

Article

Short-Term Prediction of the Solar Photovoltaic Power Output Using Nonlinear Autoregressive Exogenous Inputs and Artificial Neural Network Techniques Under Different Weather Conditions

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Abstract: The power generation by solar photovoltaic (PV) systems will become an important and reliable source in the future. Therefore, this aspect has received great attention from researchers, who have investigated accurate and credible models to predict the power output of PV modules. This prediction is very important in the planning of short-term resources, the management of energy distribution, and the operation security for PV systems. This paper aims to explore the sensitivity of Nonlinear Autoregressive Exogenous Inputs (NARX) and an Artificial Neural Network (ANNs) as a result of weather dynamics in the very short term for predicting the power output of PV modules. This goal was achieved based on an experimental dataset for the power output of a PV module obtained during the sunny days in summer and cloudy days in winter, and using the data in the algorithm models of NARX and ANN. In addition, the analysis results of the NARX model were compared with those of the static ANN model to measure the accuracy and superiority of the nonlinear model. The results showed that the NARX model offers very good estimates and is efficient in predicting the power output of the PV module in the very short term. Thus, the coefficient of determination (R^2) and mean square error (MSE) were 94.4–97.9% and 0.08261–0.04613, respectively, during the summer days, and the R^2 and MSE were 90.1–89.2% and 0.281–0.249, respectively, during the winter days. Overall, it can be concluded that the sensitivity of the NARX model is more accurate in the summer days than the winter days, when the weather conditions are more stable with a gradual change. Moreover, the effectiveness of the NARX model has the specificity to learn and to generalize more effectively than the static ANN.

Keywords: photovoltaic; ANN; NARX; short-term prediction; solar energy; clean energy; renewable energy



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1. Introduction

Photovoltaic (PV) systems have recently become widely used worldwide. Therefore, PV systems have been classified as an essential technology that will make a positive contribution to the supply of clean and sustainable electrical power in the future. One of the main problems facing this technology is the effect of several weather variables. These variables are solar radiation, ambient temperature, cloud variation, wind speed, dust accumulation, and relative humidity [1,2]. These variables lead to serious growth and serious challenges in PV systems, such as fluctuating and unstable power generation. These challenges have made researchers think about various models and techniques to forecast and manage the power production of PV systems.

According to previous studies, forecasting techniques can be classified into four main types: (1) physical models, (2) statistical models, (3) software computing, and (4) hybrid types [3]. Firstly, in a brief definition, the physical model depends on a set of equations to solve the output characteristics of the PV module. The physical model is characterized by simplicity if it depends only on solar radiation, and it can become more complex if ambient

temperature and humidity are also considered in addition to solar radiation [4]. Secondly, statistical models depend on experimental data that have been analyzed by applying time-series data and measured parameters [5]. Statistical models can be classified into linear regression [6], multivariate linear regression [6], nonlinear regression [6], autoregressive moving average (ARMA) [7], and autoregressive (AR) [8] models. In general, statistical models depend on different parameters of weather conditions [9]. The data of parameters can be categorized according to the time period into very short, short, medium, and long-term time periods. The differences between the physical model and the statistical model are that (1) the statistical model is simpler than a physical model, and (2) the physical model is suitable for long periods between one and two days (long forecast horizons) and the statistical model is suitable for short horizons. Thirdly, the software computing technique includes various numerical simulations and software like Artificial Neural Networks (ANNs) [10,11]. ANN models are very efficient because of the excellent outcomes achieved, especially in actual applications [12,13]. The models of ANNs can learn from experience to build and solve nonlinear relationships between a number of input parameters and one or more output parameters. This ability of ANNs lies in overcoming some of the limitations found in conventional prediction techniques [14]. Hence, the ANN models have a higher level of accuracy than the conventional statistical techniques [15]. Finally, hybrid techniques are defined as a combination of the three aforementioned techniques. The goal of hybrid models is to overcome some of the limitations of a single technique or to improve the outcomes of the suggested technique [16]. According to previous studies, dynamic ANNs for forecasting the power output of PV modules can be divided into three types: (1) nonlinear regressive, (2) Nonlinear Autoregressive with Exogenous Inputs (NARX), and (3) Layer Recurrent Neural Networks (LRNNs) [17]. NARX is considered the most effective of all types of dynamic neural networks for modeling time series with nonlinear behavior because it considers the past-period values of variables [18]. In general, a lot of parameters have an effect on the forecasting output of the PV model. These parameters can be enumerated as the forecast horizon, forecast model input, prediction performance, and preprocessing of input data [19]. The forecast horizon or span of time is considered an important parameter for forecasting models. So, it is classified into three [20] or four categories [21]. Mainly, forecasting can be divided into four types depending on the duration of time: long-term (1 to 10 years), medium-term (1 month to 1 year), short-term (1 h to several hours), and very short-term (1 min to several minutes). The above description of forecasting categories gives an indication that the very short- and short-term categories are very useful for designing integrated systems for managing energy and scheduling energy dispatching.

In previous studies, several works were published that predicted the power output of PV modules applying NARX with various proposed time series. Louzazni et al. [22] proposed the NARX model to forecast the power output of PV modules with a one-month time series. They used three different algorithms to train and optimize the best performance of an ANN, which were named Levenberg–Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient. Their results showed that the effectiveness of the ANN model was highly influenced by weather conditions and input data. Natsheh and Samara [23] developed both NARX and deep feed-forward (DFF) models to predict the maximum power output of PV modules. The structure of the ANN consists of four exogenous inputs and two outputs. Comparing the two models, the results analysis showed that the time of prediction for the power of PV in NARX was half the execution time required to obtain the same prediction with the DFF with an accuracy of ± 0.18 W. The NARX model and a hybrid NARX with a corrective vector multiplier (CVM) were applied by Rangel-Heras [24] to forecast the power output of PV modules under the effect of time series 24 h ahead of solar irradiance (clear sky) and ambient temperature. His findings showed that the hybrid model NARX-CVM increased forecasting skills by about 34% against the NARX model alone. A novel technique of an ANN using NARX with genetic optimization was proposed by Hassan et al. [25] to forecast the power output of PV for the ultra-short

term (horizon: 5, 15, 30, and 60 min) in arid desert climates. Their findings from the proposed model improved as the forecasting horizon narrowed, with improvements of up to 58.4%. Pamain et al. [26] designed and implemented an autoregressive ANN model using MATLAB software to predict the power output of PV modules under various weather parameters like ambient and PV module temperature, solar irradiance, humidity, and wind speed. Four algorithms were selected to train, test, and validate the data in the ANN model. These algorithms are named Levenberg–Marquardt optimization, Bayesian regularization, resilient propagation, and scaled conjugate gradient. The results of each algorithm were investigated in agreement with the experimental findings. In addition, performance indices showed that the Bayesian regularization provides good processing capabilities compared to other algorithms. One-hour-ahead forecasting for solar irradiance and ambient temperature was used by Almonacid et al. [27] to forecast the power output of PV modules using dynamic Artificial Neural Networks. The results obtained from the ANN model showed an acceptable degree of accuracy one hour ahead of these parameters. In a study by Frederiksen and Cai [28], they used the NARX model to predict the power output of a PV plant for one week ahead, half-hourly. Sloped extra-terrestrial irradiance and weather data of the United Kingdom were used as input parameters. The findings of the ANN model showed that sloped extra-terrestrial irradiance, in combination with cloud cover as one parameter of weather data, resulted in optimal performance for the model. Ghenai et al. [29] applied ANN and Levenberg–Marquardt algorithms for short-term forecasting of PV–battery systems used for powered electrical vehicles in the United Arab Emirates. The main finding indicated that the ANN models have an excellent ability to simulate the complex analysis with good accuracy. Okieh et al. [30] proposed the integration of a Nonlinear Autoregressive model with Long Short-Term Memory (NARX-LSTM) to predict solar radiation, with the aim of optimizing the output of a PV system in the southwest of France. The results show that the NARX-LSTM model improved the forecasting accuracy of daily solar radiation, leading to enhancing the reliability of the PV power plants. Al-Dahidi et al. [31] used a tiered NARX model for forecasting the daily power generation of PV systems located in Amman, Jordan. The main findings indicated that the performance of the NARX model is better when the data of weather conditions and outputs of PV modules are consistent with the data of previous days.

