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Prediction of Electric Power Demand of HVACs for Operating Rooms in Case of Dynamic Set Points of Temperature: A Case Study

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Abstract: In healthcare settings, particularly in areas such as operating rooms and intensive care units, there is a need for a dynamically controlled temperature environment that can adapt to the changing needs of both patients and healthcare workers. This is due to the fact that the desired temperature can vary depending on the condition of the patient and the specific requirements of surgical and treatment procedures. To address this need, our objective is to develop a tool for predicting the electric power needed to maintain a desired temperature in these critical care areas. Previous research has employed artificial learning algorithms and mathematical equations to predict electric power for various types and sizes of buildings, with promising results. However, our study focuses specifically on critical care areas within hospitals and utilizes fluctuating temperature set-points to predict power demand using historical weather data and Building Management System (BMS) data. We employed both Multi-Layer Artificial Neural Network (ML-ANN) and Long short-term memory (LSTM) models for this purpose and found that ML-ANN outperformed LSTM. The results showed that the ML-ANN model performed better than the LSTM model, with a testing accuracy of 96% compared to 78% for the LSTM model. This indicates that the ML-ANN model was more accurate in predicting the power consumption for the desired temperature in the operating room.

Keywords: Heating Ventilation and Air-Conditioning (HVAC); Operating Theaters (OTs); Feed-Forward Back-Propagation Neural Network (FFBP NN); Long Short-Term Memory (LSTM).

1. Introduction

Electric power is identified as the third-largest factor among other expenditures in the healthcare sector after staff salaries and medicines, hence energy consumption is recognized as a major cost factor. It was also revealed that most of the electricity is consumed for air-conditioning which is measured as more than 50% of the total building electricity use. The highest Energy Use Intensity (EUI) value was found for the hospital's critical area i.e., Operation Theaters (OTs). In OTs, the EUI value is about three times higher than that in other areas and offices in the hospital [1]. For proper energy management, prediction is important which we have worked out in our research. This work can be integrated with the Building Management System (BMS) for real-time prediction of energy. We followed the steps given in Figure 1, throughout our research. HVAC is a system that is designed to provide a comfortable environment to the occupants and recommended environmental conditions for the machines or processes. The basic components of HVAC are Air Handling Unit (AHU), Supply Air System, and Outlet/Exhaust Air System. The AHU's housing or casing is normally made from metal. It contains the fan, coils, filters, etc. This casing protects these systems from outside damage and deterioration due to water and dust. Moreover, to prevent condensation, a drain pan is installed in this housing. A mixing box is also known as an air-mixing plenum. On-air inlet side, a damper is installed for controlling the volume of air. The mixing box mixes the returned air which returns into the AHU and is also used to suck fresh air from outside for air exchange in the room [2]. As per ASHRAE standards, for the OTs, it is not recommended to mix the air due to the risk of infection, therefore, the air is returned outside through the exhaust system of AHUs. It also contains a filter to suck dust-free air from the outside. In AHUs, cooling and/or heating coils are used for achieving the desired heat or cool temperature environment. The tubes of the coils are made up of copper and the fins are of aluminum. However, these coils can be configured in different ways as per the requirement. For example, when we change the number of fins, this consequently changes the design of the fin. Such options are preferred which lead to the prevention of corrosion, not freezing very much, and do not transfer moisture. Most of the time, a High-Efficiency Particulate Air (HEPA) filter is used in laboratories, clean rooms, laminar airflow cabinets of operating rooms, and manufacturing facilities where dust-free air is required.

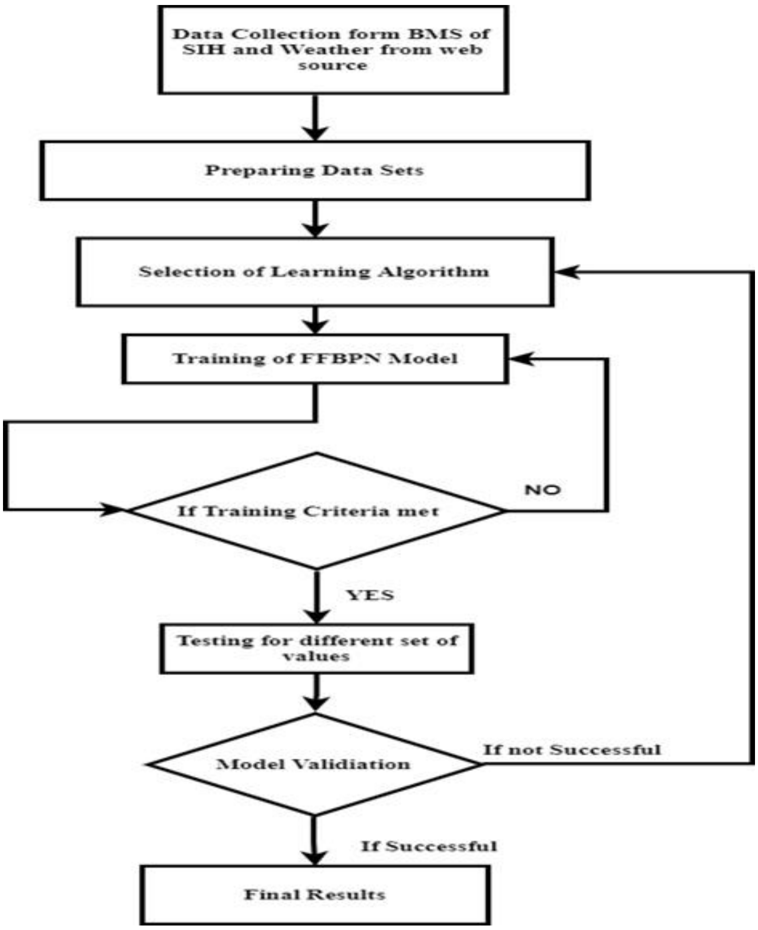

Figure 1. Framework for HVAC Load Predection

The advantage of HEPA filter is to filter the air and block the particles up to 99.97%. A size of 0.3 microns of particles can be removed or blocked including dust, even bacteria, and other unwanted particles or air contaminants [3]. For winter or cold-temperature conditions, humidifiers are used in AHUs. These are available in several types, such as Spray Types, Steam Pan Types, and Steam Grid Types, just like filters and fans. The basic work of humidifiers is to produce steam that will enter the room for controlling humidity. Another important part of AHU is its centrifugal fan, which is required for distributing cool or hot air to various areas to achieve the desired volume of air in Cubic Feet per Minute (CFM) [4]. This paper describes artificial intelligence (AI) techniques to predict the power consumption of HVAC systems installed in OTs of a regional renowned hospital, by using AI algorithms of Multi-Layer Artificial Neural networks (ML-ANN), long short-term memory (LSTM) and machine learning regression techniques of K-nearest neighbor (K-NN) and Logistic Regression Algorithm [5]. Simulation results are given in the section of results and comparative analysis of proposed models has been demonstrated in the discussion section containing the conclusion of the research. Building energy behavior is sophisticated and uncertain; yet, various models can make simple predictions, such as statistical models, and artificial intelligence with neural networks is the most often implemented. You will get a survey of recent work on predicting building energy usage in [6]. As it is difficult to foresee energy computations in building due to high dependency on many factors including weather conditions, building structure and characteristics, lightning, and many other environmental conditions. A prediction model of NN for energy consumption in the building was used in [7] [8], [9]. It was observed that over 40% of the total energy is consumed in European Union countries. In China, according to statistical data, it accounted for 28% in 2011 and was predicted to reach 35% by 2020. In old approaches, the modeling of a dependable and efficient estimator for power consumption estimation is critical for achieving appropriate energy demand management. Various forecasting methodologies have been used for building energy use over the last two decades, such as engineering techniques, statistical techniques, ANNs, SVMs, fuzzy logic, grey model techniques, etc. ANNs are the most extensively used energy prediction algorithms currently available and their improved models. An Improved Particle Swarm Optimization (IPSO) method is used to optimize ANN's weights and threshold values, which is effective in improving the fitting ability of the ANN model [10],[11]. Using multi-layer perceptron ANN, an actual case study was conducted to forecast the electrical consumption of the Cellini medical clinic in Turin, Italy. It is based on a backpropagation training algorithm and can predict load demand of the upcoming day of a large capacity hospital using loads, data about the type of day (e.g. weekday/holiday), time of day, and weather data as inputs [12].

