Impact of Correlation of Plug Load Data, Occupancy Rates and Local Weather Conditions on Electricity Consumption in a Building Using Four Back-propagation Neural Network Models

Moon Keun Kim[ad1], Yang-Seon Kim[b1], Jelena Srebric[c]

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

[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

[1] These authors contributed equally to the research and manuscript.

Abstract

This study explores approaches to evaluates correlation how significantly plug load data, occupancy rates, and local weather factors affect the actual electricity consumption of a commercial building in seasonal changes and it predicts electricity usage in buildings using four Back-propagation neural network (BP-NN) algorithms: Levenberg–Marquardt Back-propagation (LMBP), Quasi-Newton Back-propagation (QNBP), scaled conjugate gradient (SCG), and Bayesian regularization (BR). In order to evaluate the impact performance of each input parameter, an impact value was used for these experimental datasets. The results demonstrated that the artificial neural network (ANN) model using the LMBP algorithm has better performance in forecasting electricity consumption in a building. Compared to the other three ANN method results, the LMBP model represented a higher accuracy of 1.07 to 2.23% and lower error rates. Through impact factor analysis, plug load data were found to highly impact the electricity consumption, and temperature had a significant impact in the summer. However, temperature did not largely influence the results in the winter because the gas boiler heating systems used in the building had little impact on the actual electricity consumption. These methods are helpful in analyzing input factors how each element influences energy consumption. The four proposed BP-NN methods can be used as reliable approaches.

Keywords: artificial neural network; energy prediction; plug load; occupancy rates; environmental elements; back-propagation

1. Introduction

Buildings and construction areas are responsible for 24% of carbon dioxide emissions and over 40% of the world's total final primary energy consumption (Agency, 2008; A. S. Ahmad et al., 2014; Becerik-Gerber et al., 2014; de la Rue du Can & Price, 2008; Programme, 2009). Therefore, estimating electricity consumption in buildings is a major concern for creating smart performance improvements, energy distribution, building facility management, operation and diagnosis, and smart building practices in future cities (Walter & Sohn, 2016; Zeng, Liu, & Yu, 2019). Various studies have presented the effects of occupancy diversity and surrounding weather conditions on the total energy consumption and greenhouse gas emissions in

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buildings (Yau & Hasbi, 2013; Zhai & Helman, 2019). Using artificial neural network prediction methods, many studies have provided methods to predict electricity consumption in buildings (Bordass, Cohen, Standeven, & Leaman, 2001; Haberl & Bou-Saada, 1998; Y.-S. Kim, Heidarinejad, Dahlhausen, & Srebric, 2017; Y.-S. Kim & Srebric, 2017). Energy consumption in buildings is affected by many factors such as building envelope (shape, size, and depth of materials), lighting, types of HVAC (heating, ventilation, and air conditioning), surrounding local weather conditions, and occupants' energy demand (Azar & Menassa, 2012; Lupato & Manzan, 2019; Ren & Cao, 2019; Yalcintas & Akkurt, 2005; Yuan, Farnham, Azuma, & Emura, 2018). In general, a building's construction set, lighting, and HVAC are fixed elements in a building and do not significantly influence the actual electricity demand. However, occupancy rate, local weather elements, and plug load data can affect the total electricity demand and determine electricity consumption patterns in a building. The plug load data are the amounts of electric energy used by products powered through ordinary alternating current (AC) plugs and do not include energy uses such as HVAC and lighting ("Electronics Come of Age: A Taxonomy for Miscellaneous and LowPower Products," 2006). Therefore, this study is a sensitivity analysis that explores the prediction of how significantly plug load data, occupancy rates, and local surrounding weather conditions impact the electricity consumption of a commercial building. Numerous data-driven algorithms have been proposed and developed for energy prediction modeling (M. W. Ahmad, Mourshed, & Rezgui, 2017; Deb, Zhang, Yang, Lee, & Shah, 2017; Hsu, 2015; Li et al., 2018; Ye & Kim, 2018), such as linear and multi-layer regression, support vector machine, and artificial neural networks (ANNs) (Khalid, Javaid, Rahim, Aslam, & Sher, 2019; Walter & Sohn, 2016; Ye & Kim, 2018; Zeng et al., 2019). Recent review studies have provided variable classifications of the existing algorithms with good accuracy (Biswas, Robinson, & Fumo, 2016a; Li et al., 2018). Compared to regression and statistical methods, ANN algorithms have demonstrated better accuracy and brought forward the opportunity to predict energy consumption effectively (Magalhães, Leal, & Horta, 2017; Sekhar Roy, Roy, & Balas, 2018; Yuan et al., 2018). In particular, the ANN methods are some of the main algorithms currently used to predict electricity consumption in buildings (A. S. Ahmad et al., 2014; M. W. Ahmad et al., 2017). ANNs provide the function and structure of biochemical reactions such as in human brains by performing nonlinear processing (A. S. Ahmad et al., 2014; Deb et al., 2017; Ye & Kim, 2018). ANNs are self-learning systems and can constantly adjust their approach to adapt to variable environments when processing many types of information. Therefore, ANNs have been widely used in pattern recognition to forecast changes in processes, improve accuracy, optimize decision making, and other tasks (Ye & Kim, 2018).

In this study, we propose novel analysis strategy how plug-load data, occupancy rate, and climate factor are correlated with building energy consumption in seasonal changes. And how each element significantly impacts on energy consumption in an office building in four seasons. The proposed predictive control strategy is based on four ANNs, back-propagation neural network (BP-NN) algorithms as a sensitivity analysis: Levenberg-Marquardt Back-propagation (LMBP), Quasi-Newton Back-propagation (QNBP), Scaled conjugate gradient (SCG) algorithm, and Bayesian regularization (BR). This study explores, with the help of applied impact factors designed with ANNs' training and outputs using input elements, plug load data, occupancy rates, and weather factors such as solar irradiance, wind speed, temperature, and humidity ratio, and predicts the actual electrical energy consumption of a commercial building using these four BP-NN approaches.

The main objectives of this study are:

- Analysis of the variation in the plug load data, occupancy ratio, weather data and electricity consumption data based on experimental data in a commercial building.

- Prediction of electricity consumption in a building using four BP-NN algorithms: Levenberg-Marquardt Back-propagation (LMBP), Quasi-Newton Back-propagation

(QNBP), Scaled conjugate gradient (SCG) algorithm, and Bayesian regularization (BR) as a comparative analysis.

- Investigation of the effect of plug-load data, occupancy ratio, and weather conditions which are temperature, humidity ratio, solar irradiance and wind speed on electricity consumption with sensitivity analysis.

