Hindawi
Modelling and Simulation in Engineering
Volume 2021, Article ID 8897443, 10 pages
https://doi.org/10.1155/2021/8897443

Research Article

Energy Analysis of Commercial Buildings Using Artificial Neural Network

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Received 22 August 2020; Revised 8 February 2021; Accepted 19 February 2021; Published 12 March 2021

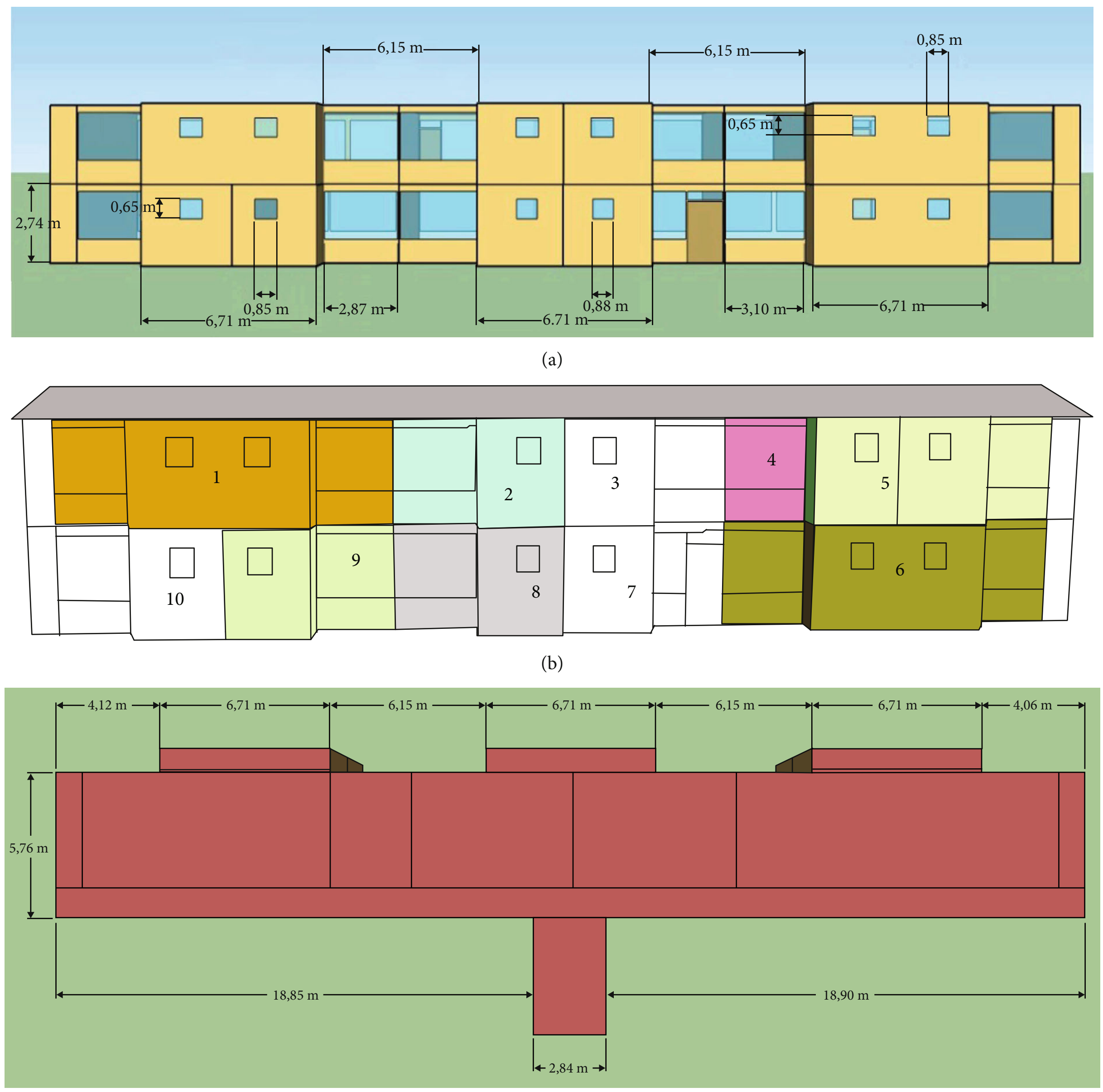
Academic Editor: Houari Ameur

Energy consumption in buildings especially in offices is alarming and prompts the desire for more energy analysis work to be done in testing models that can estimate the energy situation of commercial buildings, and the key contributing factors are based on human factors, work load, and weather variables like solar radiation and temperature. In the research, the administration block of the University of Energy and Natural Resources, Ghana, was selected and modeled for energy analysis using SketchUp. Daily energy consumption of the building was generated with EnergyPlus indicating the electricity consumption of the block for the year 2018 for which 68.7% was used by equipment in the block, 26.98% on cooling, and the rest on lighting. The Artificial Neural Network model which had weather variable and days as input neurons and cooling, lighting, equipment, and total building electricity consumption as output neurons was modeled in MATLAB. The model after training had R values for training, validation, and testing to be 0.999 and validation performance of $1.7 * 10^{-04}$. It was able to predict the energy consumption for lighting, cooling, and equipment very close to the results with minimal. The results from the ANN model prediction were compared with the EnergyPlus simulations. The maximum deviation profile for the following parameters (lighting, cooling, and equipment) is 13%, 8%, and 4%, respectively. The large difference in the lighting and cooling is the difficulty involved in predicting human behaviour and weather conditions. The least value recorded for the equipment is due to its independence on external factors.

