Forecasting of Photovoltaic Power Output in Maiduguri using Feed Forward Neural Network

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Abstract

The increasing integration of photovoltaic (PV) power systems into the energy grid necessitates accurate forecasting of their output to ensure efficient and reliable operation. This research investigates the application of a Feedforward Neural Network (FFNN) for forecasting the PV power output in Maiduguri. The proposed FFNN model utilizes historical weather data and other relevant parameters to predict the power output of PV systems. The research evaluates the performance of the FFNN model using two key metrics: Mean Absolute Percentage Error (MAPE) and Pearson correlation coefficient (R). The FFNN model achieved a low MAPE of 8.9093, indicating its effectiveness in accurately predicting PV power output. Additionally, the model exhibited a high Pearson correlation coefficient (R) of 0.7632, demonstrating a strong linear relationship between the predicted and actual power output values. To validate the performance of the FFNN model, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was employed as a benchmark. The ANFIS model yielded a higher MAPE of 15.0048 and a lower Pearson correlation coefficient (R) of 0.3533 compared to the FFNN model. These results highlight the superiority of the FFNN model in accurately forecasting the PV power output in Maiduguri.

Keywords: Feed forward neural network, Forecasting, Photovoltaic Power Output, Absolute Percentage Error, Mean absolute percentage error

Prévision de la production d'énergie photovoltaïque à Maiduguri à l'aide d'un réseau neuronal Feed Forward

Résumé

L'intégration croissante des systèmes d'alimentation photovoltaïques (PV) dans le réseau énergétique nécessite une prévision précise de leur production pour garantir un fonctionnement efficace et fiable. Cette recherche étudie l'application d'un réseau neuronal Feedforward (RNFF) pour prévoir la production d'énergie photovoltaïque à Maiduguri. Le modèle RNFF proposé utilise des données météorologiques historiques et d'autres paramètres pertinents pour prédire la puissance de sortie des systèmes photovoltaïques. La recherche évalue les performances du modèle RNFF à l'aide de deux mesures clés : le pourcentage d'erreur absolu moyen (PEAM) et le coefficient de corrélation de Pearson (R). Le modèle RNFF a atteint un faible PEAM de 8,9093, ce qui indique son efficacité à prédire avec précision la production d'énergie photovoltaïque. De plus, le modèle présentait un *coefficient de corrélation de Pearson (R) élevé de 0,7632, démontrant une forte relation linéaire entre les valeurs de puissance de sortie prévues et réelles. Pour valider les performances du modèle RNFF, un système d'inférence adaptative neuro-fuzzy (ANFIS) a été utilisé comme référence. Le modèle ANFIS a donné un PEAM plus élevé de 15,0048 et un coefficient de corrélation de Pearson (R) inférieur de 0,3533 par rapport au modèle RNFF. Ces résultats mettent en évidence la supériorité du modèle RNFF pour prévoir avec précision la production d'énergie photovoltaïque à Maiduguri.*

Mots-clés: réseau neuronal Feedforward, prévision, puissance de sortie photovoltaïque, pourcentage d'erreur absolu, pourcentage d'erreur absolu moyen

يتطلب التكامل المتزايد لنظم الطاقة الكهروضوئية في شبكة الطاقة التنبؤ الدقيق بإنتاجها لضمان التشغيل الفعال والموثوق به يبحث هذا البحث في تطبيق شبكة فيد-فوورد العصبية للتنبؤ بإنتاج الطاقة الكهروضوئية في ميدوغوري، يستخدم النموذج المقترح بيانات الطقس التاريخية وغيرها من البارامترات ذات الصلة للتنبؤ بإنتاج الطاقة للنظم الكهروضوئية يقيم البحث أداء النموذج باستخدام مقياسين رئيسيين: الأول متوسط خطأ النسبة المئوية المطلقة والثاني معامل ارتباط بيرسون(0.7632) إثبات وجود علاقة خطية قوية بين قيم خرج الطاقة المتوقعة والفعلية.للتحقق من أداء النموذج، تم استخدام نظام الاستدلال العصبي الضبابي التكيفي كمعيار أسفر نموذج ANFIS عن MAPE أعلى من 15.0048 ومعامل ارتباط بيرسون أقل من 0.3533 مقارنة بنموذج FFNN تسلط هذه النتائج الضوء على تفوق نموذج FFNN في التنبؤ الدقيق بإنتاج الطاقة الكهروضوئية في ميدوغوري

