Predictions of Electricity Consumption in a Campus Building Using Occupant Rates and Weather Elements with Sensitivity Analysis: Artificial Neural Network vs. Linear Regression

Moon Keun Kim[a,d], Yang-Seon Kim*[b], Jelena Srebric[c]

[a] Department of Architecture, Xi'an Jiaotong – Liverpool University, Suzhou, China, 215123

[b] Mechanical Engineering Department, College of Engineering, Wichita State University, Wichita, KS 67260, USA

[c] Department of Mechanical Engineering, University of Maryland, College Park, MD 20742, USA

[d] Department of Civil Engineering and Energy Technology, Oslo Metropolitan University, N-0130, Oslo, Norway

*Corresponding author.
Email: yang-seon.kim@wichita.edu

Abstract

This study compares building electric energy prediction approaches that use a traditional statistical method (linear regression) and artificial neural network (ANN) algorithms. We investigate how significantly occupancy rates and local environmental conditions, such as temperature, humidity ratio, solar radiation, cloud type, and wind speed, impact the actual electric energy consumption of a campus building for both working and non-working days. To analyze the degree of impact of each input data type element, an impact value factor was applied to these data sets. The results illustrate that the ANN modeling was more accurate and stable than the linear regression method in predicting the electricity consumption for working days. By impact factor analysis for working days, occupancy rates were found to strongly dominate the electricity consumption in the building, while temperature and humidity also affected the results. However, there were no accuracy differences between the two models in predicting electricity consumption on non-working days because different data type elements had similar impact on the non-working day results. The two models—linear regression and ANN with a Levenberg–Marquardt Back Propagation (LM-BP) algorithm—were able to meet the long-term and real-time hourly prediction requirements for electricity consumption of an actual building based on occupancy rates and local environmental conditions. The analysis of the input element changes on a macroscopic scale is helpful in predicting how each element influences electric energy consumption in buildings with numerical impact factor. The proposed ANN method with LM-BP algorithm can be used as a reliable approach, compared with the linear regression modeling, for predicting the electricity consumption of a building.

Keywords: linear regression; artificial neural network; energy prediction; occupancy rates; environmental elements

1. Introduction

Building sectors account for a large portion of the global greenhouse gas emissions and total primary energy consumption (Agency, 2008; A. S. Ahmad et al., 2014; Becerik-Gerber et al.,

 DOI: https://doi.org/10.1016/j.scs.2020.102385

2014; de la Rue du Can & Price, 2008; Programme, 2009). Therefore, predictions of building energy use is crucial for building performance improvements, energy management and savings, fault detection and diagnosis, and optimization of smart building practices (Lü, Lu, Kibert, & Viljanen, 2015; Walter & Sohn, 2016; Zeng, Liu, & Yu, 2019). Literatures described how climate changes impact on building energy consumption and suggested solutions to reduce the impact (Andrić, Koc, & Al-Ghamdi, 2019; Chen, Yang, & Zhao, 2007; M. K. Kim, Baldini, Leibundgut, & Wurzbacher, 2019; M. K. Kim & Choi, 2019; Yau & Hasbi, 2013; Zhai & Chen, 2005; Zhai & Helman, 2019). Many studies also have provided methods for predicting building energy consumption with good accuracy (Bordass, Cohen, Standeven, & Leaman, 2001; Haberl & Bou-Saada, 1998; Y.-S. Kim, Heidarinejad, Dahlhausen, & Srebric, 2017; Y.-S. Kim & Srebric, 2017). However, the predicted and actual energy consumption rates show discrepancies due to actual occupancy and weather conditions that could significantly impact building energy consumption (Azar & Menassa, 2012; Farah, Whaley, Saman, & Boland, 2019; Y.-S. Kim et al., 2017; Lupato & Manzan, 2019; Moazami, Nik, Carlucci, & Geving, 2019). Building energy consumption is influenced by the building envelope (construction materials, window size, and material shape and volume), lighting, heating, cooling, air ventilation, and the occupants' electricity demands. Normally, the building envelope construction sets are fixed; however, lighting, heating, cooling, air ventilation, and electricity demands are affected by occupancy diversity and local weather conditions (Baldini, Kim, & Leibundgut, 2014; Capeluto, 2003; M. K. Kim et al., 2019; M. K. Kim & Choi, 2019; Pombeiro, Santos, Carreira, Silva, & Sousa, 2017; Sabzi, Haseli, Jafarian, Karimi, & Taheri, 2015; Yalcintas & Akkurt, 2005). Therefore, this study investigates the prediction of how significantly occupancy rates and weather conditions impact energy consumption of a campus building.

For electricity consumption prediction modeling, various mathematical algorithms have been proposed and developed (M. W. Ahmad, Mourshed, & Rezgui, 2017; Deb & Lee, 2018; Deb, Zhang, Yang, Lee, & Shah, 2017; Hsu, 2015; Shi, Liu, & Wei, 2016; Xie, Ouyang, & Gao, 2016; Ye & Kim, 2018) such as fuzzy mathematics, wavelet analysis, support vector machine, artificial neural network (ANN), grey system method, and linear regression analysis (A. S. Ahmad et al., 2014; M. W. Ahmad et al., 2017; Khalid, Javaid, Rahim, Aslam, & Sher, 2019; Ma et al., 2019; Maghyereh, Awartani, & Abdoh, 2019; Shi et al., 2016; Trigo-González et al., 2019; Walter & Sohn, 2016; Xie et al., 2016; Ye & Kim, 2018; Zeng et al., 2019). In particular, traditional linear regression and the ANN technique is one of the main algorithms currently utilized for predicting electricity consumption in buildings (A. S. Ahmad et al., 2014; M. W. Ahmad et al., 2017; Y.-S. Kim et al., 2017; Y.-S. Kim & Srebric, 2017; Ye & Kim, 2018). Traditional linear regression methods have been widely used to determine the degree of similarity between elements by measuring the quadratic error (Chung, 2012; Pombeiro et al., 2017; Hideo Tanaka, 1987; Hideo Tanaka, Hayashi, & Watada, 1989; H. Tanaka & Watada, 1988). ANNs mimic the function and structure of the human brain by performing nonlinear processing (A. S. Ahmad et al., 2014; M. W. Ahmad et al., 2017; Deb et al., 2017; Ye & Kim, 2018). In addition, it has large-scale parallel structure computing with a distributed large storage capacity (M. W. Ahmad et al., 2017; Ye & Kim, 2018). To adapt to variable environments, the neural network system approaches with self-learning dealing with various information types (A. S. Ahmad et al., 2014; Ye & Kim, 2018). Thus, they have been widely used in pattern recognition for prediction, decision-making, process control, and other tasks (Đozić & Gvozdenac Urošević, 2019; Elsheikh et al., 2019; Mohandes, Zhang, & Mahdiyar, 2019). Many studies have applied the Levenberg-Marquardt Back Propagation (LM-BP) algorithm to improve the neural network's slow convergence, limited accuracy, and relatively low efficiency (K. M. Kim et al., 2019; Singh, Gupta, & Gupta, 2007; Xia et al., 2018; Ye & Kim, 2018). Recently, utilizing of the sensitivity of prediction of building energy consumption model is developed because the sensitivity is related to the robustness and performance of the prediction model (Feedback Control, 2010; K. M. Kim et al., 2019). However, this study presents how each element dominates the total electricity consumption in buildings with ANNs.

In this study, we propose a building energy prediction approach that uses traditional statistical method (linear regression) and ANN algorithms with sensitivity analyses using impact factors of occupancy ratio and local weather condition. Many studies involved the building energy prediction methods with ANNs algorithm, however, this study investigates how significantly the occupancy rates and environmental elements—such as temperature, humidity ratio, wind speed, solar radiation, and cloud type—dominate the actual electricity energy consumption of a campus building using two main prediction methods. Additionally, as a sensitivity analysis, this study explores novel approaches as to how occupancy ratio and local climate variations can influence the actual electric energy consumption of an office building using a traditional linear regression model and ANN approach with the help of numerical impact factor. As a further study, we can forecast electricity consumption in various building spaces such as office, shopping mall, and industrial buildings using occupancy ratio and local weather conditions based on the advanced training methods of ANNs.

2. Building energy consumption models

2.1. Linear regression

To define the baseline energy consumption methods of a building, the international measurement and verification protocol accepts linear regression models as a framework to implement and predicts energy consumption (G.Woodal, 2012; Pombeiro et al., 2017). This model needs a large number of characterization variables to improve the accuracy of linear regression models in complex design process (Gabbar, Bondarenko, Hussain, Musharavati, & Pokharel, 2014; Pombeiro et al., 2017). The linear regression method can indicate the similarity between two data elements; the results are presented as a linear model with a coefficient to explain the relations (Pombeiro et al., 2017). With linear relations, the model is well accepted in the definition of the general consumption scenario; however, with non-linear relations, the model is quite limited in determining the relation with a variation of results as well (Bianco, Manca, & Nardini, 2009; G.Woodal, 2012; Pombeiro et al., 2017; Reddy, 2011; Toe & Kubota, 2013).

A linear regression model presents the normality assumption, which pertains to the following:

$$y = \beta_0 + \beta_1 x + \epsilon$$
(1)

Here, y is the outcome variable, x is an independent variable, parameter β_0 is the $\bar{y}$ value when $x = 0$, and ϵ represents the errors.

A linear regression implements minimization of the total sum of squares—that is, the additional error of the sum of squares with the regression sum of squares (Pombeiro et al., 2017; Reddy, 2011):

$$\sum_{k=1}^{n}(y_k - \bar{y})^2 = \sum_{k=1}^{n}(y_k - \hat{y}_k)^2 + \sum_{k=1}^{n}(\hat{y}_k - \bar{y}_k)^2$$
(2)

where y_k is the real value in observation k, $\bar{y}_k$ is the mean value of y_k in n observations, and $\hat{y}_k$ is the value of y modeled by the regression model for observation k.

2.2. Artificial neural network (ANN)

Currently, several types of neural networks have been proposed (Amber, Aslam, & Hussain, 2015; Chae, Horesh, Hwang, & Lee, 2016; Hsu, 2015; Kumar, Aggarwal, & Sharma, 2013; Li, Hu, Liu, & Xue, 2015). Among them, four main improved algorithms have been suggested: The backpropagation (BP) neural network, Hopfield neural network, Kohonen maps, and radial basis function (RBF) neural network. At present, BP neural networks have been mainly applied in areas—such as energy prediction modeling, pattern recognition, intelligent control, and information processing—and the predicted results have agreed well with actual experimental data (Amber et al., 2015; Chae et al., 2016; Hsu, 2015; K. M. Kim et al., 2019; Ye & Kim, 2018).

