Modelling soil deposition predictions on solar photovoltaic panels using ANN under Malaysia's meteorological condition

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ABSTRACT

Solar photovoltaic (PV) panels performance is influenced by various external factors such as precipitation, wind angle, ambient temperature, wind speed, transient irradiation, and soil deposition. Soiling accumulation on panels poses a significant challenge to PV power generation. This paper presents the development of an artificial neural network (ANN)-based soil deposition prediction model for PV systems. Conducted at a Malaysian solar farm over three months, the research utilized power output data from the inverter as model output and meteorological data as input variables. The model employed the Levenberg-Marquardt backpropagation method with Tansig and Purline activation functions. Performance assessment via statistical comparison of experimental and simulated results revealed a coefficient of determination (R^2) value of 0.68073 for the ANN architecture of 5 input layers, 30 hidden layers, and 1 output layer (5-30-1). Sensitivity analysis highlighted relative humidity and wind direction as the most influential parameters affecting PV soiling rate. The developed ANN model, combined with sensitivity analysis, serves as a robust foundation for enhancing the efficiency of smart sensors in PV module cleaning systems.

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1. INTRODUCTION

With the persistent drive to reduce carbon emissions and promote clean energy, the utilization of solar photovoltaic (PV) systems is anticipated to escalate in the foreseeable future. It's imperative to comprehend the impact of soil deposition on PV systems, particularly as solar energy gains traction as a sustainable and renewable energy source [1]. Soil deposition on solar modules occurs when dirt and dust accumulate on their surfaces, diminishing their sunlight capture and electricity generation capabilities [2]. Factors like wind, rain, or human activity contribute to this soil accumulation. Reduced sunlight absorption and power generation happen when the modules' surfaces are covered in dirt and dust [3], resulting in decreased energy output, lower overall efficiency, and increased maintenance costs for the system [4].

The output of solar PV panels is affected by parameters such as precipitation, wind angle, ambient temperature, wind speed, transient irradiation, and soil deposition. As these panels are installed outdoors and exposed to atmospheric conditions, the accumulation of soiling becomes a significant issue, leading to disruptions in PV power generation [5]. Soiling is the primary cause of transmittance losses, panel degradation, and subsequent power losses [6], [7]. Several studies have investigated the impact of soil deposition on solar PV systems. For instance, Jaszczur *et al*. [8] conducted a numerical simulation study focusing on dust accumulation on PV panels in regions with high dust levels, particularly for panels used in street light posts. In a similar vein, Fernández-Solas *et al*. [9] proposed five analytical techniques to predict real-time PV performance, introducing a novel dust shield design to mitigate dust accumulation. Wu *et al*. [10] proposed a numerical simulation method to model dust accumulation and analyze its effects on power generation under varying wind conditions, demonstrating its effectiveness in managing soiling in windy environments. While, Polo *et al*. [11] predicted soiling loss to address its impact on solar energy output, evaluating their models using data from the PVLib package and testing under summer conditions in Madrid. Additionally, Pérez *et al*. [12] proposed an artificial intelligence model for predicting energy losses due to soil deposition on solar panels, incorporating meteorological factors and electrical parameters into their model.

Although existing literature lays the groundwork for studying soil deposition prediction models, few studies use artificial neural network (ANN) methods for this purpose. Most research focuses on countries with seasonal climates, overlooking regions with consistent climates like Malaysia. There is also a lack of analysis on how meteorological factors in Malaysia affect soiling accumulation, highlighting the need for further investigation.

Research in this area could improve predictive maintenance and reduce operation and maintenance costs for solar PV installations. By examining the relationships between variables such as precipitation, wind angle, temperature, wind speed, transient irradiation, and soil deposition, an ANN model can predict soil deposition under different conditions. This study aims to enhance PV system performance by mitigating soil deposition, thus increasing efficiency and reducing electricity production costs [3]. Additionally, addressing panel cleaning costs could lower maintenance expenses. The ANN model will be trained with various meteorological variables to understand their impact on soiling deposition. A multi-variable linear regression (MLR) model will be used to assess the ANN model's accuracy.

The paper is structured as follows. In section 2, we describe the overall framework and system architecture of the soil deposition prediction model and the influence of input parameters estimation using global sensitivity analysis (GSA). In section 3, the results of the best ANN model architecture are presented, along with an evaluation of the parameters that most significantly affect the model. Finally, section 4 provides the conclusion of the study.

