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Prediction of Energy Generation for Hydropower and Photovoltaic Systems using Artificial Neural Network Modelling

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Abstract

Energy contributes significantly to national socio-economic and political development, and essentially, there is a restriction on socio-economic activities, development, and quality of life when the energy supply is limited. Hydropower and solar PV are the key contributors to sustainable energy supply among the renewable energy sources in the world. This paper has demonstrated an application of an intelligent algorithm for the modelling and simulation of energy generation for the Shiroro hydroelectric power plant alongside the power output of solar PV in Nigeria. MATLAB software was used to perform the programming by developing two forecasting models. Thus, hydrological data for Shiroro hydropower station spanning from 1990 to 2023 was used for the analysis alongside experimental data for the photovoltaic systems for Minna, Niger State, Nigeria (as a case study). Artificial neural network (ANN) models were developed to mimic and simulate the energy generation outputs for the two scenarios. A reverse energy generation forecast was carried out to assess the complementarity between the two given scenarios concerning power production viability. Hence, based on the lower value of RMSE 0.8% and high correlation value of 1, the artificial neural network (ANN) model for the solar PV generation outperformed the model of Hydro power plant with a reasonable accuracy, which ascertained that the model was reliable and could be used for prediction at 95% confidence level. It is expected that the outcomes from the prediction models in this study will have high economic value in enhancing effective management and planning strategies of the Shiroro hydropower plant station in Nigeria.

1. Introduction

The two significant indices used in determining a country's development are the availability of electrical energy and a nation's per capita energy consumption (Motwani *et al.*, 2013). This is because any nation's social and economic progress depends heavily on electricity, and without sufficient electricity, homes, companies, and society cannot operate at their full potential (FALEYE, 2012). While energy demand is growing, its primary sources, such as coal, natural gas and oil, being the principal source of energy worldwide, are beginning to be exhausted due to over-consumption, which has created severe problems of global warming and climate change (Al-Waeli *et al.*, 2018). Nigeria uses a combination of renewable and non-renewable energy sources to generate electricity (Sambo *et al.*, 2010). It is reasonably rich in renewable energy sources such as solar, wind, and vast water-power resources. The country's hydroelectric power and Gas-fired systems take precedence in the current energy mix. However, the amount of power generated from these sources has drastically reduced over time due to several managerial issues such as inadequate infrastructures, poor maintenance services of the turbines and power generation mechanisms (Sambo *et al.*, 2010). Numerous issues, such as insufficient budget, transmission and distribution losses, and inadequate infrastructure, hamper Nigeria's power sector. Consequently, power outages are frequent, and many houses and businesses depend on backup generators. Nigeria, the largest economy in sub-Saharan Africa, will have better prospects and potential for growth and industrialization when the power sector is improved substantially (Okoye *et al.*, 2023).

Nigeria only produces about 4,000 MW of power per day, significantly far below the energy needs. Several bottlenecks ranging from regulatory uncertainties, gas supply limitations, transmission and distribution system constraints, and substantial design flaws have prevented Nigeria's power sector from becoming commercially viable despite efforts to overcome its problems (Okoye *et al.*, 2023). To this end, the Nigerian Electricity and Regulatory Commission (NERC), which is a regulatory body for the regulation of electricity in Nigeria, has set a target of boosting the shares of renewables in electricity generation, with 16.6% coming from hydropower, 3.7% from wind and 3.3% from solar energy respectively (Akorede *et al.*, 2017). Hydropower (HP) has been counted as one of the few energy sources of great significance since the beginning of the twentieth century, and it can help stabilize fluctuations in the volatile energy market (Tilg *et al.*, 2017). However, developing hydropower plants is mostly capital-intensive and causes significant threats to aquatic ecosystem preservation and environmental concerns. (Khaniya *et al.*, 2020). As such, forecasting energy production from renewable energy sources such as hydropower plants and solar photovoltaic grids is imperative. It would optimize the load demand and manage the operations within the hydropower plants, such as routing excess water for other beneficial purposes. Load forecast has been an attractive research topic for decades and in many countries worldwide, especially in fast-developing countries with higher load growth rates. Besides, through a forecast of energy generation, the upgrading of power generation, transmission and distribution capacities, and sufficient funding for power systems and facilities could be planned. Moreover, outcomes obtained from energy forecasts are used in different endeavors in the power sector, such as system expansion, maintenance and operational schedule, efficient inter-tie-tariff settings and effective planning strategies (Saeed &Ossama, 2015).