A BP neural network is composed of three layers: input, hidden, and output (Bocheng Zhong, 2015; K. M. Kim et al., 2019; Kumar et al., 2013; Xu, Zhang, Wang, Wang, & Zhang, 2015; Ye & Kim, 2018). Each layer system includes parallel computing neuron networks. These neuron networks are similar to biological nervous systems. Many neurons comprise a network with numerous functions. Each neuron is closely and completely interconnected with those of different layers, whereas neurons in the same layer are not connected with each other. The layer structure in a BP neural network is illustrated in Fig. 1.

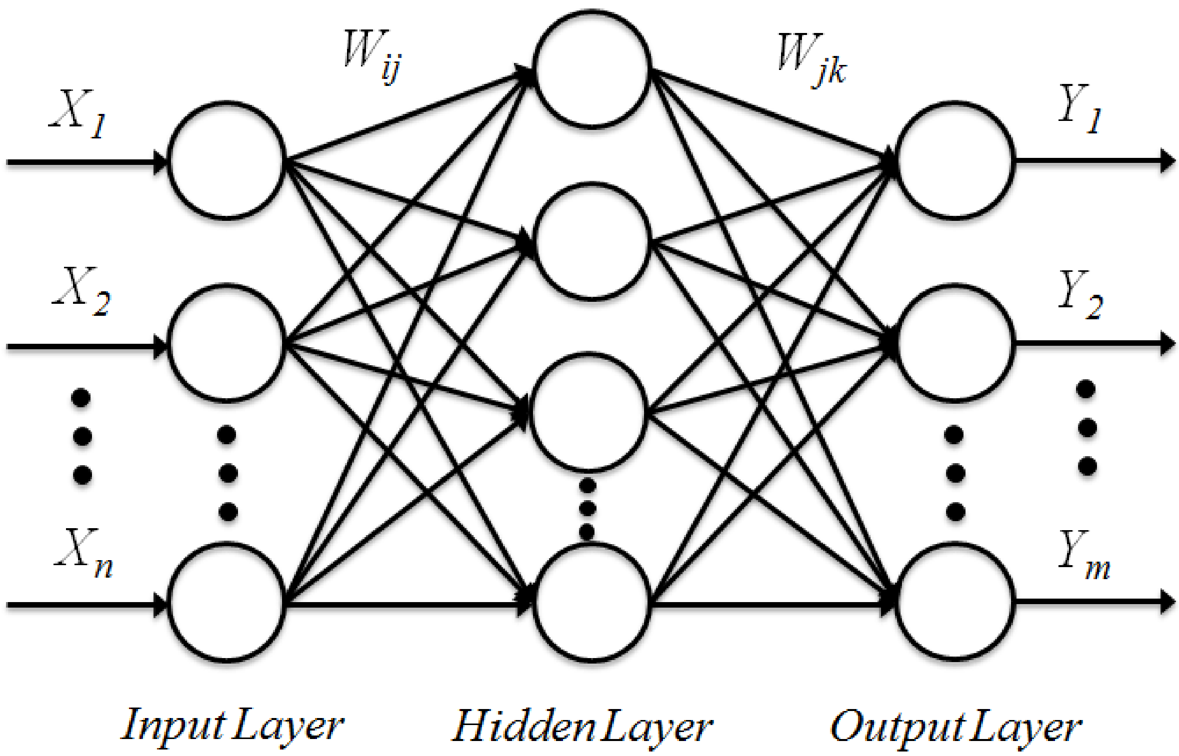

Figure 1 Three-layer BP neural network structure

As shown in Fig. 1, X_1, X_2,…, X_n are the input variables in the input layer of the BP neural network, which are composed of the elements that influence electricity energy consumption in a building, such as occupancy rates, temperature, humidity ratio, solar radiation, and wind speed (Azadeh, Ghaderi, & Sohrabkhani, 2008; Ekici & Aksoy, 2009; Kumar et al., 2013; Neto & Fiorelli, 2008; Wong, Wan, & Lam, 2010; Xu et al., 2015). Y_1, Y_2, … Y_n are the output values corresponding to the model for predicting electricity consumption in a building.

a. Forward propagation in a BP neural network (Jia et al., 2015; K. M. Kim et al., 2019; Lek & Guégan, 1999; Xu et al., 2015; Ye & Kim, 2018; S. Yu, Zhu, & Diao, 2008).

The output value of the hidden layer is as follows:

$$o_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - d_j\right) \quad j = 1,2,\dots,l \qquad (3)$$

The output value of the output layer is as follows:

$$Y_k = f\left(\sum_{j=1}^{l} o_j w_{jk} - d_k\right) \quad k = 1,2,\ldots,m \qquad (4)$$

Based on the BP neural network defined, the mean square error (MSE) is calculated for the predicted and actual output vectors. The function is defined as follows:

$$E_k = \frac{1}{2}\sum_k (F_k - Y_k)^2 \qquad (5)$$

To calculate the accuracy of the results, this study used calibration standards: the normalized mean bias error (NMBE), and the coefficient of variation of the root mean square error (CVRMSE), widely accepted by ASHRAE Guideline 14-2002 (ASHRAE, 2002). The corresponding equations are shown as follows:

$$CVRMSE = 100 \times \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2\right]^{1/2}}{\bar{y}} \qquad (6)$$

$$NMBE = \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)}{\bar{y}} \times 100 \qquad (7)$$

b. Error in a BP neural network (Azadeh et al., 2008; Bocheng Zhong, 2015; K. M. Kim et al., 2019; Xu et al., 2015; Ye & Kim, 2018; F. Yu & Xu, 2014)

By substituting (1) and (2) into (3), the performance error function is obtained as follows:

$$E_k = \frac{1}{2}\sum_k \left(F_k - f\left(\sum_{j=1}^{l} w_{jk} f\left(\sum_{i=1}^{n} w_{ij} x_i - d_j\right) - d_k\right)\right)^2 \qquad (8)$$

By the error function derivation of the weights and threshold of the output point, we have the following:

$$\frac{\partial E_k}{\partial w_{jk}} = -(F_k - Y_k) f'\left(\sum_{j=1}^{l} O_j\, w_{jk} - d_k\right) O_j' \qquad (9)$$

$$\frac{\partial E_k}{\partial d_k} = (F_k - Y_k) f'\left(\sum_{j=1}^{l} O_j\, w_{jk} - d_k\right) \qquad (10)$$

We obtain the error of the output node as follows:

$$\delta_k = (F_k - Y_k) f'\left(\sum_{j=1}^{l} O_j w_{jk} - d_k\right) \qquad (11)$$

By substituting (9) into (7) and (8), we obtain the following:

$$\frac{\partial E_k}{\partial w_{jk}} = -\delta_k O_j' \qquad (12)$$

$$\frac{\partial E_k}{\partial d_k} = \delta_k \qquad (13)$$

In the Levenberg-Marquardt (LM) algorithm, after a series of optimizations, the weights approximations and threshold are formulized into Eq. (10) (Bocheng Zhong, 2015; Hao, Li, & Wang, 2013; K. M. Kim et al., 2019; Ye & Kim, 2018; Yoo & Seul, 2017):

$$x(k+1) = x(k) - [\boldsymbol{J}^T\boldsymbol{J} + \mu\boldsymbol{I}]^{-1}\boldsymbol{J}^T e \ , \quad (14)$$

where $\boldsymbol{J}$ is the Jacobian matrix and the coefficient $\boldsymbol{\mu}$ is a constant that is greater than zero. $\boldsymbol{I}$ is a unit matrix and $\boldsymbol{e}$ is the error. When $\boldsymbol{\mu}$ is near zero, this method is equivalent to the Newton method. The Gauss–Newton method also denotes the performance in that when the error is closer to the minimum value, the accuracy is much higher, and the calculation is faster. Therefore, the LM algorithm model results can be sufficiently improved with the convergence speed, as well as ensuring better accuracy (Bocheng Zhong, 2015; Hao et al., 2013; K. M. Kim et al., 2019; Ye & Kim, 2018; Yoo & Seul, 2017). The neural network training process is illustrated in Fig. 2.

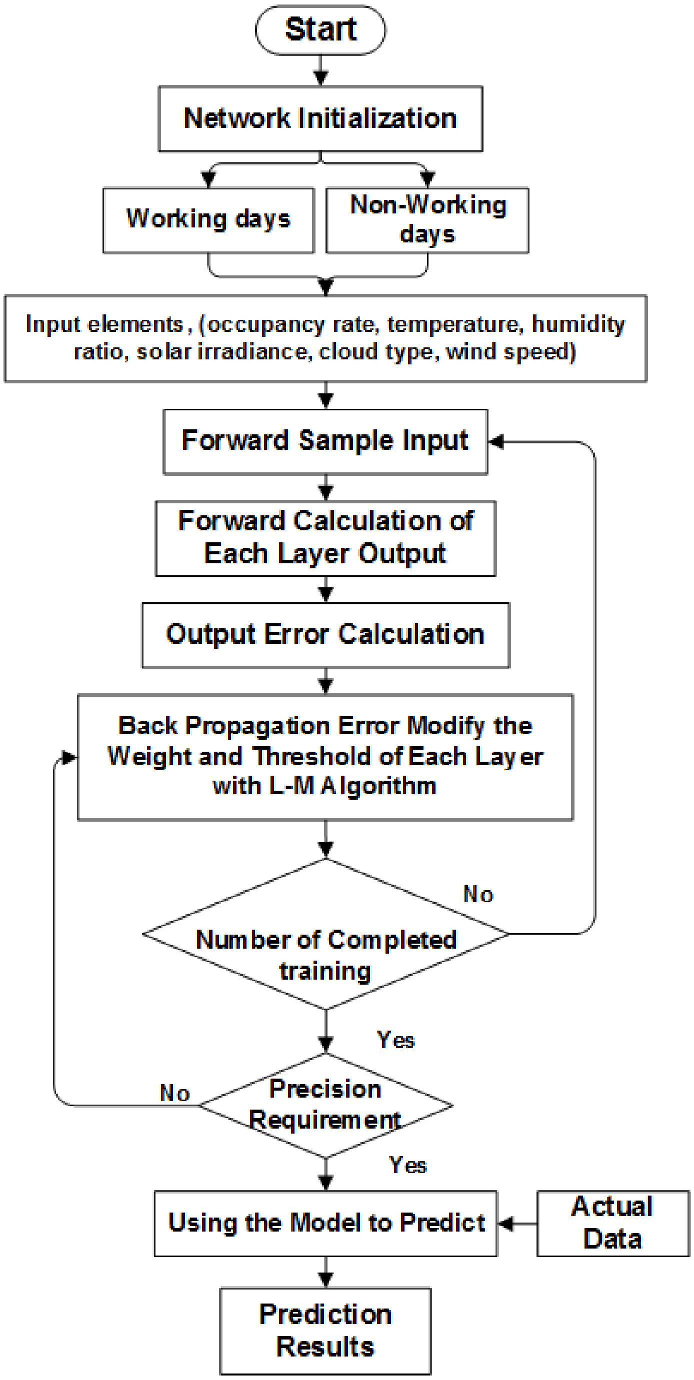

Figure 2 Training process for the artificial neural network

2.3. Data collection and analysis

We collected the building occupancy rates and electricity consumption of a campus building in University Park, PA, in the U.S. The building area is 6939 m^2 and it is composed of three stories that comprise 17.3 % lecture rooms, 41.5 % offices, 31 % common areas, and 9.6 % laboratories. To measure occupancy rates in the building, we placed an infrared thermal sensor (PC-THI60-N, Sensource) with a 5 % error in front of the main entrance. The sensor detects direction of movement and counts occupants coming and going from its field of view (Y.-S. Kim et al., 2017; Y.-S. Kim & Srebric, 2017). We collected a total of 157 days' worth of hourly data of building occupancy rates and electricity consumption between August 14, 2013 and April 28, 2014. Additionally, we used local weather data recorded in the National Solar Radiation Database (NSRDB) (Laboratory, 2019).