- Application of the predictive analysis in four seasons.

2. Building energy consumption models

2.1. Back-propagation Neural Networks

Today, several algorithms of neural networks have been developed (Amber, Aslam, & Hussain, 2015; Chae, Horesh, Hwang, & Lee, 2016; Hsu, 2015; Kumar, Aggarwal, & Sharma, 2013; Li, Hu, Liu, & Xue, 2015). Among them, four main algorithms have been currently proposed and used: the Hopfield neural network, Kohonen maps, back-propagation (BP) neural network, and radial basis function (RBF) neural network. Many studies have applied BP neural networks in areas such as information training and processing, electricity prediction and modeling in buildings, pattern recognition and applications, and intelligent control and distribution; the forecasting results have been in good agreement with actual data (Hsu, 2015). This study applied four BP-NN algorithms that exhibit good performance and are used widely: LMBP, QNBP, SCG, and BR (Amber et al., 2015; Hsu, 2015; K. M. Kim et al., 2019).

A typical BP neural network consists of three interconnected layers in parallel: the input, hidden, and output layers (Bocheng Zhong, 2015; K. M. Kim et al., 2019; Kumar et al., 2013). Each layer has more than one neuron operating parallel computing networks and the neurons vary for each layer independently (Biswas, Robinson, & Fumo, 2016b). Figure 1 shows an example of a neural network.

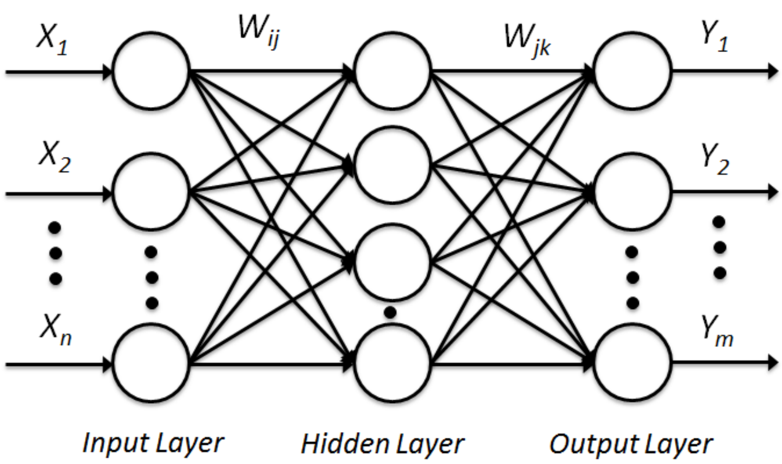

Figure 1 Three-layer BP neural network structure (Ye & Kim, 2018)

As illustrated in Figure 1, X_1, X_2,…, X_n are the input elements in the input layer, which can represent the elements that can impact electricity consumption in a building, such as plug node data, occupancy rates, temperature, humidity ratio, solar irradiance, and wind speed (Azadeh, Ghaderi, & Sohrabkhani, 2008; Kumar et al., 2013; Neto & Fiorelli, 2008; Wong, Wan, & Lam, 2010; Xu, Zhang, Wang, Wang, & Zhang, 2015). Y_1, Y_2, … Y_n are the output nodes corresponding to the model using input and hidden nodes to forecast electricity consumption.

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

The output node of the hidden layer is as follows:

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

Where f is a function, w_{ij} is the weight in the hidden layer and n is the number of input nodes and d is the threshold of each node

The output node of the output layer is as follows:

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

w_{jk} is the weight in the output layer, l is the number of hidden layer, and m is the number of output nodes.

Based on the BP neural network modeling, the mean square error (MSE) can be obtained from the predicted and actual measured values by the following function:

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

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

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

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

2.1.1. Levenberg-Marquardt Back-propagation (LMBP)

The Levenberg-Marquardt Back-propagation (LMBP) algorithm was designed for loss functions. It is a popular alternative approach to the Gauss-Newton method for finding the minimum of squares of nonlinear functions. In the Levenberg-Marquardt (LM) algorithm, after a series of optimizations, the weight approximations of the Hessian matrix and threshold are formulized into Equations (5,6, and 7) (Bocheng Zhong, 2015; Hao, Li, & Wang, 2013; K. M. Kim et al., 2019; Yoo & Seul, 2017):

$$H = \boldsymbol{J}^T\boldsymbol{J} \quad (5)$$

$$g = \boldsymbol{J}^T\boldsymbol{e} \quad (6)$$

$$x(k+1) = x(k) - [\boldsymbol{J}^T\boldsymbol{J} + \mu\boldsymbol{I}]^{-1}\boldsymbol{J}^T e \qquad (7)$$

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 Gauss-Newton method.

This algorithm is one of the fast training functions for neural networks, and some studies have reported that LMBP has better accuracy and stability in relatively small scale networks; however, it requires more memory than other algorithms (Fun & Hagan, 1996; Magalhães et al., 2017).

2.1.2. Quasi-Newton Back-propagation (QNBP)

Newton's algorithm is designed for fast optimization as an alternative to the conjugate gradient methods. The basic process of Newton's method is as follows:

$$x(k+1) = x(k) - A(k)^{-1} g(k) \qquad (8)$$

Where $A(k)^{-1}$ is the Hessian matrix at the current values of the weight and biases, and $g(k)$ is the gradient.

The Quasi-Newton Back-propagation (QNBP) model is used to decrease the deficiency of the conventional back-propagation structure. One of the main limitations of the QNBP model is that reduction of accuracy leads to delaying convergence (T. Ahmad & Chen, 2019). However, the overall predicting performance, speed, accuracy, and reliability of the QNBP model are better than data-mining and ensemble models (T. Ahmad & Chen, 2019).

2.1.3. Scaled Conjugate Gradient (SCG) method

The scaled conjugate gradient (SCG) method is considered a second-order information learning procedure (Amaral, Ribeiro, & de Aguiar, 2019; Ribeiro, Duque, & Romano, 2006). SCG illustrates a variation of the conjugate gradient method and it avoids the line-search per learning literation. The SCG method is as follows:

$$S_k = \frac{E'(w_k + \sigma_k p_k) - E'(w_k)}{\sigma_k} + \lambda_k p_k \qquad (9)$$

Where, S_k is scaling factor, E' is the gradient of the global error function, λ_k is initial value, $0 < \sigma_1 \leq 10^{-6}$, p_k is conjugate weight vector, w_k is a weight vector, and σ_k is initial value, $0 < \sigma_1 \leq 10^{-4}$.

This algorithm is faster and more effective than the standard back-propagation and gradient descent in training neural networks; SCG avoids the time consumption in line-searches per learning iteration (Møller, 1993).