The experimental results show the validation of the machine learning model for assessing the expected energy usage of the healthcare building[13]. Three categories were used to offer a full review and simulation of the main thermal building models. The first group of models is based on physical and fundamental principle modeling (white box) [14]. The statistical models, on the other hand, provide a considerably simpler structure (black box). The black box is used to forecast energy usage and heating/cooling requirements. Finally, a hybrid method (grey box) is an approach that combines physical and statistical modeling methodologies. The grey-box model is the most effective approach for managing building energy use, according to the comparison and simulation results [15], [16]. Based on the air-conditioning system of a University Library in Guangzhou, this study uses the LSTM deep learning model. The findings show that the LSTM model can make more accurate predictions. When compared to the Auto-regressive Moving Average model, the daily energy consumption projection was lowered by 11.2 percent (MAPE). The hourly energy usage projection has been lowered by 16.31% [16]. Additionally, the MAPE's daily energy consumption estimate was decreased by 49% and the hourly energy consumption prediction was lowered by 36.61% when compared to the backpropagation neural network model [17]. The power consumption prediction was done using deep learning and electricity consumption data from a specific area of Binhe New City. The data comprises the power system's electrical usage data from June 1, 2017, to December 31, 2017. Binhe New City has a section in the northern coastal area that is part of the industrial and commercial economic circle [18]. Deep learning models for short-term power consumption forecasting and LSTM models for long-term electricity consumption forecasting were developed to complete the forecasting of time series power consumption. Finally, it was discovered through analysis that the LSTM model's short-term electricity consumption prediction error rate was low [19]. With data from three years (2017-2019), two companies with varied power usage trends were chosen. During deep learning, a Deep Neural Network (DNN) and an LSTM were used to estimate medium and long-term power predictions. The input, hidden, and output layers are the three layers of the proposed DNN model. The hidden layer was composed of 100 nodes and an input layer of one node. The activation function ReLU was used to overcome the vanishing gradient. Regardless of the power usage pattern, the suggested DNN outperformed the LSTM in the experiments. Furthermore, the proposed DNN outperformed the proposed LSTM in terms of prediction error and calculation time. However, the limitation was that it does not consider whether data related to seasonality [20].

2. Problem Statement and Objectives

The building energy behavior is complex and uncertain. The energy management of a healthcare building is a crucial task for the researchers and different load prediction models are applied to supply uninterruptible power load to the healthcare building. There are many models which can make an easy-to-use prediction like statistical models and artificial intelligence, and the most prominent method is neural networks, which are widely used. The need of the problem is to propose a model that can achieve the given objectives:

To predict the power consumption of cooling & heating of HVAC of ORs of the selected hospital using AI techniques.

The model will be processed on dynamic set points of temperatures of ORs inside the hospital. Because in ORs both the patient and healthcare workers desire different temperature environments at different stages which depend upon the condition of a patient and the requirements of surgical and treatment procedures. Therefore, the need for a dynamically controlled temperature environment and availability of required heating/cooling electric power is relatively more necessary for the provision of a better healthcare environment to the patients as compared to other commercial and residential buildings where only comfortable room temperature is required.

2.1 Case study

The Shifa International Hospital (SIH), Islamabad Pakistan was established on September 20, 1987. SIH is about a 550-bed hospital. It is categorized as a quaternary care hospital. SIH is providing quality healthcare services not only to local patients but as well as patients of international communities since its establishment. It is also certified by Joint Commission International (JCI). JCI is an international accreditation of healthcare facilities that focuses on quality and patient safety. SIH is one of the 3x hospitals in Pakistan that achieved this certification. We have chosen the Operation Theaters (OTs) of SIH as a case study.

SIH has a state-of-the-art complex of operating rooms (ORs). Almost all of the major and minor surgeries are being performed in these ORs. The major surgeries also include heart bypass surgeries, liver transplants, corneal transplants, bone marrow transplants, total knee replacement, and Neuro surgeries. ORs Complex is shown in Figure 2.

Figure 2. Outside View of Operating Rooms of SIH

The operating rooms are completely airtight and supply-return air ducts are installed which are connected to separate AHUs on the back end. The dimension of ORs is 22′-6″ x 25′-10″ x 9′-5″ (WxLxH). An internal view of one of the ORs can be seen in Figure 3.

Figure 3. Operating Rooms- Internal View

2.2 Dataset

The data sets used in the study were created using temperature data from the building management system (BMS) of a specific building (SIH) and weather data from a web source [21]. The BMS data contains information about the indoor temperature, set/desired temperature, wind speed, and solar irradiation, while the weather data includes information about the weather conditions in the location of the building (Islamabad). The data sets include five types of data: Indoor Temperature, Set/Desired Temperature, Wind Speed, and Solar Irradiation. The target output of the data sets is the power consumption by the building's HVAC system for achieving the desired temperature. It's worth noting that the data sets contain features for each phase of the HVAC system, including Room Temperature (R_T), Set Temperature (Set_T), Wind Speed (W_Speed), and Solar Radiation (S_Radiation) for the Red, Yellow, and Blue phases. A total of 671 entries for each feature and target were collected, with a frequency of recording these values at 10 minutes intervals through the BMS.

The data sets used in the study were created using temperature data from the building management system (BMS) of a specific building (SIH) and weather data from a web source. The results of the study could be used to optimize the HVAC system's performance and energy efficiency by predicting power consumption in real-time and making adjustments accordingly. Through the use of summary statistics and graphical representations, exploratory data analysis refers to the critical process of doing the first examinations of data to uncover patterns, spot irregularities, test hypotheses, and quality affirmation. For visualization of data sets (features and target) variable we used Exploratory Data Analysis (EDA) [22] for preprocessing of datasets for each phase Figure 4, shows the distribution of datasets.

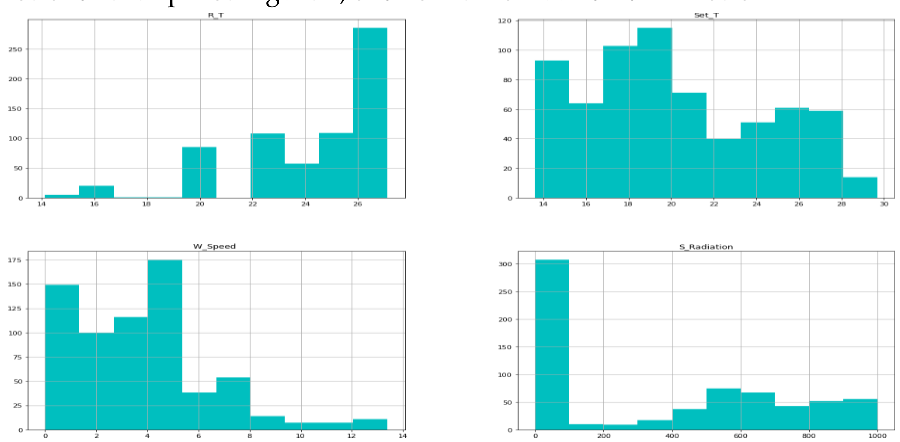

Figure 4. Exploratory data analysis of HVAC Datasets

To strengthen our models, we now eliminate prefixes using the regression model. Using pandas ".corr()" in Python 3.10.1 while using Google Colab API, this technique is used to find correlations, as well as the correlation matrix which is visualized using a heatmap in the seaborn library. We may deduce that there is no linear relationship between different predictors because the correlation is zero. However, unless we are using a Linear Regression model on the data sets, it's okay to exclude those characteristics.

