Contents list available at IJRED website

Int. Journal of Renewable Energy Development (IJRED)

Journal homepage: https://ijred.undip.ac.id

Research Article

Artificial Neural Network Prediction Model of Dust Effect on Photovoltaic Performance for Residential Applications: Malaysia Case Study

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Abstract. Dust accumulation on the photovoltaic system adversely degrades its power conversion efficiency (PCE). Focusing on residential installations, dust accumulation on PV modules installed in tropical regions may be vulnerable due to lower inclination angles and rainfall that encourage dust settlement on PV surfaces. However, most related studies in the tropics are concerned with studies in the laboratory, where dust collection is not from the actual field, and an accurate performance prediction model is impossible to obtain. This paper investigates the dust-related degradation in the PV output performance based on the developed Artificial Neural Network (ANN) predictive model. For this purpose, two identical monocrystalline modules of 120 Wp were tested and assessed under real operating conditions in Melaka, Malaysia (2.1896° N, 102.2501° E), of which one module was dust-free (clean). At the same time, the other was left uncleaned (dusty) for one month. The experimental datasets were divided into three sets: the first set was used for training and testing purposes, while the second and third, namely Data 2 and Data 3, were used for validating the proposed ANN model. The accuracy study shows that the predicted data using the ANN model and the experimentally acquired data are in good agreement, with MAE and RMSE for the cleaned PV module are as low as 1.28 °C, and 1.96 °C respectively for Data 2 and 3.93 °C and 4.92 °C respectively for Data 3. Meanwhile, the RMSE and MAE for the dusty PV module are 1.53°C and 2.82 °C respectively for Data 2 and 4.13 °C and 5.26 °C for Data 3. The ANN predictive model was then used for yield forecasting in a residential installation and found that the clean PV system provides a 7.29 % higher yield than a dusty system. The proposed ANN model is beneficial for PV system installers to assess and anticipate the impacts of dust on the PV installation in cities with similar climatic conditions.

Keywords: Dust effect, PV performance, ANN, Yield forecasting, Electrical output

Article history: Received: 22nd Oct 2021; Revised: 12th Dec 2021; Accepted: 24th Dec 2021; Available online: 8th January 2022
How to cite this article: Ahmad, E.Z., Jarimi, H.., and Razak, T.R. (2022) Artificial Neural Network Prediction Model of Dust Effect on Photovoltaic Performance for Residential Applications: Malaysia Case Study. *Int. J.Renew. En. Dev.*, 365-373
https://doi.org/10.14710/ijred.2022.42195

1. Introduction

The growth of photovoltaic (PV) technology accounts for more than 33% of installed capacity worldwide and continuously gains demand to contribute to energy sustainability. Despite the slow progress due to the impacts of the COVID-19 pandemic, renewable energy was the only source of energy generation to register a net increase in total capacity in 2020 (Green 2019). Consequently, PV deployment has become a competitive option for electricity generation for residential and commercial applications in many countries. As PV technology develops, several factors remain critical to ensure greater penetration to the national grid, including further improvements in cost and performance. In particular, the PV output performance responds quickly to rapid changes in solar irradiance that may reduce its efficiency and reliability.

The common issue that degrades the PV output performance is dust depositions caused by harsh climatic conditions, local air pollution, and seasonal variations (Al-Addous *et al.* 2019; Hammad *et al.* 2018; Mani & Pillai 2010). Depositions of dust on the front glass of PV modules not only reduce the irradiance absorption but aids in the hotspot phenomenon (Rajput *et al.* 2019). From the total absorbed solar irradiance by the Photovoltaic (PV) module only approximately 20% is converted into electricity (Jarimi *et al.* 2021). The remaining part is causing an unwanted increase in module temperature that is wasted as heat. The panel's efficiency is further reduced by 10–25% for PV installations due to several factors, such as losses in the balance of the system (Kazem *et al.* 2020a). Dust accumulation on the front panel also creates a shade that adversely affects the module operating temperature. Since dust deposition is site-dependent, different modelling methodologies have been proposed in various literature, subdivided into ratio-dependent models,

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derating factor models, statistical models, and Artificial Neural Network(ANN) models (Younis & Alhorr 2021). Theoretically, the impact of dust accumulation on the PV performance has also been investigated by (Kaldellis & Kapsali 2011). The developed theoretical model is based on the capacity factor ratio (CF/CF0) that strongly relies upon the dust compositions factor. Another mathematical model is developed by Jamil *et al.* (Jamil *et al.* 2020) to establish a correlation between dust derating factor (f_{dirt}) and PV systems output. The findings show that dust deposition reduces the PV system output power by 22.26% for 12 months of observation periods.

