Solar Energy 266 (2023) 112138

Contents lists available at ScienceDirect

Solar Energy

journal homepage: www.elsevier.com/locate/solener

Optimal cleaning schedule in solar PV using the biography-based helianthus optimization enabled coupled deep network

Upendra Pal Singh [a,*], Subhash Chandra [b]

[a] Electrical Engineering, GLA University, 17 Km Stone, NH-2, Mathura-Delhi Road, Mathura 281406, UP, India
[b] GLA University, 17 Km Stone, NH-2, Mathura- Delhi Road, Mathura 281406, UP, India

ARTICLE INFO

Keywords:
Solar photovoltaic
Photovoltaic and Hybrid biography-based Helianthus optimization

ABSTRACT

The research aims to develop a system that determines the optimal intervals for cleaning solar PV panels to maximize their efficiency and minimize power loss due to dust accumulation. The research utilizes data related to daily solar photovoltaic tariff rates, power generation, and conditions of dust accumulation on PV panels. To monitor the performance of PV panels, the research involves forecasting power generation. If the power generation falls below a predefined threshold, it indicates a need for cleaning. Dust particle loss conditions are analyzed using an optimized Support Vector Machine (SVM) coupled with a Deep Convolutional Neural Network (CNN) model. This model processes PV panel images to identify dusty conditions. The Deep CNN model extracts features from PV panel images, such as color-based statistical features and local gradient patterns. These features are crucial for identifying dusty conditions. The optimal cleaning schedule is determined based on the detection of dust particle loss conditions. Cleaning is initiated when the conditions warrant it. The novelty of this research lies in the development of a deep learning model for both detecting dust particle loss and forecasting power generation. This model is trained using data that includes daily tariff rates and dust particle loss information. The research proposes a new optimization method called "biography-based Helianthus optimization (HBBHO)" specifically designed to suit the characteristics of sunlight. This method is employed to schedule cleaning activities. The proposed approach achieves impressive accuracy, precision, sensitivity, and specificity, with values reaching 96.53% for most metrics, except for specificity, which is at 96.21%.

1. Introduction

Sustainable Development Scenario [1] of the International Energy Agencies, using renewable energy will be a key part of the answer for every problem of reducing carbon dioxide (CO2) emission from energy conversion, which is a significant global issue. Due to sunlight's radiation, solar PV systems are hugelyaccepted everywhere, which has the advantage over wind energy systems, whose power generation is distinguished by a very variable source (wind). A photovoltaic cell is the little part utilized to transform solar energy into electrical energy. The ability of a solar cell to convert light energy into electrical energy is determined by the semiconductor technology used during production [2]. Shading conditionacts as a crucial element in photovoltaic (PV) systems that lowers efficiency and decreases the amount of energy that attains the PV modules [3]. To prevent being shaded by trees and buildings, PV can be built in carefully considered places. However, dust deposition shadow constantly affects how much electricity is generated by solar panels. To mitigate the drawbacks of dust buildup, PV modules must be cleaned. Although some washing of the modules can be accomplished by wind and rain, full spotlessness must be guaranteed by cleaning through hand and detergents [4,5].

The cost of (PV) energy has been deduced [6]. The rise in advanced facilitiesis employing solar energy by low cost and relative cleanliness [7]. Street lights, photovoltaic water pumpings, PV freezers, self-sufficient photovoltaic dwellings,and communal power plants are a few examples [8]. To correctly calculate the dust particle rate, the second approach compares the short circuit current between a soiled PV cell and a clean cell [9]. It is argued that photovoltaic (PV) generation could help with issues connected to climate change. With the usage of PV, projected that the emissions created by the generation of energy will decrease. Traditional power generation, which relies on raw materials like coal, gas, and water, is regarded as a mature and optimized technology. The participation used in [10,11] to organize for factors that determine system performance include environment, PV system,

* Corresponding author at: Solar PV cleaning scheduling using HBBHO.
E-mail addresses: upeendra.singh79@gmail.com (U.P. Singh), Subhash.chandra@gla.ac.in (S. Chandra).

https://doi.org/10.1016/j.solener.2023.112138
Received 28 June 2023; Received in revised form 29 September 2023; Accepted 6 October 2023
Available online 10 November 2023
0038-092X/

installation, cost, and other variables. Environmental aspectscomprise things like dust, soiling, temperature, shade, and solar irradiance [12]. However, employing solar energy hasa set of difficulties, chief among which is the loss of dust particles or the accumulation of foreign particles on the surface of solar photovoltaic collectors. Obstacles to the widespread adoption of solar PV technology include dust particle loss, which leads to power losses of up to 70 % [13–15].

Due to dust particle loss, inclusion of dirt, sand, and additional impurities on the surface of the modules, photovoltaic (PV) systems suffer significant losses [16,17]. Absorbing, reflecting, and deflecting some of the incoming light, the layer of dirt reduces the PV cell's capacity to convert solar into electrical energy [18]. The module layer typically becomes dirty during dry spells and can be dirt-free manually or artificially [19]. Numerous factors, some environmental and others installation-related, damage the amount of dust and silt that accumulates on PV panels [20]. PV lifespan and effectiveness in modules were reduced due to the accumulation of dirt and dust over time on solar array surfaces. Particle loss from dirt and dust affectsPV's with PR performance ratio [21,22]. Solar cells convert solar irradiance into direct current electricity via the photovoltaic effect. Monitoring variables such as ambient temperature, humidity, wind speed, airborne dust, and solar irradiance is crucial since weather conditions have a collision on a solar PV module's efficiency [23]. Airborne dust particles are selected by the wind and carried to the PV module's front surface, where they prevent sunlight from reaching the solar cell junction beneath the glass and lower the PV module's output [24]. The techniques used in fault diagnosis for Proton Exchange Membrane Fuel Cells (PEMFCs) are explored. One of the strengths of this approach is the integration of PEMFC knowledge into the deep learning training process. This enhances fault diagnosis performance by utilizing domain-specific insights, even with limited measured EIS data [25]. The utilization of complex neural networks for feature extraction from EIS data enables the model to effectively capture the intricacies of complex impedances. The adoption of complex neural networks may lead to increased computational complexity, potentially demanding more computational resources [26]. The integration of supercapacitors and fuel cells in the HESS offers improved and optimized operation for load–frequency control applications. The incorporation of adaptive neural networks and sliding mode control can make the control algorithm complex, potentially requiring advanced computational capabilities. The fault diagnosis in PEMFCs benefits from deep learning and domain-specific knowledge integration, while control of HESS and robotic systems utilizes neural networks for adaptive and robust control. The main challenges across these techniques include computational complexity and data dependency, which should be considered in their practical implementation [27]. Since the inception of PV plants, diverse technologies for dust prevention and cleaning have emerged [28]. Robotic cleaners, electrostatic removal, self-cleaning layers, and automated water cleaning stands as the prevailing methods currently employed. Choosing the right cleaning mechanism holds vital importance, contingent upon the specific plant size and location [29]. Beyond the selection of cleaning methods, determining the optimal cleaning timing is a crucial consideration. Relying solely on visual inspection for cleaning decisions proves inadequate in terms of energy economics, necessitating a more strategic approach [30,31].

The research objective is to optimize solar power generation from photovoltaic systems (SPVs) by continuously monitoring panel dust levels. This work presents dual contributions: initially, forecasting daily SPV output and formulating a loss function by contrasting actual system power with acquired data. Subsequently, in cases of significant loss, attention is directed toward panels, prompting scheduling for cleaning. Image analysis of panels detects dust accumulation, informing a priority-driven cleaning schedule. This power prediction employs an attention-based deep-layered model; loss calculation relies on predicted power. Attention triggers upon surpassing a set loss threshold, initiating cleaning guided by an objective function-enabled HBBHO algorithm. The scheduling priorities are established by HBBHO, leveraging a hybrid support vector machine (SVM) and Deep Convolutional Neural Network (Deep CNN) model to pinpoint dust conditions.

Attention-based deep layered model: The proposed attention-based deep layered model is engaged in the automatic prediction of power generation with powerloss as the objective function.

Hybrid biography-based Helianthus optimization(HBBHO): The role of the HBBHO algorithm is to schedule the cleaning in the SPV module based on the power loss associated with the generation unit and the dusty conditions of the PV. Moreover, the training of the proposed optimized SVM coupled Deep CNN model and attention-based deep layered model is supportedby the HBBHO algorithm such that the optimal tunable parameters are decided by the proposed HBBHO algorithm.

Optimized SVM coupled Deep CNN model: The model is employed for identifying the dust particles in the SPV so that the decision from this model supports the optimal cleaning schedule in the PV.

The whole research of the manuscript follows: A review of the conventional research is presented in section 2 with the challenges considered for the research. System design is presented in section 3 followed by the proposed method for maximizing the generation is highlighted in section 4. The achievements of the research follow section 5 and the implications of the research are detailed in section 6.

2. Literature review

A unique dynamicrepresentation of the PV output power profile that incorporates dust collection was introduced by Armaghan Cheema et al. [32] using a chain model. The method's advantage was reduced error and resolution of the practical problem, but the cost was increased complexity and processing time. A hybrid-based cleaning schedule policy with periodic planning and dynamic adjustment was suggested by Zhonghao Wang et al. [4] for improving PV system operations and maintenance. The method's simplicity was a benefit, but high cleaning costs and scheduling issues made cleaning go slowly. A low-cost monitoring system for cleaning operations on photovoltaic modules during the day was examined by Matthias Heinrichaet al. [9]. The method's advantage was that predictive service eliminated the need for human data entry; nevertheless, it used less energy and memory. An approach for enhancing the PV panel cleaning schedule was discussed by David L. Alvarez et al. in their study [12]. Soiling on panel surfaces reduces the yield of PV systems. The technology had the advantage of lessening the effects of emissions and soiling accumulation, but it also came at a higher expense for operations and cleaning. To reduce the number of days between subsequent cleaning periods, KudzanayiChiteka et al. [15] evaluated the impact of altering daily dusty rates. The method's benefits included a reduction in energy and financial losses, but the computing complexity was substantial. The effects of recognizing CPs in the PV soiling extraction were examined by Leonardo Micheli et al. [19]. The method's benefit was a reduction in modeling mistakes and the overfitting problem, but it required a lot of power. A technique based on computer vision was presented by Kamal Adel Abuqaaud and Azzeddine Ferrah [21] to verify dirt and dust on PV surfaces with advantage was its quick processing and easy implementation, but its disadvantages were high recognition rates and low conversion efficiency. In an outdoor experiment, Rizwan Majeed et al. [24] evaluated how cleaning with a practical homemade cleaning system influenced the performance of the PV module as a result of dust accumulation. Although this method effectively removes dust and uses less water, it has too many overfitting issues. Sameer Al-Dahidi et al. [31]. Leveraging data-driven ensemble methodologies for forecasting solar Photovoltaic (PV) power output holds great promise, mainly due to their adeptness in managing the intermittent characteristics of solar energy. In this study, a comprehensive ensemble strategy is introduced, comprising refined and varied Artificial Neural Networks (ANNs), aimed at enhancing predictions of solar PV power production 24 h in advance. The ANNs are fine-tuned