2. RESEARCH METHOD

2.1. Overall methodology framework

Figure 1 illustrates a thorough flowchart of the project. In order to choose the most suitable type of data for this project, simplification of the project's scope is entailed in the data-gathering procedure. The goal of this project is to use ANN to estimate the soiling rate of solar PV panels. To create an ANN architecture for estimating soiling rate, data including precipitation, wind angle, ambient temperature, wind speed, transient irradiation, and power generated were measured. In the subsequent step, the mean absolute percentage error (MAPE), determining the percentage error of the model's numerical estimates, and the coefficient of determination (R^2), indicating the linear relationship between experimental and simulated data, served as the mathematical error criteria for comparing and obtaining statistical comparisons of the ANN models. Finally, the conditional and unconditional cumulative distribution functions (CDFs) were employed between the partially additive and partially nonlinear (PAWN) sensitivity analysis as a measurement of distance due to its low computational cost and effective outcomes for nonlinear computational models [13].

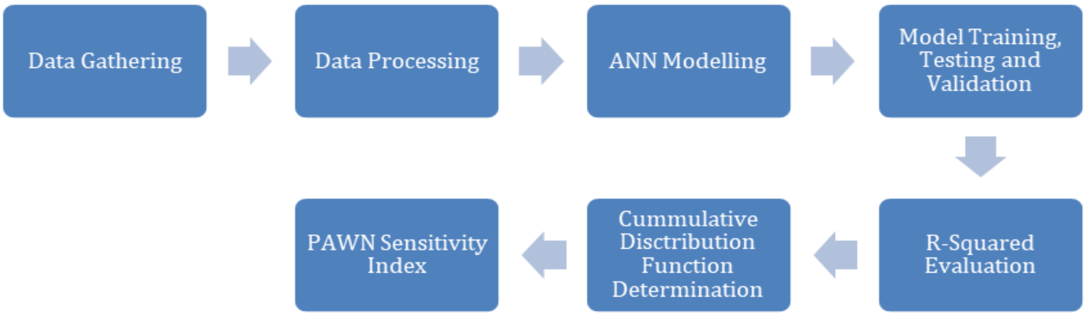

Figure 1. Flowchart of research methodology

2.2. Artificial neural network modeling process
2.2.1. Data acquisition and pre-processing
ANN soil prediction model was developed for a solar farm located in the central of Peninsular Malaysia. To identify the soiling rate over time, power generated at the inverter was recorded. The established weather station there was used to collect the remaining data. In the pre-processing part of the soil deposition prediction model, the data is prepared and processed to ensure its quality and suitability for training the ANN model. The collected data is examined for missing values, outliers, and inconsistencies. Missing values can be handled by imputation techniques, such as mean or median substitution, or using advanced methods like regression-based imputation. Outliers can be identified and treated based on statistical techniques or domain knowledge. Correlation analysis helps to understand the relationships between different meteorological factors and soil deposition. Variables that exhibit a high correlation with soil deposition are typically retained for model training.

2.2.2. Soiling rate calculation
The power generated by a solar PV system is directly related to the intensity of sunlight falling on the panels. As soil accumulates on the panel surface, it acts as a barrier, reducing the transmittance of sunlight through the panel. This results in a lower amount of sunlight being converted into electricity by the PV cells, thereby reducing the power generated. The relationship between power generated and soiling rate in solar PV systems is based on the impact of soiling on the efficiency of the panels. Soiling, or the accumulation of dirt and dust on the panel surface, reduces the amount of sunlight reaching the PV cells. This reduction in sunlight absorption leads to a decrease in power output from the PV system. The soiling rate is calculated using (1) and (2).

$$G = \frac{P}{A} \tag{1}$$

$$\tau_e = \frac{G - G_{moy}}{G}$$

$$G_{moy} = \frac{Gi}{72} \tag{2}$$

Where G is received irradiance by the solar PV glass, P is power generated, A is area, Gmoy is transmitted irradiance by the solar PV glass, G*i* is regularly measured by the solar PV glass, *72 is No of elementary rectangles of equal dimensions, G*i* and G both have been measured using a solar power meter.

2.2.3. Artificial neural network architectures design and training
The estimation of functions that have many parameter variables is suitable to be modeled using ANN. An ANN neuron assigns the appropriate weighting factor (W) to each input parameter. A transfer function's output value, which is derived from the bias (b) and weighted inputs summed together, influences how nearby neurons react [5]. An input layer, a hidden layer or layers, and an output layer typically make up an ANN's architecture. To address the non-linear multivariable issue, ANN goes through an iterative training phase. To carry out this process, certain algorithms are used, with the Back-Propagation algorithm being one of the most used ones [14].

