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Artificial neural network weights-based new formula for solar power plant energy prediction

Muhammed Sabri Salim[1*], Naseer Sabri[2], Ali Abdul Rahman Dheyab[3]
[1,3]Department of Electronics and Communication Engineering, Al-Nahrain University, Iraq; muhsabri1967@yahoo.com (M.S.S.) ali.abdulrahman.1@nahrainuniv.edu.iq (A.A.AR.D.)
[2]Technical Engineering College, Al-Farahidi University, Iraq; naseersabri@yahoo.com (N.S.)

Abstract: Renewable energy, particularly solar power, is crucial for national development, but forecasting its electrical power output remains a challenge. Environmental parameters like irradiance, temperature, and wind speed impact photovoltaic systems' power. This research presents a unique approach using artificial neural network's weights to compute the output power of a photovoltaic system across various operating situations. The study utilized an experimental dataset of 28296 samples to train an artificial neural network (ANN), with the output power of a photovoltaic station serving as the target parameter and irradiance, temperature, and wind speed as the input parameters. Next, utilize the ANN's weights to create a distinct model for predicting the production of electricity. The new formula's results were more accurate than the meteorological service's local measurement data for weather prediction, which showed mean square error, an average absolute percentage deviation, and linear correlation of 0.0592, 0.984%, and 0.9688, respectively. The acquired formula makes these results accessible and usable even in the absence of the relevant ANN software.
Keywords: *ANN, Deep learning, Levenberg Marquardt algorithm, Renewable energy, Solar energy, Solar power plant.*

1. Introduction

Renewable energy, including solar energy, is a sustainable solution that uses sunlight to generate electricity through innovative photovoltaic technology. The environmental and technological benefits of a PV system are, however, heavily impacted by financial and technical factors. Public funding is crucial for consumers to rely on renewable energy sources. Climate factors, including air temperature, relative humidity, wind speed, and amount of sunshine, influence photovoltaic module manufacture.

Artificial intelligence is needed to predict peak power outputs and improve the power harvesting capability of PV modules. Researchers recommend using Optimum Power Factor Monitoring (MPPT) technology and other experimental methods to achieve optimal performance. Nevertheless, these approaches need a great deal of information on the module's characteristics and needs, which isn't always accessible or easy to communicate.

Techniques like Maximum Power Factor Tracking (MPPT) are used to improve energy collecting efficiency, but these methods have a drawback of relying on incomplete understanding of the module's physical characteristics and manufacturing needs, which are often unidentified.[1]-[6]

An investigates numerous approaches for calculating the power of PV modules, such as different PV power prediction methodologies and their accuracy produced by Kaaya et al.(2021) [7]. R. Nageem (2017) challenged the multiple input support regression model, which was previously proposed [8]. S. A. Jumaat (2018) created an artificial neural network (ANN) utilizing Malaysian data to generate predictions based on surrounding vectors [9]. Sabrian, H. et al. (2014) presents an ANN-based solar power modeling approach. The power output of solar panels was represented by two neural network architectures: feedforward back propagation and general regression neural network.

