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Research article

Energy consumption prediction in an office building by examining occupancy rates and weather parameters using the moving average method and artificial neural network

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ABSTRACT

Occupancy rate refers to the level of usage and presence of individuals within a building or a specific space. This factor can have a significant impact on building energy consumption. When the occupancy rate in a building is high, naturally, energy consumption also increases. This correlation might be due to the increased use of lighting, heating, and cooling, higher numbers of electrical and electronic devices, and similar factors associated with the presence of people in the building. One of the modern methods in the energy field involves empirically utilizing occupancy monitoring tools in buildings and analyzing the relationship between such utilization and building energy consumption through artificial neural network tools. In this research, a camera sensitive to entry and exit was installed at the entrance of an office building in Tehran, Iran. By doing so, the rate of entry and exit was accurately monitored. In the next stage, by investigating the impact of this entry and exit rate on the building's energy consumption, the energy consumption amount was predicted using an artificial neural network and a statistical method (moving average). The results indicate errors of 9.8 and 4.5 for the respective methods, highlighting that the artificial neural network yields the most accurate outcomes. Moreover, the study's findings suggest a direct correlation: as occupancy rates increase, the predicted energy consumption values also rise.

1. Introduction

Studying the effect of weather parameters and occupancy rates on energy consumption in buildings is very important. Therefore, looking at the impact of these parameters on energy calculations in buildings, such as predicting energy consumption, can play an essential role in identifying issues and problems in this area [1]. Understanding these parameters can be very important in optimizing the thermal performance of buildings [2]. The occupancy rate has a significant effect on building energy consumption. The higher the

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occupancy rate, the higher the energy consumption will be. This is because more people in a building means more lighting, more use of electronics and appliances, and more heating or cooling needs. On the other hand, a lower occupancy rate can lead to energy waste, as heating or cooling systems may still be running even when fewer people are in the building. Therefore, it is essential to consider occupancy rates when designing and operating structures to optimize energy efficiency [3]. Weather parameters and occupancy rates both have significant effects on building energy consumption. Higher occupancy rates lead to higher energy consumption due to increased lighting, electronics, and heating or cooling needs. In addition, weather parameters such as temperature, humidity, wind speed, and solar radiation can also affect energy consumption. For example, heating systems need to work harder in colder climates to maintain comfortable indoor temperatures. In comparison, air conditioning systems need to work harder in warmer climates to keep indoor temperatures cool. Humidity levels can affect the efficiency of cooling systems, and wind speed can affect the rate of heat loss or gain through windows and doors. Solar radiation can also affect energy consumption, increasing the need for cooling in sunny areas or reducing the need for heating in areas with more direct sunlight. Therefore, it is essential to consider weather parameters and occupancy rates when designing and operating buildings to optimize energy efficiency. This can be achieved using intelligent building systems that adjust heating and cooling systems based on occupancy rates, weather forecasts, and real-time data [4]. The effect of occupancy rate and weather parameters on building energy consumption can be calculated using various methods, including energy modeling software, building energy audits, and data analysis [5]. Energy modeling software can be used to simulate the energy performance of a building under different occupancy rates and weather conditions. The software considers various factors such as building orientation, insulation, HVAC systems, lighting, and appliances to estimate the energy consumption of the building. Building energy audits involve a detailed analysis of a building's energy usage and performance. This includes collecting data on occupancy rates, weather conditions, and energy consumption [6]. The data is then analyzed to identify areas where energy efficiency improvements can be made. Data analysis involves collecting and analyzing data on occupancy rates, weather conditions, and energy consumption. This data can be used to identify trends and patterns in energy consumption and develop strategies for optimizing energy efficiency. Overall, the effect of occupancy rate and weather parameters on building energy consumption can be calculated using various methods, depending on the level of detail and accuracy required [7].

The study of climate parameters and occupancy rates concerning building energy consumption has been an active area of research for several decades. The research has focused on understanding the impact of climate parameters and occupancy rates on energy consumption and developing methods and strategies to optimize energy efficiency. Here is a brief background history of research on the study of climate parameters and occupancy rates:

1970s–1980s: The early research on the impact of climate parameters and occupancy rates on building energy consumption was focused on developing mathematical models to predict energy consumption. These models considered factors such as building orientation, insulation, HVAC systems, lighting, and appliances to estimate the energy consumption of the building [8].

The 1990s–2000s: In the 1990s and 2000s, research focused on developing more sophisticated models that considered the impact of climate parameters and occupancy rates on energy consumption. Researchers also started to investigate the effects of occupancy patterns on energy consumption and the potential for occupancy-based control strategies to improve energy efficiency [9].

2010s-present: In recent years, research has focused on developing advanced simulation software and data analysis tools to understand better the impact of climate parameters and occupancy rates on energy consumption. Researchers have also investigated the effect of weather-based control strategies, such as weather forecasts, to adjust heating and cooling systems [10].

Overall, research on climate parameters and occupancy rates has evolved from the early development of mathematical models to the current use of advanced simulation software and data analysis tools. The research has consistently shown that both climate parameters and occupancy rates significantly impact energy consumption and that energy efficiency can be improved through occupancy- and weather-based control strategies [10].