The sophisticated applications of ANN have drawn researchers attention in modelling the impact of dust accumulation. (Bouaichi *et al.* 2019) developed a soiling rate model based on the multiple linear regression (MLR). Ground measurements data as a function of environmental variables were used to investigate the impact of soiling in semi-arid climate. The developed ANN model showed an accuracy with r^2 = 0.813 and around 0.026 in the RMSE. Another ANN model was proposed by (Al-Kouz *et al.* 2019) to investigate the effects of dust and ambient temperature on the PV performance. The extreme learning machine (ELM) models were used to estimate the PV conversion efficiency. A similar ANN approach was conducted by (Li *et al.* 2017) to predict the dust removal efficiency. The list of recearchers who have conducted modelling of dust effects to PV performance worldwide is summarised in Table 1.

Table 1
The summary on the recent development on modelling of dust effects to PV performance

Location	Type of study/Findings	References
Ben Guerir, Morocco • Temperature (18 to 37 °C) • Average RH=57%	• Mathematical model (MLR, MLRWI, and ANN) • based on MLR exhibits the lowest correlation (r^2=0.23) • based on MLRWI (r^2=0.48) • based on ANN marked the best accuracy (r^2=0.813)	(Zitouni *et al.* 2021)
Shibpur, India • Temperature (19 to 28 °C) • Average RH=70%	• Mathematical model based on daily yield • The developed model has a deviation of ±6% from the measured data (consider varying humidity and precipitation).	(Sengupta *et al.* 2021)
Indoor setup	• Dust concentration-photoelectric conversion efficiency model (DC-PCE) • The proposed model accuracy is 83.12% and valid for low irradiance level (below 300 W/m^2).	(Fan *et al.* 2021)
Sohar, Oman (Subtropical, dry climate)	• Mathematical model (Regression analysis) • The proposed model accuracy is 89.6% and only valid for homogenous dust deposition.	(Kazem *et al.* 2020b)
Harare, Zimbabwe (warm and temperate)	• Multivariate linear regressions (MLR) and ANN. • The developed ANN model (R^2 is 97.91%) more accurate than MLR model (R^2 is 79.69%).	(Chiteka *et al.* 2020)
Zarqa, Jordan (hot and arid)	• ANN model and extreme learning machine (ELM) • The optimized ANN+ELM model predicts the best accuracy (R^2=91.4%).	(Al-Kouz *et al.* 2019)
Oregon State University, Oregon United States of America • Temperature (3 to 15 °C) • Average RH=53%	• Mathematical model • The proposed model uses ambient airborne concentrations of PM_{10} and $PM_{2.5}$ under variable deposition velocities (with PRISM hourly rain database).	(Coello & Boyle 2019)
Krakow, Poland • Temperature (-3 to 19 °C) • Average RH=84%	• Mathematical model • The proposed theoretical dust dependent model is only applicable to highly polluted environment; represent specific cases of a narrow range. • They proposed model splitting to distinguish effect of dust on various climate conditions.	(Jaszczur *et al.* 2019)
Zarqa, Jordan (hot and arid)	• Multivariate linear regressions (MLR) and ANN. • The developed ANN model (R^2 is 90.0%) more accurate than MLR model (R^2 is 87.7%). • Major system performance affected by dust accumulation and ambient temperature.	(Hammad *et al.* 2018)
Southern Portugal • Temperature (12 to 25 °C) • Average RH=65%	• Mathematical model (soiling ratio, SR) • The proposed model fits the experimental data with R^2 = 0.95. • Larger time frame may not be suitable with the proposed model due to a certain loss of sensitivity.	(Conceição *et al.* 2018)

Table 2
The parameters in equation (1)- (6) and the values

Parameters	Values	Reference
Module efficiency (STC) (η_{STC})	22.6%	(Mittal *et al.* 2018)
Power output (STC) (P_{STC})	120W	Module datasheet
Derating due to Power (k_{power})	Dimensionless All values were determined under real operating conditions	(Omar & Shaari 2009)
Derating due to module temperature (k_{mm})		
Derating due to irradiance (k_g)		

Focusing on the PV performance, as shown in Table 1, the gap that has been identified from the existing literature is that, no studies were conducted on the influence of dust deposition under tropical climates of hot and high humidity weather throughout the year. (Klugmann-Radziemska 2015; Mani & Pillai 2010) reported that dust degradation effects are worse in tropical regions due to lower PV inclination angles and rainfall contributing to the dust settlement. As the influence of dust is highly dependent on geographical location, thus making it is vital for predicting a site-specific model under unpredictable Malaysia climatic conditions. This paper contributes to understanding the influence of dust deposition on the PV performance under Malaysia climates. This study would be beneficial for forecasting energy deliverables from PV systems to the grid by considering several losses factors, including dust deposition. The present study highlights the theoretical background of the influence of dust deposition on output performance and the experimental setup for on-site observations under Malaysia climates. Besides, it highlights Artificial Neural Network (ANN) modelling to predict the measured dataset using the R programing language.