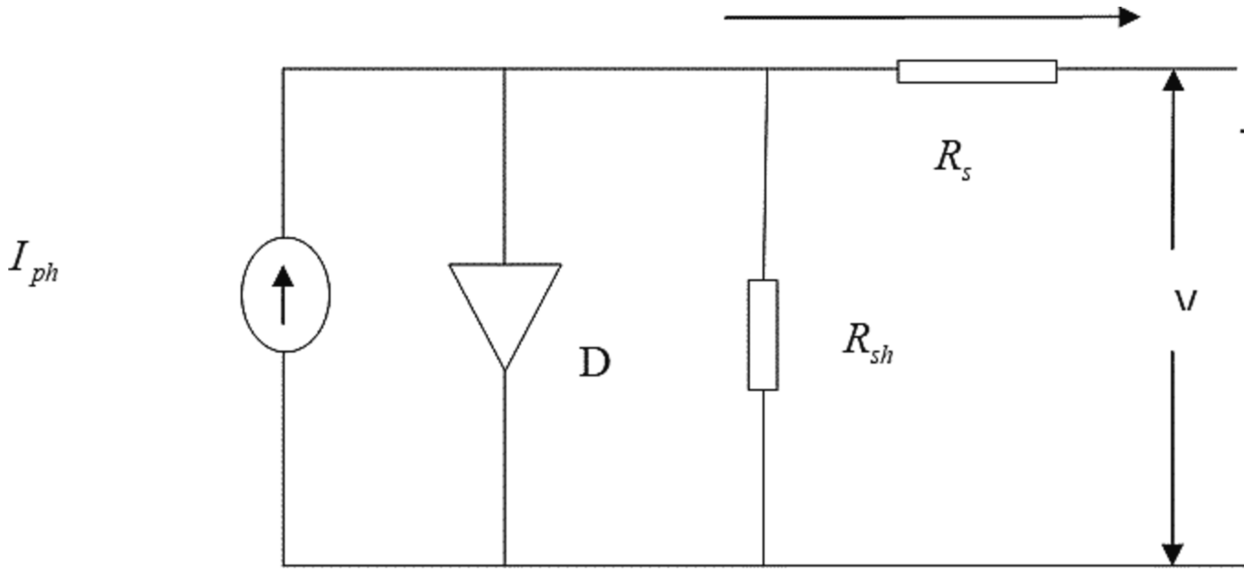

Fig. 1. Schematic diagram of the PV model.

concerning hidden neuron count and diversified by incorporating diverse training datasets, a process facilitated by both trial-and-error methodologies and BAGGING techniques. Nevertheless, there is no single approach capable of precisely predicting solar PV power production.

2.1. Challenges

- Optimal scheduling to clean PV is a challenging issue in the effective operation of PV systems [2].
- The optimization of PV cleaning is challenging since the assessment of the dust particle loss rate depends on both time and location [12].
- However, the unpredictable, indirect, and volatile characteristics of the weather conditions provide practical challenges for the installation of PV into the grid [2].
- Moreover, employing solar cellscontains drawbacks. The most significant of them is the filth accumulation of foreign materials on the surface of solar photovoltaic collectors [15].
- Dust particle losses are the main issue and difficulty in making a PV system function well in Pakistan's climate [24].

3. System modeling and description

3.1. Photovoltaic panel modeling

Photovoltaic cells are considered a long-lasting source from the photovoltaic cell models, which assists the energy production through single diode circuit mode in Fig. 1. Here, the model contains a current source belonging to solar radiating radiation, cell temperature, and a diode. Hence, they are induced with the saturation current dependent on the operating situation into the series and shunt resistive resistance as given by,

$$I = I_{ph} - I_d - I_{sh} \tag{1}$$

where I_{ph} means photo-generated through current belongs to the irradiance and temperature conditions, I_d is the diode current, I_{sh} is current across R_{sh} and I meant to be as a current of the solar cell.*D*- is the diode modeling the P/N junction of the solar cell.

Eq. (1) belongs to the indication of solar irradiance, the temperature level of the cell with their reference value which is generally contributed from the sections of a manufacturer by PV modules. They operated under a certain operating performance as Standardarized Test Conditions (STC) with an irradiance is 1000 W/m^2 and a cell temperature is 25C.The coefficients within Eq. (1) are contingent upon incident solar irradiance, cell temperature, and their respective reference benchmarks, as real-world conditions invariably deviate from these standards, and discrepancies can perturb the actual values of these pivotal parameters, appraising these coefficients under authentic operational circumstances stands as a paramount objective in this research, ensuring an accurate mathematical model for PV modules. Additionally, manufacturer-provided reference parameters under STC manifest inaccuracy when applied to outdoor conditions [22]. To address this, the current study introduces a methodology relying on outdoor measurements and mathematical formulations to ascertain reference benchmarks for said parameters. Subsequently, the assessment of these five model parameters, accounting for the authentic irradiance and temperature conditions of the target PV module, is established in alignment with their designated reference values. The comprehensive procedure detailing these steps is expounded upon in the ensuing sections.

$$I_{ph} = \frac{G}{G_{ref}}\left(I_{ph.ref} + M_{ICC}\left(T - T_{ref}\right)\right) \tag{2}$$

Eq. (2), G and T stands for the irradiance and temperature of the PV, G_{ref}&T_{ref} denotes irradiance and temperature with the standard test conditions, M_{Icc} is the temperature coefficient of current, $I_{ph.ref}$- photo-generated current.

$$I_d = I_{sat}\left(\exp\left(V + \frac{R_s I}{nV_t}\right) - 1\right) \tag{3}$$

I_{sat}- means the reverse diffusion current of the diode from a solar panel, n defines the diode ideality factor, and V_t denotes the thermal voltage. n-denotes the total series of cells and V represents the voltage source of the solar cell.

$$I_{sh} = \frac{V + R_s I}{R_{sh}} \tag{4}$$

Substituting the ideals of I_d and I_{sh} in Eq. (1),

$$I = \frac{G}{G_{ref}}\left(I_{ph.ref} + M_{ICC}\left(T - T_{ref}\right)\right) - I_{sat}\left(\exp\left(\frac{V + R_{sh}}{nV_t}\right) - 1\right) - \frac{V + R_s I}{R_{sh}} \tag{5}$$

where, R_s&R_{sh} is the series and shunt resistance of the solar panel cells. Furthermore, the quality of solar cells is calculated through the mea-

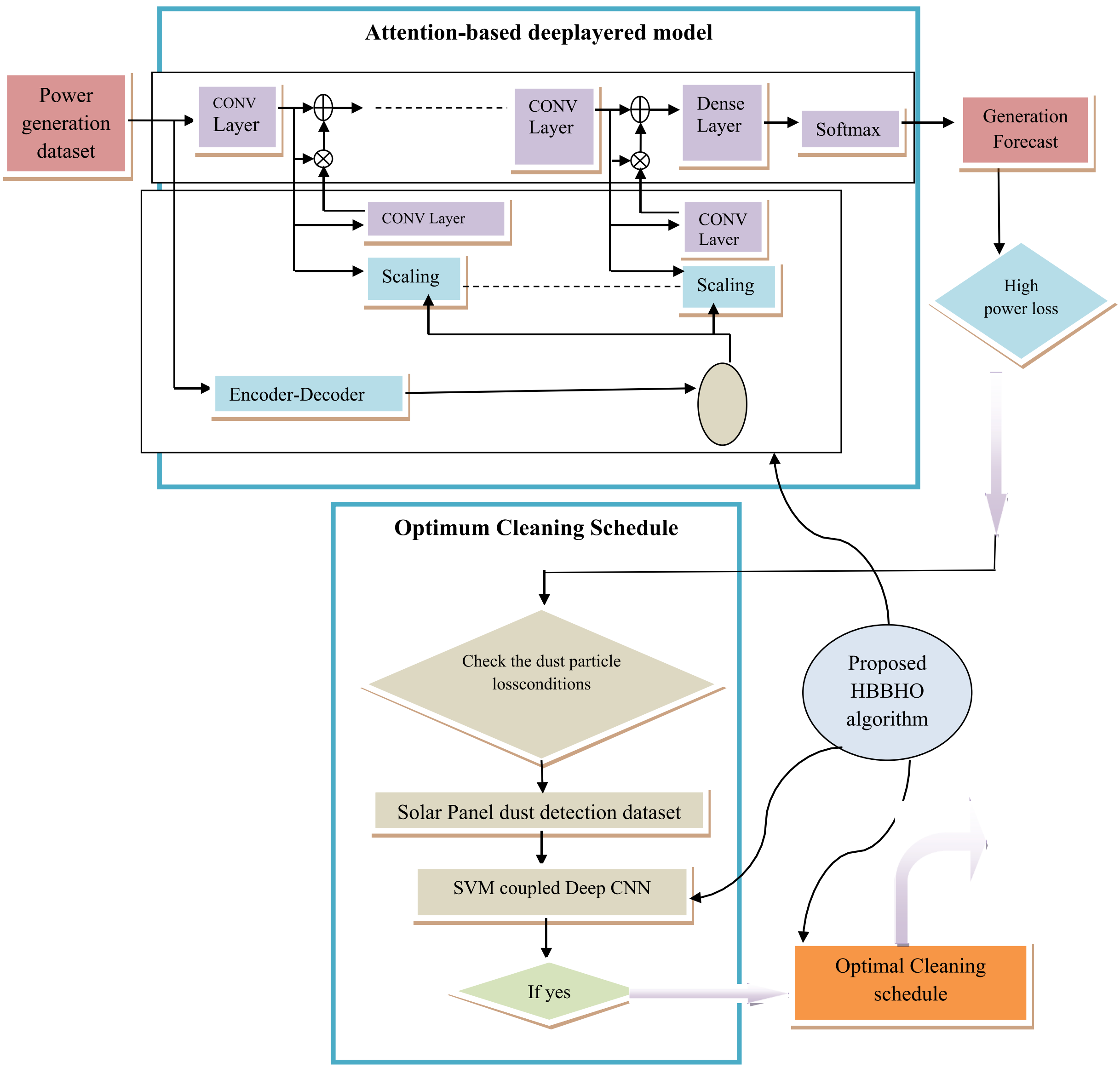

Fig. 2. Schematic representation of the PV optimal cleaning schedule.

surements of both current and voltage characteristics directly, most of the high-power energy generation cells would be connected with parallel branch connections. The PV model is measured through the daily power generation from the solar array cells of the panel.