2.1.4. Bayesian Regularization (BR)

The Bayesian regularization (BR) back-propagation method follows a network training function, updating the bias and weighting values according to Levenberg-Marquardt optimization (Ballabio & Vasighi, 2012; Lapuschkin, Binder, Montavon, Muller, & Samek, 2016). The algorithm can reduce a combination of squared errors and weights. After that, it decides the correct combination that generalizes accurately (Heydecker & Wu, 2001; Sun, Chen, Li, Qin, & Wang, 2017). The BR method adds a term to this equation to improve the generation capability as follows (Sun et al., 2017):

$$F = \beta E_D + \alpha E_{w,} \qquad E_w = \frac{1}{2}\sum_{k=1}(w_i)^2 \qquad (10)$$

Where F is the objective function, E_D is the sum of squared errors, E_w is the sum of squared network weights, and α and β are objective function parameters (MacKay, 1992).

The BR method sometimes provides better performance when datasets are smaller; however, this is not always the case (Lapuschkin et al., 2016; Ploskas & Samaras, 2016). This algorithm can minimize the potential for overfitting and local solution errors.

The neural network training processes used in this study are shown in Figure 2.

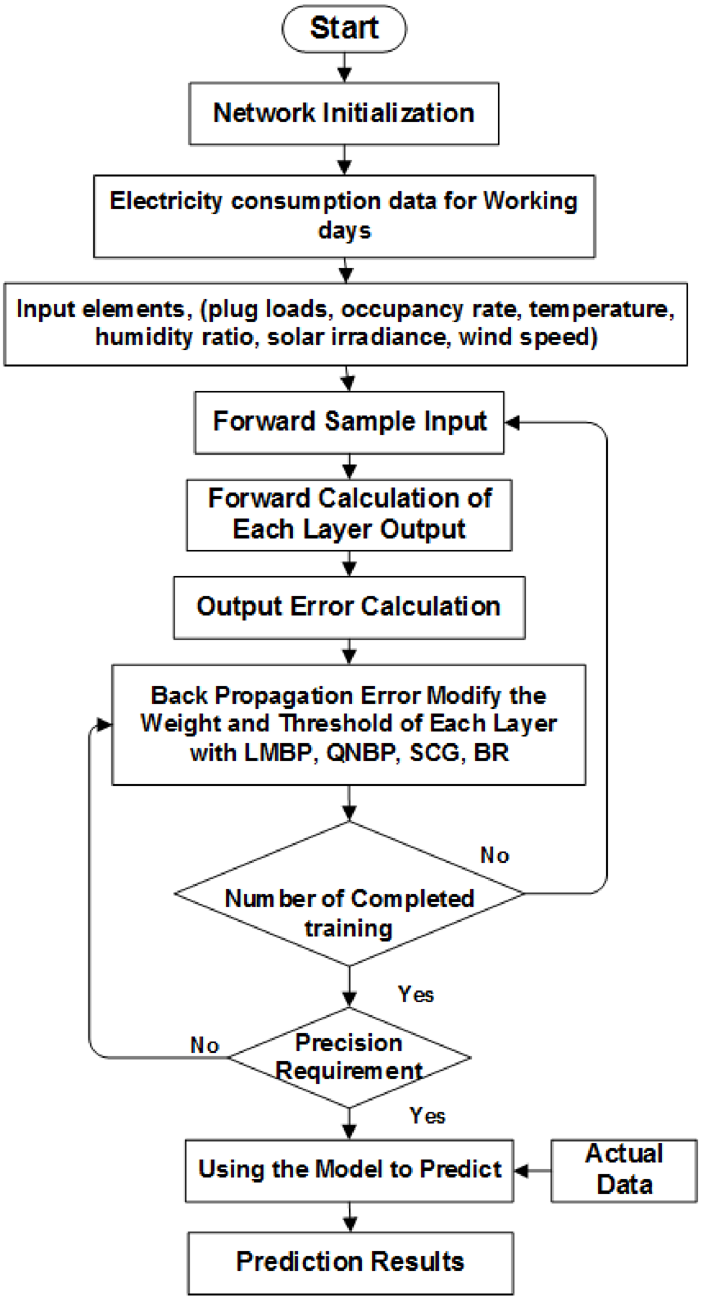

Figure 2 Training process for the artificial neural network

2.2. Data collection and analysis

This study collected the plug loads, building occupancy rates, and electricity consumption of a commercial office building in Philadelphia, PA, USA. The building size was 6140 m^2 and it consisted of three stories and a ground floor, and was made up of 40% office space and 60% common areas including conference rooms. The building had a sub-metering system to measure the electricity consumption of each plug load circuit. The sub-metering units monitored the energy loads of air handling units, condensing units, and lighting circuits, as well as whole-building power consumption. The power monitoring system used the Veris Multi-

Circuit meter (Version E31A) (Delgoshaei, Xu, Wagner, Sweetser, & Freihaut; Y.-S. Kim & Srebric, 2017). Video-based detecting sensors were used to collect occupancy rates in the building (PC-VID2-N, Sensource) (Y.-S. Kim et al., 2017) and the error rate of the sensors was within 5%.

This study collected a total of 284 days' worth of hourly data for the building's plug loads, occupancy rates, and electricity consumption between May 1, 2013, and February 28, 2014. Additionally, we used the local hourly historical weather data of Philadelphia recorded in the National Solar Radiation Database (NSRDB) (Laboratory, 2019). The data collected for analysis were categorized into two groups: working and non-working days; however, we used only the working days' data to predict the electricity consumption because the non-working days' data were insufficient for training and testing. Through ANN simulations as sensitivity analysis, we investigated the effect of occupancy rates, plug loads, and local weather elements and conditions on the building's total electricity consumption. Moreover, with the working-days' data (185 working days or 4440 hours) were further separated into training (165 working days or 3960 hours) and test data (20 working days or 480 hours). In the prediction model, this study determined the input nodes that influenced total building electricity consumption as plug loads, number of occupants, temperature (^{o} C), humidity ratio (g/kg), Global Horizontal Irradiance (GHI; W/m2), and wind speed (m/s). All the collected data are illustrated in Figure 3.