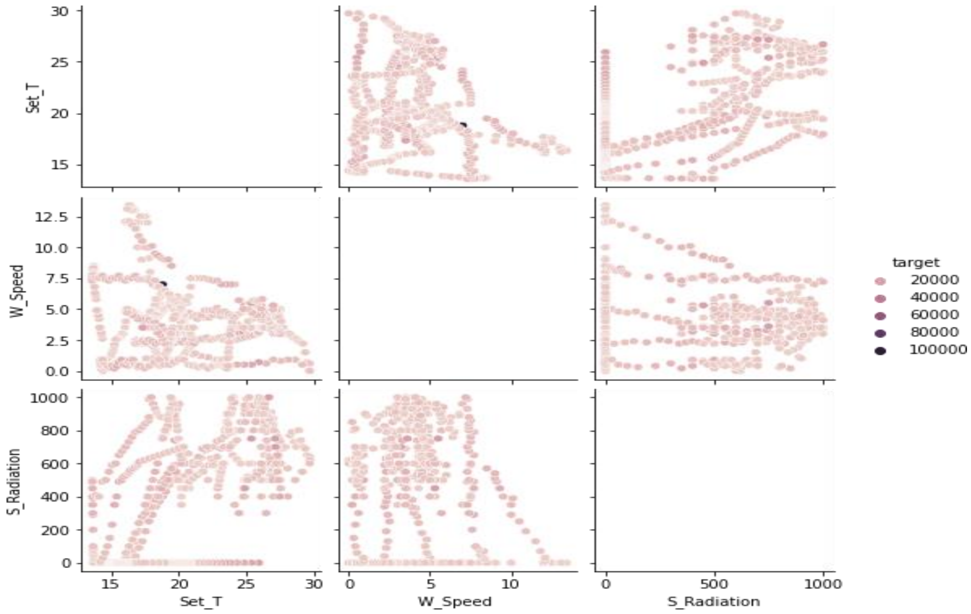

Figure 5. Co-relation and Varience of Features in Dataset of HVAC Load Predection

For Normalization of our data set we use Principle Components Analysis (PCA) to yield the spread of data in Figure 5, also describe the correlation in visual with features, have no redundant values, and out-lairs. Thus may deduce from Figure 6, that "Solar Radiation (S_Radiation)" seems to correlate with "Set Temperature (Set_T), but no relationship to "Wind Speed (W_Speed)".

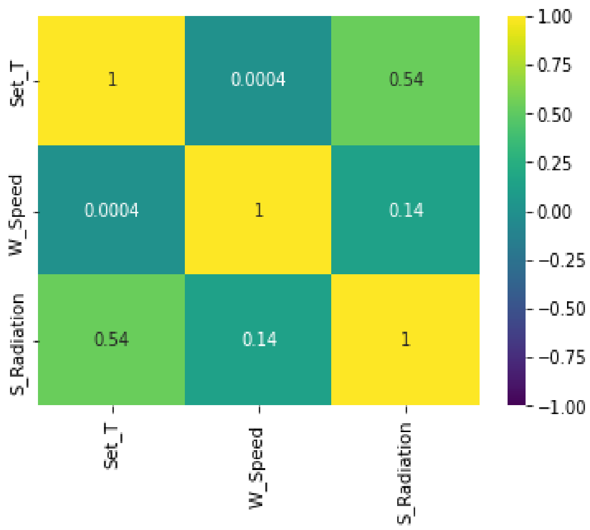

Figure 6. Heat Map of Dataset

3. Methodology

3.1 Multi-Layer Artificial Neural Network (ML-ANN)

Artificial Neural Networks (ANN) are popular models of AI. These are based on the biological structure of the human brain's natural neural cells. The basic components are linked by these cells [23]. It works in the same way as neurons do in the human brain as the logic processing unit. In the human brain neural network, a typical biological neuron included a cell body, a tubular axon, and a slew of hair-like dendrites, ANNs are a non-parametric statistical modeling technique that, when compared to traditional correlations, makes them a powerful and efficient forecasting tool for estimating the attributes of complex systems [24],[25]. There are three modes of operation of ANN namely supervised, reinforced, and unsupervised learning [26]. A set of targets are compared with the outputs of ANN and weights are updated in ANN an by using error signal in supervised learning. There are no targets given in reinforced however, it's similar to supervised learning. Although this algorithm gives a grade to the ANN performance. Unsupervised learning uses input data only for updating weights [27].

The ANN learns to organize various patterns of input into different groups. Single-layer feed-forward (SLFF) multi-layer feed-forward (MLFF), and recurrent networks are the three primary forms of ANN typology [23]. When data is to train linearly separable, a single-layer feed-forward network is useful. The single-layer feed-forward network would have difficulty trying to accurately model the function if the data we are trying to model is not linearly separable or the function has complex mappings [28].ANN is one of the good performing, easy-to-implement, and simple algorithms of artificial intelligence. It can learn complex and non-linear functions. ANN makes it possible to estimate nonlinear models without having to provide an exact functional form. Connected points in ANN are called neurons or nodes which receive the data inputs and decide whether the output should be passed on to the next layer as an input in the case of multi-layer ANN [29]. These inputs are multiplied by some weights and then summed up. The result to appear on the output is determined by applying a threshold function to this summation. The threshold function, which determines the neuron's output, can be linear or non-linear. Among different kinds of ANN, a Multi-layer Feed-forward Neural Network (MLFNN) is the most popular, which uses a back-propagation learning algorithm [30]. Hidden layer(s) with computational nodes known as hidden neurons are present in these types of ANN topology in which data moves forward [31]. The input data is sent into the input layer, which introduces the values of the inputs to the network, before being passed to the hidden layer(s) to be processed [32]. The last hidden layer then passes the processed data to the output layer, where the results are obtained. Every neuron in the output and hidden layer(s) is linked to every neuron in the previous layer [33]. The basic architecture of ANN is shown in Figure 7, wherein X1, X2, and Xn presents the input of the neuron. W1, W2, and Wn are their weights, θ is the threshold value or bias and Y represents the output as shown in Equation 1.

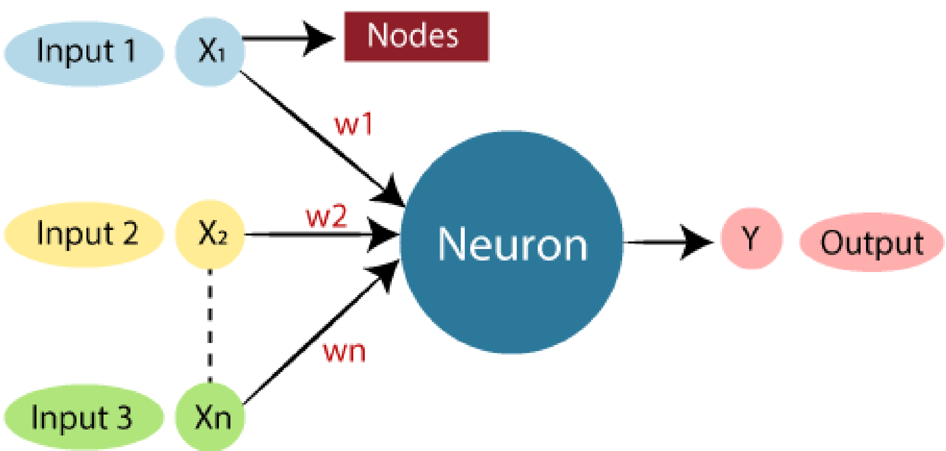

Figure 7. Basic Architecture of ANN

The cost function is in Equation.1 of ANN

$$J(\theta) = \frac{1}{2M}\sum_{i=1}^{M}(h\,\theta(X^i - Y^i)^2 \quad (1)$$

The output of the neuron is denoted by Y . we used sigmoid as an activation function for this this study. The logistic function, often known as the sigmoid activation function, has long been a popular activation function for neural networks [34]. The function's input is adjusted to a value between 0.0 and 1.0. Inputs that are significantly bigger than 1.0 are changed to 1.0, and values that are significantly smaller than 0.0 are snapped to 0.0. The function's shape for all conceivable inputs is an S-shape ranging from zero to 1.0. It was the default activation on neural networks for a long period, until the early 1990s. which is shown in Equation.2.

$$F(X) = \frac{1}{1 + e^{-x}} \quad (2)$$

ANN is trained using feedback propagation, as a supervised learning algorithm. This approach requires a data set for training and their expected outputs. It adjusts the weights of the neurons autonomously. The weights are corrected according to enforced learning principles, resulting in unique knowledge from the data. A typical feed-forward neural network (MLP)with backpropagation is shown in Figure 8.