* Correspondence: muhsabri1967@yahoo.com

Data from 2006-2010 was used for training and testing. FFBP showed better performance compared to GRNN [10]. Zhang, Lu, Y. et al. (2022) present the power-law model (PLM) as a new approach to forecast the current-voltage properties and output power of photovoltaic (PV) modules under different operating situations. The technique is straightforward and unambiguous, reducing computational complexity. Different PV modules confirm it, demonstrating greater concordance with experimental findings under varied environmental conditions. Under different circumstances, the approach can accurately forecast the output qualities of PV modules [11]. Bimenyimana, S. et al. (2017) employed a training, recognition, and screening technique to provide monthly and yearly solar module power projections. They discovered that a nonlinear autoregressive semantic network effectively predicted solar module output power, with the maximum efficiency levels recorded at stages 3 and 6, demonstrating its potential for reliable prediction [12]. Dandil, E. and Gurgen, E. (2017) suggests a model that uses heuristic algorithms and artificial neural networks (ANNs) to forecast monthly power outputs from photovoltaic (PV) panels. When it comes to estimating power outputs from panels installed at six different degrees of tilt, ANN-trained with PSO outperforms the Back-Propagation and Clonal Selection Algorithm [13]. Solar photovoltaic power forecasting techniques, such as those based on statistics and artificial intelligence, were investigated by Khan, S. et al. (2022). The efficacy of several models is validated using hourly data from Quaid-e-Azam Solar Park, a 100 MW solar power facility in Pakistan. We recommend recurrent neural networks as the top model because of their excellent accuracy in all kinds of weather, but particularly when the sky is overcast [14]. Baaran, K. et al. (2020) assessed machine learning and deep learning approaches used to estimate PV power generation from 2010 to 2020, identifying flaws and making suggestions for further study [15]. Elamim, B. et al. (2020) conducted research in Mohammedia, Morocco, using an artificial semantic network to estimate energy output from solar panels. The system employed a feedforward neural network to assess hourly data on sunlight intensity, air temperature, and solar panel efficiency. The research discovered a substantial link between power degrees on sunny and gloomy days, demonstrating the system's performance [16].

Khan, M. A. et al. (2022) employed an artificial neural network (ANN) trained on the Levenberg Marquard technique to properly anticipate the energy output of a solar power system. They employed a dataset of 28,296 data points and attained a 98% accuracy rate and a mean square error of 0.0604 using regression analysis [17]. To diagnose route loss in WSNs, Salim, M.S. et al. (2024) used a neural network-based approach. Taking into account route losses, distance, and antenna height, the model achieves a very accurate result with an average absolute deviation (AAD) of 0.36% [18]. Two new approaches, combining a parametric technique with deep learning, were introduced by Naoumi S. et al. (2024) to find the entry and exit angles in bistatic ISAC systems. The DL-based technique beats the parameterized method, with comparable performance and lower complexity [19].

Lin, GQ. et al. (2020) offer an improvement to the moth-flame optimization approach for estimating solar power production. They use an assist vector device to improve data variety, reduce the likelihood of embedding bad solutions, strike a balance between discovering and processing features, and apply an alteration controller based on the Cauchy distribution. Their technique increases optimization effectiveness, decreases grid influence, and improves system integrity in Australian solar power systems [20].

Neural networks are excellent tools for approximating nonlinear functions and are employed in a variety of applications. Artificial neural networks use small, linked processing units to transport data and determine the relationship between inputs and outcomes. The connection weights increase with each item in the three levels (input, hidden, and output). The training phase of a neural network is critical, and backpropagation is the most used approach. However, backpropagation of gradient descent training techniques is often inefficient for real-world problems. Faster algorithms, such as conjugate gradient (CG), Levenberg Marquardt (LM) , and Gauss Newtonian (GN), use typical numerical optimization methods. These algorithms are often quicker than conventional approaches, making them appropriate for real-world applications [21]-[22]. Olden, J.D. et al. (2004) utilized simulation to investigate several ways for assessing the importance of parameters in artificial neural networks. They discovered that the connection weight methodology outperformed all other strategies. In order to find out how important a parameter is, this method takes into account the connection weights between input and hidden neurons as well as between hidden and output neurons [23].

Research indicates that ambient temperature and solar radiation values are of critical importance in forecasting PV manufacturing, taking into account all environmental factors, including energy, and the final energy usage of the PV component to obtain reliable forecasts. This study set out to develop a new formula based on network weight and measure the quantity of energy produced by artificial neural networks within solar stations. The accuracy of this ANN-based formula was explored and compared with the correlation of Local Measurements Data (LMD). Because of the obtained formula, users can access and utilize these findings even without access to the corresponding ANN software. The study is organized into six sections: literature review, solar cell model and I-V equations, passing methodologies, simulations and results, analysis and discussion, and research conclusions.

