Nigerian Journal of Engineering Science Research (NIJESR).
Vol. 5, Issue 3, pp.39-50, September, 2022

ISSN: 2636-7114
Journal Homepage: https://www.iuokada.edu.ng/journals/nijesr/

Comparative Performance Analysis of Machine Learning Algorithms for Predicting Output Power of Soiled PV Modules

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Manuscript History
Received: 14/06/2022
Revised: 07/08/2022
Accepted: 15/09/2022
Published: 30/09/2022

Abstract: Photovoltaic (PV) system soiling losses have been proven to vary between areas and time. These losses can add a lot of unpredictability to the output of a PV system. With a greater understanding and predictability of these losses, the variability of PV system output, operation, and maintenance costs associated with cleaning systems might be better understood. Due to the nonavailability of solar radiation measuring equipment at the meteorological stations, especially in developing countries, it is essential to deploy the usage of machine learning algorithms to predict the performance of PV systems under soiling conditions. In this work, a comparative performance analysis of two promising Techniques: Hammerstein-Weiner (H-W) and Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented. Data used in this work was gathered from the University of Abuja's Faculty of Engineering, Nigeria. These two unique models are simple to use and are an upgrade to the existing models in the literature. The models' prediction accuracy were assessed using metrics such as the R and R^2 while the error analysis was conducted using MSE and Root Mean Square Error (RMSE). The results revealed the models developed in this work performed well in estimating the predicted power of a soiled PV module with minimal error. H-W model has a better performance in the training phase with R and R^2 having 0.9904 and 0.9809 respectively in training and testing respectively. However, the ANFIS model recorded a better performance of 0.9735 and 0.9477 for R and R^2 respectively in the testing phase.

Keywords: *Photovoltaic, Hammerstein-Weiner, ANFIS, Prediction, Soiling*

INTRODUCTION

Due to its economic merit (quick price reduction) and environmental merit (emission), solar energy conversion devices have been urged to replace conventional non-sustainable energy gathering systems(Faskari *et al.*, 2022). Solar photovoltaic devices are considered to be the most promising clean energy source among renewable energy technologies, owing to the continual growth in fossil fuel prices and their environmental impact (Badamasi *et al.*, 2021; Faskari *et al.*, 2022). Areas inside the worldwide Sun Belt with abundant solar irradiation appear to have a high concentration of air dust which has been recognized as the primary degrading element that has a negative impact on PV performance, particularly in the desert, arid, and semi-arid regions(Kazem and Chaichan, 2019).

This degradation varies by location and exposure duration making it extremely difficult to calculate a worldwide soiling rate uniformly, spurring regional research. Photovoltaic (PV) system soiling losses have been proven to vary between areas and time. These losses can add a lot of unpredictability to the output of a PV system. With a greater understanding and predictability of these losses, the variability of PV system output, operation, and maintenance costs associated with cleaning systems might be better understood(Qasem *et. al.*, 2012). The soiling or dust layer might be opaque, porous, or partially transparent depending on how dust accumulates on the PV module. Module soiling is influenced by wind speed and dust concentration (Chanchangi *et al.*, 2020), as well as other environmental parameters such as organic material deposition, water-soluble salts, surface tension, and particle energetics PV production, which has been established to be exactly proportional to the incidence of solar irradiance on the panel's surface (Aly *et al.*, 2019). The sun irradiance reaching the solar cell's surface and its operating temperature define the PV module's output power.

The high cost of soiling monitoring equipment is one of the main reasons for the scarcity of trustworthy soiling data. Low-cost tools that can provide accurate insight into soiling impacts are needed (Valerino *et al.*, 2020). Artificial Intelligence (AI) is widely used in practically every single sector of Electrical Engineering research from Estimation/Prediction to optimization (Shui *et al.*, 2011; Najashi *et al*, 2014; Adebayo *et al.*, 2018; Xia *et al.*, 2019; Dutta *et al*, 2020; S.I. Abba *et al.*, 2021; Omeje *et al.*, 2021) has overseen a boom in its application to tackle several problems. Due to its robustness, noise tolerance, and capacity to work with multivariable and nonlinear information, Machine Learning (ML) algorithms have been used as a useful tool for modeling phenomena in PV systems in recent years. Factors that have a negative impact on dust deposition and the performance of PV systems were examined in (Ghosh, 2020). The various ways in which dust deposition can be a hurdle to India's PV-based energy security plan were also explored. Cleaning techniques that are currently available were also discussed. The nature, size, and morphology of dust particles differ depending on where they are found. Dust deposition is reduced by increasing the PV tilt angle, as well as by strong wind speeds and heavy rain showers. Their findings showed that higher PV tilt angles, high wind speeds and heavy rain showers, minimize dust deposition.