In this paper, several ANN architectures were evaluated to identify a model that accurately predicts the rate of PV glass soiling. Figure 2 depicts the basic ANN architecture, which comprises one neuron in the output layer and five neurons in the input layer, which stand in for the precipitation, wind angle, ambient temperature, wind speed, and transient irradiation. The transfer functions utilized for nonlinear solutions are the linear transfer function for the output layer and the hyperbolic tangent sigmoid for the hidden layer. Explaining research chronologically, including research design, research procedure (in the form of algorithms, Pseudocode, or other), how to test, and data acquisition [15]–[17]. The description of the course of research should be supported by references, so the explanation can be accepted scientifically [18], [19]. Figure 2 and Table 1 are presented center, as shown below and cited in the manuscript [15], [20]–[25].

A functioning database was made for soil deposition on PV panels, precipitation, wind angle, ambient temperature, wind speed, and transient irradiation using the data that the measurement equipment collected based on Table 1. The database was randomly divided into three different parts for the ANN training process: 80% went to the training phase, 10% to the validation phase, and 10% to the testing phase. The random division approach was used to make sure that the data distribution was accurately approximated.

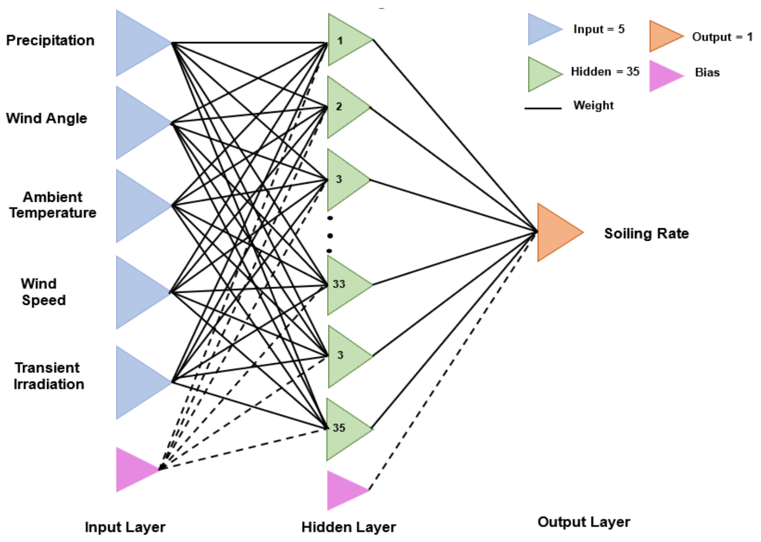

Figure 2. ANN architecture for soiling rate estimation

Table 1. Parameters used for the mathematical modeling process

Parameters	Min	Max	Units
Inputs			
Precipitation	0.2	89	[mm]
Wind angle	1	358	[°]
Ambient temperature	27.5	35.8	(°C)
Wind speed	0.1	4.1	(m/s)
Transient irradiation	4	1238	(W/m²)
Output			
PV glasses soiling rate	0.9927	0.9999	[%]

2.2.4. Statistical comparison of artificial neural network models

The Levenberg-Marquardt (LM) backpropagation algorithm-a Newton method derivation-is one of the best techniques for accelerating the convergence of ANN structures. It was applied to choose the ideal bias values and weights. It offers simpler calculation and less weighted error propagation than systems with two or more hidden layers. The mathematical error criteria used for the comparisons were the MAPE, which computes the percentage error of the model's numerical estimates, the root mean square error (RMSE), which assesses the variation between the model's predicted and experimental measures, and the coefficient of determination (R^2), which establishes the linear relationship between experimental and simulated data.

$$RMSE = \sqrt{\frac{(t-y)^2}{n}} \tag{3}$$

$$MAPE = \frac{\left|\frac{t-y}{t}\right|}{n} \times 100 \tag{4}$$

$$R^2 = 1 - \frac{(t-y)^2}{(t-\bar{y})^2} \tag{5}$$

Where t is the measured PV glass soiling rate, y is the simulated ANN output, and $\bar{y}$ is the average experimental PV glass soiling rate.

