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An Artificial Intelligence and Machine Learning Model to Estimate the Cleaning Periodicity for Dusty Solar Photovoltaic (PV) Modules in A Composite Environment

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Abstract

Solar energy is harnessed on a considerable scale nowadays. By 2030, the solar power output is expected to increase to 2500 GW marginally. High cell temperatures and soiling significantly affect the performance of solar photovoltaic systems. This study clarifies the effect of dust deposition on the transmission and output power of photovoltaic modules. The analytical and machine-learning models were developed to analyze the effects of soil deposition on the photovoltaic panels. The field data were used to train and test the algorithm for developing the machine-learning model. An optimum cleaning and maintenance schedule is then proposed based on the site's environmental conditions. The novelty of the research was to gather environmental parameters in real-time conditions that affect the soiling rate of photovoltaic panels, further affecting the conversion efficiency of photovoltaic panels. Based on the theoretical model developed, the cleaning frequency of the module was observed to be 18 days, considering 5% power loss and dust density accumulation of $2 g/m^2$. A random forest model was developed considering ambient temperature, solar irradiance, relative humidity, wind speed, dust concentration, and energy generated. The predicted cleaning frequency is observed to be 25 days using the random forest model.

Keywords: *Machine learning, Dust, Solar panel, Soiling, Reliability*

1.0 Introduction

Solar energy is becoming increasingly popular as a clean and sustainable alternative to traditional fossil fuels. As the world becomes more aware of the impact of climate change and the need to reduce carbon emissions, future energy sources will increasingly depend on solar energy. Since the early 2000s, exponential growth has been observed in the usage of PV modules, and its markets have developed tremendously during this time. Solar energy is clean, free, inconsumable, abundant, and a safe energy source. The dependence on solar power will boom in the upcoming years due to rising energy demands and environmental issues.

In recent years, installed solar energy capacity has increased from 627 GW in 2020 to 843.09 GW, with India having 49.34 GW of solar energy capacity. As there is a steady increase in the contribution of photovoltaic

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power, there are various studies carried out to increase the efficiency of photovoltaic materials. In a day, solar panels face variations in temperature, irradiance, relative humidity, partial shading, etc. These variations in factors cause fluctuation in the panel's conversion efficiency, resulting in insufficient power generation and malfunctioning components of solar panels.

Conversion efficiency refers to the power generated by the amount of solar energy falling on the photovoltaic panels. The conversion energy of photovoltaic (PV) panels varies due to variations in solar irradiance, temperature, wind speed, and various PV faults. PV systems are vulnerable to common faults, decreasing their performance and operating life. Early detection and diagnosis of faults are crucial to avoid the breakdown of the PV system. These faults can be classified based on whether they occur on the DC or AC side. Additionally, DC side faults are related to the panels and the environmental factors causing them, whereas AC side faults are related to the electrical circuit.

Amongst all the occurring faults, dust deposition, referred to as soiling, is studied thoroughly in this work. Soiling can significantly decrease the conversion performance of PV systems. Different grain particles can reduce the power output of a solar PV system. Further, literature studies do not consider real-time environmental factors, and reliable solutions are insufficient.

2.0 Literature Review

Photovoltaic systems are prone to various electrical and environmental faults. However, soiling is one such environmental fault that requires constant attention as it is a recurring process. Studies concerning the effect of dust accumulation on PV panels emphasize the need to find measures to mitigate the impact of soiling and optimize the overall performance of the PV system. This research will contribute to reducing the operational costs of PV projects and maximize the power generated. Dust deposition can be attributed to several factors. Dust deposition can be particularly high in arid regions, where rainfall is scarce and vegetation cover is low. PV panels located near sources of pollution, such as factories and power plants, may experience higher levels of dust deposition due to the presence of airborne particles. In addition, construction sites, unpaved roads, and mining activities can generate significant amounts of dust that can settle on nearby PV panels. Weather conditions, such as high winds and dry weather, can increase the amount of dust in the air and lead to higher levels of dust deposition. PV systems degrade over time if they are not cleaned periodically. The dust deposited in layers makes it difficult for the sun's rays to fall on the solar cells; this results in lower power generation and efficiency. According to literature reviews, the unclean panel's power output decreased by 9% after 55 days. Some dust particles that are deposited on the surface cause PV cells to suffer permanent damage. The short circuit current decreases by a greater percentage than the open circuit voltage as deposition accumulates over time[1].

