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Average Midterm Electrical Load Forecasting for Duhok City Based on Artificial Neural Network

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Abstract

The demand of the city of Duhok for electricity is increasing and this requires efforts to provide the required load. Building new electricity generation units and/or importing electricity from neighboring countries are available to fulfill these needs. Therefore, it is vital to have earlier information about electrical demand. Midterm electrical load forecasting is useful to estimate the required power to be extracted from power systems in a time span of one year. In addition, it provides information that is necessary for planning the maintenance, expansion, and improving system performance of electrical power generation. These have an impact on reducing the operational costs and the emission of power plants through reducing the fuel consumption. Therefore, this paper proposes a medium-term load forecasting based Artificial Neural Network (ANN) and applies it on Duhok city power system. Available data for the power system of the city is used in the ANN to predict the load demand up to the year 2025. Using ANN in forecasting has importance because of its simplicity, easy implementation, yet effective and superior performance.

1. Introduction

Electricity load forecasting is an essential task for a reliable and secure operation of power systems [1], accurate load forecasting has a great importance and represent great saving for network; it helps to make right decisions about power generation, transmission, and distribution in order to provide high quality electric power to the consumer in a secure and economic manner [2][3], Proper load forecasting helps to decrease costs due to energy shortage or its oversupply. A study from the California energy commission indicates possibility of saving millions of USD yearly by improving solar energy and accurate electrical demand predicting [4]. Load forecasting or load predicting process is to achieve future information about electrical load based on past load recordings, which aids in making appropriate decisions to maintain a balance between power generation and power consumption [5][6][7], this process also indicates whether to build new electrical generation units or work for improving the existing generation units [10]. Mid-term load forecasting methods can be classified into two types, time series methods and machine learning methods. Early studies used time series methods which depend on linear models that based on statistical data [9] such as linear regression method employed in [10], and the exponential smoothing method studied in [11] where the developed model offered high accuracy in forecasting. Time series models are doing well in linear forecasting problems are not efficient for complex nonlinear loads [12]. Therefore, machine learning method, such as ANN, can be used to handle nonlinear functions and perform electrical load forecasting efficiently [13]. Electrical load forecasting using ANN has started since early 1990s [14], and applications of hybrid ANNs model with statistical methods or other intelligent techniques have received great attention since 2007 [15]. Current studies have shown that ANN represents an efficient tool for handling other power system problems like load flow analysis, voltage stability analysis, fault detection and excreta [16]. Neural Networks (NNs) can model non-linear relationships and can learn complex relationships between input set and output set vectors without the need for a function representing relationship between these sample sets, where a high value regression value , with a very low mean square deviation is achieved. Therefore, many researchers use ANN for forecasting studies such as mid-term load forecasting [17], [18]. In [17] electrical load forecasting is studied for daily electrical load over duration of one year using different ANN algorithms. ANN algorithm requires a large amount of data samples to perform midterm forecasts efficiently. To overcome the lack of data, the study in [18] proposed a multi-model feed forward neural network (NN) combining the outputs of the nonlinear auto regressive NN for load demand forecasting. The proposed model in [18] can deal efficiently with small amount of load data and performs better than the conventional approaches.

The author in [19] proposed a novel hybrid approach in which the periodic behavior is forecasted using Fourier series and NN is used to forecast the trend. The available load forecasting studies investigated and showed that many factors are affecting load demand, and it is difficult to identify which factor has the greatest impact. However, in many places, the weather conditions and temperature are the main factors and have a direct impact on the consumption of electrical energy. A study is performed in [20] using ANN to predict weather-sensitive factors of electrical load. Factors of wind speed and humidity are also added and investigated in the study as two essential weather factors for accurate forecasting in [21]. However, accurate forecasting of the load is a challenging task due to the complex and dynamic nature of electricity consumption, which is influenced by different factors such as economic conditions, and consumer behavior [22], [23]. Based on the duration of prediction, the forecast of electrical load can be classified into four types:1) very short term load forecasting which usually predicts loads for a time frame less than one day, 2) short term load forecasting predicts load for a time period greater than one day up to one week, this is used in controlling and scheduling of power systems [24], 3) midterm load forecasting in time frame of a week to a year and plays important role in fuel supply scheduling and maintenance of power system [25], 4) and long term load forecasts that is used for the future planning of electric power system and span from a year to about fifteen years [26]. This study considers midterms load forecasting for Duhok city power system using Artificial Neural Network.