2. Theoretical background

2.1 Photovoltaic performance

The accumulation of dust has two significant influences on the PV performance: (i) it reduces the transmittance of absorbed solar irradiance, and (ii) it behaves as a partially shaded module (Al Siyabi *et al.* 2021; Tripathi *et al.* 2017). Thus, a lower electrical output is produced due to dust accumulations. The short circuit current generated is highly influenced as the photocurrent is linearly proportional to the transmittance. So, the thicker the dust deposition, the lower the short circuit current. The following equation gives the convention for I_{sc} (Oh 2019):

$$I = I_0\left[exp\left(\frac{qV}{k_BT}\right) - 1\right] - I_{SC} \quad (1)$$

where I_0 is the saturation current density, q is the electron charge, k_B is the Boltzman constant, and T is the temperature. Furthermore Various methods have been proposed to determine the module efficiency through simplified working equations (Ahmad *et al.* 2021; Mittal *et al.* 2018; Zainuddin *et al.* 2015). However, the following equation is used to determine the PV module efficiency described as follows:

$$\eta = \eta_{STC}[1 - \beta(T_{PV} - T_{STC})] + \gamma LogG \quad (2)$$

where η_{STC} is the module efficiency at standard test condition, G is the solar irradiance measured in W/m^2, and T_{PV} is the PV module temperature. β and γ are the temperature and solar irradiance coefficients, respectively. The values for η_{STC}, β, and γ are given in the module datasheet. However, under real operating conditions (ROC), the amount of power, P_{ROC} from the PV module can be determined using the following equation (Omar & Shaari 2009):

$$P_{ROC} = P_{STC} \times k_{power} \quad (3)$$

where k_{power} can be determined by the following equation:

$$k_{power} = k_{mm} \times k_{temp} \times k_g \times k_{dust} \times k_{age} \quad (4)$$

where *Pstc* is the power rating as per manufacturer specification (Wp), k_{mm} is the derating factor due to module mismatch, k_{temp} is the derating factor due to module temperature, k_g is the peak sun factor obtained by dividing the instantaneous irradiance with 1000 W/m^2, k_{dust} is the dust derating factor due to soiling effect, and k_{age} is the derating factor due to PV module's aging. In this study, k_{mm}, and k_{age} parameters are constant throughout the experiment and can be grouped as α. Therefore, equation (2) becomes;

$$P_{ROC} = P_{STC} \times k_{temp} \times k_g \times k_{dust} \times \alpha \quad (5)$$

Theoretically, the values of k_{temp} and k_g can be estimated using the following equations:

$$k_{temp} = 1 + \left[\left(\frac{\gamma_{pmp}}{100\%}\right) \times (T_{PV} - T_{STC})\right] \quad (6)$$

$$k_g = \frac{G}{1000} \quad (7)$$

Meanwhile, the forecasted derating factor in this study is computed using equation (8) (Omar, Ahmad Maliki, S.Shaari 2012):

$$Y_{exp} = P_{array\_STC} \times PSH_{poa} \times k_{deration} \times \eta_{sub\_syst} \quad (8)$$

where Y_{exp} is the expected yield measured in kWh, P_{array_stc} is the PV system sizing in Watt, PSH_{poa} is the peak sun hors (plane of array) measured in hours, $k_{deration}$ is the total derating factor as discussed in Section 2.1, and $\eta_{subsystem}$ is the subsystem efficiency considering the inverter and cabling.

3. Research methodology

3.1 The experimental setup

The experimental setup was developed under the local climatic conditions of Malacca, Malaysia (2.1896° N, 102.2501° E). According to the geographic latitude, the modules were inclined at an angle of 18 ° facing the South for optimum PV orientation. The setup consists of two identical monocrystalline PV modules (120 Wp); a clean module was used as the reference, while the other was left uncleaned for one month, as illustrated in Figure 1. The core elements for measurements are the recorded weather data as inputs to the neural network prediction for the second part of this study. The monitoring and equipment measurements are based on the Malaysia Standard MS IEC 61724:2010. All measurement parameters were recorded from 09:00 a.m. to 04:00 p.m. between 2s time intervals.

3.2 ANN modelling approach

The modelling approach used an artificial neural network to predict the dataset using the R programing language. Specifically, we used package neuralnet (Günther & Fritsch 2010) that is available in the CRAN repository.