The advantage of ANN is that it trains the neural network by adjusting the weights of connection between elements to perform a particular function. For example, if we wanted to train a neuron model to approximate a specific function, the weights that multiply each input signal will be updated until the output from the neuron is similar to the function. ANN is made up of parallel-operated elements which allow increasing calculation speed over slower sequential processing [35]. One of the most difficult aspects of ANN modeling is determining the appropriate network structure. The hidden layer of the network is comprised of an optimal number of neurons [36]. The performance of the ANN is dependent on it, thus choosing the best value for neurons is crucial. If the network's number of neurons is less than the ideal, the network will not train appropriately, and the results will be inaccurate [37]. Furthermore, if a large number of neurons is used in comparison to the optimum amount, poor interpolation quality might arise, which is known as an over-fitting problem [38], [39]. The electric supply to the HVAC system is three-phase. Our target date has voltages of 3 phases. We have trained our network using the output of one phase and for testing, we compared the data of the other phase.

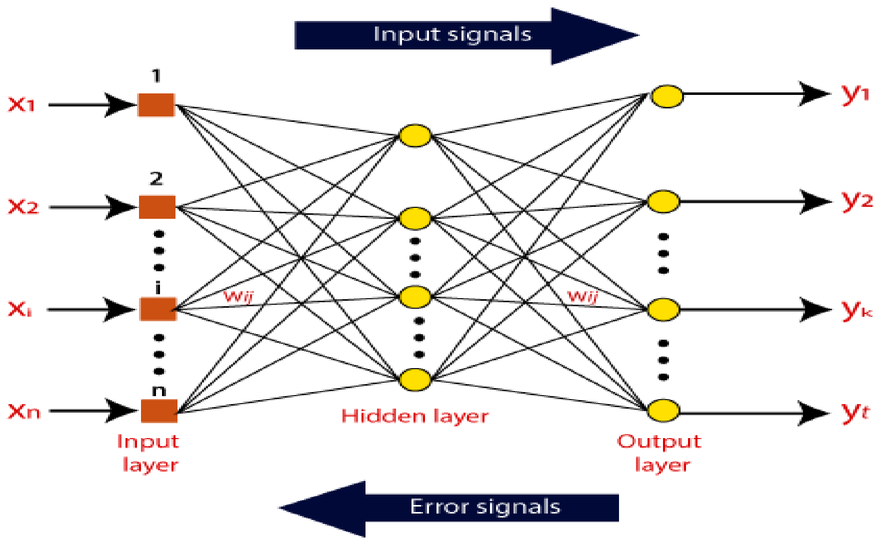

Figure 8. Feed Forward & Back Propagation Multi-Layer ANN

The difference was negligible. For the development of our proposed ANN model, three steps were followed i.e.Training, Testing, and then Validation. 70% of data is used during training, and 15% for each invalidation and testing process [40]. During the first stage, if training criteria are met, the model proceeds to the test stage otherwise, it is recalled for retraining again. We also tested our data sets to find it is performing. After successful testing of our model, we finalized it as well as validated it. In the different research, it can be seen that most of the time the Feed-Forward (FF) network is used while following the Back Propagation method. Like other ANNs, its objective is also to learn and map the relationships between inputs and outputs. Moreover, this network also adjusts the weights and threshold values of the system in such a way as to get the desired results with fewer errors [41].

A typical ANN performance flow chart is shown in Figure 1, xk and xi are the new value and initial value of the variable respectively and wiki is variable/neuron weight. The activation function is shown in the equation 2 FFBPN model developed by using MATLAB R2020b. In the training phase, FFBPN based model is trained using simulated data. when the model failed the expectation during the initial stage of training, we did re propagate the process until it meets the requirements. Levenberg Marquardt Back Propagation Algorithm (LMBPA) is used in the training phase of FFBPN based model [42]. LMBPA is the fastest method for training the FFPBN-based model [43]. The following properties and parameters were set during Neural Network Training

1. Training function: mainly (Levenberg-Marquardt)
2. Number of hidden layers: Seven (7)
3. Number of Iterations: 122 Epochs
4. Validation Folds: 6
5. Gradient at last epoch: 0.0088568
6. Transfer function (training): tanh
7. Transfer function (testing): purlin

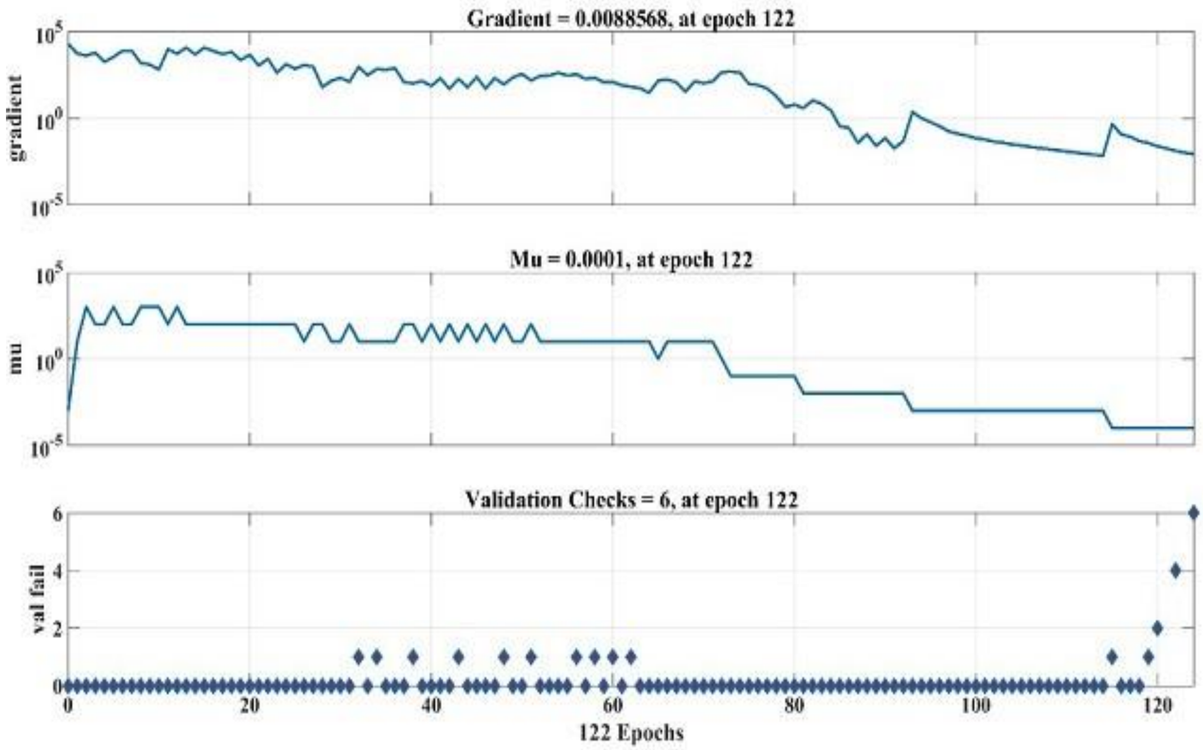

Figure 9. Traning of ANN Model and fine Tuning of Parameters

The standard 3 layers concept is used as:

Input layers:

We pass our all input features to the ANN model as the name suggestet the input take the input in form of vector and pass it to the hidden layers.

Hidden layers:

Hidden layers take the features from the input layers which have layer after layer and assign the weights to each features in vectors the hidden layers performs all the calculation by mutiplying with input and weight of each feature and add them to find the hidden features and patterns,after passing into outlayers then through backpropegation the weights is updated for each iteration of the model.we used sigmoid function as activation function is all our hidden layers.

