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Optimizing photovoltaic power prediction using computational methods and artificial neural networks

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Original Research

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Abstract:

This paper focuses on utilizing an Artificial Neural Network (ANN) to predict photovoltaic (PV) panel output power. Since solar power output is fluctuating and depends on climatic, geographical and temporal factors, precise prediction requires the implementation of computational approaches. The aim of this research is to develop ANN algorithms that anticipate solar power output and enhance the structure of them by incorporating the derating factor due to dirt (k_{dirt}) into account. The effectiveness and dependability of the ANN are determined using MATLAB software. By comparing the Mean Squared Error (MSE) of four different values of derating factor due to dirt which are 0.8, 0.88, 0.9 and 0.98 in ANN predictions comprehend with 4 input layers and 10 hidden layers. Direct data input is obtained through a photovoltaic solar panel at University Tun Hussein Onn Malaysia (UTHM). Comparative analysis also has been carried out after the results has been obtained from the mathematical equations. The daily solar power output predictions are effectively achieved by the deployed ANN. As the result, the optimal k_{dirt} has been selected which is 0.8 based on its ability to produce the most accurate ANN predictions than the other values of k_{dirt}.

Keywords: Power prediction; Solar output; ANN; MSE; Derating factor

1. Introduction

Renewable energy, mainly solar energy, is an imperative solution to the world's increasing power requirements while also reducing the negative environmental effects [1]. Not only that, wind, solar, biomass and tidal energy are also the examples of renewable energy sources in Malaysia. One of the significant renewable energy sources with the ability to fulfill future energy demand is PV solar cells [2]. Solar power uses PV cells to transform sunlight into electricity along with its low cost and great efficiency, through the use of materials like silicon [3, 4]. This also enabling the utilization of the sun's abundant and renewable energy. This renewable energy source which is sustainable for the environment offers an economical alternative for traditional fossil fuels and is essential in reducing emissions of greenhouse gases and reducing the damaging impacts of climate change [5, 6]. Solar power has grown into an increasingly significant factor in expanding the global energy inventory, boosting energy self-sufficiency, as well as providing a major contribution to a future that is more environmentally friendly as technology advances and related costs reduction. It is crucial to take into account the possibility of employing eco-friendly renewable energy sources and expanding the amount of them in the global main energy supply [7].

The PV panel will only produce electricity in parallel with its rated capacity while operating under Standard Test Conditions (STC) [8]. STC requires 1000 Watts of solar energy per square meter of solar irradiation and a temperature of 25 degrees Celsius. Prediction is therefore required because of weather variations, which might affect power output. In order to develop PV systems, climate data such as temperature and sun irradiances are required, as solar panel output will not produce in accordance with its rating [9]. In addition, predictions of solar power output, involving parameters such as temperature, sun hours, and weather, are also influential.

The predictions using computational method rely on several equations and complex computations [10]. In addition, the equation involves choosing the suitable value of der-

ating factor due to dirt. Dirt builds up on the surface of photovoltaic panels, frequently carried by wind-driven dust particles, which prevents the sunlight from being taken in, which is necessary for converting solar energy into electrical power. Consequently, this occurrence lowers the PV system's overall performance as well as its power output [11]. Nonetheless, it is probable that this value does not yield precise predictions owing to the present state of the PV panel. Consequently, this research endeavors to ascertain the accurate k_{dirt} value aligned with the current condition of the PV panel. Consequently, ANN which is self-learning, self-organizing and high-speed computing capabilities are employed in power output value prediction in order to improve the prediction process. In addition, algorithms based on ANN have the advantage of requiring a lesser computational effort and providing a potential solution for multi-variable issues without requiring understanding of mathematical computations between parameters [12–15].
By using a computational approach, this research aims to predict the photovoltaic power output at University Tun Hussein Onn Malaysia (UTHM), Batu Pahat, Johor, Malaysia. located at approximately 1.8548° N latitude and 103.0810° E longitude. Daily data on the power output values of the PV panel utilized for the prediction is collected at 12:00 pm, when the sun is at its highest point and visible brightly overhead. In order to put it briefly, ANN algorithms have been developed using MATLAB for predicting PV power output. Furthermore, it was designed and developed to compute solar power production while comparing it to real data.