As presented in Figure 2, the methodology process details as follows:

(i) Import data

First, the measured data were imported to the R programming language. The data consist of two independent variables, which serve as the input parameters, namely IN_1 and IN_2, and the dependent variable, which represents the output, i.e., OUT_1. Description of these input and output variables are specified below.

- IN_1 : G, Solar irradiance (W/m^2)
- IN_2 : T_{amb}, the ambient temperature (ºC)
- OUT_1: T_{pv_ave}, the average PV module (ºC)

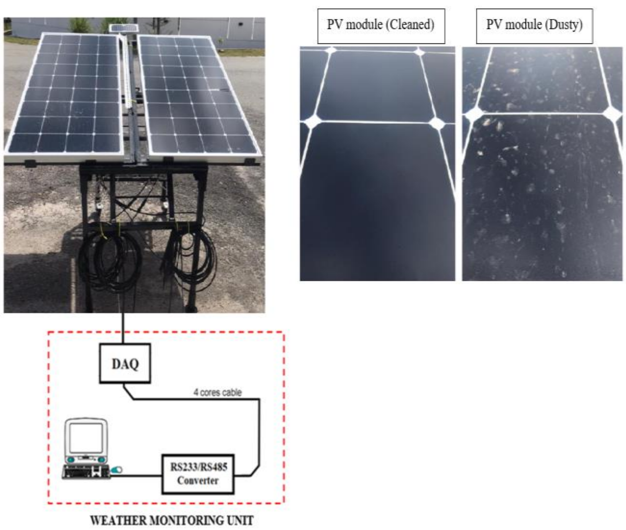


Fig. 1 The experimental setup

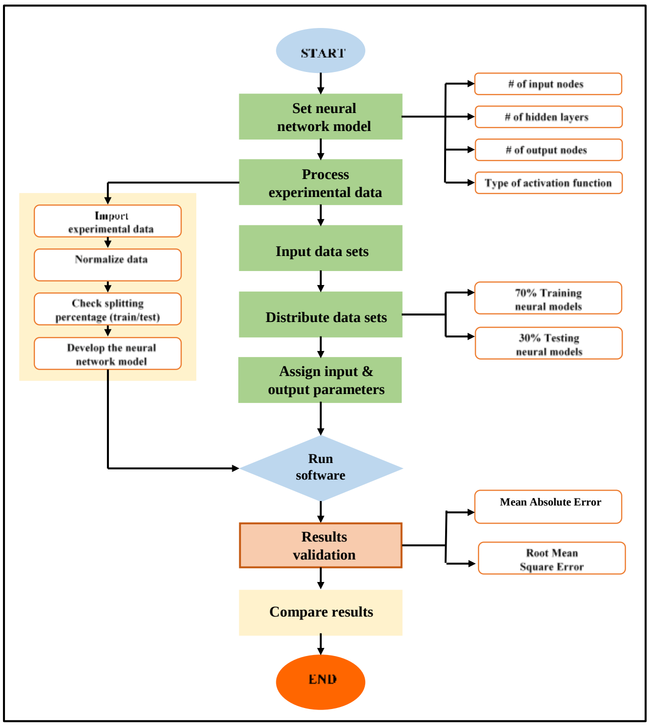


Fig. 2 Neural network modelling methodology used in this study

(ii) Normalization

In accordance with the standard practices for training a Neural Network, the dataset is normalized so that the mean is as near to zero as possible before being input into the model. In general, normalizing the data accelerates learning and leads to quicker model convergence. Additional normalization is required since the data from various scales and units with different ranges must be translated into one with the same scale and unit. When creating a model in ANN, it is critical to modify the weight of neurons during data training to eliminate bias in the model. It is made possible by normalizing the data, preventing very large or tiny weights. Then, the trained dataset is normalized to obtain a mean close to 0. In this study, we apply the most common Min-Max Normalization method.

(iii) Split dataset into train and test dataset

In machine learning, the performance of the algorithm is evaluated using a train-test split technique whereby a dataset is divided into two subsets namely, model fitting dataset for 'training', and test data set for 'testing' (Razak *et al.* 2021). It is important to note that the second dataset is not involved in the data' training', but perform as an input element into the model developed where predictions are then made and compared to the expected values. The common split percentages include: Train: 80%, Test: 20%, Train: 70%, Test: 30%, Train: 60%, Test: 40% and Train: 50%, Test: 50%. This study first trained and tested the datasets based on the aforementioned common split percentages.