1. Introduction

The residential sector in Ghana accounts for about 47% of total electricity consumption in the country [1], but generally, in the building industry, commercial buildings under construction account for 40% of every nation's energy consumption [2]. The generation of electricity in Ghana was 33% hydropower, and 67% from thermal power plants operating on fuels including losses [3]. The energy consumption in commercial buildings in Ghana is due to the discomfort people go through as a result of climate factors, building styles, heavy closure, and improper or excessive use of electrical gadgets, among others. The imperative hot and humid tropical nature of the climate of Ghana makes climatic conditions predominantly fall outside the human comfort zone and thus requires cooling for about 50 to 100% of the year using an air conditioner (AC) [4]. The hot climatic conditions allow the use of refrigerators and electrical fans to cool consumables and circulate cold air in buildings, respectively. "Furthermore, most building designs are neither supported by a detailed analysis and evaluation of thermally relevant features nor by considerations about orientation, envelope, glazing ratio, shading devices, and thermal mass. Thus, design decision making is not sufficiently informed by pertinent expertise pertaining to energy-efficient building design methods" [5]. To this end, heavy closure in buildings also prevents daylight from providing enough visibility; hence, people resort to the use of electric lighting during the day.

The residential sector has been the fastest-rising energy-consuming sector with an average growth of 6.3% over the last decade prompting the sector will be consuming more than 4400 MW by 2020 [6]. The increasing energy demand



(c)

Figure 1: Modeled UENR administration block ((a) frontal view, (b) thermal zones and (c) top view).

in the commercial building sector among other factors is caused by numerous newly constructed air-conditioned commercial buildings, especially in the metropolitan areas [5]. The use of energy simulation tools like EnergyPlus, Esp-r, and Designer's Simulation Toolkit (DeST), with Artificial Neural Networks (ANNs), has proven to be good tools for accurate information on electricity forecasting in commercial buildings.

ANNs as part of the current know approach to energy analysis are information processing systems that are nonalgorithmic, nondigital, and intensely parallel. They learn the relationship between the input and target variables by studying previously recorded data. An ANN resembles the biological neural system, composed by layers of parallel elemental units, called neurons. Fundamentally, a neuron receives inputs over its incoming connections, combines the inputs, performs a nonlinear operation, and then outputs the final results [7].

So far in Ghana, some researches have been done on energy consumption capturing key points on energy efficiency situations [8], analysis of household energy choice [9], energy generation and consumption, [10], thermal comfort evaluation of high-rise buildings in Accra [2], energy performance of office buildings [5], etc. Also, in other parts of the world, energy researches have also been carried out including the forecasting of energy consumptions of offices and residential buildings using traditional (conventional) and computational intelligence approaches. A model was developed for an office building with nine input parameters classified under weather conditions, building design, and

Table 1: Building specification.

Type	Name	Material
Wall	Exterior wall	100 mm sandcrete plaster 150 mm sandcrete block 100 mm sandcrete plaster
Window	Side windows	3 mm thick glass 13 mm window air fill 3 mm thick glass
Partition	Medium partitions	G01a 19 mm gypsum board F04 wall air space resistance G01a 19 mm gypsum board
Wall	Heavy/medium partitions	10 mm sandcrete plaster 100 mm brick 10 mm sandcrete plaster
Roof	Medium roof/ceiling	100 mm heavyweight concrete tiles Ceiling air space resistance Ceiling tiles Roofing sheet Roof deck
Floor	Medium floor	Floor tiles 100 mm heavyweight concrete

Table 2: Zones and their internal gains for the administration block.

Thermal zones	People	Lights/floor area (J/(s·m^2))	Electric equipment/floor area (J/(s·m^2))
One	4	4.374	194.410
Two	5	4.374	178.910
Three	8	5.230	712.540
Four	9	4.460	21.770
Five	25	5.150	27.540
Six	5	4.752	57.874
Seven	4	4.955	327.598
Eight	3	4.880	66.210
Nine	3	4.814	122.900
Ten	4	5.607	43.160
Eleven	2	1.088	—

day type with four output variables (cooling, heating, electric lighting, etc.) in Hong Kong [7].