The data collected were divided into two groups—working and non-working days—to analyze how significantly the occupancy rates and weather conditions impacted building electricity consumption in different operating environments. Moreover, to simulate electricity energy consumption using linear regression and ANN models, the working and non-working data groups were further separated into training (90 working and 40 non-working days) and test data (14 working and 7 non-working days). In the model, we defined the input nodes that impacted building electricity energy consumption as occupant number, temperature (^{o} C), humidity ratio (g/kg), direct normal irradiance (DNI; W/m2), wind speed (m/s), and cloud type (0: clear–12: smoke). All corrected data are presented in Figure 3–9.

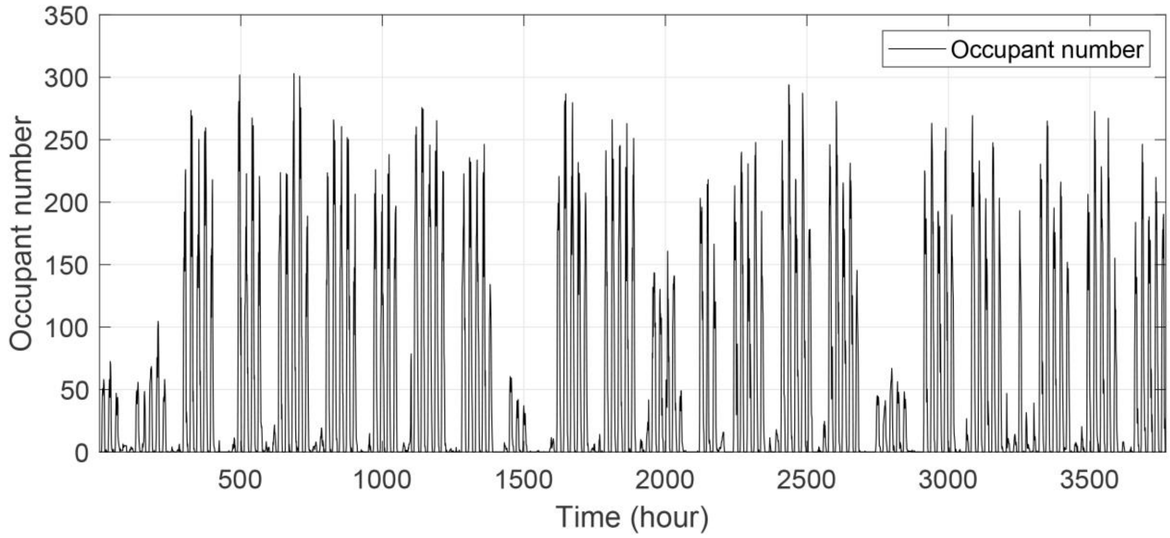

Figure 3 Historical data: Number of occupants (157 days, August 14, 2013 to April 28, 2014)

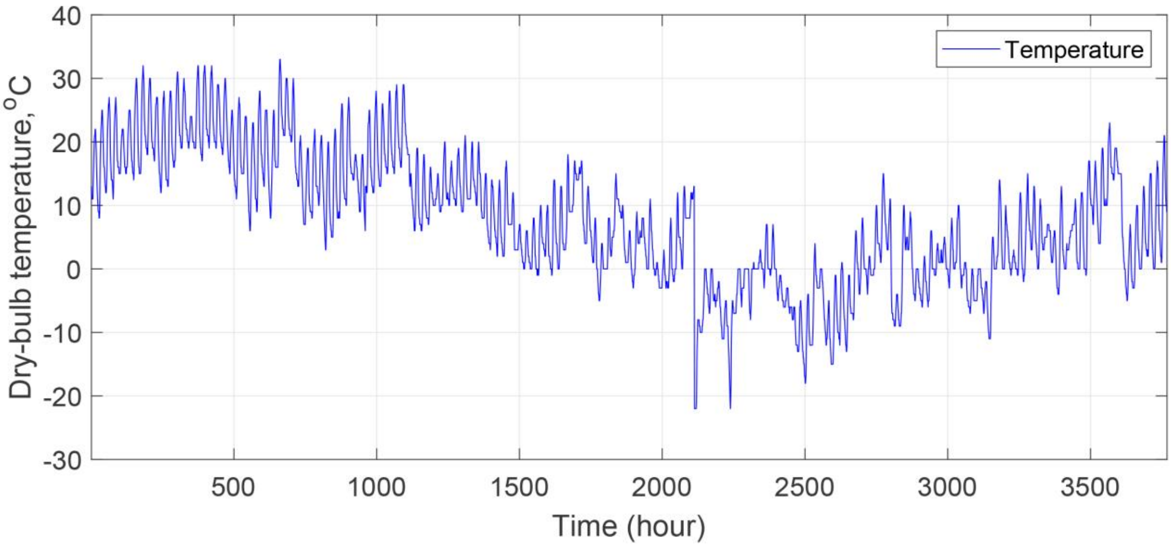

Figure 4 Historical data: Dry-bulb temperature (157 days, August 14, 2013 to April 28, 2014)

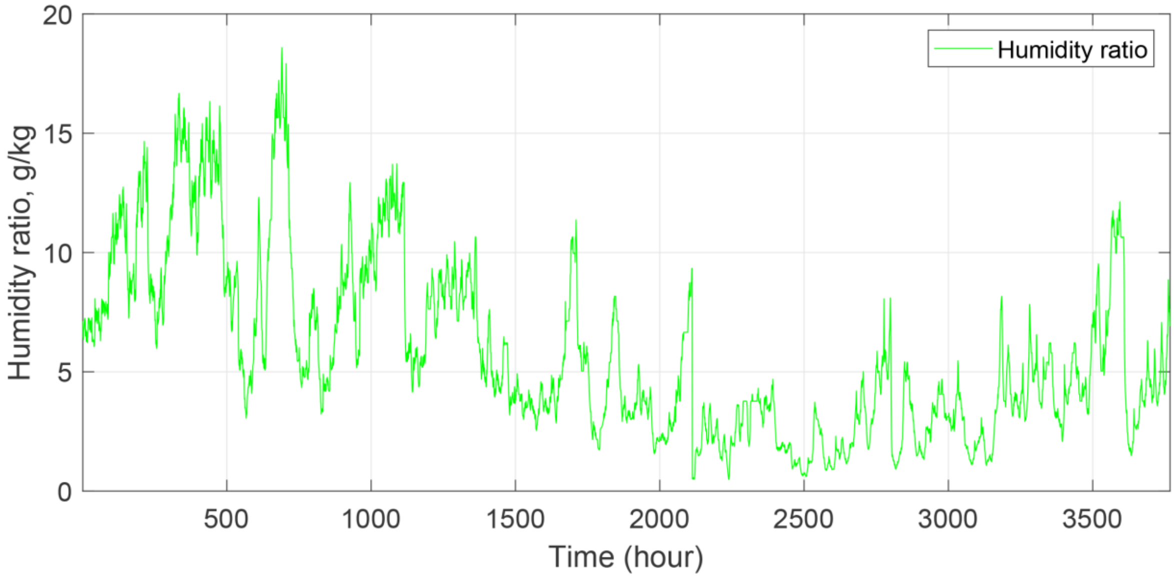

Figure 5 Historical data: Humidity ratio (157 days, August 14, 2013 to April 28, 2014)

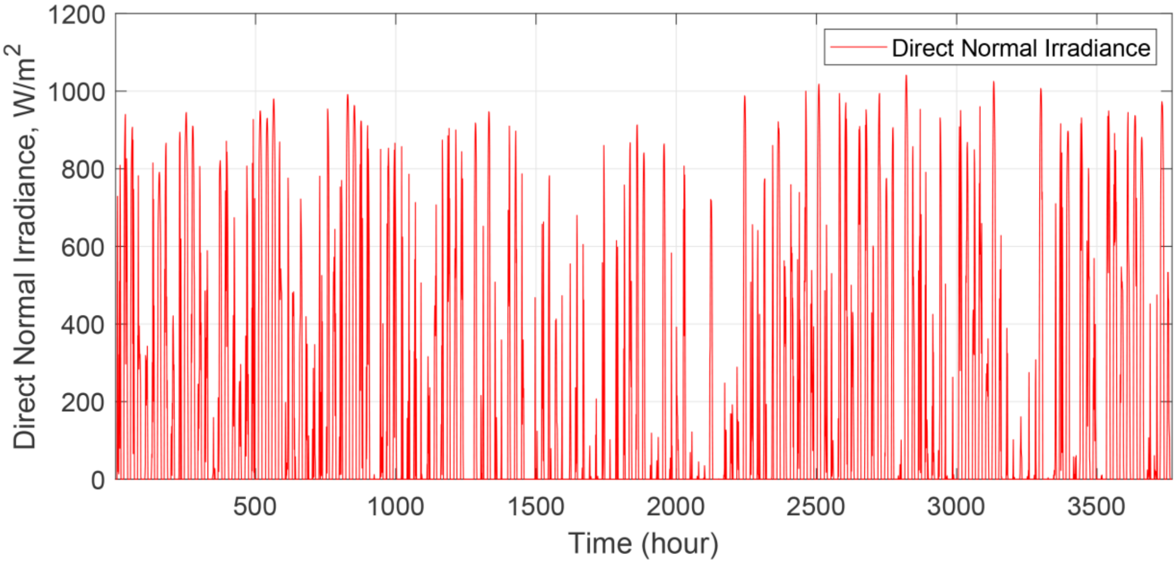

Figure 6 Historical data: Direct normal irradiance (157 days, August 14, 2013 to April 28, 2014)

