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ANN–IoT Enabled Predictive Framework for Performance Assessment and Maintenance Scheduling in Floating Solar Photovoltaic (FSPV) Systems

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Abstract

With the rise of solar Photo-Voltaic (PV) energy, the need for optimized land usage and enhanced energy yield has drawn significant attention. Although the solar industry is highly developed and extensively researched, conventional PV installations require large land areas. To address this challenge, Floating Solar Photo-Voltaic (FSPV) systems have emerged in recent years as a promising solution, as they substantially reduce land requirements. While FSPV systems are installed on water surfaces and are often assumed to experience lower dust exposure, airborne particulates resulting from high pollution levels, nearby agricultural activity, and regional atmospheric conditions still lead to measurable soiling losses. The present research utilizes an Internet of Things (IoT) and Artificial Neural Network (ANN)-based predictive architecture, originally developed for land-based PV modules, and successfully generalizes it for FSPV systems. The real time data from ACME Solar power plant database of PAVAGADA AC-50MW and DC-67.46MW with latitude-14.260099ºN/longitude-77.471534ºE of site are taken in account to create the prediction model. was conducted to adapt and validate the model. The results demonstrate notable improvements, with annual energy yield increasing by 8–15% and cleaning costs reduced by 30–40%.

Keywords: Floating Solar PV, Artificial Neural Networks, Internet of Things, Aquaculture Integration, Biofouling Prediction, Performance Degradation, Smart Agriculture

Introduction

Today's global world of photovoltaic technology has seen significant changes owing to environmental conditions, sustainable development challenges, increasing fossil fuel costs, and the growing demand for energy. Solar photovoltaic cells have also experienced a substantial rise in deployment and interest [1], [2]. As of the reported installed PV capacity it has been projected that this industry will continue to undergo exponential growth through 2050.

Floating solar photovoltaic cells represent a very promising solution because of their reduced land usage. Their deployment not only addresses land-use limitations but has also shown encouraging performance outcomes. PV modules have been installed on reservoirs, lakes, and aquaculture ponds, yielding positive results [3]. The global market for FSPV has grown considerably, increasing from virtually zero in 2010 to nearly 5 MW by 2023, with China leading this development, followed by Japan, South Korea, India, and the United States [3].

Despite their placement on water, FSPV installations still experience dust deposition, which remains a key factor affecting performance. Wind-borne particles resulting from agricultural activities and regional atmospheric conditions contribute significantly to this issue [4], [5]. Numerous case studies have reported that soiling is a crucial challenge in floating installations located near agricultural or dust-prone areas, indicating the need for further attention and research in this direction.

Dust is an imperative parameter that attenuates solar irradiance incident on the PV modules and out-turns low optimum yield in terms of Power Conversion Efficiency (PCE) of the module. Various sources viz. pollution, vehicular movement, environment, results in dust accumulation on the top-region of FSPV with course of time. Typically, the diameter of accumulated dust particles is < 10μm (diameter) in most cases, although this size can vary with particular area and environment. J Chen. et al. [6] stated that during the dry season, after one week of exposure, the dust accumulation reaches 0.644 g/m^2, resulting in a 7.4% reduction in PV output power. H Wang et al.[7] stated that PV module performance will be greatly impacted by the accumulating effect of particulate pollution on both the reduction of solar radiation and the lowering of efficiency. The research work on impact of dust on solar modules is also reported by E. Roumpakias [8]. In 2014, Darwish et al. [9] investigated how the type of dust pollution affected photovoltaics. Following a review of fifteen different forms of dust, they concluded that sand, silica, soil, ash, calcium, and limestone had a greater impact on photovoltaic cells. The thickness of dust has a direct impact on the module and is calculated with the help of linear regression [8]. Badarpur sand with varying types, fly-ash, rice-husk, brick powder, chalk powder and sand are the 6 different forms of dust used to clear the fact that with decrease in particle size, solar panels' power is significantly reduced [9]. In 2017, Abderrezek et al.[10] examined how dust affected the electrical and thermal performance of solar panels, discovering that experiments conducted both indoors and outdoors resulted in efficiency decreases of 17.76% and 9.92%, respectively. Paudyal and team reported 29.76% efficiency drop in a dusty module w.r.t. cleaned module [11].