In the same vein, the feedforward neural network model approach was used to design and predict hourly load profiles, where both the relevant input variables and the number of free parameters were systematically treated. The model building process was divided into three parts as the "identification of all potential relevant input," "the selection of hidden units for this preliminary set of inputs" through an additive phase, and "the removal of irrelevant inputs and useless hidden units" through a subtractive phase [11]. Relatedly on the use of ANNs, a comparison between a simple model based on ANN and a model based on physical principles with EnergyPlus was used as an auditing and predicting tool to forecast building energy consumption of the Administration Building of the University of Sao Paulo as a case study. The study shows that both models are suitable for energy consumption forecast. Additionally, a parametric analysis was carried out for the considered building in EnergyPlus in order to evaluate the influence of several parameters such as the building profile occupation and weather data on such forecasting [12]. With other related research, it is proven that ANN gives satisfactory results with deviation of 3.43% and successful prediction rate of 94.8–98.5%. [13–15].

The research work is meant to produce a model that is capable of predicting the energy consumption of buildings taking the administration block of the University of Energy and Natural Resources, Ghana, as the working domain.

2. Methods and Materials

The steps followed for the modeling and simulation of the domain energy consumption behaviour are demonstrated below.

2.1. Domain of Study Area. The University of Energy and Natural Resources (UENR) administration block located on the university campus Sunyani, Ghana, was selected for the study. The administration block is made up of two floors with 10 offices and a corridor located behind. The building houses about 29 working staffs of the university with an occupancy density of 17.63 m^2 per person. Regular working days in the building are the weekdays from the hours of 8:00 GMT to 16:00 GMT. The administration block is located at latitude 7.3°N and longitude -2.4°E. It is made of sandcrete and concrete blocks, glass windows, ceilings, and metal sheet roofing. The building has a total floor area of 519.86 m^2, a gross window-to-wall ratio (WWR) of 26.06%, and a net air-conditioned area of 388.83 m^2.

2.2. Modeling of Domain. The dimensions of the physical building and data for the building simulation parameters including internal gains (heat gain from solar heat gain, equipment usage, lighting, etc.) and schedules were taken to facilitate modeling and simulation. Modeling of the domain was based on the offices, and number of conditioned and unconditioned areas observed which was coded from zone 1 to zone 11 (Figure 1(b)). SketchUp 2019 software was used to model building features and designate thermal zones with building material specifications and building loads. These parameters were used by the software to generate building geometry data as an input file for EnergyPlus simulation. The modeled building (Figure 1) shows the walls and windows, which are made of sandcrete blocks and glasses, respectively. Sections of the modeled building were designated as thermal zones due to deliberate boundaries created between rooms and the floor considering heat transfer surfaces and heat storage materials [7].

Further details were specified into the model base on the building specifications (Table 1) and the load assigned to the various thermal zones. Key features considered include surface types and categorization base on thermal zone creation, building surfaces, fenestration surfaces, internal mass, shading and site details, and construction classes. The construction class allowed the specification of construction elements

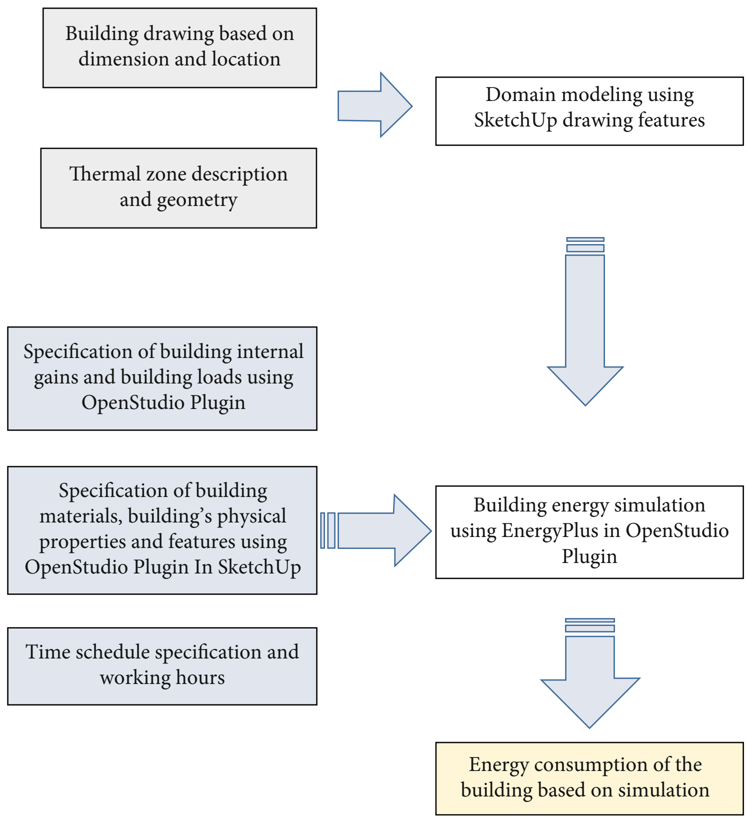


Figure 2: Neural network model design.

of the building. These elements in most cases represent the characteristics of the building. Typical of which are the wall, window, partitions, roof, and floor.