According to the mentioned previous studies, it can be concluded that the NARX model is the most effective and accurate among the other dynamics models, especially in analyzing and forecasting the nonlinear relationships in very short time periods. This accuracy of NARX models is achieved due to the fact that they take into account the values of variables in the past period. Furthermore, none of the previous studies implemented the NARX models and took into account the sensitivity of the model due to the climate dynamics for the very short term. In this paper, Nonlinear Autoregressive Exogenous Inputs (NARX) was proposed and analyzed as a method to accurately observe the sensitivity of estimating the power output of PV modules as a result of the weather dynamics in the very short term. The main contributions of this study lie in the following points: (1) the NARX model was suggested to quantitatively estimate the power output of PV modules; (2) the suggested model was implemented with experimental data obtained via PV modules during the summer and winter days and compared with a traditional ANN approach; and (3) the NARX model takes into account the sensitivity of estimating the power output in sunny and cloudy conditions.

2. Methodology of NARX Technique

NARX is a type of ANN model that can be described as a recurrent dynamic network with feedback connections and is useful for modeling nonlinear systems with time-series data [32]. Its main advantage lies in accepting time series represented as dynamic inputs [33]. The NARX model performs better than the traditional ANN model due to the back-propagation through time of the algorithm [34]. Thus, it is used in many applications, such as pattern classification, forecasting, function approximation, optimization, and

control systems [35]. The NARX architecture can be classified into two architectures [36], closed-loop and open-loop architecture, as shown in Figure 1.

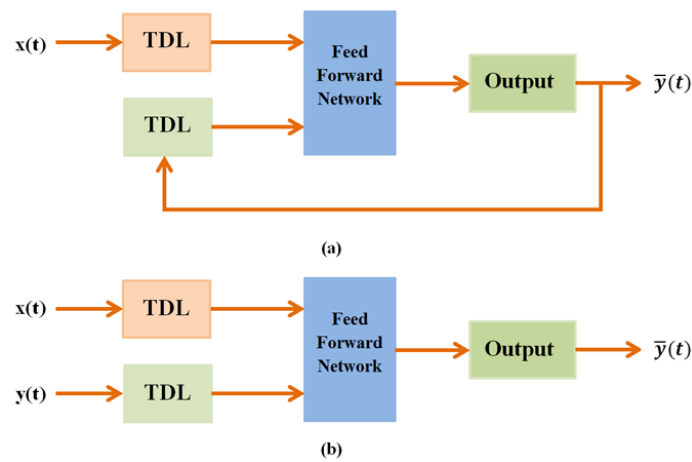


Figure 1. Block diagram showing the architectures of NARX: (a) closed-loop and (b) open-loop.

Mathematically, the equation of the closed-loop NARX can be represented as follows [30]:

$$\bar{y}(t+1) = F(\bar{y}(t), \bar{y}(t-1), \dots, \bar{y}(t-n_y), \dots, x(t+1), x(t), x(t-1), \dots, x(t-n_x)) \quad (1)$$

The open-loop equation can be represented by [30]:

$$\bar{y}(t+1) = F(y(t), y(t-1), \dots, y(t-n_y), x(t+1), x(t), x(t-1), \dots, x(t-n_x)) \quad (2)$$

where $\bar{y}(t+1)$ is the predicted power output of NARX at time $(t+1)$; F is the mapping function of the neural network; $\bar{y}(t), \bar{y}(t-1), \bar{y}(t-n_y)$ are the old output values of NARX; $y(t), y(t-1), y(t-n_y)$ are the desired values of the time series that experimentally represents the power output; $x(t), x(t+1), x(t-n_x)$ are the inputs of NARX that experimentally represent solar radiation, ambient temperature, and wind speed, respectively; and n_x and n_y are the number of input and output delays.

In the closed circuit, the forecasting values are derived from the present and past input values $x(t)$ and the past forecasted values of the time series $\bar{y}(t)$. Meanwhile, in the open circuit, the future value of the time series $y(t-1)$ is forecasted from the present and past input values $x(t)$ and the past values of the time series $y(t)$.

3. Evaluation of NARX Model

To evaluate and verify the performance and suitability of the NARX model, the statistical criteria are typically used to determine the difference between the measured and predicted values. The most important of these criteria are the Mean Squared Error (MSE) and coefficient of determination (R^2) [37,38]. MSE is calculated by:

$$MSE = \frac{1}{N} \sum_{i=1}^N (P_{mea} - P_{for})^2 \quad (3)$$

where P_{mea} is the measured power and P_{for} is the forecasted or predicted power.

R^2 is determined by:

$$R^2 = 1 - \frac{\sum_{i=1}^m (P_{mea} - P_{for})^2}{\sum_{i=1}^m P_{mea}^2 - \frac{\sum_{i=1}^m P_{for}^2}{m}} \quad (4)$$

4. NARX Network Construction

A closed-loop NARX configuration was used in this study. Some of the important parameters selected to build the structure of the NARX model can be summarized as follows:

- According to the examined and collected parameters, three nodes were selected in the input layer, namely, solar radiation, ambient temperature, and wind speed, while one node was selected the output layer (power output), which was calculated from the measured current and voltage of the PV module.
- Typically, datasets are divided into 70% for training, 15% for validation, and 15% for testing, although the percentage can vary according to the size of the datasets [39,40].
- The number of neurons in hidden layers was selected to be 7 according to the mathematical formula of [41], which proposed setting the number of neurons as $(j = 2n + 1)$, where j is the number of neurons and n is the number of input parameters.
- The sigmoid function is used as an activation in hidden layers, while a linear function is used as an activation function in the output layer.
- For the training algorithm, the Levenberg–Marquardt algorithm is selected to minimize the sum-of-square error of the model [42].
- The number of delayers is equal to 2 [22].

Figure 2 shows a more detailed flowchart of the proposed NARX and the traditional ANN model construction.

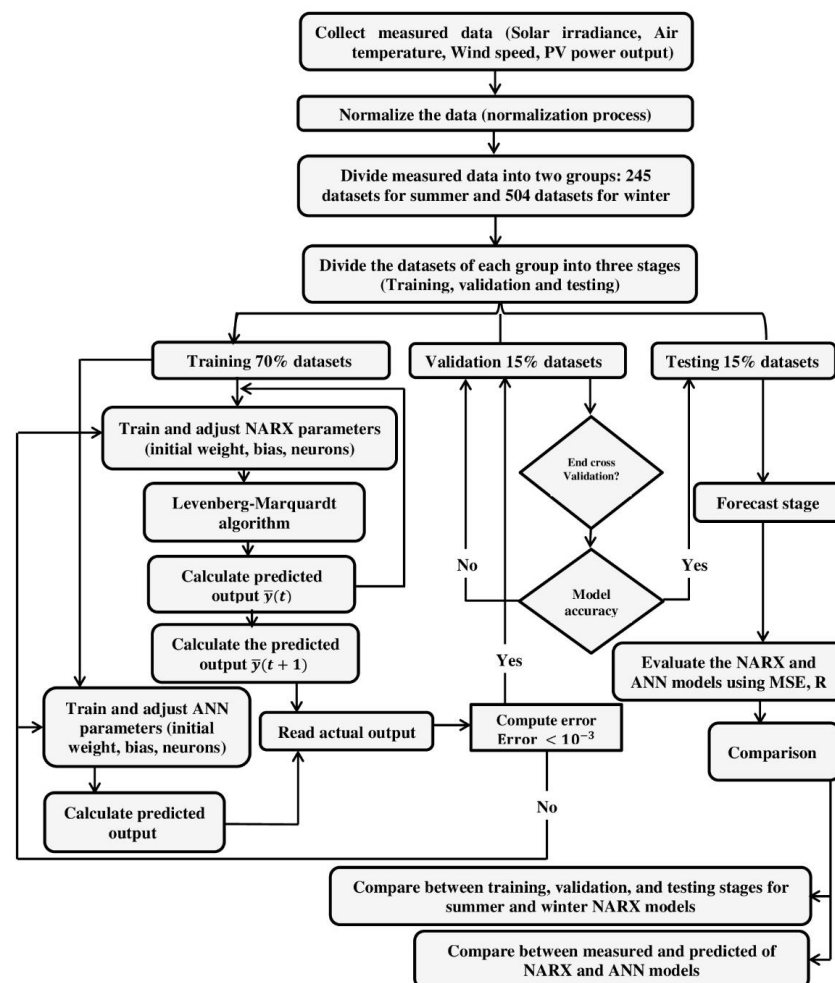


Figure 2. Construction sequence and block diagram of the proposed NARX and ANN models.