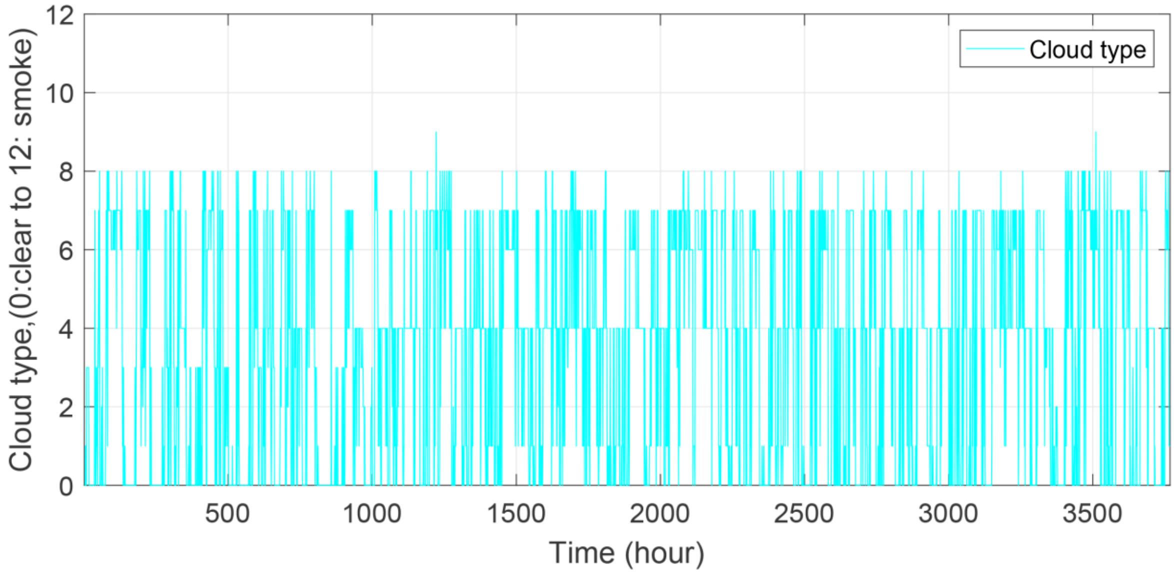

Figure 7 Historical data: Cloud type (157 days, August 14, 2013 to April 28, 2014)

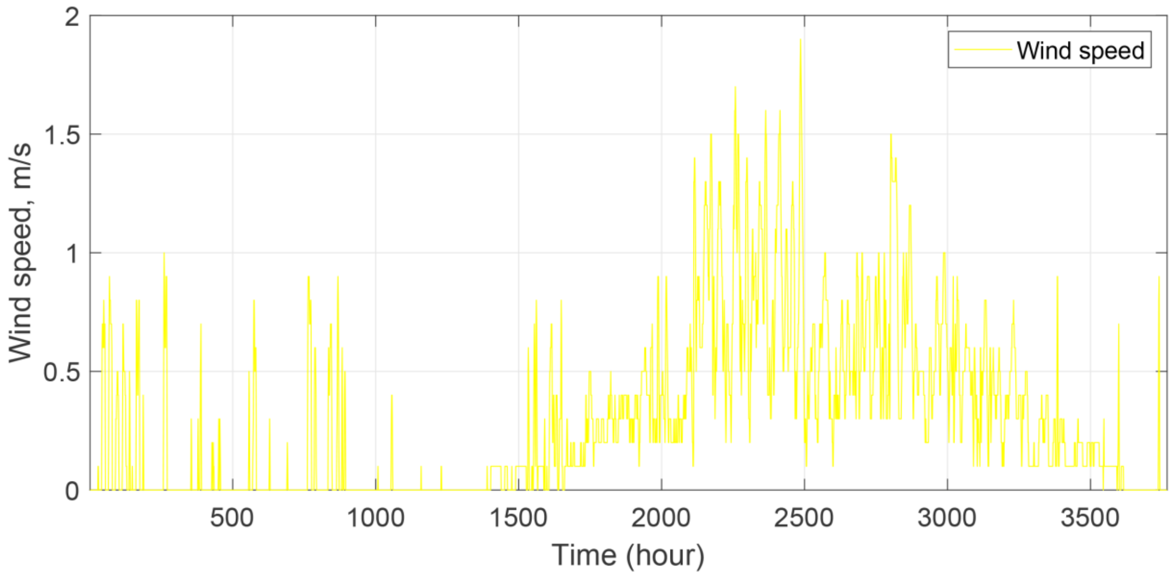

Figure 8 Historical data: Wind speed (157 days, August 14, 2013 to April 28, 2014)

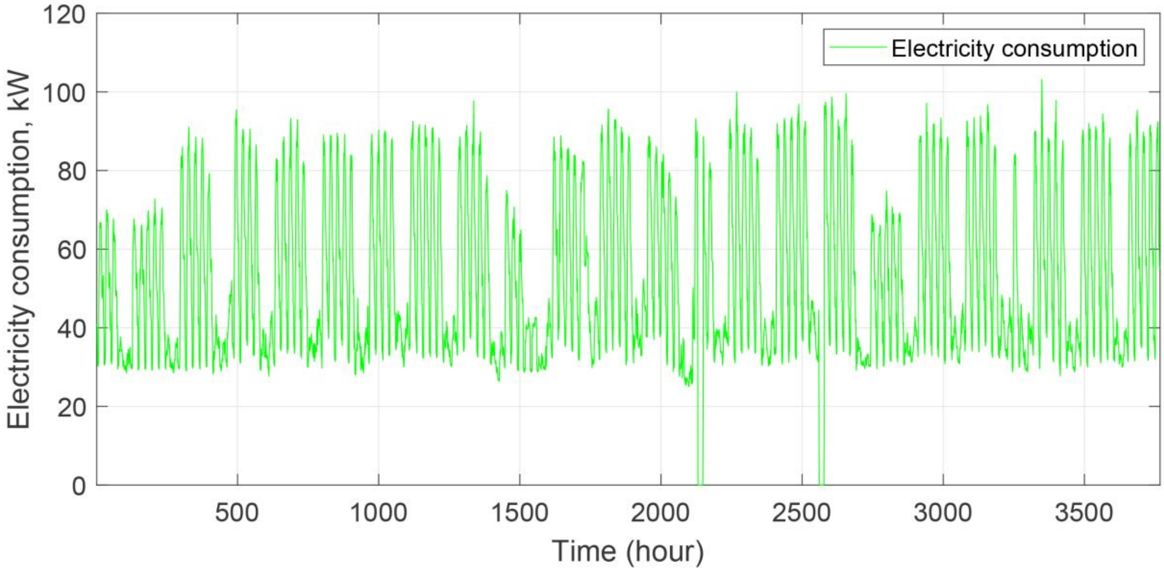

Figure 9 Historical data: Electricity consumption (157 days, August 14, 2013 to April 28, 2014)

Figure 10 shows the steps for predicting energy consumption with variable input parameters.

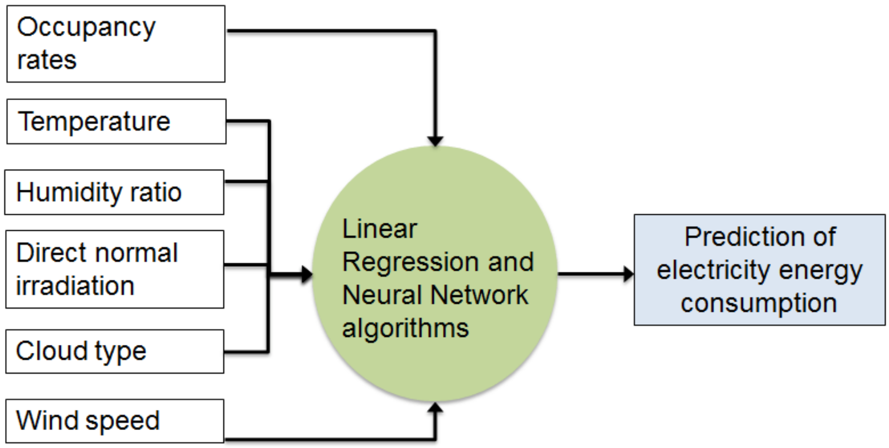

Figure 10 Model for predicting electricity consumption with variable input parameters

2.4. Comparison Methodology

To evaluate correlation among the input parameters in this study, we used an impact factor value (IV), where the magnitude of the absolute value represents the magnitude of effect, and positive and negative values represent the direction of impact (K. M. Kim et al., 2019; Y. H. Liu, 2015; Ye & Kim, 2018). The IV evaluation calculates the impact of each input node parameter based on statistical approaches after the module training process. The IV is determined based on statistical calculations after training with input node and actual energy consumption values. The process for calculating the IV is as follows: Testing node values are adjusted by adding or subtracting 10 % of their original values to form new testing samples. The value is utilized as an impact of each element adding or subtracting because the impact value denotes a linear relation between the results changed.

Subsequently, the adjusted testing nodes are simulated with an actual experimental value as a prediction. Finally, the differences between the predicted values using two test sample nodes originated and adjusted determine the IV. After the analysis, we could evaluate how much each element impact on electricity consumption and determine that an element is significantly necessary or neglected for the prediction.

$$Impact\ factor\ value\ (IV) = \frac{\left|\frac{y_{test\ results} - y_{test\ results\ with\ adding\ or\ subtracting\ 10\%\ of\ sample}}{y_{test\ result}} \times 100\right|}{0.1} \quad (15)$$

For determining the number of hidden nodes and layers, this study follows the formula (K. M. Kim et al., 2019; Tang Zhong, 2012; Y. H. Liu, 2015; Ye & Kim, 2018)

$$p < \sqrt{n+m} + a \quad (16)$$

where p is the range of numbers, n is the input node number, m is the output node number, and a is a positive integer that is less than 10 (Amber et al., 2015; Tang Zhong, 2012).

3. Results

In this study, we used two methods—linear regression and an ANN with an LM-BP algorithm—to predict electricity consumption profiles for a campus office building. The models were trained on a total of 3778 hourly data representing 157 days of occupancy rates and weather parameters, temperature (°C), humidity ratio (g/kg), normal direct irradiation (W/m^2), cloud type (0-12), and wind speed (m/s). This study denotes the accuracy of each model and also estimates how significantly the occupancy rates and weather parameters influence the amount of electricity consumed in a building. Moreover, using this modeling, we can predict long-term energy consumption rates based on occupants' diversity and climate variations. We used two prediction methods—Linear regression and an LM-BP neural network with occupant number, temperature, humidity ratio, normal direct irradiance, cloud type, and wind speed as the input layers, and electricity consumption as the output layer.

The training data for the simulation set contained measured and historical data for 90 working days and 40 non-working days. The electricity consumption results were predicted for 14 working days, and 7 non-working days using linear regression and ANN to validate each algorithm compared with the actual measured values. The two models were evaluated based on accuracy and error rate for two scenarios; the results are shown in Figure 11–14. In general, the linear regression and ANN models performed well at forecasting the electricity consumption of the campus office building for working and non-working days. Compared with the linear regression method results, those of the ANN model exhibited better performance with good accuracy in predicting the electricity consumption on working days in the building. However, there were no significant differences between linear regression and the ANN model in predicting the electricity consumption for non-working days, because none of the elements used as input factors had a significant impact on actual electricity consumption for non-working days. The details are shown in Figure 17 and 18.

