

A Review of Artificial Intelligence Tools for the Management of Cleaning and Tracking in Photovoltaic Systems



A. Boussiri^{1*}, Y. A. E. Kadi¹

¹Engineering and Applied Physics Team, Higher School of Technology, Sultan Moulay Slimane University, Morocco.



ABSTRACT: Solar Photovoltaic System (SPV) is a rapidly expanding renewable energy source integrated into national power grids and off-grid systems worldwide. Therefore, the effective management of power systems and the energy industry needs accurate solar energy forecasting, ranging from short-term predictions of a few seconds to longer-term forecasts up to one week in advance. Hence it is well recognized that the presence of dust particles on the surface of photovoltaic (PV) modules substantially influences their overall performance. Subsequently, the resultant decrease in energy generation significantly impacts the financial earnings. A range of methodologies have been used to address the limitations associated with solar radiation forecasting. The use of machine learning (ML) algorithms provides a range of techniques for predicting solar radiation. Additionally, integrating artificial intelligence (AI) and ML may collectively enhance the optimization of cleaning intervals for photovoltaic (PV) modules. In the same manner, the development of a sun tracking algorithm aims to accurately determine the location of the sun in order to optimize the reception of solar energy. This article aims to critically review the current research on maintenance and tracking strategies for PV panels while presenting a novel application of AI and ML algorithms. Finally, this review presents a comprehensive analysis comparing traditional approaches with AI techniques to demonstrate the significant impact of AI algorithms in PV systems.

KEYWORDS: Cleaning and tracking, Soiling, Photovoltaic system, Machine learning, Artificial intelligence

[Received Dec. 17, 2023; Revised Sep. 9, 2024; Accepted Sep. 13, 2024]

Print ISSN: 0189-9546 | Online ISSN: 2437-2110

I. INTRODUCTION

The Artificial intelligence (AI) and machine learning (ML) are crucial for the modern world in almost all areas, such as education, manufacturing, maintenance, research, and everyday living (Sobuz *et al.*, 2024a, Hasan *et al.*, 2023, Sobuz *et al.*, 2024b). The increasing popularity of photovoltaic (PV) technology comprises about 33% of the globally installed capacity and consistently experiences increased demand as an approach to advancing energy sustainability (Ahmad *et al.*, 2022). The cost of PV power continues to have a downward trend. The use of solar energy as a renewable and environmentally friendly power source is increasingly being embraced by many facilities, including autonomous photovoltaic systems for residential or communal power generation and municipal lighting, among others (Edenhofer *et al.*, 2011). For example, China exhibited the most substantial increase in capacity, with a contribution of 307 GW, surpassing its yearly capacity of 253 GW in 2020. In contrast, the United States significantly increased its solar capacity, reaching a growth rate of 27%, resulting in a total solar generating capacity of 94 GW. Figure 1 illustrates the progression of worldwide solar capacity from 1996 to 2021 in the seven prominent nations engaged in solar energy production (Ritchie

and Roser, IRENA). Nevertheless, the full utilization of standalone PV systems in these locations remains largely untapped due to insufficient maintenance. This deficiency in upkeep may result in diminished performance, equipment failure, and abandonment, particularly in the absence of local repair capabilities (Serpa and Zilles, 2007).

Soiling significantly impaired solar module performance, as shown by previous studies (Sayyah *et al.*, 2014, Pavan *et al.*, 2011). This degradation is attributed to various causes, including the deposition of pollutants, the buildup of dust or organic particles, and the presence of bird droppings that effectively obscure the module surface. The measurement of soiling is of major significance as it enables the calculation of economically suitable intervals for cleaning operations (Babay *et al.*, 2024). Furthermore, the regular or suboptimal procedures used to clean PV panels diminish the PV system's electrical viability and result in elevated operating and maintenance expenses (Paul, 2022). Nevertheless, the measurement of soiling losses presents challenges due to its dependence on several factors, including atmospheric conditions (Darwish *et al.*, 2015), particle characteristics (Darwish *et al.*, 2015), module surface conditions, and orientation of the module (Maghami *et al.*, 2016).

*Corresponding author: boussiriayoub@gmail.com

doi: <http://dx.doi.org/10.4314/njtd.v21i4.2228>

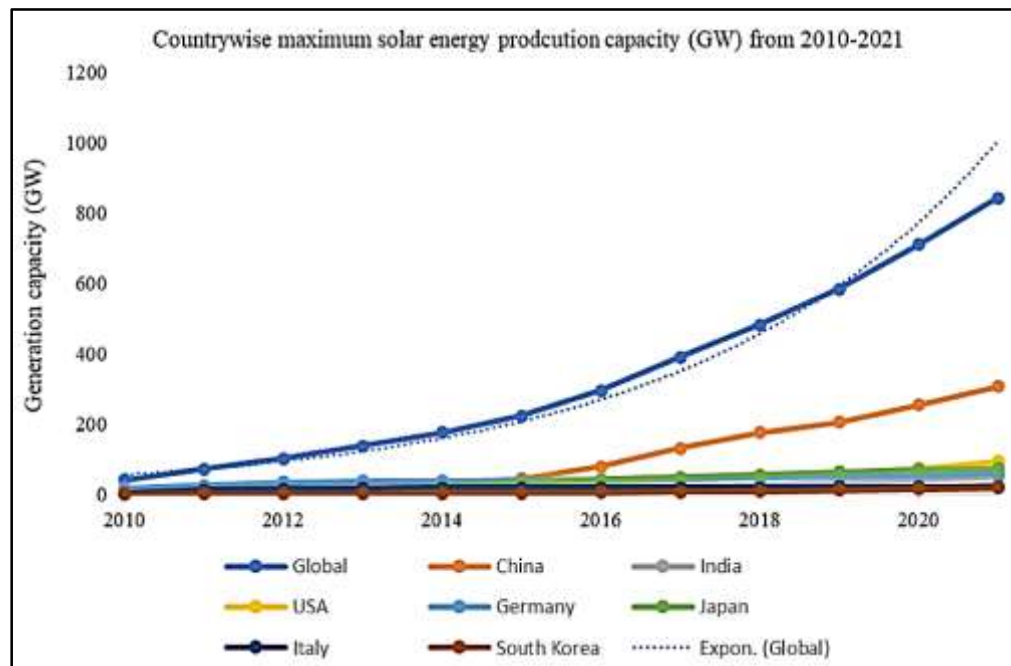


Figure 1: Seven nations account for most of the world's solar energy production (Ritchie and Roser).

This is likely why many publications use statistical techniques or machine learning algorithms to enhance the precision of the estimation of soiling losses. Pulipaka and Kumar (2016) introduced an ANN model to calculate soiling losses and solar power production. This model utilizes the irradiance signal and relevant pollutant properties. Their study (Pavan *et al.*, 2013) used a regression model to estimate the losses caused by soiling on solar panels. The inputs for this model were irradiance and cell temperature. The authors also conducted a comparison using Bayesian Neural Networks, which were determined to have superior performance in this context. ANN has been used to predict PV soiling, considering environmental factors such as particulate matter concentration, relative humidity, and wind speed (Javed *et al.*, 2017).

The sun tracking algorithm is developed to track the sun's position to receive maximum solar radiation (Munawar *et al.*, 2023). A robotic arm with four degrees of freedom was used as a mechanical structure to position the solar cell under the sun for greater flexibility. AI has the potential to enhance the intelligence of solar forecasters by enabling them to attain high levels of accuracy. This is accomplished via advanced techniques such as feature extraction and nonlinear mapping, which facilitate extracting relevant information and mapping complex relationships (Qazi *et al.*, 2015). Additionally, AI systems exhibit strong compatibility with various PV power prediction scenarios, allowing for their effective application in diverse settings. Furthermore, AI systems possess a certain degree of logical reasoning capability, further enhancing their ability to provide accurate solar forecasts. The effectiveness of AI algorithms in estimating solar radiation and PV power has been shown (Feng, 2018). In their study, Barbieri *et al.* (2017) investigated cloud-based models used for the prediction of solar energy. Their findings revealed that the battery's temperature and solar radiation emerged as the primary determinants (Barbieri *et al.*, 2017). Wang *et al.* (2017) have

released a comprehensive overview of contemporary deep-learning methodologies used in the prediction of wind and solar electricity.

Conventional techniques involving cleaning and tracking of solar systems involve manual cleaning methods that are labor-intensive, time-consuming, and often inefficient, as they follow fixed schedules rather than responding to the actual soiling levels on the panels. This can lead to either overcleaning, which wastes resources like water and cleaning agents, or undercleaning, which allows dust and debris accumulation to reduce energy output. Additionally, tracking systems often rely on static or rule-based algorithms, which lack the flexibility to optimize performance under varying environmental conditions such as cloud cover or temperature fluctuations. These methods also fail to provide real-time monitoring, making it difficult to respond promptly to changing conditions. AI-driven tools, such as machine learning models, can address these gaps by providing predictive maintenance, optimizing cleaning schedules based on real-time data, and dynamically adjusting tracking angles to maximize energy production.

Certain scientists use empirical methods to anticipate solar power output. However, these models are inadequate in enhancing the accuracy of predicting nonlinear time series data pertaining to solar power generation. In order to enhance the predictive accuracy of nonlinear time series SPG, researchers use artificial intelligence techniques and a mix of machine learning methods. The neural network (NN) is favored by scientists as a supervised learning system for several purposes. Analysts have shown a preference for using NN in the field of image processing due to its several benefits. These advantages include its ability to self-learn, effectively address issues associated with information loss, and exhibit adaptability (Robles Algarín *et al.*, 2018). Nevertheless, in recent years, there has been a lack of research examining the forecast of

solar energy from an AI standpoint despite the abundance of related studies. The recent trend of publications relevant to

photovoltaic solar systems along with their maintenance and tracking is illustrated in Figure 2 (Abdulla *et al.*, 2024).