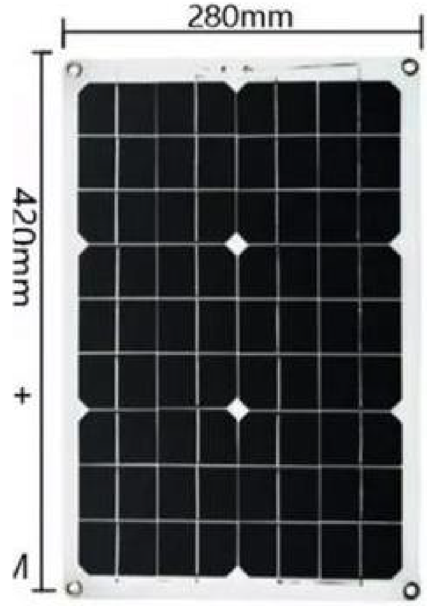

Figure 1. The PV solar panel.

Table 1. The specifications of PV solar panel.

Features	Specification
Power	18W ± 5%
Size	420 × 280 × 2.5 mm
DC output	12V/1.5A
USB output	5V/1.7A
Type	Mono solar panel
Material	Aluminum substrate

2. Material and methods

In order to gain a deeper understanding of the findings, theories, preceding corresponding works and other material related to this research, a preliminary literature review was undertaken for the first phase of the research. After then, data that required to take into account a number of parameters such as the temperature of the solar panel and the solar irradiance. These parameters were utilized in the computation method to calculate the generated output power. Then, based on actual data collecting and predicts of solar power generation, an ANN model generated and developed.

2.1 PV module datasheet

The PV module utilized in this project is an 18 W aluminum substrate monocrystalline solar panel with 15 degrees tilt angle, illustrated in figure 1. The specifications of the PV module are detailed in Table 1, as it is recognized as a crucial dataset for power output prediction. Furthermore, the real PV power output is determined by the multiplication of PV voltage and current, both measurable from the sensors which can be observed by the Blynk application.
Additionally, the geographical coordinates of UTHM, positioned at 1.8573° N latitude and 103.0821° E longitude, position it within a diverse cultural and ecological environment. The significance of implementing geographical factors into account when predicting PV power output is shown by this top-notch site, which helps establish a comprehensive and seamless integration with the current infrastructure and the surrounding environment.

2.2 Temperature

In this research, PV cell temperature (T_{cell}) is required for power output prediction. It is because, the output power and efficiency are dependent on the temperature. The cell temperature is obtained from the PV cells at the research location. The temperature data are obtained three times a day which are taken at 12 p.m. by using the digital thermometer as in figure 2. The cell temperature data collected are used to calculate the prediction of PV power output. Section 2.4 outlines the calculations used to compute the cell temperature.

2.3 Solar irradiance

Daily solar irradiance is obtained from the solar power meter to be utilized in calculating PV power output. The measurement work is carried out by placing the solar power meter as in figure 3 next to the solar panel and observing until the value reaches the maximum level. Daily solar irradiance was taken as one of the inputs in the prediction of power output in ANN configuration.

Figure 2. Digital thermometer.

Figure 3. SM206-Solar power meter.

2.4 Equations

The ambient temperature and solar irradiation of the area must be included when predicting power output. Furthermore, the datasheet's rated power of 18 W is important for calculating predicted output power. The cell temperature, T_{cell} calculated in the first step using equation (1) [16] where T_{amb} is ambient temperature (°C), NOCT is Nominal Operating Cell Temperature (°C) and G is solar irradiance. Furthermore, the power output prediction was achieved by considering all derating factors and multiplying them by the power rating from the datasheet, as indicated in equation (2) [16] where $k_{\text{power-deration}}$ is total derating factors related to power, k_{mm} is derating factor due to module mismatch of power, k_g is peak sun factor, k_{dirt} is derating factor due to dirt and k_{age} is derating factor due to ageing [16].
Cell or module temperature at Real Operating Condition (ROC) , as in:

$$T_{\text{cell}} = T_{amb} + \left[\left(\frac{\text{NOCT} - 20 \text{ deg C}}{800 \text{ Wm}^{-2}} \right) \times G \right] \quad (1)$$

where:
T_{cell} is solar cell temperature (°C),
T_{amb} is ambient temperature (°C),
NOCT is Nominal Operating Cell Temperature (°C),
G is solar irradiance.
Derating factor of power due to cell temperature (k_{tem-p}) accounts for the impact of temperature variations on PV module performance. Temperature derating accounts for these effects by adjusting performance expectations based on the prevailing temperature conditions.
The reduction in overall power output caused by inconsistencies in the performance characteristics of individual PV modules signifies the derating factor due to module mismatch of power, k_{tem-p}. These variations may arise including manufacturing tolerances, which can lead to differences in the electrical properties of modules even within the same batch. Additionally, the impact of dirt, dust and other contaminants on the surface of PV panels reflects for k_{dirt} which is derating factor due to dirt. Accumulated debris can obstruct sunlight and reduce the amount of energy harvested by the system. By the same token, PV modules are subject to degradation over time due to prolonged exposure to environmental stresses such as UV radiation, temperature fluctuations and moisture which addresses to derating factor due to ageing (k_{age}). This degradation manifests as a gradual decline in performance and efficiency, resulting in reduced power output from the PV system.
Power output for ROC is:

$$\begin{aligned} P_{\text{ROC}} &= P_{stc} \times k_{\text{power-deration}} = \\ &P_{stc} \times k_{mm} \times k_{tem-p} \times k_g \times k_{\text{dirt}} \times k_{age} \end{aligned} \quad (2)$$

where:
P_{ROC} is power at ROC (W)
P_{stc} is power at STC (W)
$k_{\text{power-deration}}$ is total de-rating factors related to power (decimal)
k_{mm-p} is derating factor due to module mismatch of power (decimal)
k_{tem-p} is derating factor of power due to cell temperature (decimal)
k_g is peak sun factor (decimal)
k_{dirt} is derating factor due to dirt (decimal)
k_{age} is derating factor of power due to ageing (decimal)

$$\text{Peak sun factor (PSF)}, \;\; kg = \frac{G}{1000} \quad (3)$$

PSF, also known as the solar constant, is a parameter used in PV system design which indicates the ratio of the solar irradiance that gets generated at a given time and place to the solar irradiance which would be received under a clear sky with the sun at its highest position in the sky. As opposed to locations with cleaner sky and less atmospheric interference, the values are often lower in areas with high levels of air pollution or regular cloud cover. Besides, it also can change based on a number of variables, including weather, season, time of day and geographic location. Furthermore, limitations like trees, buildings or topography may reduce the PSF even further, which might affect the PV systems' total energy output.

Four distinct derating factor values resulting from dirt accumulation which are 0.8, 0.88, 0.9 and 0.98 are considered in the analysis. The recommended value of k_{dirt} is 0.98 which indicates for a 2% loss attributed to mismatch [16, 17]. Thus, the calculation of MSE between measured and calculated output current of the solar PV cell [18]:

$$\text{MSE} = \frac{1}{N}\sum_{P=1}^{N}(P_{real} - P_{cal})^2 \tag{4}$$

where N is the number of the measured values while P_{real} and P_{cal} represent the real and calculated power ouput of PV panel, respectively.

2.5 ANN configuration

PV power output values are predicted using ANN and the predicted results compared to the computed PV power output values in order to determine the MSE. MSE detection is essential for improving the ANN prediction values. The default number of hidden neurons which is 10 is selected. Figure 4 illustrates the optimized MLPBP ANN model, which consists of an input layer (PV cell temperature, solar irradiance, PV power rating, derating factor due to dirt), a hidden layer and an output layer (real data of PV power output). The optimized ANN model is shown in figure 5. It is executed with the aid of the MATLAB Neural Network Toolbox.

3. Results and discussion

Following the installation of solar panels, the power output value directly collected at 12 p.m. every day for 20 days as tabulated in Table 2. By using equation (1) until (3) based on the measured data while changing the derating factor due to dirt values as in Table 3.