2. Photovoltaic Cells Model

2.1. The PV Module's Power Output

To design and evaluate PV system performance, an accurate model should reliably forecast a power-voltage (P-V) and voltage - current (V-I) curve under real operating conditions. To better understand the electrical functions of PV systems, researchers frequently use the "five-parameters model," a similar circuit. Figure 1 depicts a circuit with a photocurrent supply I_L, a resistance known as shunt R_{sh} and a diode connected in parallel, and a series resistance R_s. The following statement may be used to create the mathematical model of a solar cell based on this simplified circuit and get the I-V curve: [24] [17].

$$I = I_l - I_o(e^{\frac{(v+IR_S)}{nT_c}} - 1) - \frac{(v+I.R_S)}{R_{sh}} \quad (1)$$

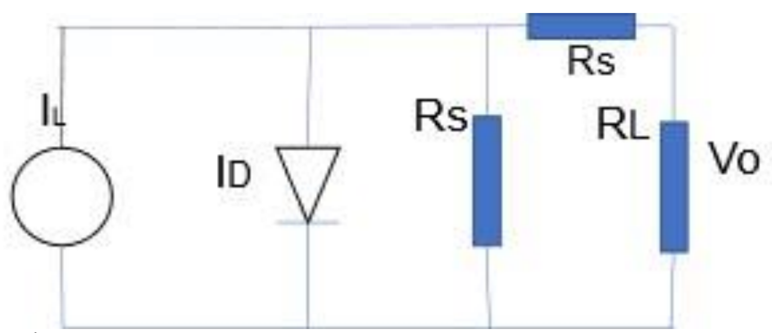

Figure 1.
A basic solar cell equivalent circuit [24].

where T_c is the cell absolute temperature, I_o is the diode reverse saturation current, and n represents the perfect parameter, all of which are controlled by the silicon temperature. I_L is also dependent on the sun irradiation. It is well-known that the "peak power" determines how well a photovoltaic panel works. This is the highest amount of electric power that the panel can produce when exposed to 1 kW/m^2 of solar irradiation G and the cell temperature is 25°C. The operating point may be found for given values of G, T_c, and R_L by drawing lines of the various loads R_L on the I-V characteristic; the red circles represent the greatest power points. The majority of maximum power point tracking algorithms that have been published in the literature use linear approximations to determine the best operating point of a generic PV system as: [25][26]

$$V_{mpp} = V_c \cdot V_{OC} \quad (2)$$

where V_{oc} is the open circuit voltage, V_c is a constant of proportionality (voltage factors) that depends on the properties of the PV array utilized, and V_{mpp} is the maximum voltage and current, respectively. Direct techniques, on the other hand, are an alternative since they allow you to determine the greatest amount of power produced straight from the voltage and current readings of your PV generator. If that's the case, they work well in any temperature and light condition [17]. Some DC/DC converters, also known as maximum power point tracking (MPPTs), may include all techniques, both direct and indirect, for use in standalone systems. More and more, approaches including fuzzy logic controllers and artificial neural networks and have been used for MPP searching with great success as of late [24].

3. Artificial Intelligent Network

Being a black box that does not need specific knowledge about the system or processes to function, ANN is useful for regression issues because to its flexibility and power, which are obtained from experimental data. The research determines the power output of a PV module using artificial neural networks (ANN). There is a set order to the phases in the ANN process, and each step may be adjusted independently. The collected values are then controlled by a function, such as gradient, linear, or sigmoid functions [27]. There is a tight connection between the ANN process and how neurons work, as seen in Figure 2. Artificial neural networks (ANNs) use regularization methods and backpropagation training to minimize error and reduce overfitting. However, backpropagation has a slow convergence rate, potentially causing overfitting. For functional approximation issues, researchers have developed regularization methods like Levenberg-Marquardt (LM) to improve mean squared errors (MSE), and backpropagation algorithms to accelerate convergence [28- 34].