5. Experimental Setup and Data Collection

An experimental investigation was carried out to collect the dataset used for driving the training and testing stages of the NARX model. For that purpose, the output characteristics of the polycrystalline PV module were measured using an I-V tracer (PV200 made by Seaward Electronic Ltd., Durham, UK) with an accuracy of $\pm 0.5\%$ V and $\pm 0.1\%$ A, as shown in Figure 3. The technical data of the PV module are $P_{\max} = 165$ W, $I_{sc} = 9.81$ A, $V_{oc} = 22.05$ V, $I_{mp} = 9.17$ A, and $V_{mp} = 18$ V. Furthermore, the solar survey (SS200R) was used to measure the solar irradiance, ambient temperature, and PV module temperature with resolutions of 1°C and 1 W/m^2 . In addition, a digital anemometer was used to measure the wind speed with an accuracy of ± 0.1 m/s.



Figure 3. Setup of PV module with measuring devices.

The experiments were conducted at the Middle Technical University, which is located in Baghdad, Iraq (33.3152° N, 44.3661° E). In total, 749 readings were gathered in the winter and summer seasons during 2023. Those readings were divided into 504 readings in January and 245 readings in August. The readings of January were collected during 3 days (2 sunny days and 1 cloudy day), with 7 h of testing each day. The measurements of the PV power output were performed with a step of a 2.5 min time interval. The readings of August were collected during 7 days, with 7 h of testing each day. The power output measurements were performed with a step of a 12 min time interval.

Several tests on the PV module were considered to select the dataset of the NARX configuration. The dataset includes the weather conditions (solar irradiance, ambient temperature, and wind speed) and power output of the PV module. Figure 4 shows the steps of testing, collecting, and analyzing the NARX model using MATLAB R2016b software.

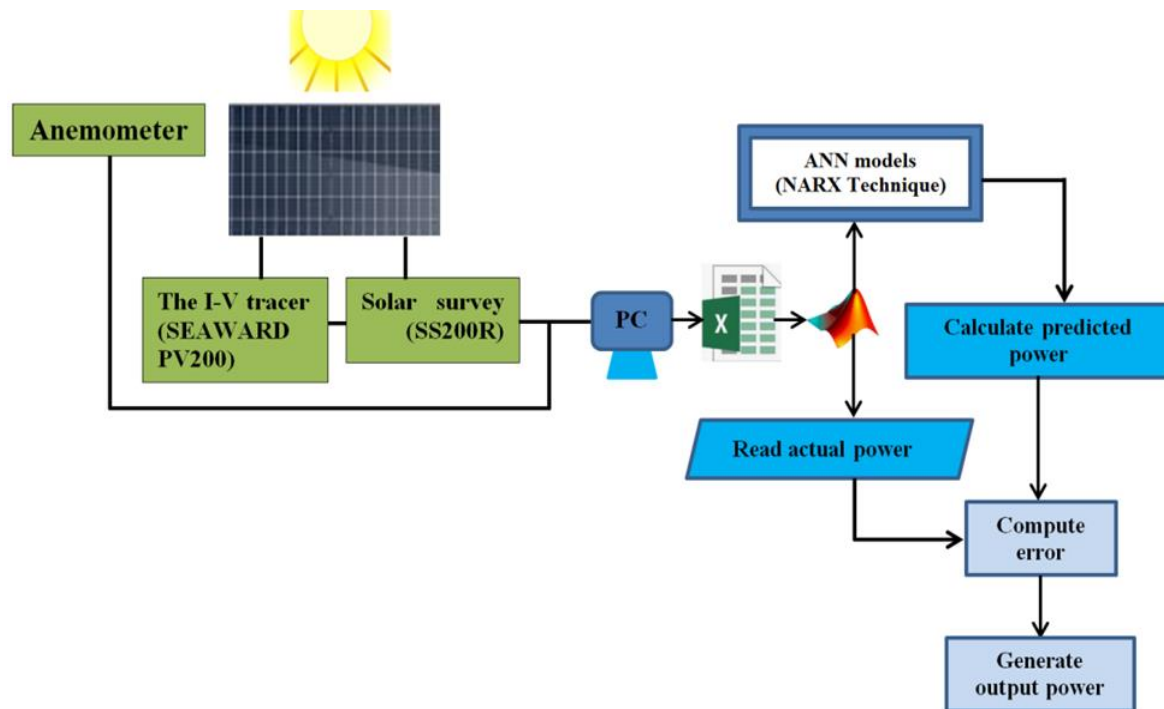


Figure 4. Steps of testing, collecting, and analyzing.

6. Results and Discussion

6.1. Weather Data

To achieve the requirements of the NARX model, the impact of weather conditions on the power output of PV modules was tested in the summer and winter seasons in Baghdad, Iraq, from 8:00 AM to 3:00 PM. The results obtained during the experiment period are depicted in Figures 4 and 5. Figures 4 and 5 show the impact of solar irradiance, ambient temperature, and wind speed on the power output of PV modules in the summer and winter seasons, respectively. It is evident from Figure 5 that the power output values of the PV module in summer reached a maximum value of 140.8 W at a solar irradiance of 998.5 W/m², ambient temperature of 43.5 °C, and wind speed of 2.5 m/s. Additionally, the power output values of the PV module in winter reached a maximum value of 132.8 W at a solar irradiance of 939.7 W/m², ambient temperature of 21.9 °C, and wind speed of 1.75 m/s, as shown in Figure 6. More details about the relationship between the power output of the PV module and weather conditions are presented in Table 1. These details include the equation formula and the coefficient of determination.

Table 1. Correlation parameters of the relationship between the input parameters and power output.

Input (X)	Output (Y)	Equation Formula	R ²	Conditions
Solar irradiance	Power	$Y = 0.128X + 4.04$	0.951	Summer
Solar irradiance	Power	$Y = 0.1283X + 5.82$	0.861	Winter
Air temperature	Power	$Y = 4.693X - 70.6$	0.602	Summer
Air temperature	Power	$Y = 3.34X - 21.6$	0.531	Winter
Wind speed	Power	$Y = 37.46X + 35.46$	0.918	Summer
Wind speed	Power	$Y = 29.2X + 40.23$	0.810	Winter