In their 2023 study, Divyanshu Sood et al. investigated the impact of occupancy on energy consumption in multi-scale residential building archetypes using simulation-based evaluation. The study aimed to evaluate the effectiveness of occupancy-based control strategies in improving energy efficiency in residential buildings. The study used a simulation model to estimate the energy consumption of different residential buildings at different occupancy rates. The model considered factors such as building orientation, insulation, HVAC systems, lighting, and appliances to estimate the energy consumption of the building. The study's results showed that occupancy rates significantly impacted energy consumption, with higher occupancy rates leading to higher energy consumption. The study also found that occupancy-based control strategies could improve energy efficiency by adjusting the heating, cooling, and lighting systems based on occupancy rates. The study also evaluated the impact of different occupancy patterns on energy consumption, such as weekdays versus weekends. The results showed that occupancy patterns significantly impacted energy consumption and that occupancy-based control strategies could be tailored to specific occupancy patterns to improve energy efficiency. Overall, the study highlights the importance of considering occupancy rates and patterns when designing and operating residential buildings to optimize energy efficiency. The study also demonstrates the usefulness of simulation-based evaluation in evaluating the impact of occupancy rates and patterns on energy consumption and developing occupancy-based control strategies to improve energy efficiency [11]. In 2023, Zixu Yang et al. compared the energy performance of novel dual-temperature cooling systems using field testing and simulations. The study aimed to evaluate the effectiveness of these systems in improving energy efficiency in buildings. The study evaluated two different dual-temperature cooling systems, one using a heat pump system and the other using a direct expansion (DX) system. The systems were tested in a real-world building and evaluated using simulation software. The study results showed that both systems improved energy efficiency more effectively than traditional cooling systems. The heat pump system was found to be more effective in reducing energy consumption, with a 25% reduction compared to the DX system. However, the DX system was more cost-effective, with a lower initial cost and a simpler installation process. The study also evaluated the impact of occupancy rates on energy consumption and found that higher occupancy rates led to higher energy consumption. The study suggests that occupancy-based control strategies could be used with dual-temperature cooling systems to improve energy efficiency further. Overall, the study highlights the potential of dual-temperature cooling systems to improve building energy efficiency. The study also demonstrates the usefulness of both field testing and simulation software in evaluating the energy performance of these systems and developing strategies to optimize their effectiveness [12]. In their 2023 study, Ali Maboudi Reveshti et al. investigated the effect of new and old weather data on the energy consumption of buildings affected by global warming in different climates. The study aimed to evaluate the impact of climate change on building energy consumption and the importance of using up-to-date weather data in building energy simulations. The study used a simulation model to estimate the energy consumption of different types of buildings under different weather conditions. The model considered factors such as building orientation, insulation, HVAC systems, lighting, and appliances to estimate the energy consumption of the building. The study results showed that using old weather data in building energy simulations can lead to significant errors in estimating energy consumption, particularly in regions affected by global warming. The study also found that using up-to-date weather data can improve the accuracy of building energy simulations and lead to more effective energy efficiency strategies. The study also evaluated the impact of different climate zones on energy consumption and found that buildings in hot and humid climates were particularly affected by global warming and required more effective energy efficiency strategies. Overall, the study highlights the importance of using up-to-date weather data in building energy simulations and developing effective energy efficiency strategies to address the impact of global warming on building energy consumption. The study also demonstrates the usefulness of simulation models in evaluating the impact of climate change on building energy consumption and developing strategies to optimize energy efficiency [13]. In their 2021 study, Sicheng Zhan and Adrian Chong conducted case studies across different building types to investigate the relationship between building occupancy and energy consumption. The study aimed to evaluate the impact of occupancy rates on energy consumption and identify potential strategies to improve energy efficiency in buildings. The study analyzed data from three building types: hotel, office, and residential. The data included occupancy rates, HVAC system performance, lighting, and appliance energy consumption. The results of the study showed that occupancy rates had a significant impact on energy consumption in all three building types. Higher occupancy rates increased energy consumption, particularly in hotels and office buildings. The study also found that occupancy-based control strategies, such as adjusting the heating and cooling systems based on occupancy rates, could improve energy efficiency in all three building types. The study also identified the importance of considering the type of building and its specific energy consumption patterns when developing occupancy-based control strategies. For example, the hotel required more frequent adjustments to heating and cooling systems due to the high turnover of guests. In contrast, the residential building required more attention to lighting and appliance energy consumption. Overall, the study highlights the importance of considering occupancy rates and developing occupancy-based control strategies to improve energy efficiency in different types of buildings. The study also demonstrates the usefulness of analyzing building data to identify areas for energy efficiency improvements [14]. In 2021, Yuan Jin et al. developed a machine learning-integrated approach to forecast building occupancy. The study aimed to improve the accuracy of occupancy forecasts, which can help building managers optimize energy consumption and efficiency. The study used a temporal-sequential analysis approach, which considers the temporal patterns of occupancy data, to preprocess the data before applying machine learning algorithms. The study evaluated three different machine learning algorithms: random forest, neural network, and support vector machine, to forecast occupancy rates. The study results showed that the machine learning-integrated approach significantly improved the accuracy of occupancy forecasts compared to traditional methods. The study found that the random forest algorithm performed the best in forecasting occupancy rates, with an average accuracy of 92.5%. The study also demonstrated the approach's usefulness in optimizing energy consumption and improving energy efficiency. By accurately forecasting occupancy rates, building managers can adjust heating, cooling, and lighting systems based on occupancy rates to reduce energy consumption during periods of low occupancy. Overall, the study highlights the potential of using a machine learning-integrated approach to forecast building occupancy and improve energy efficiency. The study also demonstrates the usefulness of considering temporal patterns in occupancy data when developing occupancy forecasting models [15].

A study conducted by Varun Kumar et al. delves into thermal distribution modeling with ANNs. Specifically, their research focuses on predicting the transient thermal distribution of a stretching or shrinking longitudinal fin. By employing ANNs, they offer an innovative approach to tackling the intricate heat transfer dynamics within the fin, enhancing our understanding of heat distribution in such systems [16]. One notable contribution in this context is the work by J. Suresh Goud et al. which focused on heat transfer analysis within a longitudinal porous trapezoidal fin utilizing a non-Fourier heat conduction model. The authors introduce an innovative application of ANNs combined with the Levenberg-Marquardt approach to enhance the understanding of heat transfer dynamics in such geometries. By leveraging ANNs, they advance our grasp of heat conduction mechanisms in complex configurations [17]. A significant contribution to this landscape is the research by Kumar et al. that delves into convective heat transfer analysis within a wavy fin. The authors introduce a stochastic Levenberg-Marquardt neural network implementation, offering a novel approach to understanding convective heat transfer dynamics. Employing ANNs with stochastic variations enhances our comprehension of heat transfer phenomena in complex geometries [18]. A notable contribution in this context is the work by G. Sowmya and R. S. Varun Kumar that assesses transient thermal distribution in a moving porous plate with temperature-dependent internal heat generation. Employing the Levenberg-Marquardt backpropagation neural network, the authors introduce an innovative approach to understanding such systems' complex heat distribution dynamics. By leveraging ANNs, they advance our understanding of transient heat transfer in moving porous plates with intricate internal heat generation mechanisms [19]. A notable contribution in this arena is the work by Varun Kumar et al. that employs backpropagated neural network modeling for the non-Fourier thermal analysis of a moving plate. By harnessing ANNs, the authors introduce a novel approach to understanding the intricate dynamics of thermal conduction in moving containers, mainly focusing on non-Fourier heat transfer phenomena. Their work advances our understanding of transient heat distribution in systems with moving components [20]. A significant advancement in this field is the research conducted by K. Nagaraja et al. (2022), which provides an insightful overview of applications utilizing Artificial Neural Networks (ANNs) to assess the ramifications of the COVID-19 pandemic. The authors highlight the remarkable versatility of ANNs in deciphering the intricate dynamics of the pandemic. This research yields valuable insights into areas such as disease transmission patterns, the allocation of healthcare resources, and the formulation of effective policy strategies. The study effectively underscores how ANNs can potentially guide critical decision-making processes in the face of unprecedented events [21].