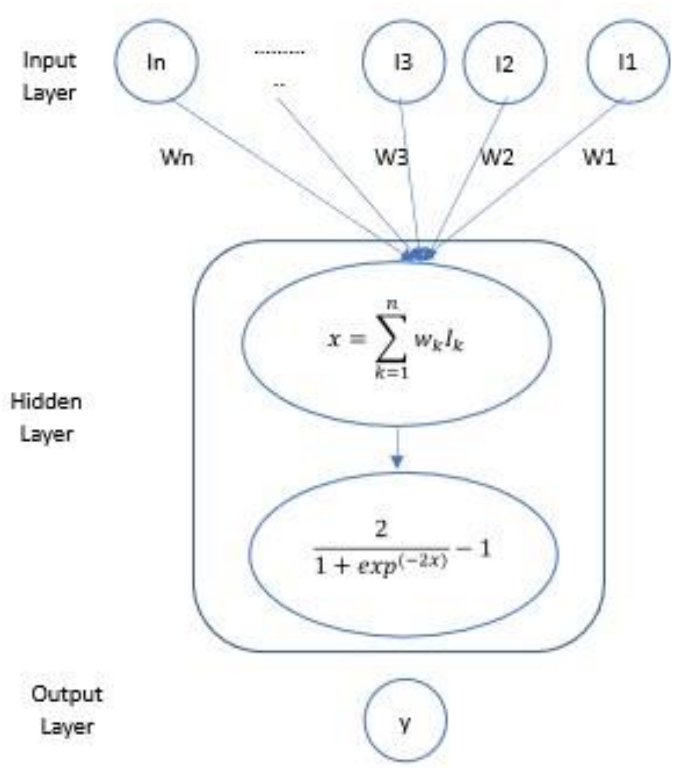

Figure 2.
Neurons' basic workings in the neural system.

4. Simulation and Results

4.1. PV Power Station and Data Preparation

This study uses a comprehensive dataset from the Science Data Bank and Reference PVOD (a photovoltaic power output dataset), to predict the energy production of a solar plant [35][36]. The dataset contains 271,968 records from 8 stations with different capacities. The data for one station (station00), containing approximately 28,896 samples, was used. The experimental data used for training the artificial neural network included wind speed, incident solar radiation, and ambient

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temperature as input data, while the peak power was selected as the output parameter. In addition, the Pearson connection technique was used to identify relevant features in analytical information, with radiation having the greatest effect on energy production, followed by wind and heat. The PV power plant station 00 boasts a capacity of 6600 KW, utilizes poly-silicon PV technology, has 26000 panels, a south 33° array tilt, a global horizontal irradiance pyranometer, and is located at latitude and longitude of 38.04778° and 114.95139° [24][36].

4.2. ANN Implementation

The implementation of an artificial neural network (ANN) requires considering the specific architecture and scenario. The ANN acts as a black box, adjusting hyperparameters to achieve the highest slope value and lowest MSE. Levenberg Marquardt (LM) algorithms are used, with layer size 10 chosen for superior training, validation, and test accuracy. Training is terminated when performance or progression conditions are met. The change in mean squared error (MSE) across the 54 iterations of the LM algorithm's training, testing, and validation phases is shown in Figure 3. With each iteration, the image shows how the Mean Squared Error (MSE) value changes. The most impressive validation performance is shown in Epoch 86, which has an MSE of 0.05759.

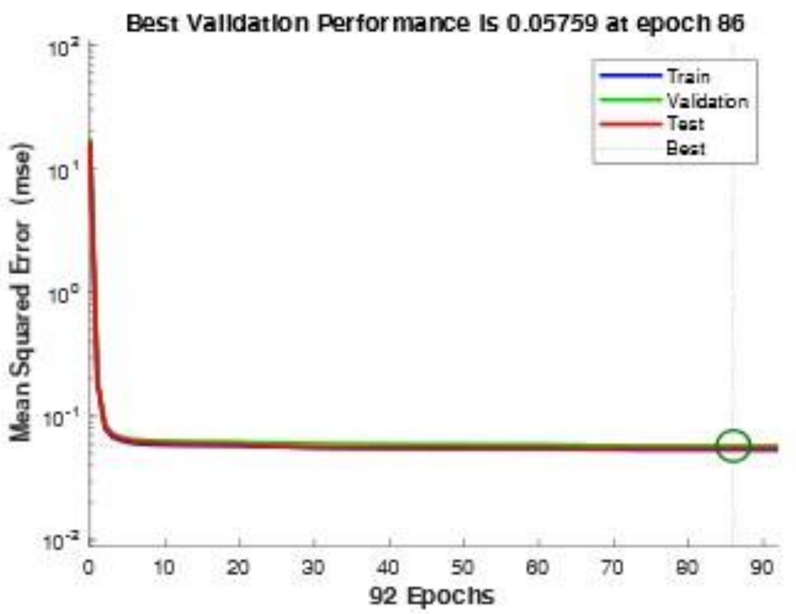

Figure 3.
LM-trained ANNs' mean squared error vs. epoch count.