The work of (Arsić *et al.*, 2020), the findings of statistical modeling of ground-level ozone concentrations in the air around Zrenjanin (Serbia) were given. The authors wanted to know how ozone concentrations were affected by the following predictors: SO2, CO, H2S, NO, NO2, NOx, PM_{10}, benzene, toluene, m,p-Xylene, o-Xylene, and ethylbenzene in the air, as well as meteorological data (the wind direction, the wind speed, air pressure, air temperature, solar radiation, and RH). The tools employed for the mathematical study of the suggested occurrence were multiple linear regression analysis (MLRA) and artificial neural networks (ANNs). The results reveal that ANNs produce superior estimations of ozone levels at the monitoring location than the multilinear regression model, which was used previously. For soiling prediction, an artificial neural network (ANN) model and a multiple linear regression (MLR) model with meteorological and environmental factors as variables were developed *(Chiteka et. al.*, 2020). To discover all of the key soiling factors from the specified list of parameters for use in predictive modeling, the study uses a specific method, the Boruta algorithm applied in the random forest technique. Also, a soiling forecasting algorithm that predicts the quantity of soiling on a solar PV collector based on selected daily meteorological and environmental data. In (Shapsough *et. al.*, 2019), the authors presented a study using neural network-based modeling algorithms and sensor data to estimate the power output of solar systems in soiling situations. Only solar irradiation, ambient temperature, and maximum power point (MPP) characteristic variables of photovoltaic (PV) modules obtained from online current-voltage (IV) tracers at the site of a PV installation were used, which used linear regression models and artificial neural networks. Actual monitoring data from two 100-Watt PV modules installed in the UAE were used to train and evaluate the two models.

The findings suggest that the maximum power output of dirty PV modules can be predicted with an accuracy of around 97 percent. The proposed models outperform more sophisticated models in the literature in terms of accuracy. The reliability and validity of existing evaluations that focus on the impact of various environmental conditions on the performance of a photovoltaic (PV) system were examined (Mustafa *et al.*, 2020). Four environmental parameters impacting system performance (dust deposition, water droplets, bird droppings, and partial shade conditions) are evaluated simultaneously. The findings of this study show that dust, shade, and bird fouling have a substantial impact on PV current and voltage, as well as collected PV energy. The most significant influence on PV module efficiency was shading. Increases in shade area on a PV module surface of a quarter, half, and three quarters resulted in 33.7 percent, 45.1 percent, and 92.6 percent power reductions, respectively. The impact of water droplets on the PV panel, on the other hand, had the opposite effect, lowering the panel's temperature, which increased the potential difference and enhanced the power production by at least 5.6 percent. Furthermore, dust deposition lowered power output by 8.80% and efficiency by 11.86%, while birds fouling the PV module surface was discovered to reduce PV system performance (Al-Bashir *et al.*, 2020). Presents a mathematical model for predicting and estimating PV output power using an MLR. Solar irradiance, cell temperature, and wind speed make up the datasets used with the MLR model. With R2 values of 96.5% the model predicts generated electricity, with solar irradiance being the most effective parameter. The model's effect is not substantial due to the low wind speed in the geographical region where the experiment was conducted. Using a multiple linear regression (MLR) model, (Ribeiro *et al.*, 2021) provided a statistical methodology for estimating energy losses due to soiling deposition on solar modules. Environmental samples make up the datasets (solar radiance, environmental temperature, humidity, and wind speed). The test is performed to see if the difference between the MLR model's predicted values and the observed values is due to soiling. The system's validation trials are based on a one-year dataset of environmental and electricity generation data from a solar plant in Brazil's northeast. The daily energy loss estimates ranged from 2.20 percent to 12.31 percent in less than a month, according to the findings. The present daily power demand is predicted to exceed 17,520 megawatts, with a peak generation capacity of 5,300 megawatts (MW). According to certain sources, Nigeria's electricity demand will increase by 16.8 times by 2030, from 77,450 megawatts in 2025 to 119,200 megawatts in 2030 (Ozigis *et al.*, 2022). It can be seen from the available literature that most works concentrated on applying ANN-based methods with minimal attention being given to comparing how newer models perform against one another. In this work, a comparative performance analysis of two promising Techniques: Hammerstein-Weiner (H-W) and Adaptive Neuro-Fuzzy Inference System (ANFIS) is presented.

MATERIALS AND METHODS

2.1 Study Area

Nigeria is Africa's most populated and economically strong country, which accounts for the enormous need for electricity (Wolde-Rufael, 2006). Because it is situated between 4°N and 14°N latitude, it receives a lot of solar radiation throughout the year. This energy could be put to good use in the development of solar power systems (Johnson and Ogunseye, 2017). Nigeria has a lot of potential for solar energy and receives a lot of sunlight in the region of 19.8 MJm2/day of solar energy and 6 hours of sunlight on average per day. Over 427,000 megawatts (MW) of concentrated solar power and photovoltaic output are projected to exist in the country (Okafor et al., 2021). The current study was conducted in Abuja, Nigeria's capital city, which is at the confluence of the Niger and Benue rivers (Abba *et al.*, 2021).