3.2. Daily power generation through PV panel

Normally, generating solar energy on an hourly basis could be due to global horizontal and beam irradiance intruding on the PV that occurs freely from SOLCAST.

$$I_{Ti} = I_{Hb}R_{bi} + I_{Hd}R_{di} + (I_{Hb} + I_{Hd})R_{gri} \tag{6}$$

where, I_{Ti}, I_{Hb}, I_{Hd} represents the hourly irradiance occurrence on a tilted plane, hourly beam irradiance, and hourly diffuse irradiance, next the standards from the tilt factor for beam irradiance, diffuse irradiance, and ground reflected irradiance are denoted by R_{bi}, $R_{di,}$ R_{gri} respectively. γ_i, φ_i, α_i *and* η_i, are noted to be the hour angle, latitude, tilt angle, and declination angle.

$$R_{bi} = \frac{Sin(\varphi_i + \alpha_i)Sin\eta_i + Cos(\varphi_i + \alpha_i)Cos\eta_i Cos\gamma_i}{Sin\varphi_i Sin\eta_i + Cos\varphi_i Cos\eta_i Sin\gamma_i} \tag{7}$$

$$R_{di} = \frac{1 + \text{Cos}\alpha_i}{2} \tag{8}$$

$$R_{gri} = \rho \frac{1 - Cos\alpha_i}{2} \tag{9}$$

The declination between the hour-wise angle is induced into the day number as n_d

$$\eta_i = 23.34Sin\left[\frac{360}{365}(284 + n_d)\right] \tag{10}$$

$$\mu_p = Cos^{-1}(-\tan\varphi_i \tan\delta_i) \tag{11}$$

Generation from the PV panel is measured in terms of the incoming irradiance as in Eq. (7), where,P_{aj}&W_{pj} indicates the power generated by the solar photovoltaic array and the peak hour installed power. λ_{aq}, λ_{refer} belongs to the PV power generating efficiency of aqueous and reference voltage with ambient temperature denotes by T^{am} then, the temperature effects were assigned based upon the predictable power generation, and the actual power generation is noticed for every day under consideration. Further, T_{refen} denotes the temperature reference in the range of

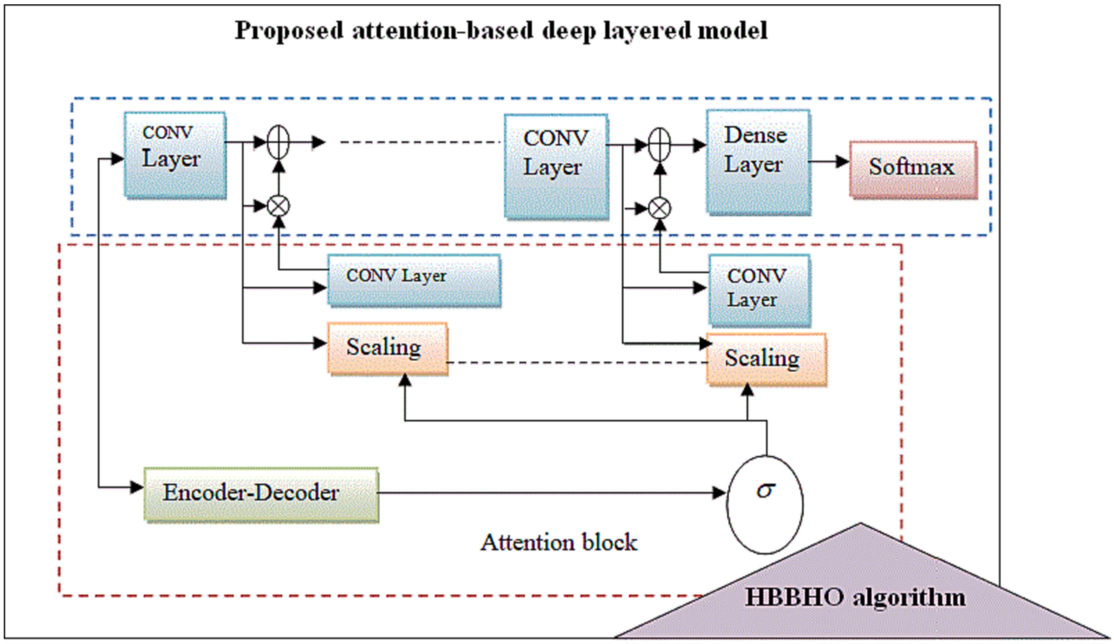

Fig. 3. Architecture of proposed attention-based deep layered model.

25 degrees Celsius and μ_p is the period taken for power generation. T_{NOCT} is the nominal operating cell temperature of 20 deg Celsius, while G_{NOCT} is chosen with 800 W/meter square. The difference between the expected power generation (E_{epg}) and actual power generated (E_{apg}) is the powerloss contributedby the dust particles which $\overline{H_Q}$ means the high range in temperature.

$$P_{aj} = \left(\frac{\lambda_{ab}}{\lambda_{refer}}\right)\left(\frac{I_{Ti}}{1000}\right)W_{pj} \tag{12}$$

$$\lambda_{ab} = \lambda_{refer}\left[1 - \alpha_i\left[T^{am} - T_{refer} + (T_{NOCT} - T_{ab})\frac{\overline{H_Q}}{G_{NOCT}}\right]\right] \tag{13}$$

$$R_S = \frac{E_e - E_\beta}{E_e}\% \tag{14}$$

where, E_e and E_β represents the apparent power and real power, and P_a is the peak installed power.

$$E_e = P_a \times 1\,hour \tag{15}$$

Thus, the daily power generating power is calculated using the electricity tariff data, which is employed for the power generation forecast, followed by monitoring the power loss. In short, the daily generation is predicted using the attention-based deep layered model, and the dust particle present in the PV is tracked using the optimized SVM coupled Deep CNN model, and the detailed description of the novelty is explained in the section below.

4. Proposed methodology and description

The research aims to facilitate the optimal cleaning of the solar PV at the optimum intervals for which an optimal scheduling algorithm alongwith the cost function and deep learning-based dust particle loss detection model isconsidered to ensure the cost-effective cleaning at the optimum intervals. Normally, the daily SPV tariff is required for forecasting the power generation to monitor the power loss conditions associated with the PV. If the power generation is found to be poor, not meeting the daily tariff conditions, the dust particle lossconditions are validated for which the PV dusty images are acquired and the dust particle loss conditions are analyzed using the optimized SVM coupled Deep CNN model for which the color-based statistical features and local gradient patterns of the PV panel imagesare extracted and employed for identifying the dusty conditions. The optimal cleaning schedule follows the dust particle loss conditions, and the schedule is enabled based on the dusty criteria in the PV. The novelty of the research relies upon designing the deep learning model for the dust particle loss detection and power generation forecast in which the power daily tariff and dust particle loss information is employed for training the deep model. Then the forecasting model declares the higher power loss conditions and dust particle loss states of the PV panel, the cleaning phenomenon is initiated optimally for which a new optimization is designed based on the characteristics of the sunlight. Fig. 2 likely illustrates the design and concept of an optimal cleaning schedule for solar PV systems.

4.1. Solar power generation dataset

Solar power is meant to be free and clean energy achieved through traditional fossil fuels. However, the energy efficiency is not much better because there have been several needs to be taken in the ideal selection of installation under critical conditions to obtain the huge amount of energy. And, there is a need for a proper prediction and monitoring model for tracking the power output into the particular array of solar power generators, which may be affected due to some environmental conditions.Hence, this research considers the daily tariff information https://github.com/anantgupta129/Solar-Power-Generation-Forecasting and dusty conditions of the PV https://www.kaggle.com/datasets/hemanthsai7/solar-panel-dust-detection for tracking and monitoring the power generation from SPV systems.

4.2. Attention-based deep layered model for power generation forecast

Solar power forecasting is the process of collecting and evaluating the generated data from the power for predicting under various zones to mitigate the fault/generation defects in solar intermittency. Solar power forecast helps to monitor and control the operation of solar power plants as the generation could be affected by the external parameters of the SPV, such as location, plant layer, shading and rooftop orientation, system design, equipment quality, operations, and maintenance [33]. The main risk factors influencing the generation are changes in environmental variables, such as ambient temperature, moisture, and dust available on the panels, as well as the amount of radiation from the sun on the panel. Additionally, the accumulation of dirt on the outermost layer of solar panels lowers their effectiveness; in general, output loss from dust is regarded as occurring at the highest rate, creating a key path in the monitoring and cleaning of the solar panels. It is highly particular to notice that dust accumulation is the major risk factor that naturally varies throughout the day. Once the generation of power tends to be poor considering the daily tariff condition then, there would be availability of dust particles in the PV panel indicated.Therefore there must be usage in optimal cleaning schedule for monitoring and cleaning the panels with the reduction in both maintenance cost and use of resources. Deposition models, particularly data-intensive, site-specific deposition models, are used to produce accurate forecasts in dust. Deposition algorithms are responsible for determining the density of the mass of dust falling on the PV module. In this research, an automatic detection model is employed for locating the dust accumulation in PV, which is named an optimized SVM coupled Deep CNN model, whereas the forecast is supported by the attention model. Fig. 3 depicts a specialized DL model designed for forecasting power generation in the context of PV systems.

In this section, the power generation forecasting is performed using the attention-based deep layered model that monitors the PV power loss and supports in cleaning schedulingof the PV. To enable superior selection attention and performance, the proposed attention-based deeply layered model utilizes and combines scale-specific localized attention contexts to global attention settings through one-body and multi-scale head realization. The suggested attention-based deep-layered model considerably differs from previous attention mechanisms and is created specifically for data analysis thanks to the single, undivided self-attention system with greater capacity and scalability in the networked architecture. This model of deep learning is related to multiple types of attention processes, such as local and global attention. Both the macro- and micro-level correlations between the data are understood by deep neural networks (DNNs). While the description of micro-level connections permits fine-grained attention throughout small local regions, the classification of macro-level dependencies enables a neural network to concentrate its focus from an overall relational perspective, including connections within the entire data. Therefore, the attention mechanism uses an array of macro-level and micro-level connections in conjunction to support global and local attention. This promotes progressive, more focused attention as information moves throughout the network. This is illustrated in Fig. 2, which demonstrates how the DNN correctly detects the power loss present in the dataset. The global attention processes are explicitly described in a single structure with substantially larger capacity by the local attentions, which contain several scale-specific heads streaming into different scales of the primary network architecture. This integrated framework improves the modeling capabilities of the self-attention module by giving local attention and global distant spatial context and enabling them to operate at different scales. To do this, a scale-specific module is fed the input sample by an encoder-decoder block, which then formulates the global modeling.