Renewable energy technology today has assumed multifaceted directions, including hydropower, which generates electricity from the gravity of falling waters (Oussama *et al.*, 2016). Thus, harnessing electricity from hydropower is considered one of the most practicable and sustainable power generation methods worldwide. Notably, developing countries have just explored 23% of their economically feasible hydropower projects relative to developed countries, which have exploited 70% of their potential to help boost economic development. Moreover, the hydropower industry is most likely to be prone only to risk if and when confronted by detrimental impacts of climatic changes either due to the unavailability of water in the basin area for an extended period or excessive amount of water resulting in landslide or soil erosion in the catchment area. The Nigerian power sector is beleaguered by various challenges, including inadequate infrastructure, transmission and distribution losses, and insufficient funding, leading to incessant power outages within the country. Therefore, Medium and long-term forecasts of energy generation from hydropower plants based on realistic indicators are crucial, not only to optimize the demand for renewable energy growth but also to manage the operations within the hydropower plant to aid system expansion, maintenance and operational schedule, efficient inter-tie-tariff settings and effective planning. Nevertheless, the future prediction of hydropower production is a very complex task due to the nonlinear nature of the input functions and spatial and temporal variations of the meteorological datasets, such as rainfall, temperature, and evaporation output from prediction models. It is against this background, therefore, that the paper presents an intelligent algorithm model using an artificial neural network (ANN) to forecast the energy generation for the Shiroro Hydro power plant and PV power output for Minna and Bida Metropolis, respectively.

2. Hydropower Plants Potential in Nigeria

Nigeria is one of the West African countries also known as the giant of Africa, which borders Niger to the north, Chad to the northeast, Cameroon to the east, the Gulf of Guinea (Atlantic Ocean) to the south and Republic of Benin to the west as depicted in Figure 1 Nigeria's geographical coordinates is approximately 9.08170 N latitude and 8.67530 E longitude with a population of over 200 million people (Okoye *et al.*, 2023). In Nigeria, Hydropower is one of the most important sources of electricity for base load. Despite its high initial investment costs, Hydropower is a cheap and clean electricity source. Nigeria has several inland rivers with significant hydroelectric potential. The rivers Niger and Benue, as well as their tributaries, form the heart of Nigeria's river system, providing a renewable supply of energy for large-scale (greater than 100 MW) hydropower production. Furthermore, numerous minor rivers and streams can be used for small-scale (less than 10 MW) hydropower plants (Aliyu *et al.*, 2013).

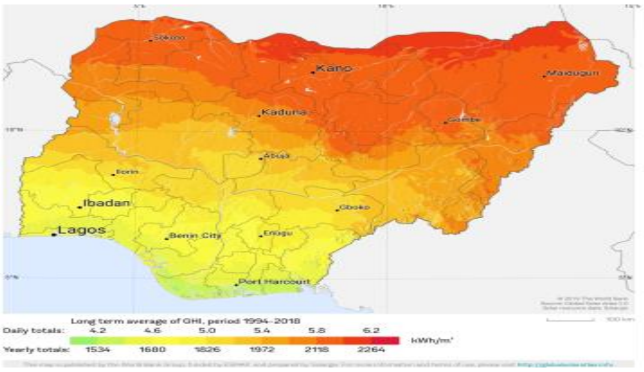

Fig.1: Map of Nigeria showing different geopolitical zones (Solargis, 2025).

Hydropower accounts for 16% of the world's total energy production and 80% of Nigeria's. Its inception in Nigeria dates back to the early 1960s when the Kainji Dam was commissioned in 1968. The Kainji Dam on the Niger River was built to generate electricity for the teeming population and regulates water flow for irrigation and navigation purposes concurrently. The dam has an installed capacity of 760 MW, the Jebba Dam has an installed capacity of 578 MW, and the Shiroro Dam has 600 MW installed capacity (Ahmed & Bashir, 2020). Conceptually, the primary purpose of these dams (Jebba, Kainji on River Niger and Shiroro on River Kaduna) is to produce power using turbine and to serve as an engine of growth and national development (Slocum *et al.*, 2016; Usman &Ifabiyi, 2012). Nigeria has a total of twenty-three (23) power-generating plants spread across the country that are connected to the national grid with the capacity of generating 11,165.4 MW of electricity. Besides, the Zungeru and Mambilla hydropower plants are also undergoing speedy construction to ensure timely completion, with over 6000MW combined energy capacity when entirely on stream. Thus, the nation's power capacity is expected to increase maximally by 2020 (Ezeanyim *et al.*, 2018). Generation companies (GenCos) and distribution companies (DisCos) of Nigeria manage these plants (Ezeanyim *et al.*, 2018).

2.1 The Shiroro Hydropower Plants Station

Shiroro Dam is situated in the Northern region of Nigeria and is located on 9.9751^0N, 6.8344^0 E of Niger State, Nigeria. The dam was established in 1990 with an estimated capacity of 600MW of electricity to be channelled into the national grid besides the other existing hydropower plants available in the country. The hydroelectric facility, also called the Shiroro Dam Reservoir, is located in the Shiroro Gorge on the Kaduna River, about 60 kilometres from Minna, the capital of Niger State, which is near Abuja, the federal capital of Nigeria. The reservoir is filled with streams that originate from the plateaus in the north and the coastal highlands in the lower Niger Valley. The dam reservoir's surface area is 320 km long, holding approximately 6.0000 × 109 m^3 with a maximum usable storage of 4.600 × 109 m^3 of water, and its broadest cross section is 17 km, measuring 32 km in total length. It is a concrete gravity dam standing about 98 meters (322 feet) and stretching approximately 700 meters (2,297 feet), as shown in Figure 2. The reservoir provides a significant water source for irrigation and supports the surrounding ecosystem. The dam operates a hydroelectric power station with four turbine units with a combined installed capacity of 600 MW. (Ezeanyim *et al.*, 2018).