Introduction

The utilization of renewable energy sources has gained significant attention in recent years due to the escalating concerns over environmental sustainability and the limited availability of fossil fuels. Among various renewable energy sources, solar energy has emerged as a promising solution to meet the ever-increasing energy demands. The photovoltaic (PV) technology, which converts sunlight directly into electricity, has experienced rapid growth and widespread adoption worldwide (Kusuma *et al.,* 2021).

To optimize the integration of solar energy into the existing power grid, accurate forecasting of PV power output is crucial. Accurate forecasts enable grid operators, energy planners, and system operators to efficiently manage the variability and intermittency associated with solar power generation. Effective forecasting techniques contribute to better grid stability, improved energy management, and enhanced utilization of solar resources (Priyadi *et al.,* 2020).

In the context of Maiduguri, a city located in north-eastern Nigeria with abundant solar resources, forecasting the PV power output becomes imperative. Maiduguri, the capital of Borno State, experiences long hours of sunshine throughout the year, making it an ideal location for solar power generation. However, due to the region's geographical location and weather patterns, solar power output can exhibit significant fluctuations, making accurate forecasting challenging.

The FFNNs have received great deal of attention by the researchers in Forecasting of Photovoltaic Power Output due to flexibility in data modeling. Massucco *et al.* (2019), proposed a novel hybrid methodology for the day-ahead forecasting which has been implemented and validated on a real PV plant. Gao *et al. (*2019) proposed two day-ahead forecasting models for different weather conditions. Harrou *et al.* (2020) proposed Forecasting of Photovoltaic Solar Power Production Using LSTM Approach to accurately forecast short-term photovoltaic solar power. González *et al.* (2017) proposed Photovoltaic power forecasting using simple data-driven models without weather data for an accurate one-day ahead forecasting models with only information of past generated power as input. Zhou *et al* 2019 proposed a new hybrid model based on LSTM and attention mechanism for short-term photovoltaic power forecasting. Konstantinou *et al.* (2021) proposed the utilization of a deep RNN model to deal with PV forecasting problems.

This research aims to address the forecasting of photovoltaic power output in Maiduguri, utilizing a Feedforward Neural Network (FFNN) approach. Neural networks have proven to be effective in capturing complex nonlinear relationships and patterns within data, making them suitable for modeling and forecasting PV power output. By training an FFNN model on historical solar power generation data, weather data, and other relevant parameters, it becomes possible to predict the future PV power output with improved accuracy.

Methodology

This section explains the procedure followed in this work. The case study of this work would be presented, along with the description of the instrument at the PV system. For the Feed Forward Neural Network (FFNN) models, normalization was used on the relevant variables. A feed forward neural network with back propagation in MATLAB was chosen to create a model for the PV-module located at Maiduguri, Nigeria.

Case Study – The PV Plant

The generated power's data was obtained from the photovoltaic system that is installed to supply PV power to water boreholes at Culvert Junction, Indimi Road of Maiduguri metropolitan council. This system is shown in Plate 3.1. This system has a total power 4 KWp and is composed of 12 PV modules of 325W Sunmodule Bisum SW and Inverter.

Figure I: Picture of the plant

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

Table I: 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

Chosen Inputs and Output of the Model

To train, validate and test the FFNN a set of data is required. For network with supervised learning as the MLP, it must contain the inputs of the network and the respective desired output. Since this work aims at the prediction of power generated by a photovoltaic system, the desired output is the generated power itself and the inputs are chosen based on the variables related to this generation. Therefore, those were chosen to form the input vector of the network.

Desire Output Vector

In this study, the information required was DC current and voltage. Thus, the PV power (P_{pv}) was used as desired output to the FFNN and its calculated using the expression:

$$P_{pv} = I_{DC} \times V_{DC} \quad (2.1)$$

To build the desired output vector, a set of measured corresponding to the months of September 2021 to February 2022 were used. The data was measure in an interval of one hour, therefore, in a day one would have 10 samples. Since the PV system only works during the day and this data covers only the period between 7 o'clock in the morning to 16 o'clock in the afternoon.