Given an input sample of $y \in K^{g\times s\times b}$, where g, s, b are the width, height, and quantity of input channels, the encoder-decoder $D(\cdot)$ represents the global attended details in a new feature space $A_D \in K^{g\times s\times b}$ having identical dimensions as the input data and $y \in K^{g\times s\times b}$ represents a single point in that space. The global attention vector A_D is then fed to a multiple-level-specific attention model $L(\cdot)$ together with the scale i output feature map H_i to extract the consistently observed information for each scale separately. The output $L(A_{D,})$ is the final focus map for scale, which integrates both local and global attention in a single, separate map. The feature map that is used for scale i is subsequently multiplied by this map before it is passed into the next processing step. The global attention block $D(\cdot)$ builds an integrated attention map from an input sample, synchronizes local attention blocks, and links them to ensure that they are in sync with the most important global focus data during training. The following is a description of the two primary parts of the proposed deep learning model.

a) ***Global attention:*** The network's multiple scale attention blocks must all be consistent with the encoder-decoder's $D(\cdot)$ for it to function. It incorporates the input image's overall focus. This is imposed when the encoder-decoder $D(\cdot)$ back propagates various scale attention defects during training. The input x is converted to a latent space map of features $x \in K^{g'\times s'\times b'}$ by the encoder block using a down-sampling network G.Due to the down-sampling network G removal of irrelevant features, the latent space feature map x has smaller dimensions than the latent space feature map y. The decoder block then uses the up-sampling network P to produce the output A_D using the context vector x as input.Here, it is assumed that $A_D \in K^{m\times n\times b}$ offers a weight map for each pixel in the supplied image. The weight map can offer useful insights to determine and demonstrate how it arrives at a choice, which is one advantage of this strategy.
b) ***Local attention:***Before feeding the global attention maps to the main network, the scale-specific attention maps of features have to be constructed. This task can be completed by using many scale-specific attentions to correctly link the attention block to the classification blocks at different scales. Consider a classification block that consists of I convolution blocks and a pair of feature maps $H_i, \ldots H_I, \ldots H_I$ to go along with it $H_i \in K^{m_i\times n_i\times b_i}$. From the data in the feature map H_i, the attention block generates an attention map $\overline{A_i} \in K^{g_i\times g_i\times b_i}$, which it then applies to the features map H_i to convert and create $\overline{H_i}$. The general procedure can be described as follows:

$$\overline{H_i} = L_i(H_i, A_D) \otimes H_i + H_i \tag{16}$$

Where,A_D represents the global attention map produced by Encoder-Decoder $D(\cdot)$ and $\otimes$ stands for element-wise multiplication. The scaling-specific modules $L(\cdot)$ are created as follows to create an effective operation,

$$\overline{A_i} = L(H_i, A_D) = N_i\left(A_i', H_i\right) \tag{17}$$

$$A_i' = T_i(\sigma(A_D)) \tag{18}$$

Where T_i is a bilinear interpolating operation that converts the input shape's height and width to $s_i \times g_i$, and $\sigma(\cdot)$ is a Sigmoid function used element-wise to compute the tensor A_D. N_i is an output shape ($s_i \times g_i \times b_i$) convolutional block. For good accuracy, one layer of convolution with a filter size b_i is sufficient, which calls for efficient tuning of the hyperparameters, which is carried out using the HBBHO method. Bilinear interpolation's key advantage is that it preserves the same global attention map of features across all scales, which is afterward adjusted for each scale using multiple scale-specific attentions. The advantages of the model depend on the self-attention block and the main model's optimized training, and as a result, the system demonstrates faster convergence. Additionally, this configuration enables the model to use any pre-trained algorithm for the primary purpose. The suggested deep learning-based forecasting model is displayed in Fig. 3.

4.2.1. HBBHO algorithm for optimal tuning of the deep layers in the attention-based deep-layered model

The optimal tuning of the classifiers and the cleaning schedule is performed using the proposed HBBHO optimization, which wasdesigned based on the characteristics of sunlight and nature characters.

a) Motivation

Normally, optimization plays animportant role in Engineering applications and in this research, the classifier training and the cleaning schedule of PV is performed using the proposed optimization. The significance of the optimization relies upon the ability to hold an effective balance between the explorationand exploitation stages. In the existing biography algorithm, the exploitation seems poor leading to the generation of the unstable form of a solution, which contributes to the poor convergence, while the features of sunlight in optimization surrender an improved convergence rate due to a faster convergence phenomenon. Hence, hybridizing the characters of biography and sunlight generates a quality solution, which is nothing but the quality parameters for tuning the classifier and quality schedule mechanism for PV cleaning to maximize the power generation in the SPV system.

b) Mathematical Modeling of Hybrid Biography based Helianthus Optimization

I) ***Initialization:*** Initialize the values of helianthus solutions randomly

$$X^{t+1} = X_t^{\min} + rand_1\left(X_t^{\max} - X_t^{\min}\right) \tag{19}$$

where $X_{\min}^t$ means the solution corresponding to the main fitness function, $X_t^{\max}$ is the solution concerning maximum fitness measure, X^{t+1} represents the initial value of the solution, and $rand_1$ is the random arrangements of the helianthus.

II) ***Fitness measure:*** The Fitness function is measured based on the determination of the power loss,

$$Fit = \sum_{\min} Power_{loss} \tag{20}$$

The power loss is maintained below the predefined threshold and at any conditions, a higher loss indicates the requirement for the scheduling mechanism. The detailed power loss expression is shown in Eq. (29). While training the classifier, the objective function is based on the accuracy that is contributed by the power loss, and the objective function in terms of the scheduling would be the scheduling cost, power loss, and dusty status of the PV.

III) ***Solution Update based on the rules of sun direction and orientation of particles:*** The optimization is designed with the characteristics regarding the particular behavior to identify the best orientation movements towards the Sun. Moreover, helianthus belongs to the random generation by measuring the minimum and maximum range of availability due to the incident rays from sun radiations. A million generation levels were created for exploring more solutions within a quick production of the best solutions. Helianthus stimulus the directions towards the sun by,

$$\overrightarrow{A_j} = \frac{Q^* - Q_j}{\|Q^* - Q_j\|} \tag{21}$$

where Q^* and Q_j denotes the generation of the best and current solution. The movement of the helianthus direction towards the sun is expressed as

$$B_p = \beta \times \|F_i + F_{i-1}\| \times G_k(\|F_i + F_{i-1}\|) \tag{22}$$

where, β means the inertial displacement, $G_K(\|F_i + F_{i-1}\|)$ represents the probability function.

The algorithm replicates the Helianthus inverse square law radiation which was meant to be inverse production for the intensified values deduced instantly through reduction of distance. The algorithm deduces the minimum range of the sun by recognizing the stability function of the solution. Moreover, the heat enhancement from the sun's radiations was prolonged into the exploration and exploitation periods.

i) Case 1: $N < N_{inter}$: During this condition, the exploration could be started by exploring how much amount of heat is received from the sun radiations under the generation time for the solar panel. Moreover, they are received with less heat which creates a global best solution for the sun. Heat generation was formulated into biography optimization. The help of the biography algorithm describes a wide distance of the species within a short duration of time as well as notifies the species' movements. Optimum sizing problems' complexity from the helianthus algorithm is reduced in the biography algorithm which investigates how species travel, around and finish their destination.

$$S_K^{T+1} = S_K^T\left(1 - a_1^K.\Delta T - a_2^K.\Delta T\right) + S_l^T.a_1^L.\Delta T + S_{K+1}^T.a_2^{K+1}.\Delta T \tag{23}$$

Where a_1 and a_2 represents the changes/adjustments in orientation, here the K solution index in the habitat which accompanied the equation in terms of time as $(K+1)$ undergoes 3 conditions they are contributed into the adjustments of the orientation with change in time, ΔT- Change in time and $K.L, K+1$-refers to solution index, a_1^K, a_2-

$$S_K^{t+1} = \frac{1}{2}\left[S_K^t + d_i + S_i + S_K^T\left(1 - a_1^k.\Delta T - a_2^k.\Delta T\right) + S_i^t\left(a_1^l.\Delta T\right) + S_K^T a_2^{K+1}.\Delta T\right] \tag{24}$$

Where d_i indicatesthe direction in radiation and S_i is the individuality of the sun, equation (2) is intercepted with the Nernst equation as E

$$S_K^{t+1} = \frac{1}{2}\left[S_K^t + d_i + S_i + S_K^T\left(1 - a_1^k.\Delta T - [E]a_2^k.\Delta T\right) + S_i^t\left(a_1^l.\Delta T\right) + S_K^T a_2^{K+1}.\Delta T\right] \tag{25}$$

$$S_K^{t+1} = \frac{1}{2}\left[S_K^t + d_i + S_i + S_K^T\left(1 - a_1^k.\Delta T - \left[E_0^0 - kT_e - \beta_s l(j)\frac{T_q P}{T_q P + 1} + \frac{SK}{2q}\left(D_{H_2}\sqrt{D_{o_2}}\right)\right]a_2^k.\Delta T\right) + S_i^t\left(a_1^l.\Delta T\right) + S_K^T a_2^{K+1}.\Delta T\right] \tag{26}$$

K Denotes fuel cell temperature q represents the Faraday constant, E_0^0 denotes reference potential, β_s defines constant factor, T_e experimental constant, D_{H_2} and D_{o_2} hydrogen and oxygen partial pressure, pressure as P, $l(j)$ and denotes the largest value of the function. Due to most of the sun, they failed to achieve power generation with less heat solution, after this the optimal cleaning is processed with the incidence of dust particles to the layers of solar panel.

ii) Case 2: $N > N_{inter}$: The above condition was processed for the exploitation stage to measure the heat radiations from the sun the updating process for the algorithm is easy for the farther movements of the sun would produce the required amount of heat.

$$C_{\max} = \frac{\|Y_{\max} - Y_{\min}\|}{2 \times H_a} \tag{27}$$

H_a The maximum number of species available $Y_{\max}Y_{\min}$ means the maximum and minimum restrictions for the functions of the panel. The global best solution was generated through the measurements of a particular period. The random value of the population was achieved through the best solution by determining the time of optimal scheduling with the dust particles by measuring the power loss function in algorithms.

$$S_K^{t+1} = S_{k,global}^{best} + \alpha\left(S_K^t - S_{partref}^t\right) \tag{28}$$

IV) ***Termination:*** Exploration and exploitation stagescontributed to the optimal solution for the classifier training and cleaning schedule of the SPV.