This study determined the best splitting percentage by employing the trial and error approach. The accuracy of the model was evaluated using the accuracy measures; root mean square error (RMSE) and mean absolute error (MAE) presented in equations (9) and (10), respectively. It is widely known that no single accuracy metric can be deemed the "best" in calculating accuracy. We used a novel accuracy metric termed the Unscaled Mean Bounded Relative Absolute Error (uMbRAE) in this investigation, which is presented in equation (11) (Chen *et al.* 2017). The accuracy measure uMbRAE combines the best aspects of numerous alternative measures to solve typical flaws with current measures that are sensitive to forecasting outliers or 'noise'.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - x_{pre}\right)^2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - x_{pre}\right| \tag{10}$$

$$uMbRAE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left(x_i - x_{pre}\right)}{\left|x_i - x_{pre}\right| - \left|x_i - x_{pre}{}^{*}\right|} \tag{11}$$

(iv) Create a Neural Network Model

The most practical effect of ANN is in the following three areas: modelling and forecasting, signal processing, and expert systems. In this study, the ANN predictive ability was implemented related to the auto-associative memory of specific neural networks. In this study, the multi-input single-output (MISO) method maps the inputs to only one output variable, as illustrated in Figure 3 (Razak *et al.* 2021). There are three sets of ANN models for each dataset. In this case, the dataset mapping is as follows: (IN_1, IN_2, → OUT_1).

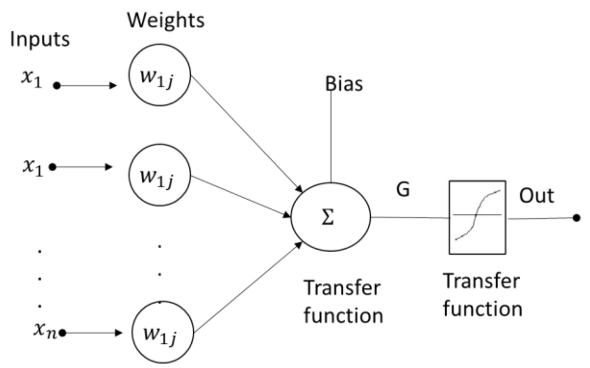


Fig. 3 An example of ANN model in MISO structure

4. Results and discussion

4.1 On the selection of neural network architecture

By taking into consideration both the training error and the test accuracy, Table 3 summarizes the best splitting percentage and the neural network architecture for the cleaned and dusty PV module for output parameter 1 OUT_1 (the PV temperature). We have found that, The best spliiting percentage for both cleaned and dusty PV module temperature prediction is 70%-30% with 2 hidden layers of 4-1 neural nodes, and 3-2 neural nodes respectively (i.e. hidden layer 1 has 4 nodes and hidden layer 2 has 1 node for the cleaned PV module, and hidden layer 1 has 3 nodes and hidden layer 2 has 2 nodes for the dusty PV module).

4.2 Modelling of cleaned and dusty PV module temperature using ANN

This section employed the ANN prediction model in the MISO structure based on the selected splitting percentage and neural network architecture to predict the output 1 (OUT_1) for cleaned and dusty PV modules. The PV module performance prediction throughout the day was conducted by feeding all the input parameters into the ANN model based on two sets of experimental data, namely Data 2 and Data 3. Then, the data was denormalized to obtain the relationship between the input parameters to predicted results of OUT_1 throughout the day. Using RMSE ad MAE accuracy analysis, the predicted output parameters were then compared against the measured data for the ANN model for validation purposes.

The impact of the dust accumulation on the PV module temperature (OUT_1) with the reference of solar irradiance at a different time of the day was evaluated. As can be seen from Figure 4 and Figure 5, the recorded temperature for the dusty PV module is found to fluctuate with the change in the solar irradiance, while the cleaned PV module is less affected by the variation in the solar irradiance. In addition, when closely monitored, the temperature difference between the dusty and cleaned PV module was higher between 1 to 3.69 °C. This may be attributed to dust, which is responsible for the dissipation of heat absorbed by the PV module.

Table 3
Splitting percentage and the neural network architecture for PV temperature (OUT_1)

PV	Split %	Hidden layer		Accuracy analysis		
		1	2	MAE	RMSE	uMbRAE
Dusty	70%-30%	4	1	0.0230	0.1516	0.0165
Cleaned	70%-30%	3	2	0.0746	0.2731	0.8875

Furthermore, the anticipated PV temperature profiles are in good agreement with the experimental measurements throughout the aforementioned period for the cleaned PV module, as shown in the figures. However, this is not the case with the dusty PV module. The accuracy study shows that the predicted data using the ANN model and the experimentally acquired data are often in good agreement, with MAE and RMSE for the cleaned PV module are as low as 1.28 °C, and 1.96 °C respectively for Data 2 and 3.93 °C and 4.92 °C respectively for Data 3. Meanwhile, the RMSE and MAE for the dusty PV module are 1.53°C and 2.82 °C respectively for Data 2 and 4.13 °C and 5.26 °C for Data 3.

