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Optimization of photovoltaic power output predictions: a comparative analysis of artificial neural network algorithms with varied hidden layers

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Abstract

This paper explores the impact of hidden layers in the prediction of the photovoltaic power output of a polycrystalline Photovoltaic module using an artificial neural network with four different algorithms: Levenberg-Marquardt optimization, Bayesian regression, scaled conjugate gradient and scaled resilient propagation. Error function estimations were designed in MATLAB software and trained between 1–20 hidden layers' configurations. Solar irradiance, ambient temperature, module temperature, wind speed and relative humidity are the five inputs to the artificial neural network model. The predictability of the power output using the four algorithms at a varied number of hidden layers was investigated using a time series seasonal average data set of 631 points obtained under outdoor conditions. 70% of the data set was used for training while validation and testing used 15% each. Results showed that all algorithms exhibited commendable prediction performance across all algorithms, with average mean square errors of 0.03042, 0.02679, 0.078 and 0.0709 for Levenberg-Marquardt optimization, Bayesian regression, scaled conjugate gradient and scaled resilient propagation, respectively. High coefficients of determination further confirmed accuracy, with values of 0.98669 for Levenberg-Marquardt optimization, 0.98996 for Bayesian regression, 0.96046 for scaled conjugate gradient and 0.96541 for scaled resilient propagation. The Bayesian regression algorithm outperformed other algorithms. These findings offer valuable insights for enhancing PV system performance and promoting sustainable energy solutions.

Keywords: *Algorithms; Artificial Neural network; Power output; Predictions Varied Hidden Layers, PV module*

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Introduction

The worldwide energy situation is undergoing a transformative shift towards sustainable and environmentally friendly sources of power generation (Gielen *et al.,* 2019; Pamain, Rao and Tilya, 2022). Solar photovoltaic (PV) systems have emerged as a prominent contributor to this transition, harnessing energy from sunlight and converting it into electricity (Armaroli and Balzani, 2016; Victoria *et al.,* 2021). As the adoption of PV technology continues to rise, accurate prediction of photovoltaic power output has become a critical concern for system operators, energy planners and researchers alike (Ahmad, Madonski, Zhang, Huang and Mujeeb, 2022). The variability in solar radiation, atmospheric conditions and module characteristics introduces inherent unpredictability into PV power generation (Pamain *et al.,* 2022). To mitigate this unpredictability and maximize the efficiency of

PV systems, precise predicting methods are essential (Qazi *et al.,* 2015). Artificial Neural Networks (ANNs) have emerged as promising tools for modeling and predicting complex relationships in various domains, including renewable energy (Hoang *et al.,* 2021; Wazirali, Yaghoubi, Abujazar, Ahmad and Vakili, 2023). ANNs are particularly well-suited for capturing the complex and non-linear dependencies between input parameters, such as solar radiation, temperature and module specifications and the resulting PV power output (Ahmed, Sreeram, Mishra and Arif, 2020; Sobri, Koohi-Kamali and Rahim, 2018).

One crucial architectural aspect of ANNs that significantly influences their predictive performance is the configuration of hidden layers within the network (Chen *et al.,* 2022; Mazrou, 2009). The number of hidden layers and the number of neurons in each layer play pivotal roles in determining the network's capacity to capture the underlying patterns and relationships in the data (Bouzidi, Boudries and Amad, 2020; Hammami, Sayed-Mouchaweh, Mouelhi and Ben Said, 2020). However, the optimal configuration of hidden layers for accurately predicting PV power output remains an open question and require a central focus (Ahmed *et al.,* 2020; Hoang *et al.,* 2021).

This paper presents an in-depth investigation into the prediction of photovoltaic power output characteristics using artificial neural networks, with a particular emphasis on exploring the impact of different numbers of hidden layers on prediction accuracy and computational efficiency by employing a suite of performance metrics, including mean square error (MSE) and the coefficient of determination (R-squared). Moreover, the vital aspect of computational efficiency is considered, recognizing its practical significance in real-world applications. Additionally, the investigation extends to encompass a selection of four distinctive ANN algorithms: Levenberg-Marquardt optimization (LM), Bayesian regression (BR), scaled conjugate gradient (SCG) and scaled resilient propagation (RP). These algorithms represent a spectrum of ANN methodologies, each offering unique strengths and adaptabilities in modeling and prediction.