Fig.2: Shiroro hydro Power Plant (Ajibola *et al.*, 2017).

2.2 Renewable Energy (RE) Forecasting Approaches

An energy forecast is a process of estimating the energy generation from different sources. Thus, the fast technological development in the 21st century has made forecasting an essential task in today's power system. Forecasting could be defined as estimating a future event by casting forward past data (Gor, 2005). Past data are methodically merged in a predefined manner to estimate the future. The forecast is mainly carried out before estimating future work regarding sales, production, or any other aspect of business activity. Forecasts are pertinent in integrating renewable power generation in electricity market operations since markets ought to be cleared in advance, while market participants shall then make decisions even before that. This is true for all types of electricity markets, from real-time to futures markets, via the more classical day-ahead (forward) ones (Abolarin, 2015).

Generally, two different approaches are utilized for energy generation forecasting. The first approach is the top-down approach, where the prediction is done at the peak level. The second approach is called the bottom-up approach, where the prediction is made from lower levels and the parameters' prediction is collected to higher levels of forecasting order. The bottom-up approach is more meaningful and suitable for seeking the individual value for the predicted parameters. An overview of a bottom-up approach for predicting the energy generation for each renewable energy source is illustrated in Figure 3 accordingly. Considering the hydropower renewable energy source, forecasting energy production from hydropower plants is necessary to optimize the demand for renewable energy and manage the operations within the hydropower plant (e.g., routing excess water for other beneficial purposes) aiming for environmental sustainability.

Nevertheless, the future prediction of hydropower production is very complex due to the nonlinear nature of the input functions and spatial and temporal variations of the meteorological datasets, such as rainfall, temperature, and evaporation. As such, it is expected that output from prediction models may have high economic value in regulating sustainable energy development projects such as hydropower (Yadav& Sharma, 2010). An energy forecast is a process of estimating the energy generation from different sources. Thus, the fast technological development in the 21st century has made forecasting an essential task in today's power system. Forecasting could be defined as the process of estimating a future event by casting forward past data (Gor, 2005). The forecast is mainly carried out before planning to estimate future work regarding sales or production or any other aspect of business activity. Forecasts are pertinent in integrating renewable power generation in electricity market operations since markets ought to be cleared in advance, while market participants shall then make decisions even before that. This is true for all types of electricity markets, from real-time to futures markets, via the more classical day-ahead (forward) ones (Abolarin, 2015).

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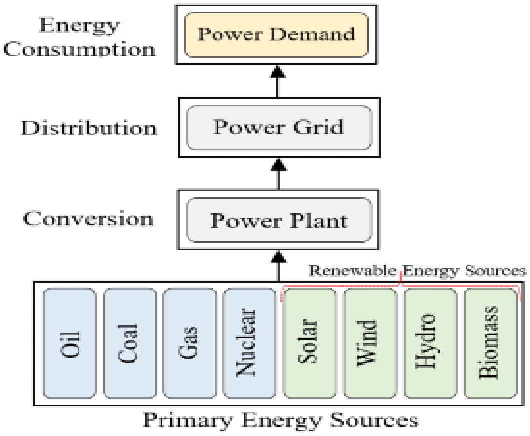

Figure 3: Bottom-up approach for energy generation forecasting(Szarucki *et al.*, 2022).

3. Materials and Methods

The overall strategy for the energy generation projection comprises two distinct methods: applying machine learning algorithms for forecast prediction and collecting and processing data for the two renewable energy sources under consideration. This study used the numerical computing software MATLAB R2022B version and the data analysis add-in package of Microsoft Excel to perform analysis.

3.1 Data Sets for the Shiroro Hydropower Station

In the present study, twenty-seven years of data (between 1990 and 2023) were obtained from the management of Shiroro hydropower station. These data comprised one thousand two hundred and twenty-four (1,224) monthly averages and were categorized into input variables and target responses. The input variables comprise reservoir inflow, turbine discharge, and reservoir elevation, while the target variable is power generation.
The procedures implemented in the actualization of the hydropower energy generation forecast are outlined below in stepwise order:

1. The collection of monthly average data from Shiroro hydropower station to include reservoir inflow, reservoir elevation, net operating head, and energy generation.
2. Data processing
3. Application of Artificial neural network (ANN) model
4. Training the ANN network with the train data using the Back Propagation algorithm.
5. Testing the trained model using test data, followed by the performance evaluation using mean square error (MSE), mean absolute percentage error (MAPE) and correlation coefficient (R).
6. The application of the developed model is to forecast energy generation for the Shiroro power station.
7. Results and discussions.