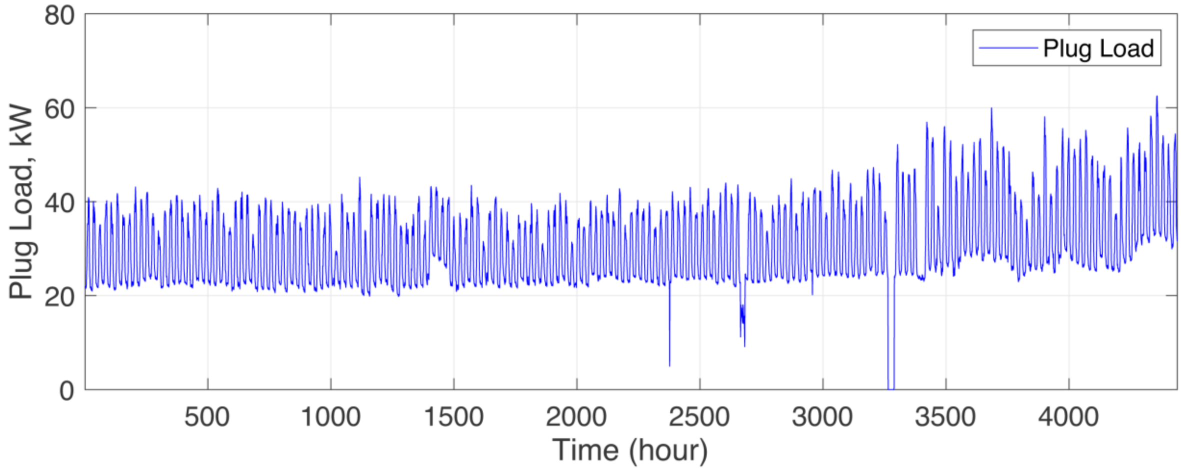

Figure 3 Collected data: Plug load (185 working days, May 1, 2013, to Feb 28, 2014)

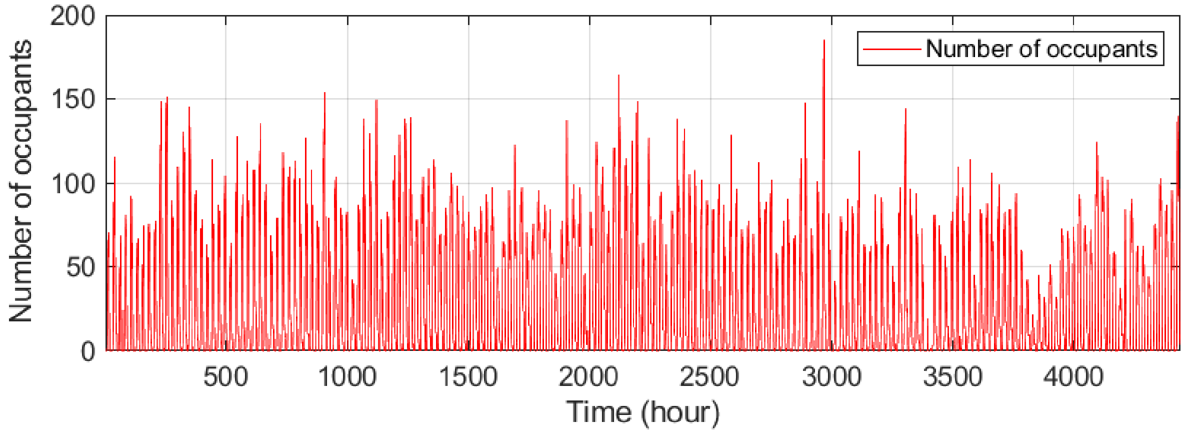

Figure 4 Collected data: Number of occupants (185 working days, May 1, 2013, to Feb 28, 2014)

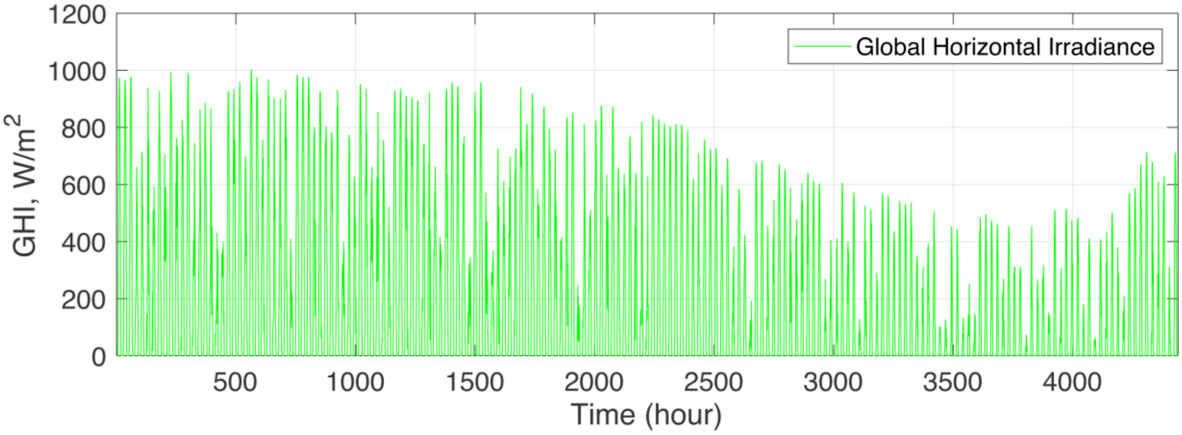

Figure 5 Weather data: Global Horizontal Irradiation (GHI), (185 working days, May 1, 2013, to Feb 28, 2014)

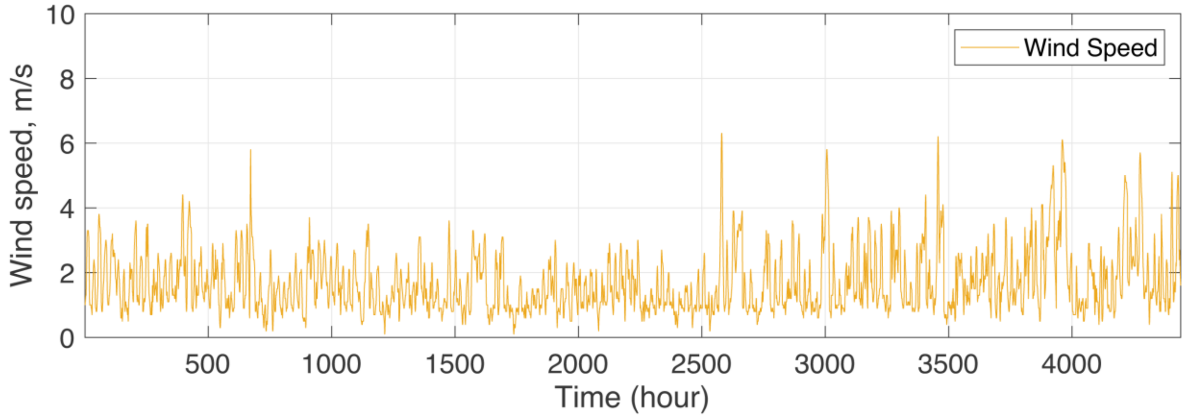

Figure 6 Weather data: Wind Speed (185 working days, May 1, 2013, to Feb 28, 2014)

