 8.22% for working and non-working days, respectively, while the RMSE were and 579.59 and 543.52 for working and non-working days, respectively. Error rates of the RBF neural network results were 7.14% and 10.47% for working and non-working days respectively and RMSE values were 607.54 and 633.10 for working and non-working days, respectively. Thus, the BP neural network exhibited a better predictive capacity than the RBF neural network. Furthermore, the predicted values on working days were more accurate than those on non-working days. During the training process, the number of working days greatly exceeded the number of non-working days. Hence, it is concluded that increasing the number of training data improves prediction accuracy. This study has some limitations remaining that require further study. A multi-complex building was selected and electricity consumption of the HVAC system was predicted. However, the experimental data could vary according to occupancy rate, seasonal changes, energy sources, and facility management. Consequently, further studies need to consider additional elements that can impact HVAC energy consumption, thereby improving the accuracy of predictions.

CONCLUSIONS

This study explored predictive capacities of two ANNs. Back Propagation (BP) and Radian Basis Function (BRF) Neural Networks were utilized with input nodes, e.g., temperature, humidity ratio, and wind speed, which were used to predict the HVAC energy consumption of a multi-complex building. We evaluated the performance of two neural network algorithms using machine learning and test data for validation and the predicted results were compared with the real HVAC electricity consumption data. The BP neural network was 0.37-2.25 % more accurate and stable than the RBF neural network. However, the results of the two algorithms exhibited good agreement with observed values and the differences in accuracy ranged between 0.25 and 8.5 %. Training the RBF neural network was faster than the BP neural network, and therefore, both neural networks can be effectively used to predict HVAC electricity consumption from three climate factors: temperature, humidity ratio, and wind speed. Variations of temperature and humidity ratio exerted a larger impact on HVAC electricity consumption than wind speed. The rates of HVAC energy consumption on working days were higher than on non-working days. Increasing the volume of training data could improve the accuracy of prediction. The comparative prediction study of HVAC energy consumption in the multi-complex building demonstrated that ANN methods have good agreements with real data measured related to HVAC system, working and non-working days and climate factors. In the future works, we could illustrate that more ANN algorithms and more input factors such as plug-load data, seasonal changes, HVAC system types, and occupancy rates could have affected the accuracy of prediction methods and how each element could impact on energy consumption in buildings in local areas.

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