When dust deposition on solar photovoltaic panels was analysed, it was discovered that the recorded daily dust deposition densities ranged from 7.5 to 42.1 mg/m^2, while the measured weekly dust deposition densities ranged from 25.8 to 277.0 mg/m^2. The amount of precipitation and humidity had a big impact on the dust that was left behind. Dust deposition was also controlled by additional forces, such as electrostatic forces[2]. Accumulated dust on solar photovoltaic panels significantly affects solar irradiance and temperature. This effect is studied experimentally by depositing soil with different gravimetric densities. According to the study's findings regarding particle size, dust with small particles reduced PV performance more than dust with large particles did. Additionally, the presence of grained particles caused abrasions on the glass surface itself or on anti-reflective coatings, which increased the opacity of the glass surface. This mineral has a difference in light absorption and reflection, which can cause a difference in the performance of photovoltaic modules contaminated with this dust[3]. The impact of dust accumulation on flat glass transmittance, anti-reflective coated glass spectrum transmittance, and the physical and chemical characteristics of dust are studied. The findings showed a 20% overall transmittance decrease and a 35% decrease in spectral transmittance. Additionally, dust deposition was seen after 45 days of 5g/m^2 outdoor exposure. Due to the increasing contact area between the particle and the surface, the adhesive forces of particles considerably increased as the particle size grew. The chemical composition of dust saw an increased percentage of oxygen followed by calcium and silicon (60%) of dust particles. It was also concluded that increased inclination resulted in reduced dust deposition and transmittance reduction[4].

A new method was developed for calculating dust accumulation of photovoltaic modules and estimating module maintenance frequency in desert areas. The results estimate the cleaning frequency decreased to 20 days when there was an increase in representative average diameter up to 20μm and increased to 78.2 days when there was an increase in inclined angle up to 75 degrees. Additionally, for 2 g/m^2 of accumulated dust density, the cleaning standard was a 5% reduction in power[5]. A research study shows the electrical performance characteristics in natural conditions with the help of a novel concept – The photovoltaic soiling index. The observed results were reported in comparison with a clean reference PV Panel. In comparison to the output voltage and current of the reference PV panel, the output voltage was reduced by about 39% and the average output current by about 45%, respectively. The overall wattage capacity was, on average, 65% less than the standard PV panel. To compare performance, the dust collection was conducted for three months, and the reference PV panel was cleaned daily[6]. The effect of performance on solar power output was studied, and it was revealed that dust storms significantly reduce power output by almost 20%. More than a 50% decrease is observed in power output if the system is not cleaned for over six months. A Cleaning schedule was proposed, which recommended cleaning of PV panels -at least once every two weeks. The review focused on different cleaning schedules for different environmental conditions. In case of sandstorms, it should be cleaned immediately. It was also observed that solar trackers enhance power output and reduce the dust effect by 50%.

While comparing different PV modules, it was reportedly observed that polycrystalline modules with a solar tracker had higher backside temperatures as compared to monocrystalline modules[7]. The results of test data analysis showed that the temperature of dust-coated PV modules is always lower than that of clean modules, both under no-load and load situations, and that the temperature of dust-coated PV modules drops with an increase in dust density. The relative transmittance rate decreased (80%) logarithmically, and relative output power decreased linearly with increasing dust deposition density[8]. Seven months of dust deposition on panels in Palestine resulted in a power reduction of 9.99% and an average power reduction of 2.93% per month[9]. Computational Fluid Dynamics (CFD) analysis was conducted for ground-mounted solar panels to study the airflow and dust deposition behavior. It showed that at a wind speed of 2 m/s and a particle diameter of 150 μm, the dolomite dust material experiences a maximum percentage of deposition rate equal to 10.8% [10]. Fault detection in solar PV systems is challenging, so some authors have suggested using artificial intelligence techniques. The authors advise focusing more on data-gathering activities that can hasten the adoption of AI techniques in the power and energy sectors. Additionally, utilizing AI techniques can simplify the maintenance task[11]. With the use of special algorithms for diagnosing PV defects, such as Multilayer Perceptron's and Probabilistic Neural Networks, numerous errors that can arise in PV systems have been examined. Even with a noisy dataset, the results showed that the Multilayer Perceptron neural network had greater precision. The results demonstrated a maximum accuracy of 100% for identifying disconnected strings and 99.1% for identifying short-circuited modules[12]. After seven (07) months of monitoring, a 270 W monocrystalline PV module's performance study was conducted using a Support Vector Machine (SVM) as a classification and analysis approach. This study demonstrates the value of SVM classification and Artificial intelligence in handling databases for photovoltaic system monitoring[13].