2. Midterm load forecasting

Midterm load forecasting is necessary for estimating the amount of power generation, the size of load consumption, and future planning, expansion and maintenance of substations [27]. Electrical load forecasts must be based on historical load data of the desired area. Electric load demand can be divided into two forms, average load demand measured in (kilowatt-hours or megawatt-hours), and peak load demand measured in (kilowatts or megawatts) [28]. Peak load demand studies are usually carried out by engineers. Different techniques and methods are used by researchers for forecasting the average load demand such as regression analysis, time series, fuzzy logic and ANN [2].

3. Electricity consumption and variables

This study considers Duhok city in Kurdistan region-Iraq as a case study. Duhok city is an example of a developing area that has a sharp increase in energy consumption due to the growth in its population and urban expansion. The correlation of load consumption and time has a very complex nonlinear relation depending on various complex factors like weather, population, and economic growth [30].

A. Energy Consumption Demands in Duhok City

The data of average energy load demand of Duhok city that is required for the midterms load forecasting study is obtained from the Electricity Control Center in Duhok city. The data obtained is the monthly average energy consumption for the period from January 2015 to December 2024. As shown in Fig. (1), the monthly average energy consumption shows a nonlinear relationship with time. For a specific month, the load is increasing annually. For a particular year, the highest energy demand was in January and/or February, while the minimum demand was recorded in May and/or October. Fig. (2) Shows the average energy. consumption for the last three years. The average energy consumption graphs show two local minimums in May and December and two local maximums in February and July. The energy consumption in February is significantly higher than the consumption in July. The climate of Duhok city is generally fluctuating; summers are warm and dry, while winters are cold and snowy. The difference in temperature between the seasons greatly affects the load consumption in a way that load peaks are observed in summer and winter each year. Fig. (3) Represents monthly average temperature profile for 2024. The lowest average temperature is observed in January and the highest average temperature occurred in July.

B. Variables influencing energy consumption demands

In general, several variables have an impact on the behavior of power system and particularly affect the power consumption demand. The variables that affect energy consumption can be classified into two groups. The first group of variables is the weather variables and population which are considered in this study. The weather parameters are related to the seasonal climate changes and include maximum temperature, minimum temperature, average temperature, rainfall. Other weather affecting parameters like humidity and wind speed are not considered in this study. The second group variables are economic variables of the country, which is not considered in this study.

4. Artificial neural network

Recently the study of the ANN models is gaining more attention because of their ability and efficiency to solve problems that are hard to solve using the known conventional methods. ANN is selected for the study in this paper since it can approximate non-linear functions of the load profile for electrical system. Furthermore, ANN can handle many parameters or variables, provides solutions for forecasting problems with predictive results, and have a feature for continuous learning [31]. ANN is a computational system, made up of a number of simple, and highly interconnected processing units named artificial neuron. Information is processed as response to external inputs. Fig. (4) Shows the architecture of an ANN model. Each neuron can have a number of inputs but only one output. The connections between neurons have weights which represent the strength of a specified input. The neuron executes the sum of its weighted inputs. The output is calculated by applying a non-linear function to the summed result. The non-linear function, which is known as the activation function, enables the ANN to perform complex problems [32]. TANSIG activation functions of Fig. (5) Is mostly used in hidden layer for NN models to perform electrical load forecasting [33].