Fig. 1 Location of Study Area Abuja Nigeria (Courtesy Google Earth)

2.2 Modelling

In this study, two models were proposed; Hammerstein-Wiener, ANN, and Adaptive Neuro-Fuzzy Inference System (ANFIS) for the prediction of the expected output power of the PV module using the input-output combination in equation (1), the data set was partitioned into two sections, with 60% of the data being used for training and 30% being used for testing and 10% for validation. One of the most crucial aspects of any AI-based modeling is the selection of dominant input parameters.

$$Volt + Curr + WS + Temp \ = EP \tag{1}$$

Where $Volt$ is the voltage, $Curr$ is current, WS is wind speed, $Temp$ is the temperature and EP is the estimated power.

2.2.1 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The neuro-fuzzy network is a five-layer feed-forward network that uses neural network learning techniques and fuzzy reasoning to translate an input space to an output space. The ANFIS architecture is seen in Fig. 2. The limitations of fuzzy logic and ANN can be overcome with ANFIS. The model combines the capabilities of both ANN and fuzzy logic to build a process that can handle complicated non-linear interactions between a set of input and output (Elkiran *et al.*, 2018; Mohammadi *et al.*, 2020). (Elkiran, Nourani and Abba, 2019) contain a wealth of information on ANFIS.

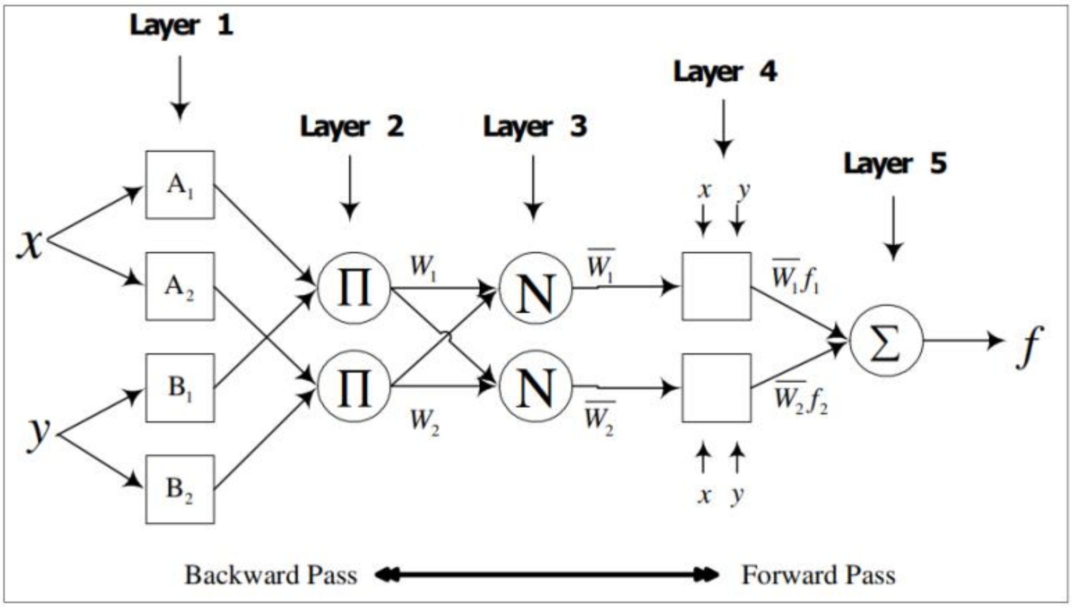

Fig. 2 ANFIS architecture

2.2.2 Hammerstein-Weiner (H-W)

The H-W model is a nonlinear system identification model that does a good job of sorting dynamic linear and nonlinear statics features while being easy to identify (Jaiswal *et al.*, 2016) with a linear block sandwiched between two static nonlinear gains, the model is a nonlinear-linear-nonlinear (N-L-N) model. The H-W model's structure is shown in Fig. 4. H-W has been applied in a variety of applications in recent years, including hybrid biosystem control (Huang *et al.*, 2020), all-solid-state Li-ion battery design (Semaoui *et al.*, 2014), defect detection systems for unmanned aerial vehicles (UAV) (Rajasekar *et al.*, 2015), and so on. In Fig. 3, f represents the static nonlinear unit that converts the input data u(t), y(t) is the output of the module The model's target function can be determined as shown below;

$$\{y(t) = \grave{y}(t) + e(t) \quad (2)$$

$$\{E = \sqrt{\textstyle\sum_{t=1}^{N} e^2(t)} = \sqrt{\textstyle\sum_{t=1}^{N} [y(t) - \grave{y}(t)]^2} \quad (3)$$

$$\left\{E_M = \sqrt{\textstyle\sum_{t=1}^{N} \left[y(t) - \frac{1}{N}\textstyle\sum_{t=1}^{N} \grave{y}(t)\right]^2} \right. \quad (4)$$

$$\left\{Fit = \left(1 - \frac{E}{E_M}\right) * 100\% \right. \quad (5)$$

Where, N is the number of samples and e(t) is the absolute difference between the actual and expected output of the model, E stands for the loss function, EM stands for the Euclidean norm of the difference between the expected and output mean values, and the fitting degree is fit (a fit of 100 percent is ideal). The fitting degree can be used as a criterion for determining the accuracy of the system identification model when the loss function value is at its smallest.