Previously conducted research related to the dust deposition effect on solar panels is mainly based on the development of analytical models or actual experimentation. Very few researchers have focused on the dust study using Artificial intelligence techniques or real data. So, in this research work, the influence of dirt accumulation on solar panel energy performance is studied. An analytical model is developed by considering the dust concentration and power loss irrespective of the environmental parameters. Further, the Artificial Intelligence and Machine Learning (AIML) model is developed considering environmental parameters and real data collected from an education institute in Pune. A dust fouling review conducted put forth an estimated cleaning periodicity. The relationship between Net energy delivered (GWh/year) and cleaning periodicity (days) was derived. A variation of optimum cleaning periodicity was observed with percentage energy loss annually.

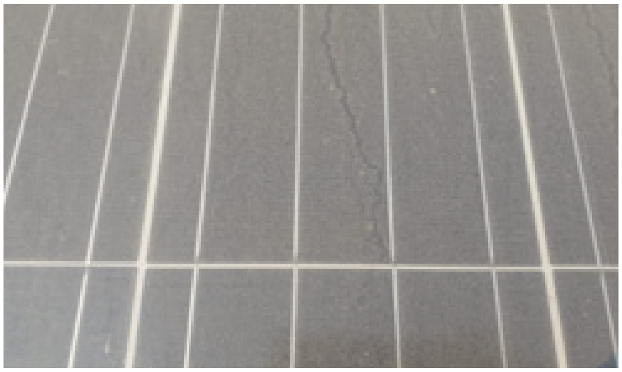
3.0 Soiling Effect on Solar PV System

The performance of the system can be greatly impacted by soiling, which is the buildup of dirt, dust, pollen, and other particles on the surface of solar PV panels. The system's power output is decreased by soiling because less sunlight reaches the solar cells. Actual accumulated dust on the solar panel is shown in Figure 1.

The effect of soiling on a solar PV system depends on several factors, including the type and amount of debris that accumulates on the panels, the panels' orientation and tilt angle, and the installation site's location and climate. Dust collection on the surface of solar PV panels can significantly reduce the power output of a solar power system. This causes dust particles to block and scatter incoming sunlight, reducing the amount of light that reaches the solar cells. The amount of power output loss due to increased dust on the panels is affected by several factors, including the type and amount of dust, the panels' orientation and tilt angle, and the installation site's location and climate. Solar PV systems installed in arid or dusty environments are generally more prone to dust accumulation and experience greater power output loss due to dust. This poses a major concern as dirty solar panels can lead to decreased energy production, increased operating costs, and reduced return on investment for solar power projects.

From extensive literature studies, it has been observed that even a thin layer of dust on the surface of solar PV panels can reduce the power output of the system by up to 5%, while thicker layers of dust can cause even greater reductions in power output. Additionally, dust accumulation can cause hotspots on the surface of the panels, which can lead to permanent damage if not addressed. In the analysis conducted, around 4.4% of energy losses were due to accumulated dust on the surface of photovoltaic modules, and in periods without rain, the daily energy losses were reported to be higher than 20%[14]. In addition, a 50% reduction was observed in PV power output after six months of outdoor exposure in Dhahran–KSA. At the same time, a ten percent reduction in PV module efficiency was observed after a hundred days of outdoor exposure testing in Qatar[15].

