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Day Ahead Forecasting of Photovoltaic Power Output in Maiduguri Using Feedforward Neural Network

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ABSTRACT

With the increasing use of large scale grid-connected PV system, accurate forecasting approach for the power output PV system has become an important issue. Power planning is necessary for cost efficiency of power generation in which power forecasting is an essential part. For the Feed Forward Neural Network (FFNN) models, pre-processing techniques was used on the relevant variables. In this research work, FFNN based model was designed to forecast the next day PV power output of Maiduguri depending on available variables (Time of the day, day of the week, temperature, relative humidity, wind speed, cloud cover and PV power output) for the model. The FFNN based models were designed in the MATLAB® (R2015a) environment. Hence based on the results obtained from this research, it can be concluded that the FFNN based model performance is satisfactory for predicting next day PV power output. From the mean absolute percentage error (MAPE) value of 8.9093 on the test data set, it can be concluded that the Model had a better MAPE value which is an indication that the system performance is better than ANFIS which had 15.0048 as MAPE.

Keywords: Feed Forward Neural Network (FFNN), APE (Absolute Percentage Error), MAPE (Mean Absolute Percentage error).

INTRODUCTION

Solar energy which is free and abundant in most parts of the world has proven to be an economical source of energy in many applications. The energy that the earth receives from the sun is so enormous and lasting and that the total energy consumed annually by the entire world is supplied in a short while. The sun is a clean and renewable energy source, which produces neither green-house gas effect nor toxic waste through it utilization (Rekioua & Matagne, 2012).

Photovoltaic (PV) is a technology in which radiant energy from the sun is converted to direct current (DC) electricity. The most important advantages of photovoltaic system are:

i. The photovoltaic processes are completely solid state and self-contained.

ii. There are no moving parts and no material consumed or emitted.

iii. They are non-polluting emission.

iv. They required no connection with existing power source or fuel supply.

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v. They may be combined with other power sources to increase system stability.

vi. They can withstand severe weather conditions.

vii. They consume no fossil fuels - their fuel is abundant and free.

viii. They can be installed and upgraded as modular building blocks; more photovoltaic modules may be added as power demand increases.

The watt peak power prices were considerable increases and also couple with lack of power (power outage) in Maiduguri for some months has led to large - scale application of photovoltaic system in several areas within the metropolis.

Compared with conventional fossil energy sources, Small-scaled Stand-along photovoltaic (PV) systems are the best option for many remote applications around the world. Small-scale Stand-along photovoltaic (PV) system now provide power for hundreds of thousands installation throughout the world. They have the potential to be used in millions more, particularly in developing countries. (Rekioua & Matagne, 2012).

PV penetration provides many environmental and economic benefits, but the stochastic behaviour of the solar power may also introduce technical issues such as generation schedule, operating reserve, market regulation, without robust and precise forecast (Tuohy et al., 2015).

A reliable forecast is the key for several smart-grid applications (Adinolfi et al., 2013), such as optimal dispatch, (Ming et al., 2018), active demand response, grid regulation, and intelligent energy management (Van der Meer, Mouli, Mouli, Elizondo, & Bauer, 2016). PV forecasting represents a large research topic which can be characterized by the time horizon related to the prediction (Das et al., 2018):

i. Very short/short-term forecasting, wherein the time horizon varies from seconds to 24 or 48 hours;

ii. Medium-term forecasting, this analyse periods up to one month;

iii. Long-term forecasting, wherein the prediction horizon can be set to 1–10 years.

Among these, the 24 hours ahead prediction horizon is crucial for the scheduling of the conventional generation, and many national grids codes (Conte, Massucco, Saviozzi, & Silvestro, 2017) and require punctual and precise power forecasting. In addition, in countries with a day-ahead electricity market, large renewable energy source (RES) plants can act as producers providing sale bids, wherein the actual production must follow a scheduler offer that is provided through a forecasting approach. For these reasons, this research focuses on a day-ahead forecasting of PV power output in Maiduguri using Feed Forward Neural Network (FFNN) which is a type of artificial neural network (ANN).

