



Solar Irradiance Forecast using Feed Forward Neural Network: A Case Study of Zaria Town

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Abstract

This study aims to forecast solar irradiation using Artificial Neural Network (ANN), with the goal of developing a high-performance prediction model based on real meteorological data. Lack of sufficient meteorological data in Nigeria necessitate the development of model to forecast solar irradiance for optimal utilization. The model is designed to predict daily solar irradiation for Zaria town, providing valuable insights to the utilities managing solar energy generation and monitoring systems. Feed forward Neural Network (FFNN) was applied to perform day-ahead solar irradiance forecasting. We employ a day-ahead persistence model as a baseline, a commonly used method in solar irradiance forecasting research. It operates under the assumption that current conditions will persist over the forecast horizon. Specifically, it uses the irradiance values from the previous day as the predictions for the following day. The findings highlight the significance of meteorological factors (such as minimum humidity, maximum temperature, day, month, and wind direction) in the FFNN model training. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used to evaluate the performance of the model. The RMSE of 4.46 W/m² and MAE of 2.52 W/m² obtained indicate an excellent performance of the FFNN model. The model outperformed the Persistence model in predicting daily solar irradiance, indicating its superiority solar irradiance forecast. The results show the ability of the model to forecast day-ahead solar irradiance in Zaria town which can address the issue of non-recorded meteorological data.

Keywords: Solar irradiance, forecast, feed forward neural network, renewable energy consolidation.

1.0 Introduction

The most abundant, clean, and dependable renewable source of energy in Nigeria, and many other countries, that is also free, has been identified to be solar energy [1, 2]. Effective design of solar power systems require accurate knowledge of solar irradiation [3, 4]. With the ongoing shift toward clean energy and a hydrogen-based economy—driven by fossil fuel depletion and environmental concerns—hydrogen production from renewable sources has gained significant attention, particularly through photovoltaic systems in off-grid areas [5, 6]. However, obtaining precise data on horizontal solar radiation is crucial for effect electricity production through photovoltaic technology. This, therefore, has led to the development of various algorithms that are based on available meteorological data in the study areas [7].

In the case of Nigeria, there are only a few meteorological stations, most of which are government-owned. However, due to the lack of solar radiation measuring equipment in these stations, there is no official record of solar radiation data in the country. Additionally, many of these stations have incomplete meteorological records, including temperature, sunshine duration, and other key parameters. This limitation underscores the need for developing reliable algorithms to predict horizontal solar radiation [8].

In a photovoltaic (PV) system, solar irradiance at ground level is one of the most crucial factors affecting performance, as it directly influences the amount of electricity generated [9]. Therefore, accurate prediction of solar irradiance is vital for PV system operators. Reliable forecasts not only support efficient planning and operation but also help lower operational costs. The time resolution of forecasting methods can vary significantly—from just a few seconds up to several days. High-resolution forecasts, with intervals of only a few seconds, are mainly used for system stability and control purposes [10]. Very short-term forecasts, also known as now-casting, typically cover timeframes from 3 to 15 minutes and are useful for scheduling, dispatching, and resource allocation [11]. On the other hand, short- to medium-term forecasts, which range from a few hours to several days, play a key role in grid management, load balancing, and unit commitment decisions [12, 13]

A variety of models that are statistical, physical, or empirical, have been developed to forecast solar irradiance. In statistical models, predictions are made either by considering the solar irradiations as a time series data or through the use of machine learning techniques [14]. For instance, [15] employed the former to forecast hourly solar power values for up to 36 hours while [16] employed the latter approach by designing an ANN model that

uses meteorological variables as input to predict hourly solar irradiance. [17] compared autoregressive models and neural networks for solar forecasting. In [18], neuro-fuzzy dynamic model was used to predict the irradiance for five-minute. [19] implemented a Kalman filter for statistical post-processing. Additionally, regression analysis techniques have been applied to predict solar irradiance within a five- to 15-minute horizon [20]. Physical models, on the other hand, calculate total irradiance by combining ground-reflected, direct, and diffuse components, based on the zenith angle, altitude, and surface azimuth angle [21].