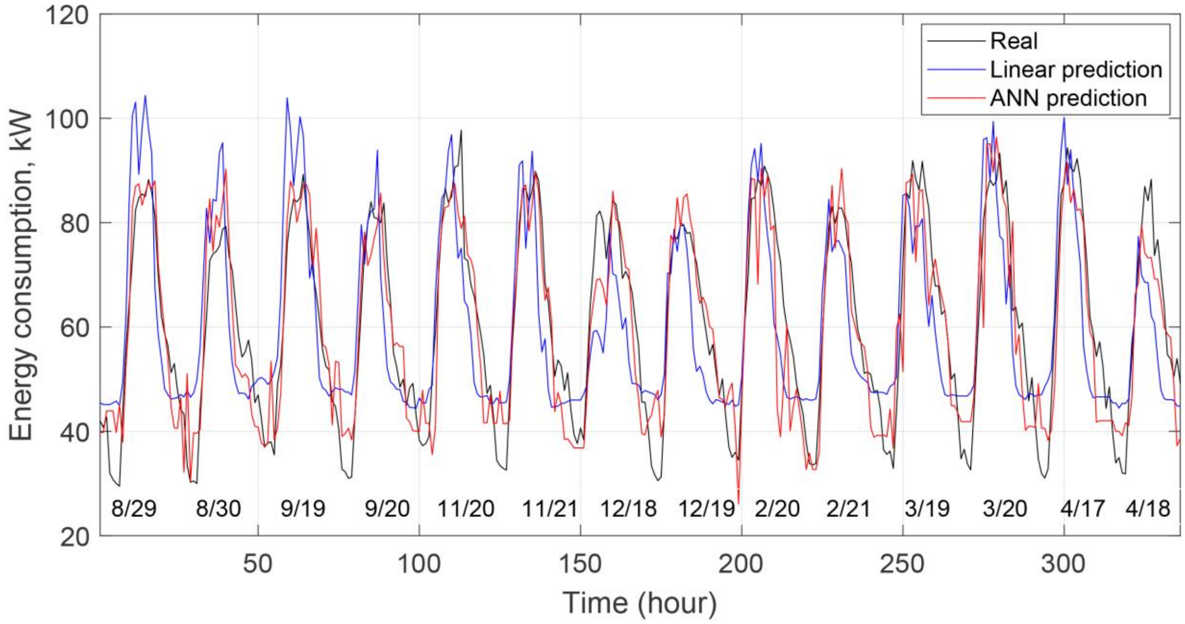

Figure 11 Prediction output of linear regression and ANN modeling compared with real values measured for working days

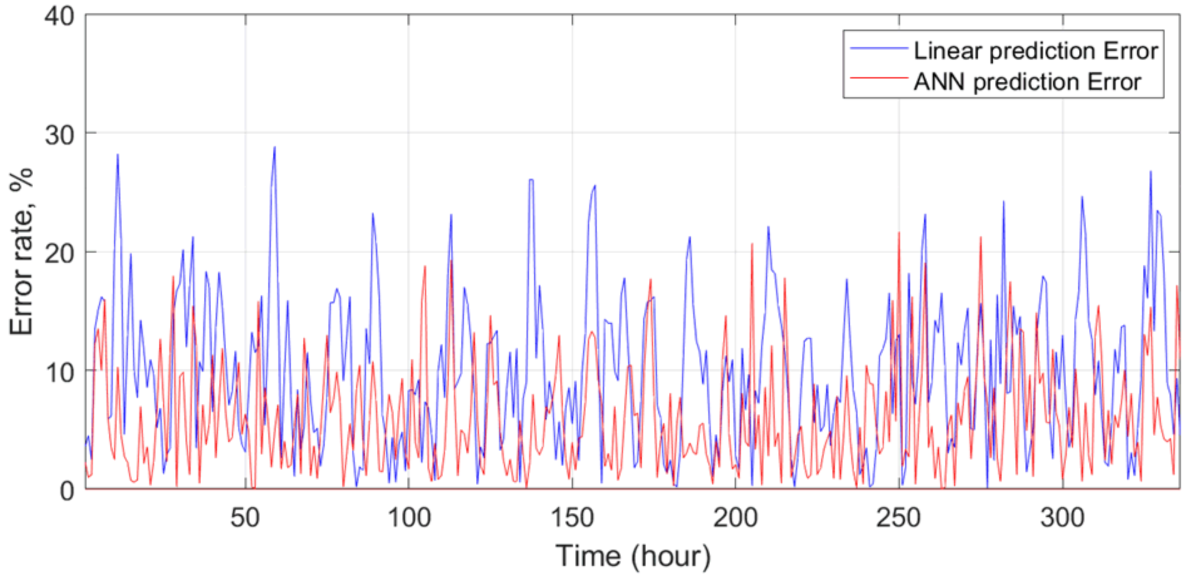

Figure 12 Error rates of the two prediction models—linear regression and ANN—for working days

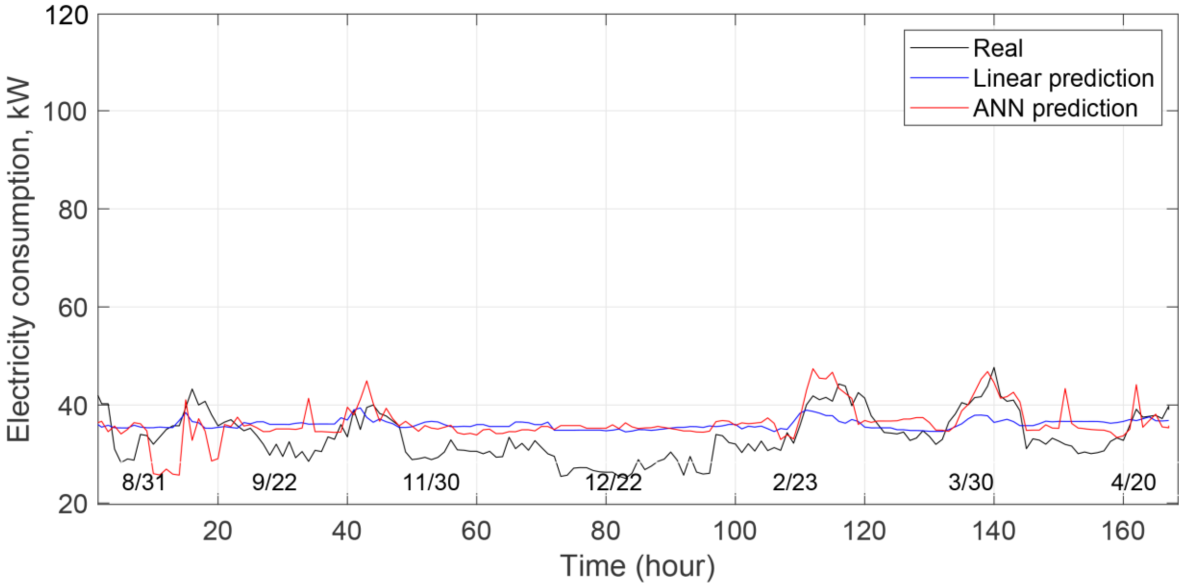

Figure 13 Prediction output of linear regression and ANN modeling compared with real values measured for non-working days

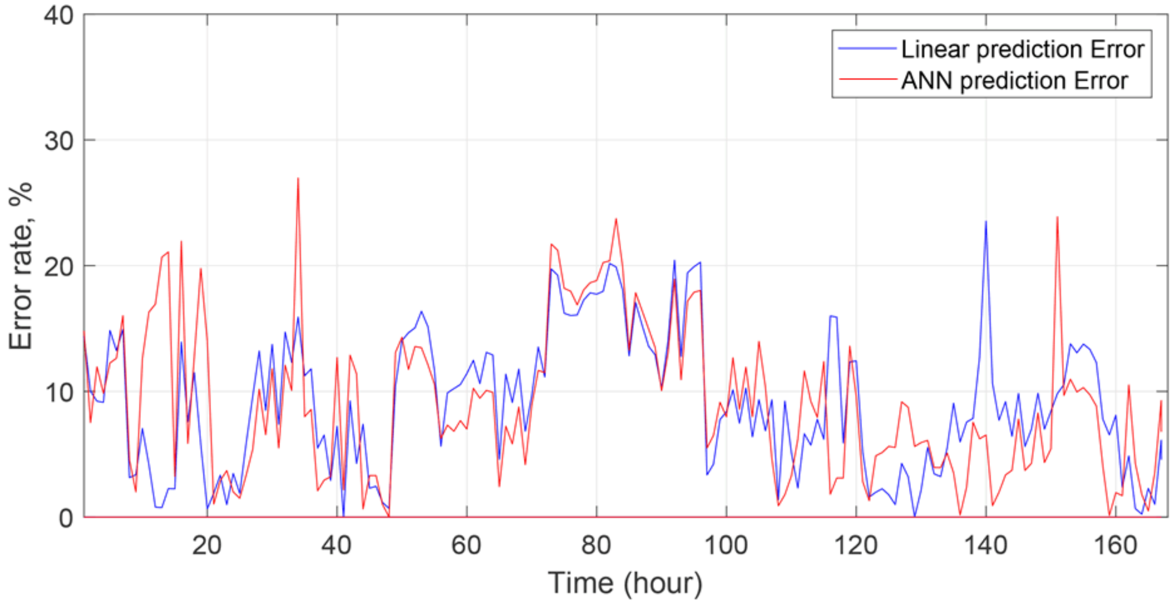

Figure 14 Error rates of the two prediction models—linear regression and ANN—for non-working days

Table 1 Comparison of linear regression and ANN

	Normalized mean bias error (NMBE)		Coefficient of variation of the root mean square error (CVRMSE)	
	Working	Non-Working	Working	Non-Working
Linear regression	17.61	13.80	11.54	5.04
ANN	10.97	13.90	7.36	5.19

The normalized mean bias error (NMBE) and coefficient of variation of the root mean square error (CVRMSE) results of each model are presented in Table 1. The NMBE and CVRMSE for the linear regression method in predicting electricity consumption on working days were 17.61, and 11.54, respectively, which were higher than those of the ANN method, which corresponded to 10.97 and 7.36. Thus, NMBE and CVRMSE were improved with the ANN method. However, the differences of NMBE and CVRMSE values between the two models in predicting electricity consumption for non-working days were small at 0.1 and 0.15, respectively. Thus, the ANN method could maintain higher stability when predicting the electricity consumption of the building on working days. However, both methods to predict energy consumption for non-working days have large differences of accuracy and stability. Overall, this study illustrates that the ANN method achieves more stable and accurate predictions than the linear regression method—even if there is no special difference between the two models in predicting electricity energy consumption for non-working days.