To better understand these factors and how they affect the performance of solar PV systems in different environments, research is needed in this field. However, studies regarding this problem are quite limited. There is a need for research to identify effective and efficient methods for cleaning solar panels and minimizing the impact of soiling on solar power output. This includes developing optimal cleaning schedules with the help of Artificial Intelligence and Machine learning techniques. Overall, soiling is an essential area for research because improving the performance and reliability of solar PV systems is crucial to advancing the adoption of solar energy as a sustainable and cost-effective source of electricity. By better understanding the impacts of soiling and developing effective mitigation strategies, research



(a)

(b)

Figure 1. (a) Close view of dusty solar panel (b) Dusty solar panels.

can help to increase the power output and economic viability of solar PV systems.

4.0 Site Details

The setup is installed at 18.6517° N, 73.7616° E in Pune, as shown in Figure 2. Pune is a city in Maharashtra, India, with over 4 million people residing in the city. It serves as a commercial, industrial, and residential sector, which results in dust-generating activities around the city. The location where the setup is installed has a bus stand, railway station, and a main road nearby, along with construction around the area collectively contributing to the dust generation. All these activities result in particulate matter that can settle on the surface of the solar panel. Construction sites result in dust, debris, and other airborne particles that can affect the surface of the panels. Pune has a semi-arid climate bordering a tropical wet climate and

Figure 2. Installed 100 kW capacity grid connected polycrystalline PV system.

average temperatures ranging from 19^0 C to 33^0 C. The city has three seasons and experiences heavy dust winds during May. March to May are the warmest months, July to September are the wettest, and December to January are the coldest. The setup is installed approximately 30 m above the ground. The research study is conducted on Polycrystalline PV systems; detailed specification is given in Table 1. The setup comprises 100kW capacity polycrystalline silicon modules connected to the compatible inverter. Polycrystalline panels have a lower efficiency than monocrystalline panels but are still popular for homeowners and businesses looking to switch to solar energy. They are also more environmentally friendly than traditional fossil fuel energy sources.

Table 1. Specification of PV panel

Capacity in (kW)	100 kW
Total Sanctioned load (in kW)	300 kW
Nos of Modules (in nos)	300
Type Of Solar Module	Polycrystalline
Module Efficiency	18%
Latitude, Longitude	Latitude: 18°38'N, Longitude: 73°45'E
DC Voltage and current DCDB	100kW-V_{dc}-1000 volts, I_{dc} - 6*36 amp 50KW - 1000 volts, I_{dc} - 3*36 amp
AC Voltage and current at Inverter	100kW - 400 volts, 145 amp 50kW - 400 volts, 80 amp
Input Voltage	58–850V DC Nominal
Output Voltage	230V_{AC}/400V_{AC}, 50Hz
Efficiency	80% at 50% of load and more than 90% at full load

5.0 Theoretical Model

The theoretical model proposed is based on the literature review carried out, focusing more on the alignment of the end goals of this theoretical model, which in turn is to get reliable cleaning periodicity[16]. The model is validated using the parameters of the experimental site and considering 5% power loss criteria due to dust density accumulation of 2g/m^2. Power loss and dust density criteria were decided based on the conclusions drawn from a thorough literature survey. The cleaning timing of PV modules is concluded based on various parameters. Surface friction velocity, which represents the magnitude of the friction stress caused by the airflow on the surface, is a function of deposition velocity in the usual formulations. Surface Friction Velocity,

$f^* = \sqrt{s/u}$

u = air velocity,

Also, Wall shear stress,

s= ½×S_f×u× v^2 (2)

Where, S_f = skin friction parameter

v= free stream velocity = local wind velocity

Skin friction parameter,

$S_f=0.592R_{ex}^{-1/5}$ (3)

Where, R_{ex} = local air Reynolds number

The speed of particle deposition, D_v is based upon calculated friction velocity from the below equations,

$D_v=(5.15\times10^{-8}\times f^*\text{-}5.63^{-1})\ d_p^{-1.263}\ d_p<0.0512\ (f^*)^{0.427}$ (4)

$D_v=3.7\times10^{-5}\times d_p^{1.9143}(\cos\theta)\ d_p>0.3577(\cos\theta)^{-0.41}, \cos\theta>0$ (5)

$=0\ d_p\ >g(f^*, \cos\theta), \cos\theta \le 0$ (6)

$=f\ (f^*, \cos\theta, d_p)$ for others (7)

The third element of this equation can be insignificant due to the installed PV modules' tilt angle, which is less than 90 degrees, in this investigation. The cleaning time (T) can be estimated by[16]

$T = P_d\ \times A/A\ \times C_D \times D_v$ (8)

$T=P_d/(C_D\times D_v)$ (9)

where, P_d = particle accumulation density for specific power loss,

C_D = ambient air's particle mass concentration

D_v = particle deposition velocity

This calculation is based on the dust and wind conditions of the site under study. The above theoretical model is being validated using the real-time parameters of the site.