In (Sivaneasan, Yu, & Goh, 2017) proposed an improved solar forecasting algorithm based on artificial neural network (ANN) model with fuzzy logic pre-processing. The proposed model also includes an improved error correction factor aimed at minimizing the forecast error by incorporating the error from previous 5-min forecasted output to the input layer. The clear-sky model and weather data obtained from a weather station in Singapore are used for training the developed model. The numerical result prove that the error correction factor coupled with a pure ANN can significantly improve solar irradiance forecast accuracy due to the adaptive error correction ability. A slight improvement can also be achieved by incorporating a fuzzy logic pre-processing to classify cloud cover index based on relative humidity, rainfall and the time of the day.

In (Nespoli et al., 2019) proposed the analysis the 24-h-ahead power forecasting performance of the two methods; the results show the good forecasting performance of both methods in the case of sunny days. While the hybrid method shows an excellent performance for some specific days, the second method under study shows a more stable and consistently good performance. The forecasting performance of both methods drops significantly for cloudy days. Again, while the performance of the hybrid method is better for some specific days, for at least one day the prediction is rather poor, and the method that feeds exclusively on data from the dataset shows more stable performance on both Normalized Mean Absolute Error (NMAE) and weighted mean absolute error (WMAE) metrics.

In (Aprillia, Yang, & Huang, 2020) proposed a short-term PV power forecasting algorithm based on a CNN-SSA. Convolutional neural network (CNN) regression is used to construct the prediction model, and salp swarm algorithm (SSA) is used to identify the optimal CNN parameter. CNN classification is used for the CNN-SSA to obtain the correct weather type. The results show the proposed method provided better accuracy than the benchmark algorithms did. The proposed algorithm provides a simple approach.

In (Yadav, Pal, & Tripathi, 2019) proposed a new hybrid approach to photovoltaic energy prediction. The proposed approach used Particle swarm optimization (PSO) algorithm to optimize adaptive neuro-fuzzy inference system (ANFIS) parameters. After optimization, the ANFIS parameters were updated and tested. The predicted results of the proposed method were compared with some existing methods BPNN and ANFIS. As a result, it is clear that the predicted result of the proposed method is significant in four seasons. The average % MAPE of the predicted result is 8.42 % of the proposed method. Four-week Symmetric mean absolute percentage error (sMAPE) is much better than previous reference methods, with mean sMAPE being 6.88. Therefore, the proposed method shows the promising result of photovoltaic energy with acceptable computing time.

In (Su, Batzelis, & Pal, 2019), a comprehensive performance assessment among some of the most popular PV power forecasting methods is performed on a common dataset. Non-linear Autoregressive Neural network with exogenous input (NARXNN) is found to be superior over other neural networks due to its dynamic feedback mechanism. Random Forest (RF) performs the best among the intelligence algorithms. There is a seasonal effect on the forecasting problem; summer and autumn are easier to forecast than spring and winter. The training process of a neural network exhibits great randomness, while intelligent algorithms are generally more robust. The proposed Hybrid method performs most favourably among all methods, correcting erroneous fluctuations and negative forecasting. In fact, a major conclusion from this investigation is that simple combination of several good models can generate a more reliable prediction than any single method on its own. This may be found useful especially when there is no complete data for model training.

In (Shi, Zhu, Yuan, Hao, & Wang, 2018), based on the influence of environmental factors on the output power of PV power generation, based on the limit learning machine, a forecasting model of PV power output is set up with weather types, and the historical power data of the PV power station is reasonably divided according to the different weather types, and the weather type is further classified by the grey correlation analysis method. The output results of improved equal-dimension grey (IEDG) model are used as the input of the extreme learning machine (ELM) model, and ELM model is trained and tested. The prediction results are analyzed to get the following conclusions: IEDG-ELM proposed in this paper can effectively predict the output power of PV systems under various weather conditions, IEDG-ELM models proposed in this paper has a relatively accurate prediction ability and strong applicability.

ARTIFICIAL NEURAL NETWORKS

The artificial neural network method is inspired by biological neurons, is an information processing system, non-algorithmic and massive parallel learning technique. ANNs are used to link inputs and outputs using a historical database to generate outputs when they are missing(Monteiro, Fernandez-Jimenez, Ramirez-Rosado, Muñoz-Jimenez, & Lara-Santillan, 2013).