The above steps are summarized in a simple flow chart presented in Figure 4.

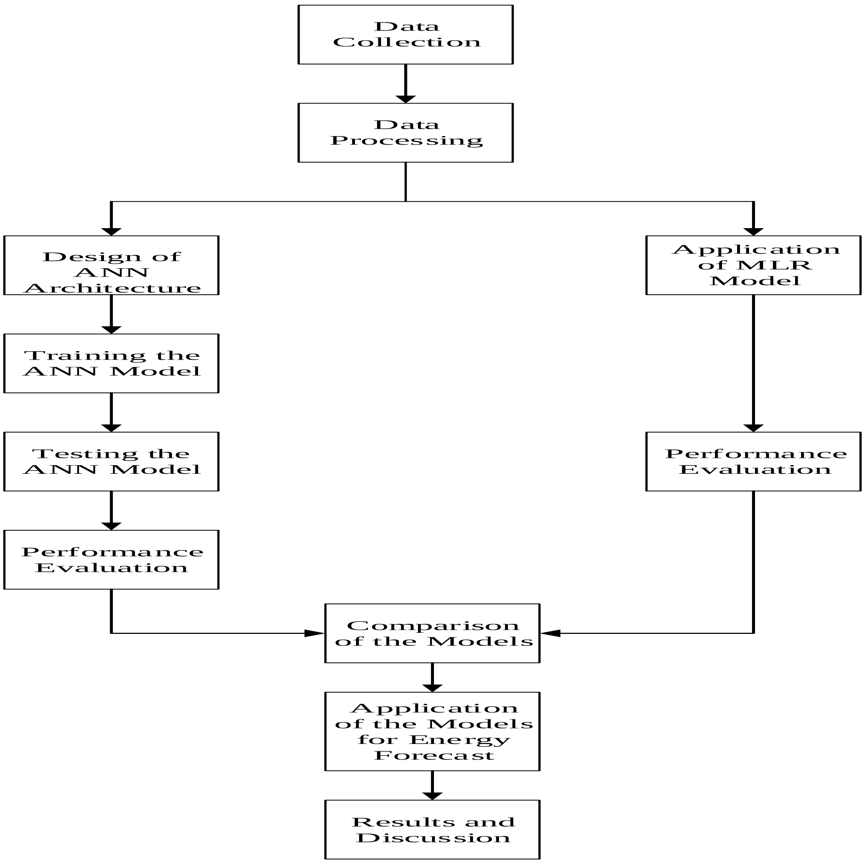

Fig.4: Methodology Block Diagram.

3.2 Solar ANN Design and Implementation

An extensive database of specific data representing the analyzed physical system is required to employ and train ANN architecture. In this regard, a test facility comprising Photovoltaic panels was installed and set up at the Renewable Energy Center (REC) in Bida Niger State, Nigeria. The monitoring systems for the system setups comprise two 250-watt (W) photovoltaic modules with specifications outlined in Table 1 while tilted at an angle of 38^{o} facing south. Several thermocouples comprising temperature, voltage, and solar radiation sensors alongside a data acquisition system were attached to the modules to record data generated during the experiment. All data were collected at one (1) minute intervals and stored for further comparison and analysis.

Table 1: Specification of the Photovoltaic module.

Electrical Properties	Specifications
maximum power (Pmax) (W)	250 W
voltage at Pmax (V)	30.4 V
current at Pmax (A)	8.22 A
open-circuit voltage (Voc) (V)	37.5 V
short-circuit current (Isc) (A)	8.74 A
cell type	Monocrystalline
module Efficiency (%)	15.54
dimensions (mm)	1638 (h) × 982 (w) × 40 (d)
weight (kg)	20

3.3 Data Analysis for the ANN Network

In the present analysis, the ANN model was developed in MATLAB version 2023, based on a three-layer feed-forward network with tangent sigmoid activation function in hidden layers and linear activation function in the output layer. All the data sets used in the solar ANN forecast were normalized between 0 and 1. Once the tests had been run and the errors had been compared, it was decided to create an ANN with ten hidden neurons.
The following parameters comprising solar radiation data, the surface temperature of the PV panel, load voltage and load current were used as inputs, and only one parameter, maximum load power, was predicted as an output. Before the neural network can be constructed, it is essential to clearly understand the input parameters that will be used. The input parameters used in an ANN must be variables that characterize the process. Thus, an analysis was undertaken to determine which variables would make up the network's inputs. This process eliminated variables with little or no contribution to the network output. As such, the physical data used for the training of ANN architecture for solar energy prediction were as follows:

i. Surface temperature T_{surf} [^{0}C];
ii. Solar radiation [G];
iii. Open circuit voltage V_{OC} [V];
iv. Short circuit current I_{SC} [A];