Regular cleaning can have a negative impact on the solar panel, natural methods are unreliable, and mechanical methods run the risk of damaging FSPV. The installations of FSPV are expensive, for this reason, replacement is not recommended. Furthermore, it is not practically possible to clean solar panels installed in sophisticated locations frequently, nor is it feasible to clean PV modules connected to the grid. Evidently, the dust cleaning model of the solar PVC module needs a more robust approach. The present study aims to develop an artificial neural network (ANN)-based Internet of Things (IoT) prediction model using real-time cleaning data and projected output efficiency statistics as per PVSYST v6.74. Solar plant generating schedule forecasting is necessary to estimate its outputs on a daily/weekly/monthly basis in advance, which may validate reliable functioning. The output reliance of solar plants is exposed to myriad parameters and deep study on the PV plant forecasting model has turned into a great concern. Frequent manual cleaning of PV systems is impractical, expensive, and may cause abrasive damage to PV glass surfaces. Mechanical and robotic cleaning solutions are not always feasible for large, remote, or floating installations. Therefore, determining the optimal cleaning time—rather than cleaning at fixed intervals—is crucial for maximizing plant efficiency while minimizing operational costs and avoiding unnecessary wear [12-17]. A review by Chawla et al. further stresses that intelligent monitoring and predictive dust-cleaning mechanisms are essential to sustain long-term PV performance [12].

The past research work focuses on the effectiveness of Artificial Neural Networks (ANNs) in modeling nonlinear relationships between dust accumulation, environmental conditions, and PV performance [18]. When integrated with an Internet of Things (IoT) sensor network, ANN-based systems can continuously analyze real-time irradiance, particulate concentration (PM10/PM2.5), temperature, humidity, and electrical parameters to estimate dust-induced degradation and trigger optimal cleaning alerts [19]–[21].

In the proposed work, the experimental data of Pavagada Solar Park is used which covers an area of 53 square kilometers, Tumkur, Karnataka India 14.25°N 77.45°E . This park produces 2,050 MW of power. It is the world's second largest photovoltaic power station. As of 9 April 2019, the total commissioned capacity of Pavagada Solar Park was 1,400 MW, with a total anticipated capacity of 2,050 MW by December 2019 [22], including an additional 450 MW that has been put into service, bringing the project's overall capacity to 1850 MW in November 2019, making it the largest solar power facility globally. Block 1 and Block 2 out of 10 Blocks of solar park are only considered on paper. The area has plenty of land and strong solar radiation, yet it doesn't get much rain. Situated on an elevated plateau encircled by rocky hills, the Pavagada Taluk is situated in a semi-arid zone.

Table 1: Pavagada Solar Park Site Parameters and Plant Specifications

Site Parameters		Plant Specifications	
Country	India	SPV NAME	ACME Kurukshetra Solar Energy Pvt. Ltd.(Pavagada- Block 1)
State	Karnataka		ACME Rewari Solar Energy Pvt. Ltd. (Pavagada- Block 2)
District	Tumkur	AC CAPACITY (MW)	Pavagada- Block 1 50

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Site	Pavagada Solar Park		Pavagada- Block 2 50
Latitude	14.260099ºN	DC CAPACITY (MW)	Pavagada- Block 1 67.4593
Longitude	77.471534ºE		Pavagada- Block 2 67.731
Session	2019-20	Inverter per Block:	TBEA 1.25 MW * 4

Proposed Framework

Given that manual or scheduled cleaning approaches can be inefficient—either causing unnecessary water/labor usage or allowing prolonged performance degradation—predictive dust-related maintenance becomes crucial. Data-driven methods, especially Artificial Neural Networks (ANN), have proven effective in modelling the nonlinear influence of dust deposition, meteorological conditions, and environmental parameters on PV output [12]. By integrating Internet of Things (IoT) sensor networks for real-time monitoring of irradiance, particulate concentration (PM10/PM2.5), temperature, and PV electrical characteristics, ANN-IoT frameworks can accurately forecast dust-induced performance loss and determine optimal cleaning intervals.

Thus, focusing on dust behavior remains essential for both terrestrial and floating PV systems. A predictive ANN–IoT approach tailored specifically to dust accumulation provides a robust solution for maintaining performance ratio (PR), maximizing energy yield, and minimizing unnecessary cleaning operations across diverse PV installation environments.

Before getting into the specifics of the techniques, the two machine learning models, Regression (Linear and Polynomial) and ANN (Artificial Neural Network) are discussed [18].