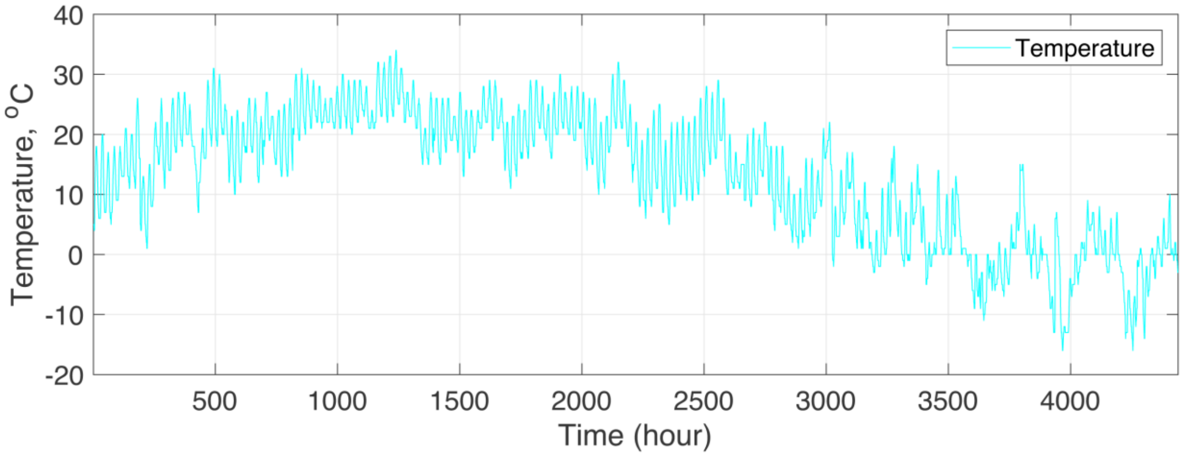

Figure 7 Weather data: Dry-bulb temperature (185 working days, May 1, 2013, to Feb 28, 2014)

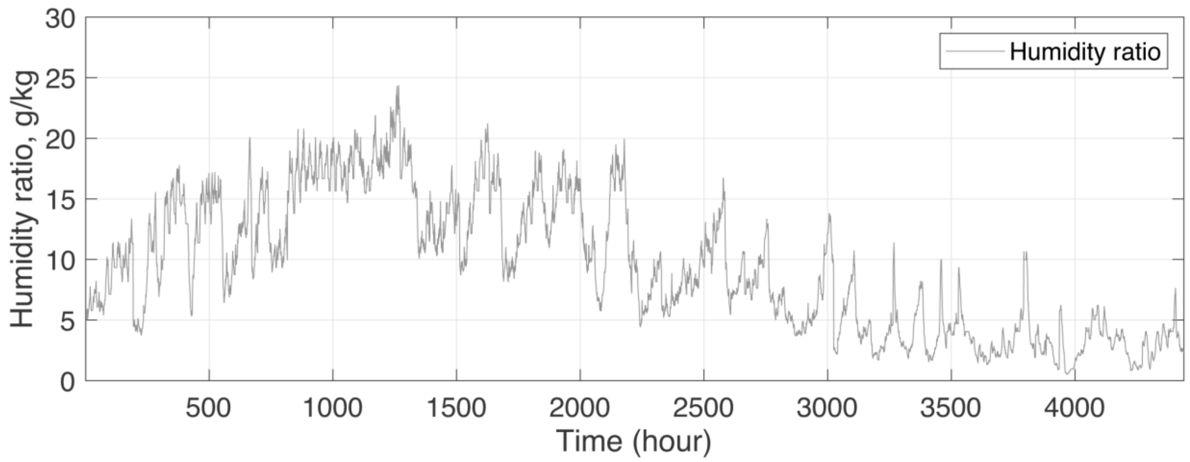

Figure 8 Weather data: Humidity ratio (185 working days, May 1, 2013, to Feb 28, 2014)

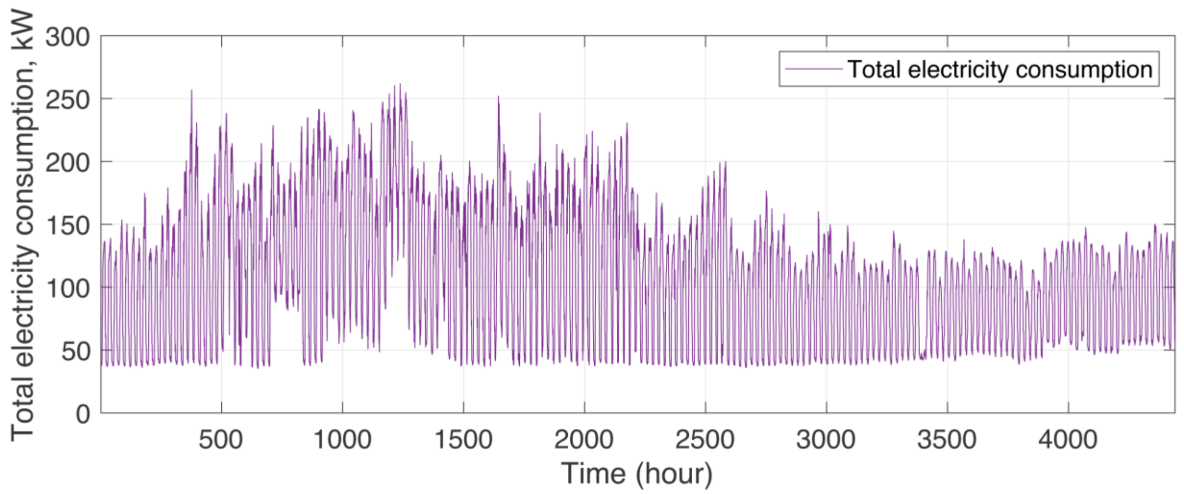

Figure 9 Historical data: Electricity consumption (185 working days, May 1, 2013, to Feb 28, 2014)