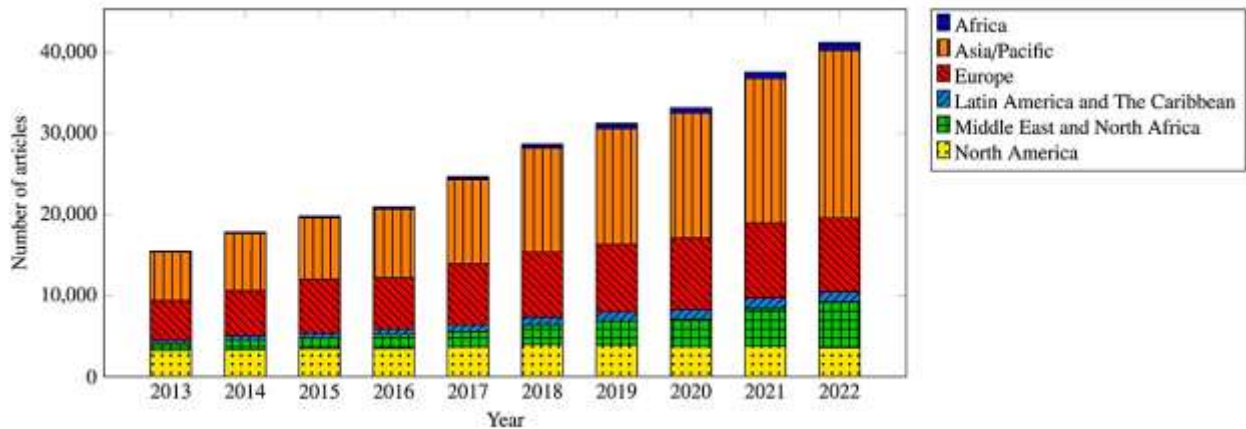


Figure 2: Photovoltaic systems relevant publications in recent years (Abdulla *et al.*, 2024).

This article provides a concise overview of the current methodologies used for the cleaning and tracking procedures in PV systems. Additionally, the problems associated with current manual processes of cleaning and tracking are identified. Following this, this paper reviews several ANN and ML techniques used in sun radiation forecast and cleaning optimization. The review also addresses the prediction accuracy using several performance metrics. In conclusion, the most appropriate algorithms for the cleaning and tracking of PV technology have been identified.

II. CURRENT PRACTICE FOR DETECTING CLEANING INTERVALS WITHOUT USING ARTIFICIAL INTELLIGENCE

Photovoltaic systems are installed externally and subjected to various environmental factors. The variables exhibit regional variation and may occasionally attain significant levels, such as acid rain, pollution, dust, and snow. Other weather variables, including solar irradiation, temperature, and relative humidity, significantly influence photovoltaic (PV) performance. Additionally, certain variables, such as wind velocity, have the potential to damage the PV structure (Chaichan *et al.*, 2015). Darwish *et al.* (2013) determined that the damage caused by the air conditioning could be as high as 25%. The cleaning of photovoltaic systems presents challenges due to elevated pollution levels in urban

areas. Regular cleaning of photovoltaic systems is essential for minimizing environmental impacts and maintaining high productivity and efficiency (Derakhshandeh *et al.*, 2021).

Manual cleaning is a straightforward method for cleaning photovoltaic (PV) systems, relying on water to eliminate accumulated dust. This traditional method necessitates labor and incurs high costs, particularly in contexts where clean water is limited or unavailable. Alvarez *et al.* (2020) examined the frequency and cost associated with cleaning methods. The study proposed a cleaning methodology to identify the optimal strategy, considering factors such as cost, equipment efficiency, and other system parameters. Most photovoltaic panels are coated with tempered borosilicate glass, which can be easily cleaned using water. In newly produced photovoltaic systems, a tight glass is utilized to enhance light absorption and reduce reflectivity; however, these surfaces are still prone to the accumulation and deposition of fine nanoparticles, necessitating effective cleaning measures. Current cleaning methods encompass manual and semi-automatic approaches that necessitate substantial water usage and involve significant labor, thereby elevating costs. Additionally, contemporary cleaning methods, including electrostatic techniques (Salamah *et al.*, 2022), are being evaluated for robotic applications in cleaning photovoltaic systems. However, Figure 3 illustrates the most conventional PV cleaning techniques used in today's world.



(a) Vacuum cleaning



(b) Automated facility for cleaning



(c) Brush cleaning



(d) Sprinkler water cleaning

Figure 3: Traditional cleaning practices.

The impact of dust deposition on the power output of PV panels is well acknowledged. However, a lack of established mathematical models that precisely characterize this connection exists. However, Darwish *et al.* (2021) conducted a correlation between dust accumulation and PV output, as seen in Figure 4.

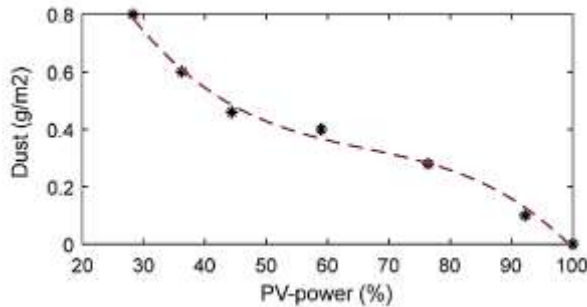


Figure 4: Normalized PV power output as a function of dust density.

Several strategies may be used to either reduce or avoid the loss of soiling (Sarver *et al.*, 2013). Naeem and TamizhMani (2015) have implemented a system for detecting and eliminating soiling comprising twenty-four polycrystalline silicon modules. These modules have the same nameplate data and construction, including a glass superstrate. They were installed on an unregistered rooftop facing south, situated at ASU-PRL in Mesa, near Phoenix, Arizona, USA. The modules exhibited a tilt angle of 20°, which closely aligns with the tilt angles often seen in a diverse variety of residential photovoltaic (PV) systems deployed across the United States. A current shunt was used to short-circuit each module. Their proposed method is illustrated in Figure 5.

In another research, Wang *et al.* (2020) investigated the design of a cleaning schedule for PV systems deployed in real-world conditions. The authors suggested that PV strings should be considered optimal optimization units. The difficulty of scheduling cleaning activities was formulated as an infinite scheduling problem, and a periodic scheduling approach was introduced to enable optimization of the problem. The suggested methodology entails the development of customized cleaning plans that consider the prediction of climatic conditions, PV power output, and dust accumulation on PV strings. This approach goes beyond the traditional consideration of cleaning frequency alone.



Figure 5: Methodology of the Soiling Analysis (Naeem and TamizhMani, 2015).

The use of actual PV plant data in the case study illustrated the efficacy of the suggested approach and provided evidence of its ability to enhance outcomes. The researchers concluded that the suggested strategy performs better when subjected to a shorter preparation limitation. As cleaning service prices rise, the disparity between the initial and final amounts diminishes.

In a separate investigation, the impact of different daily soiling rates was examined with the objective of reducing the duration between consecutive cleaning periods (Chiteka *et al.*, 2020). A study was conducted to build and improve an empirical model for quantifying soiling loss in a 3.6 kW power plant, to reduce the frequency of cleaning cycles. Chiteka *et al.* (2020) developed an adaptive computational intelligence technique known as Particle Swarm Optimization (PSO) to optimize the cost function described in Equation (1).

$$C_T = \frac{214}{N} C_c + \sum_{i=1}^n \frac{1}{2} (N + 1) (E_{ei} - E_{ai}) \quad (1)$$

Where, C_T = Total cost associated with the cleaning and soiling process of the PV system

N = Total number of cleaning cycles in which the model is applied

C_c = Cost associated with each cleaning cycle

E_{ei} = Expected energy output and

E_{ai} = Actual energy output at time period i .

They concluded that the soiling rates varied throughout various days and months, indicating that soiling cannot be assumed to remain consistent throughout the year.

Jiang *et al.* (2016) adopted an innovative approach in which the estimation of cleaning time is determined by considering particle deposition velocity and accumulation density. However, this technique overlooks the significant role of rainfall as the most effective cleaning agent for the removal of dust particles. Following rainfall, the presence of rainwater facilitates the removal of soluble dust particles from the glass covers of photovoltaic (PV) modules, enhancing their efficiency (Appels *et al.*, 2012). Hence, this approach exhibits greater precision in arid regions characterized by very little precipitation. In addition to precipitation, wind may also serve as a natural mechanism for cleansing the soiled cover of PV modules.

Rodrigo *et al.* (2020) introduced an innovative approach to enhance the efficiency of cleaning schedules in solar systems by minimizing the levelized cost of energy. The approach considers the life cycle expenses, enabling an investigation of how the investment cost of the system affects the optimal cleaning schedule. Moreover, it does not rely on economic income data, which is often associated with ambiguity. The analysis suggests that the ideal proportion of yearly soiling losses is influenced by both the cost of cleaning and the cost of the system, as seen in Figure 6.

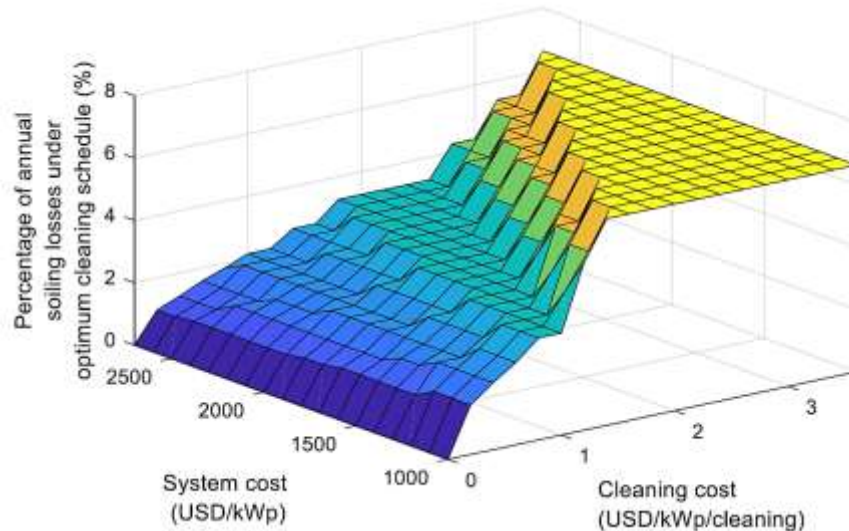


Figure 6: Cleaning and system costs are a function of the percentage of yearly soiling losses under the optimal cleaning schedule.