PV module has accumulated dust which ranges between 0.4 and 400μm, with the maximum number of particles to be 20μm,

Therefore, d_p= 20μm, θ = 18.64

Here θ = Tilt angle of panel = Latitude of the site

Hence, particle deposition velocity, using (5)

$D_v = 3.7\times10^{-5}\times d_p^{1.9143}\ (\cos\theta)$

where $d_p>0.3577(\cos\theta)^{-0.41}, \cos\theta >0$

$D_v = 0.01084$

C_D = ambient air's particle mass concentration = Average PM10 concentration of location from 2022-2023 = 122.31μg/m^3

Based on the literature data, the cleaning criterion to be a 5% reduction in power output is equivalent to the accumulation of 2g/m^2 dust is considered.

$T= P_d/(C_D\times D_v)$

=18 days

Based on the calculations, the PV module's cleaning time must be 18 days according to the criteria set. The model is based on the published work and has been developed with an assumption of 2g/m^2 dust density accumulation, which might vary.

6.0 Machine Learning Model for PV Panel Cleaning Frequency

Various input parameters and target variables are finalized to develop a machine-learning model. Also, multiple algorithms are tested to check which gives the maximum accuracy regardless of noise and irregularities in datasets. These input parameters are manipulated and decided based on their influence on the target variable, according to the study of Kara Mostefa Khelil *et al*. Probabilistic Neural Network is the best-suited algorithm with a response time of 30 seconds and a high value of statistical concepts like accuracy, sensitivity, and precision compared to others[13].

But for the input parameters like solar irradiance, ambient temperature, and power at Maximum Power Point (MPPT), multilayer perceptron neural networks have shown much more suitability with higher accuracy than probabilistic neural networks[17]. Different algorithms show variations in accuracy for the detection of solar PV faults. The studies conducted in Morocco suggest that by using Artificial Neural Networks (ANN) with 80% training data, 10% validation data, and 10% testing data, we can estimate the soiling rate on solar photovoltaic panels. An Artificial neural network model was developed to estimate the soiling rate considering the environmental parameters relative humidity, wind speed, direction, sun irradiation, temperature, and precipitation with decreasing sensitivity index[18].

The study focuses on comparing results between other machine learning models. The random forest regression model is the most appropriate, as the desire to complete

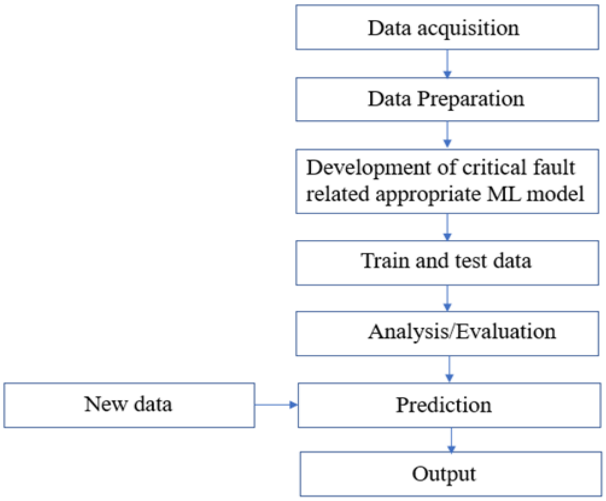


Figure 3. Block diagram of AIML methodology.