Fig. 3 Hammerstein Weiner Model

2.3 Data Collection and Processing

The data for this study was gathered from the University of Abuja's Faculty of Engineering, which is located at 8°58' 38.4"N, 7°10' 324"E. Based on field measurements taken at the test site, the PV soiling impact was computed. At the same time, the test site's environmental factors were measured. Data were collected on a daily basis for three months, from April 13 to July 13, 2016. The most commonly used statistic for calculating soiling loss is the soiling ratio. This measure, which is detailed in the IEC 61724-1 standard (Tran and Kim, 2021), is the ratio between the performance of a soiled PV device in outdoor settings and the performance of the same PV device without soiling. Values of PV performance loss due to soiling are available for 90 days, of which 80 days were used for modeling in which all selected variables' measurements were accessible. Two techniques of cross-validation were utilized to guarantee there was no overfitting or underfitting in the training and testing data. With the data split, the hold-out cross-validation procedure was used first. 60 percent of the data was used to train the models, and 40 percent was used to evaluate them in this study.

2.4 Performance Evaluation Metrics

The most significant factor in determining the effectiveness of forecasting models is their accuracy(Najashi and Feng, 2014). As a result, commonly used error metrics are utilized to analyze and compare the outputs of prediction models. To compare the performance success of the forecasting models employed in this work, metrics such as coefficient of determination (R^2), correlation coefficient (R), mean square error (MSE), and root mean square error (RMSE) were used.
Coefficient of Determination (R^2) reveals how effectively a model can predict a collection of data. Its values range from 0 to 1. Better performance is indicated by an R^2 value approaching 1.

$$R^2 = 1 - \frac{\varepsilon(X_i - Y_i)^2}{\varepsilon(X_i - X*_i)^2} \quad (6)$$

where X_i are values of the x-variable in a sample, Y_i is values of the y-variable in a sample and $X*_i$ is the mean of the values of the x-variable. The correlation Coefficient (R) is the square root of the coefficient of determination (R^2) value. Its values range from 0 to 1. Better performance is indicated by an R-value approaching 1.

$$R = \sqrt{\left(1 - \frac{\varepsilon(X_i - Y_i)^2}{\varepsilon(X_i - X*_i)^2}\right)} \quad (7)$$

The RMSE provides information on the prediction on the model's short-term performance. Its value is always positive and is closer to zero as possible

$$\text{RMSE}=\sqrt{\left(\frac{1}{N}\sum_{I=1}^{N}(x_i - y_i)^2\right)} \quad (8)$$

The value is always positive, it measures the error performance of the inputs.

$$\text{RMSE}=\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \quad (9)$$

Where n is the number of data inputs.

RESULTS AND DISCUSSION

In this study, the ANFIS and H-W models were used to train and test an input combination from our measured dataset. Many daily observations of four independent variables (current, voltage, temperature, and wind speed) as well as a dependent variable (power predicted) related to PV module soiling effects are included in the dataset. The data were standardized to a value between -1 and 1. The main benefit of employing the H-W model is that it has a visible relationship with linear systems, making it easier to implement than alternative non-linear models like neural networks. The ANFIS model, on the other hand, benefits from both numerical and language expertise. The ability of the ANN to classify data and discover patterns is also used by ANFIS.

Compared to the ANN, the ANFIS model is more transparent to the user and causes fewer memorization errors (Şahin and Erol, 2017). Both models were developed using MATLAB software 2021a. using an HP desktop with 16GB Ram, core i7 processor.

Table-1 Prediction results for the Models

	TRAINING		TESTING	
MODEL	R	R^2	R	R^2
H-W	0.9904	0.9809	0.9054	0.8197
ANFIS	0.9795	0.9593	0.9735	0.9477

Table-2 Error Results for the Models

	TRAINING		TESTING	
MODEL	MSE	RMSE	MSE	RMSE
H-W	4.5417	2.1311	26.3425	5.1325
ANFIS	9.6731	3.1101	7.6338	2.7629

A summary of the models' performances in terms of prediction (R and R^2) and error (MSE and RMSE) results are presented in Tables-1 and 2 respectively. From Table-1 it could be seen that the H-W model has a better performance in the training phase with R and R^2 having 0.9904 and 0.9809 respectively. However, the ANFIS model recorded a better performance of 0.9735 and 0.9477 for R and R^2 respectively. This might be due to small testing data available as the data used in the study is for only 3 months. A similar scenario was experienced in the error results presented in Table-2. From the table, H-W recorded fewer errors in terms of MSE (4.5417), and RMSE (2.1311) at the training phase as compared to ANFIS model MSE (9.6731), RMSE (3.1101). ANFIS however outperformed H-W in the testing phase with MSE (7.6338) and RMSE (2.7629).

