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Research Article

Improving the Efficiency of Photovoltaic Panels Using Machine Learning Approach

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Photovoltaic (PV) solar panels account for a major portion of the smart grid capacity. On the other hand, the accumulation of solar panels dust is a significant challenge for PV-based systems. The accumulation of solar panels dust results in a significant reduction in the amount of energy produced. Because of the country's low wind velocity and rainfall, frequent cleaning of solar panels is necessary either by manual or automated means. Cleaning activities should only be initiated when absolutely essential to reduce maintenance costs and increase the power output of solar panels that have been projected to be affected by dust accumulation. In this paper, we develop a deep belief network model to detect the dust particles in the solar panels installed as a large unit. The study takes into account various input metrics that includes solar irradiance, temperature level, and dust level on the panels. These metrics are used for the estimation of the level of dust present in the atmosphere and how often the panels can be cleaned at regular intervals. The simulation is conducted to test the efficacy of the model in cleaning the panels. The results are estimated in terms of accuracy, precision, recall, and F-measure. The results of the simulation show that the proposed model achieves higher accuracy rate of more than 99% than other methods.

1. Introduction

The use of thermal power plants contributes to the acceleration of global warming. In contrast, the fossil fuels that are used in these plants are getting increasingly expensive and difficult to come by. As a result, the integration of renewable energy sources into power systems has become a global imperative. Solar, wind, biomass, geothermal, and fuel cells are just a handful of the renewable energy sources that can be used to power electric grids and other energy systems.

The demand for natural gas and oil tends to increase dramatically in recent years, causing countries to look for alternative energy sources. Solar power and renewable energy technology are being actively considered as viable alternative energy sources and other countries across the world. With its favourable temperature and geographical location, it is home to the world's highest solar power generation. As a result, solar energy has become the most widely used renewable energy source.

Photovoltaic panels are made with semiconductor materials, which are employed in the manufacturing process. The inherent properties of photovoltaic materials have an impact on the efficiency of photovoltaic systems. Solar panel output is therefore dependent on the materials used in their manufacture as well as the coating applied to the glass on which they are constructed.

As a result, several impediments to the widespread use of solar energy in underdeveloped countries. The impact of dust is one of the most significant considerations. Because of the country's geographic location, the pace at which dust accumulates is extremely high. A build up of dust on photovoltaic panels causes them to degrade quickly, which results in a significant reduction in their power production. Both the environmental conditions and the qualities of the dust play a role in determining the amount of dust that accumulates in a given area. The weight, shape, and size of the dust particles are all characteristics of the dust, whereas environmental elements include the weather and the particle location [1–3].

Additionally, the wind might have an impact on dust settling. A large amount of dust collects on the surface of solar panels in regions, causing the power output of solar photovoltaic panels to decrease at the fastest rate. Climate factors such as the temperature and humidity of the surrounding air have an impact on dust settlement. Solar panels lose their efficiency as a result of increased dust accumulation on them as the temperature and humidity rise [4].

As a result, solar panels should be cleaned on a regular basis to ensure maximum efficiency. However, if no cleaning procedures are required, this strategy is not cost-effective and may result in a waste of resources [5]. It is critical to determine the quantity of dust on solar panels and to begin cleaning procedures as soon as possible in order to maximise output while reducing maintenance costs. The impact of dust collected on panels varies depending on the weather conditions and the size of the dust particles. The output power of PV panels also fluctuates depending on the location, the properties of the dust, and the temperature of the environment. As a result of this limitation, the outcomes of research undertaken in one country cannot be generalised to other countries.

It is feasible to employ the process described in this paper in other countries, but not the data or findings. As a result, it is vital to continuously monitor the quantity of dust in photovoltaic farms and to take appropriate steps to reduce maintenance costs while simultaneously boosting output. In fact, the generality of the methodology given herein distinguishes it from other approaches as it can be used to detect dust accumulation regardless of where it occurs.

In this paper, we develop a deep belief network model to detect the dust particles in the solar panels installed as a large unit as in Figure 1.

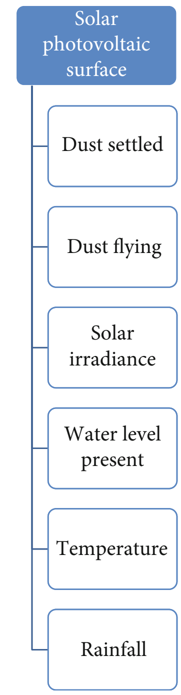

Figure 1: Main sources of data collection on PV panels.