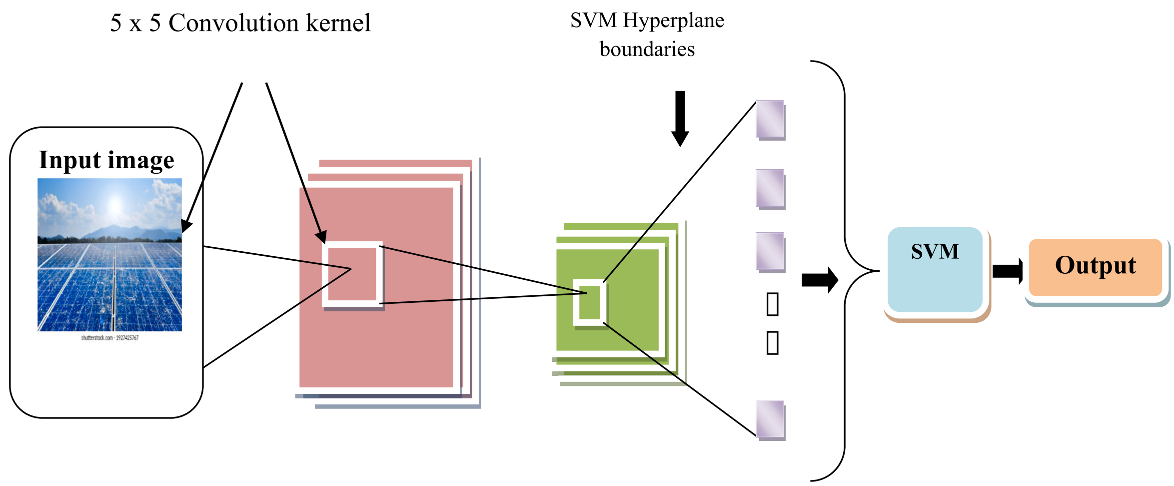

Fig. 4. Architecture of SVM coupled deep CNN.

Algorithm: Pseudo code for HBBHO

Initial the random population of maximum and minimum value
$X^{t+1} = X_t^{\min} + rand_1\left(X_t^{\max} - X_t^{\min}\right)$
Determine the fitness function
$\sum_{\min} Power_{loss}$
Calculate the objective function
Objective function: Power Loss
Updating solution for the HBBHO
{
Exploration stage
{
Case 1:$N < N_{inter}$
$$S_K^{t+1} = \frac{1}{2}\left[S_K^t + d_i + S_i + S_K^T\left(1 - a_1^k.\Delta T - \left[E_0^0 - kT_e - \beta_s l(j)\frac{T_qP}{T_qP+1} + \frac{SK}{2q}\left(D_{H_2}\sqrt{D_{o2}}\right)\right]a_2^k\cdot\Delta T\right) + S_i^t\left(a_1^l.\Delta T\right) + S_K^T a_2^{K+1}\cdot\Delta T\right]$$
}
Exploitation stage
{
Case 2:$N > N_{inter}$
$$S_K^{t+1} = S_{k,global}^{best} + \alpha\left(S_K^t - S_{partref}^t\right)$$
}
Generated with the best solution
Terminate the result
{
T = t + 1
}
End of the result
}

Based on the optimization-based attention model and power loss objective, the PV is susceptible to be detected for the dusty condition using the optimized SVM coupled Deep CNN model as shown in section 4.3. When the power generation is predicted using the attention-based deep layered model, and the generated power loss of the system is found to exceed the loss threshold then, the PV dusty detection is done using the SVM coupled deep CNN. The power loss associated with the PV due to the accumulation of dust particles ismodeled below.

$$L_e(t) = \frac{P_{clean} - P_{dustparticles}}{P_{clean}} \times 100 \tag{29}$$

where, P_{Clean}&$P_{dustparticles}$ denotes the power output for the clean and dust particles in the solar panel, and $L_e(t)$ means the dust particle coefficients of the solar panel.

4.3. *Optimized SVM coupled deep CNN model for identifying dusty conditions in PV*

The optimized SVM coupled deep CNN is proposed for identifying the dust particles in the SPV panel for scheduling the PV cleaning to meet the daily generation tariff. The input to this module is the SPV image, which is pre-processed and subjected to feature extraction using the color-based statistical features including the mean, variance, standard deviation, and entropy of the PV image pixels, and local gradient patterns (LGP) of the PV panel images. Using the features of the PV image, the dusty conditions of the PV are analyzed using the proposed model that proposes the CNN architecture for extracting the informative features for the identification of dustthrough learning the invariant local features very effectively. From unprocessed image features, optimized SVM coupled deep CNN can extract the most discriminating information. Once the CNN is trained using the HBBHO algorithm, SVM-based class labeling is performed using the hyperplane class separation. The output from CNN's hidden units serves as a feature vector for the SVM

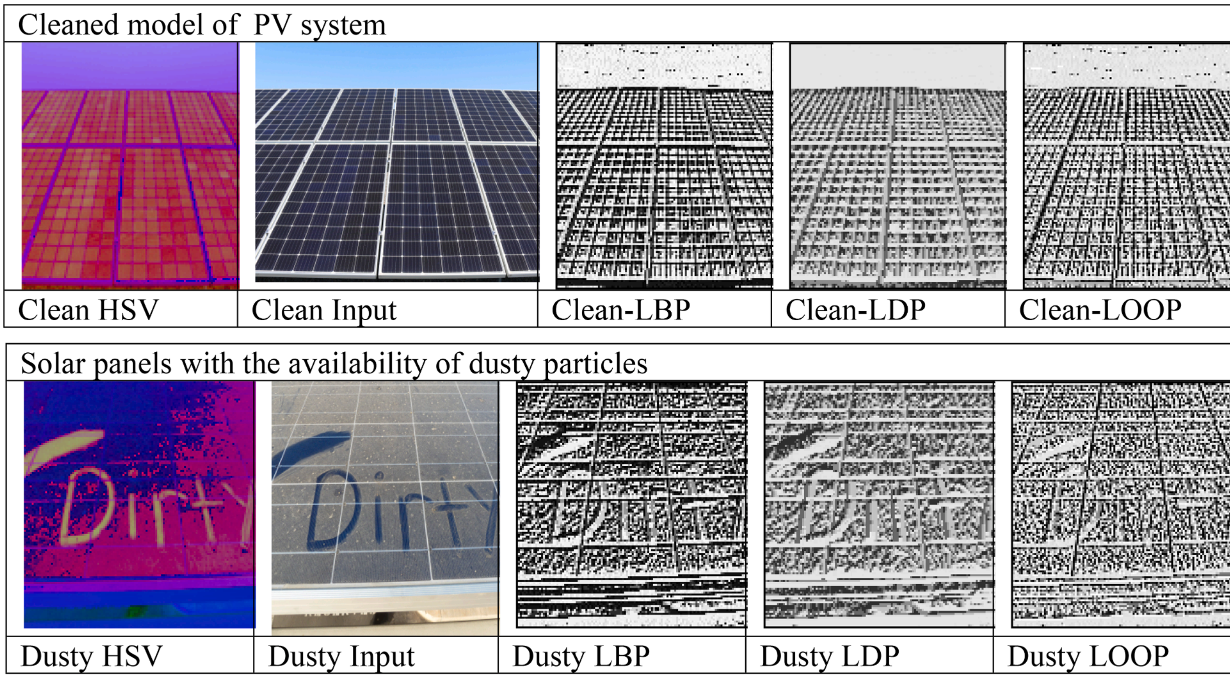

Fig. 5. Experimental results of the scheduling to clean the dust particles in the solar panel model using SVM-based deep CNN.

training phase, and CNN's responsive field feature determines the effective sub-regions. In the suggested method, a 5×5 kernel/filter is used to extract the most recognizable elements from the initial input images. An output with dimension $(n-k+1)\times(n-k+1)$ is created by convolving an input neuron from an input layer with a $k \times k$ filter in the layer of convolution.

In the HBBHO algorithm, the features are discriminatedthrough the hyperplane boundary ensuring the capacity to decrease the generalization error. An optimum hyperplane is established using optimization for detecting the dusty conditions of the PV.

Fig. 4 represents the hybrid architecture that combines the capabilities of SVM and CNN for identifying dusty conditions in PV. Once the dusty conditions of the PV are identified using an optimized SVM coupled deep CNN model, the cleaning schedule is initiated based on the optimization, HBBHO algorithm.

4.4. Optimum cleaning schedule for solar panel system

The optimal cleaning schedule is performed using the HBBHO optimization based on the generated power loss and the dusty conditions that affect the power efficiency. The solar radiation and temperature have severe issues in producing the output power from the solar cells, then the dust particles available in the surroundings which could be deposited on the region of the PV module started to create a dust layer on it. Due to this, there is an occurrence of negative effectson the solar irradiation to solar cells, and mostly the presence of sand or dust accumulated on the glass of the solar cell could damage the transmittance of light and the intensity of the solar radiation. Scheduling the cleaning of solar panel strings is possible only during the daytimeoperating conditions of PV. The HBBHO algorithm is employed for scheduling the cleaning process for which the panels for cleaning are arranged in the order of the maximal power loss contributing modules to enhance the generation accuracy of the SPV system.

Exploration and exploitation of the HBBHO algorithm gathered the dust particle availability through the classifier and scheduled the optimal cleaning of the solar panel to satisfy the threshold values. The best solution indicates the optimal hyperparameters of the classifier in the case of the classifier training and scheduling time and model in the case of the cleaning schedule highlighting the role of the optimization in two specific instances of this research. The significance of this research is most pronounced in the realm of industrial applications within conveying systems. By optimizing the engineering parameters, it becomes feasible to operate an energy-efficient system with a feeder device that responds primarily to two input variables. Enhanced efficiency can be achieved as the process transitions from the dilute phase to the dense phase regime, marked by reduced airflow—a validation of the energy efficiency enhancement.

5. Result and discussion

While traversing the atmosphere, solar radiation experiences noteworthy attenuation, primarily attributed to its resemblance to light-waves. This behavior entails absorption by atmospheric particles, reflection by water vapor, air molecules, dust, and pollutants, as well as backward scattering [6]. The presence of scattering dust diminishes the direct solar radiation component [7], consequently elevating the diffuse irradiance component [8,9]. The extent of radiation attenuation is contingent upon both the composition and volume of pollutants [10]. The aforementioned factors emphasize that dust can significantly impede the efficiency of a solar photovoltaic system. From an economic standpoint, a dust deposition density of around 1 g/m2 has the potential to result in losses of up to 40€/kWp [5]. Significantly, the presence of dust contributes to further dust buildup, which means that even a minor initial dust deposit can result in a considerable decrease in performance, particularly for unattended PV panels situated in remote locations. The impact of dust accumulation depends on specific time and site conditions. Without regular and proper cleaning, the accumulated dust on the panel's surface will thicken and may become resistant to removal by rainfall [21]. It is advisable to clean panels frequently in areas prone to drought, areas with pollution, and moderately dusty environments, with immediate cleaning recommended after a dust storm [17,21,33]. Panels equipped with plastic or epoxy covers require more frequent cleaning maintenance compared to those with glass covers.The power generation forecast andHBBHO Tuned SVM coupled deep CNN Model for optimal dust detection is implemented for scheduling the PV cleaning process, which is enumerated in the section below.