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

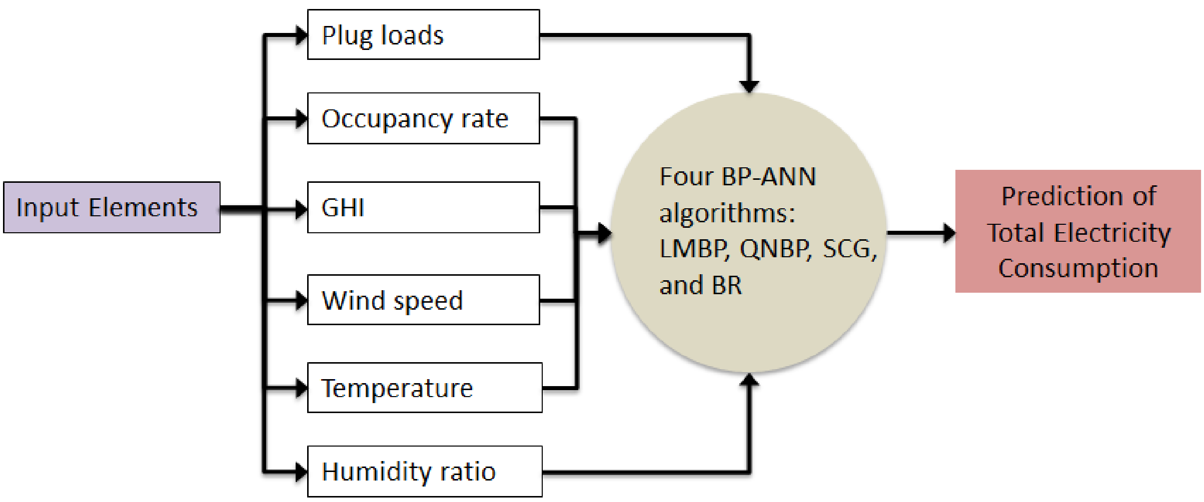

Figure 10 Model for predicting electricity consumption with various input parameters

2.3. Comparison Methodology

In order to evaluate the correlation performance among the input elements, this study used an impact factor value (IV), where the differences in the values indicate the magnitude of impact, and positive and negative values show the directivity of the effect (Y. H. Liu, 2015). According to some studies, the effect of adjusting each node element calculates the impact factor values with statistical approaches after the ANNs training process (Ye & Kim, 2018).

The process to calculate the IV is as follows: After the training process of the ANNs is completed, each testing parameter value is added or subtracted by 10% of its original value to create new testing samples. The value with 10% addition or subtraction is performed as an impact of each added or subtracted element because the analyzing impact value represents a linear relationship between the changed results. Subsequently, the adjusted testing nodes generate the results that are compared to an actual result value using the original testing node as a prediction.

Finally, the magnitude difference between the predicted values determines the IV value and the results could evaluate the performance of the impact each parameter has on the total electricity consumption in a building (K. M. Kim et al., 2019).

$$Impact\ factor\ value\ (IV) = \frac{\frac{y_{test\ results\ with\ adding\ or\ subtracting\ 10\%\ of\ sample} - y_{test\ results}}{y_{test\ result}}}{0.1} \qquad (11)$$

To validate the accuracy and error rate of the four BP-NN algorithms, this study used the coefficient of variation of the root mean square error (CVRMSE), and the normalized mean bias error (NMBE). The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Guideline 14-2002 indicates the equations for these two values as follows (ASHRAE, 2002):

$$CVRMSE\ (\%) = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2\right]^{1/2}}{\bar{y}} \times 100 \qquad (12)$$

$$NMBE\ (\%) = \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i)}{N \times \bar{y}} \times 100 \qquad (13)$$

3. Results

This study illustrated approaches to evaluates correlation how significantly plug load data, occupancy rates, and local weather factors affect the actual electricity consumption of a commercial building in seasonal changes. This study used four BP-NN methods—LMBP, QNBP, SCG, and BR algorithm—to predict the electricity consumption profiles for an office building located in Philadelphia, USA. The models were trained on a dataset of a total of 185 working days or 4440 hours of the building's plug load (kW), occupancy rates, and weather parameters: Global Horizontal Irradiation (W/m^2), wind speed (m/s), temperature (°C), and humidity ratio (g/kg). This study presents the accuracy and error rate of the four BP-NN models and evaluates how significantly the plug load data, occupancy rates, and weather factors impact the total amount of electricity consumed in the building. Moreover, using ANN methods, we can forecast long-term electricity demand depending on the variation of plug load data, occupancy rate, and weather conditions. Training data of 165 working days (3960 hours) and test data of 20 working days (480 hours) were simulated to predict the total electricity consumption using the four models to validate each algorithm against the actual measured values. The performances of the models were evaluated on accuracy and error rates for various scenarios; the results are shown in Figures 12 and 13.

Generally, all four BP-NN models performed well at predicting the electricity consumption of the office building for the working days. Of the four, the LMBP model represented better performance with a higher accuracy of 1.07 to 2.23% and lower error rates, and the QNBP indicated relatively higher error rates and lower accuracy with overfittings. However, there were no significant differences among the four models in predicting electricity consumption. The details are illustrated in Figures 11 and 12.

The ANN models exhibited significantly higher error rates for the non-working hours (7 pm to 8 am) than for the working hours (9 am to 6 pm). We estimated that the input parameters, i.e. plug load data, occupancy rate, and weather conditions could not significantly impact the electricity consumption during the non-working hours in the building. Accordingly, other elements could influence the results, such as building maintenance plans, facility management schedules, and other devices operating in non-working hours. Further study is required to find the elements that strongly affect electricity consumption during the non-working hours.

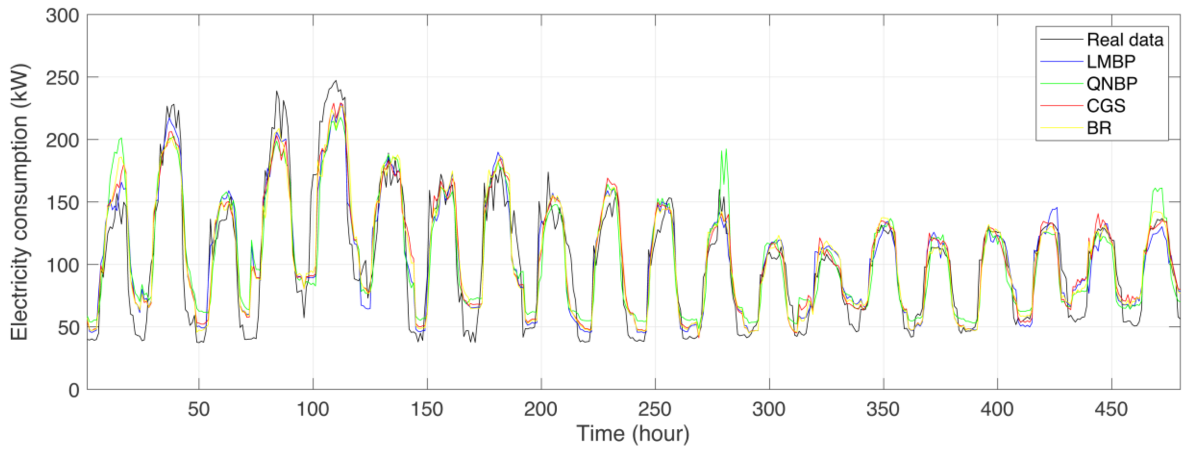

Figure 11 Prediction of electricity consumption of the four models compared with real values measured for working days