Normally, the neurons in NN are arranged in three main layers, one input layer, one or more intermediate or hidden layers, and one output layer. The input layer delivers data to the network and the output layer is used to deliver the output variables to output. The feed forward back propagation (FFBP) based Levenberg-Marquardt algorithm is a supervised learning algorithm used widely for training NN. This algorithm is a forecasting algorithm , in which the difference between the predicted outputs and actual outputs (the error) is calculated, then the deviations or errors propagated back and multiplied by inputs, new weights were adjusted. [34], the cycle of weight adjustment can be defined as a learning process [35]. This learning process is repeated for a number of iterations or epochs until the weights converge and the error is at minimum value. The regression of NN (R) or correlation coefficient value during training and testing indicates whether the results of the proposed model fit with the original values or not [20]. The number of neurons in the hidden layer must be tested to find the optimal weight before forecasting the power demand. In this paper, different numbers of neurons from 5 to 24 in the hidden layer are investigated. Finally, 22 neurons were utilized for their best performance. To obtain accurate load forecasting, it is necessary to select a proper sample data set. The learning process of the ANN requires a large data set. This paper uses data of average monthly energy consumption of ten years to train the ANN model. Various factors like weather temperature (maximum, minimum and average temperature), precipitation, and population were considered and introduced into the ANN model. These factors represent the feature of the input dataset of the model for enhancing the quality of load forecasting. The architecture of the proposed ANN model is shown in Fig. (6). the inputs and outputs feature for ANN model are shown where the forecasting is denoted by energy consumption E output. The input-output dataset is separated into two groups, a training group and a testing group. The former group is composed of load data of nine years from January 2015 to December 2023, this represents 90% of the input data and is used to train the ANN model and adjust weights. The second group uses 10% of input data to verify the validity of the model, which is obtained from January 2024 and December 2024. After defining the input and output data sets, the ANN model is created to train, test and perform load forecasting. Fig. (7) Shows a diagram for the electrical load forecasting for next year (2025). The ANN model uses historical input-output data set from beginning of -108 to the end of -12 months for training and from the end of -12 to end of 0 for testing to forecast the load of the end of 0 to the end of +12 for forecasting.

To measure the accuracy of forecasted results, the mean square error (MSE) of Equation (1) is used. The MSE error of the load forecast represents the amount of deviation between actual and predicted values [31].

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(Yi - Y\prime i)^2}{n} \quad (1)$$

Where Y_i is the actual load, Y_i' is the forecast load and n is the number of sample. Each neural networks system is unique since it has different input and output features. Fig. (8) Shows the flowchart of the ANN model [36], which explain that the collected data divided in to two groups, the first for training and the second for testing, first group goes through created NN and trained, when it reaches the desired the desired accuracy, the NN will be ready for testing the second group, finally we can predict for the future demand.

5. Simulation results analysis and discyssion

As mentioned earlier, this paper uses ANN model to perform the midterm load forecasting for the city of Duhok as a case study. The database consists of the average monthly energy consumption of ten years from January 2015 to December 2024. The inputs of the ANN model are historical temperature, rainfall and population. The output is the midterm forecast for the average monthly energy consumption. Several training algorithms are tested in the training process, such as traingdm, traingdx, trainrp, and trainlm. The trainlm (Levenberg-Marquardt) algorithm provided the best results. The proposed ANN is a two-layer FFBP network with Tansigmoid based neurons in hidden layer and output layer as shown in Fig. (9). It is observed that 22 neurons in the hidden layer provide minimum percentage error for nearly 9 months. Fig. (10) Represents the outputs of the ANN model for regression values of 0.98 and 0.99 for training and testing, respectively, the validation value is 0.998 that is used to monitor the learning process and prevent over fitting. The testing set is used to evaluate the final performance of your ANN on unseen data.. The output results of the ANN model fit with the original values very well. The MSE performance of the ANN model training is shown in Fig. (11). The MSE graph indicates a very low deviation between the forecasted and actual values of the load. The MSE approaches a value of (3.7e -12) after 13 iterations. This implies high accuracy for the ANN model in forecasting the midterm average monthly load. Fig. 12 shows obtained results from testing the trained ANN for the year 2024 period. Fig. (12)(A) Shows the actual and forecasted energy consumption in kWh on Y-axis versus the months Y-axis of the year, while Fig. (12)(B) Shows the percentage error (%Err.) which is equal to difference between the forecasted and actual loads divided by actual value multiplied by hundred, it indicate that the error is very small, for four months it is less than %2, only three months error reaches %2.84. The test (forecasted) load results of the ANN model and the actual loads of the year 2024 with the percentage of error between them are listed in Table 1. The results indicate the efficiency of the ANN in predicting electrical load demand. A maximum percentage of error of 2.84% is observed in August. This represents a high degree of accuracy in the ability of neural networks to forecast electric load, the study in [28] obtained results of percentage error near to that obtained in this work. According to Table 1, the total average load consumption in 2024 was 4053 kWh while the forecasted consumption by the ANN model is 3984 kWh. The total error in the actual and the forecasted consumed energy is 69 kWh per year. After training and testing the ANN model, it can now be used to forecast the future load for the upcoming 12 months in 2025 using the same variables, hidden layers and training algorithms. Table 2 lists the forecast results of the ANN model for energy consumption in 2025. As expected from the historical data from 2015 to 2024, the total energy consumption will increase to 4187.06 kWh in 2025. This is 134.06 kWh higher than the consumed energy in 2024. The forecasted energy consumption also shows an increase in load during hot and cold months due to fluctuation in temperature. The increase in energy consumption (total and monthly) compared to 2024 is expected because of urban expansion in the city.