Figure 15 and 16 present how much each input elements impact on electricity consumption in the building on working days using the linear regression and ANN prediction methods, respectively. Occupancy rates mainly dominated the electricity consumption in both the linear regression and ANN methods. The former predicted that the occupancy rates more highly dominated electricity consumption compared with results ANN method. Three main parameters—occupancy rates, temperature, and humidity ratio—strongly impacted the actual electricity consumption in the building. Three other parameters—DNI, cloud type, and wind speed—could be neglected to consider the actual effect. Especially in the winter season, five environmental parameters—DNI, cloud type, wind speed, temperature, and humidity ratio—had less of an impact on the building electricity consumption compared with other seasons. This study estimates that a centralized steam heating system does not impact electricity consumption; however, a chilled water supply for cooling and dehumidification could affect actual electricity consumption in a building. Additionally, the occupant numbers detected did not describe the occupant characteristics, such as student, lecturer, guest, or officer. For example, occupants stationed in the office would highly impact actual building electricity consumption relative to a guest, student, or lecturer who temporally reside in the building. On this basis, in further study, we could consider another parameter—such as plug-load data or guest numbers—to reduce error rates.

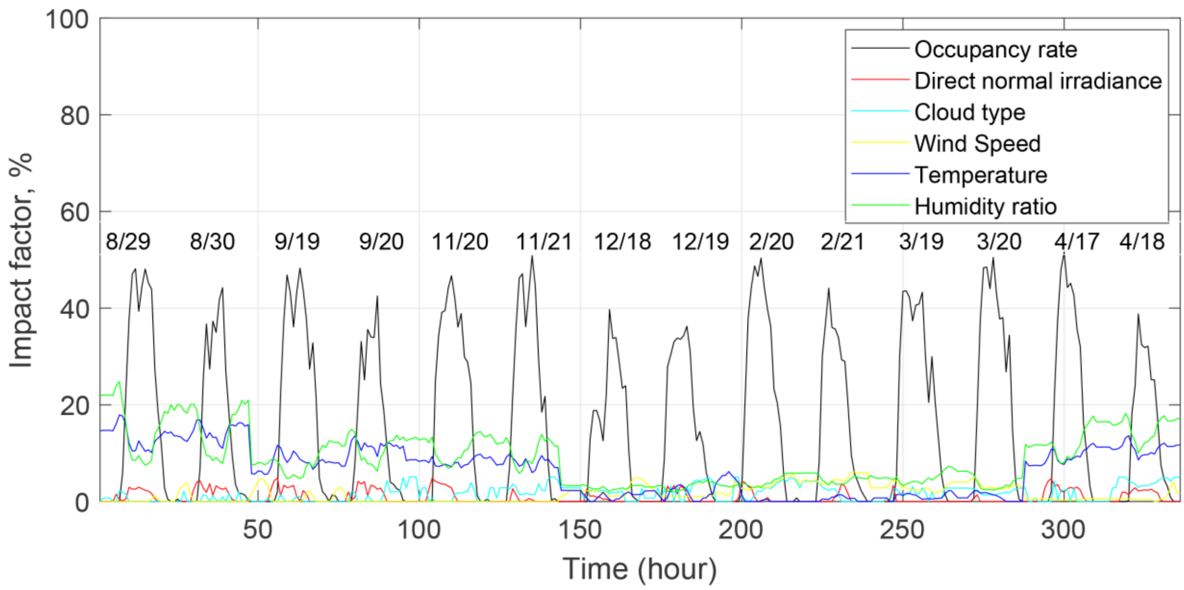

Figure 15 Impact factor rates of input parameters for working days by linear regression method

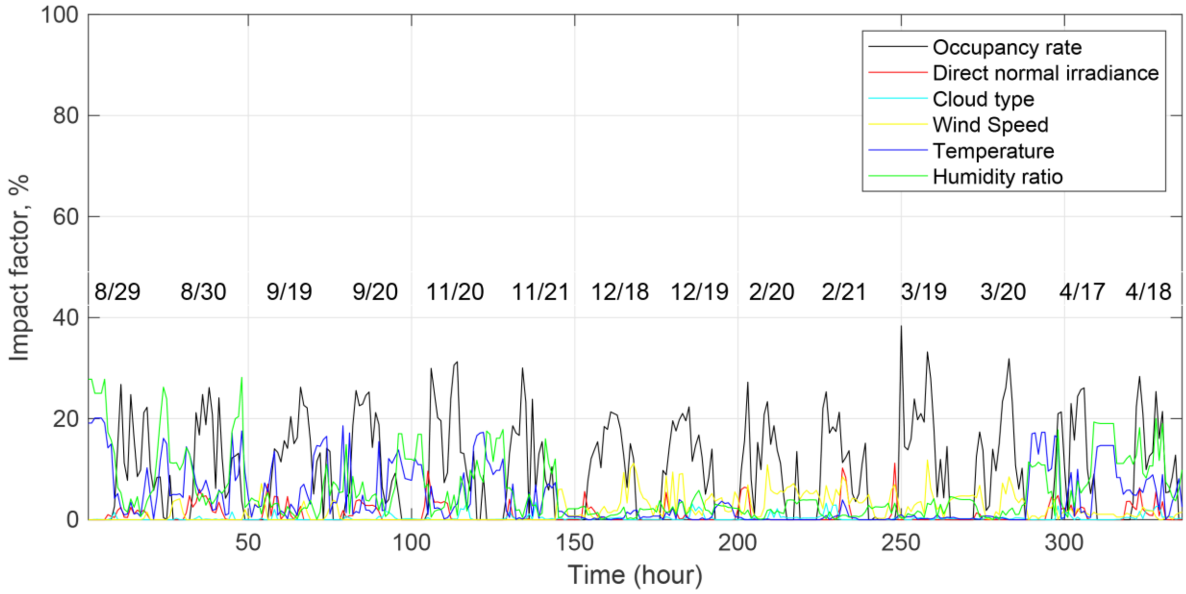

Figure 16 Impact factor rates of input parameters for working days by ANN method

Figure 17 and 18 show the impact factors of each parameter for non-working days for the two prediction models. For non-working days, low occupancy rates and other environment parameters rarely influence the electricity consumption. Therefore, these parameters could be ignored to predict the electricity consumption on non-working days and holidays in the building. Accordingly, further study should find elements that more significantly impact non-working-day energy consumption. For example, facility management plan, building maintenance, and building closing plan for holidays could be considered for predicting electricity consumption on non-working days and to find the dominant factors in simulation.

The results presented that the ANN model was highly accurate and stable compared with the linear regression method in predicting the electricity consumption for working days. The ANN model with LM-BP algorithm has significant potential for forecasting electricity energy consumption in the campus building. By impact factor analysis, occupancy rates were found to highly impact the electricity consumption in the building, and temperature and humidity were also significant in the summer season. However, the last two elements did not significantly affect consumption in the winter season because the centralized steam heating system had little influence on the electricity consumption in the building. However, there are no special accuracy differences between two modeling in predicting electricity consumption for non-working days because none of the input element had a significant impact on the results.

In this study, several limitations remain to be explored via further research. A campus building was selected to measure occupancy rates and electricity consumption for this study. However, measured electricity consumption rates may differ according to building type, HVAC system design, building materials, energy sources, and space performance. As such, future studies should consider additional parameters to minimize the error rates of prediction results.

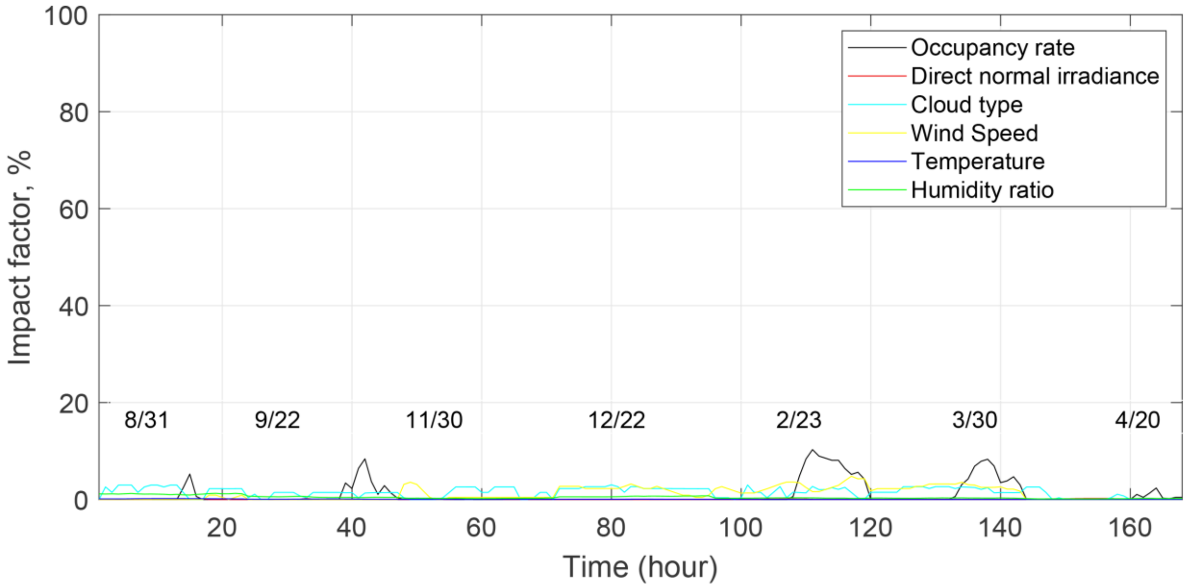

Figure 17 Impact factor rates of input parameters for non-working days by linear regression method