Furthermore, since the forecast window size chosen in this study was one hour, the data was collected in an interval of one hour. Consequently, the number of samples was 10 per day, resulting in 310 samples in one month with 31 days, 300 samples in one month with 30 days and 280 samples in one month with 28 days.

Since September to February was considered, the total number of samples was 1810.

Input Vector

The input vector was composed from weather variables. These variables were obtained from Nigerian Metrological Agency (NiMet) website. The variables are temperature, wind speed, cloud cover and humidity. These variables together with the hour of the day and day of the year composed as the network input vector. Also, it is important to notice that the parameters were obtained from the month of September 2021 to February 2022 with 1810 samples for each variable.

The format of days was chosen to consider temporal autocorrelations of the target variable, as suggested by Ceci *et al.* (2016.) Temperature and wind speed are selected because they are involved in the panel efficiency estimation. Humidity is included because it influences temperature and irradiance (Mekhilef *et al.,* 2012), and it is exploited with interesting results in several literature works (Ogliari *et al.,* 2016, Zhang *et al.,* 2017). Finally, CC represents a numerical index for the estimation of the sky covering. Notice that all the meteorological inputs were provided by Nimet. Tables II shows the variables.

Table II: Arrangement of Input and Output Matrix of 1810 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 (W)
7.00	1.00	25.33	90.00	10.67	43.00	1.50
8.00	1.00	26.67	85.00	11.33	37.00	1.04
..	..	..	..	..	..	..
..	..	..	..	..	..	..
..	..	..	..	..	..	..
..	..	..	..	..	..	..
16.00	181.00	37.67	8.00	22.33	0.00	2.60

Feature Scaling

The dataset used includes variables that are different in scale. Such cases, where different variables might have completely different scales, can lead to a false prioritization in the model of some of the variables. Hence, feature scaling of the data set is carried out to help in accelerating the calculation in the algorithm, and to improve the convergence rates. Once the dataset is trained, it requires less testing time (Thara *et al* 2019)

Normalization, which was applied here, is a common pre-processing method which reduces the dispersion of the collected data. Basically, all the data is re-scaled within a particular range from 0 to 1. The data set was normalized by computing:

$$x' = \frac{(x \times 1)}{x_{\max}} \qquad (2.2)$$

Where, x is the observed value and x' is the normalized value.

Literature revealed that normalization has a substantial impact on the output of any model since the main objective of data normalization is to ensure the quality of the data before it is fed to any model (Panigrahi, Behera 2013). Tables III shows the normalized values of the data.

Table III: Normalized values of Input and Output Matrix of 1810 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 (W)
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

Training, Validation and Test set

The data of input and desired output variables were divided into training, validation and test set. In this study, the division of the total data set was made considering 90% for the training, 5% for the validation and 5% for the testing, according to the random sampling. Therefore, the training, validation and testing contains 1630, 90 and 90 pattern respectively.

The format of the input-output set is shown in Tables III. This set was randomly divided following the considerations made above. For each training-validation process, division was made, thus different patterns could be presented to the net. In addition, during the training of the network, the order of the elements in the set was randomly reorganized after each epoch. A Feed forward Multilayer Perceptron network, with no feedback connection, performing a non-linear input-output mapping of the problem, using inputs x(t) to obtained outputs y(t).

To generate this model, the input-output showed in was used. Thus, for each epoch of training, 1810 input-output patterns were presented to the network. Other aspects were also taken into account, such as the origin of the network data and the possibility of its practical application. Some considerations were made for the proposed network, as the parameters to train the network. These parameters are Maximum number of epochs (N_{epochs}), Tolerance (Tol), Combination coefficient (μ), Parameter (β), Learning rate (η), Activation function used in the hidden layers, Maximum number of hidden layers, Minimum number of hidden layers, Maximum number of neurons, Minimum number of neurons.