2.3. Internal Gains. Internal gains (Table 2) of the building entail the specification of the number of users in the block, lights, and electric equipment being used in each thermal zone.

2.4. Weather File. Energy consumption simulation of the geometry requires a local weather data that represents the weather patterns of the domain location in order to generate accurate energy consumption due to solar heat gains of the building [7]. The weather data used for the simulation was a one-year weather data which was that of 2018, obtained from the Earth Observation Research and Innovation Center (EORIC) on the University of Energy and Natural Resources campus, Sunyani. The weather file contained the site location parameters such as the latitude and longitude, time zone, and 30 minutes' variable recordings for temperature, gust speed, dew point temperature, solar radiation (both diffuse and normal), relative humidity, wind direction, wet bulb, and dry bulb temperature.

2.5. Generating Electricity Load Base on the Modeled Domain. An estimated energy consumption for the domain was generated from the modeled building using the building geometry data, internal gains, and local weather data in EnergyPlus. EnergyPlus is a simulation program designed for modeling buildings with all their associated heating, ventilating, and air conditioning equipment [16]. The building simulation programs have sets of mathematical models (nonlinear dynamic models, linear dynamic models, transfer function models, etc.) that seek to explain quantitatively how each component of a building behaves under given circumstances. EnergyPlus takes building geometry data that describe the modeled building and the weather data. The simulation program's results were used in designing the neural network model (Figure 2).

A neural network as defined learns the relationship between the input and output variables by studying previously recorded data. Designing neural networks involved series of chronological steps which were five in general. These steps include data collection, data preprocessing, building network, training network, and testing network model performance [17]. The neural network model was designed in MATLAB R2016b using the NNTool box.

2.6. Data Collection. Collecting and preparing sample data was the first step in all five steps taken towards the design of the neural network model. Measured weather data for temperature, dew point, solar radiation, relative humidity, wind speed, and wind direction for three years' period (2017 to 2019) were sourced from EORIC, Sunyani. These data were processed and used as the input data.

2.7. Data Preprocessing. Data preprocessing was done to make the data suitable for training the neural network model. This was done by first generating missing data points to have a full data set since some data points in the weather file were