Fan *et al.* (2020) presented a novel approach named Alternative Cleaning and Dust Detection Method (ACDDM) for PV modules. The proposed methodology for detecting the need for cleaning PV panels takes into account economic considerations, making it applicable to large-scale solar power stations using various cleaning techniques. The ACDDM approach deviated from the conventional technique by identifying the disparity in output between the clean and dirty panels at the start of the designated time frame. The ACDDM hardware detection system, which was suggested, was deployed in the Shandong region starting from 2017. Based on the conclusion of their study, the implementation of the ACDDM resulted in an annual increase in the output above 1.33% and a net return of over 0.78% after deducting the cost of cleaning (Fan *et al.*, 2020).

Jones *et al.* (2016) proposed an innovative theoretical framework known as The Optimized Cleaning Interval (OCI). The OCI is determined by minimizing the cost per unit of energy sold during a single cleaning interval. This interval is marked by a cleaning operation at the beginning, incurring a cost denoted as CC. Subsequently, revenue loss is progressively increased until the optimal interval is reached. At this point, cleaning the PV plant is recommended again. The overall cost includes the expenses incurred due to energy loss and the expenses associated with the cleaning procedure.

III. THE CURRENT METHOD AND PROCESS FOR TRACKING PHOTOVOLTAIC SYSTEMS

Numerous studies have delved into exploring and developing innovative methodologies geared toward optimizing power tracking in PV systems. These techniques play a vital role in ensuring that PV systems operate at peak efficiency by consistently harnessing their maximum power potential. It is worth noting that the available maximum power output can fluctuate due to environmental factors and shading effects. An illustrative example is when passing clouds cast shadows over solar panels, leading to alterations in the available solar irradiance. In such scenarios, the challenge of maximum power tracking becomes inherently dynamic and time-varying. In response to these complex conditions, the field has witnessed the emergence of the Maximum Power Point Tracking Technique, commonly abbreviated as MPPT. MPPT techniques are specifically engineered to adeptly trace and lock onto the optimal power point, even in the presence of nonlinear weather conditions or shading effects. This technological advancement stands as a crucial solution in ensuring that PV systems continually operate at their highest power output potential, regardless of the challenges posed by

fluctuating environmental conditions and shading phenomena (Saravanan and Babu, 2016).

Nsengiyumva *et al.* (2018) examined the optical performance of Inclined South-North (ISN) single-axis tracked solar panels through a mathematical formula that estimates the annual collectible radiation for both fixed and tracked panels. In regions of China with significant solar resources, the research indicated that the maximum annual collectible radiation on ISN single-axis tracked solar panels was approximately 96–97% of that on dual-axis tracked panels. Research indicated that sun-tracking techniques are ineffective in regions with low solar resources, demonstrating a strong correlation between the solar resources available in a region and the observed increase in annual solar gain (Seme *et al.*, 2020). Compared to conventional fixed solar panels set at an optimal tilt angle, inclined sun tracking techniques demonstrated an increase of over 30% in annual solar gain in regions with high solar resources, while the increase was below 20% in areas with low solar resources (Li *et al.*, 2010). Tomson (2008) presented an analysis of the performance of PV modules utilizing daily two-positional tracking. The study assessed symmetrical and asymmetrical positions along the north-south axis and determined the optimal positions for two-position tracking. It was determined that two positional exposures yield greater gains compared to a fixed collector positioned at an optimal angle. The most feasible options for the South-East directed and 45° tilted collector were an eastward deflection of -30° and a westward deflection of +60°.

Malav and Vadhera (2015) has employed a single-axis solar tracking system that utilizes a control algorithm to adjust the panel's position in both directions. Power consumption is minimized through the use of a stepper motor that activates at discrete intervals, in contrast to traditional tracking systems (Malav and Vadhera, 2015).

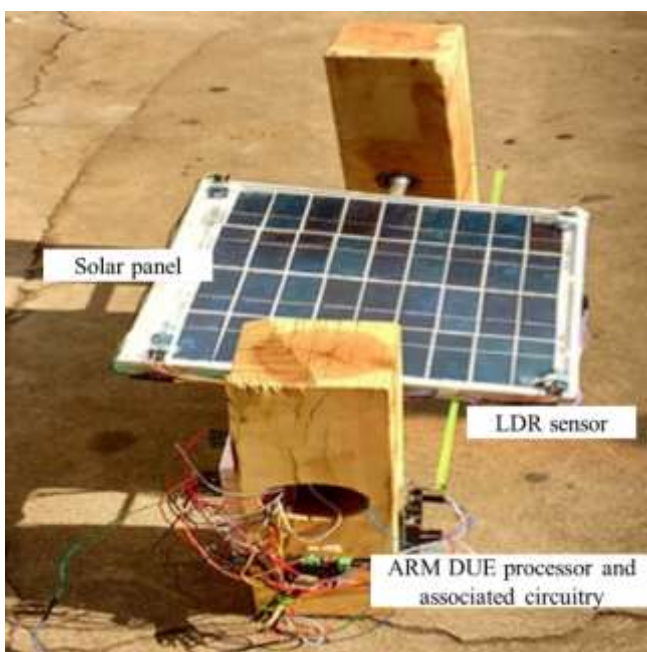


Figure 7: Single-axis tracker PV system using ARM processor (Sumathi *et al.*, 2017).

An automatic solar tracker based on a single-axis microcontroller has been implemented. The system was tested in Vellore, a small town in Tamil Nadu, India, located at a latitude of 12.91°N. The implementation of a single-axis tracker demonstrates greater efficiency by reducing the complexity and energy demands associated with a dual-axis system. The single-axis system is affixed to rigid ends, ensuring stability as the panel transitions from an eastward to a westward orientation throughout the day. The experimental setup is illustrated in Figure 7 (Sumathi *et al.*, 2017). Fathabadi (2016) presented a unique dual-axis solar tracker that operates without sensors and functions offline. The tracker could be used in both PV systems and solar concentrators. The solar tracker under consideration is an economically efficient tracking system characterized by a straightforward design. It exhibits a remarkable level of precision in properly following the sun's trajectory, with a minimal tracking error of just 0.430. The provided Figure 8 displays the schematic design of the PV system, which incorporates the suggested solar tracker.

In contrast, Zhu *et al.* (2020) introduce an innovative single-axis tracking framework for a photovoltaic (PV) system with the aim of augmenting solar radiation output. The analysis of the properties of the tracked panel involves the development of its normal vector. The validity of this technique has been shown by numerical validation, using a solar radiation model that incorporates the geometric connections between the sun and the earth.

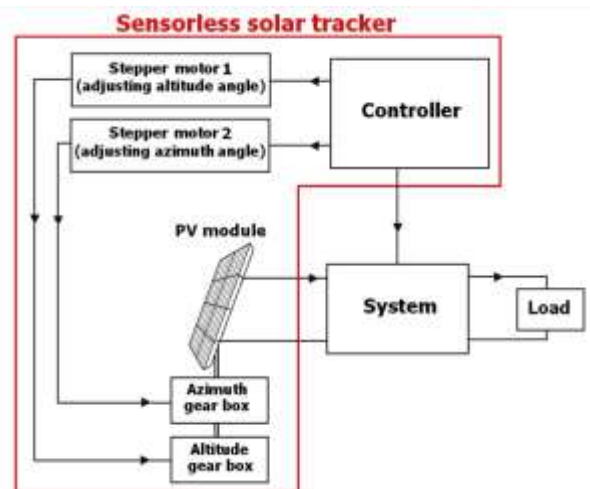


Figure 8: The suggested offline sensorless dual-axis solar tracker (Fathabadi, 2016).

Jamroen *et al.* (2020) successfully developed and deployed an automated dual-axis tracking system. The suggested tracking system design aims to precisely align the photovoltaic (PV) module along both the main and secondary axes to monitor the sun's course. This is achieved via the use of digital logic design using light-dependent resistors (LDRs). The system used a pseudo-azimuthal mechanism to provide stable movement, while the LDR was adopted and mounted in a straightforward configuration to minimize tracking mistakes resulting from complex orientations. The data indicates that the energy efficiency of the PV system exhibits a notable

improvement of 44.89% compared to the stationary flat-plate system (Jamroen *et al.*, 2020).

Chowdhury *et al.* (2019) effectively constructed a real-time solar tracking system using the AA algorithm, which can be executed on an 8-bit microcontroller. The AA technique for solar position identification has a little extra hardware need. Furthermore, the execution duration of the sun tracking code was less than one second, indicating its suitability for real-time applications using an 8-bit microcontroller. The experimental findings confirm that the solar tracking system developed in this study exhibited greater performance compared to the fixed flat-plate system for solar energy generation.

IV. AI TECHNOLOGIES IN THE OPTIMIZATION OF PV SYSTEM CLEANING INTERVALS

A. ANN modeling approach

1) Import data: The first stage of ANN modeling involves the importation of the dataset. In the investigation of Ahmad *et al.* (2022), the collected data were imported into the R programming language. The dataset included two distinct independent variables, which were utilized as input parameters, and a dependent variable, which represented the result. The neural network modeling framework that is most frequently applied is displayed in Figure 9.