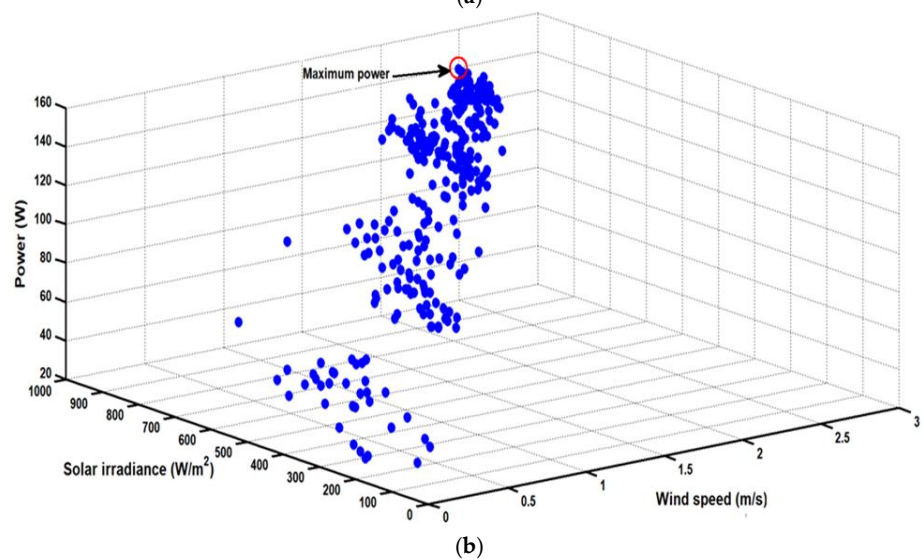
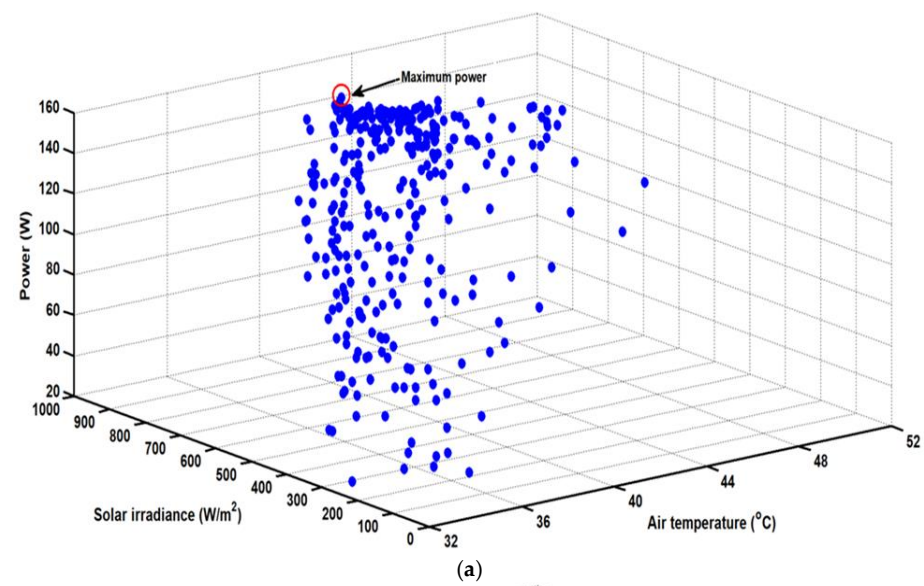


Figure 5. Variation in power output in summer under the impacts of (a) solar irradiance and ambient temperature, and (b) solar irradiance and wind speed.

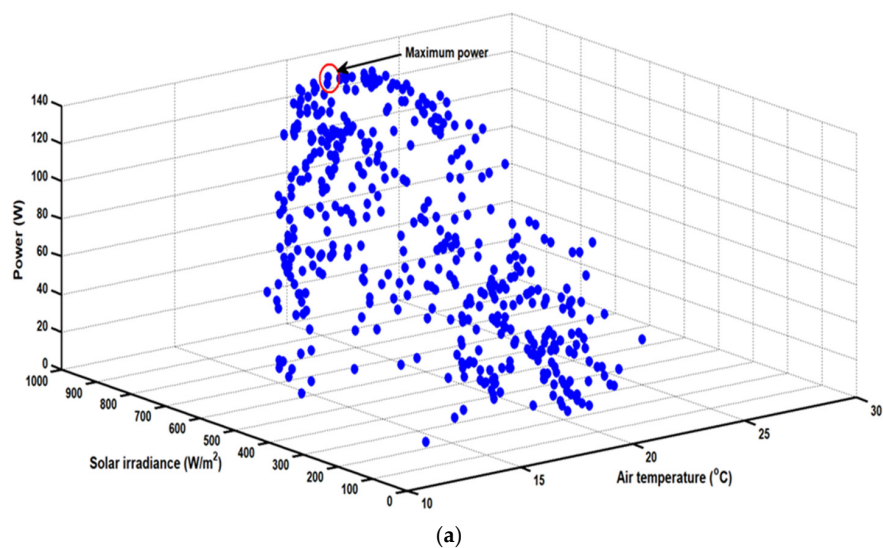


Figure 6. Cont.

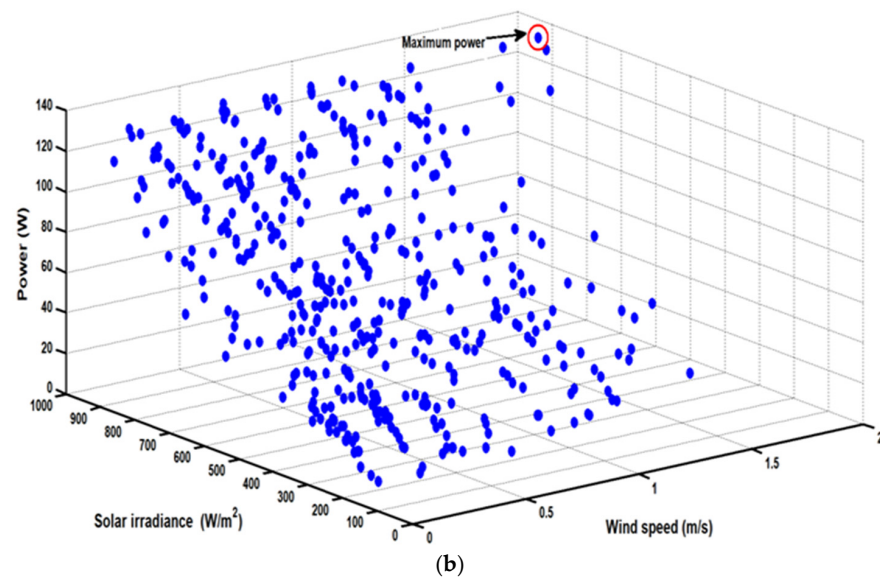


Figure 6. Variation in power output in winter under the impacts of (a) solar irradiance and ambient temperature, and (b) solar irradiance and wind speed.

6.2. Best Curve Fit

To validate the performance of NARX models for summer and winter (sunny and cloudy) days, the regression plots were generated to show the convergence between the target and output of the model. The four plots in Figure 7 show the curve fits of training, validation, testing, and all data. As shown in each figure, the dashed line represents the perfect case between the output model and the target when the output is equal to the target, while the solid line represents the best fit curve between the output model and the target. According to the values of the coefficient of determination (R), the training stage data indicate a good fit, with R more than 0.9 for all models (summer and winter), where R was recorded as a maximum value in the summer model and a lower value in the winter–cloudy model. In the validation stage, it can be noticed that the R values ranged between 0.976 and 0.843. For this, the curve fit is reasonably good in the summer model and gradually declines in the winter–cloudy model.

6.3. Performance Evaluation of NARX Model

Figure 8 shows the variations in predicted (output) power and measured (target) power of the PV module for the training, testing, and validation stages of the NARX model. It can be observed from the plots that the predicted values of NARX followed a similar pattern to the measured values across the days of the test. However, this pattern differs between summer and winter days. The predicted values followed the measured values closely on summer days, with slight cases of underestimation and overestimation. However, underestimation and overestimation were increased on winter days, especially on cloudy days (i.e., the underestimation and overestimation of NARX were more conspicuous for winter than summer days). This may be attributed to the fact that the sensitivity of this NARX model is more accurate on days when the change in weather conditions is gradual rather than fluctuating as on winter days.

The predictive performance of the NARX model on summer and winter days was evaluated using MSE and R^2 . Comparatively, from Table 2, the values of R^2 are between 94.4% and 97.6% for the three stages of the NARX model on summer days. Meanwhile, the MSE ranges between 0.08261 and 0.04613 for the three stages. Additionally, the values of R^2 and MSE for the NARX model on winter days ranged between 90.1% and 89.2% and 0.281 and 0.249 on sunny days, respectively. The values of R^2 and MSE for the NARX model ranged between 90.0% and 84.3% and 0.24 and 1.04 on cloudy days. This shows that the

model achieved high accuracy in the summer days, while this accuracy decreased in the winter days, especially during cloudy days.