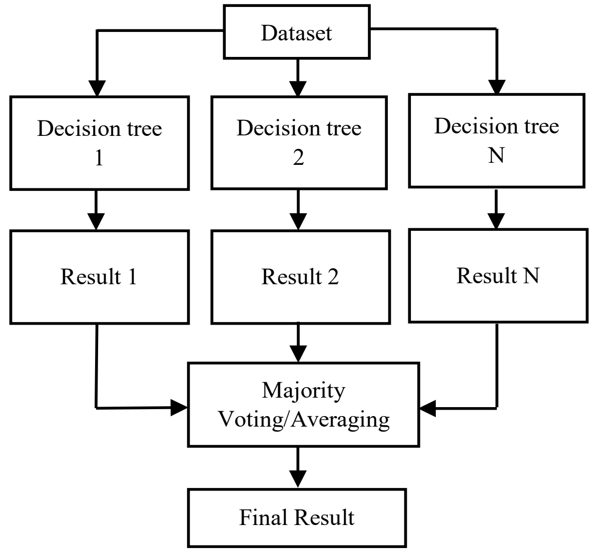


Figure 4. Schematic diagram of the random forest model.

increases by only 3-4% (depending on the data used) at the start of the Solar Radiation (SR) prediction. RF algorithms perform very well from the start without leveraging hyperparameters or custom data. It shows an accuracy of 89.30%[19].

So, the literature shows that the most used Artificial neural network family is the Multilayer perceptron neural network (MLP); along with other algorithms mentioned, the random forest has shown good accuracy when dealing with variable data. An AIML model using other algorithms was also developed to prove the accuracy of random forests. Comparisons of different models and their accuracy details are given in Table 3. Concerning the literature studied and model developed, the algorithm that has been considered for further evaluation is Random Forest. According to the proposed methodology, the models will be trained, tested, and validated to form a comparative analysis that can help finalize a model best suited for the data collected. Based on the literature data, the proposed methodology follows the path mentioned in Figure 3.

The real-time data collected from the experimental setup is further processed to remove unwanted and redundant noise in the dataset, which can cause outliers or inaccuracies in the output of the machine learning model. The processed dataset is then divided into training and testing data based on which the algorithms will be trained, and parameters affecting the target variables will be considered to build a suitable training model. During training, the machine learning model is given a large amount of input data, which would help discover patterns in data. Once this process is completed, the training model is tested with the help of another unseen subset known as the testing data. The testing dataset will help in understanding the progress of the training model, which in turn will help optimize and improve the model's accuracy. A comparative analysis of the training models of various algorithms is tested, and based on the accuracies and efficiencies the model provides; a suitable AIML model will be selected that best suits the requirements and parameters of the data collected during the field test. The results obtained after running the models on cross-validation data will check which set of hyperparameters gives us the best results for different combinations of hyperparameters. Those sets of hyper-parameters will be chosen for the final model. After the validation process, the final performance of the proposed algorithm will be tested on new or unknown PV module faults to see how well the model can detect the soiling effect. Once the model is tested, evaluated, and validated, the model with the highest accuracy and efficiency is selected as the final machine learning model. This model will be implemented to develop a strong relationship between dust deposition and variation in generated power.

Table 2. Comparison of algorithms with their R^2 scores

Sr. No	Algorithms tested	R^2 value
01	Random Forest Regression	0.7086
02	Support Vector Regression	-0.0754
03	Sequential Neural Network	0.4585
04	Linear Regression	0.3320
05	Decision Tree Regression	0.4010

In the present work, an effort has been made to develop an Artificial Intelligence and Machine learning model utilizing the data obtained from the Educational Institute, Pune, India, to predict the panel cleaning frequency in composite climate. This model can generate a relationship between the PV module energy output and the major environmental parameters like solar irradiance, relative humidity, wind speed, and ambient temperature. The process of applying machine learning to a dataset to predict unknown values includes three general steps: data before feature extraction, training the predictive model, and monitoring the training dataset's accuracy and pre-measurement training model of test data. First, the obtained data is pre-processed to be well organized and free of anomalies such as missing outliers and incorrect data values. Most significantly, relevant attributes were elicited. For developing the model, the input features considered are ambient temperature, Solar irradiance (GHI), Relative Humidity, wind Speed, dust Concentration (PM10), and energy generated. Dust concentration is taken from the AQI site for the year from January 2022 to January 2023. Month-wise energy generation of the photovoltaic System from January 2022 to January 2023 is considered for the model as shown in Figure 5. The graph represents the energy generated by solar PV panels month-wise for one year.