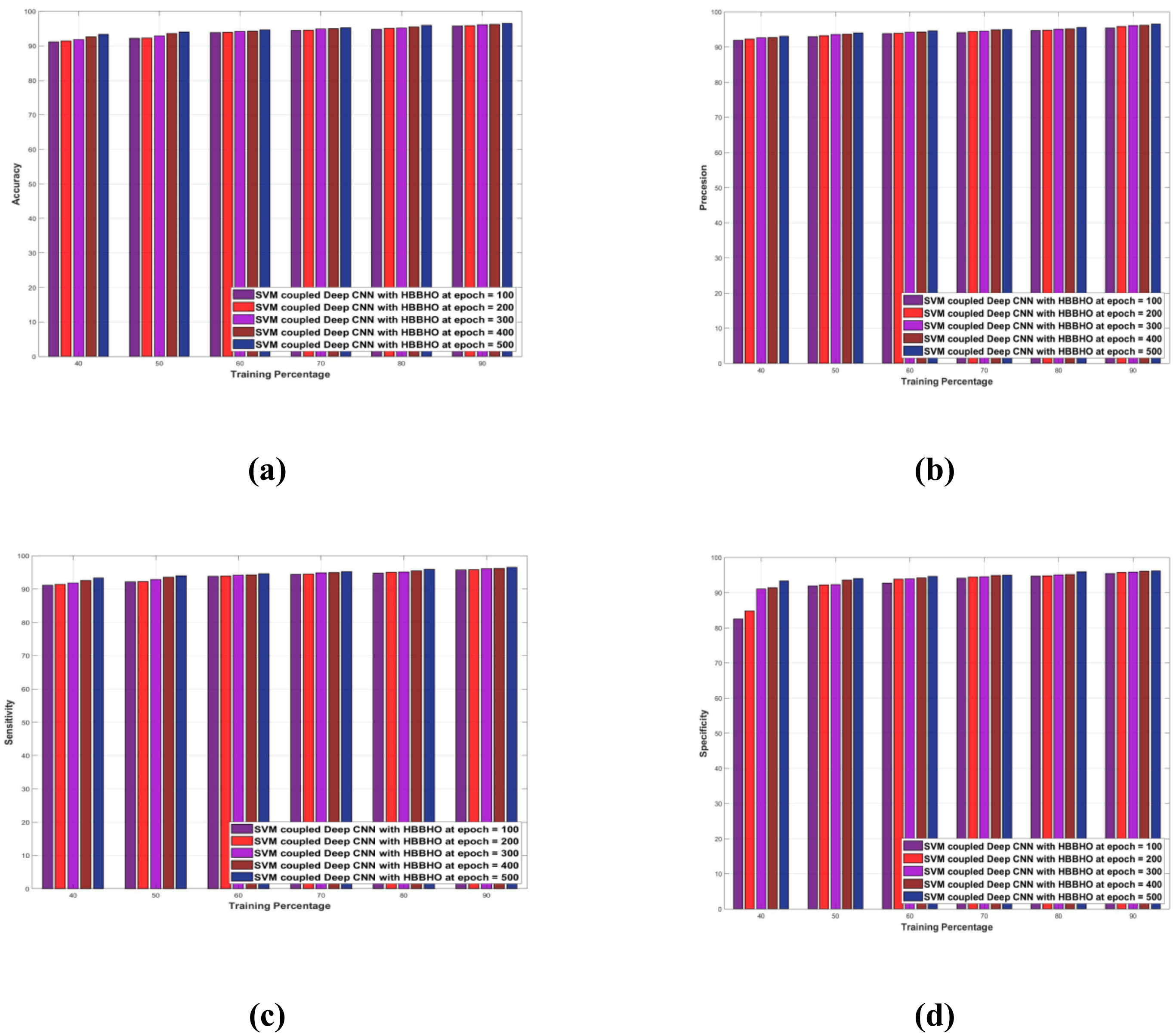

Fig. 6. Performance analysis of power loss in panel.

5.1. Simulation results

Utilizing the MATLAB software within the Windows 10 environment equipped with 8 GB RAM, the experiment is executed, centering on daily power generation records. This research entails assessing deviations between energy generation and anticipated values, followed by the computation of mean monthly figures for both projected and realized energy outputs. Consequently, a monthly cleaning regimen for the PV array is implemented, while future cleanings are orchestrated based on scheduled adjustments to threshold measurements in solar panels. This facilitates optimal cleaning strategy adjustments driven by performance changes in threshold values, typically in increments of 1000KW.

5.2. Experimental results

Experimental results were obtained through the dust particle removal in the solar panel through SVM-based deep CNN models using Dataset 1 and Dataset 2. The dust particles-based images were gathered, and cleaned through an optimal cleaning schedule and finally the cleaned images were obtained. Dataset1 explains Forecasting the power generation by solar panels through changes in environmental weather conditions. Dataset 2 enumerates the recognition of dust particles in PV, which deduces the competence of the solar panel. Fig. 5 represents the experimental results of a scheduling system designed to clean dust particles from a solar panel model using a combination of SVM and Deep CNN technologies.

5.3. Performance evaluation

The performance evaluation of the SVM with deep CNN classifier is provided for calculating the performance of the classifier with epochs under different methods, which are described briefly in the below section.

5.3.1. Performance analysis of panel with the generation of power loss

The analysis of the SVM coupled deep CNN with HBBHO was measured through the epochs values of 10,20,30,40,50,60,70,80,90,and 100 and training percentages of 40 %,50 %,60 %,70 %,80 %, and 90 %. Fig. 6 likely provides a visual representation of the performance analysis of solar panels, with a specific focus on power loss.First, the accuracy

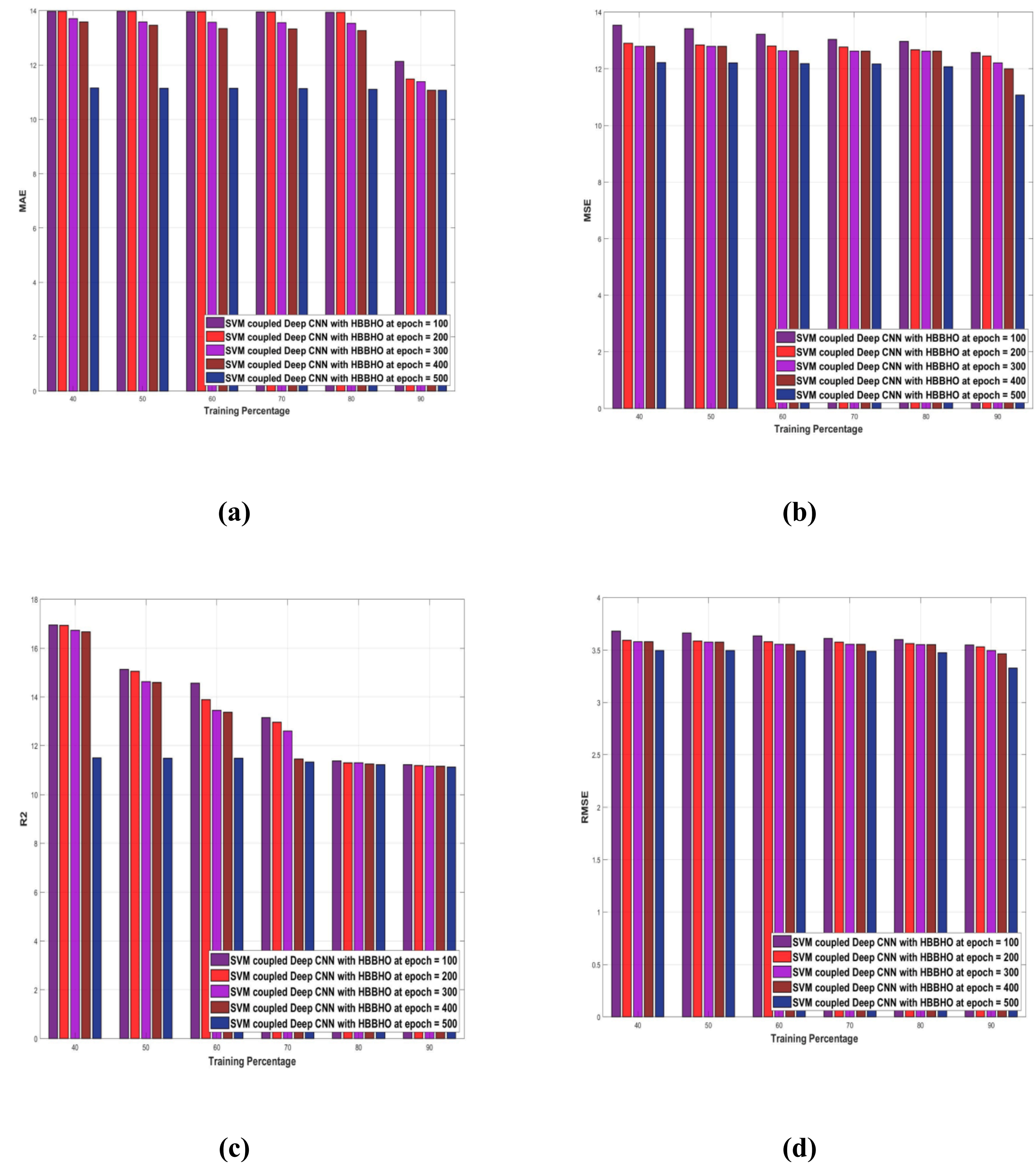

Fig. 7. Performance analysis of solar power.

level is calculated with values of 95.73 %0.95.81 %, 96.13 %, 96.21 % and 96.53 %. Precision generates 95.41 %, 95.81 %, 96.13 %, 96.21 %, and 96.53 %. Sensitivity produces 95.73 %, 95.81 %, 96.13 %, 96.21 %, and 96.53 % andspecificity creates the values of 95.41 %, 95.73 %, 95.81 %, 96.13 %, and 96.21 %.