6. Conclusion

Accurate load forecasting is important to guarantee efficient operation of power system. It is a basic requirement to balance energy generation and consumption and reduce costs associated with shortage or oversupply of energy. ANN models have shown encouraging results in predicting midterm energy consumption. This paper used ANN to perform midterm energy consumption forecast for the city of Duhok as a case study. Average monthly energy consumption data of Duhok city for the years from 2015 to 2024 to train and test the ANN model.

In this work, the midterm average energy consumption forecast in Duhok city for one year-ahead is performed using ANN. The study implemented using MATLAB, FFBP algorithm in the training process. The results showed that the algorithm is robust for weights estimation. Considering the obtained high regression (R) values and MSE, it can be concluded that the proposed ANN model is efficient for midterm electrical load forecasting in modeling the nonlinear relationship between the different weather factors, precipitation, and population growth. The results showed predictions with high precision. The proposed ANN model has four inputs, 22 neurons in the hidden layer with Tansigmoid transfer function. It is observed that the proper selection of the number of neurons and activation function resulted in reduced MSE. A maximum percentage error of 2.87% is observed between the actual and forecasted values. This study used only temperature and precipitation among many weather factors, however, other weather variables such as clouds, dust, and wind speed can be added in future studies to enhance the capability and accuracy of the proposed ANN model.

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متوسط توقعات الأحمال الكهربائية المتوقعة في منتصف المدة لمدينة دهوك استنادًا إلى الشبكة العصبية الاصطناعية

المستخلص :

إن طلب مدينة دهوك على الكهرباء يتزايد وهذا يتطلب بذل الجهود لتوفير الحمل المطلوب و بناء وحدات جديدة لتوليد الكهرباء و/أو استيراد الكهرباء من الدول المجاورة متاح لتلبية هذه الاحتياجات. لذلك ، من الضروري الحصول على معلومات مبكرة حول الطلب على الكهرباء . يعد التنبؤ بالحمل الكهربائي متوسط المدى مفيدا لتقدير الطاقة المطلوبة التي سيتم استخراجها من أنظمة الطاقة في فترة زمنية مدتها عام واحد. بالإضافة إلى ذلك ، فإنه يوفر المعلومات اللازمة للتخطيط و الصيانة والتوسع وتحسين أداء النظام لتوليد الطاقة الكهربائية ، وهذا له تأثير على تقليل التكاليف التشغيلية والانبعاثات من محطات توليد الطاقة من خلال تقليل استهلاك الوقود ، لذلك يقترح هذا البحث شبكة عصبية صناعية (ANN) تعتمد على التنبؤ بالأحمال متوسطة المدى وتطبيقها على نظام الطاقة في مدينة دهوك. يتم استخدام البيانات المتاحة لنظام الطاقة في المدينة في ANN للتنبؤ بطلب الأحمال حتى عام ٢٠٢٥.

ان استخدام الشبكة العصبية في التنبؤ له أهمية بسبب بساطتها وسهولة تنفيذها وأدائها الفعال والمتفوق ، حيث يتم تحقيق قيمة انحدارعالية تبلغ ٠.٩٨٨ مع متوسط انحراف تربيعي منخفض جدا يبلغ ٣.٧ × ١٠-١٢.

