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An Approach to Optimized the Output Power of Photovoltaic System Using Artificial Neural Networks

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ABSTRACT: With the remarkable development of technology, the global energy crisis and green technology have boosted demand for the utilization of renewable energy sources, and energy storage technology as an appealing solution to enhance power efficiency. The paper describes strategies to improve energy management efficiency by ensuring the best selection of photovoltaic (PV) solar cell characteristics while constructing a solar energy network. An artificial neural network (ANN) algorithm is integrated with the capabilities of the PVsyst6.8.5 simulation program to discover accurate value forecasts that can be utilized to achieve the best degree of effectiveness of output power values while using the energy solar system. The developed model estimates the optimal tilt angle to maximize power output from the PV module utilizing open-source data. It was demonstrated that the suggested approach, employing the Neural Networks algorithm with PVsyst 6.8.5, can efficiently estimate the predicted output power power.

Keywords- *Renewable Energy, photovoltaic (PV) solar cell, Artificial Neural Networks (ANN), PVsyst 6.8.5, title angle*

1. Introduction

With the remarkable development of technology, significant of these is the industrial aspect of plug-in electric vehicles, and energy storage technology increase in demand for electric energy, power generation, and delivery. In turn, traditional energy sources cause pollution in the environment, and this pollution has negative effects on the surrounding environment and thus on human life and health are likely to see substantial increases and problems in the next years. Thus, the increased global energy crisis pushes to "go green and demand for renewable energy sources and energy management without limiting the power consumption. Several governments have offered critical incentives to encourage the use of the most important clean sources, renewable energy sources, fostering a more decentralized approach to power distribution networks (Yang & Xiao, 2023). The clean source is solar energy and its importance comes from its permanent availability and non-interruption from the globe, which has a value of solar radiation falling on it approximately 1357 W⁄m^2. It is the main energy source used to perform solar generation tasks (Peinado Gonzalo et al., 2020).

Currently, renewable energy sources such as photovoltaic (PV) solar cell, Wind, Biomass, Micro-Turbines, etc. are now being converted into electrical energy to minimize reliance on state electricity. Photovoltaic systems have become increasingly popular and have seen very remarkable growth and are ideally suited for distributed systems, and deliver benefits such as lower power costs and lower carbon emissions. Recent studies and Ongoing research show an exponential increase in the worldwide installed photovoltaic power suited for distributed systems capacity. aimed at reducing the cost and achieving higher efficiency (Jordehi, 2016).

Recent studies indicate that installed solar power capacity is growing exponentially worldwide. As a result, power systems are switching to smart grids (SG) to meet energy requirements and satisfy consumers' ever-increasing demand for a reliable and affordable energy supply. With a demand-side smart energy management system for effective power consumption, integrating distributed energy sources or renewable energy sources into the smart grid can improve overall system efficiency. Furthermore, the integration of a small-scale PV-DG Smart grid allows the integration of the two energy sources for energy delivery in the home area, which can improve electricity systems by making the electricity supply more stable (Pawar et al., 2020).

Accordingly, renewable energy sources that are being incorporated into the smart grid offer tremendous potential to meet customer energy demand. PV storage is a necessary component of the existing grid-connected system produced data gathering for prediction models. In principle, solar PV systems can be utilized in two modes: hybrid (grid-connected in conjunction with other renewable energy sources like wind energy or conventional supplies) or standalone (off-grid linked. Although independent photovoltaic systems require massive storage systems, grid-connected PV systems have been chosen over freestanding PV systems to deliver continuous energy for extended periods, enhance voltage profile, and reduce power loss. However, to enable PVs to be securely and inexpensively incorporated as a renewable energy source into the smart grid, PV power forecasting has become an important component of the energy management system that can accurately monitor and regulate the operation of the energy supply system (Purwanto et al., 2021). Similarly, as grid-connected PV generation contributing substantial instability to the smart grid, posing significant problems to power stability or mismatch between generation and consumption (Wan et al., 2016). The scheduling of consumer loads must take into account the availability of PV energy and the utility grid, as well as the allocated priority, precise user demand forecast, and localized power availability (Rauf et al., 2016). To predict PV production based on solar irradiation levels, local weather, and other extrinsic variables, reliable prediction models require being developed.