The main contribution of the paper involves the following:

(i) The study takes into account various input metrics that includes solar irradiance, temperature level, and dust level on the panels

(ii) These metrics are used for the estimation of the level of dust present in the atmosphere and how often the panels can be cleaned at regular intervals

2. Background

According to the research literature, solar photovoltaic production can be investigated either via the use of tests or through the development of prediction models.

In [6], the effects of dust, humidity, and air velocity were investigated individually and in combination. Fine particles have a greater impact on the efficiency of solar panels. A greater tilt angle also helped to prevent dust accumulation, albeit wetness accelerated the coagulation of dust particles. Tests were carried out in [7] in order to demonstrate the effect of pollutant type and weight on the output power of solar-powered PV panels.

In [8], it was found that three unique fake contaminants were injected into the solar photovoltaic panel during the experiment. The testing included the use of pollutants as contaminants. The results revealed that solar panels produced substantially more electricity than clean panels. A comparable study into three artificial pollutants, red soil, sand, and ash, was conducted and the results were published in [9].

A 23-day test of self-cleaning coatings on solar panels was conducted [10] to see whether they were effective. When compared to panels that did not have this coating compound, the performance of the panels with this coating compound was practically equal.

A number of experiments were carried to investigate the dust impact on a solar panel performance. The dust concentrations in solar panel modules ranged from 0.0063 g/m^2 to 0.36 g/m^2, depending on the model. According to the research, a linear link was discovered between dust mass and the fall in solar output power. According to [11], satellite images and an SVM model were used to estimate cloud movement and irradiance. The autoregression model presented in [12] was used to forecast the output over a period of up to 36 hours, and the results were positive.

As reported in [13], the ANN technique provides predictions of global solar radiation based on data from weather stations throughout the world. The hourly diffuse solar irradiance was estimated using a sigmoid function regression model by the authors in [14] for all weather conditions. The model discovered a 25–35 percent relative root RMSE. The output power of a wind turbine in Turkey may be calculated using an ANN model over a variety of time periods and throughout various seasons [13]. A solar panel with a capacity of 750 watts was installed (PV). The RMSE for each season and time period was tallied separately.

In [15], the output power of California PV panels was predicted using four different approaches, one of which being the ANN method. It was decided to use a one-megawatt solar panel field to forecast one hour and two hours in the future. In terms of accuracy, the ANN surpassed all of the other forecasting methods except for one. According to the research, there was an inaccuracy of up to 20% in the other models. In the provided model, the root mean square error (RMSE) was found to be 15%. Neither the study nor the literature made any considerations for how environmental circumstances would affect the output power of the system.

Using solar modules as an example, researchers in Spain conducted a study to determine how rainfall impacts the cleaning of the modules [16]. According to a study, solar photovoltaic power plants lose 20 percent of their energy during dry seasons, compared to only 4.4 percent during wet months, due to dust accumulation on the solar panel surfaces [12].

As part of another study experiment in Morocco, the output of a solar photovoltaic panel and rainfall was measured for four months and then used to determine the accumulation of dust. The information on the amount of rain that fell came from a weather data collection centre.

Studies in [17] looked into how dust collecting affects PV panel performance in the Jazan region, despite the fact that rain occurs seldom and with a low degree of intensity. The efficiency of photovoltaic panels was found to be reduced by 10% as a result of the frequent dust collection. Lower tilt angles, on the other hand, gathered far more dust than higher tilt angles. The authors of this article were inspired to write it because they wanted to share their knowledge with others.

In [18], indications are conducted in order to determine the dust accumulated on photovoltaic surface. Much research has been conducted to determine the dust impact on photovoltaic panels. There have been a few studies conducted to determine the amount of dust that has to be eliminated before the proper cleaning procedure can begin.

3. Proposed Method

Forecasting solar panel dust accumulation accurately is crucial for investors and grid operators alike, as it affects their bottom lines. As shown in Figure 2, the research was aimed at estimating the dust level with various measurements on solar panels. If there is a significant amount of dust, cleaning procedures may be initiated. Machine learning was used in the development of this detector. The first step in developing a machine learning model for photovoltaic panels is to collect all of the data that will be needed. After that, a number of regression models are constructed and tested on the data that has been collected.

3.1. Data Preparation. Analysis of data before it is fed into the model is used to predict dust levels, which is accomplished through the use of regression models. The statistical approach helps to predict the relationship between the response and single output variable, and one or more input variables, referred to as predictors; before entering the model, the predictors and response variables should be grouped in a matrix to make it easier to understand. In this study, three factors are used to predict the value of a single output or response variable. When operating in these conditions, PV power output is influenced by three variables: the amount of solar irradiation received, the temperature of the surrounding air, and a reaction variable termed dust. A comprehensive collection of data was acquired through a series of tests, which will be discussed in further detail in the following paragraphs and which are conducted over a number of days, resulting in an extensive collection of data.