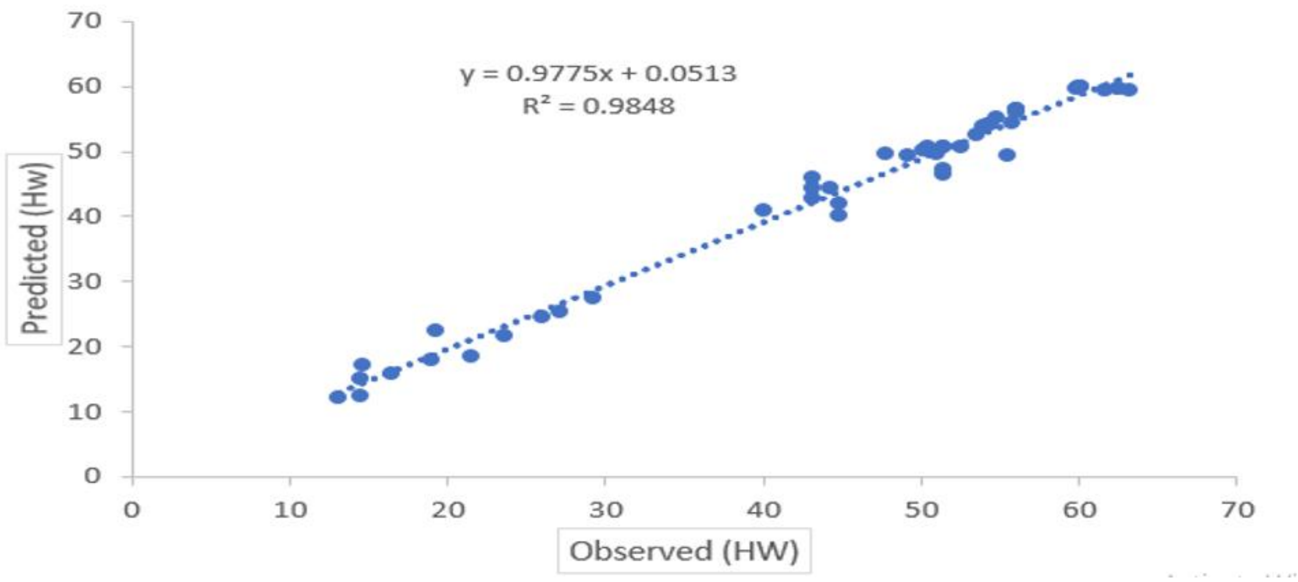

Fig. 4 Scatter Plot of H-W Training Phase

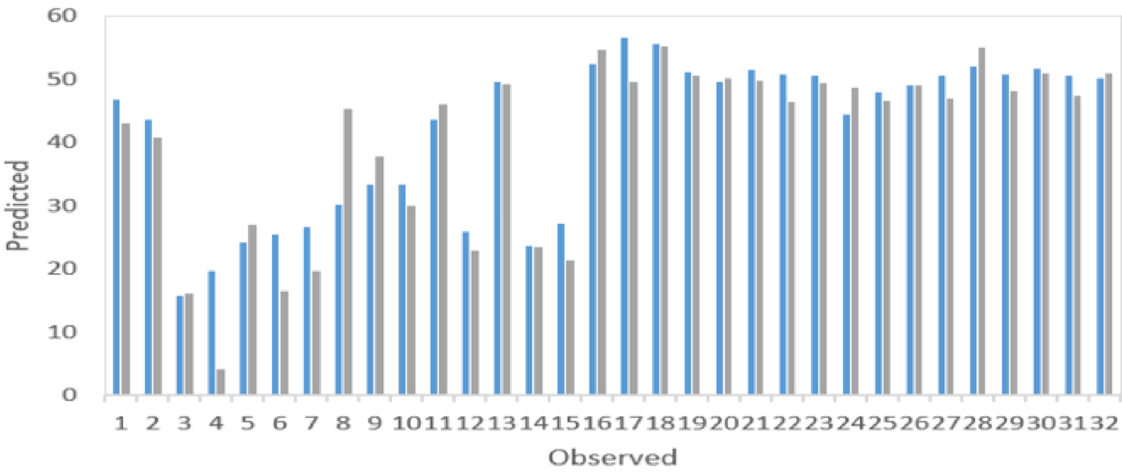

Fig. 5 Bar Plot of H-W Testing Phase

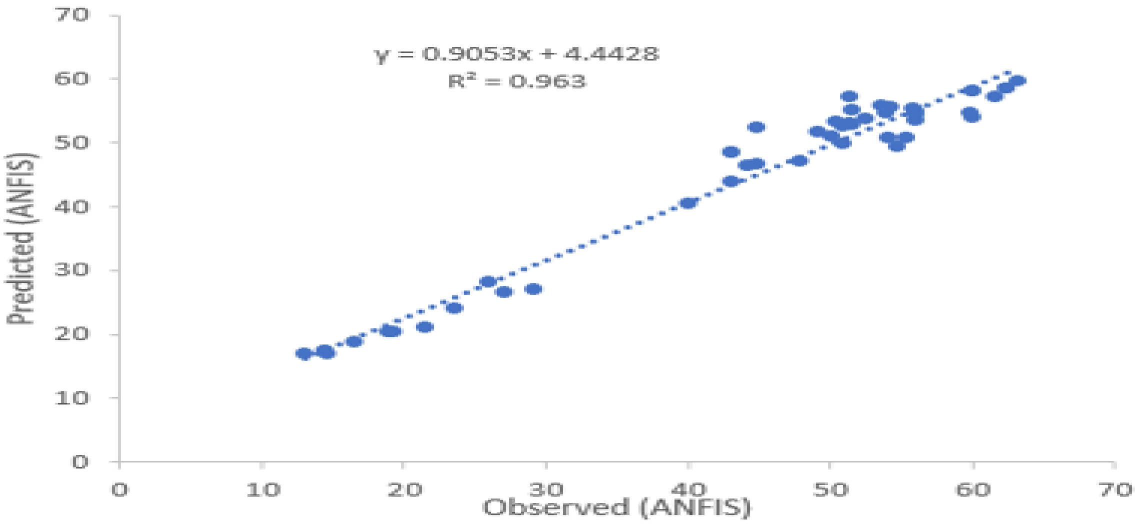

Fig. 6 Scatter Plot of ANFIS Training Phase

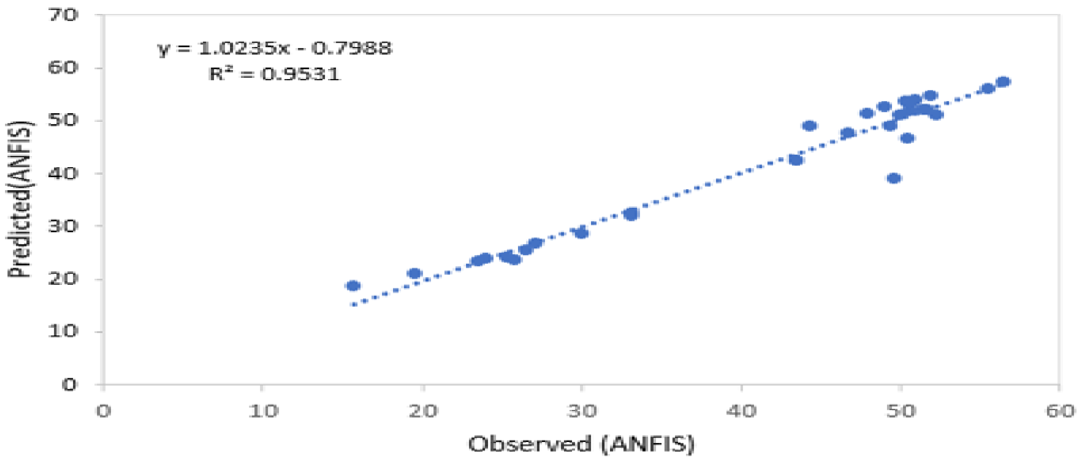

Fig. 7 Scatter Plot of ANFIS Testing

Fig. 4, 5, 6, and 7 buttress the results presented in Tables-1 and 2 evident from the Figs. The results obtained in the training phase are similar to similar works in literature where R was found to be around 99% on average (Faskari *et al.*, 2022). Likewise, the H-W model produces accuracy greater than 98% in its training phase, while that developed in (Shapsough, *et. al.,* 2019) has accuracy of 97% and when compared to (Chiteka, et. al., 2020), similar prediction accuracy is observed.

CONTRIBUTION TO KNOWLEDGE

According to the findings of this study's analysis, it is crucial to anticipate soiled output power of PV modules since they serve as the foundation for choosing appropriate mitigating measures. Cleaning measures will be arranged in advance if the energy loss from soiling is recognized in advance. As a result of knowing in advance how much energy will be produced by such a solar photovoltaic system, it will be possible to choose an alternative energy source to make up for the shortfall caused by the predicted energy loss from soiling and the subsequent cleaning process. The two models used in this study demonstrate how alternative machine learning approaches may be used to accurately forecast the output power of soiled PV modules.