In light of this, several methods based on machine learning approaches to handle demand-side management in SG have been developed (Bermejo et al., 2019) (Purwanto et al., 2021). These machine learning algorithms are frequently employed as predicting approaches to anticipate solar energy generation in conjunction with the practical operation of photovoltaic power plants given the real power curve data, a well-thought-out advance scheduling strategy, and the power generation task (Chandrasekaran et al., 2021; Li et al., 2021).

Artificial Neural Network (ANN) models are a highly fascinating tool that offers the essential framework for a computer system to examine numerous intricate inputs (Ceylan et al., 2014; Lo Brano et al., 2014). The model is made up of building blocks of intelligent systems that mimic how both human and animal brains function. neurons that can quickly process and send a signal to other neurons that are directly linked. However, significant and novel contributions have been designed use integrated ANN models (Ceylan et al., 2014; Lo Brano et al., 2014) (Adhiparasakthi Engineering College. Department of Electrical and Electronics Engineering et al., n.d.) each with a unique objective but some connection to the assessment of asset dependability and energy generation in real time models have performed well for real-time predictions to improve the efficiency of the system (Heidari,

2016) (Şahin, 2019) (ARSLAN et al., 2023). A few of these models were intended to estimate the amount of solar radiation that would be used in PV infrastructure. Particularly where learning from dynamic changes in the surrounding environment is crucial for increasing forecast accuracy.

In this paper, we propose and design a machine-learning method based on ANNs. The techniques that help to build a solar energy network in a manner that confirms the selection of the proper data and, the coordination of placing it appropriately in its suitable spot contribute to increasing efficiency. This was accomplished by incorporating two distinct computer programs, the first of which is PVsyst6.8.5. These models ensure that the right data has been chosen and insert it acceptably in its suitable location to create a solar energy network in order to estimate the stability of the operation of individual nodes in the application of a smart power grid. The performance of an ANN model is determined by the parameters selected, the algorithm executed, and the training of the dataset. Each PV parameter's operational voltage level in a power grid could potentially be assigned weights and threshold values based on how those values affect the grid's ability to function normally. Moreover, the artificial network algorithms are implemented to determine the optimal values that can be applied to the energy solar system in order to obtain the maximum output power values and the highest degree of effectiveness. The ability of ANNs using the PVsyst6.8.5 software is tested using simulation in more probable scenarios for varies temperature and irradiance values to maximize the potential output energy and improve the efficiency of the photovoltaic solar energy grid. Therefore, the contribution of this work is:

1- Utilizing the capabilities of artificial neural network algorithms (ANNs) and the capabilities of the PVsyst6.8.5 program to improve the efficiency of the photovoltaic solar energy grid and obtain the maximum possible output energy.

2- Develop an algorithm to find the optimal Tilt angle at maximum output power. Also, the algorithm measures the resulting error (MSE) between the fixed values and the tested values and compares it with other results.

The rest of the paper is organized as follows: Following the introduction Section II describes the material and Methods. The prediction algorithm is described in Section II. The proposed designed ANN method is described in Section III. Simulation and results are reported in Section V.

2. Material and Methods

One of the most significant challenges that comfort researchers and companies after implementing solar energy systems is increasing efficiency and satisfying customer demand loads. In order to properly build a solar energy network, this research addressed a strategy that helps to increase efficiency by verifying the proper data selection and placing it in the right place. This was accomplished by combining two different computer programs, the first of which is PVsyst 6.8.5, and the second of which is an artificial network method. As previously said, the optimum values could potentially be utilized to achieve the optimal level of performance and output power values for any energy solar system.

PVsyst 6.8.5 is a design and simulation program that is used by researchers, architects, and engineers interested in working in the field of solar energy, as it is characterized by its easy use. The program is characterized by having a huge database of meteorological data for most of the sites and areas on the surface of the globe, as it is characterized by the possibility of manually inserting data whose data was not available in the program, we must define some inputs for the program under which we can get the desired results.