Figure 1

Experimental setup of weather station and PV module

Material and Methods

A polycrystalline silicon PV module with dimensions of 550 × 680 × 30 mm^3 was tested experimentally on the rooftop building at the University of Dodoma (6.1630° S, 35.7516° E) as indicated in Figure 1. The Standard Test Condition (STC) specification have the following values: open-circuit voltage (V_{oc})= 22.4 V, short-circuit current (I_{sc}) = 2.95 A, optimum operating voltage (V_m) =17.8V, optimum operating current (I_m) = 2.84 A and maximum power ($P_{m)}$ = 50 W. The module parameters measured include PV surface current, voltage, power output and module temperature while weather parameters recorded were solar irradiance, wind speed and relative humidity using TP2700wc pro-weather station by Tycon power systems. The data acquisition system for the measurement of electrical parameters uses a microcontroller mega 2560 interfaced with different sensors. The current and voltage measurements were recorded using the INA219 sensor while surface module temperature was recorded by LM 35 temperature sensor. Solar irradiance was measured by TES 132 solar power meter. All measurements were recorded at an interval of 1 minute between 7:00 hr. to 17:30 hr. for a period of three months during the winter season (June to August 2019) of Dodoma.

ANN Methodology

ANN algorithms; LM, BR, RP and SCG designed in MATLAB software were used to predict the Power output generated by p-Si PV module. Figure 2 depicts a schematic representation of the model. The model input parameters are ambient temperature, module temperature, irradiance, relative humidity and wind speed while the target is Power output. Each algorithm was trained by varying number of hidden layers between 1 and 20 with 2 taped delay line. The weight and bias value were set into initial value before training process. Then, out of 631-time series sample data used, 70% was used for training while 15% was used for testing and another 15% used for validation.

The neurons model used is mathematically described as follows

The j^{th} hidden layer unit is fed with input given by

$$n_j'=\sum_{i=1}^{5} w_{ji}\, x_i+b_j' \quad (1)$$

where, w_{ji} is the weight of the i^{th} input unit and b_j' for j=1, 2…10 represents the bias for the hidden layer neuron and x is the vector inputs; ambient temperature, Module temperature, irradiance, relative humidity and wind speed.

The hidden layer neuron output is given by.

$$a_j^{'} = f_1\left(\sum_{i=1}^{5} w_{ji} x_i + b_j\right) \quad (2)$$

where

$$f_1(n) = tansig(n) = \frac{2}{1-e^{-2n}} \text{-1} \quad (3)$$

The neuron input to the output layer is

$$n_k^{'} = \sum_{i=1}^{10} w_{kj}\, a_j^{'} + b_k^{'} \quad (4)$$

Where w_{kj} is the weight on the connection from the j^{th} input unit, b_k' for k=1, represents the bias for the output layer neurons. The output layer y_k is the network output of interest

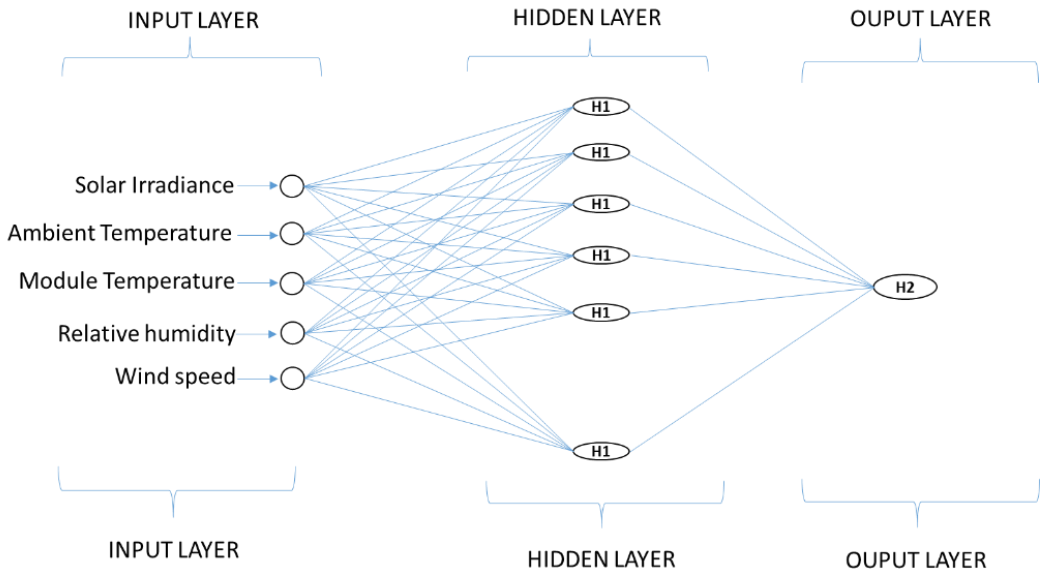
$$y_k= f_2\left(\sum_{i=1}^{10} w_{kj}\ a_j^{'}+x_j+b_k^{'}\right) \quad (5)$$

where

$$f_2\,(n) = \text{purelin}\,(n) = n \quad (6)$$

Figure 2

Schematic representation of Artificial Neural Network



Statistical measures such as testing correlation (R), coefficient of determination (R^2) and mean squared error (MSE) were used to compare each method's capabilities and performance prediction. These parameters are described as follows

Coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(P_A - P_P)^2}{\sum_{1}^{m}(P_A - P')^2} \quad (7)$$

Mean squared error

$$MSE = \frac{1}{m}\sum_{i=1}^{m}|P_A - P_p|^2 \quad (8)$$

Where, P_A is the actual measured power, P_P is a predicted power output, P' is rated power output.

Results

The results obtained for mean squared error (MSE), coefficient of correlation (R) and coefficient of determination (R^2) by varying the number of hidden neurons in the hidden layer using LM, BR, SCG and RP ANN algorithms are presented in Table 1. The number of hidden layers considered in the ANN model varied from 1-20 with 2 taped delay lines. These statistical performance indicators are useful in determining the quality of the model (Bird *et al.,* 2005; Draper and Gittoes, 2004). The smaller the MSE, the better the prediction model, while the determination coefficient (R^2), the better the models with their values approaching one (Consonni, Ballabio and Todeschini, 2010; Li, 2017).

Table 1

MSE and R^2 of the ANN algorithms for different number of Hidden Layers

HL	LM		BR		SCG		RP	
	MSE	R^2	MSE	R^2	MSE	R^2	MSE	R^2
1	0.0802	0.95803	0.0788	0.96197	0.1149	0.9408	0.2077	0.89545
2	0.0599	0.96983	0.0485	0.97652	0.1447	0.92768	0.0857	0.9577
3	0.0551	0.97151	0.0278	0.98611	0.0988	0.94901	0.095	0.97259
4	0.027	0.98704	0.0241	0.98812	0.1212	0.94199	0.082	0.96016
5	0.0233	0.98869	0.0216	0.98931	0.0809	0.96081	0.0656	0.96727
6	0.0261	0.98629	0.0201	0.99024	0.0952	0.94922	0.0603	0.97137
7	0.0212	0.98931	0.019	0.9903	0.1003	0.94998	0.0632	0.96784
8	0.0218	0.98925	0.017	0.99166	0.0392	0.98063	0.0718	0.96419
9	0.0205	0.98973	0.0183	0.99082	0.0822	0.95897	0.0691	0.96592
10	0.0228	0.98855	0.0152	0.99269	0.0937	0.95297	0.0684	0.96637
11	0.0145	0.99301	0.0138	0.99317	0.0711	0.96497	0.0691	0.96427
12	0.0155	0.99216	0.0143	0.99279	0.0637	0.96757	0.0389	0.97941
13	0.0302	0.98583	0.0121	0.99397	0.0535	0.97445	0.0371	0.98212
14	0.0133	0.99353	0.0113	0.99451	0.0449	0.97858	0.13	0.93778
15	0.0164	0.99227	0.0112	0.99449	0.086	0.95799	0.0641	0.9678
16	0.017	0.99202	0.0122	0.99355	0.0558	0.97344	0.0374	0.98159
17	0.0217	0.99012	0.0116	0.99443	0.0492	0.97624	0.0387	0.9805
18	0.0199	0.99046	0.0109	0.99475	0.0626	0.97015	0.042	0.97925
19	0.015	0.99269	0.0094	0.99539	0.0921	0.95365	0.0546	0.97452
20	0.0129	0.99353	0.0114	0.99445	0.0409	0.98008	0.0571	0.9722

As observed in Table 1 above, the performance of LM, BR, SCG and RP ANN algorithms in terms of MSE shows that despite minor fluctuations in MSE values between intermediary layers, a decreasing trend of MSE with an increasing number of hidden layers was observed for all algorithms. For the LM algorithm, a minimum MSE value of 0.0129 was observed when 20 hidden layers were used, while the maximum MSE was found to be 0.0802 when 1 hidden layer was used. In the case of the BR algorithm, good training performance was observed when 19 hidden layers were used with a minimum MSE value of 0.0094, whereas the maximum value of 0.0788 was with 1 hidden layer. The reason for such an increasing performance trend with an increasing hidden layer is due to the fact that neural networks with more hidden layers have a higher capacity to learn complex patterns and representations in the data. This increased capacity allows the model to capture more intricate relationships and nuances within the input data (Aggarwal, 2018).