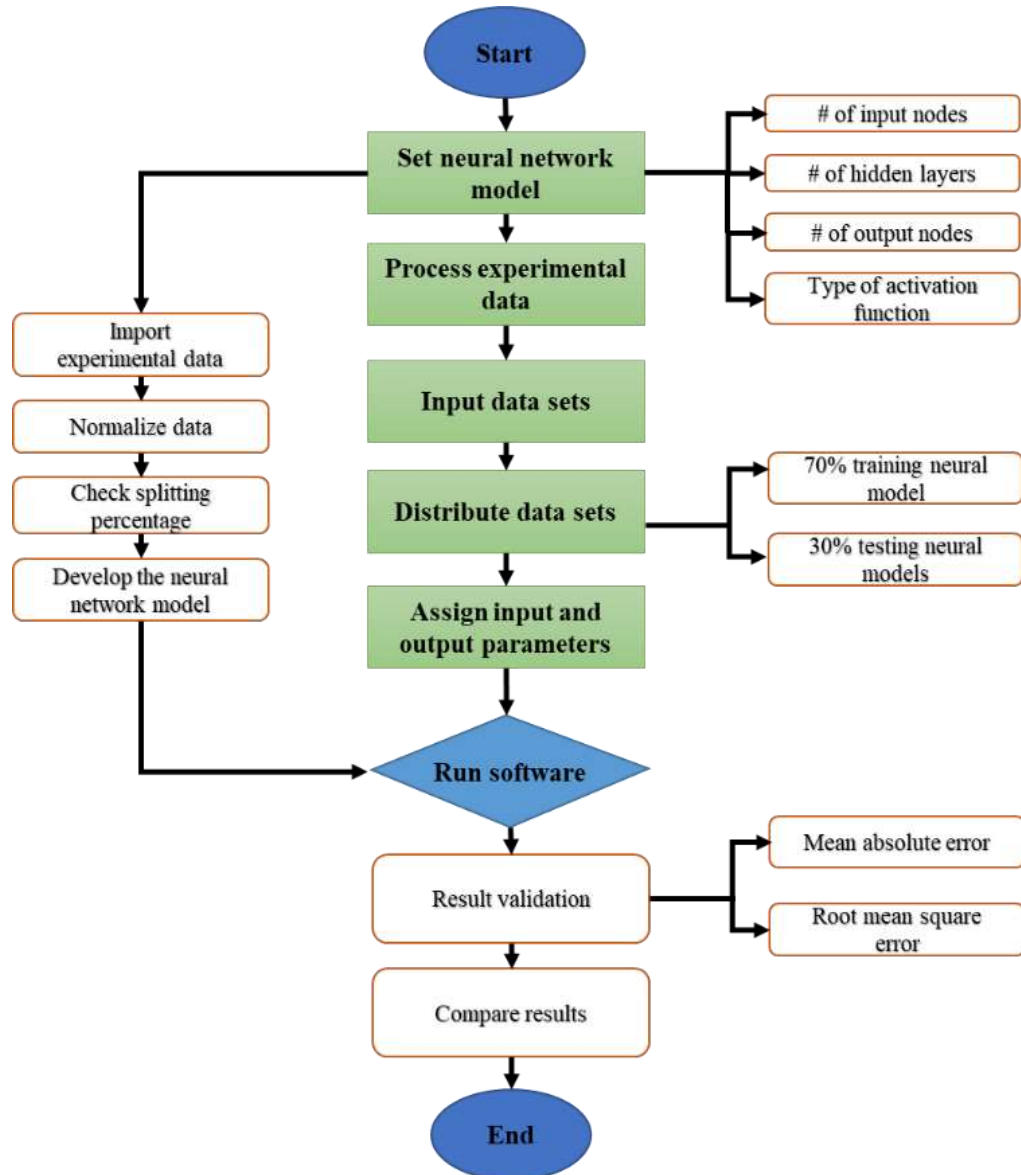


Figure 9: Neural network modeling methodology used in the study of Ahmad *et al.* (2022).

2) Normalization: As per conventional methodologies for training a Neural Network, it is traditional to normalize the dataset by adjusting its mean to approximate zero before feeding it into the model. In a general context, the process of normalizing the data expedites the learning process and

facilitates faster convergence of the model. Further normalization is necessary since the data originates from many scales and units, each with distinct ranges, necessitating translation into a unified scale and unit. In constructing an ANN model, it is essential to adjust the synaptic weights of neurons throughout the training phase to mitigate any potential

bias present within the model. The achievement of this outcome is facilitated by the process of normalizing the data, which mitigates the presence of excessively large or minuscule weights. Next, the dataset that has undergone training is subjected to normalization in order to achieve a mean value that is close to zero.

3) Split the dataset into train and test dataset: In the realm of machine learning, assessing the performance of an algorithm involves a fundamental technique known as the train-test split. This approach essentially entails partitioning a given dataset into two distinct subsets: one reserved for the model's training phase, referred to as the "training" dataset, and the other designated as the "testing" dataset (Razak *et al.*, 2020). In this scenario, the test data is fed into the trained model to generate predictions, which are compared against the expected values.

Commonly employed split percentages for this division encompass variations like an 80% training - 20% testing split, a 70% training - 30% testing split, a 60% training - 40% testing split, and a balanced 50% training - 50% testing split. In order to determine the most suitable split percentage, a number of experiments were conducted, employing a trial-and-error methodology. The effectiveness of the model was gauged using standard accuracy metrics, including the root mean square error (RMSE), mean absolute error (MAE), and relative absolute error (RAE). It is imperative to acknowledge that no one-size-fits-all accuracy metric universally reigns as the "best" for assessing accuracy in machine learning applications.

B. AI modeling for PV cleaning optimization

We conducted a comparative analysis and evaluation of the performance of numerous widely used binary classifiers using supervised learning techniques. Each method has varying degrees of implementation complexity and has the ability to generate either linear or nonlinear classifying boundaries. AI modeling is significantly important for the predictive maintenance of PV systems as it dramatically lowers the cost of post-maintenance and prevents bigger failures (Osmani *et al.*, 2020, Kurukuru *et al.*, 2021). The most common types of techniques for predictive maintenance are shown in Figure 10. As can be seen, along with other systems, ANN and MLR-based models have frequently been used in the maintenance process. According to Abubakar *et al.* (2021), the necessity for complex programming languages, back-propagation, and machine-learning processes makes ANN a less appealing option for forecasting future fault status in PV systems.

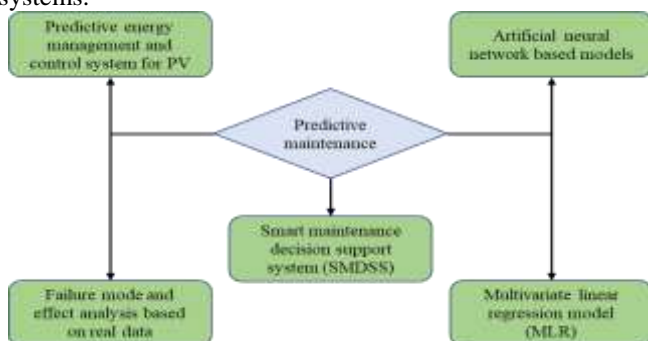


Figure 10. Different methods for predictive maintenance of PV panels.

1) Logistic Regression (LoR): Logistic regression is a straightforward and resilient model that serves as the benchmark model in the aforementioned setting. As shown in equation (2), the regression model calculates the logit transformation of the conditional expectation of a detected cleaning event, $P(C|X)$, by expressing it as a linear combination of explanatory variables $X = (x_i)$ (Hosmer Jr *et al.*, 2013). Also, b_o is the intercept or bias term in the LoR model and b_i is the coefficients for the explanatory variables (x_i), which represent the effect size or weight of each variable in predicting the outcome. The decision boundaries exhibit linearity.

$$\text{Logit} (P(C|X)) = \ln \frac{P(C|X)}{1-P(C|X)} = b_o + \sum_i b_i x_i \quad (2)$$

The computation of LoR coefficients can be achieved using the multinomial logistic regression function fit provided by MATLAB (MathWorks). The variables are initialized to a value of zero. However, the model is only constructed for statistical features (SF) and principal component analysis (PCA) features because of the large dimensionality of the time-series (TS) feature vectors, which hinders the algorithm's convergence (Heinrich *et al.*, 2020).

2) Support Vector Machine (SVM): SVM is a linear predictive model that relies on the computation of a hyperplane with a maximum margin to split data points into two distinct classes effectively (Kurukuru *et al.*, 2021). The data is transformed into higher-dimensional space by the use of a kernel function. According to the instructions of MathWorks the SVM can be trained using the fitsvm function in MATLAB. The SVM employs a Gaussian radial basis function as its kernel function (Vapnik, 1999), with a scale factor of 1. A non-linear kernel is employed to investigate the potential for projecting the relevant characteristics into a higher-dimensional space, enabling linear separability of the issue and surpassing the performance of Logistic Regression. The SVM is not trained for TS data but rather for SF and PCA features. This limitation is similar to that of logistic regression. In the study conducted by Harrou *et al.* (2019), SVM was used to identify abnormalities to improve the efficiency of PV systems, minimize maintenance expenses, and mitigate production losses. The suggested technique exhibits promise due to its inherent flexibility and its ability to bypass the need to verify assumptions on data.

3) Artificial Neural Network (ANN): The ANN is a non-linear classification model and may be conceptualized as a graph with weighted connections, where each neuron (node) performs computations using an activation function. In the study of Heinrich *et al.* (2020), as an initial methodology, a basic feed-forward architecture, consisting of a solitary, hidden layer with 100 neurons is used. The selection of the number of neurons was determined by the computation of results for neural networks, including hidden layers ranging from 5 to 2000 neurons as shown in Figure 11.