The last two parameters are important to improve the evaluation of the PV panel power output. As such their values are evaluated by using the following equations (Valerio *et al.*, 2014):

$$I_{SC} = I_{sc,ref}\frac{G}{G_{ref}} + \mu_{sc}(T_c - T_{ref}) \tag{1}$$

$$V_{oc} = V_{oc,ref} + nT\ln\left(\frac{G}{G_{ref}}\right) + \mu v_{oc}(T_c - T_{ref}) \tag{2}$$

Where the subscript ref represents the reference conditions (G = 1000 W/m^2; T = 25 ^{0}C)
Also, $\mu_{I_{sc}}$ *and* $\mu_{V_{OC}}$ are the short circuit current and open circuit voltage temperature coefficients respectively.
Over 500 datasets were used to carry out solar energy generation forecast. The experimental procedure involves strictly measuring the performances of two different photovoltaic panels: GL250W monocrystalline solar panel with the design specifications presented in Table 3.1. Meanwhile the measurement of the output power produced by the PV module was done for a period of two (2) months in order to acquire substantial and accurate data for the entire P-V curve characteristics. The database for the solar PV was validated and the correlation analysis was performed to evaluate the mutual relationship among the considered variables. In this study the topology of the input vectors for the ANN were surface temperature, solar irradiation, voltage and current respectively, while the output vector has only component which is the power output as shown in Figure 5.

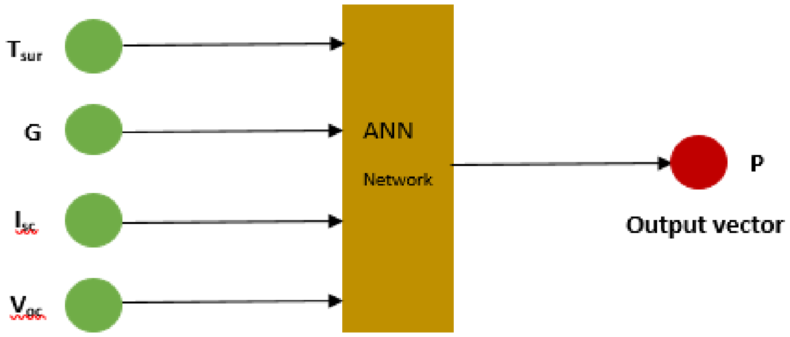

Fig.5: Definition of input and output vector of the artificial neural network.

3.4 Assessment of the Prediction Accuracy for the ANN Network

The capacity of ANN model for predicting the outputs for the Shiroro hydropower plant station were evaluated and analyzed using the following performance metrics number viz. root mean square error (RMSE), mean square error (MSE) and determination correlation coefficient (R^2) and mean absolute error given by Equations (3 -6) was used in this work to analyse the difference between real and predicted data. This is the most common way to measure the efficiency and correctness of a network during the testing and validation process. The correlation coefficient describes the degree of collinearity between simulated and measured data was and ranges from -1 to 1. If R = 0, it implies no linear relationship exists. If R = 1 or -1, a perfect positive or negative linear relationship exists between these variables. The flowing formulas were used in computing the prediction accuracies of the models (Al-Waeli *et al.*, 2019; Najafi *et al.*, 2018):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(t_i - p_i)^2} \tag{3}$$

$$R = \sqrt{\left(1 - \left(\frac{\sum_{i=1}^{n} t_i - p_i}{\sum_{i=1}^{n} {t_i}^2}\right)\right)} \tag{4}$$

$$MSE = \sum_{i=1}^{N}(t_i - p_i)^2 \tag{5}$$

$$MAE = \left(\frac{1}{n}\right)\sum(i = 1)/[y] \tag{6}$$

From the data analysis, a vector of 146 values was given to the network as training input, X, and just one single training target, (T). The variables inputted into the network were: solar radiation, PV temperature, open circuit current and voltage respectively as shown if Figure 6.

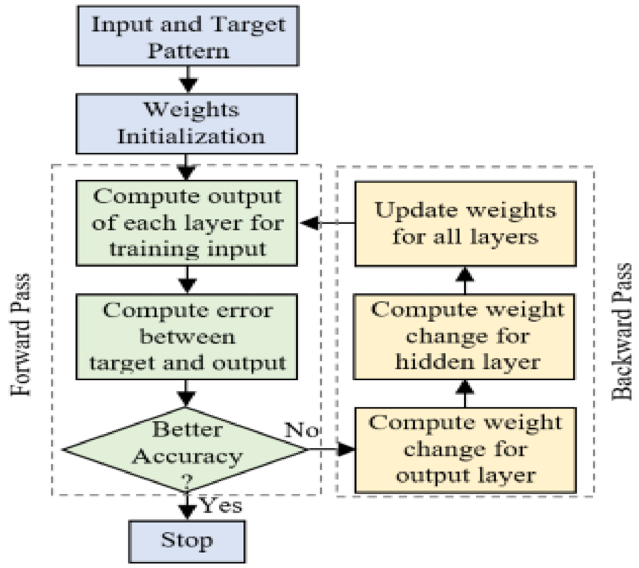

Fig.6: Flowchart for the ANN network development(Szarucki *et al.*, 2022).