These parameters are related to the learning algorithm used to perform the training. Before training the network, these variables must be defined. Furthermore, then network input-output data has to be normalized in order to avoid the saturation of the activation function. The topology used was randomly selected. However, even for the random selection, some parameters were defined, as: the maximum number of hidden layers is one, and the maximum number of neurons in the layer is eight. Those parameters were important and were based on the literature. For this problem, one hidden layer was enough to obtain a satisfactory generalization as shown in Figure II.

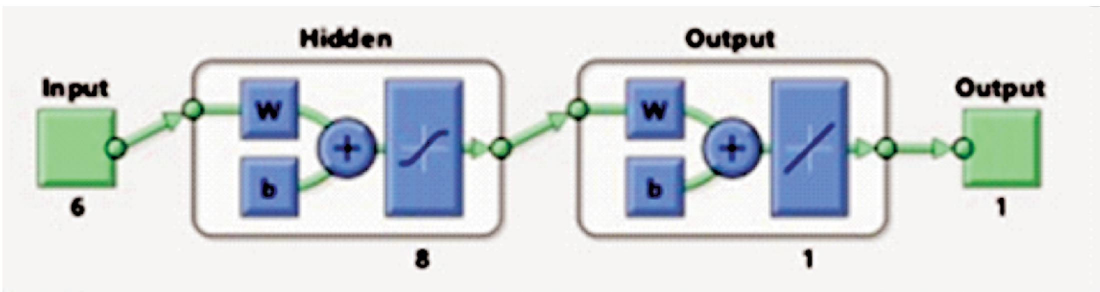

Figure II: FFNN Model

In this network, the inputs of the network will be time of the day, day of the year, temperature, wind speed, humidity and cloud cover. These parameters were presented to the network and the forecast of the power output of the photovoltaic system was done..

Training Algorithm

The backpropagation algorithm chosen was based on MATLAB's recommendations with respect to training time and memory requirements. As a model can be trained using different training algorithm, it was for this reason we decided to work with and optimize the model based on one training algorithm. The algorithm chosen was the Levenberg-Marquardt algorithm, as this is often the fastest backpropagation algorithm in the Deep Learning Toolbox and highly recommended as a first-choice supervised algorithm.

The Levenberg-Marquardt algorithm also known as Levenberg-Marquardt optimization is an iterative optimization method commonly used in nonlinear least squares curve fitting. It is name after Kenneth Levenberg and Donald Marquardt, who independently proposed the algorithm. The algorithm is particularly effective when fitting models with a set of parameters to experimental data by minimizing the sum of the squared differences between the model's predictions and the observed data. The Levenberg-Marquardt algorithms combines the advantages of two other optimization methods: the steepest descent method and the Guass-Newton method. It performs a series of iteration to adjust the parameters of the model until convergence is achieved. During each iteration, the algorithm calculates the Jacobian matrix, which contains the partial derivatives of the model with respect to each parameter. The algorithm then uses the Jacobian matrix, along with the current parameter values and the observed data, to update the parameter estimates. The update step involves solving a system of linear equations, which includes a damping term that combines the steepest descent and Gauss- Newton methods. The damping terms allow the algorithm to converge efficiently even in the presence of ill-conditioned problems. It continues to iterate until a termination criterion is met, such as reaching a maximum number of iterations or achieving a desired level of convergence. The result is an estimate of the parameters that minimize the sum of squared differences between the model's predictions and the observed data.

Results and discussion

The results obtained from the simulation of the model were discussed based on the Regression plot, Performance plot and Training State plot.

Regression Plot

This comprises of four regression analysis plots as shown in Figure III.