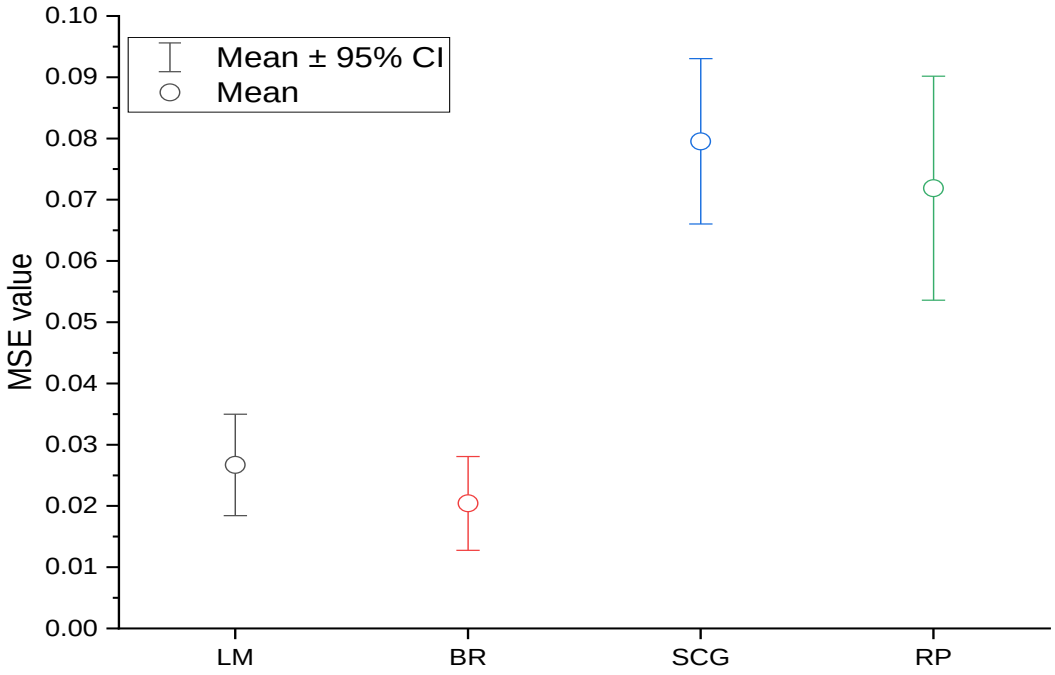
It is further observed that the decreasing trend of MSE in the BR algorithm with an increase in hidden layers is better consistent compared to the other three algorithms. On the other hand, the SCG and RP algorithms had minimum MSE values of 0.0392 and 0.0371 at 8 and 13 hidden layers, respectively. Additionally, the maximum MSE of the SCG and RP algorithms, with values of 0.1447 and 0.2077, is at 2 and 1 hidden layers, respectively. One can observe high variability in the decreasing trend of MSE between intermediated MSE for the RP algorithm as the number of hidden layers increased.

To determine the overall algorithm's performance, the average MSE for all hidden values from 1 to 20 was computed and displayed in Figure 3. It is observed from the plot that the

BR algorithm bears a minimum average MSE of 0.02043, indicating the best training performance, while on the other hand, the SCG algorithm shows the highest MSE value of 0.07954 and therefore has relative lower training performance compared to the other three algorithms.