After finishing applying the design of solar energy projects in the PVsyst 6.8.5 program with different output powers on the 100 cities that were chosen from all over the world so that we have different climatic environments, the results were taken and used in the neural network algorithm.

2.1 Overview of PVsyst 6.8.5

PV Syst6.8.5 software is used to build the main programs which include algorithms concerning solar radiation estimation, PV system yield, performance and environmental impact, and the implementation of the microgrid active power management system algorithm. In addition, PVsyst 6.8.5 is used to investigate, size, and analyze data for entire PV systems. It includes large databases of meteorological and photovoltaic system components, together with common solar energy instruments and controls for grid-connected, standalone, pumping, and DC-grid PV systems used in similar applications. (Adhiparasakthi Engineering College. Department of Electrical and Electronics Engineering et al., n.d.).

PVsyst 6.8.5 is the newest version of PVsyst software (it is one of the oldest software and was developed by the University of Geneva). This PVsyst software simulates and designs solar systems for use by engineers, architects, and researchers. offers a simple method for project evolution. It has a great database of geographical information such as latitude and longitude, also to determine the tilt angle of PV modules of inclination of the location chosen for solar cell projects. Moreover, it offers a massive library of meteorological data from various locations across the world (this information was gathered from NASA and the Meteorological Agency), and it is full of information that allows the user to utilize it immediately.

One of the program's advantages is the ability to manually insert data that was not previously available in the PVsyst software. The results are present in the form of a detailed report, these reports include graphs, tables, and percentages for missing items, the reports can also be preserved as a PDF file. There is also the possibility of using the same data in other software by exporting it from PVsyst software to other software’s. The program is specified by the following parameters: Meteorological data analysis also includes a comprehensive database of PV modules or any other solar inverter data, which are used to import solar radiation data from Meteonorm open-data sources, such as NASA and many more. Create and import PV Modules from several different overseas companies (based on your demands). Design simulation of standalone grid-connected, following are some inputs required to run the software simulation variables implemented in PVsyst:

a. Geographical data,
b. Meteorological data,
c. Incident irradiance in collector plane,
d. Incident energy factors,
e. Behavior of PV array,

f. Power losses,
g. System operating conditions (shadow, snow, cloud, dust….),
h. Energy use,
i. Normalized performance index.

2.2. Overview of Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are considered a section of the field its name "Artificial Intelligence (AI) which may also contain of Genetic Algorithms (GA) & Fuzzy logic (FL). The main model of ANN's is based on the human brain witch it has the ability of learning and generalization. Acquiring the intelligent features that it is distinguished human neural cells, is the main goal of this simulation to these cells. "Artificial" that the term means the implementation of neural nets in computer programs that have the ability to deal with a huge mathematical database when doing the learning process.

The technique of ANN's has acquired famous as a result of increased attention over the last few years, and it has become one of the fastest techniques and approaches to handle many complex worldwide problems (Ceylan et al., 2014; Lo Brano et al., 2014). In comparison to conventional programming, ANN techniques have the ability to tackle difficulties for which there are no algorithmic answers. As a result, it was determined to be appropriate for treating issues that operators and researchers must address, such as pattern recognition. For these reasons, ANNs are effectively used in numerous application sectors such as finance, medicine (clinical diagnosis, image analysis), physics, communication, and engineering (Marouf, 2018). Furthermore, ANN has been used to solve a lot of problems relating to classification, prediction, identification, and control. This is owing to their high capability to learn from experience in order to progress their performance and to adjust their inner behavior in response to changes in the environment. In addition to their capability to deal with imperfect information or random data which can be very effective. Especially in cases where it is not feasible to identify the rules or stages that lead to the solution of a problem (*Shady* Gadoue, n.d).

The basic model of a single neuron is in Figure 1, which, p an input vector, w a connection weight vector, b a bias and f an activation function, and an output. Which Fig. 2 shows a neuron model with multiple inputs (Şahin, 2019).