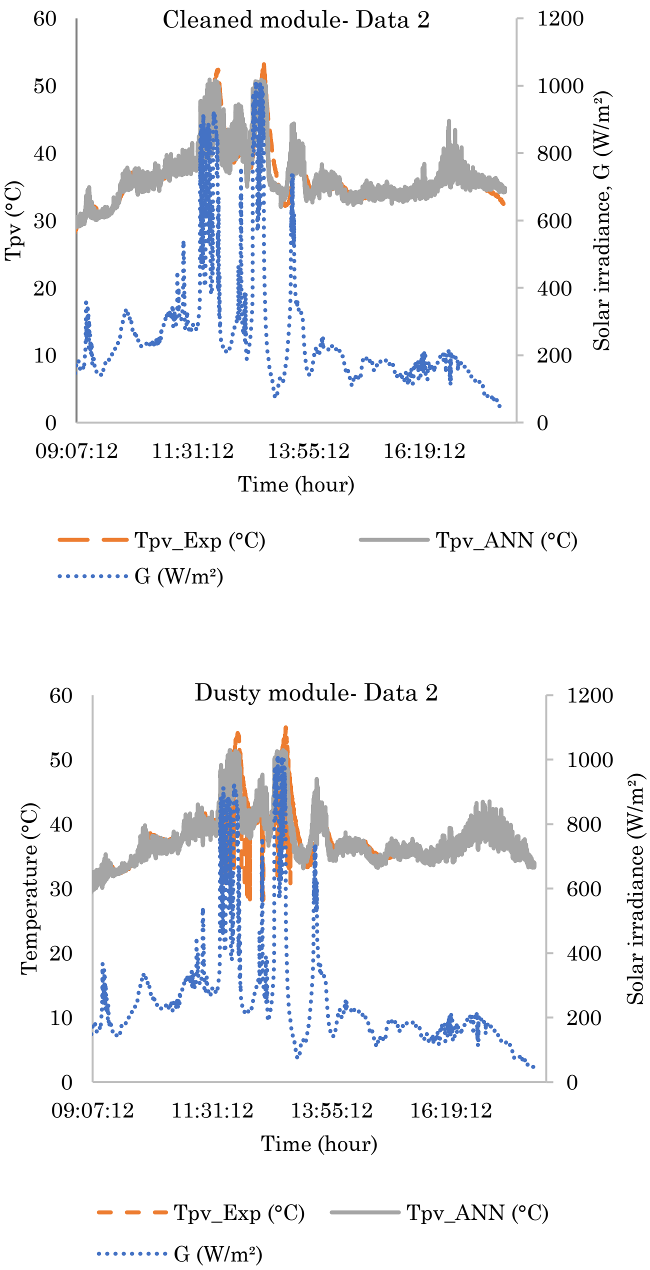


Fig. 4 Variation in Solar Irradiance, G, and PV Temperature T_{PV} for cleaned and dusty PV module with the time of the day (Data 2).