3.2. Model Training. After that, the model is fed with data from the tests, which is then trained on that data to teach it how to predict dust levels based on inputs such as the power output of PV panels, the temperature of the environment, and the amount of solar irradiation. There are two types of data collected (predictor variables and responses). Data sets are used in the model creation and validation process for both the training and testing stages. Data sets are used in both the training and testing stages.

The solar irradiance, temperature, and output power are all included in the regression models as three predictors and one response variable. The regression model predicts the dust present, which is then compared to the actual response. While training, the 5-fold cross-validation method is used. It is often used in regression models to analyse and quantify misclassification errors, which is a common occurrence. During the training phase of this method, five sets of data are picked at random from the training data set to be used in the training phase.

The four groups will be used to train and evaluate the model during the development process. This technique will be repeated numerous times in order to ensure that each group has been examined at least once before moving on. Following the training process, the difference between the actual and projected response is found determined using the data collected. When using different models, it is feasible to estimate solar panel dust collection with a different standard deviation

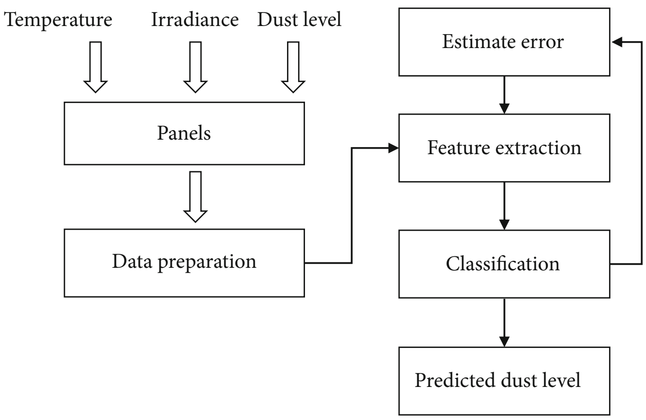

Figure 2: Proposed algorithm.

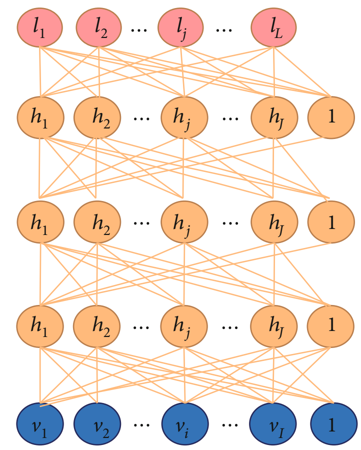

Figure 3: DBN/DNN architecture.

(RMSE). From among the available regression prediction models, the one that provides the most accurate dust estimation with the lowest RMSE is chosen. The correctness of a model can be tested by using a variety of case studies after it has been narrowed down to the most accurate one through a process of elimination.

When RBMs are trained, they are stacked together to produce a DBN. The following is an explanation of the stacking technique. Using the activation probabilities of its hidden units, a Bernoulli-Bernoulli RBM is trained after learning a Gaussian-Bernoulli RBM or a Bernoulli RBM, which is then used to train another RBM. After that, the activation probabilities of the second-layer Bernoulli-Bernoulli RBM are used as the visible data input by the third-layer Bernoulli-Bernoulli RBM. This is a three-layer RBM with three layers. The layer-by-layer greedy learning improves the training data under the stacking, which provides some theoretical evidence for this effective layer-by-layer greedy learning technique. Thus, the greedy strategy described above achieves a close approximation to the maximum probability distribution. It is vital to remember that this learning process is unsupervised and does not necessitate the use of a class label.

Different learning approaches, often discriminative, that fine-tune the weights together to improve the network performance in classification tasks are used in addition to pre-training. After that, variables reflecting the outputs from the training data are introduced to further fine-tune the performance and accuracy of the discriminative model.

The back-propagation fine-tunes the weights of a feed-forward neural network. What appears in the top layer is determined in this case. HMM-based speech recognition systems employ the top layer, shown in Figure 3 by the letters l1, l2,… lj, lL, to represent syllables, phone calls, subphones, or other speech units, while the lower layers represent additional speech units.

Phone and speech detection were among the tasks on which the generative pretraining described above outperformed random initialization across a broad range of tasks. In addition, the order in which minibatches are formed must be carefully studied prior to being implemented. As a result, it was determined that starting with a simple neural network with one hidden layer and working your way up was the most successful way to learn the DNN. Once the necessary number of hidden layers has been achieved, a complete backpropagation fine tuning procedure is carried out. Using this pretraining strategy has been proven to be effective on the battlefield.