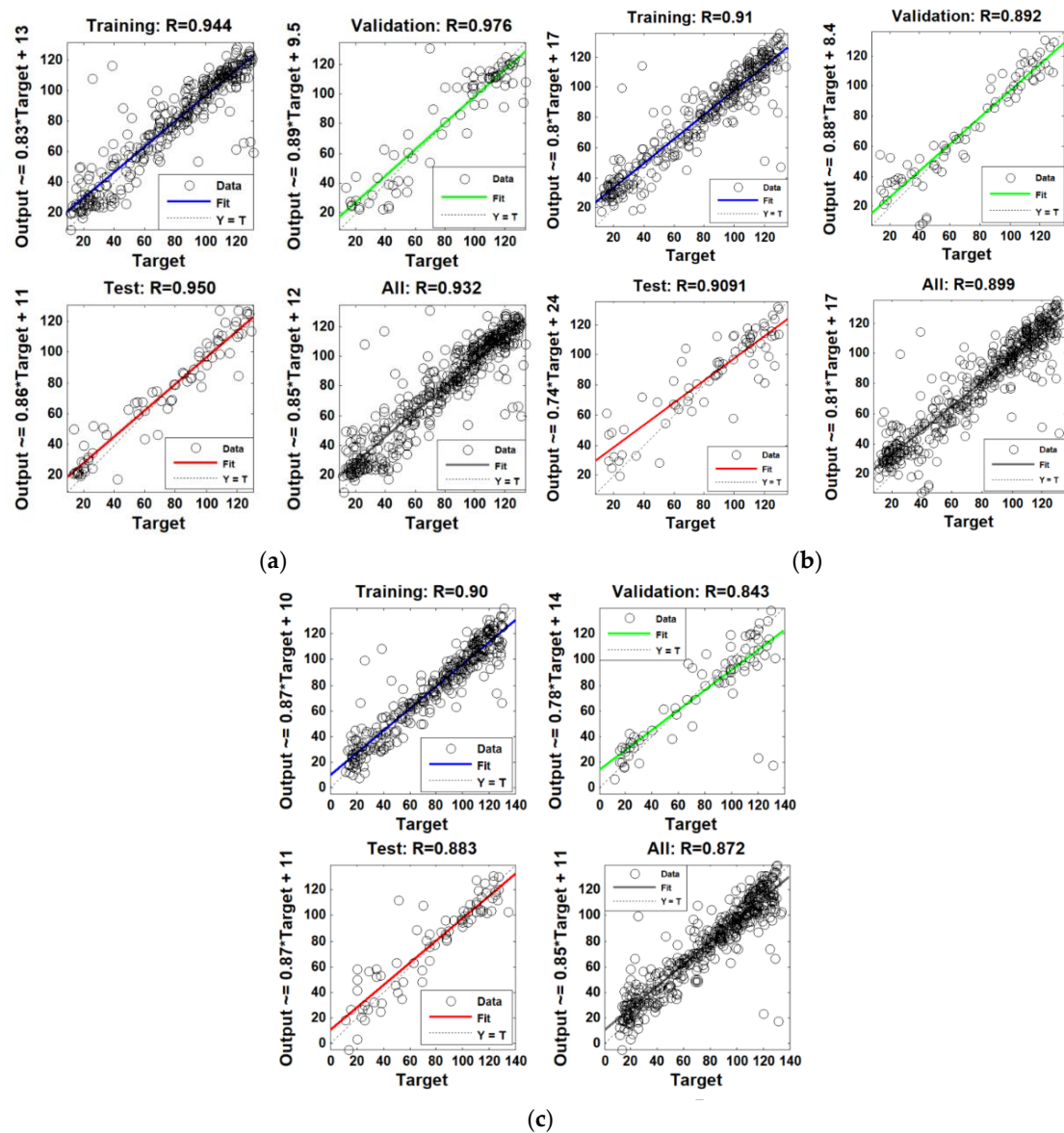


Figure 7. Best curve fit of (a) summer model, (b) winter-sunny model, and (c) winter-cloudy model.

Table 2. Statistical indices of the NARX model for training, testing, and validation stages.

Process	Summer Days		Winter Days			
	Sunny Days		Sunny Days		Cloudy Days	
	MSE	R ²	MSE	R ²	MSE	R ²
Training	0.08261	94.4	0.218	90.10	0.240	90.0
Validation	0.04613	97.6	0.249	89.20	1.040	84.3
Testing	0.07100	95.0	0.219	90.91	1.050	88.2

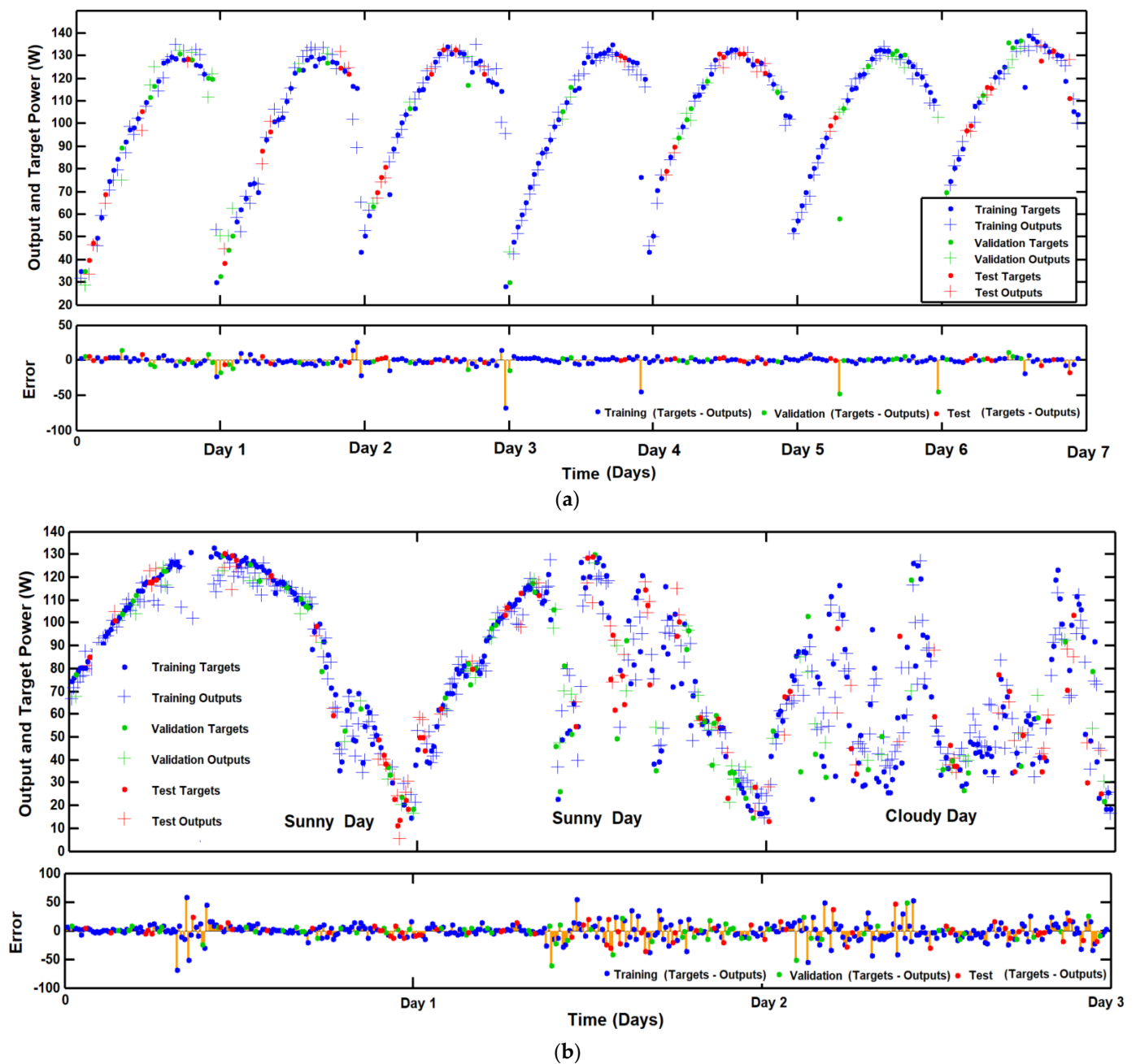


Figure 8. Variation in measured and predicted power over time during (a) summer days and (b) winter days.

For more clarification and understanding of the NARX model, the histograms of errors against the instances were plotted, as shown in Figure 9. The plots compare errors in the training, testing, and validation stages to zero errors. The zero-error line is represented in orange, while the values of errors in training, validation, and test stages are represented in blue, green, and red. These values of errors were at a minimum level on summer days, with a maximum value of about 16.1, and increased on winter days to reach 38.07.