This study aims to predict energy consumption using statistical and artificial neural network methods. The impact of occupancy rates and weather conditions on building energy consumption is also investigated using the mentioned methods (statistical and neural networks). Then, the effect of weather conditions and occupancy rates on energy consumption is compared by comparing these methods. This study clarifies how local occupancy rates and environmental conditions affect building energy consumption. Using this study, it is possible to improve processes for predicting building energy consumption and improve energy management quality in buildings. Additionally, based on the study's results, optimization of heating and cooling systems and energy management methods can be recommended to building managers. Ultimately, this study can help improve the quality of life and reduce energy consumption and greenhouse gas emissions worldwide.

2. Methods

Energy consumption data from a smart building in Tehran City (Iran's capital) (Fig. 1) was collected for this study. For energy consumption prediction, statistical methods such as factor analysis, linear regression, and time series modeling were used. In addition, an artificial neural network was used to predict energy consumption. Dispersion metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to assess the accuracy of various methods. Furthermore, data on occupancy rates and weather conditions was gathered to investigate their impact on energy consumption. Based on these variables, statistical and neural network methods were used to forecast energy consumption. Data from training and testing periods was used to assess the accuracy of various methods. The training period in this study included 60% of the data, while the testing period included 40% of the data. Finally, the best method for predicting energy consumption was determined by comparing the accuracy of various methods. The effect of occupancy rates and weather conditions on building energy consumption was also studied.

2.1. Energy prediction models in buildings

2.1.1. Moving average

A moving average is a calculation method used in statistics to analyze data points by averaging various subsets of the total data. In cases where the data has a time pattern (a time series), a portion of it can be used for averaging rather than the entire data set. Because of its ability to detect changes in data over time, this method is used to analyze time series data (equation (1) and (2)) [22].

In the following formula, k total number of data, $P_{n-k+1} to P_n$ is introduced as each of the data [13].

$$\mathrm{SAM} = \frac{P_{n-k+1} + P_{n-k+2} + \ldots + P_n}{k} \tag{1}$$

$$\mathrm{SAM} = \frac{1}{k} + \sum_{i=n-k+1}^{n} (P_i) \tag{2}$$

2.1.2. Artificial neural network

Intelligent systems, particularly artificial neural networks, are now so widely used that they can be classified as basic mathematical operations and general-purpose tools [23]. Under the umbrella term of artificial neural networks, various types of computational models have been introduced, each of which can be used for a specific set of applications. Each of these applications has been inspired by a different aspect of the human brain's capabilities and characteristics [24].

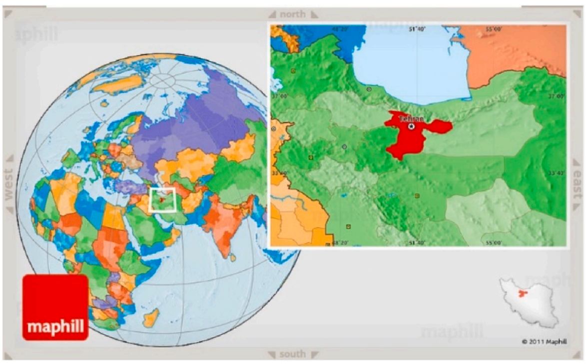

Fig. 1. Map of tehran, Iran [16].

2.1.3. Multilayer perceptron neural network

One of the most basic neural models (Fig. 2) available is the multi-layer perceptron model, which simulates the transfer function of the human brain.

The following relationships (equations (3)–(7)) are used to analyze input and output data:

The output value of the hidden layer is as follows [21].

$$o_j = \mathrm{f} + \sum_{i=1}^{n} \left(w_{ij}\, x_i - d_j\right) \ \mathrm{j} = 1, 2, \ldots, \mathrm{i} \tag{3}$$

Also, the output value of the output layer is as follows

$$Y_k = \mathrm{f} + \sum_{j=1}^{i} \left(o_j w_{jk}\, x_i - d_k\right) \ \mathrm{k} = 1, 2, \ldots, \mathrm{m} \tag{4}$$

Based on the defined neural network, the mean squared error is calculated for the predicted and actual output vectors. The function is defined as follows

$$E_k = \frac{1}{2}\sum\nolimits_k (F_k - Y_k)^2 \tag{5}$$

To calculate the accuracy of the results, this study used calibration standards. These standards include the mean normal bias error and the mean squared error correlation coefficient [22].

$$CV(RMSE) = \frac{1}{Y}\sqrt{\frac{\sum_{i=1}^{N} (Y_i - \widehat{Y}_i)^2}{N}} \tag{6}$$

$$\mathrm{NMBE} = \frac{\sum_{1}^{n} |M - O|}{\sum_{1}^{n} (O)} \tag{7}$$

2.2. Data and analysis

2.2.1. Weather data

The weather data used was obtained from the Iran Meteorological Center for 2019. These data, which consist of nine parameters, include dry air temperature, wet air temperature, relative humidity, wind speed, wind direction, radiation, etc. After obtaining the relevant data, the TMY2 file required for the considered weather conditions was created, and then the EPW file was extracted to simulate the energy of the building in 2019, and the energy consumption was analyzed by the Energy Plus software.

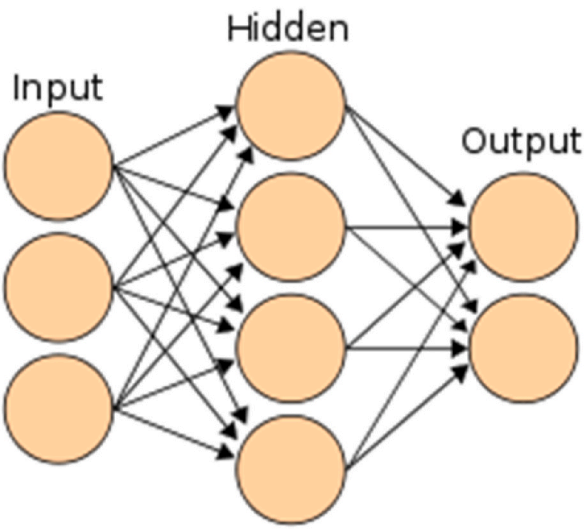

Fig. 2. A view of a multilayer perceptron neural network consisting of (input data, hidden layer, output) [19].