The process of network creation, training, and testing can be conducted using the Deep Learning Toolbox provided by MATLAB (MathWorks). In most of the literature, the training data is partitioned into three subsets: 70% for training, 15% for validation, and 15% for testing. Where the objective function

used to quantify training loss is cross entropy. The ANN is trained using TS, SF, and PCA characteristics.

In their study, Kalogirou *et al.* (2008) developed a failure detection system (FDS) for a solar-powered water heater (SPWH). The FDS incorporates an ANN and is comprised of three main components: a prediction module, a residual calculator, and a diagnosis module. The technology has the capability to accurately forecast potential malfunctions in collector components as well as defects in pipe insulation. The variety of input values used for system faults serves the purpose of validating the system. The research conducted by Mohanraj *et al.* (2009) included the prediction of the direct expansion solar-assisted heat pump (DXSAHP) parameter of system performance using ambient parameters via the successful training of an ANN network. The results indicate that the use of ANN for performance prediction of a DXSAHP is reliable and accurate.

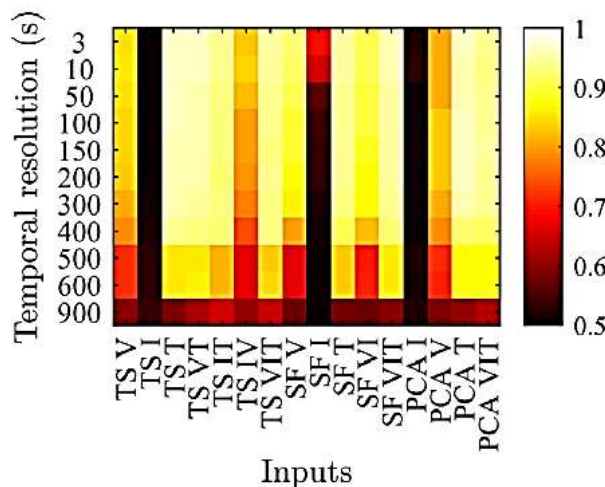


Figure 11: Accuracy of ANN system on average throughout 100 trainings (Heinrich *et al.*, 2020).

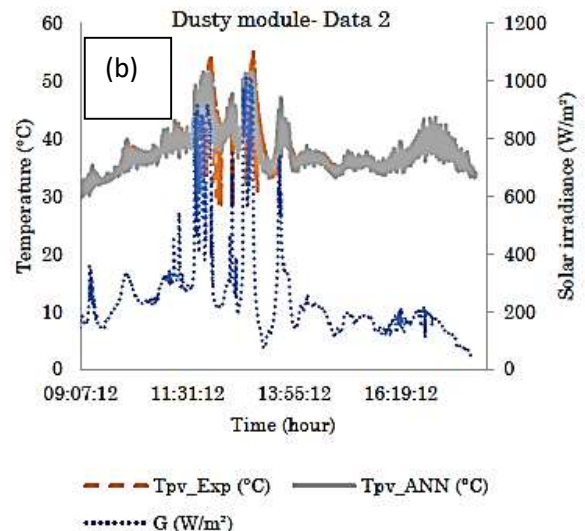
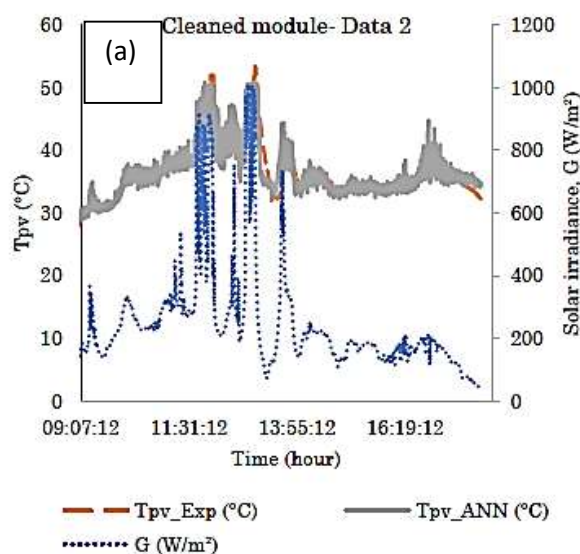


Figure 12: Variation in Solar Irradiance, G, and PV Temperature TPV for cleaned and dusty PV modules with the time of the day (Ahmad *et al.*, 2022).

Figures 12(a) and 12(b) compare the performance of a photovoltaic module under clean and dusty conditions. The data shows the experimental temperature and the predicted temperature by ANN plotted against solar irradiance. The figure shows that the cleaned module exhibits higher temperatures and more consistent solar irradiance compared to the dusty module. The dusty module shows reduced temperatures and more fluctuations in solar irradiance, indicating that dust accumulation on the surface of the module negatively affects its performance, lowering its efficiency (Ahmad *et al.*, 2022).

Kumar and Dave (2016) created a simplified ANN model for producing a control signal to activate the windscreen wiper motor. The purpose of this control signal is to facilitate the removal of dust that has gathered over the panel of 250 Wp photovoltaic (PV) modules. The ANN model has attained a high level of accuracy, around 99%, in identifying the presence of dust on photovoltaic (PV) panels. Kermadi and Berkouk (2017) suggested an ANN-based maximum power tracking (MPT) controller that comprises a two-layer feed-forward network. The neural network is characterized by its architecture, which encompasses the number of layers, the number of neurons in each layer, the sort of activation function used in each layer, and the interconnections between layers. This topology was selected after many tests to enhance the accuracy of the resultant neural network. The input variables, namely irradiance, and temperature, are sent to the hidden layer via the two neurons of the input layer. However, the suggested MPT controller has the capability of delivering the MPP voltage in any weather situation. Thus, this reduces oscillations around the MPT and enhances the effectiveness of this controller.

4) Multivariate Linear Regression (MLR): Regression analysis is a frequently employed statistical technique for examining multifactor data. It involves constructing a suitable mathematical equation that establishes a relationship between

the response variable and a collection of predictors or causative variables. Hammad *et al.* (2018) implemented an MLR model to propose Equation (3) in their study, which intends to investigate the impact of dust and temperature on the performance of PV systems.

$$\eta_n = \mu_0 + \mu_1 D_n + \mu_2 T_n + \varepsilon_n \quad (3)$$

Here, η_n is the daily efficiency on day n , D_n is the exposure day number, T_n is the average daily ambient temperature on day n , μ_0 is the intercept of the regression model, and μ_1 and μ_2 are the regression coefficients. Additionally, ε_n represents the discrepancy between the actual and predicted efficiencies of the PV system on day n .

Their research findings indicated that the mean duration between cleanings for the entire research period was found to be between 13 and 15 days when using both MLR and ANN models. Additionally, the MLR model yielded a mean duration of 12 to 13 days for individual cleaning periods (Hammad *et al.*, 2018).

5) Deep learning/network models: The use of the Deep Belief Network (DBN) model can facilitate the identification and detection of dust particles present on solar panels deployed as a collective entity. Khilar *et al.* (2022) have used a DBN architecture in their research endeavors to effectively identify and quantify the presence of dust particles on PV cells. Figure 13 illustrates the DBN architecture used in their studies (Khilar *et al.*, 2022). The outcomes were evaluated based on accuracy, precision, recall, and F-score measures. The simulation results demonstrated that the suggested model exhibits a superior level of accuracy compared to other methodologies.

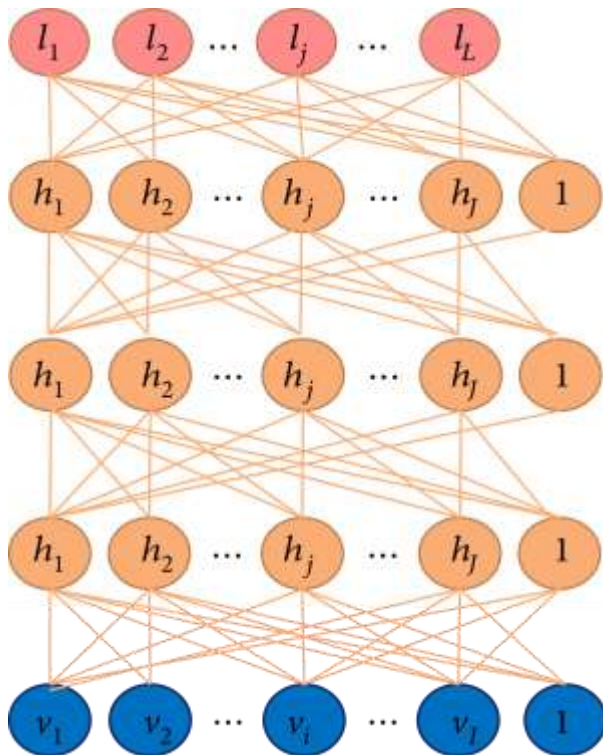


Figure 13: DBN architecture (Khilar *et al.*, 2022).

In a similar manner, Kazem *et al.* (2019) used a deep learning technique to forecast the performance of a

photovoltaic (PV) plant. This was achieved using recurrent neural networks (RNN) and Time Lag Recurrent Neural Networks (TLRN), resulting in four prediction models. The forecast is created based on the present behavior by using meteorological data, namely temperature (T) and sun irradiance (G).

V. ADVANCED AI TECHNIQUES FOR PV SYSTEM TRACKERS

A. Random Forest (RF)

The approach described below exemplifies ensemble learning, whereby different algorithms are used to generate a collection of decision trees during the training phase. The output of an RF classifier is determined by selecting the class that occurs most often among the predictions. The proposed method exhibits superiority in addressing the issue of overfitting in decision trees when applied to the training set of pictures. RF is subject to a set of regulations that dictate the management of tree combinations, tree growth, post-processing, and self-assessment. The proposed technique exhibits stability even when faced with outliers and high-dimensional parameter spaces, distinguishing it from existing ML methods. Additionally, it demonstrates robustness against overfitting. RF operates by assigning ranks to the characteristics throughout the construction of the classification model, therefore discerning the most influential features.