ANN (Artificial Neural Network):

ANN is the branch of a computing system which is designed for simulation as similar to human being for accessing the data and then synchronizing the same. ANN is the beginning of Artificial Intelligence (AI) which is capable of solving the issues a human cannot do experimentally and numerically sometimes. These are capable of producing the best results and hence availability of the data is increased.

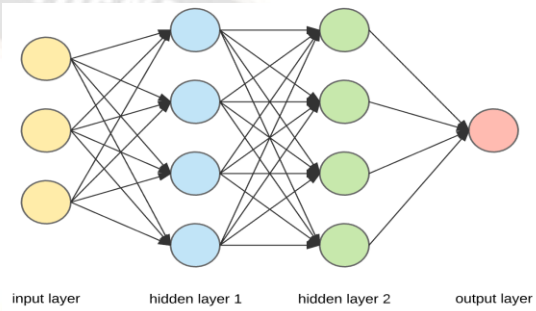

Figure 1: ANN Layered ArchitectureThe ANN layered architecture is shown in Fig.1, which is implemented using the **sckit** Python Library and data fed to ANN is constructed using **Pandas** (another python library). According to the ANN approach give random weights to create neuron and then adjust them according to the error in the output. Efficiency of the algorithm increases with number of inputs given to learn and hidden layer used. In this model 3 hidden layers are used.

Regression:

Regression is a statistical method for determining the relationship between variables. This is used in machine learning to forecast an event's result by utilizing the correlation between variables that are retrieved from the data set. One kind of regression utilized in machine learning is linear regression. Regression models attempt to predict data along a curve in polynomial regression and a straight line in linear regression.

In the proposed model, linear regression is used to determine the dirt deposition vs number of days. Here, dust thickness is in mg/sqm.

Measurement of Thickness of Dust:

The thickness of dust deposited is calculated by measuring the deposition velocity of dust on the surface, given by [11]:

$$v_d = \frac{1}{r_a + r_b} + v_s$$

where, v_d = Deposition Velocity

r_a = Aerodynamic Resistance

r_b = Quasi Laminar Resistance

$$r_a = \left\{ \begin{array}{l} \dfrac{\ln(\frac{z}{z_o}) + 4.7(\zeta - \zeta_o)}{ku_*} if\, 0 < \zeta < 1 \\ \dfrac{\ln(\frac{z}{z_o})}{ku_*} if\, \zeta = 0 \\ \dfrac{\ln(\frac{z}{z_o}) + \ln(\frac{(\eta_o^2+1)(\eta_o+1)}{(\eta_r^2+1)(\eta_r+1)})}{ku_*} + 2(\tan^{-1}\eta_r - \tan^{-1}\eta_o) if\, -1 < \zeta < 0 \end{array} \right\}$$

$$u_* = \frac{k\overline{u_x}(h_r)}{\ln(\frac{h_r}{z_o})}$$

$$r_b = \frac{1}{3u_x R_1 (E_B + E_{1M})}$$

Here, K = Von-karman Constant

u* = Friction Velocity

z = Reference Height

z_o = Roughness Length

$$\left\{ \begin{array}{l} \zeta = \dfrac{z}{L} \\ \zeta_o = \dfrac{z_o}{L} \end{array} \right\}$$

L = Monin Obhukhov Length

Based on the calculations above and using linear regression the dust for days from 0 to 20 days of continuous dust deposition is calculated and plot is provided.

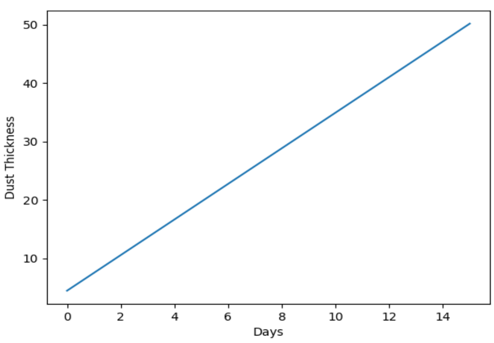

Figure 2: Linear Regression graph showing dust thickness wrt days

v_s = Settling velocity

To calculate value of Aerodynamic Resistance:

$$\left\{ \begin{array}{l} \eta_o = (1 - 15\zeta_o)^{\frac{1}{4}} \\ \eta_r = (1 - 15\zeta_r)^{\frac{1}{4}} \end{array} \right\}$$

$$v_s = \frac{1}{18} \frac{D_p^2 \rho_p g C_c}{\mu}$$

To Calculate the deposition velocity a website is also created [19].