With advancements in computational techniques and deep learning, recurrent neural networks (RNNs) have recently been explored for solar irradiance prediction [22].

2.0 Related Works

Numerous approaches for the forecasting solar irradiance (SI) have been introduced in the literature. These approaches can be broadly classified as either data-driven models (DDMs) or physical models (PMs).

Physical models (PMs) rely on numerical weather prediction (NWP) methods, which use complex mathematical equations to forecast solar irradiance [23]. While NWP performs well under steady weather conditions, its performance is mostly affected by cloudy weather due to its coarse resolution, which restricts the ability to capture detailed cloud-related information [24].

In contrast, DDMs rely on historical data, often incorporating external weather variables such as temperature, humidity, and the clearness index alongside SI measurements. These models are typically classified into two subcategories: nonlinear autoregressive (NAR) models and nonlinear autoregressive models with exogenous inputs (NARX). The NAR models predict future SI values based solely on past SI data, while NARX models enhance prediction accuracy by integrating additional exogenous inputs like temperature, humidity, and the clearness index [25].

Under the two frameworks (NAR and NARX), the DDM can be further categorized into statistical, artificial intelligence-based, and hybrid models. The statistical models are largely built on autoregressive (AR) techniques [26].

AI-based models often surpass traditional statistical approaches in solar irradiance (SI) forecasting, primarily because of their capacity to model complex nonlinear relationships between inputs and outputs. Among these, machine learning techniques have demonstrated strong potential. Commonly used models include support vector machines (SVM), feed-forward neural networks (FFNN), and adaptive fuzzy neural networks (AFNN), among others.

3.0 Methodology

The learning processes of biological neural networks that consist of interconnected information-processing units, known as neurons, inspires ANNs [27]. The architecture of the ANN is such that the neurons are organised in three layers, namely the input layer, the hidden layer, and the output layer. These models have the capability of effectively processing both linear and nonlinear problems, often outperforming traditional empirical models. An ANN can be mathematically modelled using equation (1).

$$y(x) = G(\sum_{i=1}^L \omega_i(t) \cdot x_i(t) + b) \quad (1)$$

In this context, $y(x)$ represents the output response, while $x_i(t)$, t , G , L , $\omega_i(t)$ and b denote the input variables, discrete time, the transfer function for the hidden layer, the number of neurons, the weights, and the bias respectively. Based on the connection types between the inputs, the hidden layer(s) and the output layer, ANN models can be categorized as an FFNN or recurrent neural network (RNN). This paper would use the FFNN as depicted in Figure 1. In this study, the FFNN model is configured with the following hyperparameters: a learning rate of 0.001, 20 hidden units, 1 hidden layer, full-batch gradient descent, L2 regularization, standard scaling of inputs, and is trained for 1000 epochs.

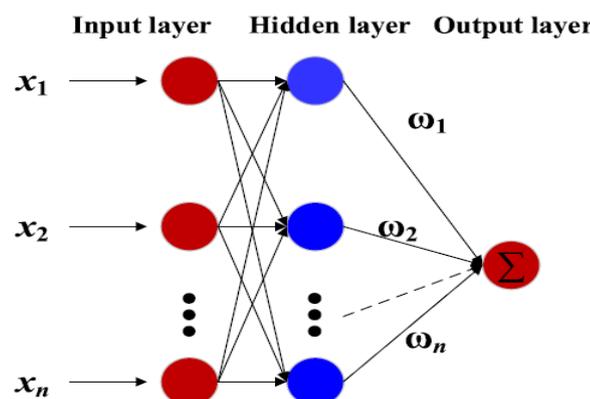


Figure 1: Architecture of Feed Forward Neural Network

To ascertain the model's performance, a good measuring metric should be chosen which quite presents some difficulties as described in [28, 29]. The broader challenge in selecting the metrics depends on their suitability in certain circumstances which results in undesirable outcomes. Root mean square error (RMSE) and mean absolute error (MAE) stand out to be major performance metric that is outstanding in accounting to the reliability of a model and as such will be used in research. The formulas for calculating RMSE and MAE are provided in Equations (2) and (3), respectively .