In a case study by Alghazo *et al.* (2023), the acquired data was partitioned into two sets for prediction: 80% of the data was allocated for training, while the remaining 20% was reserved for testing. Table 1 presents the regression outcome of the RF classifier.

B. Multilayer Perceptron (MLP)

The MLP is an ANN architecture that employs a feed-forward mechanism and utilizes the backpropagation algorithm for training purposes. The neural network architecture has at least three layers, including the input, hidden, and output layers. One distinguishing characteristic of MLP compared to other classifiers is the use of nonlinear activation functions in each of its neurons, except for the input node. Hence, it has the ability to discriminate between data points, even those that are not linearly separable. An MLP layer consists of many layers of nodes arranged in a directed cyclic graph, whereby each layer is fully linked to the adjacent one.

The MLP used in the research conducted by Alghazo *et al.* (2023), was characterized by certain characteristics. These parameters included a batch size of 100, a number of hidden layers equal to the number of attributes associated with the features (6), a total of 500 epochs, a learning rate of 0.3, and a momentum value of 0.2. The well-known MLP-ANN was used in a study to predict the power output of a 20-kWp PV plant linked to a small-scale grid in Tamil Nadu, India (Muhammad Ehsan *et al.*, 2017). The MAE exhibited a range of values between 1.92% and 11.28%.

C. Linear Regression (LR)

Linear regression is a widely used approach in the field of machine learning, often utilized to address various computational challenges. Linear regression is a statistical technique that aims to predict a dependent variable, denoted as y , based on an input feature vector,

$x = [x_0, x_1, \dots, x_n]$ It operates this by fitting a linear equation in x , represented as

$$y' = X^T a + b = a_0 x_0 + a_1 x_1 + \dots + a_n x_n + b \quad (4)$$

Where a , and b are coefficients, the variable y' serves as the predictor for the variable y . The matrix X^T represents the transpose of the matrix x . The parameters to be estimated consist of the vector $a = [a_0, a_1, \dots, a_n]$ and the scalar b . In the

typical scenario, the estimation of variables a and b is achieved by the reduction of the sum of squared errors, as expressed by Equation (5).

$$\sum (y' - y)^2 \quad (5)$$

The summation is performed over several data points, denoted as points $(y, x_0, x_1, \dots, x_n)$. One potential strategy for mitigating the issue of model overfitting is to use regularization techniques, such as L1 regularization, also known as LASSO regularization. This approach proves particularly useful as the model's complexity escalates due to the inclusion of several characteristics, denoted as n . Table 1 presents an overview of several neural network algorithms that may be used to predict solar tracking functions.

Table I: Various neural network techniques (Carballo et al., 2019).

Model Name	Details	Ref.
SSD MobileNet V1 optimized	Deep neural networks are built using depth-wise independent convolutions	(Howard et al., 2017)
SSD MobileNet V1 0.75 depth	Less cumbersome SSD MobileNet V1	(Howard et al., 2017)
SSD MobileNet V1 quantized	The quantization approach enables recognition to be performed using integer-only computations	(Jacob et al., 2018)
SSDLite Mobilenet V2	New design that boosts model and benchmark performance	(Sandler et al., 2018)
SSD Inception V2	In SSD Mobilenet V2, the inception component removes the additional layers	(Ning et al., 2017)
Mask RCNN Inception V2	Segmenting instances of objects using a simple, adaptable, and generic framework	(He et al., 2017)

D. Hybrid method-based approach

In a study conducted by Yona et al. (2013), the authors offer a hybrid technique that integrates Support Vector Machines (SVM), Self-Organization Map (SOM), and Fuzzy Logic (FL) to do one-day-ahead forecasting. This study used the SOM algorithm for weather classification, the SVM for the training stage, and the FL approach to determine the optimal training model derived from the SVM. Our hybrid forecaster and tracker's performance surpassed that of the conventional SVR and ANN models.

The research done by Frizzo Stefenon et al. (2020) provides a novel approach called wavelet long short-term memory (LSTM), which combines wavelet energy coefficient with LSTM, to predict photovoltaic output in dual-axis solar trackers. The efficacy of the suggested approach surpasses that of other solar trackers since it acknowledges the potential benefits of refraining from updating the location in certain scenarios. In the presence of cloud cover, the solar trackers engage in dynamic updates, whereby the energy used in the update process surpasses the efficiency gains achieved. Figure 14 illustrates the disparity between the actual and expected signals acquired from the experimental data.

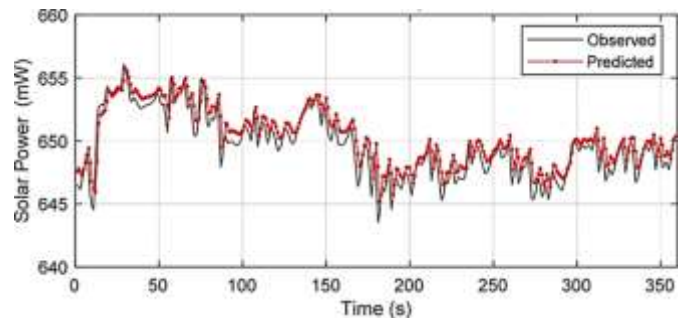


Figure 14: The disparity between the actual and expected signals (Frizzo Stefenon et al., 2020).

In their fundamental work, Lee et al. (2018) conducted an in-depth study of forecasting techniques and their progression through time. The authors used advanced methodologies and analyzed extensive time series data to enhance the accuracy and effectiveness of their analysis. The work is further structured on a hybrid LSTM approach. The findings demonstrate a reduced prediction error when compared to LR, RF regressor, SVM regression, elastic net, and other models.

E. Performance metrics

Metrics such as MAE, RMSE, and RAE are frequently employed to assess the performance of classification and prediction tasks. On the other hand, tracking error metrics are utilized to measure the effectiveness of tracking algorithms in accurately monitoring the sun's position. These measures provide guidance for identifying efficiency and model selection, therefore facilitating the attainment of optimum

energy yield and system maintenance. Consequently, these serve a crucial role in promoting efficient solar energy production.

1) Mean Absolute Error (MAE): MAE is a metric to calculate the average of all absolute errors shown in Equation (6).

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - x| \quad (6)$$

Where, n is the number of errors, $|x_i - x|$ is the absolute errors.

2) Relative Absolute Error (RAE): RAE is a method for measuring the performance of a predictive model shown in Equation (7). It compares actual earning (A) with predicted earnings (P).

$$U_1 = \frac{|\sum_{i=1}^n (P_i - A_i)|^2}{|\sum_{i=1}^n A_i^2|} \quad (7)$$

3) Root Mean Square Error (RMSE): RMSE is a metric calculated by the standard deviation from the residuals shown in Equation (8).

$$RMSE = \sqrt{(f - O)^2} \quad (8)$$

In this equation, f represents the predicted or forecasted values from the model, and O represents the observed or actual values from the experimental data.

In a study by Alghazo *et al.* (2023), the researchers examined the system's output power over six months, while considering various factors. The factors included ambient temperature, wind speed, azimuth and tilt angles of the PV module, and incident irradiance. The prediction models used in their study consist of RF, MLP, and LR classifiers. Their study's findings indicate that all classifiers have exceptional accuracy. Furthermore, it has been shown that the RF classifier exhibits the most favorable performance, as it achieves the greatest R^2 value and the lowest relative absolute error. Ultimately, the prediction classifier that exhibits the lowest level of accuracy is determined to be LR. The summary of their study output is presented in Table 2.

Table 2: Prediction classifiers: a comparative analysis of the findings (Alghazo *et al.*, 2023)

Split percentage 80% training and 20% testing			
Classifier	MAE	RAE	RMSE
Random forest (RF)	8.01	2.36	29.05
Linear regression (LR)	87.37	25.71	136.02
Multilayer perception (MLP)	9.33	2.75	40.70

VI. FUTURE STUDIES

This study extensively reviewed the current techniques and manual methods that have been used in the process of maintenance and tracking of PV systems. Additionally, how AI and ML can enhance the operation has also been illustrated in this study. Future research should focus on enhancing the robustness and scalability of these advanced AI models. Advanced deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNN), could be explored to address non-linearity and

temporal dependencies in solar radiation prediction. Additionally, the integration of hybrid models that combine empirical and machine-learning approaches may further enhance prediction accuracy across diverse climatic conditions.

The exploration of transfer learning and federated learning algorithms should be considered for improving model accuracy with minimal data input, reducing the need for extensive training datasets. Research could also examine the application of reinforcement learning for real-time optimization of PV system cleaning and tracking, especially in dynamic environmental settings. Moreover, incorporating advanced predictive maintenance techniques could offer proactive strategies for optimizing cleaning sequences and monitoring soiling levels.

VII. CONCLUSIONS

This study reviewed current trends and operation of PV system maintenance. In summary, it can be said that the incorporation of AI and ML methods can overcome the limitations of traditional operational procedures, such as labor intensiveness, time consumption, and critical issues such as overcleaning or undercleaning. Numerous machine learning models have successfully identified cleaning operations and tracking optimization performance. However, based on a study of the existing research, it has been shown that more sophisticated techniques such as RF or ANN are required to get satisfactory results in terms of temporal resolution.

ANN and RF models have shown a high level of accuracy in predicting sun radiation as well as cleaning interventions across various climatic situations. The enhanced dependability of these models may be attributed to their capacity to accommodate a larger number of input parameters in comparison to empirical models. Furthermore, ANN-oriented prediction has superior accuracy when compared to conventional models. Hence, ANN exhibits a higher level of complexity and computational requirements within the realm of renewable energy resource prediction, namely in solar radiation prediction and system design. It is suggested that future research on solar radiation prediction and cleaning optimization should use artificial neural network approaches to enhance the quality of outcomes.