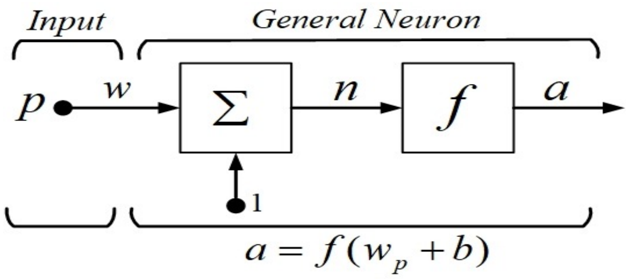

Figure 1. The basic model of a single neuron.

The output, often called net input, goes into the transfer function or activation function:

$$a = f(W_p + b)$$ (1) (Şahin, 2019)

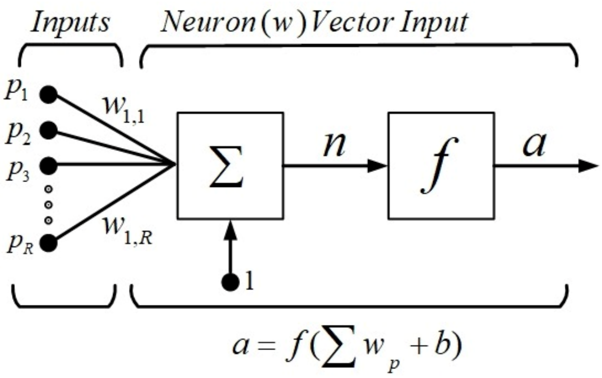

Figure 2. General principal schema of an ANN.

$$a = f(W_p + b) = f(W_{1,1}p_1 + W_{1,2}p_2 + \cdots \dots . + W_{1,R}p_R + b)$$ (2) (Şahin, 2019)

These are many different algorithms are utilized to train the ANN such as Backpropagation, forward propagation, and Levenberg Marquardt etc. However, to train the multilayer feed-forward network, the Levenberg Marquardt algorithm is generally recommended due to its robustness, supplying fast convergence. The user does not necessarily have to initialize parameters, this was achieved through repetition and experiments.

Comparing this model with human neurons, the neuron output represents the signal on the axon while the summation and transfer functions characterize the cell body and indicate the force of a synapse. However, the block diagram of both supervised and unsupervised learning techniques is defined by Figure 3 and Figure 4 respectively (ARSLAN et al., 2023).

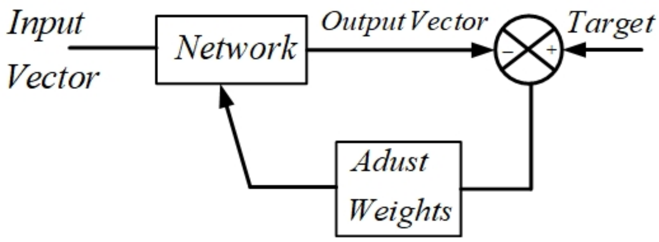

Figure 3. Supervised learning block diagram.

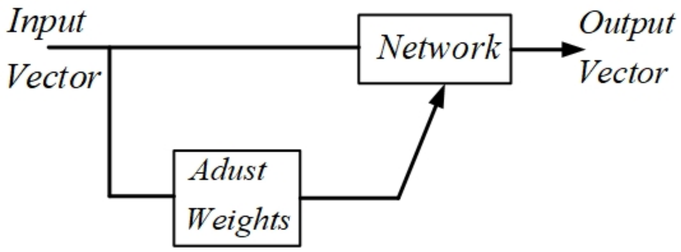

Figure 4. Unsupervised learning block diagram**.**

2.3. Description of the System

This section relates to the simulations and experiments we performed in order to compare the two systems. The system which designed by using (PVsyst) program, designed on grid as based of generate out but which selected between $(10KWp)$ to $(20KWp)$,on minimum area 51.9 m^2 (clear area 47.1m^2) and maximum area is 106 m^2 (clear area 95.7m^2) ,(GESolar) inverter, no. of inverters is between (maximum 9, minimum 1) with (MPPT) in between ((0 – 0.5)%). Mono crystalline (Sun Power) is selected as a type of PV module with maximum 65 PV modules and minimum 24 PV modules, ((maximum 15, minimum 4) strings in parallel, (maximum 10, minimum 3) modules series), which are installed in series/parallel. The operation of the simulation process shown in the following chart in Figure 5.