2.2.2. Measure the occupancy rate on selected days

The number of working days in the building was first extracted in order to predict data related to energy consumption in the building. A camera with infrared technology (Dahua-DH-IPC-HDBW4239RN-ASE) was installed in this building to record traffic for this purpose (Figs. 3 and 4). This sensor can detect people entering and exiting the building, and the operator can receive a traffic report from the camera at any time. After obtaining commuting data for working and non-working days, work was separated from each other for this study. From January 1, 2019 to September 22, 2019, 199 working days and 71 non-working days were considered for this building. Figs. 4 and 5 depict the camera's installation position as well as a general view of the building.

Also, Fig. 5 shows the occupancy rate in the target range. Fig. 6 likely shows the "occupation rate" over a specific target period, which in this case is from January 1, 2019, to September 22, 2019.

The x-axis in Fig. 6 represents the time span from January 1, 2019 (or an earlier date) to September 22, 2019. Depending on the granularity of the data, the x-axis may display dates, days, weeks, or months. It is an "hour" in this study. In addition, the y-axis shows the "occupation rate," which can be expressed as a percentage (0%–100%) or in any other relevant unit. The occupancy rate denotes the percentage of time or space occupied during the specified time period. The term used in this study is "person."

Fig. 6 depicts how the occupancy rate changes over time during the target period using data points. Each data point represents a different date or time period, and the graph may show trends, fluctuations, or patterns in the occupancy rate. The input parameters for predicting energy consumption in the building in this model are shown in Figs. 7–9 for the time interval from January 1, 2019 to 9/22/2019. Fig. 7 most likely depicts "Dry air temperature" data collected during working days from January 1, 2019, to September 22, 2019.

The x-axis in Fig. 7 is as follows: It spans the months of January 1, 2019 (or an earlier date) to September 22, 2019. Dates, days of the week (e.g., Monday through Friday), or other relevant time intervals could be displayed on the x-axis. It is called "Hour" in this study. In addition, the y-axis: It denotes the "Dry air temperature," which is typically expressed in degrees Celsius (°C). The temperature values recorded during each working day are shown on the y-axis.

Fig. 7 is made up of data points that show how the dry air temperature changes over the course of a working day. Each data point represents a different date or working day, and the graph may show daily temperature variations or trends.

Fig. 8 most likely represents data for "Relative humidity" measured during working days between January 1, 2019, and September 22, 2019. The time span from January 1, 2019 (or an earlier date) to September 22, 2019 is represented on the x-axis. Depending on the data granularity, the x-axis could display dates or other time intervals. Also on the y-axis is the "Relative humidity," which is usually expressed as a percentage (%). The values on the y-axis represent the relative humidity measured during each working day.

Fig. 9 most likely depicts "Calculation of Energy Consumption" data during working days from January 1, 2019, to September 22, 2019. The time span from January 1, 2019 (or an earlier date) to September 22, 2019 is represented on the x-axis. The x-axis could display dates or other time intervals corresponding to the specified period's working days. In addition, the y-axis represents "Energy consumption," which is typically measured in kilowatt-hours (kWh) or any other relevant energy unit. The values on the y-axis represent the calculated energy consumption for each working day.

Figs. 10 and 11 show the "Flowchart of the Training Process in an Artificial Neural Network." "Energy consumption prediction flowchart model with input parameter values" is another. The process of using input data to train an artificial neural network (ANN) to recognize patterns and make predictions is shown graphically.

Key components of the flowchart.

- Input Data: The flowchart would start with a block representing the input data, which includes the features or attributes used to train the neural network.
- Neural Network Architecture: It might show a block representing the architecture of the neural network, including the number of layers, nodes, and activation functions used.

Fig. 3. Location of the camera in the building.

Fig. 4. A view of the location of the camera that covers the entrance door of the building.

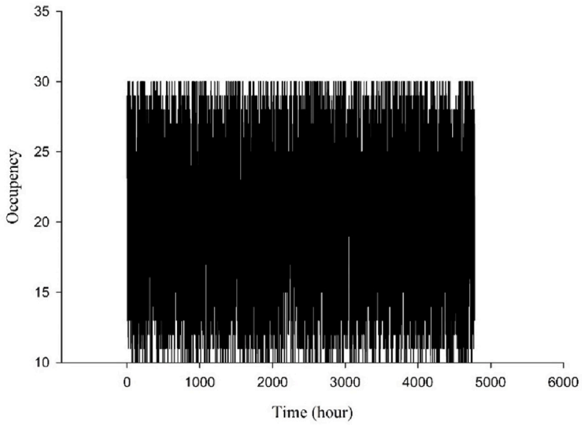

Fig. 5. Occupancy rate in the target period (January 1, 2019 to 9/22/2019).

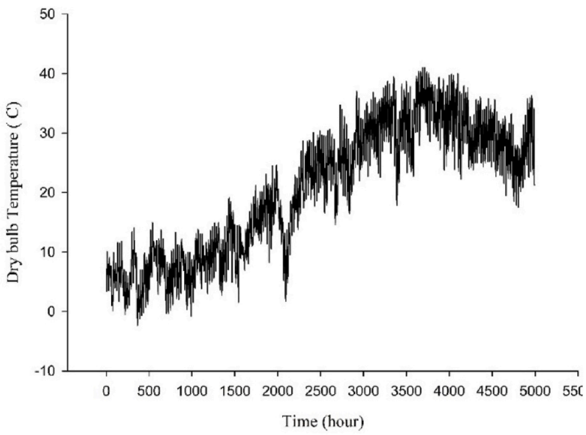

Fig. 6. Dry air temperature during working days (January 1, 2019 to September 22, 2019).

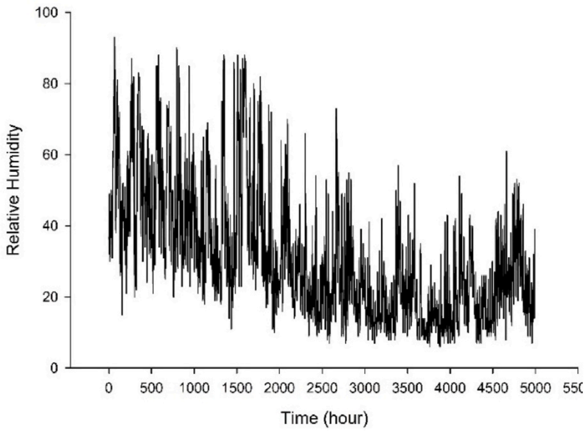

Fig. 7. Relative humidity during working days (January 1, 2019 to 09/22/2019).