In Figure 4, The closer the numbers are to 1 on a regression plot, which illustrates how well the anticipated and actual target values match up, the better. Training, validation, and testing values for the LM method used in this study are 0.98508, 0.98386, and 0.98506, respectively. When all phases are combined, the regression value is 0.98489. Table 1 displays the training outcomes and the total time that has passed.

Table 1.
ANN training outcomes using the LM method.

	Epoch	Performance	Elapsed time	Mu	Validation checks
Initial value	0	17.1	-	0.001	0
Current value	92	0.0535	0:00:15	1.00e-05	6
Target value	1000	0	-	1.00e+10	6

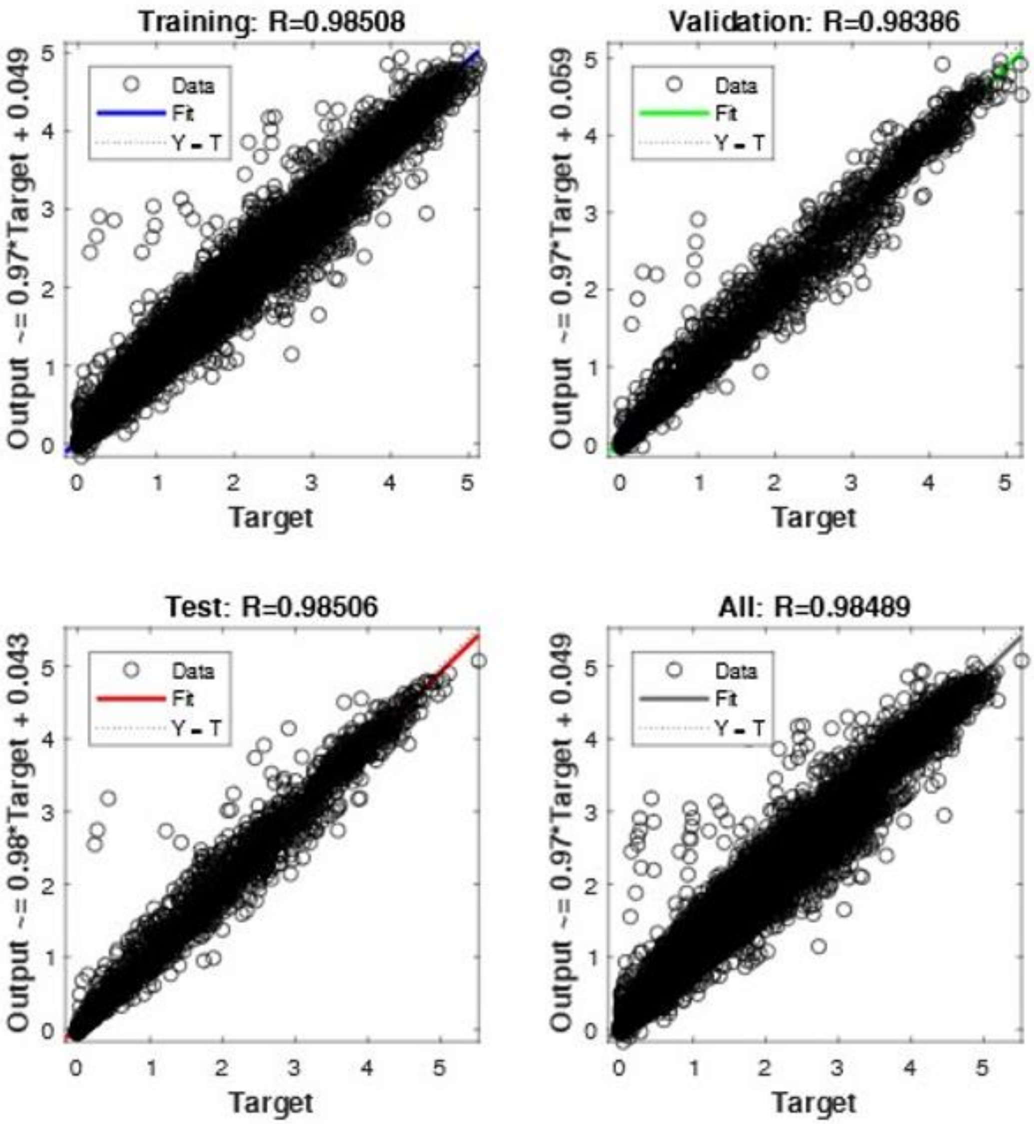

Figure 4.
Shows the results of a regression analysis on artificial neural networks (ANNs) trained using the LM method.

Data normalization may allow for an improvement in the correlation coefficient between independent and dependent parameters. What follows is a normalization of the inputs and outputs inside the interval (-1,1):

$$N = (2 \times \left(\frac{D_o - D_{min}}{D_{max} - D_{min}}\right) - 1) \qquad (5)$$

In this context, D_o represents the initial data, D_{min} represents its lowest value, D_{max} represents its maximum value, and N represents the normalized outcome. ANN aims to properly predict internal parameters using the linear correlation coefficient (R) and mean squared error (MSE). Training requires adequate data. After successful network training, test data was used to evaluate the network.

5. Results and Discussion

The artificial neural network (ANN) in this research was trained using a dataset of 28,896 experimental datapoints for photovoltaic power output from the Science Data Bank and Reference