Meanwhile, the target values were the predicted PV power output. Data from January to March 2023 was used to test different network architectures to determine the optimal design of the solar ANN. The performance and error of predictions were evaluated for a network with different numbers of hidden neurons and delays to choose the best architecture. Once the tests were done and the errors were compared accordingly, it was decided to create an ANN with a 1:2 delay and ten hidden neurons.

4. Results and Discussions

The energy generation data from (1990 – 2023) was collected from the administrative management of the Shiroro power station to carry out a ten (10) year future energy generation forecast using an Artificial Neural Network.

Figure 7 shows the graph of reservoir inflow versus turbine discharge for the Shiroro Hydropower station from 1990 to 2023. The graph is nonlinear due to the fluctuation of rainfall recorded over the entire study period.

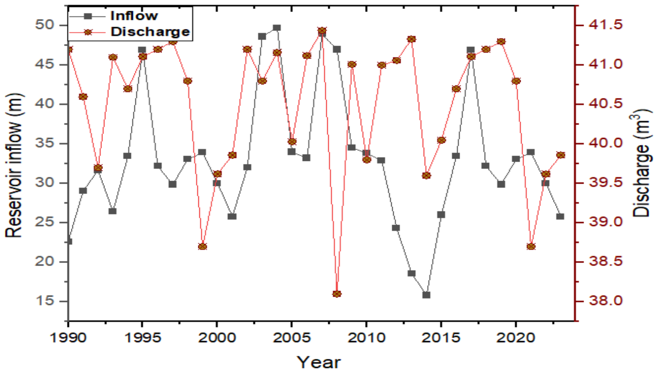

Fig.7: Variation between reservoir and discharge for the turbine.

The model was checked using the error performance index to guarantee accuracy and ensure the forecasted load was close to the actual load. The RMSE was calculated for both the training and validation data sets to achieve this. ANN worked intelligently by finding a nonlinear way to map out the corresponding values of input to target responses. Thus, the minimum point of training error that yielded the lowest RMSE and nine (9) neurons was chosen as the appropriate neural network architecture for estimating the hydroelectric generation for Shiroro hydropower station in Nigeria. These plots comprise training and test validation plots, as shown in Figure 8. They were used to validate the performance of the model network outputs. The highest regression value obtained for the hydropower forecast was 0.55369 for the training network

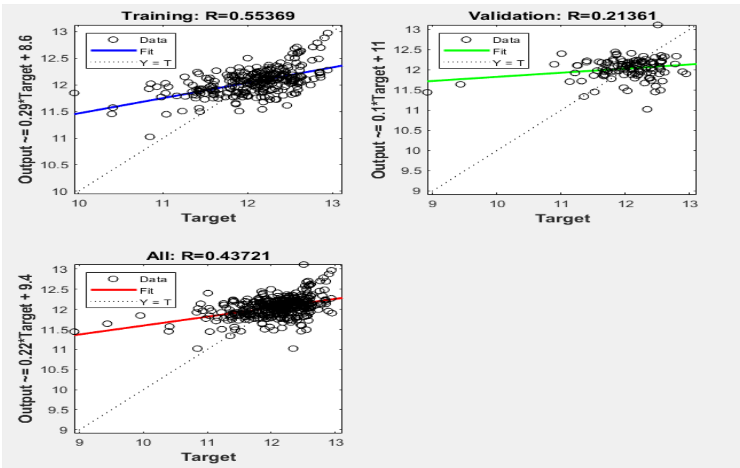

Fig.8: Error optimization for validation and testing data sets.

Figure 9 compares the actual and predicted values of energy generation for the Shiroro power station using the artificial neural network (ANN). The zoom with a corresponding high spike on various regions of the graph has shown that the model for this scenario is underfitted with respect to the forecast of the power generation output of the hydropower station. Although the pattern for actual generation was similar to the simulated generation value, there was a big gap between the estimated and actual value of the simulation. The actual generation value shows an increasing trend during the months with high solar irradiation between January and May due to the fact that those months fall within the periods of dry season conditions. Hence, those month periods are highly recommended for solar energy harvest. Stated differently, the model's oversimplification resulting from shorter training times and less regularization during training may cause gaps between the simulated and actual PV power generation. Thus, the desired output and the MLP output, as displayed in Figure 10, show that the network was able to predict the power generation of the power station with an acceptable accuracy of regression value of 0.5595, as indicated in Figure 9.