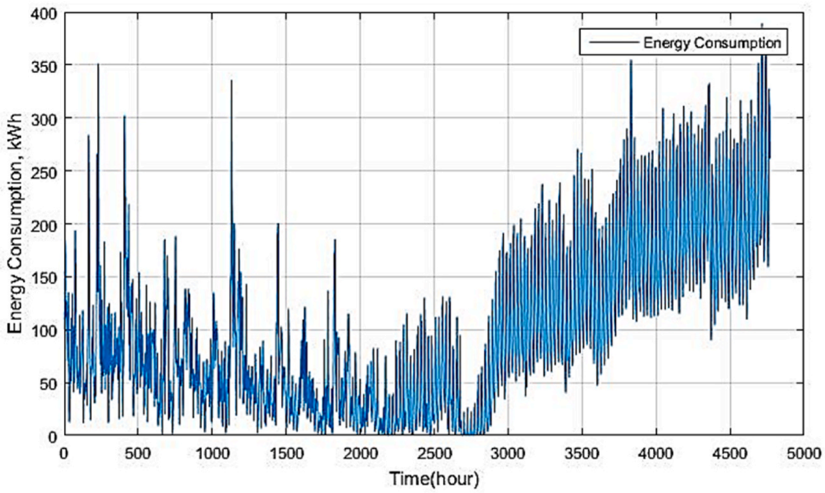

Fig. 8. Calculation of energy consumption during working days (January 1, 2019 to 09/22/2019).

- Weight Initialization: The flowchart may include a step for initializing the weights and biases of the neural network, which is crucial for the learning process.
- Forward Propagation: It would represent the forward propagation step, where the input data is passed through the neural network to generate predictions.
- Loss Function: The flowchart might include a block for the loss function, which measures the discrepancy between the predicted values and the actual values.
- Backpropagation: This step would illustrate how the neural network uses the loss function to adjust its weights and biases backward through the layers to minimize the prediction errors.
- Update Weights: The flowchart may include a step to update the weights and biases based on the gradients calculated during backpropagation.
- Repeat: The flowchart might show a loop or repetition symbol, indicating that the training process iterates through the data multiple times (epochs) to improve the model's performance.

Interpreting Fig. 10 would involve understanding the sequence of operations in the training process and how information flows through the neural network during training. The flowchart can provide insights into the underlying mechanics of the training process, which is essential for building, optimizing, and fine-tuning artificial neural network models effectively.

Here's a list of parameters that are typically used in an Artificial Neural Network (ANN) model.

1 **Input Features:** The hourly weather data.
2. **Hidden Layers:** The number of hidden layers in the network and the number of neurons in each hidden layer are (5 layer and 20 neurons for each layer)

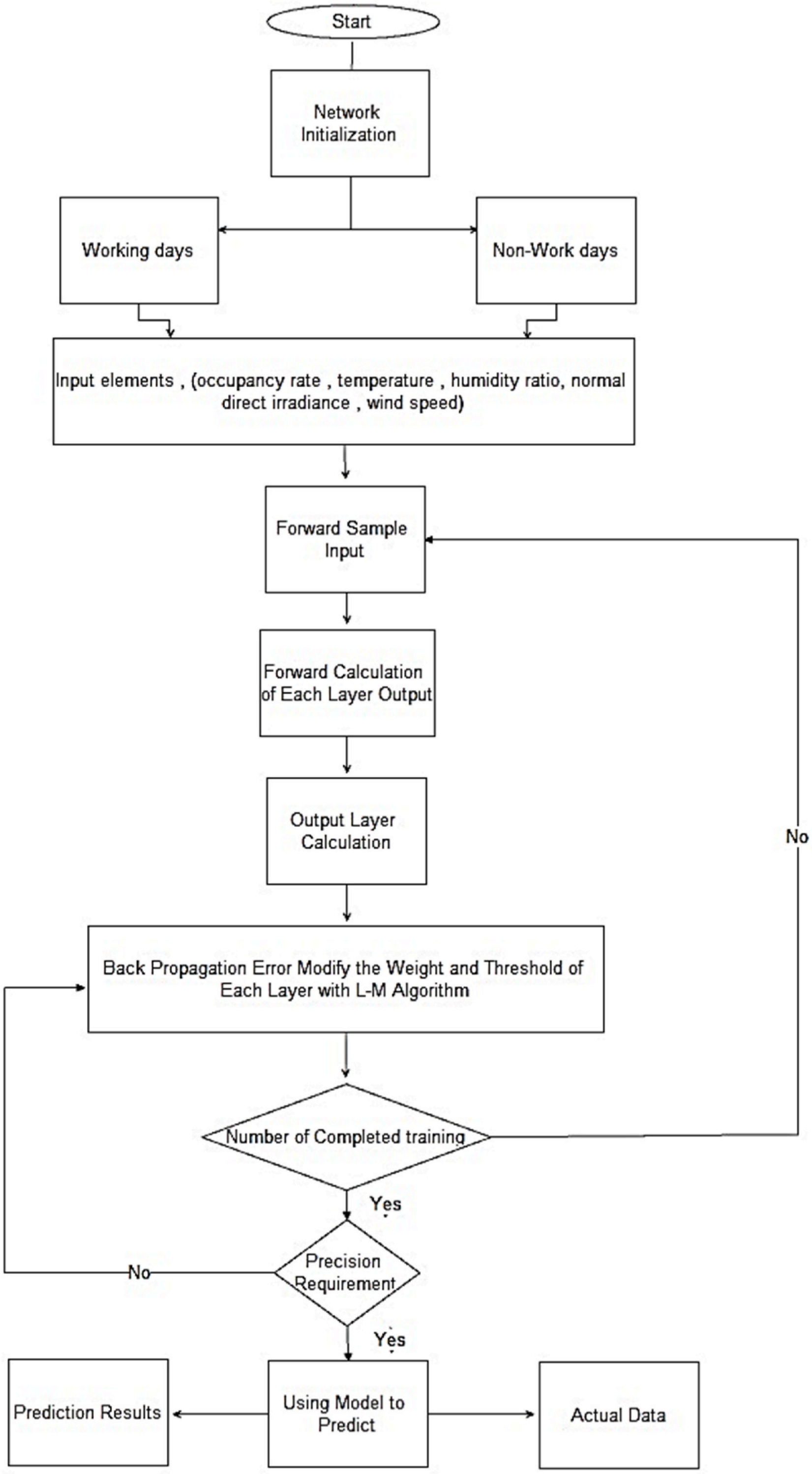

Fig. 9. Flowchart of the training process in an artificial neural network.