R1 = Correction factor for fraction of particles stick to surface

EB = Collection Efficiency from Brownian Motion

E1M = Collection Efficiency from Impaction

D = Diameter of Dust

ρ = Density of Particle

g = Gravity

Cc = Slip Correction Factor

After doing calculations the research paper concludes that the dust thickness is,

For 1st day: 7.5 - 42.1 mg/sq.m

For 7th day: 25.8 - 277mg/sq.m

Procedure to create model:

1. Theoretical data of the required modules is created using PVSyst Software.
2. Practical data of the required modules were given by Pavagada Solar Plant in the specified form.
3. For data analysis python is used as the Programming language.
4. Python Modules namely numpy, sckit, pandas were used for Machine Learning.
5. The PR ratio of plant is calculated using ANN model for various number of days and graph between number of days and PR ratio of plant is calculated.
6. The Meteorological data used in creation of model is taken from website of NASA Power Dara Access Viewer [20].

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7. Then optimized value of no. of days is calculated based on the observation.

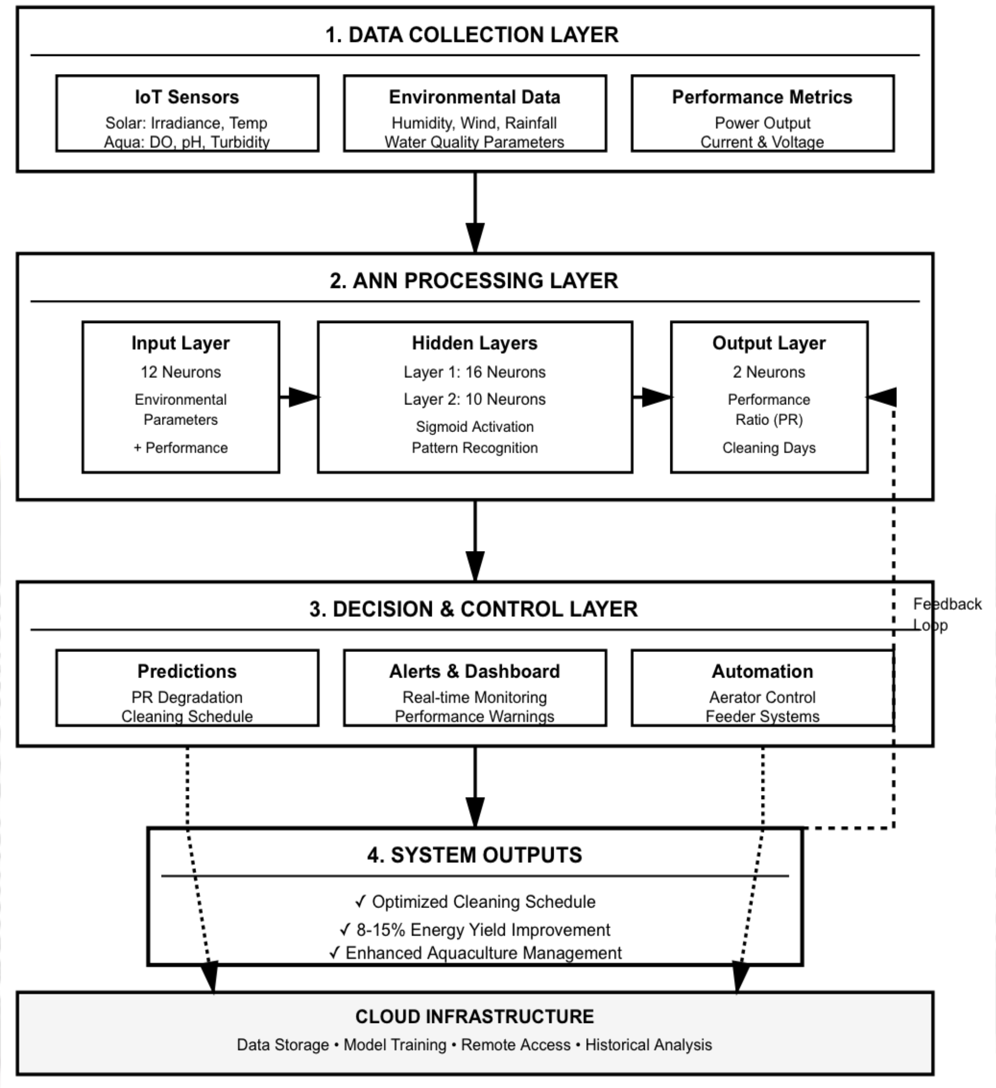

Figure 3: FSPV-Aquaculture ANN-IoT System Architecture Diagram

Based on the Hussain et al. [9], we have deduced that the module's power decreases in relation to weight and type of dust. The study tells that with a dust accumulation varying from 10 g to 50 g on the solar panel, the power is reduced significantly from 25 % to 55-63% range. With varying types of dust, say, Badarpur sand (Type 1 & 2), Fly-ash and Rice-husk, from 5 g to 25 g and then 25 gm to 50 gm, the power is decreased affectively from 15% to 45-55% and then to 70%. Here, the distribution of dust is considered uniform throughout the panel. Any significant variation is not seen with varying weights and varying radiation data-set. Among the used types of dust, Rice-husk type exists with maximum power loses and with its smallest size particle. This gives a confirmation to the fact that when size of particle is small, it will bear maximum power loss.

Another study considers the dust type like Chalk powder, Brick powder and sand, minimum layer of accumulated dust is 5gm which increases up to 50 g stating a decrease in power of the panel from 13% to 50% approx. from 5gm – 50 gm sand sample, 25 g sand sample exhibits maximum power loss when provided with measured radiation levels of 650, 750 and 850 W/m^2 giving power loss transferred as 55, 55.66 and 54.50% respectively.

Now the values of the dust deposition weight are calculated by using the formula:

Weight = density * Area of Module

Density is calculated using linear regression and formula discussed above and Area of the module is taken from the module specification.

Table 2: Showing varying efficiency with variable model number of solar panels

Model Number	P_{max}(Wp)	V_{oc}(V)	I_{sc}(A)	V_{mpp}(V)	I_{mpp}(A)	Efficiency(%)