Output layer:

The output layer has a fully connected layer recive the values from hidden layers as ANN add biase to in each layer of hidden network , after several computation in input and hidden layers we get result in output layers .then we apply some threshold for activation function in our study we use the softmax activation function for our proposed Model. Sotmax activation is high probability activation function. Out put is maped If model achived the required result when subtracting actual output from desired out put which is coast function ,else through back propegation output is propegated and weighits are updated so the number of itration we used in our study is 1000.

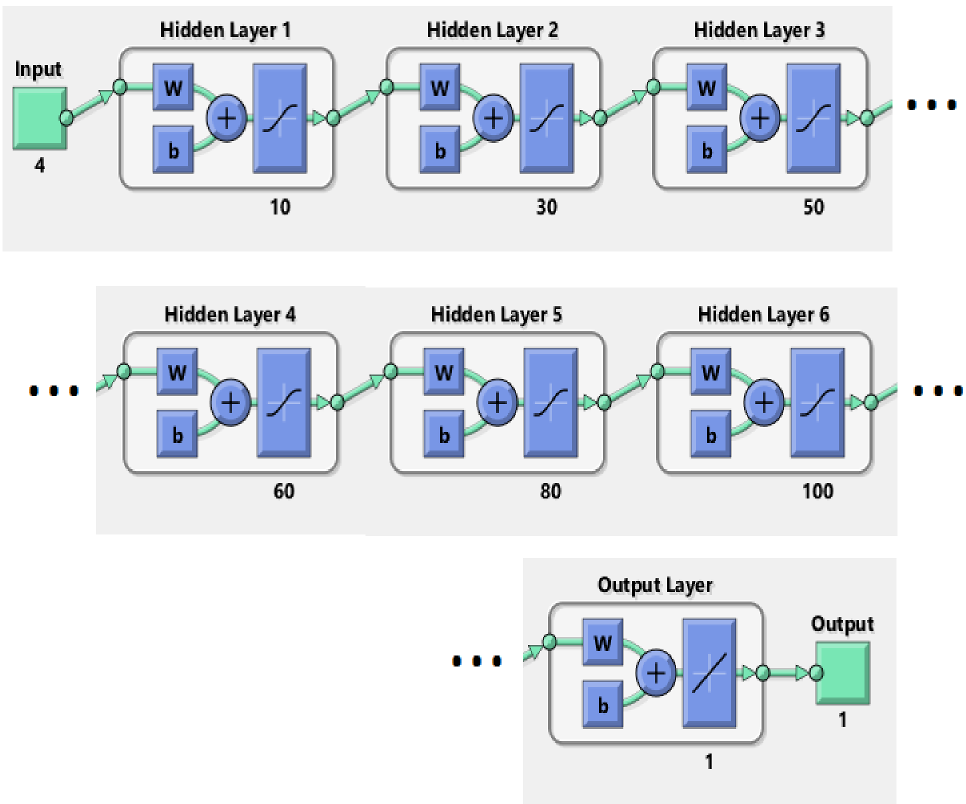

Figure 10. Proposed & designed ANN Frame work with Input , Hidden and Output layers

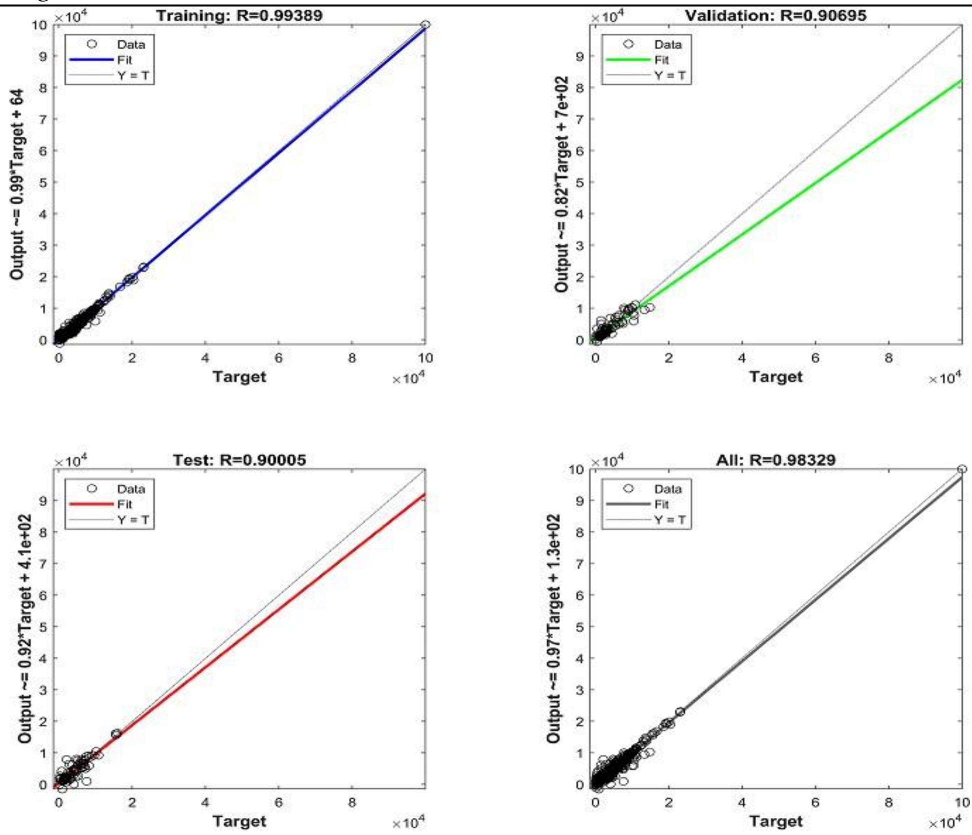

Figure 11. Training, validation, & Testing of ANN Model with varience of Dataset

After training data was completed, 15% of simulated data were used for the validation purpose of the trained model as shown in Figure 9, and Figure 10. The model was allowed to proceed to the test phase after accuracy is reached. For testing the proposed model, we will use 15% of data from the available data sets out of the remaining 30%. Looking at the value of R in Figure 11, is so close to 1 which means that the results are accurate. FFBPN consists of three layers, i.e, the input layer, the hidden layer, and the output layer. tang function used during training and the linear function (purelin) was used for testing the proposed FFBPN. Input signals are received by FFBPN through the input layer and proceed to the hidden layer which transforms it into something so that the output layer can use it in some way.

3.2 Long short-term memory (LSTM)

LSTM is an ANN technique based on the architecture of recurrent neural networks (RNN) [44]. These networks have feedback connections and process data sequentially. A typical unit of LSTM includes an input, forget and output gate along with cell state as shown in Figure 12.

Forget Gate:

Sigmoid is an important function of the forgetting gate. It decides on either to keep or forget data using sigmoid functions. The output scales between 0 and 1. The closer to 0 means to forget, and the closer to 1 means to keep on output as a vector f_t as given in Equation.3

Input Gate:

To update this gate, the sigmoid function takes the last/prior hidden state h_t and current/existing input X_t as inputs. This function decides about updating the values by first transforming these inputs to make it between the range of 0 and 1 same as discussed above. The output is denoted by a vector. The same values also pass through the tanh function to squish these between the range of -1 and 1 due to which the network keeps regulated. The result/output is denoted by $C^{\cdot}_t$ called as input activation vector. Next, we multiply the output of tanh with the output of the sigmoid function [45]. The decision to either keep or discard the data will be taken by the sigmoid output equation of the input gate given in Equation 4, as i_t.