CONCLUSION

Predicting the power yield of PV modules is critical for supplying steady solar energy in micro-grids. A comparative analysis of two promising machine learning algorithms i.e., H-W and ANFIS are presented. The majority of the works done in this field have utilized ANN-based schemes. The motivation behind this work is to compare these two unique models that are simple to use and are an upgrade of the existing models in the literature. The models' prediction accuracy was assessed using metrics such as the R and R^2 while the error analysis was conducted using MSE and RMSE. The results revealed the models developed in this work performed well in estimating the predicted power of a soiled PV module with minimal error. H-W model has a better performance in the training phase with R and R^2 having 0.9904 and 0.9809 respectively in training and testing respectively. However, the ANFIS model recorded a better performance of 0.9735 and 0.9477 for R and R^2 respectively in the testing phase. However, it was discovered that the choice of input parameters had an impact on the model. As a result, sensitivity analysis should be performed to assess the importance of input parameters, which may aid in the appropriate selection of input elements for improved predictive model performance. Furth more, the data used in this work needs to be expanded to obtain a more accurate prediction being that the data is only for three months.

CONFLICT OF INTEREST

There is no conflict of interest with regard to this research

REFERENCES

Abba, S. I. *et al.* (2021). Emerging Harris Hawks Optimization based load demand forecasting and optimal sizing of stand-alone hybrid renewable energy systems– A case study of Kano and Abuja, Nigeria', *Results in Engineering*, 12, 100260. doi:10.1016/j.rineng.2021.100260.

Abba, S.I. *et al.* (2021). Short-term load demand forecasting using nonlinear dynamic grey-black-box and kernel optimization models: a new generation learning algorithm', in *2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS). 2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS)*: 1–6. doi:10.1109/ICMEAS52683.2021.9692314.

Adebayo, O.S. *et al.* (2018). Performance Analysis of Classification Algorithms for DDoS Attack Detection in a Distributed Network Environment. , 24th – 27th April, 2018. Baze University Abuja'. Available at: http://repository.futminna.edu.ng:8080/jspui/handle/123456789/2649 (Accessed: 28 May 2022).

Al-Bashir, A. *et al.* (2020). Analysis of effects of solar irradiance, cell temperature and wind speed on photovoltaic systems performance. *International Journal of Energy Economics and Policy*, 10(1): 353.

Aly, S.P., Ahzi, S. and Barth, N. (2019). Effect of physical and environmental factors on the performance of a photovoltaic panel. *Solar Energy Materials and Solar Cells*, 200, p. 109948. doi:10.1016/j.solmat.2019.109948.

Arsić, M. *et al.* (2020). Prediction of Ozone Concentration in Ambient Air Using Multilinear Regression and the Artificial Neural Networks Methods. *Ozone: Science & Engineering*, 42(1): 79–88. doi:10.1080/01919512.2019.1598844.

Badamasi, Y.A. *et al.* (2021). Effect of Tilt Angle and Soiling on Photovoltaic Modules Losses', in *2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS). 2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS)*: 1–5. doi:10.1109/ICMEAS52683.2021.9692375.

Chanchangi, Y.N. *et al.* (2020). Dust and PV Performance in Nigeria: A review. *Renewable and Sustainable Energy Reviews*, 121: 109704. doi:10.1016/j.rser.2020.109704.

Chiteka, K., Arora, R. and Sridhara, S.N. (2020). A method to predict solar photovoltaic soiling using artificial neural networks and multiple linear regression models. *Energy Systems*, 11(4): 981–1002.

Dutta, N., Subramaniam, U. and Padmanaban, S. (2020). Mathematical models of classification algorithm of Machine learning', in. *International Meeting on Advanced Technologies in Energy and Electrical Engineering*, Hamad bin Khalifa University Press (HBKU Press), p. 3. doi:10.5339/qproc.2019.imat3e2018.3.

Elkiran, G. *et al.* (2018). Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river. *Global Journal of Environmental Science and Management*, 4(4): 439–450. doi:10.22034/gjesm.2018.04.005.

Elkiran, G., Nourani, V. and Abba, S.I. (2019). Multi-step ahead modelling of river water quality parameters using ensemble artificial intelligence-based approach. *Journal of Hydrology*, 577: 123962. doi:10.1016/j.jhydrol.2019.123962.

Faskari, S.A. *et al.* (2022). A Novel Machine Learning based Computing Algorithm in Modeling of Soiled Photovoltaic Module. *Knowledge-Based Engineering and Sciences*, 3(1): 28–36.

Ghosh, A. (2020). Soiling Losses: A Barrier for India's Energy Security Dependency from Photovoltaic Power', *Challenges*, 11(1): 9. doi:10.3390/challe11010009.

Huang, C. *et al.* (2020) 'Point and interval forecasting of solar irradiance with an active Gaussian process', *IET Renewable Power Generation*, 14(6): 1020–1030. doi:10.1049/iet-rpg.2019.0769.

Jaiswal, S., Wath, M.G. and Ballal, M.S. (2016). Modeling the measurement error of energy meter using NARX model', in *2016 IEEE International Instrumentation and Measurement Technology Conference Proceedings*. *2016 IEEE International Instrumentation and Measurement Technology Conference Proceedings*, pp. 1–6. doi:10.1109/I2MTC.2016.7520339.