RSM72-6-315P	315	45.4	9	36.85	8.55	16.2
RSM72-6-320P	320	45.5	9.1	37	8.65	16.5
RSM72-6-325P	325	45.6	9.2	37.15	8.75	16.8
RSM72-6-330P	330	45.7	9.3	37.3	8.85	17
RSM72-6-335P	335	45.9	9.4	37.45	8.95	17.3

Dimensions: 1956*992*40 cubic-mm

Result and Observations

After calculating the errors in the model, the coefficients of all the parameters that affect the efficiency of the module and, eventually, the PR ratio of the plant are the output of the model. The ANN model is created in such a way that it could be used in any general plant without any additional knowledge of the programming language. The model can easily be integrated and is scalable in nature. By means of integration, we can easily use this model in websites and create online services. By means of scalable is that model is created using OOP's approach i.e. Other components are easy to add and more inputs can be used to increase the accuracy of the model. The ANN model achieved prediction accuracy exceeding **93%** for PR forecasting and **90%** accuracy in dust-thickness estimation. Dust accumulation over 7 days resulted in a PR drop of 8–12%, consistent with field measurements. The model successfully predicted cleaning intervals with a mean error of ±1 day. The IoT system demonstrated reliable, continuous monitoring, allowing real-time alerts when dust reached critical thresholds. FSPV simulation results showed dust accumulation rates **30–40% lower** than terrestrial systems but still sufficient to cause PR losses of 5–10% over two weeks in dusty conditions.

Conclusion

Despite the common assumption that floating installations experience lower dust deposition, this work shows that airborne particles transported through pollution, agricultural activity, and local atmospheric dynamics still produce meaningful soiling losses that must be addressed for reliable power output. By integrating environmental parameters with machine-learning-based forecasting, the model accurately predicts the critical dust accumulation threshold and identifies the optimal cleaning interval. The presence of dust on solar panel is oft-times underrated problem which may be a main impediment for optimum yield of any solar plant that discern accurate cleaning time to conserver solar panel output efficiency for optimum cleaning frequency that will help to increase the performance ratio of the plant. Dust remains a significant soiling mechanism for floating solar PV systems, despite reduced deposition compared to terrestrial systems. The ANN–IoT dust-prediction model developed in this study accurately forecasts dust accumulation and PR decline for both terrestrial and floating solar applications. Predictive cleaning schedules reduce unnecessary maintenance, improve PR ratio, and enhance long-term system efficiency. This framework is scalable, generalizable, and suitable for real-time deployment in both land-based and floating PV installations.

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