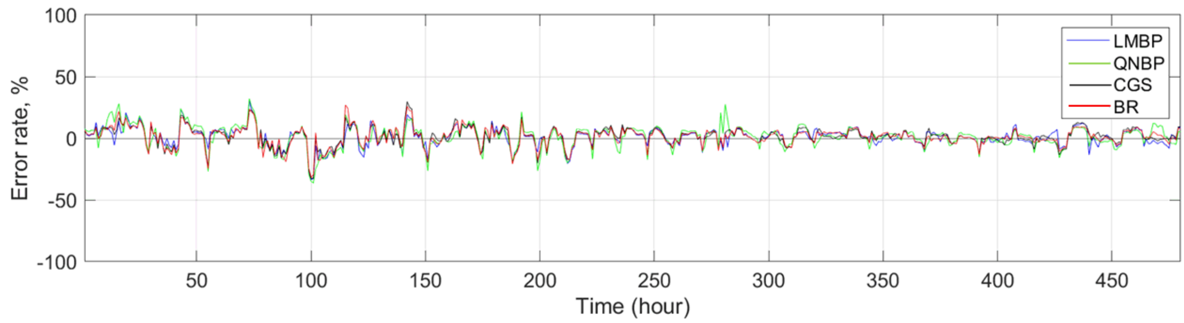

Figure 12 Error rates of the four prediction models for working days

Table 1 Comparison of Performance of the ANNs

Back-propagation ANNs	Coefficient of variation of the root mean square error (CVRMSE), %	Normalized mean bias error (NMBE), %
LMBP	18.09	2.90
QNBP	21.78	3.13
SCG	18.57	3.55
BR	18.80	3.45

Table 1 shows the CVRMSE and NMBE results of the four ANN models. The CVRMSE and NMBE values for the LMBP method (18.09 and 2.90) were lower than of the average values of other ANN methods (19.71 and 3.37). Thus, the LMBP model is a good choice in predicting electricity consumption in a building. However, the differences in the CVRMSE and NMBE among the ANN models' performance were small at 0.48–3.69 and 0.23–0.65, respectively. Thus, the other three methods could equally maintain good stability when forecasting the electricity consumption of the building on the working days. However, compared with other models, the LMBP model requires more memory and increase training times as well (Ballabio & Vasighi, 2012; Hagan, Demuth, Beale, & Jesús).

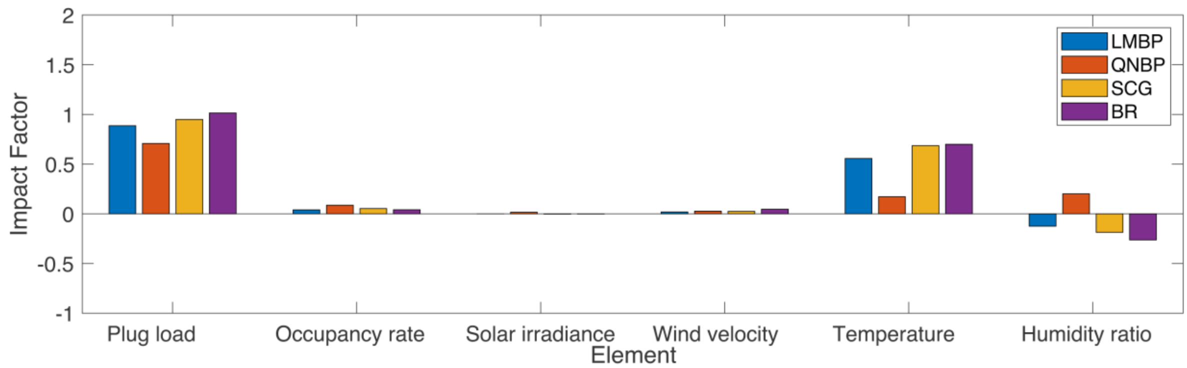

Figure 13 Average impact factors of input parameters in swing season (spring and autumn) of the four ANN models

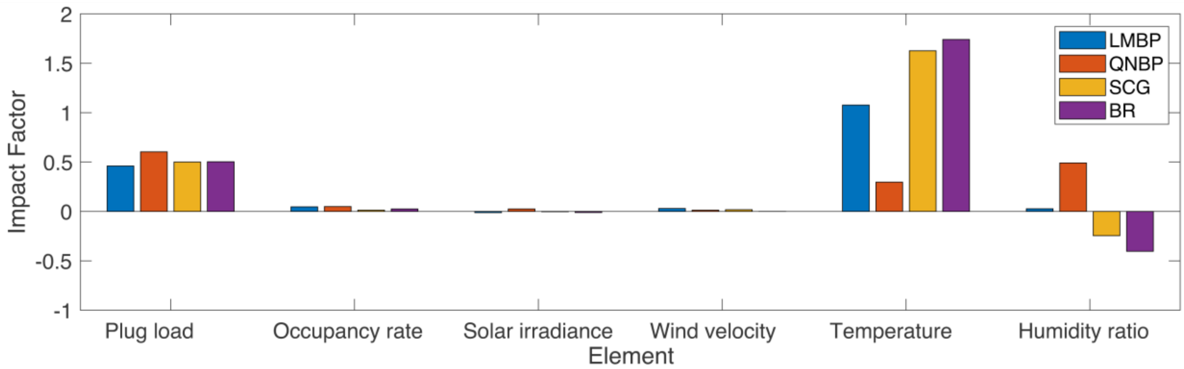

Figure 14 Average impact factors of input parameters in the cooling season (summer) of the four ANN models