3.1 ANN prediction of PV power output

PV cell temperature, solar irradiance, PV power rating and derating factors due to dirt are the input parameters that are automatically displayed in ANN configuration. The ANN reads the data gathered for this project and predicts the values of PV power generating output, requiring less training time and being suitable for use in the early phases of a comparative project [18]. The outcomes from the prediction of

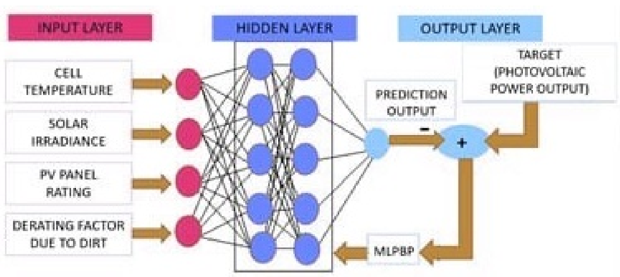

Figure 4. Optimized MLPBP ANN model.

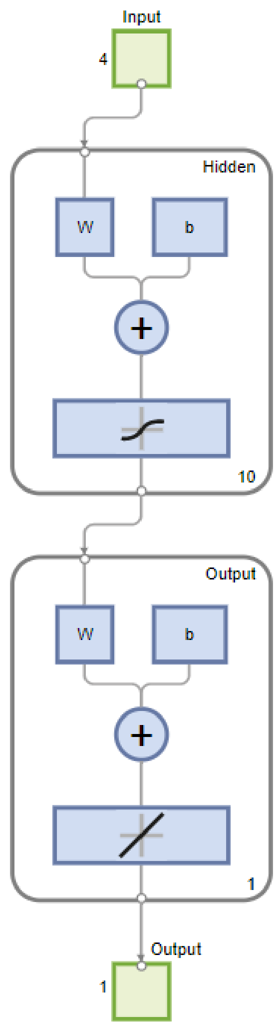

Figure 5. Optimized MLPBP ANN model.

Table 2. Real data of PV power output.

Day	PV Power output (W)
1	9.975
2	9.010
3	9.504
4	6.758
5	6.696
6	5.457
7	5.457
8	9.752
9	9.951
10	9.630
11	8.640
12	9.630
13	9.592
14	9.737
15	8.798
16	9.919
17	7.811
18	9.828
19	6.758
20	8.964

Table 3. Prediction of PV power output using computational method.

Day	PV Power output (W)			
	0.80	0.88	0.90	0.98
1	9.9738	10.9712	11.2206	12.2180
2	8.9455	9.8401	10.0637	10.9583
3	8.8871	9.7758	9.9980	10.8867
4	6.7542	7.4296	7.5985	8.2739
5	6.6429	7.3072	7.4733	8.1376
6	5.2031	5.7234	5.9810	6.65127
7	5.3165	5.8481	5.9810	6.5127
8	9.5960	10.5556	10.7955	11.7552
9	9.7993	10.7792	11.0242	12.0041
10	9.5847	10.5432	10.7828	11.7413
11	8.5627	9.4190	9.6331	10.4893
12	9.5773	10.5351	10.7745	11.7322
13	9.4826	10.4309	10.6680	11.6162
14	9.6074	10.5681	10.8083	11.7690
15	8.6198	9.4817	9.6972	10.5592
16	9.8610	10.8471	11.0936	12.0797
17	7.7155	8.4870	8.6799	9.4515
18	9.6827	10.6510	10.8931	11.8614
19	6.5211	7.1733	7.3363	7.9884
20	8.8527	9.7380	9.9593	10.8446

PV power output by the optimised ANN model is shown in Table 4.
Moreover, the MSE of ANN prediction results are shown together with the MSE of the real data calculation values to keep the analytical process continuing much easier. It clearly shows that the optimised ANN model prediction is close to the target values. The most variance values between the target and ANN prediction values are getting very close to zero and have no error.

Table 4. PV panel power output data from ANN prediction.