5.3.2. *Performance analysis of solar powerwith the generation of power loss*

Fig. 7 likely presents a graphical representation of the performance analysis of solar power generation and power loss.The performance analysis of the SVM coupled deep CNN with HBBHO was measured through the error values of 10,20,30,40,50,60,70,80,90,and 100 and training percentages of 40 %,50 %,60 %,70 %,80 %, and 90 % then the results are obtained from the Fig. 7. First, the MAE is calculated with

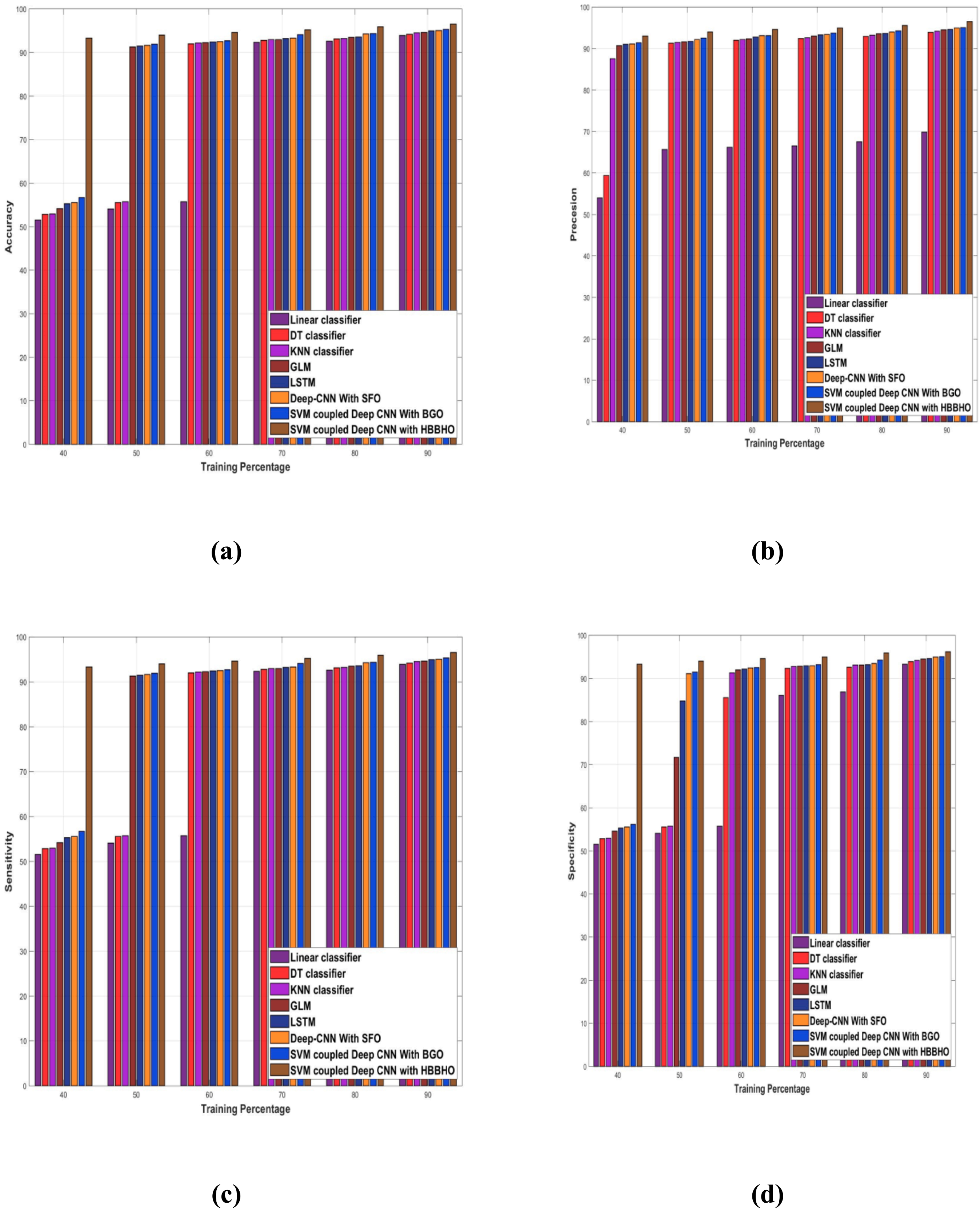

Fig. 8. Comparison analysis of panel.

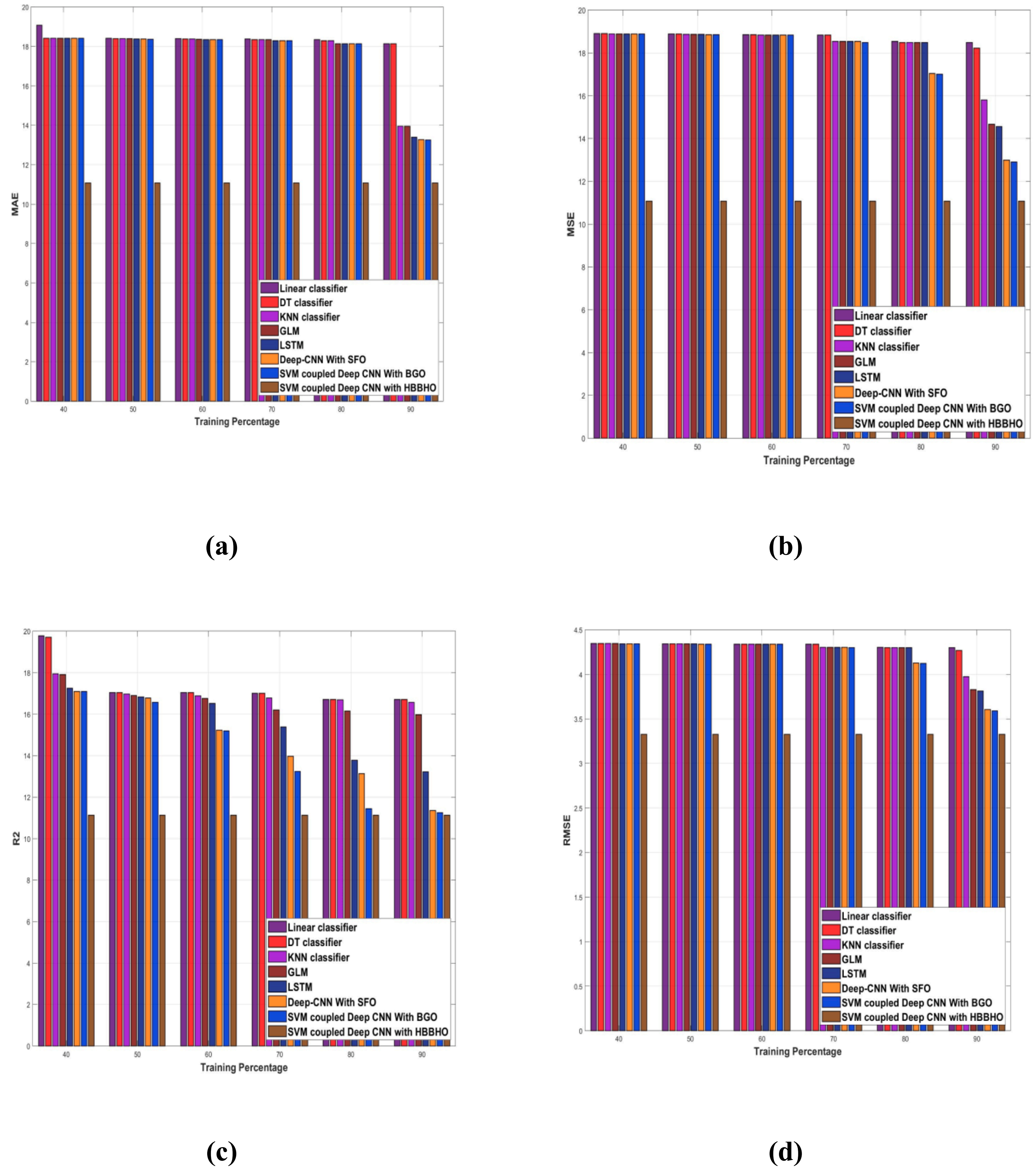

Fig. 9. Comparative analysis of power with Dataset 1.

values of 12.13 %0.11.49 %, 11.39 %, 11.07 % and 11.07 %.MSE generates 12.58 %, 12.45 %, 12.21 %, 12.00 %, and 11.07 %. R2 produces 11.21 %, 11.20 %, 11.16 %, 11.16 %, and 11.13 % and RMSE creates the values of 3.55 %, 3.53 %, 3.49 %, 3.46 %, and 3.33 %.

5.4. Comparative analysis

The comparative analysis is performed to calculate the dominance of the SVM coupled deep CNN with tuned HBHO over the existing methods.

5.4.1. Comparative methods

The methods used for the comparison of the SVM coupled deep CNN with tuned HBHOare linear classifier (LC) M_e^{1a}, DT classifier M_e^{1b}, KNN classifier M_e^{1c}, GLM classifier M_e^{1d}, LSTM M_e^{1e} Deep CNN with SFO clas-

Table 1
Comparative discussion of the HBBHO algorithm tuned SVM coupled deep CNN in solar power and panel.

Solar Panel with power loss identification					Solar power power loss identification			
Methods/Metrics	Accuracy	Precision	Sensitivity	Specificity	MAE	MSE	R2	RMSE
M_e^{1a}	93.89	69.80	93.69	93.33	18.14	18.49	16.70	4.30
M_e^{1b}	94.21	93.89	94.71.	93.89	18.14	18.23	16.70	4.27
M_e^{1c}	94.53	94.21	94.53	94.21	13.94	15.80	16.58	3.97
M_e^{1d}	94.61	94.53	94.61	94.53	13.94	14.67	15.98	3.83
M_e^{1e}	94.93	94.61	94.93	94.61	13.40	14.55	13.22	3.82
M_e^{1f}	95.01	94.93	95.01	94.93	13.27	12.99	11.36	3.60
M_e^{1g}	95.33	95.01	95.33	95.01	13.25	12.90	11.25	3.59
Proposed	96.53	96.53	96.53	96.21	11.07	11.07	11.13	3.33

sifier M_e^{1f} SVM coupled Deep CNN with BGO M_e^{1g} and SVM coupled Deep CNN with HBBHO method.

5.4.1.1. Comparative analysis of panel. Fig. 8 represents a comparative analysis of different approaches or models used in solar panel analysis. It is used to assess the performance of these approaches in terms of their accuracy, precision, specificity, and sensitivity.Then the improvement percentage generated by the HBBHO-tuned SVM coupled deep CNN is measured. Initially, the accuracy generated the improvement results of96.53 over the existing system by $M_e^{1a}-93.89$ %,M_e^{1b}-94.21–M_e^{1c}–94.53–M_e^{1d}–94.61–M_e^{1e}–94.93,M_e^{1f}-95.01–M_e^{1g}–95.33. Precision is generatedby $M_e^{1a}-69.80$ %, $M_e^{1b}-93.89$ %,M_e^{1c}-94.21 %,M_e^{1d}-94.53 %,M_e^{1e}-94.61 %,M_e^{1f}-94.93 %,M_e^{1g}-95.01 %,the precision metrics produced a value of 96.53 %. Sensitivity is generated by $M_e^{1a}-93.89$ %, $M_e^{1b}-94.21$ %,M_e^{1c}-94.53 %,M_e^{1d}-94.61 %,M_e^{1e}-94.93 %,M_e^{1f}-95.01 %,M_e^{1g}-95.33 %,the sensitivity metrics produced a value of 96.53 %. Specificity is generated by $M_e^{1a}-93.33$ %, $M_e^{1b}-93.89$ %,M_e^{1c}-94.21 %,M_e^{1d}-94.53 %,M_e^{1e}-94.61 %,M_e^{1f}-94.93 %,M_e^{1g}-95.01 %, the specificity metrics produced a value of 96.21 %.