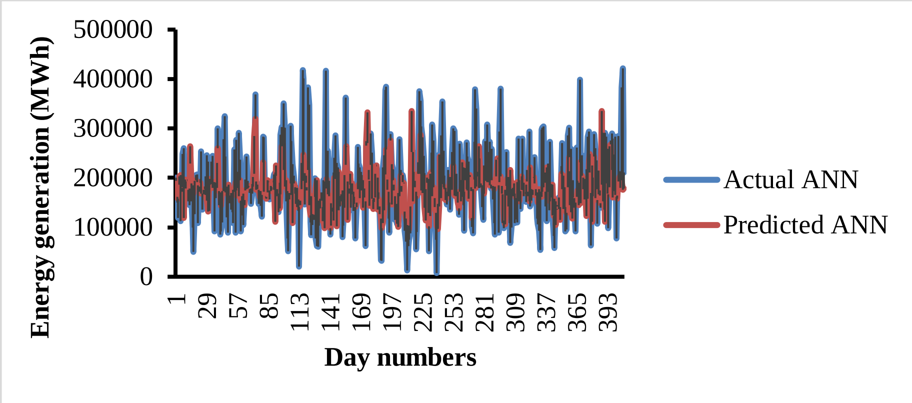

Fig.9: Comparison between Actual and Predicted energy generation for Shiroro power plant.

Once the solar ANN was trained, its performance was evaluated. Regression plots show the regression correlation between the network outputs and the network targets. They were used to validate the performance of the model network outputs. An *R* of 1 indicates that the correlation or regression line perfectly fits the data, while a 0 value means that there is no linear relationship between outputs and targets (Rodrigues *et al.*, 2014; Wang *et al.*, 2009). The regression analysis of the developed ANN model resulted in R values for training, validation, and testing, which were obtained as 0.99288, 0.99802, and 0.99903, respectively. These values were very close to 1, indicative of good agreement between the output (simulated values) and the targets (experimental values). Figure 10 shows the test data's regression, which has a value of 1 for both the training and validation, demonstrating a strong relationship between network outputs and target values. Therefore, the present work's best ANN model for solar PV prediction has an R-value for training and validation data as 1, respectively. In general, the R values obtained from Figure 10 indicate that the proposed ANN model II was best for predicting the PV power output in Nigeria with acceptable accuracy. The dotted lines in each plot represent the perfect result, which indicates outputs equal to targets.

In contrast, the solid line represents the best-fit linear regression line between outputs and targets. The scatter plot shows that specific data points have poor fits. The (R) value for the training plot was 0.99805.

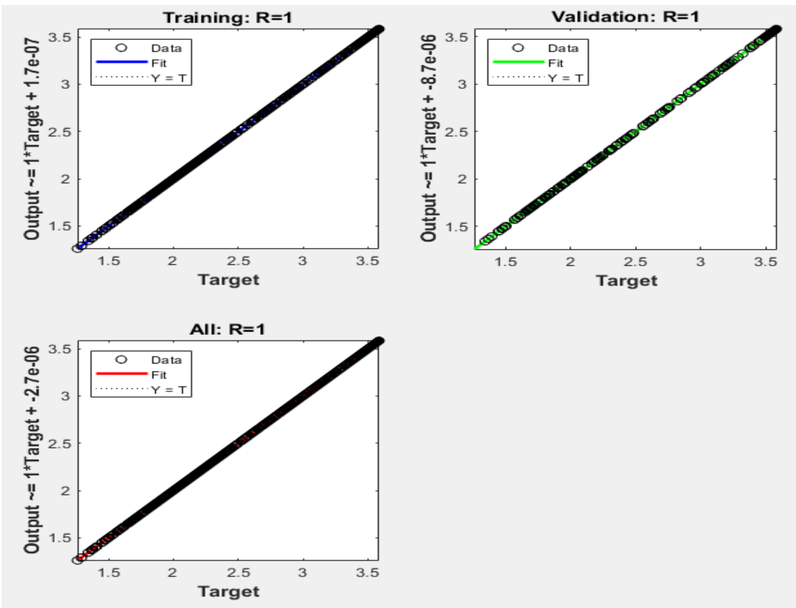

Fig10: Obtained regression plots of training and validation for solar ANN.

Figure 11 shows the trained network's result in predicting the PV power output within the training database. While the thick line gives the actual measurements of solar PV output, the values predicted by the network are given by the discontinuous asterisks line. Thus, carefully observing Figure 12 shows that the difference between actual and predicted values was not too large, and the trend of the prediction line follows the actual line at every moment.

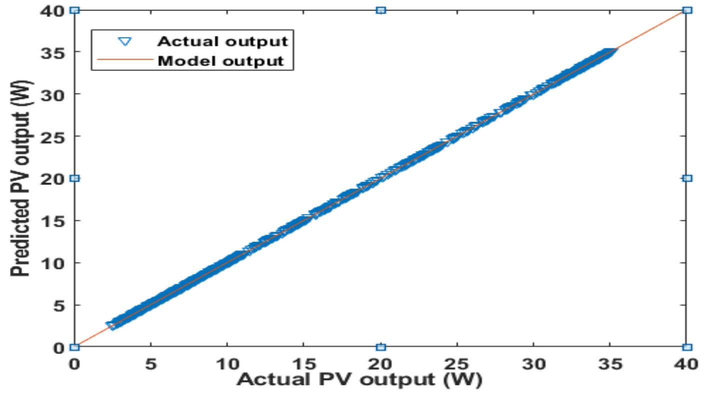

Fig.11: Obtained regression plots of training and validation for solar ANN.