The investigation will focus on analyzing the impact of the PV system's features, cleaning sequence, and tracking strategy on the performance variance. The exploration of transfer AI algorithms or deep learning methods offers intriguing avenues for circumventing the need of extensive learning datasets. The successful attainment of high accuracy in detecting cleaning interventions and optimizing tracking can enable monitoring the level of soiling in a PV system. From an application standpoint, the investigation of socio-technical studies has the potential to enhance the comprehension of local social organizations pertaining to PV systems, particularly with regard to regular maintenance. These studies would facilitate the development of a sustainable and appropriate management framework characterized by minimal environmental repercussions. This framework would aid communities in

effectively maintaining PV systems, therefore, enhancing their socio-economic influence.

AUTHOR CONTRIBUTIONS

A. Boussiri: Conceptualization, Methodology, Software, Validation, writing – original draft, Writing – review & editing. **Y. A. E. Kadi:** Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Validation.

ACKNOWLEDGMENT

This research was conducted in the Department of Physics and Mechanics, Faculty of Science and Techniques, University Sultan Moulay Slimane, Beni Mellal, Morocco.

REFERENCES

- Abdulla, H.; Sleptchenko, A. and Nayfeh, A. (2024).** Photovoltaic systems operation and maintenance: A review and future directions. *Renewable and Sustainable Energy Reviews*, 195, 114342.
- Abubakar, A.; Almeida, C. F. M. and Gemignani, M. (2021).** Review of artificial intelligence-based failure detection and diagnosis methods for solar photovoltaic systems. *Machines*, 9, 328.
- Ahmad, E. Z.; Jarimi, H. and Razak, T. R. (2022).** Artificial Neural Network Prediction Model of Dust Effect on Photovoltaic Performance for Residential Applications: Malaysia Case Study. *Int. J. Renew. En. Dev*, 11, 365-373.
- Alghazo, J.; Latif, G.; Hammad, B.; Al-Abed, M.; Sibai, F. and Al-Kouz, W. (2023).** Prediction of the Performance of a Sun Tracking Photovoltaic System using different Artificial Intelligence Techniques: Case Study in Zarqa, Jordan. *International Journal of Computing and Digital Systems*, 13, 1-1.
- Alvarez, D. L.; Al-Sumaiti, A. S. and Rivera, S. R. (2020).** Estimation of an optimal PV panel cleaning strategy based on both annual radiation profile and module degradation. *IEEE Access*, 8, 63832-63839.
- Appels, R.; Muthirayan, B.; Beerten, A.; Paesen, R.; Driesen, J. and Poortmans, J. (2012).** The effect of dust deposition on photovoltaic modules. 2012 38th IEEE photovoltaic specialists conference. IEEE, 001886-001889.
- Babay, M.-A.; Adar, M.; Touairi, S.; Chebak, A. and Mabrouki, M. (2024).** Numerical Simulation and Thermal Analysis of Pressurized Hydrogen Vehicle Cylinders: Impact of Geometry and Phase Change Materials. *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences*, 117, 71-90.
- Barbieri, F.; Rajakaruna, S. and Ghosh, A. (2017).** Very short-term photovoltaic power forecasting with cloud modeling: A review. *Renewable and Sustainable Energy Reviews*, 75, 242-263.
- Carballo, J. A.; Bonilla, J.; Berenguel, M.; Fernández-Reche, J. and García, G. (2019).** Machine learning for solar trackers. AIP Conference Proceedings. AIP Publishing.
- Chaichan, M. T.; Mohammed, B. A. and Kazem, H. A. (2015).** Effect of pollution and cleaning on photovoltaic performance based on experimental study. *International Journal of Scientific and Engineering Research*, 6, 594-601.
- Chiteka, K.; Arora, R.; Sridhara, S. and Enweremadu, C. (2020).** A novel approach to Solar PV cleaning frequency optimization for soiling mitigation. *Scientific African*, 8, e00459.
- Chowdhury, M. E.; Khandakar, A.; Hossain, B. and Abouhasera, R. (2019).** A low-cost closed-loop solar tracking system based on the sun position algorithm. *Journal of Sensors*, 2019.
- Darwish, Z. A.; Kazem, H. A.; Sopian, K.; Al-Goul, M. and Alawadhi, H. (2015).** Effect of dust pollutant type on photovoltaic performance. *Renewable and Sustainable Energy Reviews*, 41, 735-744.
- Darwish, Z. A.; Kazem, H. A.; Sopian, K.; Alghoul, M. and Chaichan, M. T. (2013).** Impact of some environmental variables with dust on solar photovoltaic (PV) performance: review and research status. *International J of Energy and Environment*, 7, 152-159.
- Darwish, Z. A.; Sopian, K. and Fudholi, A. (2021).** Reduced output of photovoltaic modules due to different types of dust particles. *Journal of Cleaner Production*, 280, 124317.
- Derakhshandeh, J. F.; Alluqman, R.; Mohammad, S.; Alhussain, H.; Alhendi, G.; Aleid, D. and Ahmad, Z. (2021).** A comprehensive review of automatic cleaning systems of solar panels. *Sustainable Energy Technologies and Assessments*, 47, 101518.
- Edenhofer, O.; Pichs-Madruga, R.; Sokona, Y.; Seyboth, K.; Kadner, S.; Zwickel, T.; Eickemeier, P.; Hansen, G.; Schlömer, S. and Von Stechow, C. (2011).** *Renewable energy sources and climate change mitigation: Special report of the intergovernmental panel on climate change*. Cambridge University Press.
- Fan, Z.; Wang, M.; Mu, J. and Yi, J. (2020).** Alternative cleaning and dust detection method for PV modules and its application. *Journal of Renewable and Sustainable Energy*, 12.
- Fathabadi, H. (2016).** Novel high efficient offline sensorless dual-axis solar tracker for using in photovoltaic systems and solar concentrators. *Renewable Energy*, 95, 485-494.
- Feng, H. (2018).** The application of artificial intelligence in electrical automation control. *Journal of Physics: Conference Series*. IOP Publishing, 062008.
- Frizzo Stefenon, S.; Kasburg, C.; Nied, A.; Rodrigues Klaar, A. C.; Silva Ferreira, F. C. and Waldrigues Branco, N. (2020).** Hybrid deep learning for power generation forecasting in active solar trackers. *IET Generation, Transmission & Distribution*, 14, 5667-5674.
- Hammad, B.; Al-Abed, M.; Al-Ghandoor, A.; Al-Sardeah, A. and Al-Bashir, A. (2018).** Modeling and analysis of dust and temperature effects on photovoltaic systems' performance and optimal cleaning frequency: Jordan case study. *Renewable and Sustainable Energy Reviews*, 82, 2218-2234.
- Harrou, F.; Dairi, A.; Taghezouit, B. and Sun, Y. (2019).** An unsupervised monitoring procedure for detecting

anomalies in photovoltaic systems using a one-class support vector machine. *Solar Energy*, 179, 48-58.

Hasan, N. M. S.; Sobuz, M. H. R.; Shaurdho, N. M. N.; Meraz, M. M.; Datta, S. D.; Aditto, F. S.; Kabbo, M. K. I. and Miah, M. J. (2023). Eco-friendly concrete incorporating palm oil fuel ash: Fresh and mechanical properties with machine learning prediction, and sustainability assessment. *Heliyon*, 9.

He, K.; Gkioxari, G.; Dollár, P. and Girshick, R. (2017). Mask r-cnn. Proceedings of the IEEE international conference on computer vision. 2961-2969.

Heinrich, M.; Meunier, S.; Samé, A.; Quéval, L.; Darga, A.; Oukhellou, L. and Multon, B. (2020). Detection of cleaning interventions on photovoltaic modules with machine learning. *Applied Energy*, 263, 114642.

Hosmer Jr, D. W.; Lemeshow, S. and Sturdivant, R. X. (2013). *Applied logistic regression*, John Wiley & Sons.

Howard, A. G.; Zhu, M.; Chen, B.; Kalenichenko, D.; Wang, W.; Weyand, T.; Andreetto, M. and Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*.

Irena (2023). Renewable Capacity Statistics. 2022 [Online].

Jacob, B.; Kligys, S.; Chen, B.; Zhu, M.; Tang, M.; Howard, A.; Adam, H. and Kalenichenko, D. (2018). Quantization and training of neural networks for efficient integer-arithmetic-only inference. Proceedings of the IEEE conference on computer vision and pattern recognition. 2704-2713.

Jamroen, C.; Komkum, P.; Kohsri, S.; Himananto, W.; Panupintu, S. and Unkat, S. (2020). A low-cost dual-axis solar tracking system based on digital logic design: Design and implementation. *Sustainable Energy Technologies and Assessments*, 37, 100618.

Javed, W.; Guo, B. and Figgis, B. (2017). Modeling of photovoltaic soiling loss as a function of environmental variables. *Solar Energy*, 157, 397-407.

Jiang, Y.; Lu, L. and Lu, H. (2016). A novel model to estimate the cleaning frequency for dirty solar photovoltaic (PV) modules in desert environment. *Solar Energy*, 140, 236-240.

Jones, R. K.; Baras, A.; Al Saeeri, A.; Al Qahtani, A.; Al Amoudi, A. O.; Al Shaya, Y.; Alodan, M. and Al-Hsaen, S. A. (2016). Optimized cleaning cost and schedule based on observed soiling conditions for photovoltaic plants in central Saudi Arabia. *IEEE journal of photovoltaics*, 6, 730-738.

Kalogirou, S.; Lalot, S.; Florides, G. and Desmet, B. (2008). Development of a neural network-based fault diagnostic system for solar thermal applications. *Solar Energy*, 82, 164-172.