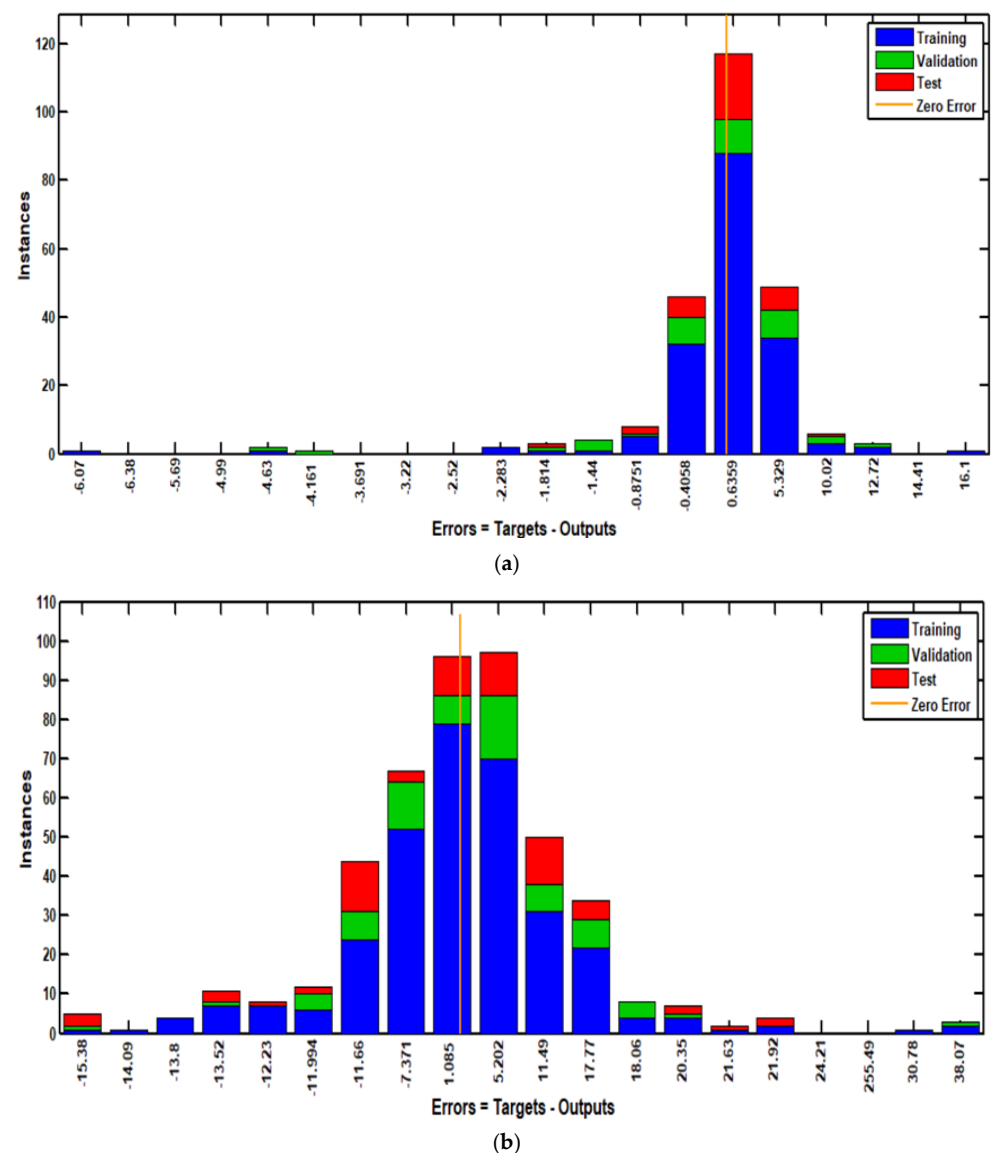


Figure 9. Error histogram for the NARX model for the values during (a) summer and (b) winter.

6.4. Comparative Analysis of the NARX Model with a Static ANN Model

A comparison between the performance of NARX and static ANN models is presented for one day in summer and winter. According to the validation stage, the optimal structure of the ANN model obtained in summer comprises five neurons with two hidden layers. Therefore, the architecture of ANN can be represented as 3-5-5-1. Meanwhile, the optimal structure of the ANN model in winter is 3-3-3-1. Figure 10 shows the performance of the NARX and ANN models in terms of MSE at the validation stage. It is clear that the NARX model in summer achieved the best MSE of 0.1 at epoch 51, while it achieved the best MSE at epoch 82 in winter. Additionally, the ANN achieved the best MSE at epochs 90 and 95 in summer and winter, respectively.

Figure 11 shows a strong correlation between the predicted and actual values of the PV power output for the NARX model, with higher values of R^2 closer to unity, while this correlation records a noticeable divergence when using the static ANN model. This confirms that the NARX model is more suitable and valid for predicting the power output of PV than the static ANN model.

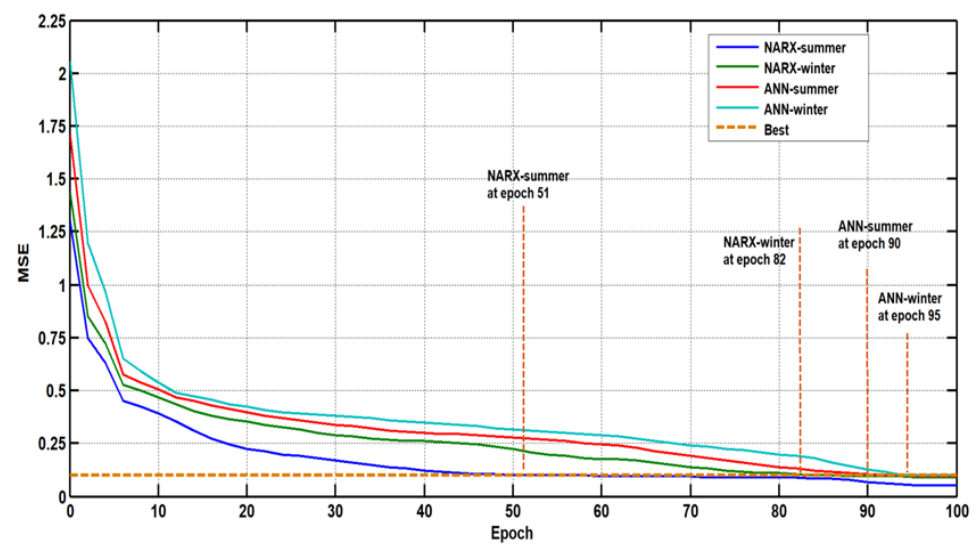


Figure 10. MSE in the validation stage for the NARX and ANN models in winter and summer.