The ANN architecture is composed of three parts:

i. input layer that receives the data,
ii. output layer where the supposedly calculated data is sent out as an output,
iii. one or more hidden layers that connect the input to the output data layers,

2.1. Feed-Forward Neural Network

In a feed-forward neural network, neurons are organized in the form of layers. Neurons in a layer receive input from the previous layer and feed their output to the next layer. Network connections to the same or previous layers are not allowed. Here, the data goes from the input node to the output node in a strictly feed-forward way. There is no feedback (back loops); that is, the output of any layer does not affect the same layer. Figure 1 shows the block diagram of the feed-forward neural network (FFNN)

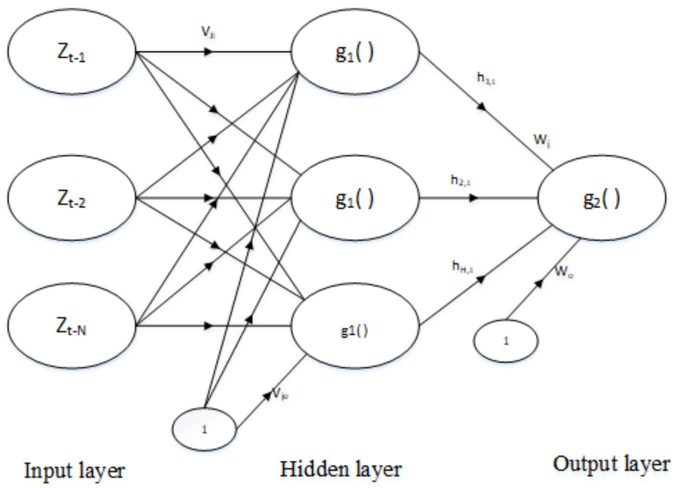

Figure 1: Architecture of FFNN

Mathematics behind ANNs

One has to start from a single neuron to have a view from a mathematical perspective to better understand how ANNs are constructed and how they develop through the training process.

A Single Neuron

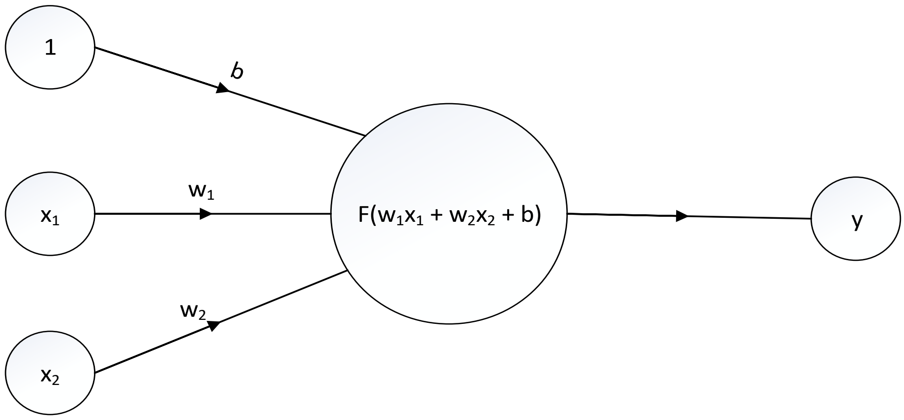

Figure 2: A single neuron of neural networks

Figure 2 shows a network consists of just one hidden layer containing one neuron. The single neuron receives input from the prior input layer, does computations, and sends the result away. We have two inputs here, x_1 and x_2, with weights w_1 and w_2 respectively. The neuron applies a function f to the dot-product of these inputs, which is $w_1x_1 + w_2x_2 + b$. Besides the two numerical input values, there is one input value 1 with weight b, called the Bias. The main function of bias is to stand for unknown parameters or unforeseen factors.

The output Y is computed by taking the dot-product of all input values and their associated weights and putting it into the function f. This function is called the Activation Function.

Multi-Layer Perceptron

There are two types of feed-forward neural networks:

i. Single Layer Perceptron: the simplest feed-forward neural network with no hidden layers
ii. Multi-Layer Perceptron: has one or more hidden layers which is useful for practical applications

One will focus on the multi-layer Perceptron because it can learn not only linear functions but also non-linear functions.

The feed-forward neural network is an example of the multi-layer Perceptron. If we have a dataset containing features and results, the multi-layer Perceptron will learn the relationship between features and results from the given data set, and predict the result for a new data point.