الكلمات المفتاحية:

الشبكة العصبية الاصطناعية ، نظام طاقة مدينة دهوك ، KRPS ، التنبؤ بالحمل على المدى المتوسط

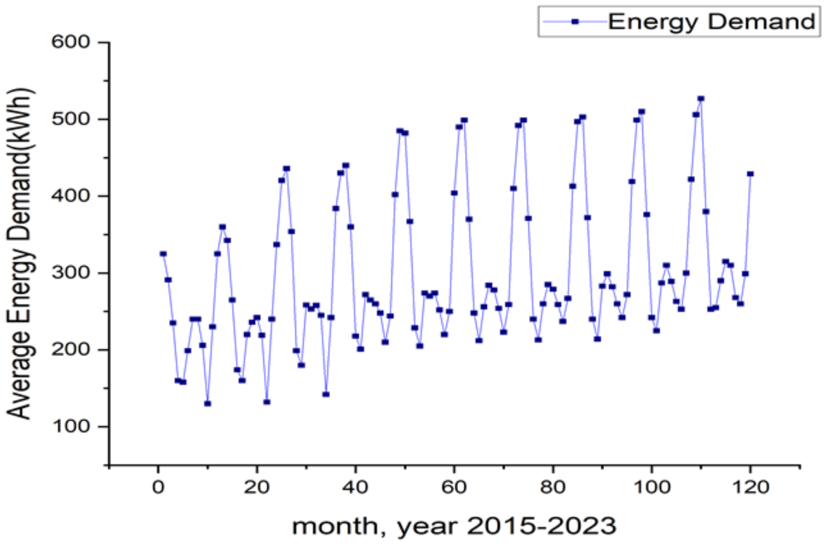

Fig. (1): Monthly average energy consumption of Duhok city from Jan. 2015 to Des. 2024.

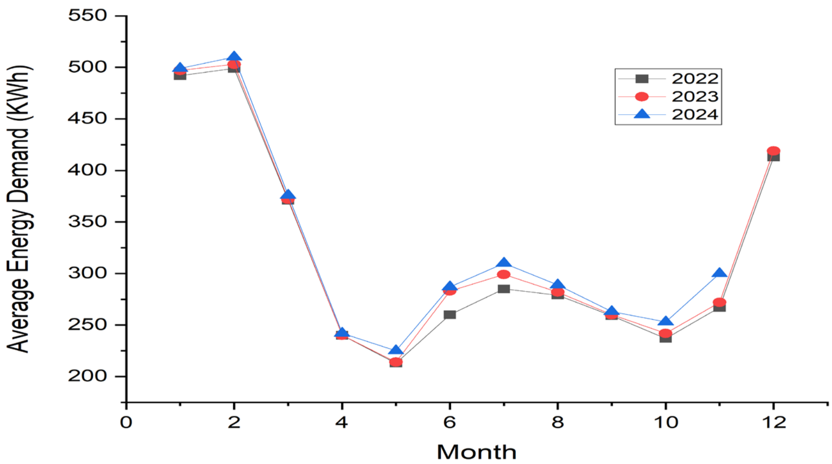

Fig. (2): Average energy consumption in Duhok city for last three years.

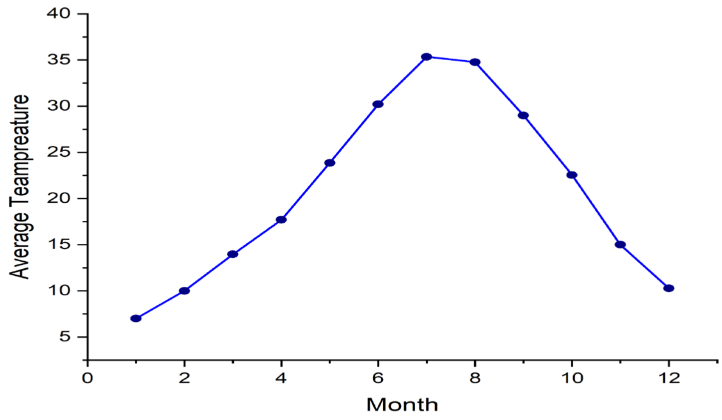

Fig. (3): Average temperature of Duhok city for year2024.