2.3. Global sensitivity analysis

The influence of each input parameter is estimated using a set of mathematical operations known as GSA. To evaluate the relationship's fitness and the model's consistency with reality. The Kolmogorov-Smirnov (KS) statistic is applied to compare the variations between unconditional and conditional CDFs as in (6).

$$KS = \max|Unconditional\ CDF - Conditional\ CDF| \tag{6}$$

A PAWN sensitivity index (Ti), that factors into account a statistic over all potential values of xi, is generated since KS depends on the fixed value of xi as in (7).

$$Ti = \underset{x_i}{stat}[KS(xi)] \tag{7}$$

3. RESULTS AND DISCUSSION

3.1. Artificial neural network–soil deposition prediction model performance

An analysis of soiling deposition prediction on solar PV systems as a function of environmental factors using several ANN architectures is presented in this section. The performance analysis was made by comparing experimental PV soiling rate observations and simulated data from the ANN prediction models. A linear regression fit between the experimental data and the model's predictions (training, testing, and validation) and the best ANN model using all the data that was provided. Several network configurations were trained and statistically evaluated changing the number of neurons in the hidden layer from 1 to 35, in order to identify the best ANN architecture. The training was performed with the aid of the ANN toolbox in MATLAB, a mathematical program.

The comparison between the simulated data from the ANN architectures and the experimental PV soiling rate measurements is shown in Table 2. The best ANN model prediction, as shown in Table 2, was made using 30 neurons in the hidden layer, creating a 5-30-1 ANN architecture. This model has the lowest RMSE of 0.00044052 and MAPE of 0.027493%.

The fit of the experimental data using the best ANN model employing all the data (training, testing, and validation) is shown in Figure 3 by a linear regression analysis. As can be seen, a linear behavior fitting of R^2 68.07%, provided by a linear regression model, achieved the highest result for the comparison between experimental (SRExp) and simulated (SRSim) data as in (8).

$$SR_{sim} = 0.6852xxSR_{exp} + 0.31389 \tag{8}$$

Table 2. ANN architecture training results

ANN architecture	RMSE	MAPE	R2	Best linear fitting
5-05-1	0.00055735	0.037579	0.48894	Y=0.1909x+0.8063
5-10-1	0.00042349	0.034249	0.65816	Y=0.7258x+0.2732
5-15-1	0.00062452	0.041643	0.35834	Y=0.3329x+0.6649
5-20-1	0.00049753	0.032994	0.59276	Y=0.6051x+0.3936
5-25-1	0.00051449	0.037843	0.56451	Y=0.629x+0.3698
5-30-1	0.00044052	0.027493	0.68073	Y=0.6852x+0.3138
5-35-1	0.00063376	0.044604	0.33921	Y=0.3635x+0.6344

3.2. Sensitivity analysis results

The conditional CDFs curves display different cumulative densities separated from their related unconditional CDFs, as seen in Figures 4-8. This behavior shows the impact of *xi* on the expected rate of PV glass soiling. The separation distance between the conditional CDFs and unconditional CDFs curves is observed to be larger for the variable's wind direction and wind speed. Thus, it can be concluded that these factors significantly affect the model response. In contrast, the curves conditional CDFs approximate to unconditional CDFs show that rainfall and ambient temperature have less of an impact on the model's output.

Figures 4-8 represents cumulative density distribution curves of the model output for each input parameter. **Error! Reference source not found.**, 5, and 6 show that the shifts in precipitation, wind angle, and ambient temperature, respectively, are directly proportional to the soiling rate. A similar case is shown in Figure 7, where the model predicts that low wind speed favors soiling deposition, which is consistent with the phenomenon's physical behavior. Finally, Figure 8 shows that increases in solar irradiance values result in a drop in the model's output response while low radiation levels result in greater dust deposition.

3.3. Sensitivity index

To summarize the findings of the cumulative density distribution curves study, a sensitivity index (Ti) is generated by taking into consideration a statistic across all possible values of xi. A value that describes the model sensitivity about the variable is provided by the Ti. The sensitivity analysis results are summarized in Table 3, highlighting the significance of transient irradiation (0.4211), precipitation (0.5576), ambient temperature (0.9771), wind angle (0.9772), and wind speed (1.01603). According to the results, wind speed (1.01603) emerged as the most significant parameter for PV soiling deposition. It is necessary to show that the parameter indexes are near to one another. It concludes that even if some have a lesser impact, their contribution is significant to the modeling process.