Generally in the input layer, one sends n numerical inputs through n units: (Zou, Han, & So, 2009).

$$X = x_1, x_2, \ldots\ldots, x_n \,/\, X \in R^n \qquad \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Then we randomly assign weights for them at the first place: (Zou et al., 2009).

$$W = w_1, w_2, \ldots\ldots, w_n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

The values for weights will be adjusted later in the training process for more accurate approximations.

In the hidden layer, one gathers all the inputs by taking the dot product of x and w, and one calls it the pre-state P: (Zou et al., 2009).

$$P = w_1 x_1 + w_2 x_2 + \ldots\ldots + w_n x_n + b = \sum_{i=1}^{n} w_i x_i + b \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

In the hidden layer, there is pre-state, which stores the dot-product of corresponding inputs and weights. This pre-state value is ready to go through a certain activation function. This is called the state S inside this hidden neuron:

$$S = \sigma(W_i x_i + b) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

There could be more hidden layers following the first hidden layer, and the state(s) S, which store the transformed values, will be the input value(s) for the next layer, all the state values become the pre-state values of the next stage. The initial input values will go through every hidden layer in the neural net, repeat the same procedure mentioned above, and finally arrive at the output layer. The output values we receive are the ultimate state values in the very last hidden layer. The above procedure explains how we set up our neural net.

SITE AND SYSTEM DESCRIPTION

Case Study – PV Plant

The data (Photovoltaic power output of 1st September 2021 to 28th February 2022) was obtained from a PV plants of twelve (12) panel, 4 kW_P supplying PV power to water boreholes at Culvert Junction, Indimi Road of Maiduguri metropolitan council located at North Eastern Nigeria (latitude 11.85^0 N and longitude 13.16^0 E) which is blessed with abundant sunlight and daylight each day. The PV plant is shown in Figure 3.1 and key information regarding the PV modules relevant to this work is presented in table 3.1.

Figure 3: picture of the plant

The pertinent parameters of the PV panel measured at Standard Test Condition (STC) are as shown in table I:

Table 1: Module Parameters

Parameters	Values
Solar cells	Sunmodule Bisum SW 325 XL duo
Peak power	325W
Rated voltage	37.7V
Rated current	8.68A
Open circuit voltage	47.0V
Short circuit current	9.28A

MODELLING AND IMPLEMENTATION

Instrument for data collection

The principal instrument used for PV data collection is a PV Controller which shows hourly measurement of current, voltage and PV power output. The data is then recorded in a log book for the periods of six months, that's from 1st September 2021 to 28th February 2022. The hourly weather data (Temperature, Wind speed, Cloud cover and Humidity) for the periods of six months for Maiduguri Metropolitan Council were also collected from Nigerian Meteorological Agency (Nimet).

Data Presentation

the Feed Forward Neural Network is applied to model the next day PV power output forecast for Maiduguri using time of the day, day of the year, hourly temperature, hourly humidity, hourly wind speed, hourly cloud cover and hourly PV power output as input and target variables. A total of one thousand eight hundred and eleven (1811) hourly data by six (6) columns (representing the input variables) for the months of September, October, November and December 2021 were used as the training data set, while a total of two hundred and seventy-one (271) hourly data by six (6) columns (representing the input variables) for the month February 2022 is used as the testing data set.

Training data set for the model

A matrix of 1811 x 7 is generated, with the row number matching the number of hours for the months of September, October, November and December 2021. The first six (6) columns represent the inputs to the FFNN model i.e. hour of the day, day of the week, next day temperature, next day relative humidity, next day wind speed and next day cloud cover respectively. The last column represents the PV power output/target as shown in table II.

Table 2: Arrangement of Input Matrix of 1811 x 7

Hour of the day (h)	Day of the week	Next day temperature (^{0}C)	Next day relative humidity (%)	Next day wind speed (m/s)	Next day cloud cover (%)	Actual PV (KW)
0.4375	0.0055	0.5891	0.9184	0.3333	0.4300	0.3750
0.5000	0.0055	0.6202	0.8673	0.3542	0.3700	0.2600
..	..	..	..	..	..	..
..	..	..	..	..	..	..