PVOD [35]. In addition, the training process used 20,227 records (70%) of the data. Validation and testing each received 4,335 records (15%) of the data serving each purpose. The LM method, which uses a hidden layer of 10 neurons, produced the best results with the lowest amount of accuracy. Table 2 shows the performance metrics for the ANN, including MSE, NMSE, MAE, MIN and MAX absolute errors, and linear correlation coefficient (R). Figure 6 depicts the mistakes that occurred throughout training, validation, and testing. Because there appears to be no significant overfitting and the test and validation sets errors have comparable characteristics, the outcome is credible. The optimal validation performance was achieved after 86 iterations, at which point the training was terminated. The graphic also displays the network's mean square error, which starts out big and gradually decreases to a lower amount. What this means is that the network is really learning.

Using the weights of the algorithm, a formula for predicting the station's output power was built based on the network training described above. Equation 6 uses the Tansig transfer function as the activation function in the hidden layer.

$$A_i = \frac{2}{1+\exp(-2E_i)} - 1, \quad i = 1{:}10 \qquad (6)$$

where the values of *Ei* are shown in Table 3. The estimated output power of station 00 (OP_{00}) was thus made possible by Eqs. (6) and (7).

$$OP_{00} = f(G, T, W)$$

$$OP_{00} = 0.3282A_1 + 0.0548A_2 + 0.1926A_3 + 0.0341A_4 - 0.0642A_5 + 0.2225A_6 + 0.0286A_7 - 2.0384A_8 + 0.4978A_9 + 0.1113A_{10} - 1.8158 \qquad (8)$$

Figure 5 displays the outcomes of the OP_{00} prediction made using this weight-based approach. When applied to all possible operating circumstances, this formula provides a statistically sound representation, as shown by R and MSE. This new model has a Linear Correlation Coefficient of 0.9688 and a Mean Square Error of 0.0592.

Table 2.
ANN model performance on test phase.