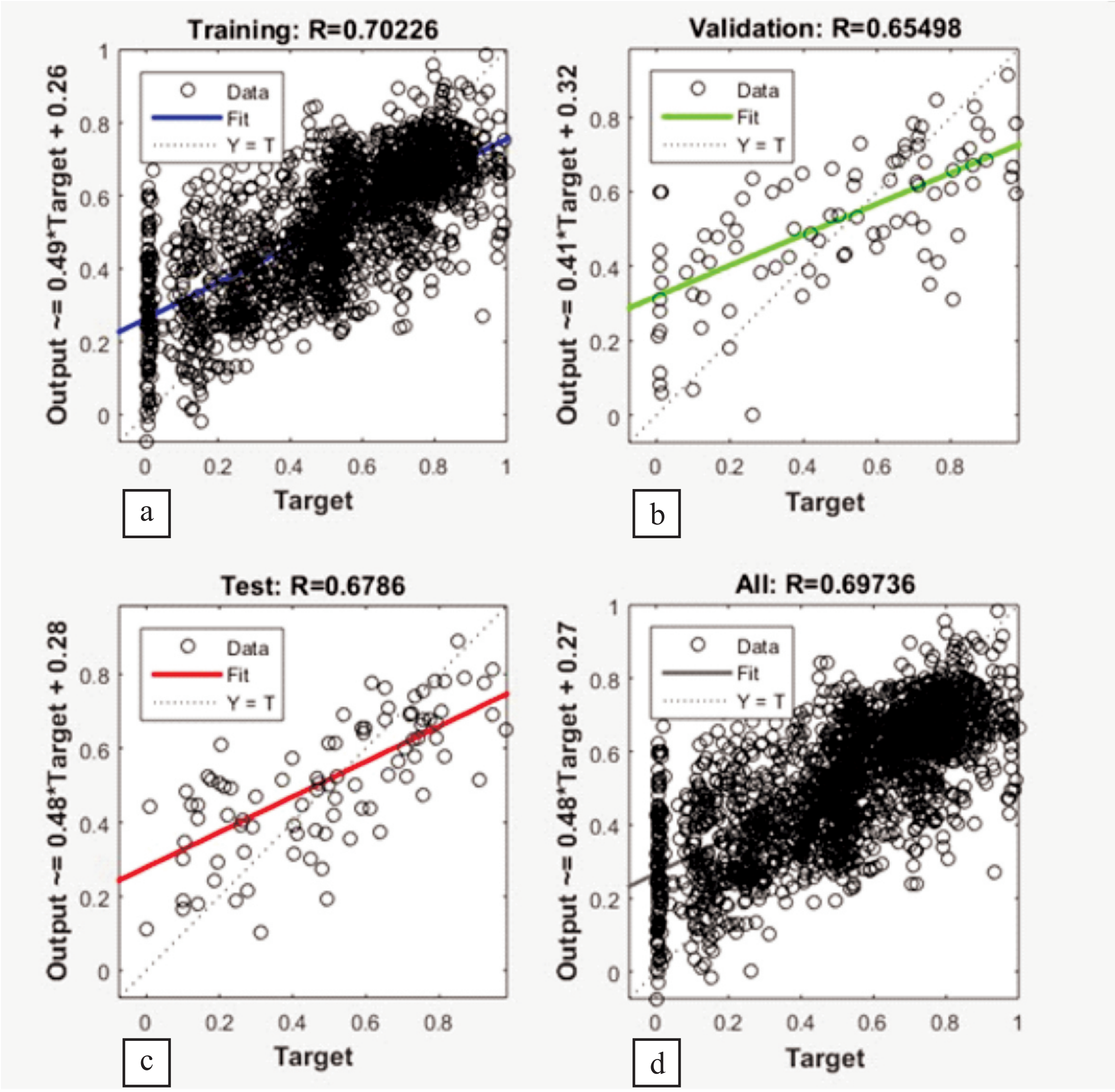

Figure III: Regression plots

From Figure III, plot (a) shows the computed network output of the training data sets Vs. the target output and has a R value of 0.70226, plot (b) is that of validation data output Vs. target output and has a R value of 0.65498, plot (c) shows the test data output Vs. the target data set with a R value of 0.6786, while plot (d) is a plot of the overall network output data set Vs. 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

This is a plot of the mean squared error (MSE) against the number of training epochs as shown in Figure IV. From the plot it can be clearly seen that the network has the best validation performance of 0.055679 at epoch 25.