Figure 3

Average MSE of each algorithm for all number of hidden layers

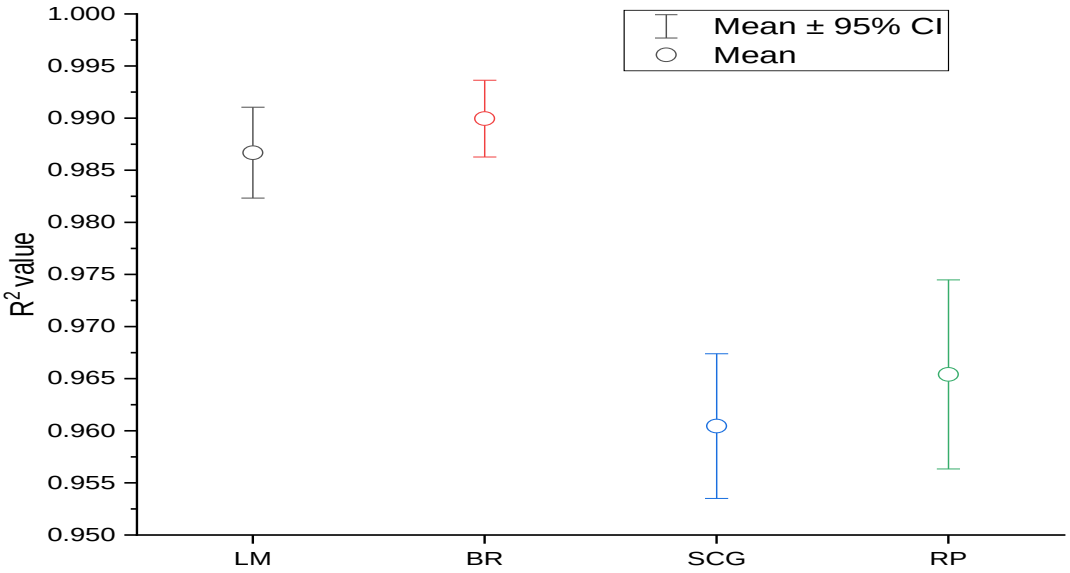


As mentioned earlier, the coefficient of determination R^2 is a statistical measure of how well the regression predictions match the real data points in the regression. As observed in table 1, the maximum R^2 value for the LM algorithm is found to be 0.99353 when 20 hidden layers are used, while the lowest R^2 observed was 0.95803 when 1 hidden layer was used. In the case of the BR algorithm, the maximum R^2 is 0.99539 for 19 hidden layers, while the minimum R^2 is observed to be 0.96197 when 1 hidden layer is used. For the SCG algorithm, the highest R^2 was found to be 0.98063 for 8 hidden layers, while the lowest R^2 was observed to be 0.92768 for 2 hidden layers. Finally, for the RP algorithm, the highest R^2 was observed to be 0.98212 for 13 hidden layers, while the lowest R^2 was observed to be 0.89545 for 1 hidden layer.

To determine the overall ANN algorithms which match well the regression predictions and real data, the average R^2 were computed for all hidden layers from 1 to 20 and presented in figure 4.

Figure 4

Average MSE of each algorithm for all number of hidden layers



It is found that, BR algorithm had highest mean R^2 value of 0.98996 while SCG showed lowest mean R^2 value 0.96046. From these outcomes one can see that BR algorithm matches well the regression predictions and the real data points in regression as compared to SCG and other algorithms.

From the results indicated in table 1 and from figures 3-4 for MSE and R^2 values trained from 1 to 20 hidden layers, it is observed that, BR algorithm exhibited the lowest MSE value of 0.0094 for 19 hidden layers while RP algorithm presented the highest MSE value of 0.2077 for 1 hidden layer. The highest R^2 value of 0.99539 for 19 hidden layers was found for BR algorithm, whereas the lowest R^2 value of 0.89545 for 1 hidden layer was observed for RP algorithm.

To learn more about how the increasing configuration of hidden layers within the network significantly influences their predictive performance, we compared the prediction and experimental power output for all ANN algorithms with the lowest MSE/highest R^2 and the highest MSE/lowest R^2 at their respective hidden layers, as presented in figures 5–8. Figures 5(a), 6(a), 7(a) and 8(a) present the comparison of prediction and experimental power output at which the ANN algorithms showed the maximum MSE/minimum R^2 with poor regression prediction, whereas figures 5(b), 6(b), 7(b) and 8(b) show the minimum MSE/maximum R^2 with the best regression for each ANN algorithm. As justified in figures 5(b), 6(b), 7(b) and 8(b), the pattern of the graphs is compatible and very close between them, with a good match between predicted and experimental power output, while in figures 5(a), 6(a), 7(a) and 8(a), the pattern of predicted power output shows a slight divergence from experimental power output. These regression prediction results are in line with the performance indicators MSE and R^2.