3.3. Dust Estimation Unit. After the model selection with the lowest root mean square error (RMSE), this regression model is extracted. The temperature, output power, and solar irradiance are fed into the system, and it can anticipate the amount of dust that will build up on the solar panel in the future. Those in charge of operating solar photovoltaic systems rely on precise dust estimates to decide the optimal time to clean the modules. When the dust level on solar PV panels surpasses a specified threshold, the amount of energy produced by the system can be considerably reduced. As a result, as soon as the level of dust collection exceeds this threshold, cleaning activities can commence. Solar photovoltaic modules should be cleaned at the most opportune time of year to save on the extra costs associated with cleaning solar photovoltaic modules on a regular basis. In the final stage, a new data set is used to test the dust estimation unit, which helps to minimise bias and evaluate accurately the performance by evaluating its accuracy.

4. Results and Discussions

It has already been stated that a large amount of data is required for both training and testing the model. Using a solar photovoltaic panel in the open air under realistic environmental circumstances, experiments were conducted to determine its performance. Researchers have looked into the impact of dust on the performance of photovoltaic panels in these types of environments. The scientists began by setting up a 400-watt solar photovoltaic panel as a test bed for their experiments.

The dust that was used in the experiment was collected from the same location where the experiment was conducted. The output power of the solar PV panel was tested under a variety of conditions, including different times of the day, varying degrees of solar irradiation, different temperatures, and different dust concentrations. For this experiment, the RS PRO Solar Power Meter ISM400 was utilised to measure solar irradiance.

Table 1: Accuracy.

Panels	ANN	BPNN	Proposed
Series parallel	0.94209	0.94432	0.95687
Parallel	0.94198	0.94357	0.95683
Bridge link	0.94117	0.94355	0.95677
Honeycomb	0.94088	0.94285	0.95664
Total cross tied	0.93368	0.94280	0.95641

Table 2: Precision.

Panels	ANN	BPNN	Proposed
Series parallel	0.87254	0.87307	0.89406
Parallel	0.85895	0.86283	0.89200
Bridge link	0.85859	0.86281	0.88695
Honeycomb	0.83920	0.84169	0.88624
Total cross tied	0.83801	0.84148	0.87110

Table 3: Recall.

Panels	ANN	BPNN	Proposed
Series parallel	0.78337	0.83903	0.94382
Parallel	0.83004	0.84054	0.94434
Bridge link	0.83978	0.84067	0.95362
Honeycomb	0.85972	0.85202	0.95580
Total cross tied	0.86925	0.90605	0.95641

Table 4: F-measure.

Panels	ANN	BPNN	Proposed
Series parallel	0.95449	0.90118	0.94118
Parallel	0.95174	0.89384	0.93457
Bridge link	0.94593	0.89250	0.93276
Honeycomb	0.93495	0.88444	0.93180
Total cross tied	0.86860	0.88444	0.89673

Table 5: MAPE.

Panels	ANN	BPNN	Proposed
Series parallel	0.08574	0.01366	0.00311
Parallel	0.18026	0.02100	0.00201
Bridge link	0.20701	0.02234	0.00192
Honeycomb	0.24857	0.04624	0.00304
Total cross tied	0.23473	0.04091	0.00304

Table 1 shows the results of accuracy between the proposed model and existing machine learning models. The results of simulation on various PV panels show that the proposed model achieves higher accuracy rate with its efficient computation.

Table 2 shows the results of precision between the proposed model and existing machine learning models. The results of simulation on various PV panels show that the proposed model achieves higher precision rate with its efficient computation.

Table 3 shows the results of recall between the proposed model and existing machine learning models. The results of simulation on various PV panels show that the proposed model achieves higher recall rate with its efficient computation.

Table 4 shows the results of F-measure between the proposed model and existing machine learning models. The results of simulation on various PV panels show that the proposed model achieves higher F-measure rate with its efficient computation.

Table 5 shows the results of MAPE between the proposed model and existing machine learning models. The results of simulation on various PV panels show that the proposed model achieves reduced MAPE with its efficient computation.

5. Conclusions

In this paper, deep belief network model is used to detect the dust particles in the solar panels installed as a large unit. The study takes into account various input metrics that includes solar irradiance, temperature level, and dust level on the panels. These metrics are used for the estimation of the level of dust present in the atmosphere and how often the panels can be cleaned at regular intervals. The simulation is conducted to test the efficacy of the model in cleaning the panels. The results are estimated in terms of accuracy, precision, recall, and F-measure. The results of the simulation show that the proposed model achieves higher accuracy rate than other methods. In the future, deep learning models can be used to improve the rate of accuracy.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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