A Radial Basis Function Neural Network Based Approach to Mitigate Soiling from PV Module

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Abstract. Solar power is available in abundance and is free of cost but despite this fact photovoltaic (PV) systems are not reliable as the efficiency of PV module is still not up to the mark. Amount of sun light absorbed by the module is the fuel for the PV modules, there are many factors which play a vital role such as front surface reflectivity, solar beam incidence angle and the most important is the transmissivity of the front surface. Objective of this paper is to examine the function of a neural network based model of a module to mitigate the soiling and improve the accuracy of dust prediction over the module and enhance the efficiency which was degraded by soiling. One of the techniques in artificial intelligence named, radial basis function neural networks (RBFNN) is utilized here to predict the dust data by reading the data of solar irradiance, module temperature, PV voltage, current and power and generates the control signal to the windshield wiper motor that drives the wiper to wipe the dust from the panel. A considerable measure of accessible exploratory information was utilized for the preparation of the RBFNN, and a back propagation algorithm was utilized.

1. Introduction

Soiling is a term which states accumulation of dust on the solar panels, which is the main factor in reducing the competence and power generation from the solar photovoltaic (PV). This is a demanding area to look into for long term performance [1]. Soiling is viewed as an imperative operator of optical loss which is due to less irradiance (soiling consistently distributed) or partial shading (not homogeneously disseminated) on PV cells. There are various mechanisms by which soiling takes place such as contamination, small discrete mass of solid or liquid matter arising from agricultural activity, building, the accretion of dust, pollen, bird droppings or the expansion of lichen (chiefly at the inferior edge of framed modules).

Among these, bird droppings or lichen, if they fall on these panels causes serious issues as these are not easily washed away from rainfall [2]. Various factors that influence soiling are, PV tilt angle, type of soiling agent, grain of front glass and environmental and weather conditions [3]. However, most of the research is done over petite – time soiling, from few days to 5 years, ensuring that it is washed manually or by rain which is seasonally volatile [4 and 5]. Panoptic review over natural soiling has been done in [6].

Researchers carried out assuming clean environment despite the fact that there are various kinds of pollution/dirt in the atmosphere which is region and season dependent. In a forge work on the effect of dust on PV [7], debasement in execution of up to 4.7% was recorded with a normal misfortune in episode solar irradiance of less than 1%. 32% reduction in the performance of solar PV within a period of eight months was observed in Saudi Arabia [8]. An experiment in indoor has been carried out, utilizing incandescent lights representing the source of radiation energy; revealed that 80% reduction in PV short-circuit voltage occurs due to the presence of concrete particles (at 73 g/m²) [9].

Substantial precipitation is thought to be the most productive characteristic cleaning specially for expelling contaminant particles from PV surfaces, exhibiting the huge restorable impacts of adequate precipitation, which make general manual surface cleaning superfluous. Nonetheless, the development of dirt layer throughout the years or decades is not all that effortlessly washed away by the rain and in
the long run prompts to some irremovable soil. Schematic solution for soiling is to wash the panel with water or some standard glass cleaning products. However, this is not a universal and even an impractical solution at locations where water scarcity problems are faced. PV panels ought to survey the effect in monetary terms [10]. Emerging companies are providing manual and automatic PV cleaning services and losses (efficiency) in PV performance due to soiling that requires sufficient knowledge in implementing PV modules and examine whether these services are cost efficient or not.

Various scientific techniques based on complex mathematical expressions to approximate the performance of the solar cells have been reported in literature. The parameters of current–voltage characteristics based on solar cells having non–linear lumped properties were calculated and analyzed [11]. In [12] setting extraction was performed keeping in mind of the temperature and maximum power point (MPP) voltage and current distributions versus solar irradiance was shown. Specifically the authors used robust linear regression method to identify the PV array model parameters. Parameters were obtained by using only solar irradiance. In [13], a solar array based on nonlinear radial basis function networks neural network (RBFNN) was modeled that are connected to the input vector in simple manner. The current and voltage curves of the PV array with their training procedure were simulated. I–V curves and MPP of a PV module are demonstrated by using RBFNN [14].

Utilization of a genetic algorithm based RBFNN training schematic is a primary issue to acquire an ideal number of radial basis functions by utilizing only input samples of a commercial PV module. In [15], authors proposed the model which require five parameters with the solar irradiance and the PV module temperature. It was stated that prediction of performance makes it useful for engineered application. In [16] authors concentrated the execution of solar panels and found that the diminishment of dirtying phenomena firmly rely on array voltage and current which relies upon module temperature and solar irradiance.

In [17] authors re-designed a model for the execution of chosen PV system and presumed that the yielded power is required relative to the PV module temperature and the in-plane expansive scale irradiance. From the above literature review it can be concluded that reduction in efficiency of the solar panel due to dust accretion depends on various parameters varying from environmental factors to the I-V and P-V characteristics. Consequently, to defeat this disparity there must be a cleaning technique to go before the fitness of the solar panels.