Environmental factors will influence the energy output of the PV system. The development of this model aims to understand the variation and optimize the energy output by suggesting optimal cleaning periodicity for the real-time conditions of the solar photovoltaic system. Random Forest Regressor model is used to train models as it shows good performance in the case of predicting cleaning frequency as compared to other algorithms. Schematic diagram of the random forest model is shown in Figure 4. A comparison of different algorithms used with their R^2 scores is given in Table 2. This algorithm is based on trees, so the scaling of the variables does not count. Any change of a single variable is implicitly captured by a tree. Random forest builds multiple decision trees on arbitrary samples of the data. This technique helps to reduce the variance and avoid overfitting. The test samples are typically taken with replacement, which is known as bootstrapping.

The code for the Random Forest Regression model is implemented in Python. The data is split into training and testing sets considering 80% and 20%. The Random Forest model is created and then trained on the training. After training the model, it is used to predict the cleaning frequency on the test set. The performance of the model is evaluated using the R-squared score. Finally, the user is prompted to enter new environmental data, which is used to predict the cleaning frequency using the trained model. The predicted cleaning frequency is 25 days using the Random Forest model.

Irradiance refers to the power per unit area received from electromagnetic radiation, typically sunlight, on a surface. It represents the amount of solar energy that is incident in a particular location over a given period. Variation of Global horizontal irradiance from Jan 2022

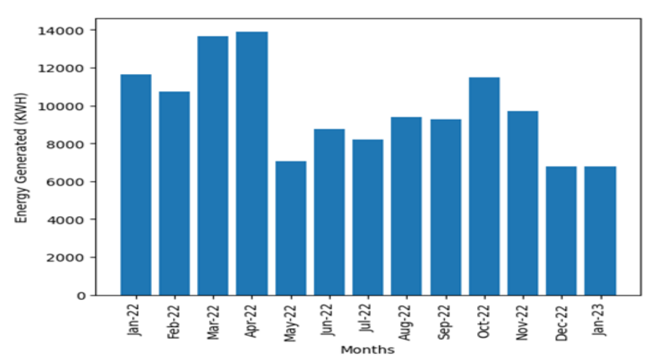


Figure 5. Month-wise energy generation.

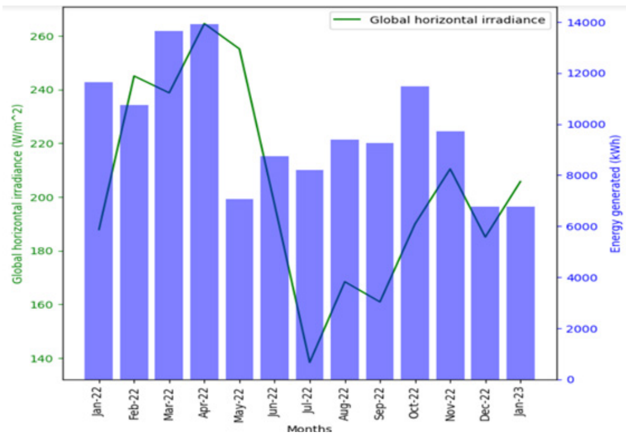


Figure 6. Month-wise energy vs. global horizontal irradiance.

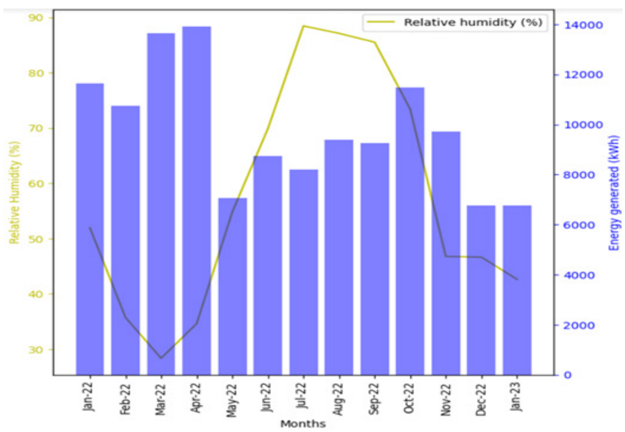


Figure 7. Month-wise energy vs. relative humidity.