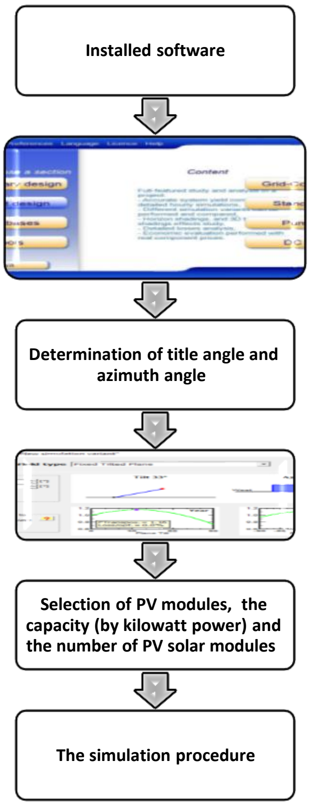

Figure 5. Simulation process.

3. Output Power Prediction

The total quantity of energy that will be produced by the project is initially calculated while designing a solar energy cell project. Accordingly, the type of panels, their number, their output energy, and the way of connecting them are determined in series and in parallel, as well as the category, capacity, and number required inverters, cable connections, chassis, etc. Nevertheless, one of the most significant challenges that project designers and implementers confront is the aforementioned sources of energy loss and the incapacity to accurately estimate these losses with the required accuracy. Hence, the result is less than expected due to these losses, which causes disruption at the moment of project approval and acceptance.

4. ANN Application Instruction

This paper uses the values obtained from the design of 100 different cities around the world in the program PVsyst 6.8.5. The study's execution was facilitated by the seasonal fluctuation observed between continents and cities, despite the fact that samples were gathered at the same time from every continent over the world with similar loads due to the broad diversity of the environment. These cities are chosen randomly from each of the six continents represented in percentage: %18 Africa, %38 Asia, %22 Europe, %5 Australia, %15North America, and %2 South America.

The 100 cities have been studied using the simulation pvsyst6.8.5, which selected random output energy loads ranging from 10 to 20 KWp. The models' completed size ranges from 48.9 to 97.8 m2, although the cells' intended area ranges from 44.2 to 88.3 m2.

The algorithm of neural networks ANN is implemented to get the best output power and determine the values of the losses that were made, the output was predicted and compared with the given output.

In the training model ANN that was created 17 variables were selected, sixteen (16) variables were used as inputs, and one variable was used as output to the system. Table 1 illustrates the seventeen (17) data used and how they are distributed in an algorithm ANN:

Table 1. The number of input and output values of the output power network.

Code	**Input variable**	**Total**
X_1	Nominal STC (KWp) of PV Module	100
X_2	Max PV (KWdc)	100
X_3	Tilt	100
X_4	Number of Modules	100
X_5	Number of Modules in Series	100
X_6	Number of Modules in Parallel	100
X_7	Umm (V) of module in Operating	100
X_8	Imm (A) of module in Operating	100
X_9	Number of Inverters	100
X_{10}	Nominal Power of Inverter	100
X_{11}	Minimum Operating Volt (V) of Inverter	100
X_{12}	Maximum Operating Volt (V) of Inverter	100
X_{13}	Product Energy per year (Mwh/year)	100
X_{14}	Performance Ratio (PR %)	100
X_{15}	Specific Production per year (Kwh/Kwp/year)	100
X_{16}	MPPT % in Inverter	100
Code	Output variable	Total
Y_1	Nominal AC Power (KWac)	100

For the purpose of training the developed artificial neural network, seventeen (17) variables were chosen and gathered as input data, while one variable was collected as an output. Additionally, 1700 variables total—1600 input variables and 100 output variables—were employed. Table 2 lists the maximum and minimum values for each of the 16 input groups and 1 output group that were employed for network training.