3. **Activation Functions:** The activation functions for each layer are sigmoid
4. **Learning Rate:** A hyperparameter that controls the step size at which the model adjusts its weights during training.
5. **Number of Epochs:** The number of times the entire training dataset is passed through the network during training. It is 986 epochs

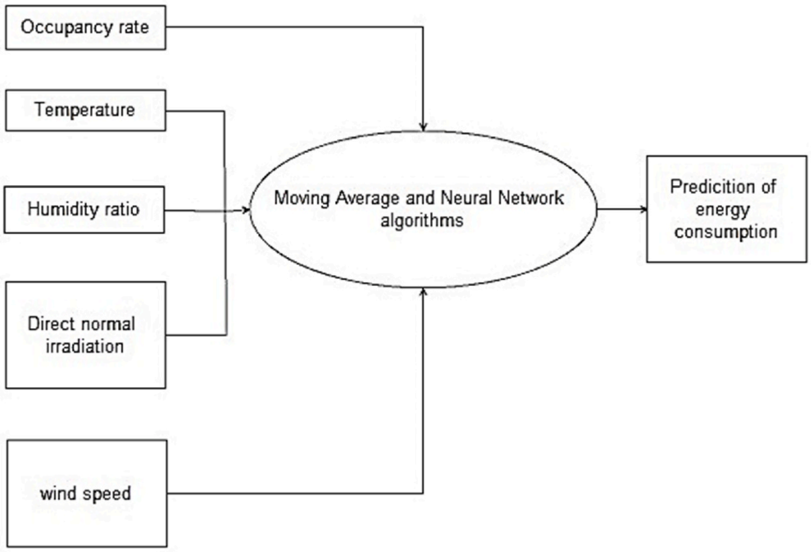

Fig. 10. Energy consumption prediction flowchart model with input parameter values.

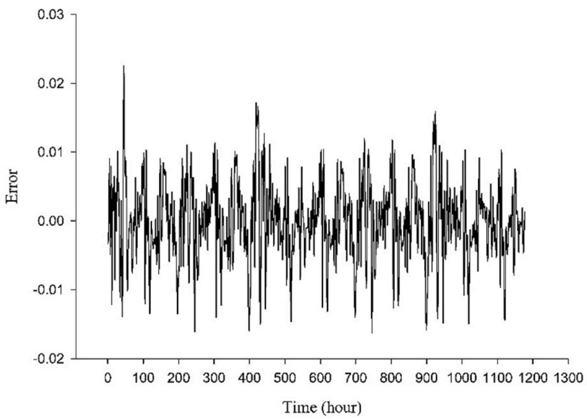

Fig. 11. The error rate of neural network.

6. **Batch Size:** The number of training examples used in each iteration of gradient descent.
7. **Loss Function:** The function used to calculate the difference between predicted and actual values during training, such as Mean Squared Error (MSE) or Cross-Entropy.
8. **Optimization Algorithm:** The algorithm used to update the weights of the network, such as Gradient Descent, Adam, RMSProp, etc.
9. **Regularization:** Techniques like L1 or L2 regularization to prevent overfitting.
10. **Dropout Rate:** The proportion of neurons randomly dropped out during training to prevent overfitting.
11. **Initialization:** Methods for initializing the weights and biases, such as random initialization or Xavier/Glorot initialization.
12. **Metrics:** The evaluation metrics used to assess the model's performance, such as accuracy, precision, recall, F1-score, etc.
13. **Batch Normalization:** Whether or not batch normalization layers are used to improve training stability.
14. **Early Stopping:** Criteria for stopping training early if the model's performance plateaus.
15. **Architecture:** The overall structure of the network, including the number of input and output neurons.
16. **Regularization Strength:** Hyperparameters controlling the strength of regularization techniques, like dropout rate or regularization coefficient.
17. **Validation Split:** The portion of the training data used for validation during training.
18. **Weight Update Rule:** The specific algorithm used to update the weights and biases of the network.
19. **Initializer Parameters:** If using a custom initializer, any additional parameters required for its configuration.
20. **Loss Weights:** Weights assigned to different classes in the loss function for imbalanced datasets.

These parameters collectively define the architecture, behavior, and training process of an ANN model. The choice of these parameters has a significant impact on the model's performance and ability to generalize to new data.

Activation functions play a pivotal role within the framework of Artificial Neural Networks (ANNs), introducing the crucial element of non-linearity to the model. This non-linearity empowers the network to grasp intricate relationships hidden within the data. The selection of the most suitable activation function for prediction hinges on the specific nature of the problem at hand, the architecture of the neural network, and the inherent characteristics of the dataset.

In the context of our research, we opted for the Rectified Linear Unit (ReLU) as the activation function. ReLU is often deemed an excellent starting point due to its computational efficiency and demonstrated success across various scenarios, particularly in the context of deep neural networks. However, it is important to acknowledge its vulnerability to the "dying ReLU" phenomenon, where neurons can become inactive during training, leading to a lack of gradient flow, particularly for extremely negative inputs.

To address this limitation, a variety of enhanced variants have emerged. Leaky ReLU, Parametric ReLU, and Exponential Linear Unit (ELU) are among the notable alternatives that can help mitigate the challenges posed by the "dying ReLU" issue. These adaptations introduce slight modifications to the original ReLU concept, thus offering improved performance and robustness.

In a visual representation, the ReLU activation function can be described as follows:

$$f(x) = \max(0, x)$$

This function returns the input value if it's positive; otherwise, it returns zero. This simple yet effective nature of ReLU makes it a popular choice for many neural network applications.

It's important to note that the choice of activation function should be carefully considered based on the specific characteristics of your data and the desired behavior of the neural network in your particular problem domain.

3. Results

In the present research, a moving average and a neural network with a multi-layer perceptron algorithm (Levenberg-Marquardt) were used to predict energy consumption in a building. In order to predict energy consumption, models were trained using occupancy rate, 4778 h of hourly data from 199 working days, and weather variables like temperature, relative humidity, wind speed, etc. This study demonstrates how the building's energy use is impacted by the occupancy rate. Moving average and artificial neural network statistical methods were used for this purpose, with 199 working days and 71 non-working days considered. The comparison of statistical results and artificial intelligence using two parameters, NMBE and CVRMSE, reveals that the error rate of the artificial Neural Network is very low when compared to the statistical method of moving average, indicating that this method (the neural network) can provide more accurate and better results than the statistical method at our disposal. Furthermore, predicting energy consumption using two methods, a moving average and an artificial neural network, demonstrates that the neural network produces far more reasonable and better results.