Considering Figure 11 and 12 as a whole, it could also be observed that the points on the plots were not far from the lines, rather most of the points were clustered within the line, which shows that the model was neither under fitted nor over fitted and was very good for prediction with 1.559 e-09 as the best validation performance for the MSE

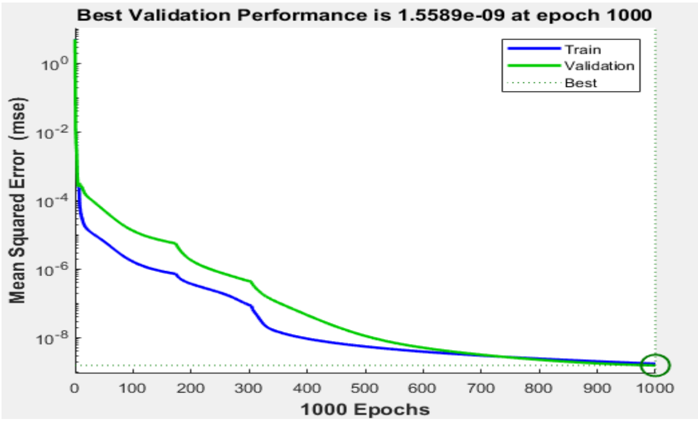

Fig.12: Obtained regression plots of training and validation for solar ANN.

The line plots are shown in Figure 13 for the actual solar power and its corresponding forecasts for the ANN model using an intelligent algorithm. The ANN's input variables were the daily solar radiation, PV surface temperature, current and voltage. They are periodically generated and updated daily to forecast the power output for the solar PV system. Therefore, the output of the forecasting model, which is the power output of the PV, does not change much by increasing the horizon time. In essence, the forecasts from the ANN model tracked the actual power better than those of the other hydropower generation model.

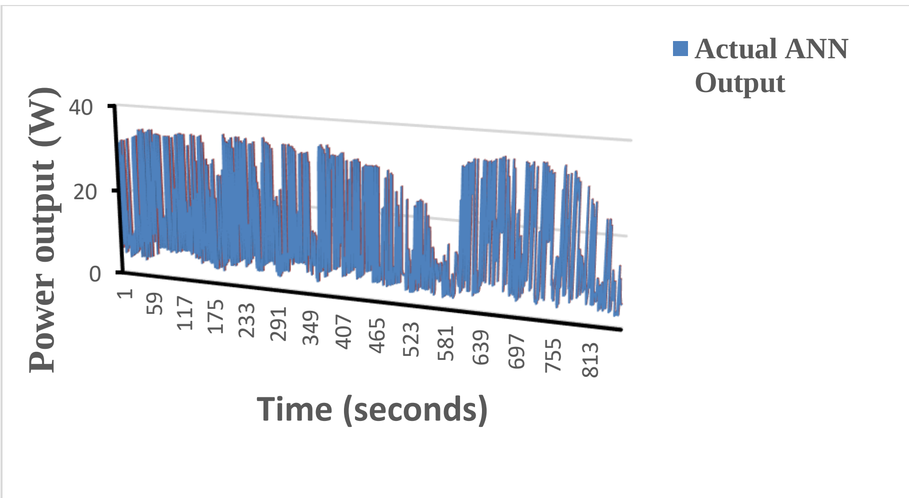

Fig.13: Comparison between Actual and Predicted energy generation for Solar PV system.

5. Conclusions

This paper has demonstrated an application of an intelligent algorithm for the modelling and simulation of energy generation for the Shiroro hydroelectric power plant alongside the power output of solar PV in Nigeria. MATLAB software was used to perform the programming by developing two forecasting models. Thus, hydrological data for the Shiroro hydropower station spanning from 1990 to 2023 was used for the analysis alongside experimental data for the photovoltaic systems for Minna Niger State, Nigeria (as a case study). Artificial neural network (ANN) models were developed to mimic and simulate the energy generation outputs for the two scenarios. A reverse energy generation forecast was carried out to assess the complementarity between the two given scenarios for power production viability. Therefore, the artificial neural network (ANN) model for solar PV generation outperformed the model of hydropower plants with reasonable accuracy, as evidenced by the lower value of RMSE 0.8% and the high correlation value of 1. It indicates that the model was dependable and could be used for prediction at a 95% confidence level. Therefore, this forecast outcome will serve as a guide for Shiroro hydropower generation to plan effectively for its future generation and prepare for any possible downturns.

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Conflict of Interest

The authors declare that there is no conflict of interest related to this research work.

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