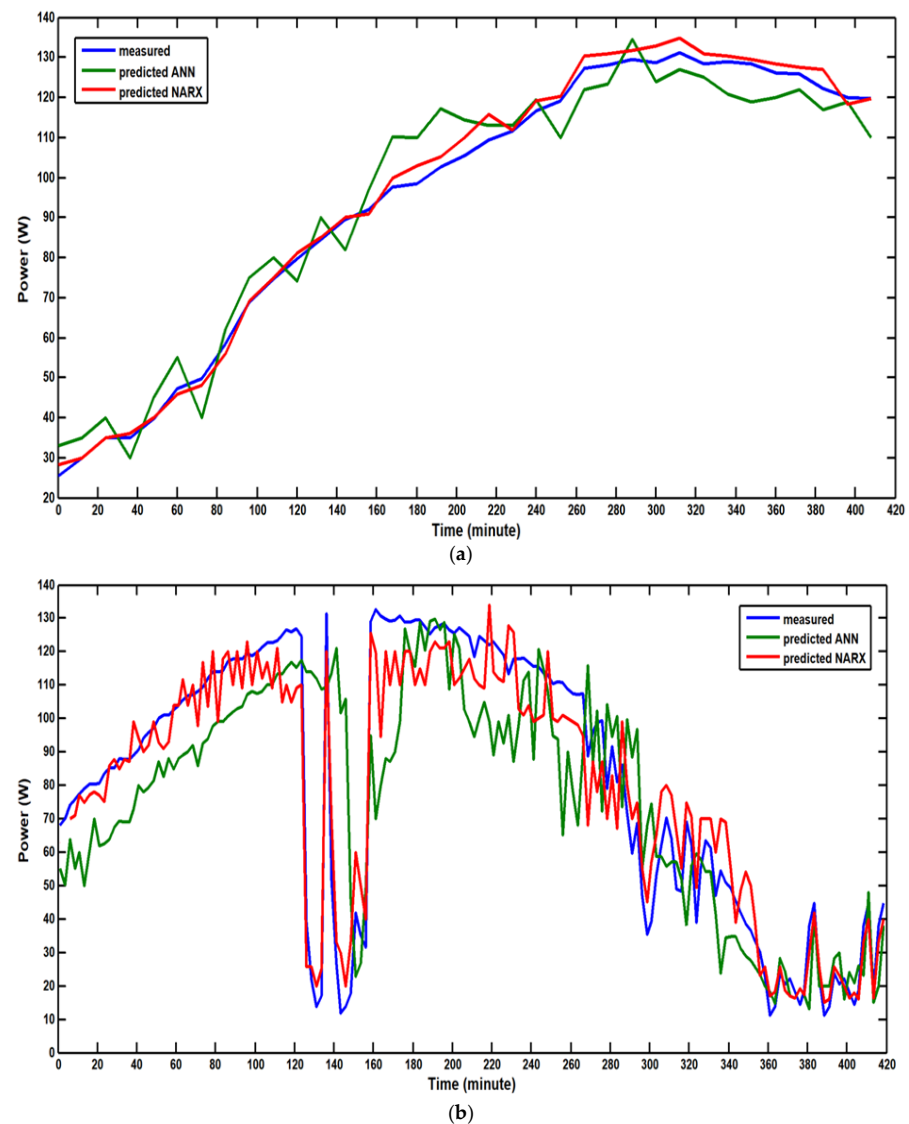


Figure 11. Comparison of validation stage between measured and predicted values of the static ANN and NARX models during (a) summer and (b) winter.

6.5. Comparative Accuracy of Present NARX Model with Previous Models

The accuracy of the current NARX model was compared with the same model in a previous study [22], as presented in Table 3. The comparison was made based on the assumptions that were found in the previous study, such as the number of neurons and the number of delayers, which were 6 and 2, respectively, while in the current study they were 7 and 2, respectively. From Table 3, it is clear that the comparison shows a good agreement between the performance of the NARX models since the R^2 value is very close in the two models, with an absolute percentage error of about 4.0%, 0.72%, and 3.6% in the training, validation, and testing stages, respectively.

Table 3. Comparison of NARX model performance with previous study.

Stages	Louzazni et al. [22]		Present Study	
	MSE	R^2	MSE	R^2
Training	43.29	98.4	8.261	94.4
Validation	44.91	98.31	4.613	97.6
Testing	38.33	98.54	7.100	95.0

6.6. Uncertainty of Power Output

The measured values have some errors that occurred during the experimental tests due to faults in experimental measurements and measuring device accuracy. Therefore, the uncertainty value of the electric power must be calculated from the uncertainties of the experimental results. The electric power output of the PV module is calculated as:

$$P = I \times V \quad (5)$$

According to the method of Kline and McKlintock [43], the uncertainty of electric power can be represented as:

$$UP = \sqrt{\left(\frac{\partial P}{\partial I} \delta I\right)^2 + \left(\frac{\partial P}{\partial V} \delta V\right)^2} \quad (6)$$

With simple calculations at measured values for current ($6.9 \text{ A} \pm 1\%$) and voltage ($17.81 \pm 0.5\%$), the calculated power equals 122.88 W. Therefore, the uncertainty of electric power is equal to 1.37 W or 1.1%.

7. Conclusions

A NARX model was suggested to predict the power output of the PV module depending on the solar irradiance, ambient temperature, and wind speed. The data were collected experimentally for seven days in summer and three days in winter, taking into consideration sunny and cloudy days. From the analysis of the NARX findings, the following conclusions can be drawn:

1. The predicted values of NARX followed a similar pattern to the measured values across the test days. This confirms that the NARX model is working very well and efficiently in predicting the power output of the PV module in the very short term.
2. The values of R^2 were recorded as being from 94.4% to 97.6% during summer days, with MSE ranging between 0.08261 and 0.04613. Additionally, the values of R^2 and MSE during winter days ranged between 90.1% and 89.2% and 0.281 and 0.249 during sunny days, while they ranged between 90.0% and 84.3% and 0.24 and 1.04 during cloudy days.
3. The predicted values followed the measured values closely on summer days, with slight cases of underestimation and overestimation. This may be attributed to the fact

that the sensitivity of the NARX model is better and more accurate in summer days when the weather conditions are more stable with gradual change.

4. The underestimation and overestimation increased in winter, especially on cloudy days. This gives an indication that the sensitivity of the NARX model tends to underperform on winter days due to the sudden and rapid change in weather conditions.
5. Comparing the NARX model with the static ANN model shows the specificity and effectiveness of the NARX model to learn and generalize more effectively than the static ANN.

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References

1. Pang, Z.; Niu, F.; O'Neill, Z. Solar Radiation Prediction using Recurrent Neural Network and Artificial Neural Network: A Case Study with Comparisons. *Renew. Energy* **2020**, *156*, 279–289. [\[CrossRef\]](#)
2. Wu, Y.-K.; Chen, C.-R.; Rahman, H.A. A Novel Hybrid Model for Short-Term Forecasting in PV Power Generation. *Int. J. Photoenergy* **2014**, *2014*, 569249. [\[CrossRef\]](#)
3. Antonanzas, J.; Osorio, N.; Escobar, R.; Urraca, R.; Martinez-De-Pison, F.J.; Antonanzas-Torres, F. Review of photovoltaic power forecasting. *Sol. Energy* **2016**, *136*, 78–111. [\[CrossRef\]](#)
4. Monteiro, C.; Fernandez-Jimenez, L.A.; Ramirez-Rosado, I.J.; Muñoz-Jimenez, A.; Lara-Santillan, P.M. Short-Term Forecasting Models for Photovoltaic Plants: Analytical versus Soft-Computing Techniques. *Math. Probl. Eng.* **2013**, *2013*, 767284. [\[CrossRef\]](#)
5. Rouchier, S.; Rabouille, M.; Oberlé, P. Calibration of simplified building energy models for parameter estimation and forecasting: Stochastic versus deterministic modeling. *Build. Environ.* **2018**, *134*, 181–190. [\[CrossRef\]](#)
6. Behera, M.K.; Majumder, I.; Nayak, N. Solar photovoltaic power forecasting using optimized modified extreme learning machine technique. *Eng. Sci. Technol. Int. J.* **2018**, *21*, 428–438. [\[CrossRef\]](#)
7. Ruiz-Arias, J.; Alsamamra, H.; Tovar-Pescador, J.; Pozo-Vázquez, D. Proposal of a regressive model for the hourly diffuse solar radiation under all sky conditions. *Energy Convers. Manag.* **2010**, *51*, 881–893. [\[CrossRef\]](#)
8. Kalogirou, S.A. Artificial neural networks in renewable energy systems applications: A review. *Renew. Sustain. Energy Rev.* **2001**, *5*, 373–401. [\[CrossRef\]](#)
9. Sobri, S.; Koohi-Kamali, S.; Rahim, N.A. Solar photovoltaic generation forecasting methods: A review. *Energy Convers. Manag.* **2018**, *156*, 535–576. [\[CrossRef\]](#)
10. Brano, V.L.; Ciulla, G.; Di Falco, M. Artificial Neural Networks to Predict the Power Output of a PV Panel. *Int. J. Photoenergy* **2014**, *2014*, 193083. [\[CrossRef\]](#)
11. Wang, S.; Zhang, Y.; Zhang, C.; Yang, M. Improved artificial neural network method for predicting photovoltaic output performance. *Glob. Energy Interconnect.* **2020**, *3*, 553–561. [\[CrossRef\]](#)
12. Ding, N.; Benoit, C.; Foggia, G. Neural network-based model design for short-term load forecast in distribution systems. *IEEE Trans. Power Syst.* **2016**, *31*, 72–81. [\[CrossRef\]](#)
13. Macas, M.; Moretti, F.; Fonti, A.; Giantomassi, A.; Comodi, G.; Annunziato, M.; Pizzuti, S.; Capra, C.A. The role of data sample size and dimensionality in neural network based forecasting of building heating related variables. *Energy Build.* **2016**, *111*, 299–310. [\[CrossRef\]](#)
14. Garud, K.S.; Jayaraj, S.; Lee, M.Y. A review on modeling of solar photovoltaic systems using artificial neural networks, fuzzy logic, genetic algorithm and hybrid models. *Int. J. Energy Res.* **2021**, *45*, 6–35. [\[CrossRef\]](#)
15. Vawda, M.I.; Lottering, R.; Mutanga, O.; Peerbhay, K.; Sibanda, M. Comparing the Utility of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) on Sentinel-2 MSI to Estimate Dry Season Aboveground Grass Biomass. *Sustainability* **2024**, *16*, 1051. [\[CrossRef\]](#)
16. Ferlito, S.; Adinolfi, G.; Graditi, G. Comparative analysis of data-driven methods online and offline trained to the forecasting of grid-connected photovoltaic plant production. *Appl. Energy* **2017**, *205*, 116–129. [\[CrossRef\]](#)