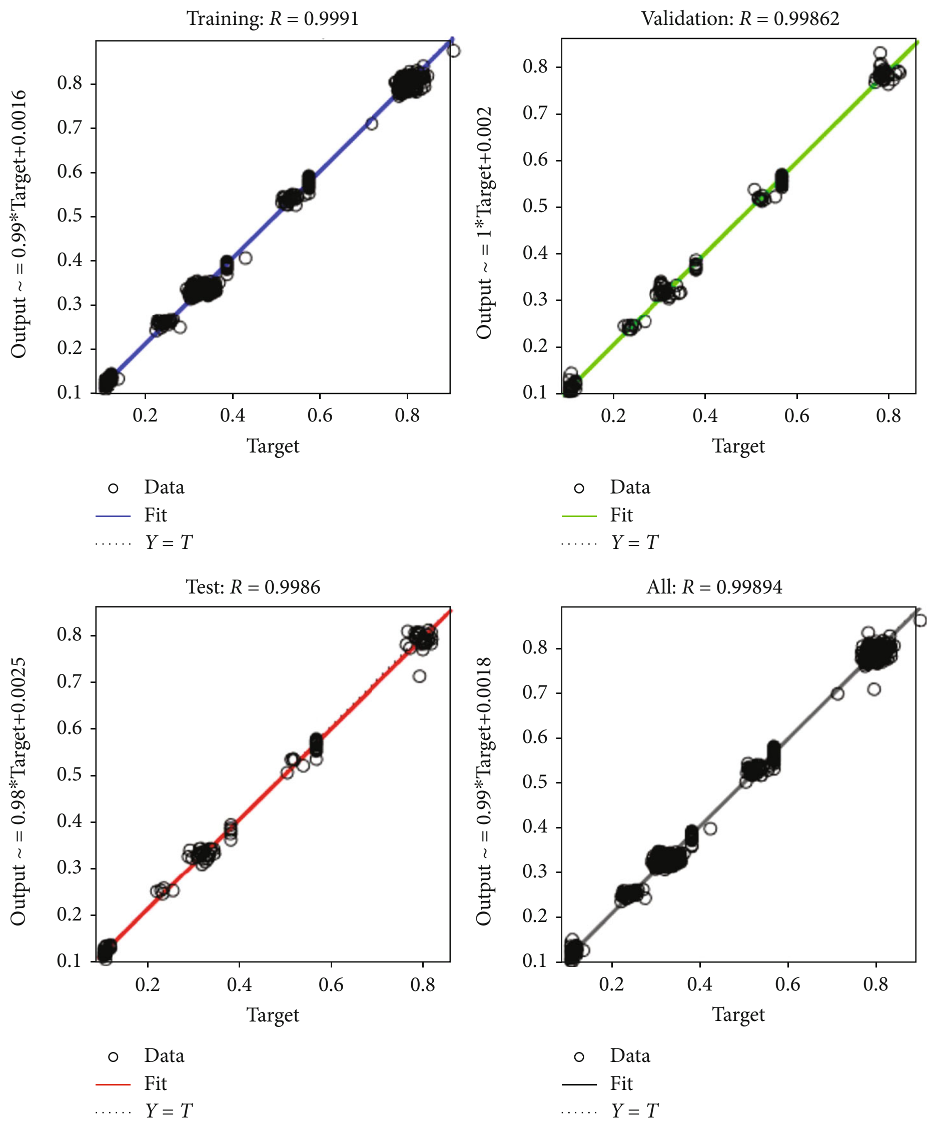


Figure 3: Regression plots.

missing. Secondly, the data was processed to remove noise (instability) and was normalized before presenting it for training. Data normalization was necessary because mixing variables with large and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude [17].

2.8. Neural Network Model Design. Building the neural network model using the NNTool box simply requires the specification of the number of hidden layers, number of neurons in the input and output layers, the transfer functions in the layers, and training function. For this work, a two-layer feed-forward neural network under the multilayer perceptron (MLP) was used. A one hidden layer network was used, but the number of neurons in the hidden layer was varied during the training process to select the best number of neurons to give a good performance of the model which was 25 hidden neurons. The number of neurons used in the input layer was simply based on the number of key weather variables and days. Before these, a correlation analysis between various variable sets to confirm their relationship with each other was done. At the end, seven weather variables were selected as input neurons; they are temperature, dew point, wind speed, wind direction, relative humidity, and solar radiation. A total of 268 data points were used for building the model; the days of the week were coded in binary (i.e., 0 and 1) and included in the input layer. The input layer has a total of 14 neurons, whereas the output layer had four neurons. The four neurons represent the target against which the weather data were trained. They include electricity consumption data points for the lighting, cooling, equipment usage, and sum of energy consumption of the building generated through EnergyPlus simulation.

2.9. Training Neural Network. Training neural networks entail the adjustment of weights in order to make the predicted output close to the target output. To achieve these, there were factors considered during the training which were the transfer functions and learning algorithm. Different types of built-in algorithms and transfer functions were investigated, during the training process, and the Levenberg-Marquardt scheme was settled on as it gave satisfactory results compared to the rest.

2.10. Cross-Validation. An important step before the training process was the cross-validation where data samples were randomly divided into subsets as training, validation, and testing data sets. It is known that the most appropriate network topology for a model is best determined based on the quality of the training data set, amount of noise (instability) in the data samples, errors, and outliers [18]. Therefore, to select the best topology, cross-validation gives us the opportunity to evaluate the performance of various network topologies using a data set different from the set used in the training process and select the one that provides better generalization results. The training set was used for training the network, computing the gradient, and updating the network weights and biases. The validation set helped in monitoring the network for overfitting, underfitting, and terminating the training process when the data fit to test level. The test subset was used in testing the trained network on its capability to generalize results. For this work, training data set was 70% for training the network, 15% for validation processes, and another 15% for testing.

2.11. Performance of the Neural Network Model after Training. The performance of the trained NN model to be used for the energy estimation was displayed during and after the training by the NNTool box GUI. The performance of the network was computed based on the Mean Squared Error by MATLAB based on the average squared difference between outputs and targets. The goal for the training is to minimize the average sum of errors. Lower values are better, and zero means no error. This is computed based on

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2, \qquad (1)$$

where n is the number of the data points and i is the period at which the load is produced or forecasted, t is the target, and O is the NN output.

An additional performance of the training was evaluated using the plots comprising of the regression, performance, and training state plots.

2.11.1. Regression Plots. The regression plots for the training, validation, and testing, respectively, are represented in Figure 3. The four plots show the output of the training, validation, and testing data for the overall network outputs against the targets after training. These plots show how the model will be able to forecast and generalize results after learning from the relationships between the input and target variables. The best training result produced an R for training, validation, testing, and all to be 0.999 for each regression plot.

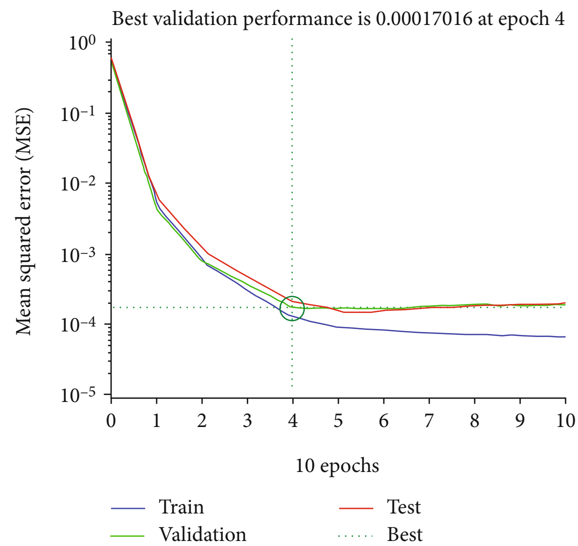


Figure 4: Performance plot.