..	..	..	..	..	..	..
..	..	..	..	..	..	..
1.0000	1.0000	0.8760	0.0816	0.6979	0.0000	0.6500

Each day of the week and time of the day correspond to the temperature, relative humidity, wind speed, cloud cover and PV of the hour of the day accordingly. This matrix is then employed as the training data set for the FFNN model.

Testing data set for the model

A matrix of 271 x 7 is generated, with the row numbers matching the number of hours in the month of February, where the first column represents the hour of the day, second column stands for the day of the week, and the third, fourth and fifth column represent temperature, relative humidity, and PV of the hour of the day respectively.

The testing data set is used for model validation which is the process by which the input vectors from input/output data sets on which the FFNN was not trained, are presented to the trained FFNN model, to see how well the FFNN model predicts the corresponding data set output values.

SIMULATION RESULTS

The results obtained from the simulation of the model were discussed based on three listed plots

- The Regression plot
- The Performance plot
- Training State plot

Regression Plot

This comprises of four regression analysis plots as shown in figure 4

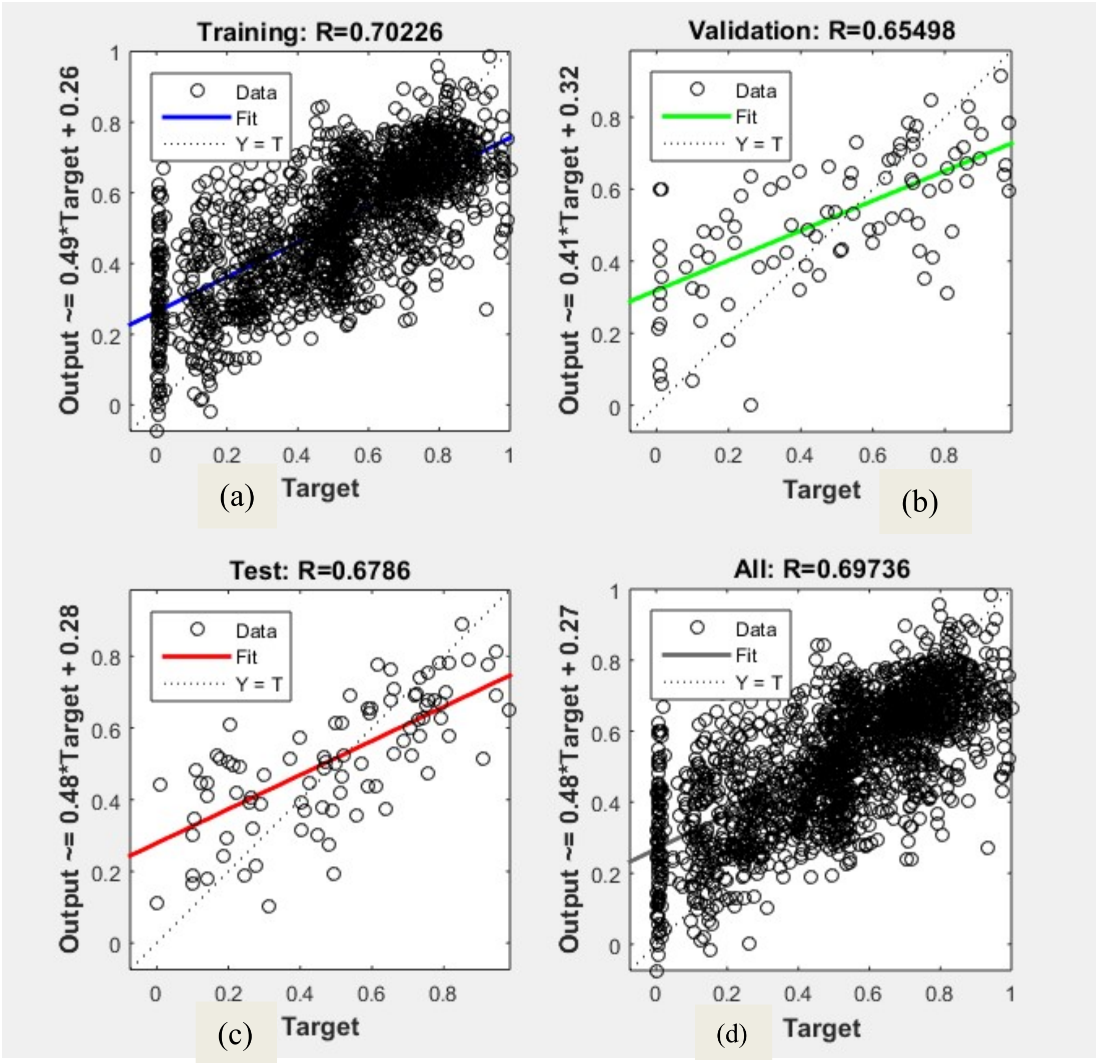

Figure 4: Regression plots.