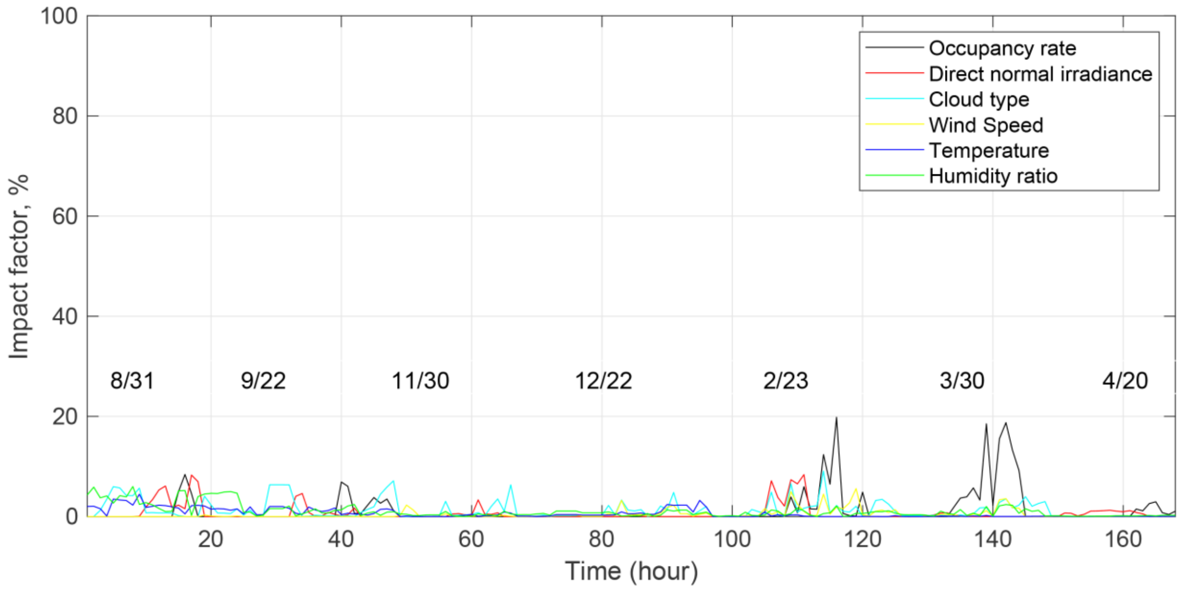

Figure 18 Impact factor rates of input parameters for non-working days by ANN method

4. Conclusion

This study explored predictive control strategies based on linear regression and an ANN with an LM-BP algorithm, where the latter was designed with input nodes from the occupancy rates and local environmental conditions (i.e., temperature, humidity ratio, DNI, cloud type, and wind speed) to predict the electricity consumption of a campus building. We evaluated the performance of each method using a training data set divided into two groups—working and non-working days—and compared the simulation results obtained with actual measured electricity consumption values comprising 157 days' worth of hourly data for the building. The results showed that the ANN model was more accurate and stable than the linear regression method in predicting the electricity consumption of working days. By an impact factor analysis, the occupancy rate was found to strongly dominate the electricity consumption in the building while temperature and humidity also affected the results, but to a lesser extent. However, there were no accuracy differences between the two methods in predicting the electricity consumption of non-working days because the input elements had a similar impact on those days. Both the linear regression and ANN model with LM-BP algorithm were able to meet the long-term and real-time hourly predicting requirements for electricity consumption in an actual building, depending on the occupancy rates and local environmental conditions. For analyzing the input element changes at a macroscopic scale, the methods are helpful in predicting how each element impacts electricity consumption in buildings. Thus, they could be useful in understanding the functioning of buildings in terms of a long-term energy consumption. For example, it is possible to evaluate how significantly climate change and global warming could impact consumption in the future. The proposed ANN method can be used as a reliable approach compared with the linear regression model for predicting electricity consumption of a building. This ANN algorithm should be updated with additional parameters to improve the accuracy of predictions in the future. However, one technical limitation should be addressed in future research: A campus building was selected for this research and we considered occupancy rates and local weather conditions to predict the energy consumption. However, occupant characteristics, plug-load data, and HVAC types could significantly influence the actual long-term building electricity consumption. Therefore, to improve the accuracy of predicting the electricity consumption for non-working days, a further study should consider other input elements that may significantly affect the actual electricity.

References

Agency, I. I. E. (2008). *Promoting Energy Efficiency Investments: case studies in the residential sector*. Paris Cedex 15: OECD/IEA and AFD.

Ahmad, A. S., Hassan, M. Y., Abdullah, M. P., Rahman, H. A., Hussin, F., Abdullah, H., & Saidur, R. (2014). A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews, 33*, 102-109. doi:https://doi.org/10.1016/j.rser.2014.01.069

Ahmad, M. W., Mourshed, M., & Rezgui, Y. (2017). Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption. *Energy and Buildings, 147*, 77-89. doi:https://doi.org/10.1016/j.enbuild.2017.04.038

Amber, K. P., Aslam, M. W., & Hussain, S. K. (2015). Electricity consumption forecasting models for administration buildings of the UK higher education sector. *Energy and Buildings, 90*, 127-136. doi:https://doi.org/10.1016/j.enbuild.2015.01.008

Andrić, I., Koc, M., & Al-Ghamdi, S. G. (2019). A review of climate change implications for built environment: Impacts, mitigation measures and associated challenges in developed and developing countries. *Journal of Cleaner Production, 211*, 83-102. doi:https://doi.org/10.1016/j.jclepro.2018.11.128

ASHRAE. (2002). ASHRAE guideline 14–2002: Measurement of energy and demand savings. In: ASHRAE.

Azadeh, A., Ghaderi, S. F., & Sohrabkhani, S. (2008). Annual electricity consumption forecasting by neural network in high energy consuming industrial sectors. *Energy Conversion and Management, 49*(8), 2272-2278. doi:10.1016/j.enconman.2008.01.035

Azar, E., & Menassa, C. C. (2012). A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. *Energy and Buildings, 55*, 841-853. doi:https://doi.org/10.1016/j.enbuild.2012.10.002

Baldini, L., Kim, M. K., & Leibundgut, H. (2014). Decentralized cooling and dehumidification with a 3 stage LowEx heat exchanger for free reheating. *Energy and Buildings, 76*, 270-277. Retrieved from <Go to ISI>://WOS:000336779000026

Becerik-Gerber, B., Siddiqui Mohsin, K., Brilakis, I., El-Anwar, O., El-Gohary, N., Mahfouz, T., . . . Kandil Amr, A. (2014). Civil Engineering Grand Challenges: Opportunities for Data Sensing, Information Analysis, and Knowledge Discovery. *Journal of Computing in Civil Engineering, 28*(4), 04014013. doi:10.1061/(ASCE)CP.1943-5487.0000290

Bianco, V., Manca, O., & Nardini, S. (2009). Electricity consumption forecasting in Italy using linear regression models. *Energy, 34*(9), 1413-1421. doi:https://doi.org/10.1016/j.energy.2009.06.034

Bocheng Zhong, K. L., Dinghao Lv, Jing Luo, Xuan Fang. (2015). *Short-term Prediction of Building Energy Consumption Based on GALM Neural Network.* Paper presented at the International Conference on Advances in Mechanical Engineering and Industrial Informatics.

Bordass, B., Cohen, R., Standeven, M., & Leaman, A. (2001). Assessing building performance in use 3: energy performance of the Probe buildings. *Building Research & Information, 29*(2), 114-128. doi:10.1080/09613210010008036

Capeluto, I. G. (2003). Energy performance of the self-shading building envelope. *Energy and Buildings, 35*(3), 327-336. doi:https://doi.org/10.1016/S0378-7788(02)00105-6

Chae, Y. T., Horesh, R., Hwang, Y., & Lee, Y. M. (2016). Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings. *Energy and Buildings, 111*, 184-194. doi:https://doi.org/10.1016/j.enbuild.2015.11.045

Chen, Q. Y., Yang, X., & Zhao, B. (2007). Particles, aerosols, and their transport in the built environment. *Atmospheric Environment, 41*(25), 5179-5180. doi:https://doi.org/10.1016/j.atmosenv.2007.03.032

Chung, W. (2012). Using the fuzzy linear regression method to benchmark the energy efficiency of commercial buildings. *Applied Energy, 95*, 45-49. doi:https://doi.org/10.1016/j.apenergy.2012.01.061

de la Rue du Can, S., & Price, L. (2008). Sectoral trends in global energy use and greenhouse gas emissions. *Energy Policy, 36*(4), 1386-1403. doi:https://doi.org/10.1016/j.enpol.2007.12.017

Deb, C., & Lee, S. E. (2018). Determining key variables influencing energy consumption in office buildings through cluster analysis of pre- and post-retrofit building data. *Energy and Buildings, 159*, 228-245. doi:https://doi.org/10.1016/j.enbuild.2017.11.007

Deb, C., Zhang, F., Yang, J., Lee, S. E., & Shah, K. W. (2017). A review on time series forecasting techniques for building energy consumption. *Renewable and Sustainable Energy Reviews, 74*, 902-924. doi:https://doi.org/10.1016/j.rser.2017.02.085

Đozić, D. J., & Gvozdenac Urošević, B. D. (2019). Application of artificial neural networks for testing long-term energy policy targets. *Energy, 174*, 488-496. doi:https://doi.org/10.1016/j.energy.2019.02.191

Ekici, B. B., & Aksoy, U. T. (2009). Prediction of building energy consumption by using artificial neural networks. *Advances in Engineering Software, 40*(5), 356-362. doi:10.1016/j.advengsoft.2008.05.003

Elsheikh, A. H., Sharshir, S. W., Abd Elaziz, M., Kabeel, A. E., Guilan, W., & Haiou, Z. (2019). Modeling of solar energy systems using artificial neural network: A comprehensive review. *Solar Energy, 180*, 622-639. doi:https://doi.org/10.1016/j.solener.2019.01.037

Farah, S., Whaley, D., Saman, W., & Boland, J. (2019). Integrating climate change into meteorological weather data for building energy simulation. *Energy and Buildings, 183*, 749-760. doi:https://doi.org/10.1016/j.enbuild.2018.11.045

Feedback Control, T. (2010). *Feedback Control Theory*: Macmillan/Georg von Holtzbrinck Publishing Group.