Performance metric	Value
R	0.9688
MSE	0.059246028
NMSE	0.030247277
Min absolute error	4.05776E-06
Max absolute error	2.719865079
MAE	0.163345531

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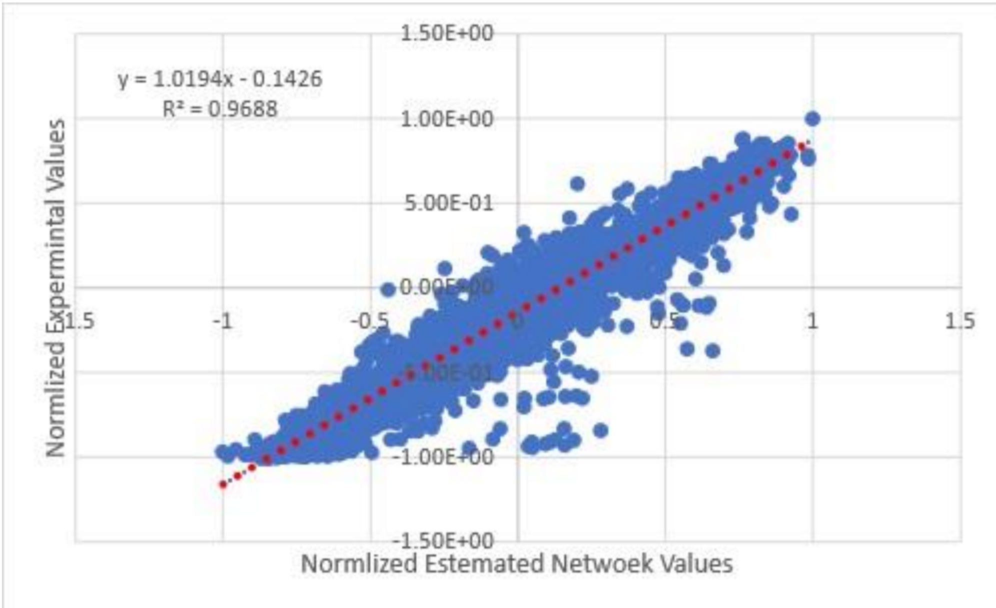

Figure 5.
Compares the network performance to the experimental data.

Table 3.
Displays the weight values that were determined by the LM method using 10 neurons.

	$E_i = w_{i1}G + w_{i2}T + w_{i3}W + b_i$			
i	W_{i1}	W_{i2}	W_{i3}	b_i
1	-2.5762	-2.2644	0.3377	3.3901
2	-0.0972	-1.449	-2.6916	2.1021
3	1.9478	0.9363	-0.5652	-1.5521
4	1.4065	1.8602	-1.0363	-0.0045
5	1.6605	2.5485	0.9001	-0.8666
6	2.0414	0.2197	0.8152	-0.6118
7	3.408	-1.3437	0.0731	0.5319
8	-0.5785	0.0449	-0.012	-0.8074
9	-0.9083	3.3105	-0.4033	2.535
10	-0.3995	1.7187	2.1487	-3.3621

In Figure 6 the Local Measurements Data (LMD) from PV power stations 00 for predictive power contrast with the results computed using this novel formula (OP_{00}), LMD and OP_{00} correlation for the same irradiance, temperature, and wind speed. The results of the proposed formula OP_{00} and the LMD data show a very good agreement.