Kazem, H. A.; Yousif, J.; Chaichan, M. T. and Al - Waeli, A. H. (2019). Experimental and deep learning artificial neural network approach for evaluating grid - connected photovoltaic systems. *International Journal of Energy Research*, 43, 8572-8591.

Kermadi, M. and Berkouk, E. M. (2017). Artificial intelligence-based maximum power point tracking controllers

for Photovoltaic systems: Comparative study. *Renewable and Sustainable Energy Reviews*, 69, 369-386.

Khilar, R.; Suba, G. M.; Kumar, T. S.; Samson Isaac, J.; Shinde, S. K.; Ramya, S.; Prabhu, V. and Erko, K. G. (2022). Improving the efficiency of photovoltaic panels using machine learning approach. *International Journal of Photoenergy*, 2022.

Kumar, S. and Dave, V. (2016). ANN based controller to mitigate soiling loss on solar panels. 2016 21st Century Energy Needs-Materials, Systems and Applications (ICTFCEN). IEEE, 1-6.

Kurukuru, V. S. B.; Haque, A.; Khan, M. A.; Sahoo, S.; Malik, A. and Blaabjerg, F. (2021). A review on artificial intelligence applications for grid-connected solar photovoltaic systems. *Energies*, 14, 4690.

Lee, W.; Kim, K.; Park, J.; Kim, J. and Kim, Y. (2018). Forecasting solar power using long-short term memory and convolutional neural networks. *IEEE access*, 6, 73068-73080.

Li, Z.; Liu, X. and Tang, R. (2010). Optical performance of inclined south-north single-axis tracked solar panels. *Energy*, 35, 2511-2516.

Maghami, M. R.; Hizam, H.; Gomes, C.; Radzi, M. A.; Rezadad, M. I. and Hajjighorbani, S. (2016). Power loss due to soiling on solar panel: A review. *Renewable and Sustainable Energy Reviews*, 59, 1307-1316.

Malav, S. and Vadhera, S. (2015). Hardware implementation of solar tracking system using a stepper motor. 2015 International Conference on Energy, Power and Environment: Towards Sustainable Growth (ICEPE). IEEE, 1-4.

Mathworks (2023a). Deep Learning Toolbox - MATLAB. [Online].

Mathworks (2023b). Train support vector machine (SVM) classifier-MATLAB [Online].

Mohanraj, M.; Jayaraj, S. and Muraleedharan, C. (2009). Performance prediction of a direct expansion solar assisted heat pump using artificial neural networks. *Applied Energy*, 86, 1442-1449.

Muhammad Ehsan, R.; Simon, S. P. and Venkateswaran, P. (2017). Day-ahead forecasting of solar photovoltaic output power using multilayer perceptron. *Neural Computing and Applications*, 28, 3981-3992.

Munawar, M. I.; Alam, I. and Ali, M. S. (2023). An efficient energy prediction model for solar energy power system using Artificial Intelligence technique. International Conference on Recent Academic Studies. 139-145.

Naeem, M. and Tamizhmani, G. (2015). Cleaning frequency optimization for soiled photovoltaic modules. 2015 IEEE 42nd Photovoltaic Specialist Conference (PVSC). IEEE, 1-5.

Ning, C.; Zhou, H.; Song, Y. and Tang, J. (2017). Inception single-shot multibox detector for object detection. 2017 IEEE International Conference on Multimedia & Expo Workshops (ICMEW). IEEE, 549-554.

Nsengiyumva, W.; Chen, S. G.; Hu, L. and Chen, X. (2018). Recent advancements and challenges in Solar Tracking Systems (STS): A review. *Renewable and Sustainable Energy Reviews*, 81, 250-279.

- Osmani, K.; Haddad, A.; Lemenand, T.; Castanier, B. and Ramadan, M. (2020).** A review on maintenance strategies for PV systems. *Science of the Total Environment*, 746, 141753.
- Paul, D. I. (2022).** Dust Deposition on Photovoltaic Modules: Its Effects on Performance. *The Effects of Dust and Heat on Photovoltaic Modules: Impacts and Solutions*, 3-46.
- Pavan, A. M.; Mellit, A. and De Pieri, D. (2011).** The effect of soiling on energy production for large-scale photovoltaic plants. *Solar energy*, 85, 1128-1136.
- Pavan, A. M.; Mellit, A.; De Pieri, D. and Kalogirou, S. A. (2013).** A comparison between BNN and regression polynomial methods for the evaluation of the effect of soiling in large scale photovoltaic plants. *Applied energy*, 108, 392-401.
- Pulipaka, S. and Kumar, R. (2016).** Power prediction of soiled PV module with neural networks using hybrid data clustering and division techniques. *Solar Energy*, 133, 485-500.
- Qazi, A.; Fayaz, H.; Wadi, A.; Raj, R. G.; Rahim, N. and Khan, W. A. (2015).** The artificial neural network for solar radiation prediction and designing solar systems: a systematic literature review. *Journal of cleaner production*, 104, 1-12.
- Razak, T. R.; Garibaldi, J. M.; Wagner, C.; Pourabdollah, A. and Soria, D. (2020).** Toward a framework for capturing interpretability of hierarchical fuzzy systems—a participatory design approach. *IEEE Transactions on Fuzzy Systems*, 29, 1160-1172.
- Ritchie, H. and Roser, M. (2020).** Renewable Energy. Our World in Data 2020 [Online].
- Robles Algarín, C.; Sevilla Hernández, D. and Restrepo Leal, D. (2018).** A low-cost maximum power point tracking system based on neural network inverse model controller. *Electronics*, 7, 4.
- Rodrigo, P. M.; Gutiérrez, S.; Micheli, L.; Fernández, E. F. and Almonacid, F. (2020).** Optimum cleaning schedule of photovoltaic systems based on levelised cost of energy and case study in central Mexico. *Solar Energy*, 209, 11-20.
- Salamah, T.; Ramahi, A.; Alamara, K.; Juaidi, A.; Abdallah, R.; Abdelkareem, M. A.; Amer, E.-C. and Olabi, A. G. (2022).** Effect of dust and methods of cleaning on the performance of solar PV module for different climate regions: Comprehensive review. *Science of The Total Environment*, 827, 154050.
- Sandler, M.; Howard, A.; Zhu, M.; Zhmoginov, A. and Chen, L.-C. (2018).** Mobilenetv2: Inverted residuals and linear bottlenecks. Proceedings of the IEEE conference on computer vision and pattern recognition. 4510-4520.
- Saravanan, S. and Babu, N. R. (2016).** Maximum power point tracking algorithms for photovoltaic system—A review. *Renewable and Sustainable Energy Reviews*, 57, 192-204.
- Sarver, T.; Al-Qaraghuli, A. and Kazmerski, L. L. (2013).** A comprehensive review of the impact of dust on the use of solar energy: History, investigations, results, literature, and mitigation approaches. *Renewable and sustainable energy Reviews*, 22, 698-733.
- Sayyah, A.; Horenstein, M. N. and Mazumder, M. K. (2014).** Energy yield loss caused by dust deposition on photovoltaic panels. *Solar Energy*, 107, 576-604.
- Seme, S.; Štumberger, B.; Hadžiselimović, M. and Sredenšek, K. (2020).** Solar photovoltaic tracking systems for electricity generation: A review. *Energies*, 13, 4224.
- Serpa, P. and Zilles, R. (2007).** The diffusion of photovoltaic technology in traditional communities: the contribution of applied anthropology. *Energy for Sustainable Development*, 11, 78-87.
- Sobuz, M. H. R.; Joy, L. P.; Akid, A. S. M.; Aditto, F. S.; Jabin, J. A.; Hasan, N. M. S.; Meraz, M. M.; Kabbo, M. K. I. and Datta, S. D. (2024a).** Optimization of recycled rubber self-compacting concrete: Experimental findings and machine learning-based evaluation. *Heliyon*, 10.
- Sobuz, M. H. R.; Khan, M. H.; Kabbo, M. K. I.; Alhamami, A. H.; Aditto, F. S.; Sajib, M. S.; Alengaram, U. J.; Mansour, W.; Hasan, N. M. S. and Datta, S. D. (2024b).** Assessment of mechanical properties with machine learning modeling and durability, and microstructural characteristics of a biochar-cement mortar composite. *Construction and Building Materials*, 411, 134281.
- Sumathi, V.; Jayapragash, R.; Bakshi, A. and Akella, P. K. (2017).** Solar tracking methods to maximize PV system output—A review of the methods adopted in recent decade. *Renewable and Sustainable Energy Reviews*, 74, 130-138.
- Tomson, T. (2008).** Discrete two-positional tracking of solar collectors. *Renewable energy*, 33, 400-405.
- Vapnik, V. (1999).** *The nature of statistical learning theory*, Springer science & business media.
- Wang, H.; Yi, H.; Peng, J.; Wang, G.; Liu, Y.; Jiang, H. and Liu, W. (2017).** Deterministic and probabilistic forecasting of photovoltaic power based on deep convolutional neural network. *Energy conversion and management*, 153, 409-422.
- Wang, Z.; Xu, Z.; Zhang, Y. and Xie, M. (2020).** Optimal cleaning scheduling for photovoltaic systems in the field based on electricity generation and dust deposition forecasting. *IEEE Journal of Photovoltaics*, 10, 1126-1132.
- Yona, A.; Senjyu, T.; Funabashi, T. and Kim, C.-H. (2013).** Determination method of insolation prediction with fuzzy and applying neural network for long-term ahead PV power output correction. *IEEE Transactions on Sustainable Energy*, 4, 527-533.
- Zhu, Y.; Liu, J. and Yang, X. (2020).** Design and performance analysis of a solar tracking system with a novel single-axis tracking structure to maximize energy collection. *Applied Energy*, 264, 114647.