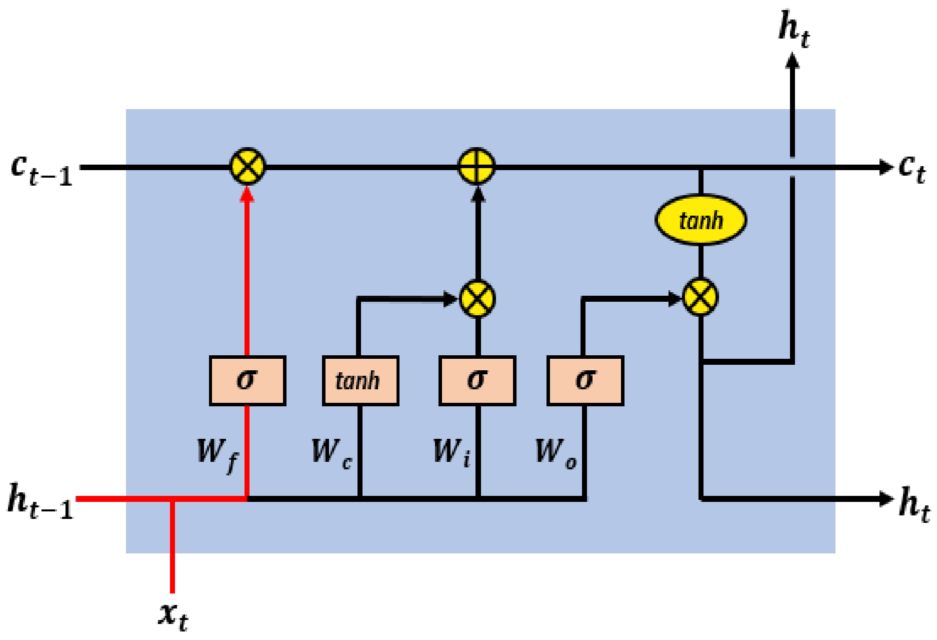

Figure 12. BasicFrame work of LSTM

Cell State:

This cell update and memorize the cell state by getting the value from point-wise multiplication of the previous state value and forgetting the vector. It will either drop or be kept. In the next step, it uses the values obtained from the input gate and performs a point-wise addition. This will update the cell state with the new values. Now this will be the new cell state denoted as vector C_t. the equation of Cell state as given in Equation 6.

Output Gate:

Output Gate generates the next hidden state h_t as given in Equation.5 which is used for predictions as it contains the information based on previous inputs. Previously hidden state h_t and current state X_t are passed through sigmoid and give us output as O_t. Then it passes the Ct to the tanh function and multiplies the output of the tanh function with the sigmoid function to decide what data will be kept by the hidden state for carrying on-wards and what to be discarded. The output O_t and give us the new hidden state h_t. Finally, this newly obtained cell state and hidden state are used on-wards accordingly to keep the process going on recurrently. Essential Equations of LSTM are given as

$$F_t = \sigma_g(W_f\ X_t + U_f h_t - 1 + b_f) \quad (3)$$

$$i_t = \sigma_g(W_i\ X_t + U_i h_t - 1 + b_i) \quad (4)$$

$$O_t = \sigma_g(W_o X_t + U_o h_t - 1 + b_o) \quad (5)$$

$$C_t = \sigma_c(W_c X_t + U_c h_t - 1 + b_c) \quad (6)$$

$$C_t = (f_t\, C_t - 1 + b_c) \quad (7)$$

$$h_t = O_t \sigma_t(C_t) \quad (8)$$

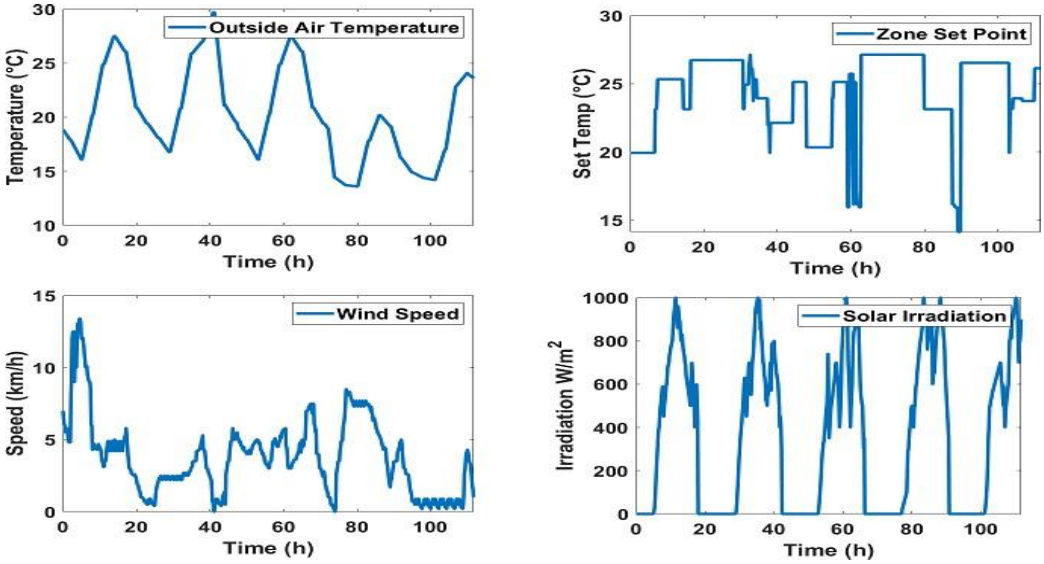

Figure 13. Graphs of Input features used in all 3-Phases

4. Results

Data sets were simulated using a variety of input and output parameters to train and evaluate a model for predicting the output power of an HVAC system. The data sets were created using different input parameters such as outside air temperature, set or desired temperature, speed of air, and solar irradiation. The corresponding outputs represented the predicted output power of the HVAC system.

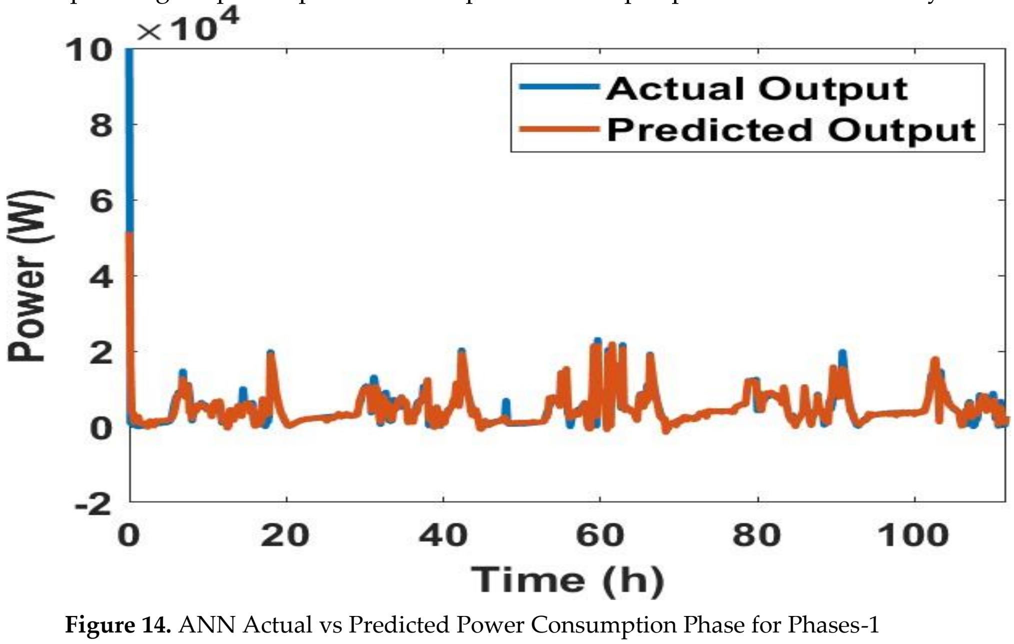

Figure 14. ANN Actual vs Predicted Power Consumption Phase for Phases-1

The best-performing data set was selected for training and the results were presented in the form of graphs. The HVAC system in question is a three-phase system, and the study focused on predicting the output power of one of the phases. The input parameters were fed into the system and the corresponding outputs were used to evaluate the performance of the model. It's worth noting that the set temperature of the HVAC system is dynamic and the user is adjusting it between 15 and 28 degrees (approximately) as shown in Figure 13, this suggests that the HVAC system is designed to be adaptable to different temperature requirements, and the model should be able to handle this kind of dynamic input. Overall, the study aimed to develop a model that could accurately predict the output power of an HVAC system based on a set of input parameters. The results of the study showed that the proposed model of ANN performed well when trained on the best performing data set, and the results were presented in the form of a graphical representation for better understanding. The graph of actual and predicted output power is shown in Figure 14, Observe that the ANN is performing very well and the results are accurate. We get testing accuracy for phase -1 remain 96.05% while the training accuracy is 98% .