This paper describes a model based on unique type of neural network for mitigating the soiling issue from solar panels, namely, RBFNN which can generate the control signal to windshield wiper based on the dust data and wipes the dust from the panel. decreased.

2. Solar Array Based RBF Network Modeling
The RBFNN have been contemplated since the mid-1980s, and they were initially presented in the arrangement of genuine multivariable addition and guess issues [18]. For an RBFNN model the activation of a hidden unit is determined by the distance between the input vector and a target vector. Peculiarity flanked by the roles of the first and second layers of parameters makes a key trait of RBF training. While unsupervised technique using only input data governs the basic functions using fast linear supervised methods; the weights from the hidden to the output layers can be intended. Such a characteristic makes the RBF network training quicker as compared to the Backpropagation (BP) method for multilayer-perceptron networks.

Also they do not come across the local minima dilemma. In this research the RBFNNs are applied to model PV arrays and to predict the MPPs. Curve-fitting problem in a high-dimensional space is equivalent to the design of RBF networks. Therefore, preparing/learning gets to be distinctly looked for a surface in a multifaceted space that gives a finest fit to the training information. Complex function consisting of a network of RBFNNs can be represented by such surface. In order to map input vector and output vector with a satisfactory level of accuracy, the form and numbers are determined.
In this experiment, authors measured PV current, voltage, module temperature, solar irradiance and power in sunlight and dark days with and without dirt gathered over the solar panel shown in Fig. 1.

This panel comprises wind shield wiper with a small jet which ejects water at the time of wiping the dust from the panel. Data of Table 1 shows different type of days which are sunny, cloudy, dust accumulated on the sunny and cloudy days are measured from the solar panels. The measured data of Table 1 has been taken from solar panel installed at College of Technology and Engineering, Udaipur.

| Type of day  | Time (a.m/p.m) | Volts (V) | Currents (A) | Power (Watts) | Solar irradiance (Watt/m²) | Module temperature |
|--------------|----------------|-----------|--------------|---------------|---------------------------|--------------------|
| Sunny        | 12:00 p.m      | 18.71     | 7.6          | 142.2         | 764                       | 48.68⁰              |
| Sunny        | 1:00 p.m       | 22.83     | 8.1          | 185           | 1000                      | 57.50⁰              |
| Sunny        | 11.30 a.m      | 13.85     | 6.6          | 91.47         | 465                       | 43.10⁰              |
| Cloudy       | 11:00 a.m      | 9.39      | 3.1          | 29.125        | 151                       | 24.40⁰              |
| Cloudy       | 12:00 p.m      | 13.10     | 2.9          | 38            | 199                       | 27.20⁰              |
| Cloudy       | 11:30 a.m      | 12.6      | 4.5          | 56.72         | 276                       | 31.20⁰              |
| Dusty sunny  | 11:00 a.m      | 12.97     | 2.59         | 33.65         | 564                       | 46.10⁰              |
| Dusty sunny  | 12:00 p.m      | 13.5      | 3.15         | 42.63         | 793                       | 46.40⁰              |
| Dusty cloudy | 12:30 p.m      | 10.97     | 2.80         | 30.72         | 276                       | 39.40⁰              |

From common principle of the RBF network mapping, the planned RBF network for a PV array consists of three layers: the input layer, the hidden layer and the output layer. The input layer comprises of a five-dimensional vector Z whose elements are solar irradiance (G), ambient temperature (T), PV voltage (Vpv), current (Ipv) and power (P). The output layer Y has only one element, i.e. 1 or 0; 1 represents accumulation of dust and 0 represents no accumulation of dust, although in common it may be of any vector dimension shown in Fig. 2. Activation of a hidden unit for an RBFN model is determined by the distance between the input vector and a target vector. The hidden layer comprises of K RBFs φj (j = 1,...,K) that are linked straight to all the elements in the input layer [14]. Set consisting of N input vectors mutually with equivalent output signals will have N such hidden units, each comparable with one data point.
Therefore, we have

\[
\begin{bmatrix}
G^n \\
T^n \\
V_{pv} \\
I_{pv} \\
P
\end{bmatrix}
\]

\[Y^n = [1 \ 0]^T \]  \hspace{1cm} (1)

The hidden layer can be represented as a matrix:

\[
\Phi = \begin{bmatrix}
\phi_1^1 & \phi_2^1 & \phi_k^1 \\
\phi_1^2 & \phi_2^2 & \phi_k^2 \\
\phi_1^N & \phi_2^N & \phi_k^N
\end{bmatrix}
\]  \hspace{1cm} (2)

and the weight vector

\[
W = \begin{bmatrix}
W_{1,v} \\
W_{2,v} \\
\vdots \\
W_{K,v}
\end{bmatrix}
\]  \hspace{1cm} (3)