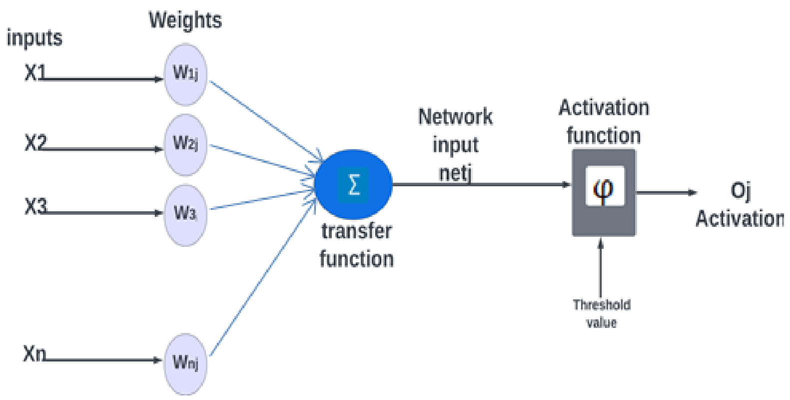

Fig. (4): Shows architecture of a neural network model [34].

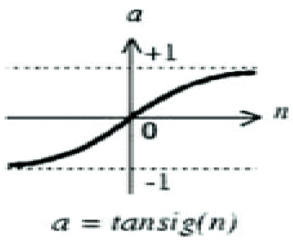

Fig. (5): TANSIG activation function [34].

Fig. (6): ANN model structure.

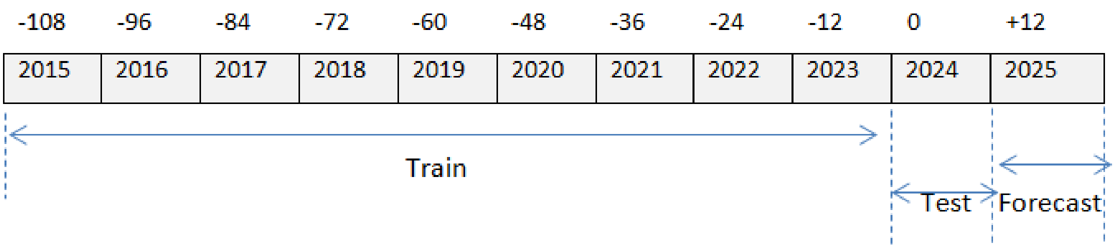

Fig. (7): Data set mapping for training, testing and predicting.

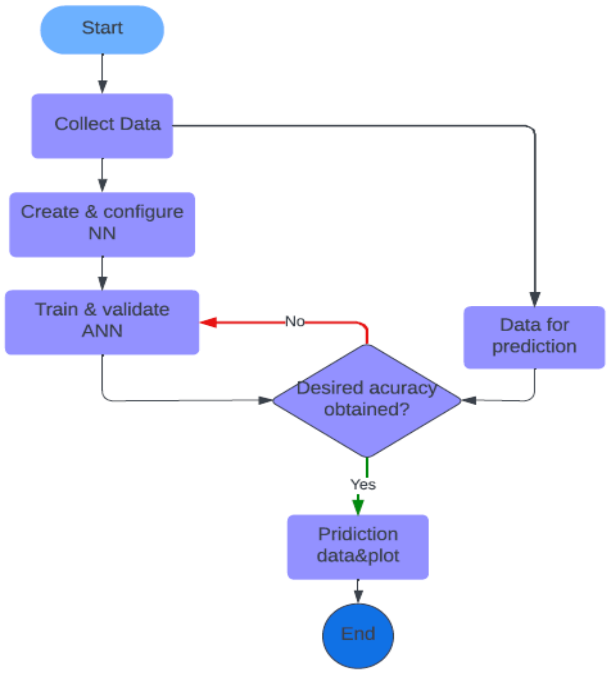

Fig. (8): Work flowchart of ANN model.