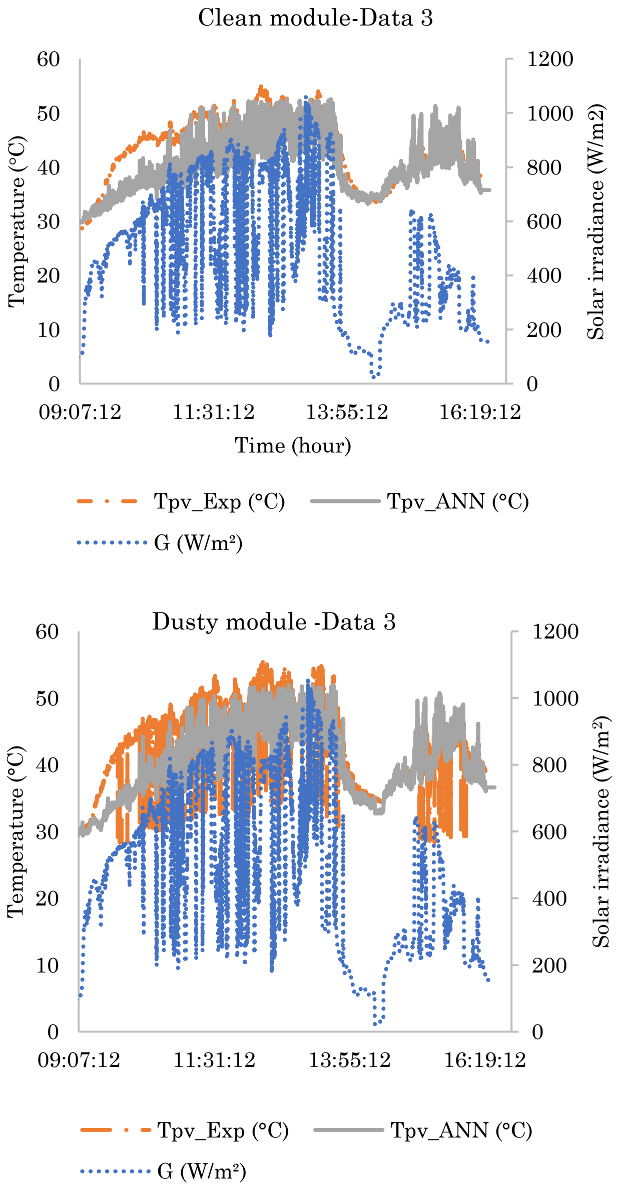
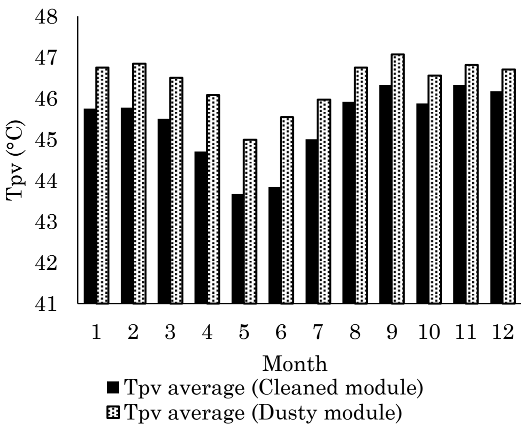


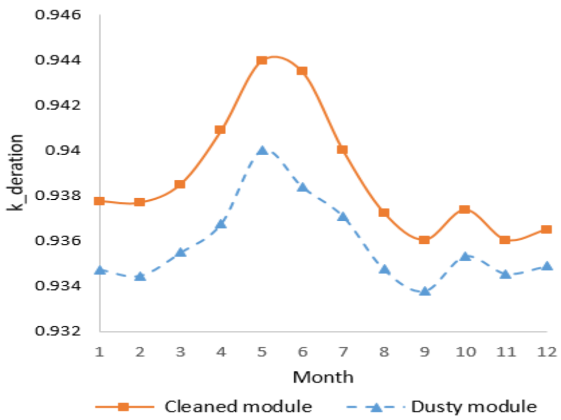
Fig. 5 Variation in Solar Irradiance, G, and PV Temperature T_{PV} for cleaned and dusty PV panel with the time of the day (Data 3).

4.3 PV average temperature 'Forecasting' using ANN prediction model

Using the validated ANN model, we have forecasted the monthly average temperature for the PV module throughout the year. The analysis is conducted by considering the input for the ANN prediction model, which are the incident solar irradiance and the ambient temperature obtained from the Meteonorm directory in TRSNSYS 18 for Malacca city, Malaysia. As shown in Figure 6(a), we found that the PV average temperature for the dusty PV module is generally higher by approximately 1% to 4 % throughout the year. Also, please note that, the variations in the forecasted module temperature are due to the changes in the ambient temperature and the amount of solar radiation absorbed by the PV module throughout the year.



(a)



(b)

Fig. 6 Forecasted (a) average PV temperature and (b) total derating factor for both clean and dusty modules

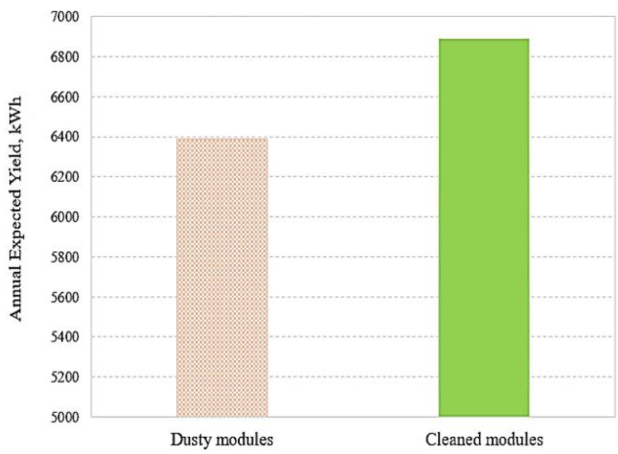
Figure 6(b) shows the impact of dust on the forecasted derating factor between cleaned and dusty modules over the year. According to the results, the average derating factor was improved by at least 0.4% when the module is cleaned. It can be seen that, the dust deposition directly influences the module temperature as well as its derating factor.