$$RMSE = \sqrt{\frac{1}{T \cdot M} \sum_{i=1}^M \sum_{t=1}^T (h(x_t^{(i)}) - y_t^{(i)})^2} \quad (2)$$

$$MAE = \frac{1}{T \cdot M} \sum_{i=1}^M \sum_{t=1}^T |h(x_t^{(i)}) - y_t^{(i)}| \quad (3)$$

where M is the number of examples in the dataset, $x^{(i)}$ represents the feature vector for the i^{th} instance, $y^{(i)}$ is the corresponding true output, and h denotes the system's prediction function. It's important to recognize that RMSE and MAE, when used alone, may not provide a complete picture of forecast accuracy, as they fail to capture the variability inherent in time series data. To address this limitation, the forecast skill metric, which offers a relative measure of improvement over a baseline model and commonly referred to as the persistence or naive model is used. This metric is defined in Equation (4)

$$s = \left(1 - \frac{U}{V}\right) \cdot 100 \quad (4)$$

A typical forecasting model should yield a forecast skill score s ranging from 0 to 100, where 100 represents a perfect forecast and 0 indicates that the model performs no better than the persistence (naive) model. The values U and V are computed over the same dataset, where $U \in \{MAPE, RMSE\}$ refers to the error metric of the forecast model, and $V \in (MAPE_{persistence}, RMSE_{persistence})$ refers to the corresponding error from the persistence model [30].

The dataset used in this study was obtained from the stations operated by the Nigerian Meteorological Agency (NIMET) which employ consistent calibration methods for gathering SI data which is measured in W/m^2 using a solarimeter. This dataset includes records for solar irradiance, minimum and maximum temperatures, minimum and maximum humidity, dew point, rainfall, day, month, year, wind speed, wind gravity, and wind direction. The data, covering a period from 2005 to 2020, was collected over this timeframe and it is for the town of Zaria (11.085542° Latitude and 7.719945° Longitude) in Kaduna state Nigeria.

Data preparation in machine learning typically involves feature scaling and encoding. Since machine learning algorithms can underperform when numerical features vary widely in scale, we standardized the data to have zero mean and unit variance. For categorical features such as hour of the day and month of the year, we applied one-hot encoding. This technique transforms a categorical feature with M distinct values into a binary vector of length M , where only the element corresponding to the original category is set to one, and all others are set to zero.

4.0 Results and Discussion

Table 1 presents the forecasting outcomes for the FFNN model, which utilizes exogenous variables as inputs. The Feed forward FFNN model has an RMSE of $4.46 W/m^2$. This result demonstrates a better performance of the FFNN model in predicting day-ahead solar irradiance.

This is consistent with the Mean Absolute Error (MAE) where FFNN records $2.52 W/m^2$. The forecasting skills shown in Table 1 consistently shows the great performance of the FFNN model as relate to the persistence model.

Table 1: Model Performance results

Models	RMSE (W/m^2)	Forecast Skill (%)	RMSE MAE (W/m^2)	Forecast Skill MAE (%)
FFNN	4.46	97.37	2.52	97.12
Persistence	170.48	0.0	87.51	0.0

As anticipated, the persistence model performs less effectively than FFNN; however, it serves as a benchmark for evaluating FFNN model.

Figure 2 illustrates the measured SI against that predicted by the FFNN and the Persistence model for the next day. Consistently, the persistence model demonstrates inferior performance compared to the FFNN. This suggests that the previous day's solar irradiance has minimal correlation with the following day's values, rendering it an unreliable predictor. Consequently, the FFNN model yields a satisfactory forecasting result.