We trained the LSTM model for same phase the accuracy for phase -1 remain 78.05% to compare the difference between the actual and predicted output power for the Red phase or Phase-1 graph for LSTM model is shown in Figure 15.

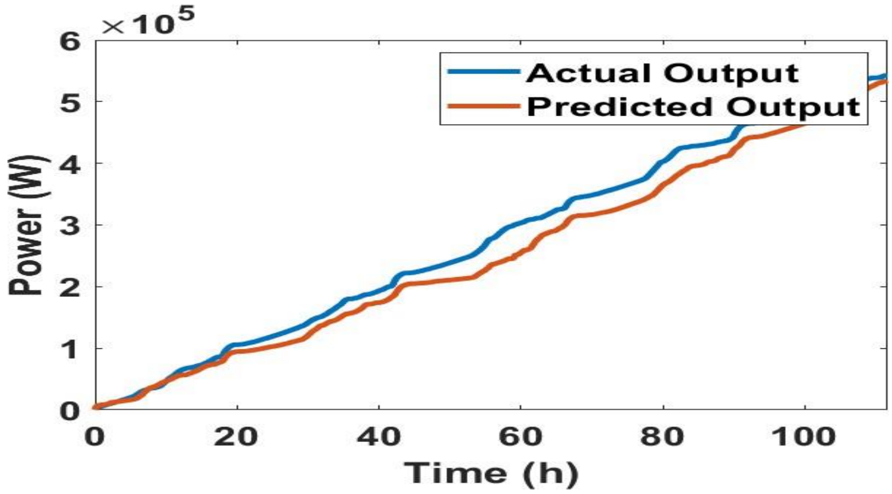

Figure 15. The LSTM of Actual vs Predicted Power Consumption Phase-1

The same trained model of LSTM has then tested for another phase a result of the LSTM model is shown in Figure 15, we have the same thing as of Phase 1 or the Red phase but as changes in temperature and wind, the training was agin done on another phase if satisfaction to removing the weight learning to be same with changing of phase datasets of input data.

The graph of actual and predicted output power is shown in Figure 14, we then observe that the ANN is performing very well and the results are accurate same as the previous results for phase-1.

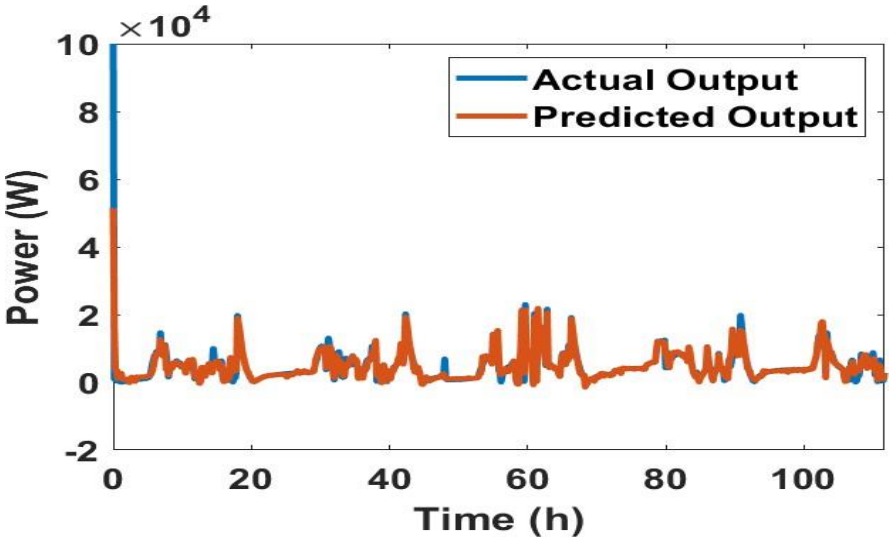

Figure 16. ANN Actual vs Predicted Power Consumption for Phase-2

But here when we checked the difference between the actual and predicted output power for phase 2, the errors are minimized as compared to the errors observed in the case of phase 1. Following the graph as shown in Figure 16.

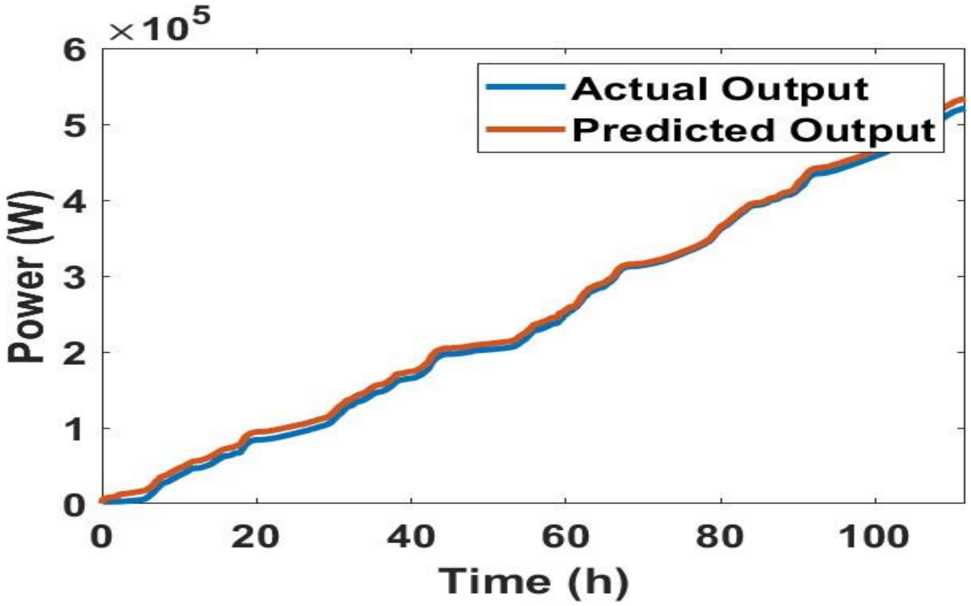

Figure 17. The LSTM of Actual vs Predicted Power Consumption Phase-2

The set of data from data sets that performed better in the case of ML-ANN for phase 2 or Yellow Phase of power record was used for the model as shown in Figure 17, the accuracy of predicting actual power consumption is 96.3% of the actual power which is consumed while labeling but for the LSTM same phase phase validation remins 77.98%. The predicted output power looks close to the actual power consumed.

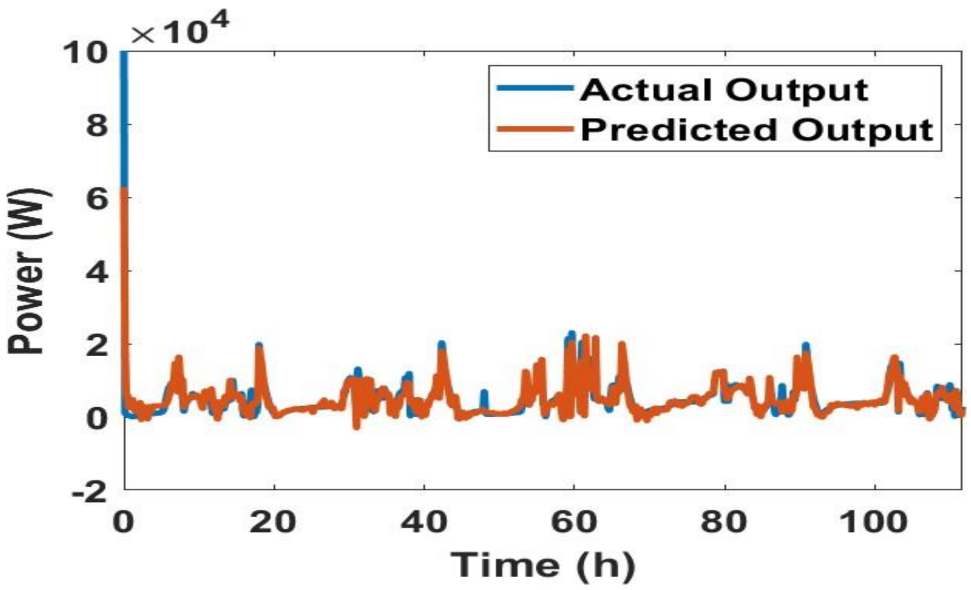

Figure 18. ANN Actual vs Predicted Power Consumption for Phase-3

But looking into the error graph, the error is less than phase-1 of ML-ANN but a little more than phase-2 of ML-ANN. The graph is shown in Figure 18. We checked for each phase as shown in figures a bit difference was seen perhaps overall accuracy variates in points around 96% for all phases of ML-ANN model for Phase-3 the accuracy is 96.38% in predicting the actual value.