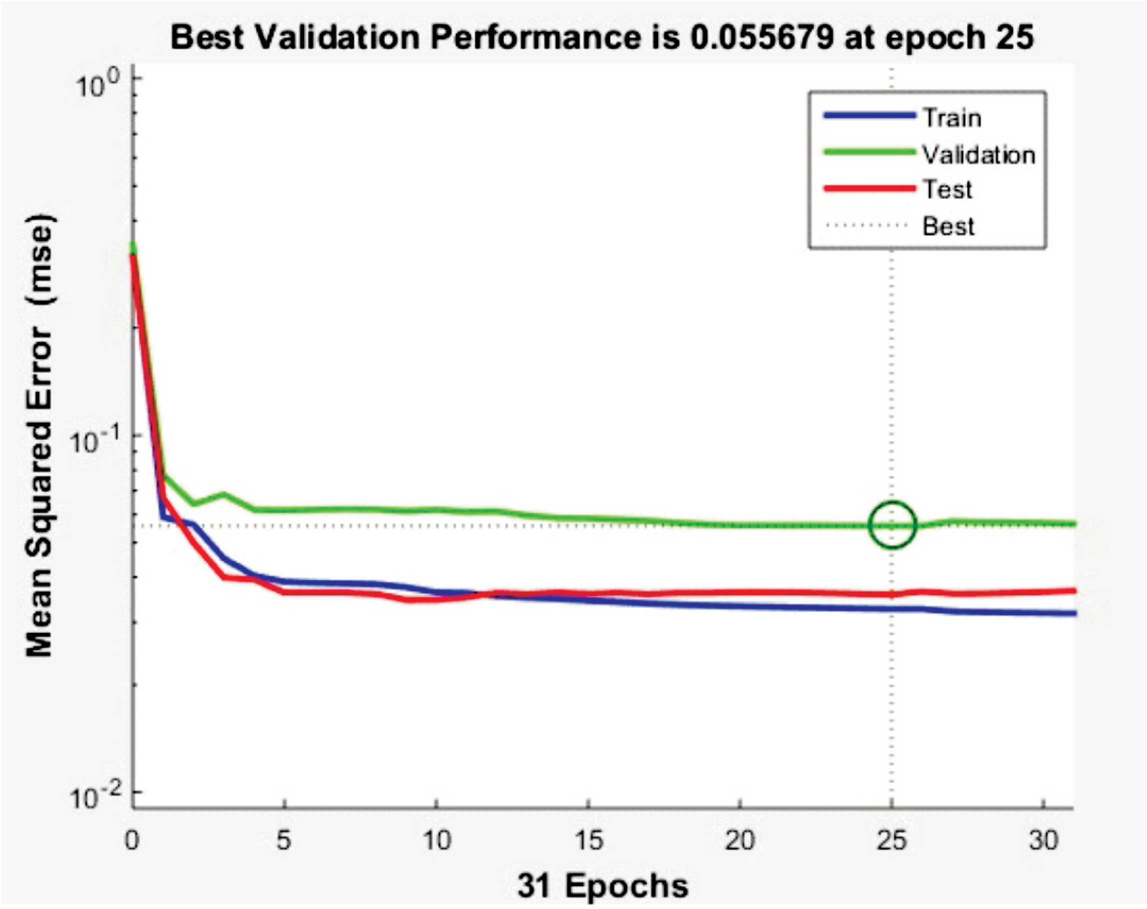

Figure IV: Performance Plot

Training State Plot
The training state plot comprises of three different plot type as shown in Figure V.

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 iterations 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.