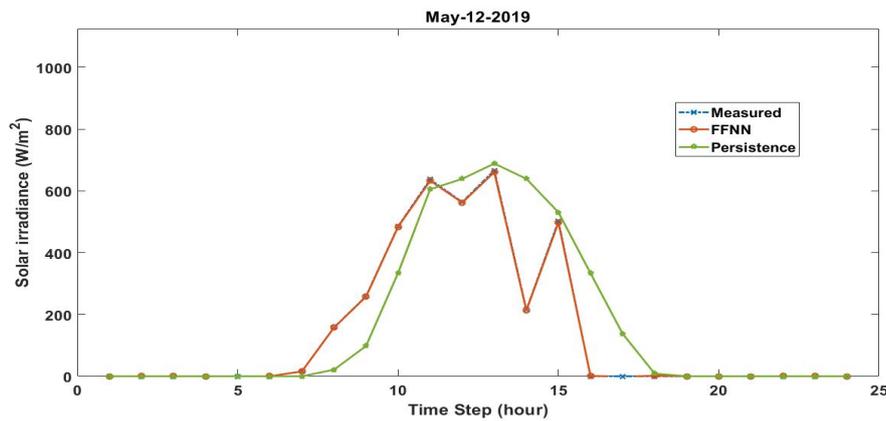
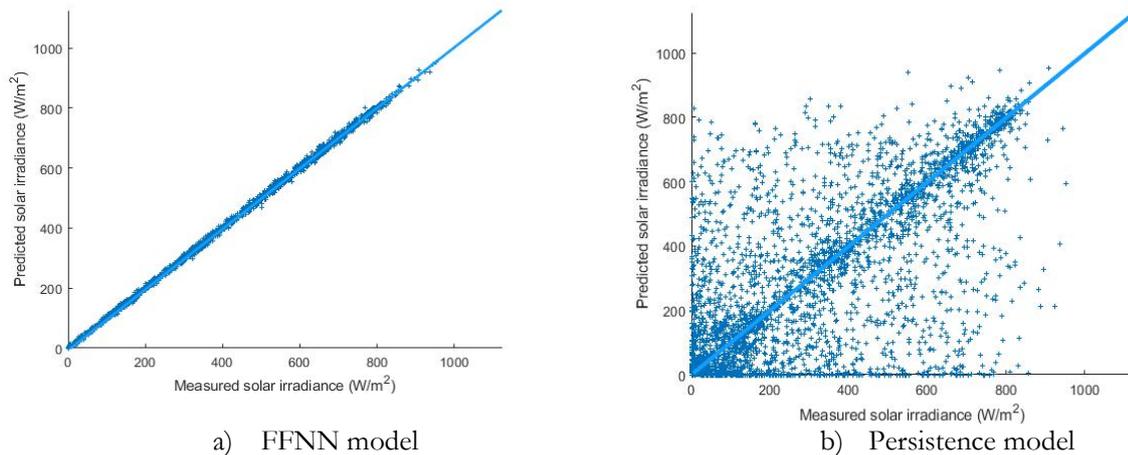


Figure 2: FFNN and Persistence models forecast against Measured Data

The comparison of the measured and predicted SIs by the FFNN and the Persistence models is illustrated in the scatter diagrams in Figure 3. Figure 3 (a) shows a well packed data pattern indicating the accuracy of the prediction for the FFNN scatter plot. The Persistence model performance that is shown in Figure 3 (b) shows a more dispersed pattern of the data. This indicates the inaccuracy of the model. The solid lines represent perfect forecasts, while the star markers denote individual prediction instances. The proximity of each star to the solid line indicates the accuracy of the prediction. Thus, the closer the star is to the line, the more accurate is the forecast made by the model.



a) FFNN model

b) Persistence model

Figure 3: Scatter Plot of Predicted Vs Measured Solar Irradiance

5.0 Conclusion

The proliferation of solar-powered microgrids has heightened the importance of accurate solar irradiance forecasting. In this study, we employed an FFNN that utilizes only exogenous as inputs from NIMET dataset.

To evaluate the effectiveness of FFNN model, it was compared with Persistence model. With appropriate regularization and hyperparameter tuning, an RMSE of 4.46 W/m² and MAE of 2.52 W/m² were obtained for the FFNN model, indicating an excellent performance. The results indicate that the FFNN model consistently outperforms the Persistence model with 97.37% for RMSE and 97.12% for MAE. The results show the ability of the model to forecast day – ahead solar irradiance in Zaria town which can address the issue of non-recorded meteorological data. Future work will look at using deep learning techniques in order to improve the accuracy of the forecast.

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