2.11.2. The Training Performance (MSE) against the Number of Epoch Plot Performance Function. This is the Mean Squared Error (MSE) versus the number of epochs. From the plots, the best validation performance occurred at the fourth epoch with a performance value of $1.7e-04$ (Figure 4). These serve as a stopping protocol that can spot a change in the course of the learning algorithm to avoid overfitting of the model. This error minimum signals transition between underfitting and overfitting of the model. A careful observation shows the training was terminated after 6 more epochs of training beyond the point of best validation since the error in the validation started increasing. The three curves were found to decrease in error as the epochs increase. At 4 to 10 epochs, the error became stable and started to increase after 10 which calls for the selection of the stopping protocol. Epoch 4 is seen as the best point as it represents the event where the three curves are together or closer to each other.

2.11.3. Training State Plots. These plots (Figure 5) are for the learning function against the number of epochs for displaying the development of the gradient function values as the number of iterations increases. The second plot (learning rate (mu) versus the number of epochs) helps observe when the network error decreases during the training process and finally the plot of validation checks which is implemented automatically for whenever a sudden modification occurs in the gradient function computation.

3. Results and Discussion

Here, the results of the various models are represented and explained for their trends.

3.1. EnergyPlus Simulation Results. EnergyPlus simulation results of the domain represent the estimated actual energy consumption of the building. The result was generated for 2017 through to 2018 and used in training the neural

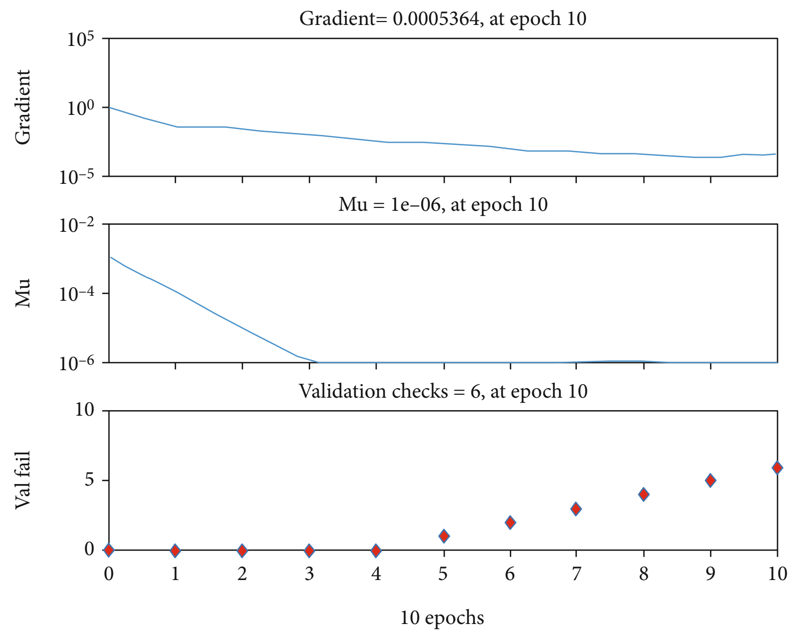


Figure 5: Training state plots.

network. This was generated based on the items used in the administration block considering lighting, cooling, and other devices in the building with building modeling parameters and weather data. The accumulative average power usage for lighting in the offices during working periods and nights is computed and plotted in kWh/day for a year. The total estimated energy used for lighting recorded for the year was 3463.64 kWh. From observation, the electricity usage for lighting is high around October to January and descends from the middle of February to a relatively low level at the end of February. There is a sharp rise from the early part of the month of March to the early part of April as well, and other intermitted rise in June. All the patterns observed in the power consumption in the year can positively be attributed to the amount of solar radiation available in the season that enters into the enclosure. Solar radiation is responsible for visibility during the day or working hours. The low solar radiation experienced from October to January of the year usually has an impact on the high power consumed for lighting. The workers in their offices use more lights these periods. It is also synonymous to say the preceding month (February) where a relatively low power was consumed for lighting had higher solar radiation recordings and same for the middle of April to May. Beyond this, the consumption around May to June and parts of December is affected by the university semester break, and nonetheless, the use of blinds in the offices is also a contributing factor affecting the solar radiation penetration into offices.

The annual energy consumption for equipment used in the block is independent of weather pattern and solely depends on the users of the building and constant work load throughout the year. This is seen to be on the average of 374.90 kWh/day on working days. For cooling energy consumed throughout the year, 54239.73 kWh of the total energy consumed was used on cooling representing 26.98%. From the profile plot on cooling, higher energy was utilized for cooling between January and May, and less power was utilized from June to October while increasing towards the end of the year. January to March is a very hot season in Sunyani so cooling becomes necessary due to thermal discomfort [4]. The period of the year with higher and lower temperatures has a corresponding increase and decrease in the energy used for cooling. Intuitively, rainy seasons from June to July and cold months like August have low daily temperatures so workers of the block do not use the air conditioners much, hence resulting in less power consumption in these seasons of the year.