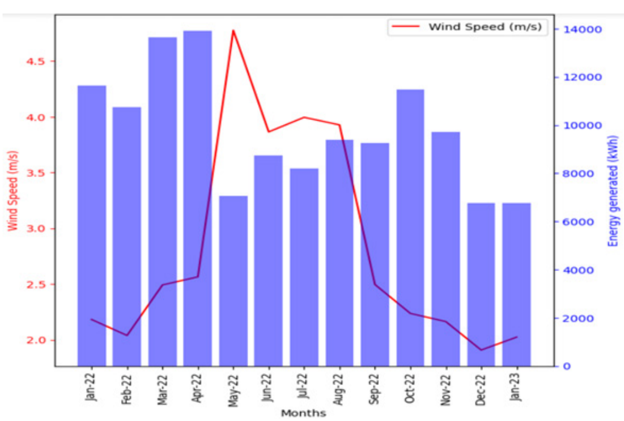


Figure 8. Month-wise energy vs. wind speed.

to Jan 2023 for the mentioned site is shown in Figure 6. The graph shows that there is a big fluctuation in irradiance.

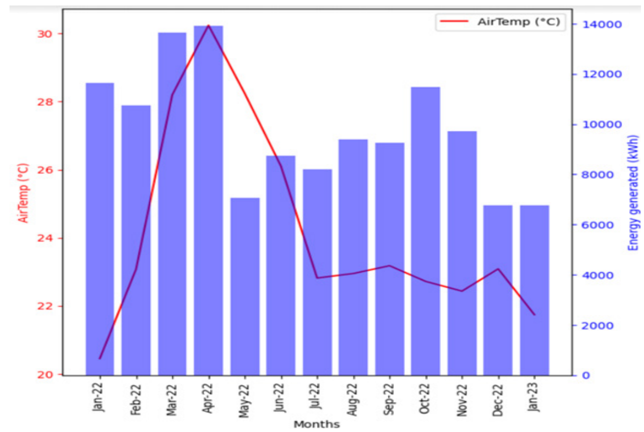


Figure 9. Month-wise energy vs. ambient temperature.

Relative humidity measures the amount of water vapor in the air relative to the amount of water vapor the air can hold at that temperature. High humidity during the rainy season reduces power generation whereas summer and winter have relatively higher power generated due to the low relative humidity. Relative humidity can affect energy generation by causing light to scatter and affect heat mitigation from the panels. The graph in Figure 7 shows higher relative humidity from June to September and starts decreasing.

Wind speed significantly affects the power generated by solar PV systems. Higher wind speeds (storms) can result in dust deposition on the surface of the PV panel. Moderate wind speeds improve panel efficiency, help in cooling the panel temperature, and can remove larger dust particles from the panel's surface. The monsoon season has high wind speeds and other climatic factors showing less energy generation. Summers show moderate wind speeds, and hence, the energy generated is maximum. Winter shows slightly less energy generation. The variation of wind speed for Jan 2022 to Jan 2023 is shown in Figure 8.

Temperature can affect the efficiency of solar PV systems and the output energy generated. In summer, the temperatures are high, but due to the location, the effects are mitigated, thereby providing good efficiency. Lower temperatures lead to lower voltages, whereas higher temperatures lead to higher voltages. The ambient temperature change is shown in Figure 9. Major temperature variation is observed after April 2022, as shown in Figure 9.

7.0 Results and Conclusion

Solar radiations are deflected due to dust accumulation, resulting in a decrease in solar irradiance. For the photovoltaic system studied here, the approximate cleaning time was calculated as 18 days, with criteria of 5% power loss due to dust density accumulation of 2g/m^2 using a theoretical model. With the help of a machine learning model developed using a random forest algorithm, the cleaning frequency of panels using real-time data is predicted. Parameters like dust accumulation, solar irradiance, relative humidity, Air temperature, wind speed, and the energy generated are used to predict the cleaning frequency. The machine learning model developed predicted the cleaning frequency of panels as 25 days, meaning panels should be cleaned after every 25 days. It is observed from the analytical model and AIML model that the optimum cleaning frequency for the educational institute site studied here should be 21-25 days. This model can be used for any site by changing the input parameters.

8.0 Scope of Future Work

This work has considered an analytical model referred from literature without considering weather conditions, so further models may also be developed considering environmental factors. Further, this study can be extended for different types of dust samples and various solar PV systems. Additionally, there is scope to study dust accumulation in other climate conditions.

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