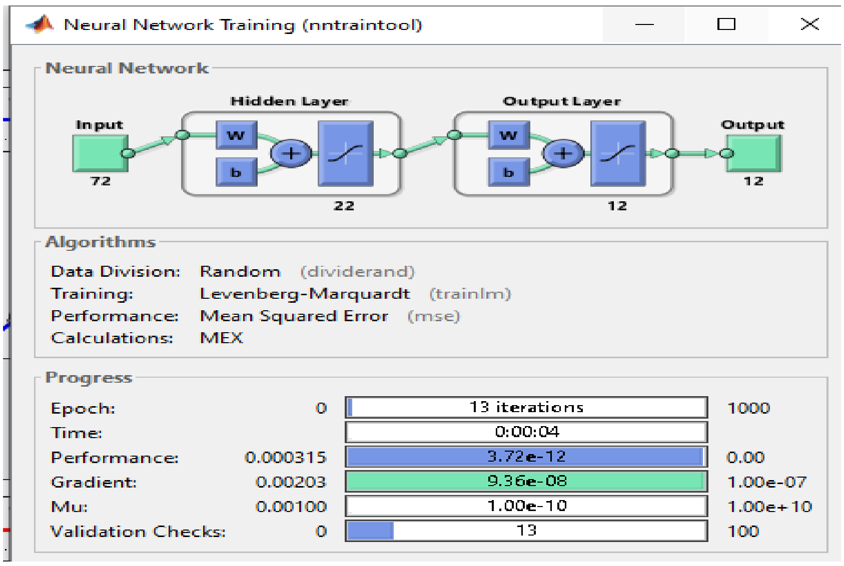

Figure. (9): A trained neural network.

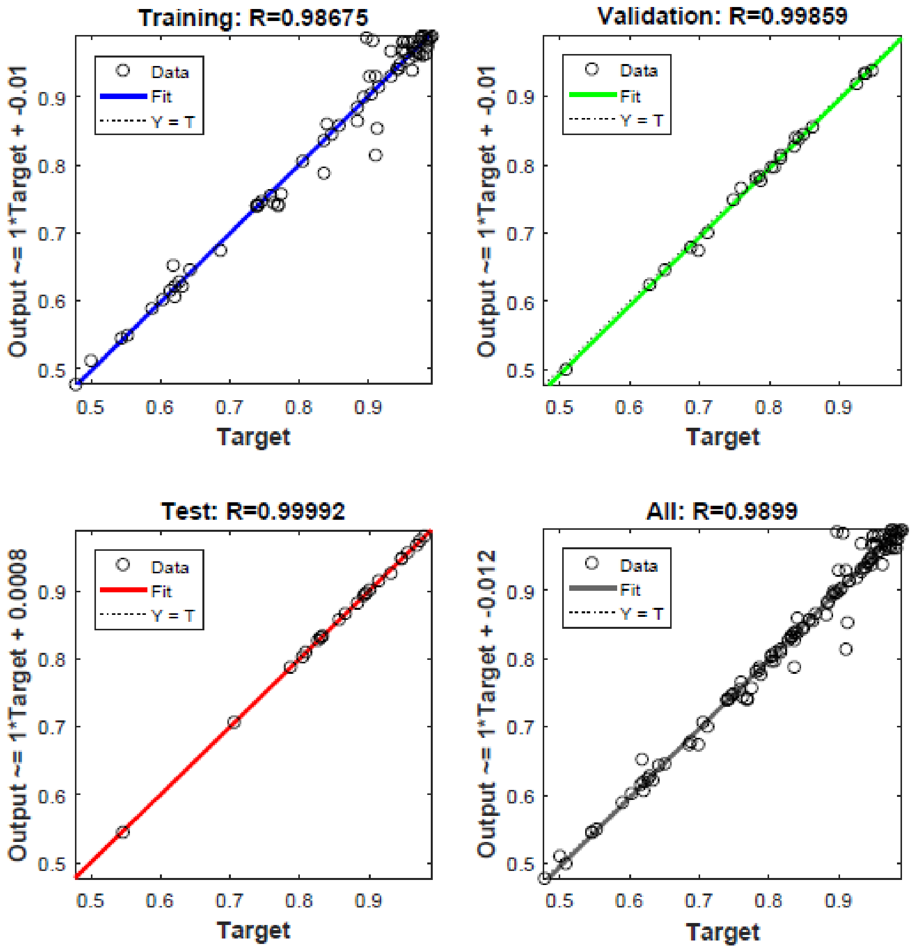

Fig. (10): Neural network regression.