Figure 4a shows the computed network output of the training data sets against the target output and has a coefficient of correlation (R) value of 0.70226, Fig. 4b is that of validation data output against target output and has an R value of 0.65498, Fig. 4c shows the test data output against the target data set with a R value of 0.6786, while Fig. 4d is a plot of the overall network output data set against the target data set and has a R value of 0.69736. It can be concluded from the plot that there is a good correlation between the overall output data and the target data.

Performance plot

In the first model, this is a plot of the mean squared error (MSE) against the number of training epochs as shown in figure 5 From the plot it can be clearly seen that the network has the best validation performance of 0.055679 at epoch 25.

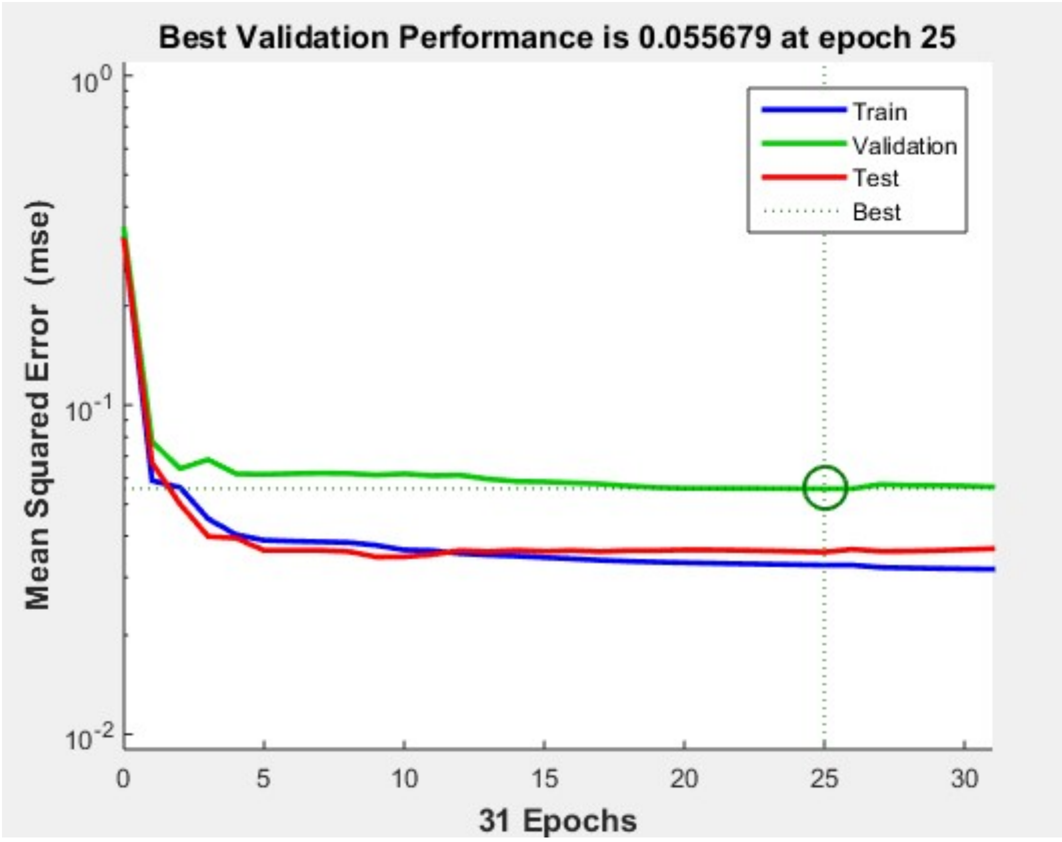

Figure 5: Performance Plot.