Johnson, D.O. and Ogunseye, A.A. (2017). Grid-connected photovoltaic system design for local government offices in Nigeria. *Nigerian Journal of Technology*, 36(2): 571–581. doi:10.4314/njt.v36i2.33.

Kazem, H.A. and Chaichan, M.T. (2019). The effect of dust accumulation and cleaning methods on PV panels' outcomes based on an experimental study of six locations in Northern Oman. *Solar Energy*, 187: 30–38. doi:10.1016/j.solener.2019.05.036.

Mohammadi, B. *et al.* (2020). Adaptive neuro-fuzzy inference system coupled with shuffled frog leaping algorithm for predicting river streamflow time series. *Hydrological Sciences Journal*, 65(10): 1738–1751. doi:10.1080/02626667.2020.1758703.

Mustafa, R.J. *et al.* (2020). Environmental Impacts on the Performance of Solar Photovoltaic Systems', *Sustainability*, 12(2): 608. doi:10.3390/su12020608.

Najashi, B.G. and Feng, W. (2014) 'Cooperative spectrum occupancy based spectrum prediction modeling', *Journal of Computational Information Systems*, 10(10): 4093–4100.

Najashi, B.G., Wenjiang, F. and Almustapha, M.D. (2014). *Spectrum Hole Prediction Based On Historical Data: A Neural Network Approach*. arXiv:1401.0886. arXiv. doi:10.48550/arXiv.1401.0886.

Okafor, C. *et al.* (2021). Moving beyond fossil fuel in an oil-exporting and emerging economy: Paradigm shift', *AIMS Energy*, 9(2): 379–413. doi:10.3934/energy.2021020.

Omeje, O.E. *et al.* (2021) 'Performance of Hybrid Neuro-Fuzzy Model for Solar Radiation Simulation at Abuja, Nigeria: A Correlation Based Input Selection Technique', *Knowledge-Based Engineering and Sciences*, 2(3): 54–66.

Ozigis, I.I. *et al.* (2022). Performance evaluation of Kainji hydro-electric power plant using artificial neural networks and multiple linear regression. *International Journal of Energy and Water Resources*, 6(2): 231–241. doi:10.1007/s42108-021-00135-3.

Qasem, H., Betts, T.R. and Gottschalg, R. (2012). Soiling correction model for long term energy prediction in photovoltaic modules', in *2012 38th IEEE Photovoltaic Specialists Conference*. *2012 38th IEEE Photovoltaic Specialists Conference*, pp. 003397–003401. doi:10.1109/PVSC.2012.6318299.

Rajasekar, V., Boppana, S. and TamizhMani, G. (2015). Angle of incidence effect on five soiled modules from five different PV technologies', in *2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC)*. *2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC)*, pp. 1–6. doi:10.1109/PVSC.2015.7355970.

Ribeiro, K. *et al.* (2021). A Statistical Methodology to Estimate Soiling Losses on Photovoltaic Solar Plants. *Journal of Solar Energy Engineering*, 143(6). doi:10.1115/1.4050948.

Şahin, M. and Erol, R. (2017). A Comparative Study of Neural Networks and ANFIS for Forecasting Attendance Rate of Soccer Games'. *Mathematical and Computational Applications*, 22(4): 43. doi:10.3390/mca22040043.

Semaoui, S. *et al.* (2014). Soiling effect on the incidence of solar inrradiance on photovoltaic array plane', in *2014 International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM)*. *2014 International Conference on Electrical Sciences and Technologies in Maghreb (CISTEM)*: 1–6. doi:10.1109/CISTEM.2014.7076960.

Shapsough, S., Dhaouadi, R. and Zualkernan, I. (2019). Using Linear Regression and Back Propagation Neural Networks to Predict Performance of Soiled PV Modules'. *Procedia Computer Science*, 155: 463–470. doi:10.1016/j.procs.2019.08.065.

Shui, A.S. *et al.* (2011). A Neural Network Ensemble-Based Approach to Sensor Fault Detection', *Key Engineering Materials*, 467–469: 923–927. doi:10.4028/www.scientific.net/KEM.467-469.923.

Tran, V.-L. and Kim, S.-E. (2021). A practical ANN model for predicting the PSS of two-way reinforced concrete slabs. *Engineering with Computers*, 37(3): 2303–2327. doi:10.1007/s00366-020-00944-w.

Valerino, M. *et al.* (2020). Low-cost solar PV soiling sensor validation and size resolved soiling impacts: A comprehensive field study in Western India. *Solar Energy*, 204: 307–315. doi:10.1016/j.solener.2020.03.118.

Wolde-Rufael, Y. (2006). Electricity consumption and economic growth: a time series experience for 17 African countries. *Energy Policy*, 34(10): 1106–1114. doi:10.1016/j.enpol.2004.10.008.

Xia, S. *et al*. (2019) 'Transferring Ensemble Representations Using Deep Convolutional Neural Networks for Small-Scale Image Classification. *IEEE Access*, 7: 168175–168186. doi:10.1109/ACCESS.2019.2912908.