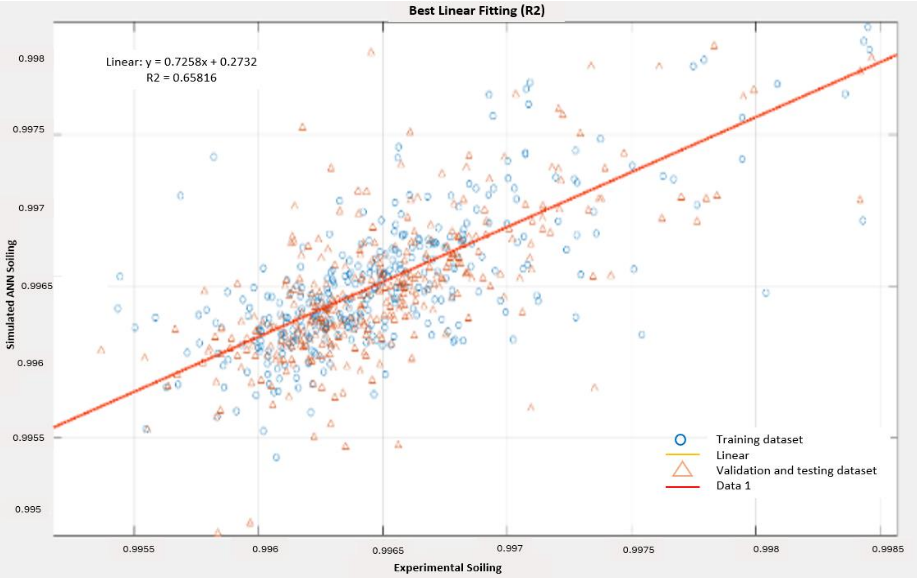

Figure 3. Linear regression fitting from the best ANN architecture

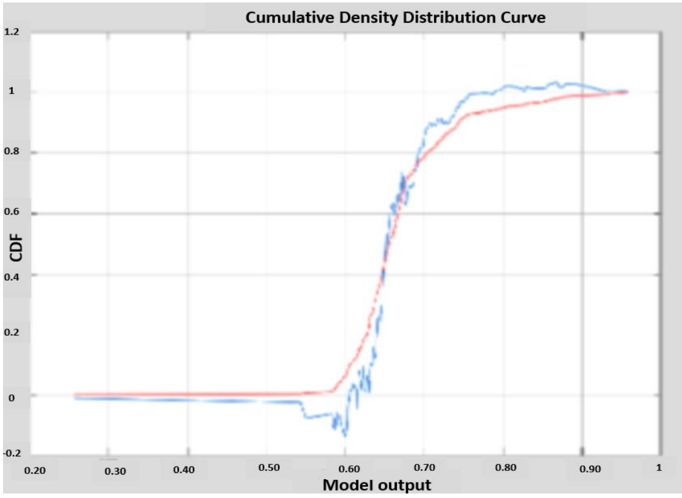

Figure 4. Cumulative density distribution curves of the model outputt based on precipitation

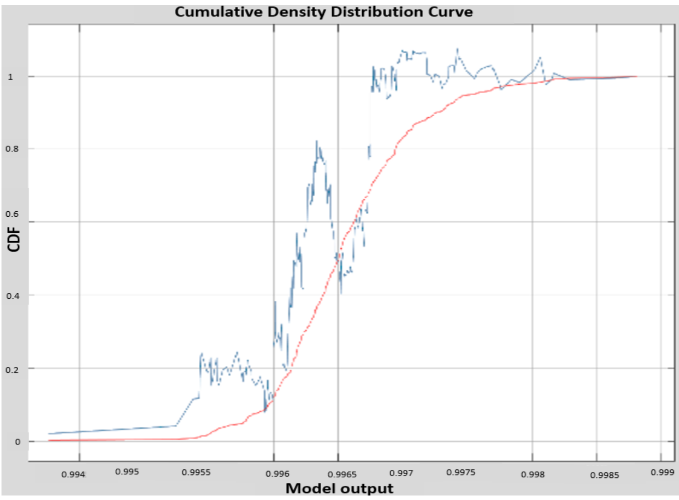

Figure 5. Cumulative density distribution curves of the model outputt based on wind angle