Figure 5

Experimental Vs predicted power out for LM algorithm for

(a) 1 hidden layer and (b) 20 hidden layers

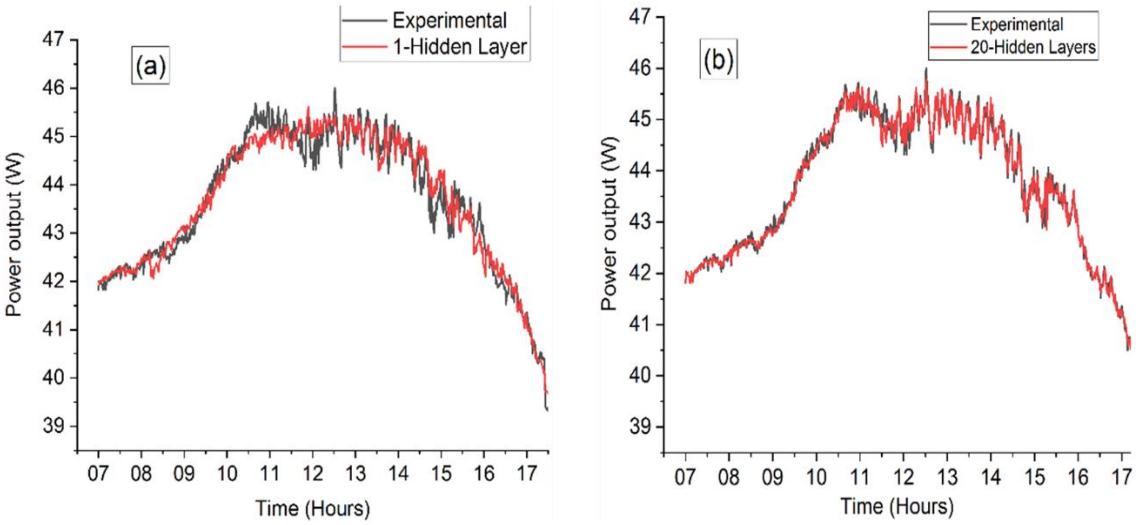


Figure 6

Experimental Vs predicted power out for BR algorithm for

(a) 1 hidden layer and (b) 19 hidden layers

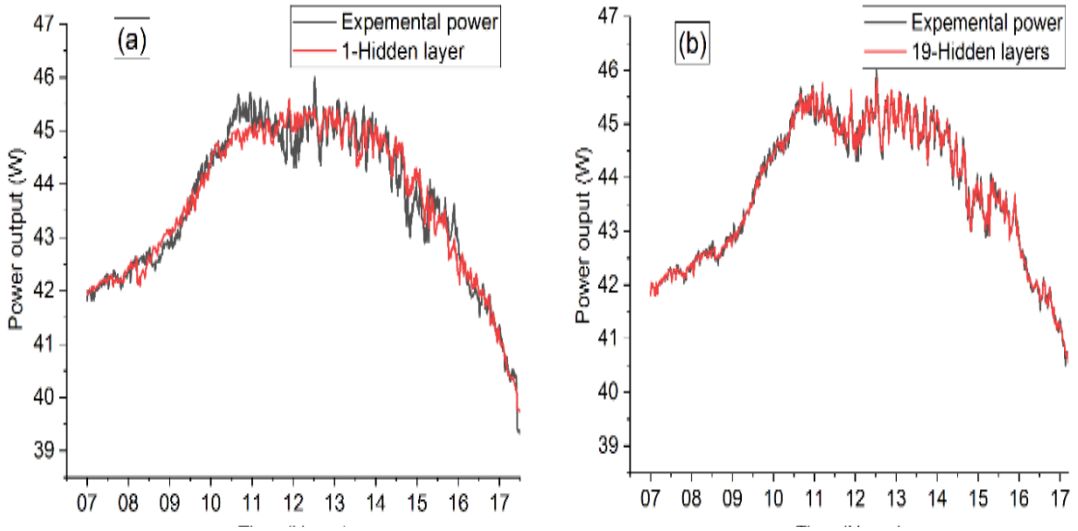


Figure 8

Experimental Vs predicted power out for BR algorithm for

(a) 1 hidden layer and (b) 19 hidden layers

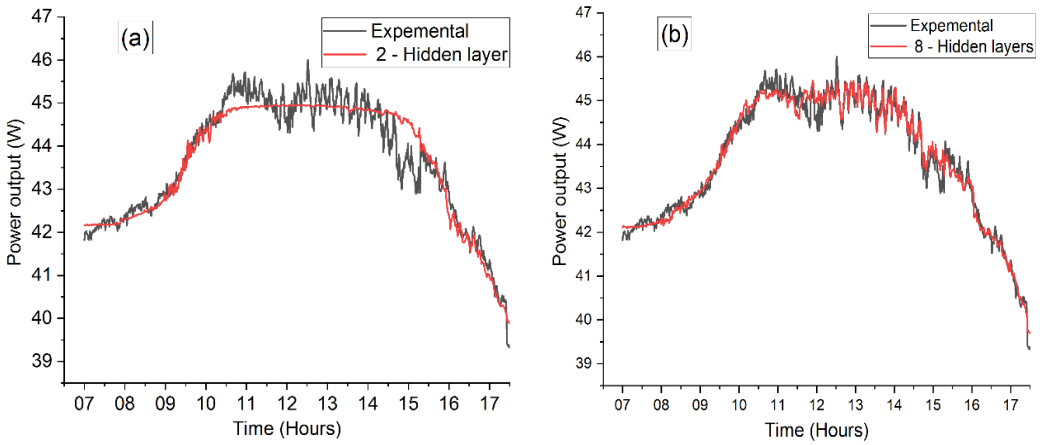
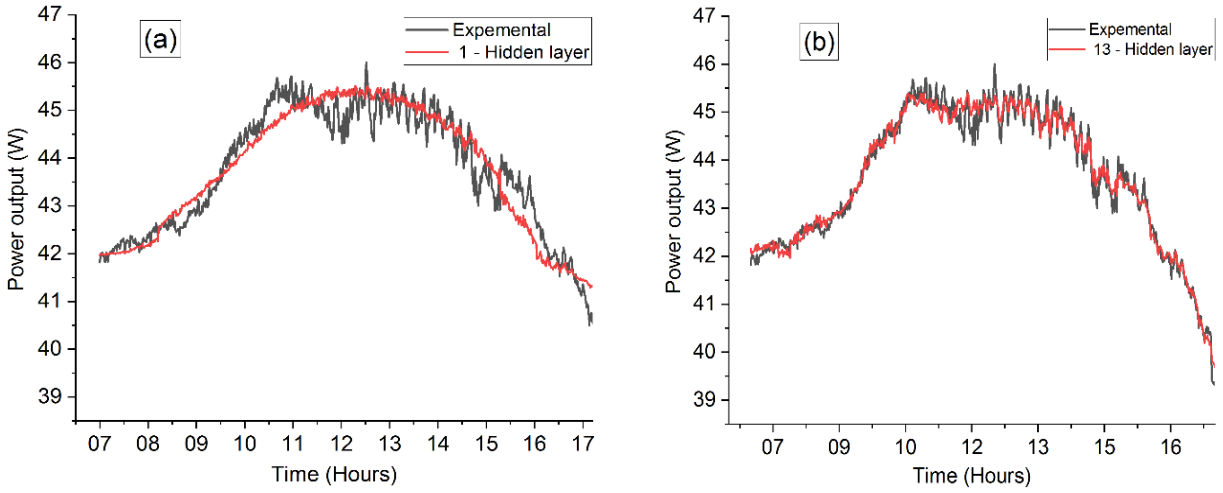


Figure 9

Experimental Vs predicted power out for RP algorithm for

(a) 1 hidden layer and (b) 13 hidden layers



Discussion

The analysis of the performance of various Artificial Neural Network (ANN) algorithms—Levenberg-Marquardt (LM), Bayesian Regularization (BR), Scaled Conjugate Gradient (SCG) and Resilient Propagation (RP)—in terms of Mean Squared Error (MSE) with varying hidden layers reveals significant insights. A general trend of decreasing MSE with an increasing number of hidden layers was observed across all algorithms, despite minor fluctuations between intermediary layers. Specifically, the LM algorithm showed improved performance with more hidden layers, achieving its lowest MSE with 20 layers, while the highest