Training State Plot

The training state plot comprises of three (3) different plot type as shown in figure 6

i) Plot (a) is a gradient against the total No of epoch. It shows the moving average of the gradient value as the number of computational iteration increases.
ii) Plot (b) is a learning rate (mu) against increasing number of epochs. It shows the rate at which the computed network error reduces as the training progresses.
iii) Plot (c) basically performs the function of validation.

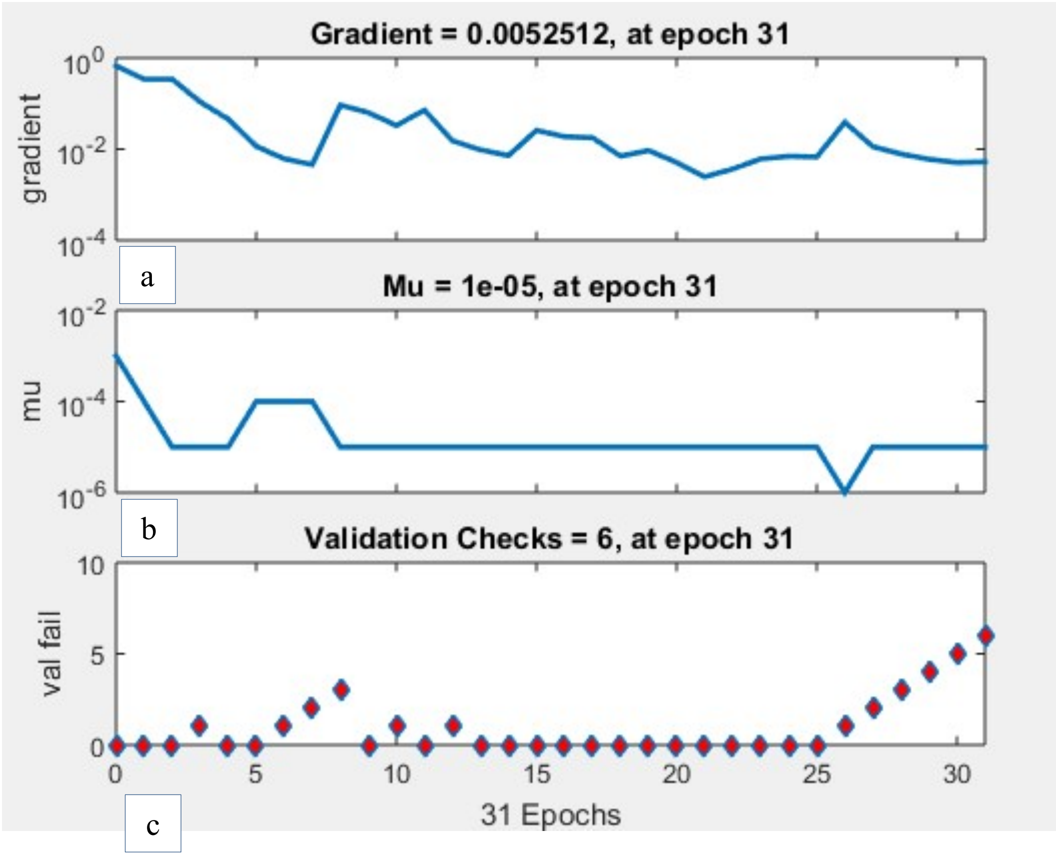

Figure 6: Training state plot

After the FFNN network training is completed, next day PV power forecast for the upcoming day can be calculated from the generated FFNN Model. For example, if we want to forecast the PV power output of February 15th, 2022. One set of inputs is given as follows:

Temperature = $T_{Feb/15/2022}$

Humidity = $H_{Feb/15/2022}$

Wind Speed = $WS_{Feb/15/2022}$

Cloud cover = $C_{feb/15/2022}$

Day of the Year = Tuesday (day 2 of the week)

Using the concept above, the next day PV power output (PV forecast) for the testing data of 2022 was obtained. From the obtained result the mean absolute percentage error (MAPE) and the R-value (Pearson's correlation) were calculated to be 8.9093% and +0.7632 for the model. The result of the next day PV power output (forecast PV) obtained from the designed FFNN model for the next day with their calculated MAPE error and r-value for model and also that of the validation tool ANFIS is shown in table III