The summation of all the factors gave the idea that the total energy consumption of the block for the year 2018 was around 201026.52 kWh with the average daily consumption being 550.76 kWh for which the equipment used takes the most with 68.07% followed by cooling 26.98%.

3.2. Neural Network Model Result and Prediction. The neural network model predictions are the estimation of the various energy consumption of the building on daily bases throughout the year and an average computational time of 100 minutes when using a 64 bit i3 PC. The capability of the NN model was tested by presenting 2018 processed weather data for estimation of energy consumption for the year 2018 as a case study. The 2018 data presented were new sets of data that were unknown to the neural network during training. The result of the ANN model prediction was compared with the EnergyPlus simulation results (Figure 6). The profile for ANN cooling load for daily consumption of the year is closely related to the EnergyPlus simulation results throughout at a percentage error between 2 and 8%.

The ANN model energy consumption for lighting gave higher prediction among the three variables that were

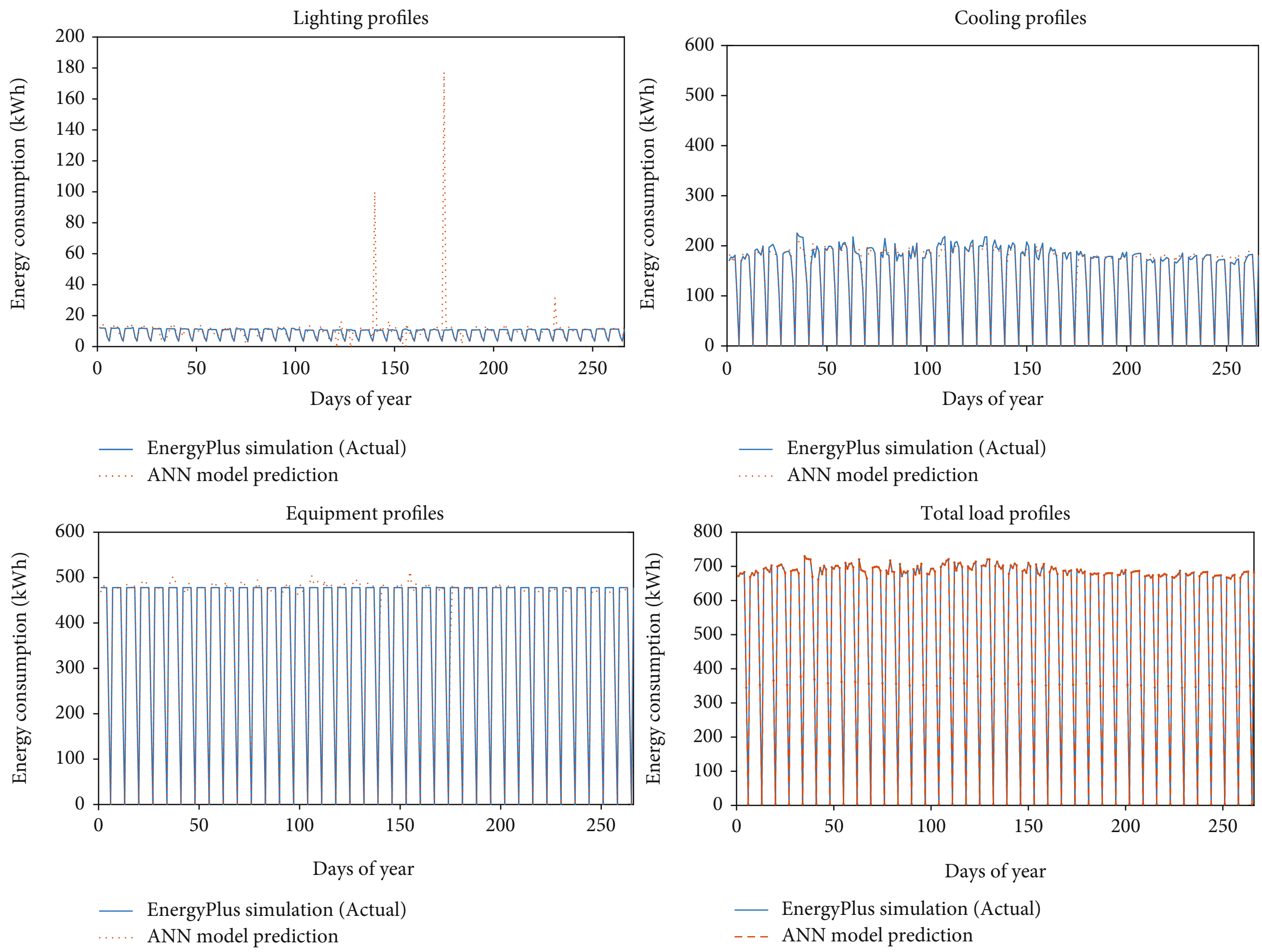


FIGURE 6: EnergyPlus simulation profiles and ANN model prediction profiles.