G.Woodal. (2012). *SMART 2011/0072: Methodology for Energy-Effficiency Measurements Applicable to ICT in Buildings (eeMeasure)*. Retrieved from Germany:

Gabbar, H. A., Bondarenko, D., Hussain, S., Musharavati, F., & Pokharel, S. (2014). Building thermal energy modeling with loss minimization. *Simulation Modelling Practice and Theory, 49*, 110-121. doi:https://doi.org/10.1016/j.simpat.2014.08.006

Haberl, J. S., & Bou-Saada, T. E. (1998). Procedures for Calibrating Hourly Simulation Models to Measured Building Energy and Environmental Data. *Journal of Solar Energy Engineering, 120*(3), 193-204. doi:10.1115/1.2888069

Hao, Y., Li, H., & Wang, H. (2013). Analysis of energy consumption and energy-saving of residential buildings based on LM-BP algorithm. *International Journal of Applied Mathematics and Statistics, 51*(24), 348-356. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-84901647577&partnerID=40&md5=7cf1090c253f22a656d355474e0fd6b5

Hsu, D. (2015). Comparison of integrated clustering methods for accurate and stable prediction of building energy consumption data. *Applied Energy, 160*, 153-163. doi:https://doi.org/10.1016/j.apenergy.2015.08.126

Jia, W., Zhao, D., Shen, T., Ding, S., Zhao, Y., & Hu, C. (2015). An optimized classification algorithm by BP neural network based on PLS and HCA. *Applied Intelligence, 43*(1), 176-191. doi:10.1007/s10489-014-0618-x

Khalid, R., Javaid, N., Rahim, M. H., Aslam, S., & Sher, A. (2019). Fuzzy energy management controller and scheduler for smart homes. *Sustainable Computing: Informatics and Systems, 21*, 103-118. doi:https://doi.org/10.1016/j.suscom.2018.11.010

Kim, K. M., Cha, J., Lee, E., Pham, H. V., Lee, S., & Theera-Umpon, N. (2019). Simplified Neural Network Model Design with Sensitivity Analysis and Electricity Consumption Prediction in a Commercial Building. *Energies, 12*(7). doi:10.3390/en12071201

Kim, M. K., Baldini, L., Leibundgut, H., & Wurzbacher, J. A. (2019). Evaluation of the humidity performance of a carbon dioxide (CO2) capture device as a novel ventilation strategy in buildings. *Applied Energy*. doi:https://doi.org/10.1016/j.apenergy.2019.03.074

Kim, M. K., & Choi, J.-H. (2019). Can increased outdoor CO2 concentrations impact on the ventilation and energy in buildings? A case study in Shanghai, China. *Atmospheric Environment, 210*, 220-230. doi:https://doi.org/10.1016/j.atmosenv.2019.04.015

Kim, Y.-S., Heidarinejad, M., Dahlhausen, M., & Srebric, J. (2017). Building energy model calibration with schedules derived from electricity use data. *Applied Energy, 190*, 997-1007. doi:https://doi.org/10.1016/j.apenergy.2016.12.167

Kim, Y.-S., & Srebric, J. (2017). Impact of occupancy rates on the building electricity consumption in commercial buildings. *Energy and Buildings, 138*, 591-600. doi:https://doi.org/10.1016/j.enbuild.2016.12.056

Kumar, R., Aggarwal, R. K., & Sharma, J. D. (2013). Energy analysis of a building using artificial neural network: A review. *Energy and Buildings, 65*, 352-358. doi:10.1016/j.enbuild.2013.06.007

Laboratory, N. R. E. (2019). National Solar Radiation Database (NSRDB). Retrieved from https://nsrdb.nrel.gov/nsrdb-viewer

Lek, S., & Guégan, J. F. (1999). Artificial neural networks as a tool in ecological modelling, an introduction. *Ecological Modelling, 120*(2), 65-73. doi:https://doi.org/10.1016/S0304-3800(99)00092-7

Li, K., Hu, C., Liu, G., & Xue, W. (2015). Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. *Energy and Buildings, 108*, 106-113. doi:https://doi.org/10.1016/j.enbuild.2015.09.002

Lü, X., Lu, T., Kibert, C. J., & Viljanen, M. (2015). Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach. *Applied Energy, 144*, 261-275. doi:https://doi.org/10.1016/j.apenergy.2014.12.019

Lupato, G., & Manzan, M. (2019). Italian TRYs: New weather data impact on building energy simulations. *Energy and Buildings, 185*, 287-303. doi:https://doi.org/10.1016/j.enbuild.2018.12.001

Ma, X., Xie, M., Wu, W., Zeng, B., Wang, Y., & Wu, X. (2019). The novel fractional discrete multivariate grey system model and its applications. *Applied Mathematical Modelling, 70*, 402-424. doi:https://doi.org/10.1016/j.apm.2019.01.039

Maghyereh, A. I., Awartani, B., & Abdoh, H. (2019). The co-movement between oil and clean energy stocks: A wavelet-based analysis of horizon associations. *Energy, 169*, 895-913. doi:https://doi.org/10.1016/j.energy.2018.12.039

Moazami, A., Nik, V. M., Carlucci, S., & Geving, S. (2019). Impacts of future weather data typology on building energy performance – Investigating long-term patterns of climate change and extreme weather conditions. *Applied Energy, 238*, 696-720. doi:https://doi.org/10.1016/j.apenergy.2019.01.085

Mohandes, S. R., Zhang, X., & Mahdiyar, A. (2019). A comprehensive review on the application of artificial neural networks in building energy analysis. *Neurocomputing, 340*, 55-75. doi:https://doi.org/10.1016/j.neucom.2019.02.040

Neto, A. H., & Fiorelli, F. A. S. (2008). Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. *Energy and Buildings, 40*(12), 2169-2176. doi:10.1016/j.enbuild.2008.06.013

Pombeiro, H., Santos, R., Carreira, P., Silva, C., & Sousa, J. M. C. (2017). Comparative assessment of low-complexity models to predict electricity consumption in an institutional building: Linear regression vs. fuzzy modeling vs. neural networks. *Energy and Buildings, 146*, 141-151. doi:https://doi.org/10.1016/j.enbuild.2017.04.032

Programme, U. N. E. (2009). *Buildings and climate change*. Paris CEDEX09, France: United Nations Environment Programme.

Reddy, T. A. (2011). *Applied data analysis and modeling for energy engineers and scientists*. New York: Springer.

Sabzi, D., Haseli, P., Jafarian, M., Karimi, G., & Taheri, M. (2015). Investigation of cooling load reduction in buildings by passive cooling options applied on roof. *Energy and Buildings, 109*, 135-142. doi:https://doi.org/10.1016/j.enbuild.2015.09.042

Shi, G., Liu, D., & Wei, Q. (2016). Energy consumption prediction of office buildings based on echo state networks. *Neurocomputing, 216*, 478-488. doi:https://doi.org/10.1016/j.neucom.2016.08.004

Singh, V., Gupta, I., & Gupta, H. O. (2007). ANN-based estimator for distillation using Levenberg–Marquardt approach. *Engineering Applications of Artificial Intelligence, 20*(2), 249-259. doi:https://doi.org/10.1016/j.engappai.2006.06.017

Tanaka, H. (1987). Fuzzy data analysis by possibilistic linear models. *Fuzzy Sets and Systems, 24*(3), 363-375. doi:https://doi.org/10.1016/0165-0114(87)90033-9

Tanaka, H., Hayashi, I., & Watada, J. (1989). Possibilistic linear regression analysis for fuzzy data. *European Journal of Operational Research, 40*(3), 389-396. doi:https://doi.org/10.1016/0377-2217(89)90431-1

Tanaka, H., & Watada, J. (1988). Possibilistic linear systems and their application to the linear regression model. *Fuzzy Sets and Systems, 27*(3), 275-289. doi:https://doi.org/10.1016/0165-0114(88)90054-1

Tang Zhong, X. T. (2012). Application and Simulation of Matlab Neural Network Tool NNTool. *Computer and Modernization, 12*.

Toe, D. H. C., & Kubota, T. (2013). Development of an adaptive thermal comfort equation for naturally ventilated buildings in hot–humid climates using ASHRAE RP-884 database. *Frontiers of Architectural Research, 2*(3), 278-291. doi:https://doi.org/10.1016/j.foar.2013.06.003

Trigo-González, M., Batlles, F. J., Alonso-Montesinos, J., Ferrada, P., del Sagrado, J., Martínez-Durbán, M., . . . Marzo, A. (2019). Hourly PV production estimation by means of an exportable multiple linear regression model. *Renewable Energy, 135*, 303-312. doi:https://doi.org/10.1016/j.renene.2018.12.014

Walter, T., & Sohn, M. D. (2016). A regression-based approach to estimating retrofit savings using the Building Performance Database. *Applied Energy, 179*, 996-1005. doi:https://doi.org/10.1016/j.apenergy.2016.07.087

Wong, S. L., Wan, K. K. W., & Lam, T. N. T. (2010). Artificial neural networks for energy analysis of office buildings with daylighting. *Applied Energy, 87*(2), 551-557. doi:10.1016/j.apenergy.2009.06.028

Xia, B., Cui, D., Sun, Z., Lao, Z., Zhang, R., Wang, W., . . . Wang, M. (2018). State of charge estimation of lithium-ion batteries using optimized Levenberg-Marquardt wavelet neural network. *Energy, 153*, 694-705. doi:https://doi.org/10.1016/j.energy.2018.04.085

Xie, Q., Ouyang, H., & Gao, X. (2016). Estimation of electricity demand in the residential buildings of China based on household survey data. *International Journal of Hydrogen Energy, 41*(35), 15879-15886. doi:https://doi.org/10.1016/j.ijhydene.2016.03.152

Xu, B., Zhang, H., Wang, Z., Wang, H., & Zhang, Y. (2015). Model and Algorithm of BP Neural Network Based on Expanded Multichain Quantum Optimization. *Mathematical Problems in Engineering, 2015*. doi:10.1155/2015/362150

Y. H. Liu, Z. P. L. (2015). *建筑能耗无线监测系统的研究与设计.* (硕士学位). Dalian University of Technology, Dalian University of Technology.

Yalcintas, M., & Akkurt, S. (2005). Artificial neural networks applications in building energy predictions and a case study for tropical climates. *International Journal of Energy Research, 29*(10), 891-901. doi:10.1002/er.1105

Yau, Y. H., & Hasbi, S. (2013). A review of climate change impacts on commercial buildings and their technical services in the tropics. *Renewable and Sustainable Energy Reviews, 18*, 430-441. doi:https://doi.org/10.1016/j.rser.2012.10.035

Ye, Z., & Kim, M. K. (2018). Predicting electricity consumption in a building using an optimized back-propagation and Levenberg–Marquardt back-propagation neural network: Case study of a shopping mall in China. *Sustainable Cities and Society, 42*, 176-183. doi:https://doi.org/10.1016/j.scs.2018.05.050

Yoo, S. G., & Seul, N. O. (2017). Design of a control cable condition prediction system for nuclear power plants using LMBP neural networks. *Journal of Institute of Control, Robotics and Systems, 23*(3), 194-198. doi:10.5302/J.ICROS.2017.17.8002

Yu, F., & Xu, X. (2014). A short-term load forecasting model of natural gas based on optimized genetic algorithm and improved BP neural network. *Applied Energy, 134*(Supplement C), 102-113. doi:https://doi.org/10.1016/j.apenergy.2014.07.104

Yu, S., Zhu, K., & Diao, F. (2008). A dynamic all parameters adaptive BP neural networks model and its application on oil reservoir prediction. *Applied Mathematics and Computation, 195*(1), 66-75. doi:10.1016/j.amc.2007.04.088

Zeng, A., Liu, S., & Yu, Y. (2019). Comparative study of data driven methods in building electricity use prediction. *Energy and Buildings, 194*, 289-300. doi:https://doi.org/10.1016/j.enbuild.2019.04.029

Zhai, Z. J., & Chen, Q. Y. (2005). Performance of coupled building energy and CFD simulations. *Energy and Buildings, 37*(4), 333-344. doi:https://doi.org/10.1016/j.enbuild.2004.07.001

Zhai, Z. J., & Helman, J. M. (2019). Implications of climate changes to building energy and design. *Sustainable Cities and Society, 44*, 511-519. doi:https://doi.org/10.1016/j.scs.2018.10.043