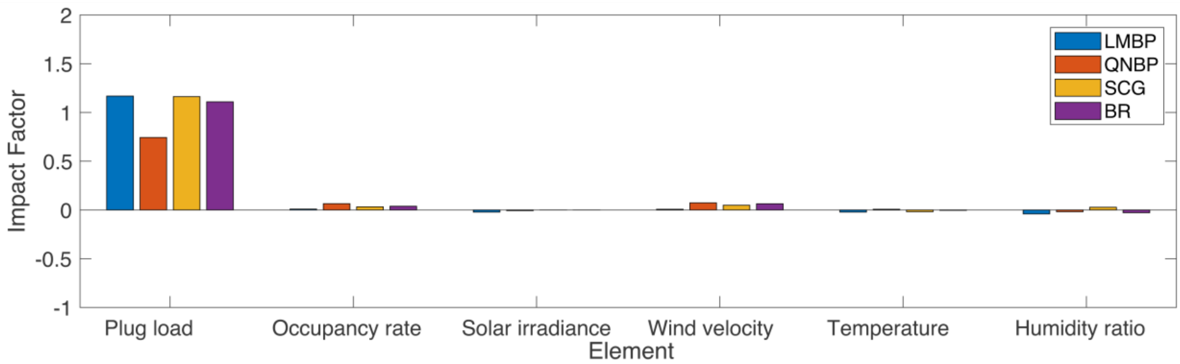

Figure 15 Average impact factors of input parameters in the heating season (winter) of the four ANN models

Figures 13, 14 and 15 represent correlation and the impact each average input factor had on electricity consumption in the building for the four ANN prediction methods, respectively, under seasonal characteristics: the swing (spring and autumn), cooling (summer), and heating (winter) seasons. Plug loads dominated the electricity consumption in all ANN methods in all seasons, and the two other main elements—temperature and humidity ratio—had significant impact on the actual electricity consumption. The other three parameters—occupancy ratio, solar irradiance, and wind speed—had slight influences on the actual electricity consumption. In the swing season (spring and autumn), both plug loads and temperature had the highest impact on the building's electricity consumption. In the cooling season (summer), temperature rise strongly influenced the total electricity consumption compared with other seasons. However, in the heating season (winter), temperature variation did not impact on electricity consumption; plug loads significantly affected the results. This study estimates that heating systems using gas boilers did not impact electricity consumption in the heating season (winter); however, the cooling systems, air handling units and condensing units for cooling and dehumidification in the building, were largely responsible for the actual electricity consumption. Occupancy rate also positively impacted the electricity consumption throughout the year, but not as much as plug loads had. Studies have described that plug loads strongly engage occupancy patterns (Anand, Cheong, Sekhar, Santamouris, & Kondepudi, 2019; Gandhi & Brager, 2016; Jenkins et al., 2019). We estimate that plug load data reflected the occupancy rate and electricity consumption in the building, thus, the actual impact of occupancy rate is lower than that of plug loads. Without the plug load input to predict the total electricity consumption in a building, we estimate that the impact of the occupancy rate could have strongly influenced the results. An interesting finding is that solar irradiance variation did not significantly impact electricity consumption throughout the year, but electricity had a high sensitivity to temperature. Additionally, wind velocity had a lower impact value than other parameters.

Additionally, the directivity of the impact factor value of humidity ratio using the ANN models is not clearly shown because the input data did not indicate weather characteristics. Temperature directly engages cooling loads, and the humidity ratio can impact cooling loads, but the humidity impact should engage temperature as well. For example, a high humidity ratio on a sunny day in the summer increases cooling loads; however, a high humidity ratio on a rainy day does not increase cooling loads. Therefore, in Figures 13 and 14, the directivity of the average impact factor of humidity ratio is not stable in the ANN models. On this basis, further studies could consider another input element that considers both sensible and latent loads such as the dew point temperature or enthalpy value to determine the correlation and directivity clearly.

The results indicated that the four BP-NN models can predict electricity consumption in a building with good accuracy and low error rates. The BP-NN model using the LM-BP algorithm had better potential for predicting electrical energy consumption in the office building compared with other three models. However, the differences in accuracy among the four ANN models are small; thus, the four ANN models could be used for forecasting electricity consumption. Through impact factor analysis, plug load data were found to highly impact the electricity consumption in the building, and temperature was also significant in the swing and summer seasons. However, temperature did not significantly influence the consumption in the winter because the gas boiler heating systems used had little impact on actual electricity consumption in the building. Thus, in winter, plug load data mainly dominated electricity consumption. Occupancy rate steadily affected the electricity consumption but not as much as plug load data did.

In this study, we found several limitations remaining to be explored via further research. An office building was selected to measure occupancy rates, plug loads, and electricity consumption for working days. However, the accuracy and error rates of predicting electricity consumption on non-working days may differ because weather conditions and HVAC loads do not influence electricity consumption for non-working days in a building. In future study, we could consider another ANN algorithm developed recently such as Long Short –Term Memory (LSTM) neural network model to compare the prediction accuracy and validations.

4. Conclusion

This study proposed a novel analysis strategy how plug-load data, occupancy rate, and climate factor are correlated with building energy consumption in seasonal changes. And how correlation of each element significantly impacts on energy consumption in an office building depending on the seasonal changes. This study represented predictive control strategies using four BP-NN models to predict electricity consumption in an office building in Philadelphia, USA. The algorithms—LMBP, QNBP, SCG, and BR—were designed with input nodes from plug load data, occupancy rates, and local weather conditions (i.e., solar irradiance, wind speed, temperature, and humidity ratio). This study evaluated the performance of each ANN model using a training dataset and test set. The simulation results were compared with actual measured electricity consumption values taken over 185 working days (or 4400 hours) for the building. The results illustrated that the ANN model using the LMBP algorithm was more accurate and stable than the other three methods in predicting the electricity consumption of the working days. However, the other three methods had good agreement with the actual experimental data because the accuracy differences were small at 0.48–3.69 for the CVRMSE and 0.23–0.65 for the NMBE. By analyzing the impact factor of the input factors, we found that the plug loads significantly dominated the actual electricity consumption in the building while temperature and humidity considerably affected the results, and other factors, such as occupancy rates, solar irradiance, and wind speed, had the least impact. Temperature strongly dominated the results in the cooling season (summer) but did not impact in the heating season (winter) because of air handling and condenser units were used for cooling in the summer, but gas boiler systems were used for heating in the winter. Thus, the impact factors of plug loads and temperature varied with the seasons. Occupancy rate positively impacted the electricity consumption in the entire year, but not as much as plug loads did. We estimate that the plug load data reflected the occupancy rate and electricity consumption in the building, thus, the actual impact of occupancy rate was lower than that of plug loads. These methods are quite helpful in predicting the impact each element has on building energy consumption. Thus, these approaches could be useful in understanding the building performance regarding a long-term prediction of energy consumption. For instance, building system types and performances could be evaluated on their impact on energy consumption in seasonal variations and climate change. The four tested ANN methods are reliable in predicting long-term energy consumption in buildings. In future works, these proposed BP-NN models should be developed with additional input elements and novel ANN models such as Long Short-Term Memory (LSTM) widely used recently could be proposed to improve the accuracy of the predictions.

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