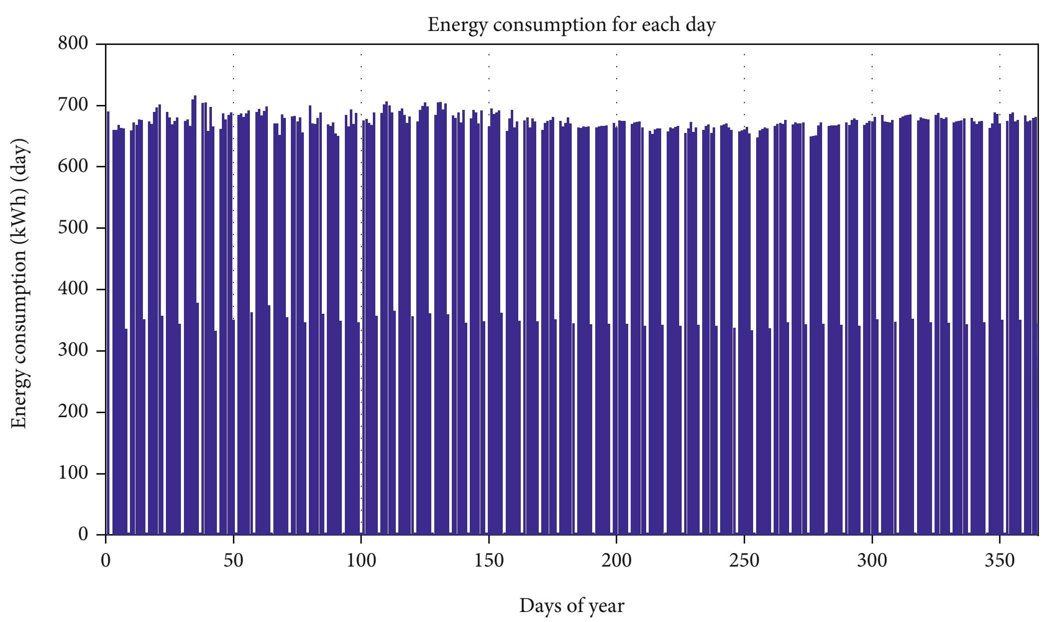


FIGURE 7: EnergyPlus daily energy consumption in the block for a year.

considered. The error between the EnergyPlus simulation and the ANN model result was higher than the rest with a maximum error of 13%. Additionally, the profile for the equipment usage for the ANN model prediction is very close to the EnergyPlus result and same for total energy consumption profile at a maximum error of 4%. The differences are due to human behaviour and unpredictable weather conditions which cannot be controlled.

To ascertain the validity of the EnergyPlus model simulation, and to confirm the simulated results, the EnergyPlus consumption (Figure 7) of the administration block for each day was compared to the real energy demand of the block for each day. The daily energy demand of the block was 694.1 kWh in 2018 as determined by [19] 2018 in a thesis submitted to UENR in 2018. The EnergyPlus daily energy consumption range from 686.42 kWh to 731.25 kWh for working days which is close to the real energy demand of the building but varies along the year because EnergyPlus considered weather conditions throughout the year.

4. Conclusion

The domain selected for the study was well modeled to generate the actual energy consumption of the block. These results were analyzed and used to draw inferences from the weather data obtained from EORIC for Sunyani where it was realized there is a relation between the energy consumed and weather variables like temperature, solar radiation, and dew point temperature. From the work, solar radiation has a direct influence on energy consumed on energy used for lighting to which an increase in solar radiation results in low consumption for lighting because there are enough visibility and vice versa for a decrease in solar radiation. This means the use of heavy closure and blinds that prevent daylights in offices contributes to high energy consumption. Also, daily temperature and cooling load have a positive relation unlike the lighting and solar radiation. Temperature increase causes thermal discomfort as a result of an increase in room temperature leading to the use of air conditioning devices in the offices. These accounts for the high energy consumption used on cooling in some parts of the year.

The ANN model designed and trained for prediction of the energy loads for the block for a year showed a great predictive capability. The results from the NN model prediction compared to the actual energy consumption were plotted and analyzed to observe the areas of overestimation and underestimation. The NN model was effective and can be used to estimate the future energy consumption of the block when trained with additional data sets.

Data Availability

The various data sets obtained from EROIC, the administration block of UENR, and the rest of the data generated and evaluated for the research are not publicly available. This research form part of a large project on energy modeling which requires the use of the data for future works. Few extracts of the data can be made available by request from the corresponding author at his/her own discretion.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by weather data taken from EORIC, Sunyani, at the University of Energy and Natural Resources and the registrar's office for granting access to the administration block.

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