Fig. 12 represents the predicted error level using an artificial neural network throughout each of the 8760 h. Fig. 12 likely represents the "Error rate of the neural network" during the training or testing process. It provides insights into the performance and accuracy of the neural network model by showcasing how the error rate changes over time or iterations.

Fig. 13 compares real-world energy consumption to values predicted by statistical methods and an artificial neural network. This chart shows that the predicted and actual energy consumption values differ slightly (also see the validation plot). Analyzing the predicted values can yield the same results as analyzing the actual values. The predicted values in this chart are the same as the values calculated using the artificial neural network method.

The x-axis in Fig. 13 represents the time period in which the energy consumption data was recorded or predicted. Dates, days, months, or any other relevant time intervals could be displayed on the x-axis. In addition, the y-axis: It represents the values of energy consumption, which are typically measured in kilowatt-hours (kWh) or any other appropriate energy unit. As a result, Fig. 13 depicts two sets of data points: a) Data points or a line representing "Actual energy consumption": These are the actual energy consumption values derived from measurements or data gathered during the specified time period. These data points are typically based on meter readings or actual energy usage records. b) The "Predicted energy consumption" data points or line: These represent the energy consumption values predicted by the model or method used for forecasting or estimation. In this case, the model may be based on an artificial neural network or any other predictive technique.

Table 1 compares two methods based on two performance metrics, CVRMSE and NMBE: "Moving Average" and "ANN" (which stands for Artificial Neural Network). These metrics are frequently used to assess the precision and performance of prediction models or forecasting methods.

3.1. *Moving average method*

- CVRMSE: The coefficient of variation of the root mean square error for the "Moving Average" method is 5.08. This value indicates the spread or variability of the prediction errors relative to the mean value of the observed data. A value of 5.08 means that the prediction errors, on average, have a spread of 5.08 times the mean value of the observed data.
- NMBE: The normalized mean bias error for the "Moving Average" method is 17.81. This value represents the average bias or difference between the predicted values and the observed values, normalized by the mean value of the observed data. A positive value of 17.81 indicates that, on average, the predictions are overestimating the actual values by approximately 17.81%.

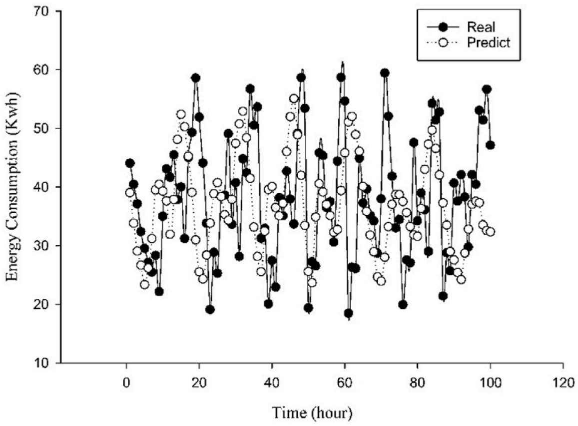

Fig. 12. Comparison of actual and Predict energy consumption ANN-based prediction with each other.

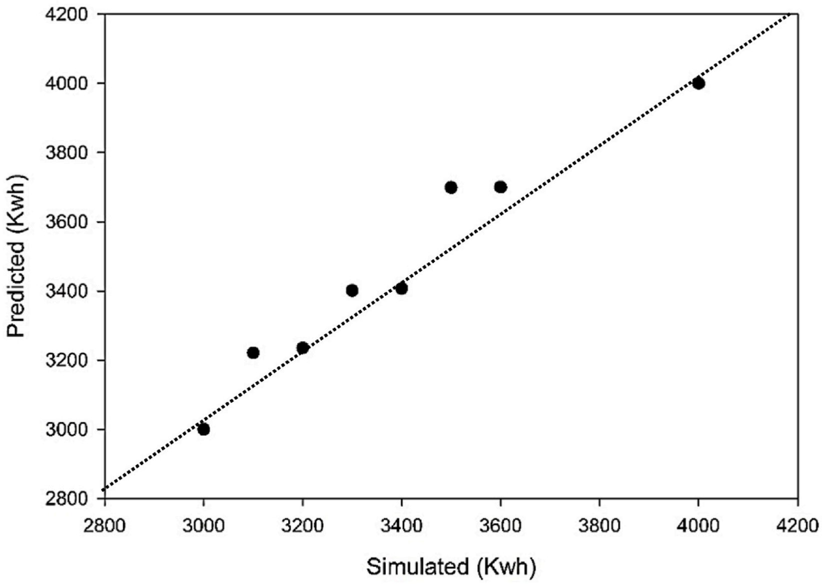

Fig. 13. Validation of the real model with artificial neural network.

Table 1
Comparison of moving average method with neural network.

Method	CVRMSE	NMBE
Moving Average	5.08	17.81
ANN	4.5	9.8

3.2. ANN (artificial neural network) method

- CVRMSE: The coefficient of variation of the root mean square error for the "ANN" method is 4.5. A lower value of CVRMSE (4.5) compared to the "Moving Average" method (5.08) suggests that the "ANN" method has less variability in its prediction errors, indicating higher accuracy.
- NMBE: The normalized mean bias error for the "ANN" method is 9.8. A value of 9.8 means that, on average, the predictions from the "ANN" method are underestimating the actual values by approximately 9.8%.

In summary, the table shows that the "ANN" method outperforms the "Moving Average" method in terms of predictive accuracy, as evidenced by its lower CVRMSE and NMBE values. However, it is important to interpret these results in the context of the specific application and data being analyzed.

Fig. 13 shows the validation of calculated energy consumption and predicted energy consumption for several selected days. This validation, which is for calculating the amount of energy consumption in terms of the amount of energy predicted by the neural network, shows that this method (the neural network) is particularly consistent with the parameters simulated in the artificial neural network.