17. Haddad, S.; Mellit, A.; Benghane, M.; Daffallah, K.O. NARX-based short-term forecasting of water flow rate of a photovoltaic pumping system: A case study. *J. Sol. Energy Eng.* **2016**, *138*, 011004. [\[CrossRef\]](#)
18. Yuan, C.; Liu, S.; Fang, Z. Comparison of China's primary energy consumption forecasting by using ARIMA (the autoregressive integrated moving average) model and GM (1,1) model. *Energy* **2016**, *100*, 384–390. [\[CrossRef\]](#)
19. Raza, M.Q.; Nadarajah, M.; Ekanayake, C. On recent advances in PV power output forecast. *Sol. Energy* **2016**, *136*, 125–144. [\[CrossRef\]](#)
20. Raza, M.Q.; Khosravi, A. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. *Renew. Sustain. Energy Rev.* **2015**, *50*, 1352–1372. [\[CrossRef\]](#)
21. Amral, N.; Ozveren, C.S.; King, D. Short term load forecasting using multiple linear regression. In Proceedings of the 2007 42nd International Universities Power Engineering Conference, Brighton, UK, 4–6 September 2007; UPEC: Créteil, France; pp. 1192–1198.
22. Louzazni, M.; Mosalam, H.; Khouya, A.; Amechnoue, K. A non-linear auto-regressive exogenous method to forecast the photovoltaic power output. *Sustain. Energy Technol. Assess.* **2020**, *38*, 100670. [\[CrossRef\]](#)
23. Natsheh, E.; Samara, S. Toward Better PV Panel's Power output Prediction; a Module Based on Nonlinear Autoregressive Neural Network with Exogenous Inputs. *Appl. Sci.* **2019**, *9*, 3670. [\[CrossRef\]](#)
24. Rangel-Heras, E.; Angeles-Camacho, C.; Cadenas-Calderón, E.; Campos-Amezcu, R. Short-Term Forecasting of Energy Production for a Photovoltaic System Using a NARX-CVM Hybrid Model. *Energies* **2022**, *15*, 2842. [\[CrossRef\]](#)
25. Hassan, M.A.; Bailek, N.; Bouchouicha, K.; Nwokolo, S.C. Ultra-short-term exogenous forecasting of photovoltaic power production using genetically optimized non-linear auto-regressive recurrent neural networks. *Renew. Energy* **2021**, *171*, 191–209. [\[CrossRef\]](#)
26. Pamain, A.; Rao, P.V.K.; Tilya, F.N. Prediction of photovoltaic power output based on different non-linear autoregressive artificial neural network algorithms. *Glob. Energy Interconnect.* **2022**, *5*, 226–235. [\[CrossRef\]](#)
27. Almonacid, F.; Pérez-Higueras, P.J.; Fernández, E.F.; Hontoria, L. A methodology based on dynamic artificial neural network for short-term forecasting of the power output of a PV generator. *Energy Convers. Manag.* **2014**, *85*, 389–398. [\[CrossRef\]](#)
28. Frederiksen, C.A.F.; Cai, Z. Novel machine learning approach for solar photovoltaic energy output forecast using extra-terrestrial solar irradiance. *Appl. Energy* **2022**, *306*, 118152. [\[CrossRef\]](#)
29. Ghenai, C.; Ahmad, F.F.; Rejeb, O. Artificial neural network-based models for short term forecasting of solar PV power output and battery state of charge of solar electric vehicle charging station. *Case Stud. Therm. Eng.* **2024**, *61*, 105152. [\[CrossRef\]](#)
30. Okieh, O.I.; Seker, S.; Gokce, S.; Dennenmoser, M. An Enhanced Forecasting Method of Daily Solar Irradiance in Southwestern France: A Hybrid Nonlinear Autoregressive with Exogenous Inputs with Long Short-Term Memory Approach. *Energies* **2024**, *17*, 3965. [\[CrossRef\]](#)
31. Al-Dahidi, S.; Alrbai, M.; Rinchi, B.; Al-Ghussain, L.; Ayadi, O.; Alahmer, A. A tiered NARX model for forecasting day-ahead energy production in distributed solar PV systems. *Clean. Eng. Technol.* **2024**, *23*, 100831. [\[CrossRef\]](#)
32. Diaconescu, E. The Use of NARX Neural Networks to Predict Chaotic Time Series. *WSEAS Trans. Comput. Res.* **2008**, *3*, 182–191.
33. Ojo, O.S.; Adeyemi, B. Application of Nonlinear Autoregressive Neural Network to Estimation of Global Solar Radiation over Nigeria. *J. Adv. Sci. Eng. (JASE)* **2020**, *3*, 68–79. [\[CrossRef\]](#)
34. Godarzi, A.A.; Amiri, R.M.; Talaie, A.; Jamasb, T. Predicting oil price movements: A dynamic Artificial Neural Network approach. *Energy Policy* **2014**, *68*, 371–382. [\[CrossRef\]](#)
35. Pham, T.; Liu, X. Training of elman networks and dynamic system modelling. *Int. J. Sys. Sci. Vol.* **1996**, *27*, 221–226. [\[CrossRef\]](#)
36. Boussaada, Z.; Curea, O.; Remaci, A.; Camblong, H.; Bellaaj, N.M. A Nonlinear Autoregressive Exogenous (NARX) Neural Network Model for the Prediction of the Daily Direct Solar Radiation. *Energies* **2018**, *11*, 620. [\[CrossRef\]](#)
37. Nespoli, A.; Ogliari, E.; Leva, S.; Massi Pavan, A.; Mellit, A.; Lughi, V.; Dolara, A. Day-Ahead Photovoltaic Forecasting: A Comparison of the Most Effective Techniques. *Energies* **2019**, *12*, 1621. [\[CrossRef\]](#)
38. Kong, Y.S.; Abdullah, S.; Schramm, D.; Omar, M.Z.; Haris, S.M. Development of multiple linear regression-based models for fatigue life evaluation of automotive coil springs. *Mech. Syst. Signal Process.* **2019**, *118*, 675–695. [\[CrossRef\]](#)
39. Forghani, R.; Chatterjee, A.; Reinhold, C.; Pérez-Lara, A.; Romero-Sanchez, G.; Ueno, Y.; Bayat, M.; Alexander, J.W.; Kadi, L.; Chankowsky, J.; et al. Head and neck squamous cell carcinoma: Prediction of cervical lymph node metastasis by dual-energy CT texture analysis with machine learning. *Eur. Radiol.* **2019**, *29*, 6172–6181. [\[CrossRef\]](#)
40. Buitrago, J.; Asfour, S. Short-Term Forecasting of Electric Loads Using Nonlinear Autoregressive Artificial Neural Networks with Exogenous Vector Inputs. *Energies* **2017**, *10*, 40. [\[CrossRef\]](#)
41. Hecht-Nielsen, R. *Neurocomputing*; Addison-Wesley Longman Publishing Co., Inc.: Boston, MA, USA, 1990.
42. Aldrich, C. *Exploratory Analysis of Metallurgical Process Data with Neural Networks and Related Methods*; British Library Cataloguing in Publication Data; Elsevier Science: Amsterdam, The Netherlands, 2002; Volume 1, pp. 56–57.
43. Kline, S.J. Describing uncertainty in single sample experiments. *Mech. Eng.* **1953**, *75*, 3–8.

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