The average percentage difference of the total derating factor is computed at 3.13 %. The results are consistent with the findings in (Tripathi *et al.* 2018) who concluded that, the PV temperature of the dusty PV module is higher in comparison to the cleaned PV module based on their indoor experimental studies. In addition, researchers (Andrea *et al.* 2019) also expressed a similar findings in their research whereby a dusty PV panel on average has higher temperature and this is believed due to the heat absorbed being dissipated by the dust on the surface of the module.

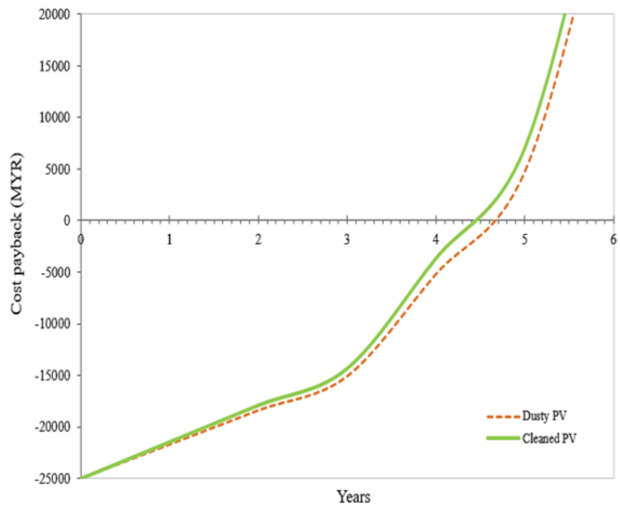
4.4 Annual yield forecasting

In this section, the energy generated by the PV system is estimated based on the ANN forecast model developed previously. The expected yield for both PV systems (cleaned and dusty) was determined based on 5 kW residential installations with 12 PV modules from Q-Cells (Q.PEAK DUO L-G5 QD-400) and an inverter from Sungrow (SG5KTL-MT). The expected yield was evaluated annually at a fixed and optimum tilt angle for both systems using equation (7). As illustrated in Figure 7(a), the expected annual yield for cleaned PV module is found higher by 7.29 % in comparison to the dusty system with the estimated power output from the panels are 6891 kWh and 6388 kWh respectively. This is aligned with the findings in (Andrea *et al.* 2019; Tripathi *et al.* 2018) which correlates the increase in the temperature of the PV module and the dust accumulation, with the drop in power output.

In addition we have also done a simple economic analysis using payback period method to justify the impact of dust on the degradation of PV modules as shown in Figure 7(b). The payback period method was used to express return on investments for both systems (Ramadan *et al.* 2018). The total initial system cost and operation and maintenance cost are taken into considerations. The payback period for dusty and cleaned PV systems is 4.7 and 4.3 years, respectively. In this regard, yield forecasting is helpful for the system installer to manage the expected deliverables uncertainty to the system owner. Besides, it will assist the stakeholders to employ an appropriate cleaning cycle to recover maximum PV module output.



(a)



(b)

Fig. 7 (a) Annual yield and (b) payback period based on the ANN prediction model

5. Conclusion and future work

This study proposed a simple ANN prediction model for estimating the PV module performance based on the impact of dust deposition. The neural network model was developed to analyze the impact of dust as a function of environmental input parameters such as solar irradiance and ambient temperature. The model was trained and validated using several datasets obtained from the experimental measurements conducted in the residential area of Malacca, Malaysia. Based on the proposed ANN model, several important findings can be concluded in the following points:

- The forecasted PV average temperature for the dusty PV module is generally higher by approximately 1% to 4 % throughout the year.
- The expected annual yield for a cleaned PV system is 7.29% higher than the dusty PV. Hence, a faster payback period is expected.

From the abovementioned key findings, the developed ANN model is beneficial for PV system installers to assess and anticipate the impacts and consequences of dust accumulation on the PV modules installed in residential areas in various cities and countries with similar climatic conditions. Future work includes a detailed investigation on the morphology of the dust particles and the collector's performance when the PV panel is left uncleaned for a different range of periods.

Acknowledgements

The authors would like to thank the Solar Energy Research Institute and Energy Efficiency Lab, FTKEE, UTeM for some of the equipment used in the experiment.

Author Contributions: Emy Zairah Ahmad: Methodology, formal analysis, writing—original draft, Hasila Jarimi: Writing, review and editing, Tajul Rosli Razak: Conceptualization, methodology, and writing. All authors have read and agreed to the published version of the manuscript.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Conflicts of Interest: The authors declare no conflict of interest.

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