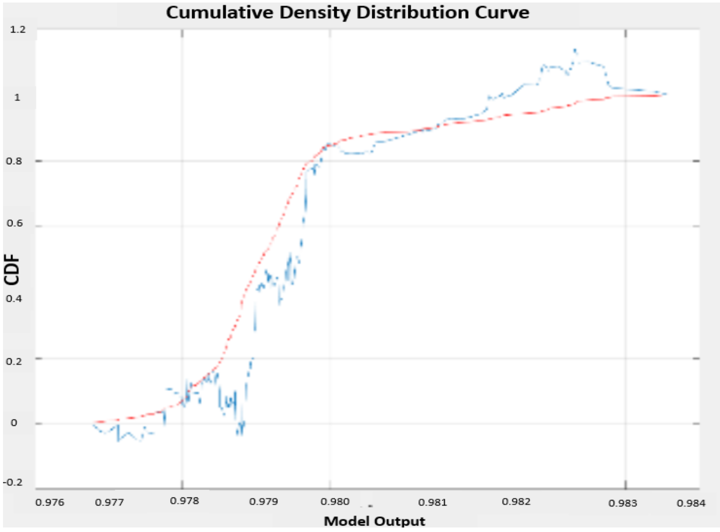

Figure 6. Cumulative density distribution curves of the model outputt based on ambient temperature

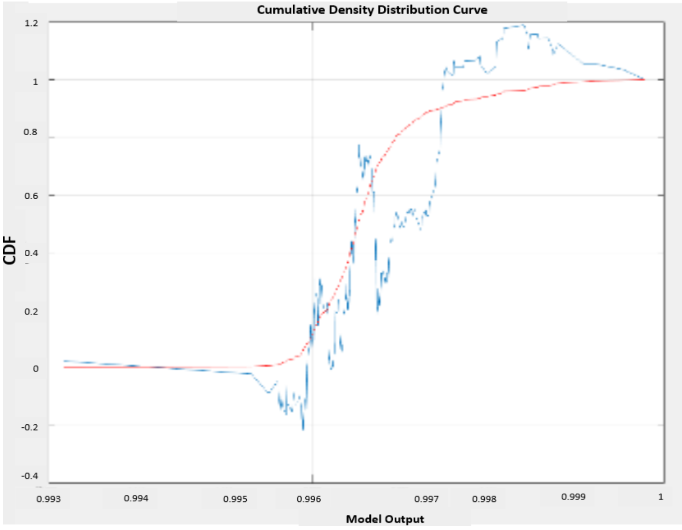

Figure 7. Cumulative density distribution curves of the model outputt based on wind speed

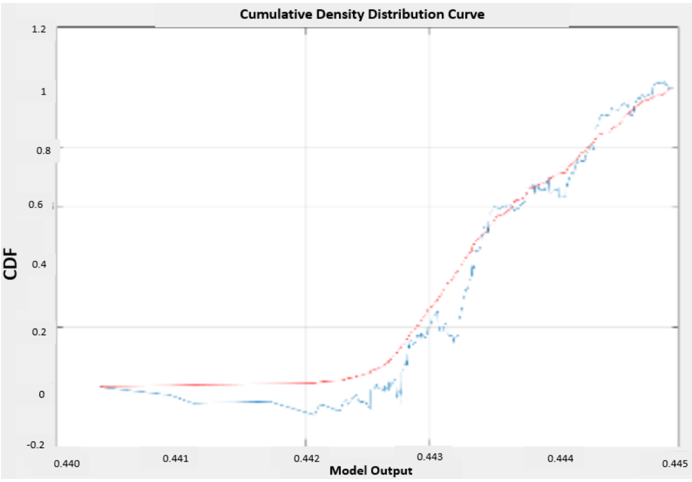

Figure 8. Cumulative density distribution curves of the model outputt based on transient irradiation

Table 3. Relative importance of input variables from training

Parameter	Sensitivity index
Precipitation	0.5576
Wind angle	0.9772
Ambient temperature	0.9771
Wind speed	1.01603
Transient irradiation	0.4211

4. CONCLUSION

The soiling rate concerning environmental variables such as precipitation, wind angle, ambient temperature, wind speed, and transient irradiation was expressed through the creation of an ANN model. The model's performance was assessed using statistical measures, comparing it to data that was not utilized during the modeling process. The statistical findings indicate that the ANN model has sufficient capability to estimate under the case study's specific set of conditions. The results of the sensitivity analysis demonstrated that each parameter significantly influences the model's output, with wind speed having the greatest impact, followed by wind angle, ambient temperature, precipitation, and transient irradiation. The sensitivity study also demonstrated how the behavior of the model's output would change if the value of each input parameter were varied across a wide range (from maximum to minimum). The sensitivity analysis employed proved to be an effective tool for elucidating the underlying physics of the phenomenon within the ANN model. This approach presents a promising framework for application in smart sensors for PV module cleaning systems, enhancing the operational efficiency of these modules. Understanding the dynamics of soiling accumulation over time can facilitate the optimization of maintenance plans and the development of more accurate forecasting models.

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