Table 2. Maximum and minimum variables used in output power model construction.

Code	Intput variable	Data used in	ANN mode
		MIN	MAX
X_1	Nominal STC (KWp) of PV Module	9.3	21.1
X_2	Max PV (KWdc)	8.8	21.2
X_3	Tilt angle	9	49
X_4	Number of Modules	24	65
X_5	Number of Modules in Series	3	10
X_6	Number of Modules in Parallel	4	15
X_7	Umm (V) of module in Operating	163	543
X_8	Imm (A) of module in Operating	23	86
X_9	Number of Inverters	1	9
X_{10}	Nominal Power of Inverter	1.8	20
X_{11}	Minimum Operating Volt (V) of Inverter	80	400
X_{12}	Maximum Operating Volt (V) of Inverter	400	850
X_{13}	Product Energy per year (Mwh/year)	10.11	39.66
X_{14}	Performance Ratio (PR %)	77.74	91.74
X_{15}	Specific Production per year (Kwh/Kwp/year)	986	2070
X_{16}	MPPT % in Inverter	0	0.5
Code	Output variable	MIN	MAX
	Nominal AC Power (KWac)	8	20

Figure 6 depicts the block diagram of a feedback multilayer perceptron (MLP) utilized in a multilayer feedback (ANN) model. However, Figures 7 and 8 show The multi-layer perceptron and the established neural network discovered via continual experimentation, respectively. The layers figures explain the various value adjustments that numerous hidden layers and the Levenberg-Marquardtt (LM) algorithm were proper to use. The best prediction was obtained with 12 hidden layers, which is the ideal number.

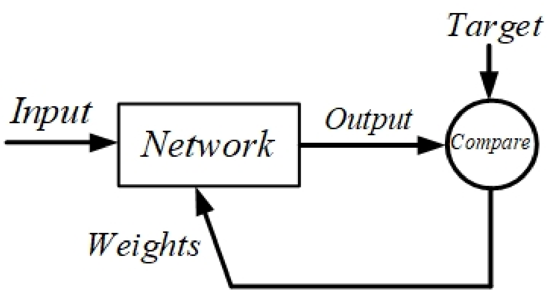

Figure 6. Block diagram for feedback network.

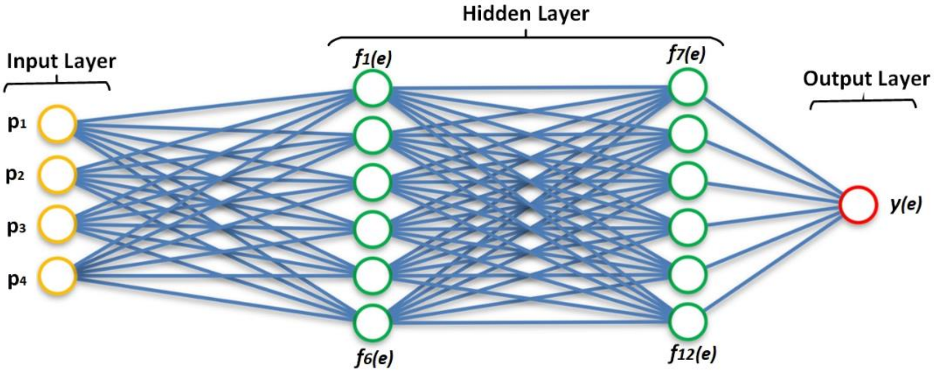

Figure 7. Architecture of a multilayer perceptron.