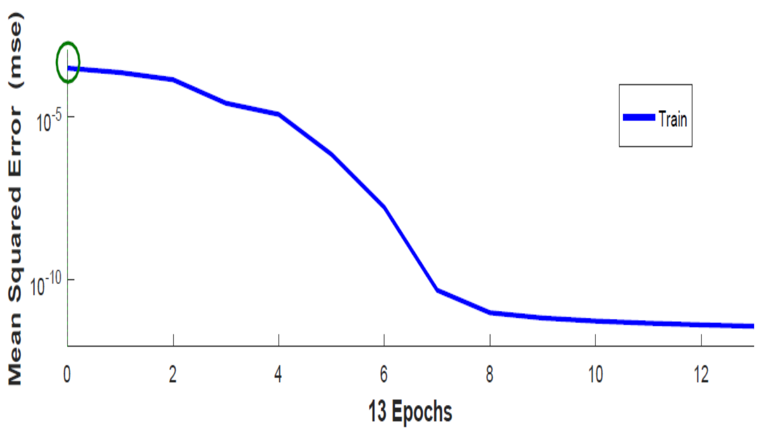

Fig. (11): MSE Performance of ANN model training.

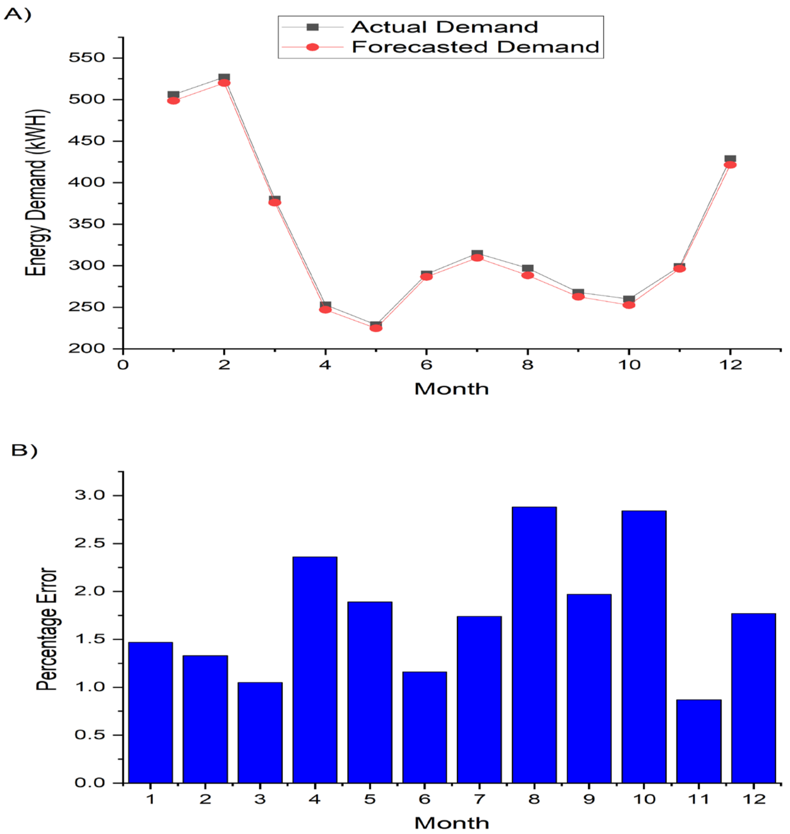

Fig. (12): (a) Actual and forecast energy demand in 2024, (B) percentage error.

Table1. Comparison between forecasted and actual energy consumption in 2024.

Month	Actual Energy (kWh)	forecast Energy (kWh)	%Error
January	506	498.5618	1.47
February	527	519.9779	1.332467
March	380	376.01	1.05
April	253	247.0198	2.363715
May	229	224.6805	1.886245
June	290	286.636	1.16
July	315	309.519	1.74
August	297	288.455	2.877104
September	268	262.7204	1.97
October	260	252.616	2.84
November	299	296.3988	0.869967
December	429	421.4067	1.77
Total	4053	3984.002	21.32

Table 2. Forecasting load for12 months in 2025.

Month	Energy Demand in (kWH)
January	510.3
February	534.11
March	387.099
April	261.445
May	262.3
June	295.9
July	323.44
August	320.022
September	274.81
October	268.29
November	312.112
December	437.234
total	4187.062