Table 3: Actual and forecast PV of 16th February 2022

FFNN				ANFIS			
Hours	**Actual PV (KW)**	**Forecasted PV (KW)**	**APE**	**Hours**	**Actual PV (KW)**	**Forecasted PV (KW)**	**APE**
7.00	0.7150	0.7097	0.7424	7.00	0.7150	0.5759	19.4545
8.00	0.8625	0.6723	22.0492	8.00	0.8625	0.5831	32.3942
9.00	0.7275	0.6447	11.3793	9.00	0.7275	0.6194	14.8591
10.00	0.6575	0.7048	7.1960	10.00	0.6575	0.7767	18.1293
11.00	0.7550	0.7708	2.0900	11.00	0.7550	0.9000	19.2053
12.00	0.8225	0.8875	7.8986	12.00	0.8225	0.8823	7.2705
13.00	0.8175	0.8516	4.1759	13.00	0.8175	0.7465	8.6850
14.00	0.7675	0.7295	4.9481s	14.00	0.7675	0.5972	22.1889
15.00	0.6000	0.6067	1.1233	15.00	0.6000	0.5643	5.9500
16.00	0.5650	0.4097	27.4906	16.00	0.5650	0.5758	1.9115

As can be inferred from Table III, the FFNN had a Mean Absolute Percentage Error (MAPE) of 8.9093 with R of 0.7632 while that of validation tool, which is ANFIS, had a MAPE of 15.0048 with R of 0.3533. From the result of the two models, it can be concluded that FFNN can predict well.

From Table III, it can be seen that the difference between the actual and the forecasted PV power output for the model is quite small. By the Graphical User Interface (GUI) in the above Table for the designed FFNN model, it is imperative to examine the reliability of the model. In order to achieve this, procedural and statistical method were used. From the MATLAB, the forecasted PV power output value in Table III was obtained.

However, the result shown in Table III was analysed in order to check the accuracy of the model. The statistical measures that were employed for these analyses are the absolute percentage error (APE) and the mean absolute percentage error (MAPE) for a day. However, the Pearson correlation coefficient (R value) was calculated using the Microsoft Excel.

The results of the research indicate that the FFNN had a MAPE of 8.9093. MAPE is a commonly used metric to measure the accuracy of a forecasting or prediction model. In this case, the lower the MAPE value, the better the model's performance. On the other hand, the ANFIS model had a MAPE of 15.0048. A higher MAPE value suggests that the ANFIS model had a larger error compared to the FFNN model. Based on this results, it can be inferred that the FFNN model performs better in terms of accuracy compared to the ANFIS model. However, it's important to note that these results are specific to the research being discussed. The performance of different models can vary depending on the dataset, the specific problem being addressed and various other factors such as temperature, humidity and wind. Therefore, it's essential to consider these results within the context of the specific study and its limitations.

From the analysis, it was observed that the obtained mean absolute percentage value (MAPE) for the FFNN model for a day ahead was in accordance to what is obtainable in (Harrou, Kadri, & Sun, 2020). This shows that the result obtained was sufficiently accurate. The R-value obtained by statistical analysis was used as a measure to validate the reliability of the model.

CONCLUSION

The sustainable development of any region is closely tied to the planning, development and management of its power source. As such, designing a model to effectively predict the next day PV power output is quite appropriate. In this research work, FFNN based model was designed to forecast the next day PV power output of Maiduguri depending on available variables (Time of the day, day of the week, temperature, relative humidity, wind speed, cloud cover and PV power output) for the model. The FFNN based models were designed in the MATLAB® (R2015a) environment. Hence, the results of the research indicate that the FFNN had a MAPE of 8.9093. MAPE is a commonly used metric to measure the accuracy of a forecasting or prediction model. In this case, the lower the MAPE value, the better the model's performance. On the other hand, the ANFIS model had a MAPE of 15.0048. A higher MAPE value suggests that the ANFIS model had a larger error compared to the FFNN model. Based on this results, it can be inferred that the FFNN model performs better in terms of accuracy compared to the ANFIS model. However, it's important to note that these results are specific to the research being discussed. The performance of different models can vary depending on the dataset, the specific problem being addressed and various other factors such as temperature, humidity and wind. Therefore, it's essential to consider these results within the context of the specific study and its limitations.

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