Day	PV Power output (W)			
	0.80	0.88	0.90	0.98
1	9.9986	10.0154	9.9753	9.9969
2	9.1025	9.0544	9.0275	9.0174
3	9.2811	9.1920	9.3158	9.3427
4	6.8161	6.8274	6.8304	6.8127
5	6.7432	6.68246	6.7796	6.7041
6	5.4293	5.3189	5.4374	5.3640
7	5.5136	5.4315	5.5864	5.4957
8	9.7373	9.6642	9.7138	9.6829
9	9.9884	9.8519	9.9787	9.9284
10	9.7238	9.6532	9.6989	9.6694
11	8.6273	8.6548	8.2679	8.6357
12	9.6657	9.6311	9.6556	9.6126
13	9.6033	9.5518	9.5651	9.5492
14	9.7509	9.6752	9.7288	9.6964
15	8.7900	8.7553	8.7435	8.7214
16	9.9026	9.9090	9.9080	9.8881
17	7.8374	7.7487	7.9072	7.8199
18	9.8484	9.8766	9.8279	10.6347
19	6.6142	6.629	6.6493	6.6442
20	9.0145	8.9715	8.9445	8.9333

3.2 MSE of PV power output

The MSE of PV power outputs that have been calculated from equation (4) for both approaches were compared to each other following the configuration of ANN. As in Table 5, the MSE of predicted power output from the ANN is more satisfactory than the calculated power output.

Table 5. MSE for PV panel power output of computational and ANN prediction.

k_{dirt}	Mean Square Error	
	Calculation	ANN
0.80	0.0340	0.0051
0.88	0.5213	0.0087
0.90	0.8616	0.0049
0.98	3.0966	0.0361

The MSE of calculation data makes a significant difference is due to fact that it dependent on calculations that are based on real data and affected by the data of environmental surroundings. In Table 5 and figure 6, k_{dirt} of 0.98 give the highest MSE value for computational method and for the ANN which are 3.0966 and 0.0361. For the smallest MSE value for computational method and for the ANN, k_{dirt} of 0.8 resulting 0.0340 and 0.0051. The MSE of both approaches for 0.88 k_{dirt} are 0.5213 and 0.0087 while 0.90 k_{dirt} are 0.8616 and 0.0049. As the result, 0.8 k_{dirt} is the best optimal k_{dirt} since it shows only slightly different between the calculation and ANN prediction compared to another k_{dirt}. Not only that, a small amount of derating factor is ideal as it indicates that the performance of the system would be less affected which resulting the PV panel provide more energy that is more reliable and continuously. This resulting of a more representative dataset, more accurate model fit and optimal parameters modification. Therefore, it clearly has shown that the MSE of ANN prediction values are approximately closer to 0 and precisely to the real data compare to the MSE of calculation data.

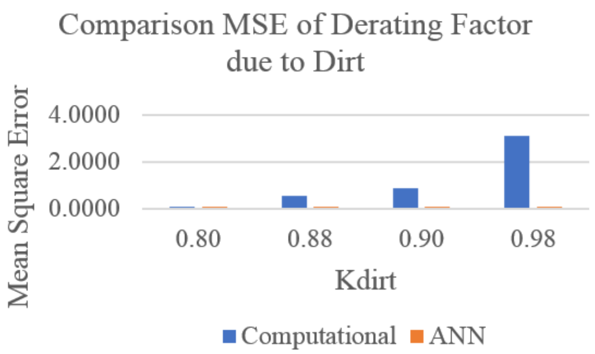

Figure 6. MSE of PV power output for derating factor due to dirt.

4. Conclusion

In conclusion, the prediction of PV power output has comprised several factors including the calculations from the real data collecting have proven successful. Furthermore, the ANN configuration has predicted PV power output in different values of derating factors due to dirt. As the result, it is preferred to have a minimal k_{dirt} in predicting PV power output as it shows how resilient the system is to environmental factors while continuing to attain outstanding efficiency levels based on the MSE errors. It shows that the MSE detection is crucial in order to enhance the prediction of ANN configuration and generating more precise result in prediction of PV power output.

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Authors contributions
Authors have contributed equally in preparing and writing the manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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