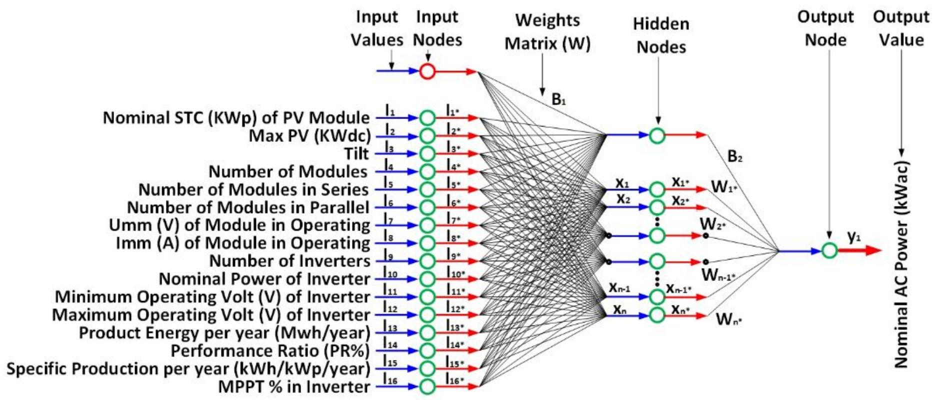

Figure 8. Structure of the established artificial neural.

5. Result and Discussion

To increase and improve the efficiency of a solar energy system, we calculate the output power according to the use of the artificial neural networks program (ANNs) that had the greatest role. The results of the values obtained from the system design were taken in a program (PVsyst6.8.5) and use it as input values for ANN. The performance of ANN was conducted through the measurement of its predictions on various datasets. The models' accuracy was expressed as mean square error (MSE), root mean square error (RMSE), and mean absolute deviation percentage (MADP).

After testing the neural network for 15 inputs for (out power), the tested results values obtained were compared with the previously installed values as shown in Table 3. The values were compared were Normalized case, and so when it was at de normalized, and the values were adjusted (denormalized) according to the following formula:

$$x_i = x' * (x_{max} - x_{min}) + x_{min} \quad (3)\ (\text{Şahin, 2019})$$

Table 3. Output power's test results.

	NORMALİZED VALUES		DE-NORMALİZED VALUES	
	Installed outputs	tested outputs	Installed outputs	tested outputs
1	0.916666667	0.915893206	19	18.99071847
2	0.166666667	0.114273647	10	9.371283764
3	0.083333333	0.091607314	9	9.099287763
4	0.733333333	0.80276872	16.8	17.63322463
5	0.233333333	0.222126954	10.8	10.66552345
6	0.166666667	0.130474225	10	9.565690697
7	0	0.034950247	8	8.419402964
8	1	0.990643424	20	19.88772109
9	0.083333333	0.092787852	9	9.113454228
10	1	0.993323093	20	19.91987711
11	0.083333333	0.072445241	9	8.86934289
12	0.166666667	0.202351878	10	10.42822254
13	0.083333333	0.064569116	9	8.77482939
14	0	0.033508109	8	8.40209731
15	0	0.032731312	8	8.392775739

The variation between the value of the output delivered as a function during system creation and construction (ANNs) and the value obtained after testing and training the network is so small that it is insignificant. The graph 6.11 displays the fluctuations in the Normalization values, which varied from (-0.79388836 to 0.231541269). It was noted that the ANN's had a fast and high responsibility and gave optimum results, so that the error between installed values and tested values (MSE) is (0.000963472), which helps in raising the efficiency of the designed system, it is also noted that: The error rate is very small, which indicates that the results are satisfactory. As a result, the PVsyst6.8.5 program and the ANN algorithm can be used as effective approaches for designing and installing solar cell systems. Table 4 shows all the forecasting error values:

Table 4. Forecasting error value

MSE		RMSE	%MADP
0.000963472		0.031039847	07.8506684

6. Conclusion

In this paper, the importance of solar energy and its superiority over the means of extracting electricity from other sources was discussed, so it was rather to find a way to raise its efficiency. This approach involved integrating of ANN algorithms with the PVsyst6.8.5 simulator program to determine the ideal tilt angle to maximize the output power. The error rate is very small, which indicates that the results are satisfactory. It was demonstrated that the suggested approach adopting the PVsyst 6.8.5 in conjunction with the Artificial Neural Network algorithm, efficiently estimates the predicted output power in the design of installation of solar cell systems. Consequently, this can aid engineers and designers in precisely calculating projected output power, saving the time spent computing output power using other applications or manually.

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