MSE occurred with only one layer. The BR algorithm also exhibited good training performance, with the best results seen at 19 hidden layers. This improvement with increased hidden layers can be attributed to the enhanced capacity of deeper neural networks to learn complex patterns and representations within the data, capturing complex relationships and distinctions (Goodfellow, Bengio and Courville, 2016; Heaton, 2018).

Interestingly, the BR algorithm demonstrated a more consistent decrease in MSE with increasing hidden layers compared to the other algorithms. The SCG and RP algorithms, however, showed their lowest MSE at intermediate layers rather than at the maximum number of layers evaluated. This variability suggests that while deeper layers generally improve performance, the optimal number of layers may vary depending on the algorithm and specific application. For instance, Arora *et al.,* (2019) LM and SCG algorithms achieved the lowest MSE using intermediate layers. Additionally, Aghelpour *et al.,* (2022) evaluated algorithms for daily pan evaporation estimation, highlighting that the BR and SCG algorithms outperformed LM, particularly noting BR's consistent performance improvement with deeper layers.

To evaluate the overall performance of these algorithms, average MSE values across all hidden layers were computed. The BR algorithm emerged as the best performer, indicating its robustness and reliability in training. On the other hand, the SCG algorithm showed the highest average MSE, highlighting its relatively lower training performance.