5.4.1.2. Comparative analysis of power with Dataset 1. The comparative analysis in Fig. 9 is based on the solar power analysis and uses several key metrics to evaluate the performance of different models or approaches. Then the improvement percentage generated by the HBBHO-tuned SVM coupled deep CNN is measured. Initially, the MAE generated the improvement results of 11.07 over the existing system by $M_e^{1a}-18.14$ %,M_e^{1b}-18.14–M_e^{1c}–13.94–M_e^{1d}–13.94–M_e^{1e}–13.40,M_e^{1f}-13.27–M_e^{1g}–13.25. MSE is generatedby $M_e^{1a}-18.49$ %, $M_e^{1b}-18.23$ %,M_e^{1c} -15.80 %,M_e^{1d}- 14.67 %,M_e^{1e}-14.55 %,M_e^{1f}-12.99 %,M_e^{1g}-12.90 %,the precision metrics produced a value of 11.07 %. R2 is generated by $M_e^{1a}-16.70$ %, $M_e^{1b}-16.70$ %,M_e^{1c} -16.58 %,M_e^{1d}- 15.98 %,M_e^{1e}-13.22 %,M_e^{1f}-11.36 %,M_e^{1g}-11.25 %,the sensitivity metrics produced a value of 11.13 %. RMSE is generated by $M_e^{1a}-4.30$ %, $M_e^{1b}-4.27$ %,M_e^{1c} -3.97 %,M_e^{1d}- 3.83 %,M_e^{1e}-3.82 %,M_e^{1f}-3.60 %,M_e^{1g}-3.59 %,the precision metrics produced a value of 3.33 %.

5.5. Comparative discussion

The method is discussed with the best values segregated are interpreted in Table 1. Hence the method created the values of a good metric by comparing the other existing methods due to the enabling of the HBBHO algorithm that efficiently tuned the SVM coupled deep CNN classifier with enhancing the characteristics of the biography and helianthus optimization.

6. Conclusion

Normally PV modules are fully affected by the segmentation of dust particles on the surface and local environment which fails to deliver the generation process from the sun daily,monthly, seasonal, and yearly. The inclusion of dust in solar panels decreases the transmission capacity and increases the temperature of the panel. First, the high generation in power loss was determined by the deep classifier then the optimal cleaning schedule was undertaken through the detection of dust particle properties From that SVM coupled deep CNN was used to specify the time of cleaning the solar panel. Afterward, the SVM coupled deep CNN could be tuned with the HBBHO algorithm the highly efficient cleaning was adapted with highly robust, fast convergence speed and fewer complexions in timeaccuracy of 96.53 %, precision of 96.53, and sensitivity of 96.53and specificity of 96.21 % achieved the high value of the panel. In the future new techniques must be used to establish cleaning the dust particles in solar panels with intimating for the classifier within a short duration of time. This research has the potential to significantly enhance solar PV efficiency by optimizing cleaning schedules based on real-time conditions, thereby increasing electricity generation from the same panels, and contributing to energy sustainability. Additionally, the cost-effective scheduling algorithm can lead to savings by ensuring cleaning occurs only when necessary, reducing operational costs and indirectly benefiting the environment by reducing the need for less sustainable energy sources.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] R. Majeed, A. Waqas, H. Sami, M. Ali, N. Shahzad, Experimental investigation of soiling losses and a novel cost-effective cleaning system for PV modules, Sol. Energy 201 (2020) 298–306.
[2] N. Khadka, A. Bista, B. Adhikari, A. Shrestha, D. Bista, B. Adhikary, Current practices of solar photovoltaic panel cleaning system and future prospects of machine learning implementation, IEEE Access 8 (2020) 135948–135962.
[3] A. Cheema, M.F. Shaaban, M.H. Ismail, A novel stochastic dynamic modeling for photovoltaic systems considering dust and cleaning, Appl. Energy 300 (2021), 117399.
[4] https://www.kaggle.com/datasets/hemanthsai7/solar-panel-dust-detection.
[5] J.A. Armstrong, L. Fletcher, Fast solar image classification using deep learning and its importance for automation in solar physics, Sol. Phys. 294 (6) (2019) 80.
[6] IEA, World Energy Outlook 2019, 2019.
[7] T. Ma, H. Yang, L. Lu, Solar photovoltaic system modeling and performance prediction, Renewable Sustain. Energy Rev. 36 (36) (2014) 304–315.
[8] I.S.E. Fraunhofer, Current and future cost of photovoltaics, *Long-term scenarios for market development, system prices and LCOE of utility-scale PV systems*, Study on Behalf of Agora Energiewende (2015).
[9] K. Chiteka, R. Arora, S.N. Sridhara, C.C. Enweremadu, A novel approach to Solar PV cleaning frequency optimization for soiling mitigation, Scientific African 8 (2020) e00459.
[10] O. Edenhofer, Intergovernmental Panel on Climate Change, and Working Group 3, Renewable energy sources and climate change mitigation: summary for policymakers and technical summary: special report of the intergovernmental panel on climate change, Cambridge University Press, New York, 2011.

[11] M.E. Meral, F. Dinçer, A review of the factors affecting operation and efficiency of photovoltaic based electricity generation systems, Renew. Sustain. Energy Rev. 15 (2011) 2176–2184, https://doi.org/10.1016/j.rser.2011.01.010.
[12] P.G. Piedra, L.R. Llanza, H. Moosmüller, Optical losses of photovoltaic modules due to mineral dust deposition: Experimental measurements and theoretical modeling, Sol. Energy 164 (2018) 160–173.
[13] S. Semaoui, A.H. Arab, S. Bacha, B. Azoui, The new strategy of energy management for a photovoltaic system without extra intended for remote-housing, Sol. Energy 94 (2013) 71–85.
[14] M.M. Fouad, L.A. Shihata, E.I. Morgan, An integrated review of factors influencing the perfomance of photovoltaic panels [Online]. Available: Renew. Sustain. Energy. Rev. 80 (2017) 1499–1511 https://linkinghub.elsevier.com/retrieve/pii/S1364032117307803.
[15] Z. Wang, Z. Xu, Y. Zhang, M. Xie, Optimal cleaning scheduling for photovoltaic systems in the field based on electricity generation and dust deposition forecasting, IEEE J. Photovolt. 10 (4) (2020) 1126–1132.
[16] S. Akbar, T. Ahmad, Enhance and maintain efficiency of solar panel using auto cleaning system, IJEW 6 (05) (2019) 159–163, https://doi.org/10.34259/ijew.19.605159163.
[17] T. Sarver, A. Al-Qaraghuli, L.L. Kazmerski, A comprehensive review of the impact of dust on the use of solar energy: History, investigations, results, literature, and mitigation approaches, Renew. Sustain. Energy Rev. 22 (2013) 698–733, https://doi.org/10.1016/j.rser.2012.12.065.
[18] K. Ilse, et al., Techno-economic assessment of soiling losses and mitigation strategies for solar power generation, Joule 3 (10) (2019) 2303–2321.
[19] H. Matthias, S. Meunier, A. Samé, L. Quéval, A. Darga, L. Oukhellou, B. Multon, Detection of cleaning interventions on photovoltaic modules with machine learning, Appl. Energy 263 (2020), 114642.
[20] S.C.S. Costa, A.S.A.C. Diniz, L.L. Kazmerski, Solar energy dust and soiling R&D progress: Literature review update for 2016, Renew. Sustain. Energy Rev. 82 (2018) (2016) 2504–2536.
[21] D.L. Alvarez, S. Ameena Al-Sumaiti, S.R. Rivera, Estimation of an optimal PV panel cleaning strategy based on both annual radiation profile and module degradation, IEEE 8 (2020) 63832–63839.
[22] M.R. Maghami, et al., Power loss due to soiling on a solar panel, Renew. Sustain. Energy Rev. 59 (2016) 1307–1316.
[23] G.P. Smestad, et al., Modelling photovoltaic soiling losses through optical characterization, Sci. Rep. 10 (1) (2020) 58.
[24] M. Leonardo, M. Theristis, A. Livera, J.S. Stein, G.E. Georghiou, M. Muller, F. Almonacid, E.F. Fernández, Improved PV soiling extraction through the detection of cleanings and change points, IEEE J. Photovolt. 11 (2) (2021) 519–526.
[25] J. Lv, J. Kuang, Z. Yu, G. Sun, J. Liu, J.I. Leon, Diagnosis of PEM Fuel Cell System Based on Electrochemical Impedance Spectroscopy and Deep Learning Method, IEEE Trans. Ind. Electron. (2023).
[26] D. Xu, J. Liu, X.G. Yan, W. Yan, A novel adaptive neural network constrained control for a multi-area interconnected power system with hybrid energy storage, IEEE Trans. Ind. Electron. 65 (8) (2017) 6625–6634.
[27] Z. Liu, O. Zhang, Y. Gao, Y. Zhao, Y. Sun, J. Liu, Adaptive neural network-based fixed-time control for trajectory tracking of robotic systems, IEEE Trans. Circuits Syst. Express Briefs 70 (1) (2022) 241–245.
[28] A.G. de Freitas, R.B. dos Santos, L.A. Riascos, J.E. Munive-Hernandez, S. Kuang, R. Zou, A. Yu, Experimental Design and Optimization of a Novel Solids Feeder Device in Energy Efficient Pneumatic Conveying Systems, Energy Rep. 9 (2023) 387–400.
[29] A.G. de Freitas, V.F. de Oliveira, R.B. dos Santos, L.A. Riascos, R. Zou, Optimization method for pneumatic conveying parameters and energy consumption performance analysis of a compact Blow Tank, J. Press. Vessel. Technol. 144 (6) (2022), 064504.
[30] A.G. Freitas, V.F. Oliveira, Y.O. Lima, R.B. Santos, L.A.M. Riascos, BATCHPUMP: an alternative to conventional blow tanks, Lat. Am. Appl. Res. 51 (2) (2021) 107–112.
[31] S. Al-Dahidi, O. Ayadi, M. Alrbai, J. Adeeb, Ensemble approach of optimized artificial neural networks for solar photovoltaic power prediction, IEEE Access 7 (2019) 81741–81758.
[32] K.A. Abuqaaud, A. Ferrah, in: A Novel Technique for Detecting and Monitoring Dust and Soil on Solar Photovoltaic Panel, 2020 Advances in, IEEE, 2020, pp. 1–6.
[33] M.R. Maghami, H. Hizam, C. Gomes, M.A. Radzi, M.I. Rezadad, S. Hajighorbani, Power loss due to soiling on solar panel: A review, Renew. Sustain. Energy Rev. 59 (2016) 1307–1316.