In Fig. 13, there are two lines representing the validation of energy consumption: the x-axis for simulated energy consumption and the y-axis for predicted energy consumption. The validation process involves comparing the actual energy consumption (simulated) with the energy consumption predicted by the neural network method. The horizontal axis represents the daily calculated energy consumption for selected days (simulated). These days could be specific days within a year or any other time period of interest. The y-axis represents the energy consumption values, measured in units such as kilowatt-hours (kWh) or any other relevant energy unit. The x-axis represents the simulated energy consumption values, which are based on actual measurements or known energy consumption data. The y-axis represents the predicted energy consumption values, which are generated by the artificial neural network (ANN) method used for forecasting or predicting energy consumption. The figure shows how well the predicted energy consumption values match the simulated energy consumption values for the selected days. When the x-axis line closely follows the y-axis line, it indicates that the predictions made by the neural network method are consistent and accurate compared to the actual data. If the x-axis line deviates significantly from the y-axis line, it suggests that the predictions made by the neural network method have higher errors or discrepancies when compared to the actual data. In such cases, further refinement of the neural network model or adjustments to the input parameters may be necessary to improve its predictive accuracy. Overall, the figure demonstrates that the neural network method is performing well in terms of predicting energy consumption, as indicated by the close alignment between the predicted and simulated energy consumption values for the selected days. This validation process is essential for assessing the reliability and effectiveness of the neural network model in simulating energy consumption patterns and providing insights into its performance under different scenarios.

Scholars such as Zhang et al. (2019) have shown that ANNs possess a remarkable capacity to capture intricate patterns and nonlinear relationships within complex datasets, rendering them particularly adept for deciphering the multifaceted dynamics of building energy consumption. This aligns seamlessly with the crux of our study, where we sought to uncover the nuanced correlations between occupancy rates and energy usage patterns [25].

The utilization of ANNs in energy-related studies has gained traction, with Li et al. (2020) highlighting their proficiency in forecasting energy consumption in various building types [26]. Similarly, Wang et al. (2018) conducted a study on residential buildings, showcasing the potential of ANNs in estimating heating and cooling loads [27]. These findings collectively endorse the ability of ANNs to predict energy usage trends across diverse building contexts.

In synergy with established statistical methods, ANNs provided a comprehensive analytical framework. While both paradigms yielded robust predictive outcomes, ANNs exhibited a distinct advantage in their predictive accuracy and ability to encapsulate complex interactions. Their capacity to decipher underlying trends, even within intricate energy consumption datasets, further solidified their status as a predictive tool of paramount significance [28].

Moreover, ANNs surpassed the limitations of conventional statistical models. Their inherent adaptability and self-learning capabilities make them well-suited for real-world applications. This adaptability holds particular significance when addressing fluctuating occupancy patterns and evolving energy consumption behaviors [29].

In summary, our study sheds light on the intricate relationship between occupancy rates and building energy consumption, a revelation propelled by ANNs. The integration of ANNs is endorsed by the body of research, showcasing their potential in deciphering complex energy dynamics. Our findings corroborate the pivotal role of ANNs in unraveling the intricacies underlying building energy consumption, in alignment with established scholarly works.

4. Conclusion

The occupancy rate's intricate influence on building energy consumption prompted us to delve into advanced methodologies, and ANNs emerged as a potent tool for analysis. ANNs offered a robust framework to model the complex relationship between occupancy rates and energy consumption. This technology excelled in capturing nonlinear patterns and subtle interactions, making it highly suitable for our investigation. By training on occupancy data and energy consumption, ANNs autonomously learned the underlying patterns, enabling accurate predictions.

In tandem with statistical methods, ANNs provided a comprehensive approach. While both avenues yielded strong predictive values, ANNs stood out due to their exceptional predictive accuracy and simplicity. Their ability to discern underlying trends, even in multifaceted datasets like energy consumption, showcased their proficiency as a predictive tool. Furthermore, the ANN methodology transcended the conventional limitations of statistical models. Its adaptability and self-learning capability enable it to adapt to changing conditions, making it well-suited for dynamic real-world scenarios. This adaptability can be especially valuable when addressing fluctuating occupancy patterns and evolving energy consumption behaviors.

In conclusion, ANNs illuminated the intricate interplay between occupancy rates and building energy consumption. Their capacity to learn, generalize, and predict patterns in vast datasets rendered them indispensable in this endeavor. The study's findings unequivocally underscored the pivotal role of ANNs in unraveling the complexities underlying building energy consumption dynamics.

The investigation of the occupancy rate, which reflects the level of human presence within a building, stands as a pivotal determinant in the realm of building energy consumption analysis. The meticulous examination of this parameter assumes a paramount role in accurately quantifying the energy utilization of edifices. In this pursuit, our study casts its focus on an office building situated in the dynamic urban landscape of Tehran, the capital city of Iran, boasting distinctive geographical attributes and climatic conditions. To supplement our analysis, an occupancy monitoring sensor was meticulously deployed to record occupancy rates during a specific period, as illustrated in Fig. 9.

The core objective of our study was to harness the potential of both artificial neural network techniques and statistical methodologies to decipher the intricate interplay between the occupancy rate and building energy consumption. The outcomes have duly demonstrated the prowess of both avenues in furnishing commendable predictive values. Notably, the outcomes gleaned from the artificial neural network approach, as showcased in Table 1, stand out as particularly noteworthy. This approach not only offers robust predictive accuracy but also excels in its simplicity, emerging as the optimal path to precise forecasting.

Moreover, the discerned insights reverberate with a resounding consensus that the occupancy rate holds a pivotal status among the constellation of variables steering building energy consumption. It is a finding of paramount significance that lower occupancy rates conduce to a corresponding reduction in energy consumption within buildings. In a broader context, the empirical results obtained for Tehran, Iran's bustling capital, and an educational establishment underline the supremacy of the artificial neural network methodology. The former boasts an error rate of 4.5, while the latter clocks in at 9.5 for prediction data based on ANN.

The cogent findings gleaned from our study further illuminate a direct correlation between escalating occupancy rates and the concurrent surge in predicted energy consumption figures. This causal relationship is indicative of the pivotal role that occupancy rate assumes in shaping the energy utilization dynamics within buildings.

The results of the study for the statistical method show that the coefficient of variation of the root mean square error for the "Moving Average" method is 5.08 and the normalized mean bias error for the "Moving Average" method is 17.81.

As well as the results of the study for the neural network show the coefficient of variation of the root mean square error for the "ANN" method is 4.5 and for mean bias error is 9.8.

CRediT authorship contribution statement

Ali Maboudi Reveshti: Writing – original draft, Validation, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Elham Khosravirad:** Writing – original draft, Software, Methodology, Formal analysis. **Ahmad Karimi Rouzbahani:** Writing – original draft, Validation, Software. **Saeed Khakshouri Fariman:** Writing – review & editing, Software, Methodology, Investigation. **Hamidreza Najafi:** Writing – review & editing, Supervision, Project administration, Investigation. **Ali Peivandizadeh:** Writing – review & editing, Visualization, Project administration, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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