The coefficient of determination (R^2) was also analyzed for these algorithms at different hidden layers. R^2 measures how well the regression predictions match the real data points, with higher values indicating better performance. The BR and LM algorithms consistently achieved higher R^2 values, indicating better alignment between predicted and actual outcomes. The BR algorithm, in particular, showed the highest mean R^2, suggesting it provides the most accurate regression predictions among the evaluated algorithms (LeCun, Bengio and Hinton, 2015).

Comparing prediction and experimental power output for the algorithms with the best and worst performance in terms of MSE and R^2 provided further insights. The best-performing configurations showed a good match between predicted and experimental outputs, reinforcing the reliability of these models. In contrast, configurations with higher MSE and lower R^2 showed more divergence between predicted and experimental outputs, indicating poorer regression performance. Overall, the results suggest that the BR algorithm offers superior performance, both in terms of MSE and R^2, compared to SCG and other algorithms. This superior performance can be attributed to its ability to better capture complex data patterns and provide accurate predictions, making it a reliable choice for tasks requiring high predictive accuracy.

The primary benefit of increasing the number of hidden layers is the enhanced capacity to learn complex patterns and non-linear relationships in the data. In the context of solar power output, factors such as irradiance, temperature and shading conditions introduce non-linearity and variability that a simple model might fail to capture. Complex networks with more hidden layers can effectively model these intricate dependencies, leading to more accurate predictions of solar power output (Goodfellow, Bengio and Courville, 2016).

Studies have shown that ANNs with an appropriate number of hidden layers can significantly improve the predictive accuracy of solar power output. For instance, deeper networks have been found to reduce the MSE between predicted and actual power outputs, indicating better performance. This reduction in error can be attributed to the network's ability to generalize better from the training data to unseen conditions, which is critical for reliable solar power forecasting (Zhang, Patuwo and Hu, 1998).

Increasing the number of hidden layers can enhance a network's learning capability. However, adding too many layers may lead to diminishing returns or even performance degradation due to overfitting. Overfitting

happens when the model becomes too complex and starts to learn the noise in the training data instead of the underlying pattern. Thus, finding the optimal number of hidden layers is crucial to balance model complexity and generalization (Hornik, Stinchcombe and White, 1989).

For practical applications in solar power optimization, using ANNs with an optimal configuration of hidden layers can lead to better management of solar energy systems. Improved prediction of power output enables better planning and integration of solar energy into the grid, enhancing the overall efficiency and reliability of the energy supply. Additionally, accurate forecasting can aid in preventive maintenance and operational strategies, reducing costs and increasing the lifespan of solar power installations.

Empirical evidence from various studies supports the positive impact of hidden layers on solar power output optimization. For instance, research has demonstrated that using deep learning models with multiple hidden layers significantly improves the accuracy of short-term solar irradiance predictions, which directly correlates with power output (Voyant *et al.,* 2017).

Conclusion

In conclusion, this study thoroughly examined the optimization of photovoltaic (PV) power output predictions using four artificial neural network (ANN) algorithms—Levenberg-Marquardt optimization (LM), Bayesian regression (BR), scaled conjugate gradient (SCG) and scaled resilient propagation (RP)—at varied hidden layer configurations. The analysis incorporated inputs such as solar irradiance, ambient temperature, module temperature, wind speed and relative humidity to account for environmental factors impacting PV power generation.

The results demonstrated that Bayesian regression (BR) achieved the highest predictive accuracy, with a mean squared error (MSE) of 0.02679 and a coefficient of determination (R^2) of 0.98996. In contrast, scaled resilient propagation (RP) had the lowest performance, with an MSE of 0.0709 and an R^2 of 0.96541. Increasing the number of hidden layers generally improved the model's ability to capture complex patterns and non-linear relationships in the data. Furthermore, the results show that while deeper neural networks generally improve the performance of ANN models in predicting PV power output, the extent of this improvement and the optimal number of layers are highly also dependent on the specific algorithm used.

The Bayesian regression algorithm, in particular, showed the best overall performance due to its consistency and robustness in handling complex data relationships. The study confirms that advanced ANN techniques can significantly enhance prediction accuracy and provides valuable insights for improving PV system efficiency

Recommendation

Future research could explore the application of these artificial neural network (ANN) algorithms in diverse environments by testing their performance with various photovoltaic (PV) module types, such as monocrystalline, thin-film, or bifacial modules, to determine if the algorithms are equally effective across different technologies. Additionally, applying these models in diverse geographic locations with varying solar irradiance, temperature and weather conditions would provide a broader understanding of how well the algorithms generalize to different climates.

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