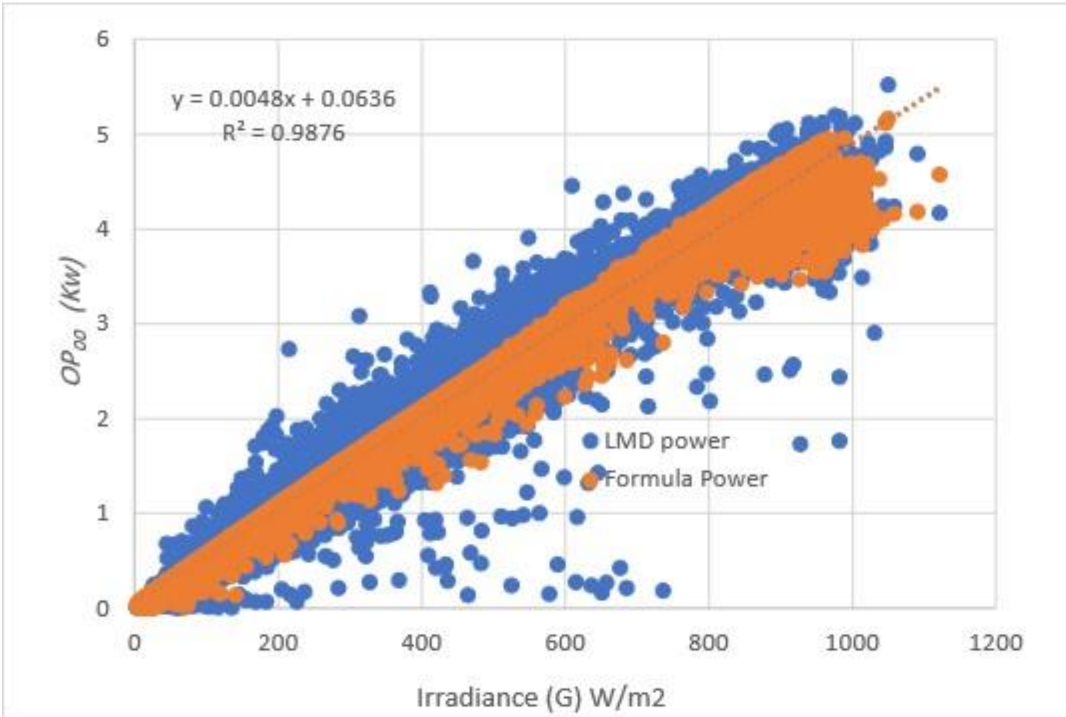

Figure 6.
The output compares the performance of the network with the experimental data.

According to this figure, the AAPD value for the correlation between the proposed formula and the local measurement data is 0.984%. Lastly, Pearson matrices were used to ascertain the input parameters' relative relevance. Figure 7 displays the results of adding the weights of the input parameters, which were 0.977772 for irradiance, 0.379 for temperature, and 0.3835 for wind speed. This suggests that irradiance has a stronger influence on the solar station's output power, significantly improving the ANN model's prediction via parameter G.

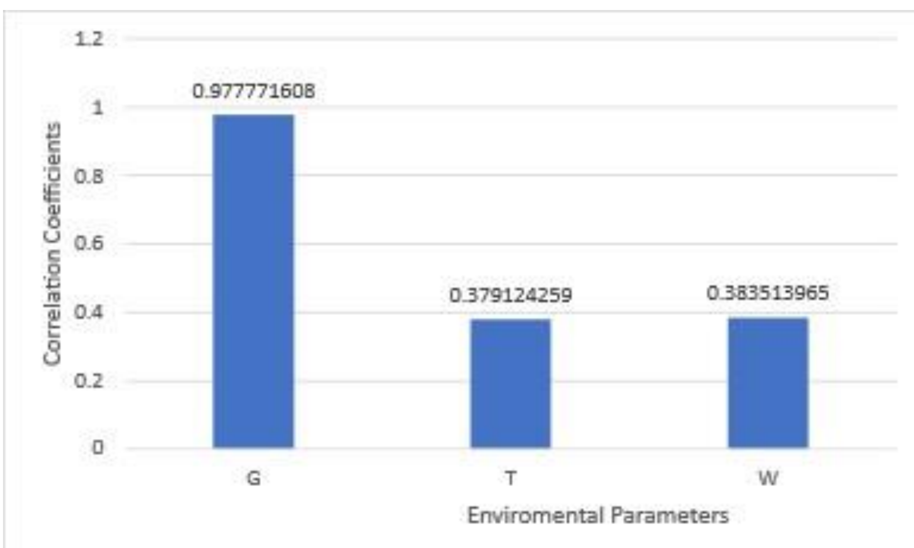

Figure 7.
The input parameters correlation analysis.

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6. Conclusions

This study develops a novel formula for predicting the output power of PV station 00 using an ANN's weights-based technique. The user may apply the formula to get these results even if they don't have the corresponding ANN software installed on their PC. It is also proven that radiation is the most important element affecting the power of a photovoltaic power plant by using Pearson matrix. Both wind speed and temperature have less influence than the irradiance factor. The output power is calculated using this novel empirical method across a greater range of irradiance, temperature, and wind speed than what can be achieved from correlations of data from local observations. The proposed formula was compared with the LMD correlation, and the formula was found to be more accurate in predicting the OP00 power output.

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