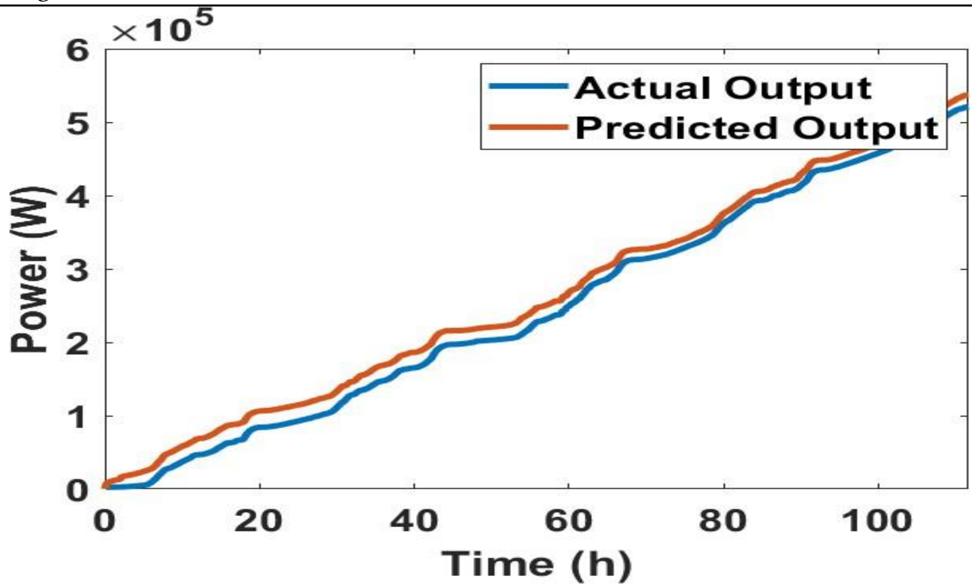

Figure 19. The LSTM of Actual vs Predicted Power Consumption Phase-3

Training, Testing, and validation of Deep learning LSTM model and tuning the Hyper parameters and in an increase of Hidden layers numbers of LSTM model doses not change the overall evaluation matrices which were around 78% after rounding as we get the 78.76% accurate prediction to that if the actual value shown in Figure 19 for Phase-3. so far we have a good result for each phase of ANN than LSTM Model.

5. Discussion

Both the ML-ANN and LSTM are performing well using the data sets of a real case of a tertiary care hospital. However, comparatively, ML-ANN outperforms LSTM in this case. The comparison graphs showing errors between actual power and predicated power can be seen in Figure 20, both LSTM and ANN Prediction is shown clearly show the result of both models, Lstm is less accurate than ANN researcher repeated for individual Phase which is Red, Blue and green and combine the result shown in Figures of comparisons for both LSTM and ANN model.

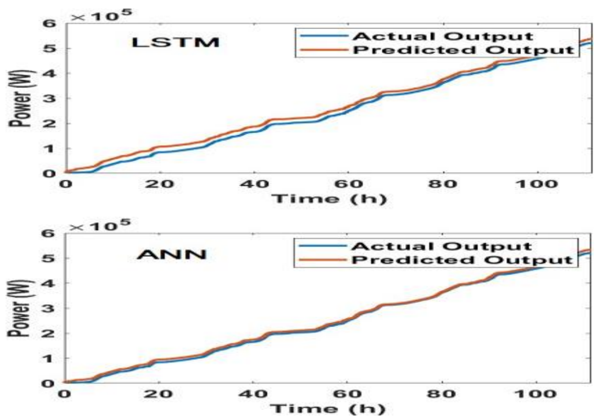

Figure 20. LSTM vs ANN Predicted Power Consumption of All 3-Phases

6. Conclusions

The study aimed to develop accurate models for predicting and controlling the temperature in an operating room. The data sets used in the study were created using real-time data from the operating room of a top hospital in the capital of Pakistan. Three different sets of input and output data were randomly selected, and each set was used for training, testing, and validation. The input data included various factors such as room temperature, humidity, and airflow while the output data represented the desired temperature in the operating room. The proposed models, ML-ANN and LSTM, were trained using the input and output data sets. The performance of the models was evaluated by comparing their predictions to the actual values. The results showed that the ML-ANN model performed better than the LSTM model, with a testing accuracy of 96% compared to 78% for the LSTM model. This indicates that the ML-ANN model was more accurate in predicting the desired temperature in the operating room. Additionally, the study also showed that the ML-ANN model was particularly effective when the desired temperature was frequently changing. This suggests that the ML-ANN model is better suited for dynamic and unpredictable environments such as an operating room. In conclusion, the study provides evidence that the ML-ANN model can be used to predict and control the temperature in an operating room with high accuracy and efficiency. And it is particularly useful when the environment is dynamic and unpredictable. The correlation matrix shows in the Figure 21, correlation coefficient between each pair of variables, where 1.00 indicates a perfect positive correlation, -1.00 indicates a perfect negative correlation, and 0.00 indicates no correlation. In this case, we can see that the output power is highly correlated with the outside air temperature, set temperature, and solar radiation, indicating that these input parameters have a strong influence on the output power.

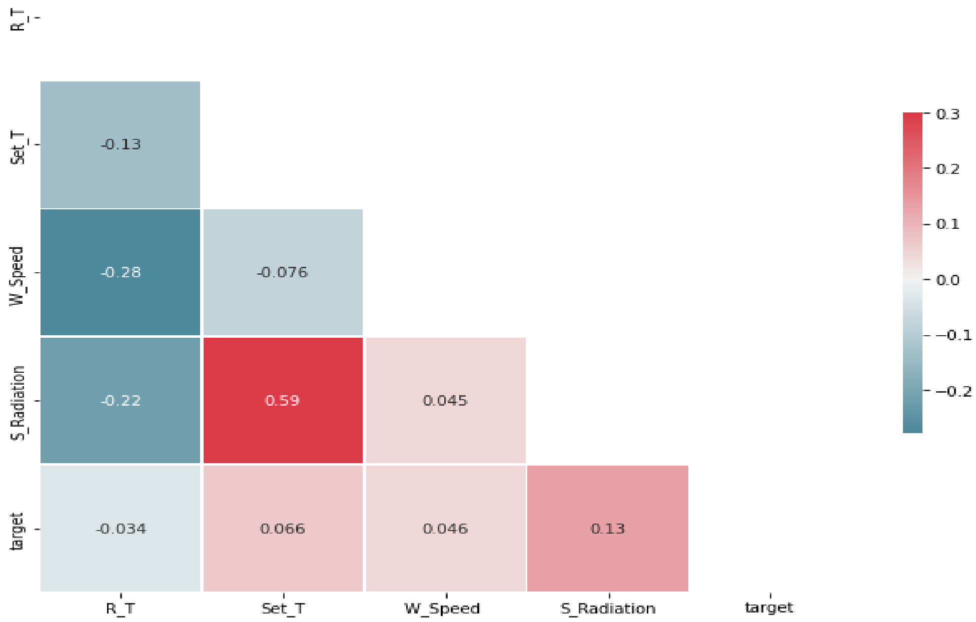

Figure 21. Correlation Metrix

The correlation between the speed of air and the output power is negative, indicating a negative correlation, which indicates that as the speed of air increases, the output power decreases[45]. This correlation matrix provides a clear picture of the relationship between the input parameters and the output parameter in this study and can be useful in interpreting the results of the study.

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