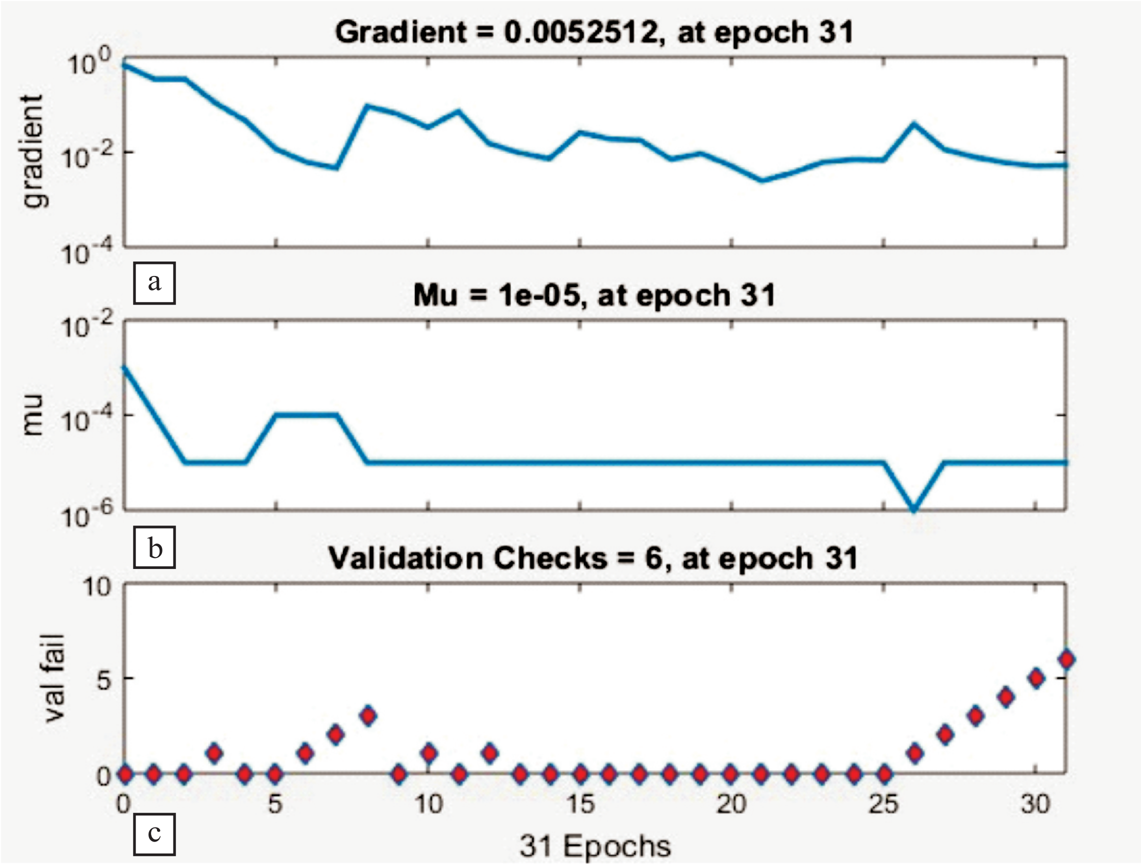

Figure V: Training state plot of FFNN model one

Performance Evaluation

As described in section 2.5, the FFNN was evaluated using MAPE and the result obtained was validated using ANFIS. The result of the performance evaluation was shown in Table IV.

Table IV: Actual and forecast PV of FFNN and ANFIS

	FFNN				ANFIS		
Hours	**Actual PV (W)**	**Forecasted PV (W)**	**APE**	**Hours**	**Actual PV (W)**	**Forecasted PV (W)**	**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	4.9481	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 IV, 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 the Table IV, the difference between the actual and the forecasted PV power output for the model is quite small is noted. 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 IV was obtained.

However, the result shown in Table IV was analysed 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 these 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 (Dias *et al* 2005). 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

This study on forecasting of photovoltaic power output in Maiduguri using FFNN successfully utilized a Feedforward Neural Network (FFNN) to forecast the photovoltaic power output in Maiduguri. The FFNN model demonstrated a mean absolute percentage error (MAPE) of 8.9093, indicating a relatively low level of forecasting error. Additionally, the model achieved a Pearson correlation coefficient (R) of 0.7632, indicating a moderately strong positive correlation between the predicted and actual values. Furthermore, the thesis employed the Adaptive Neuro-Fuzzy Inference System (ANFIS) to validate the FFNN model's performance. The ANFIS validation resulted in a slightly higher MAPE of 15.0048, suggesting a higher level of forecasting error compared to the FFNN model. Moreover, the Pearson correlation coefficient (R) obtained from the ANFIS validation was 0.3533, indicating a weaker correlation between the predicted and actual values compared to the FFNN model. Overall, the FFNN model showcased superior forecasting performance with lower MAPE and a stronger correlation coefficient. The findings of this thesis contribute to the field of photovoltaic power output forecasting in

Maiduguri and highlight the effectiveness of FFNN as a forecasting technique for similar applications.

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