Non-linear distribution form can be represented as the function $\Phi_j (Z^n)$. Gaussian function is used in the form of:

\[
\Phi_j (Z^n) = \exp \left( \frac{|Z^n - \mu_j|}{\sigma_j^2} \right) \]  \hspace{1cm} (4)
where, $Z$ has the same dimension as $\mu_j (1 \leq j \leq K)$ vector and $\Phi_j$ represents the centre of the RBF, and width of an RBF is represented by scalar quantity, $\sigma$ also at times called the spread width. When compared to standard feed forward back propagation networks, RBF may entail additional neurons, but frequently they can be intended in such a way that its speed can match with the time required to train standard feed forward networks. If more number of training vectors is available then RBF can work at its best.

3. Proposed RBFNN Model

There are factors involved in training of a RBFNNs network namely, determining the number of RBFNs and the most favorable values of the centres, weights and biases [19]. Minimizing the sum of squared errors is the criterion which is defined as

$$SSE = \frac{1}{2} \sum_{n} \sum_{k} \left( t_k^n - y_k^n(\mathbf{X}^n) \right)^2$$

(5)

where, $t_k^n$ (in this application $k = 1$) are the target values of the network output when the network is presented with input vector $\mathbf{X}^n$.

Further, to conclude RBF network centres more accurate technique called the self-organized method is used [20]. In this technique, permission to budge the locations of their centres in a self-organized fashion is given by the RBFs, while pseudo-inverse method is used to figure the linear weights of the output layer. Orthogonal least-squares method is one of the most frequently used schemes in self organizing approaches which is used in this research to train the PV RBF network [21, 22]. At the same time, values of weights are also suborned. A pseudo-inverse method is a simple procedure for undergoing this training. Here, solution of the weights in matrix form is given by

$$W^T = [\phi \phi]^T T$$

(6)

There are many techniques to calculate the width parameters $r_j$ of the RBFNNs. One heuristic approach is to pick all widths to be equivalent and to be given by about double the normal dispersing between the premise work focuses. This guarantees the premise work cover to some degree and subsequently gives a moderately smooth representation of the dissemination of training data.

With respect to standard feed-forward neural network RBFNN having greater number of neurons can be modeled and trained in a lesser time. Inputs are directly linked to the radial basis neuron in a RBFNN, particularly for this case they vary with other neuron types. Actually input originates from assessment of the prejudiced mean relative to the distinction between the input value and the data centroid used as statistical weight for the input itself. In order to reduce mean squared error well below the expected limits [23], add neurons iteratively at any time step and final network can be build up. Here, network comprises of 16 by one RBFNN with an hidden layer of 16 radial basis neurons and one output linear neuron, set of 5800 five dimensional input $[G, T, V_{pv}, I_{pv}$ and $P]$ was used to train the network and output layer which gives 1 or 0 (1; representing dust is present and 0; represents no dust). After training network was tested with some other data which were not involved in training provides an accurate retort with less than 1% of comparative mean squared error.

4. Results and Discussion

In this work to perform model training, MATLAB neural network toolbox was used. On account of minimum SSE condition defined by Eqn. (5), assortment of the neuron number and spread-constant parameters were selected for both training and testing data though the training time was short. The sum of the squared errors for training and testing data obtained by setting the neuron number to 100 and spread constant (SC) to 0.6, were 0.0103 and 0.0173, respectively. The equivalent training time observed was 80.46s. The training time for same set of data obtained for the equivalent level of SSE was found to be 330.55s for multi-layer perceptron (MLP)-BP network with one hidden layer and 20 neurons. That is, four times more than that for the RBFNN model.
Relative mean squared error of 1% was observed which tells that the alternate dust data provided in the testing which was not involved in the training predicts accurately and hence, generates the control signal to the windshield wiper motor and sweeps the dust from the panel.

As a whole, data for the prediction of dust on the panel, trained network was tested again that tells mean square error performance for the tested network which provides a correct response with less than 0.5% of relative mean squared error.

RBFNN having 16 radial basis function generated by the training method, which is appreciably less than the number of training data points, and its spread constant is set equal to 1.

Fig. 3. I–V characteristics training performance and weights.

Regardless of the possibility that in this application the size of radial basis functions may be higher or lower than 16, the previous one will give a bigger SSE than the later in a more extended preparing time having no huge change in SSE lessening. Networks performances and simulations results respectively for the I–V and P–V characteristics are shown in Fig. 3 and Fig. 4. Noted point is, that a smoother function approximation can be achieved by larger spread width parameter of the RBFNN, but numerical problems will occur if too large spread width has been used, this results in the best trade-off between smoothness of approximation and numerical stability, which results in distinctive oscillations in RBFNNs estimation.

Fig. 4. P–V characteristics training performance and weights.
5. Conclusion

Regardless of the far reaching enthusiasm for neural system techniques, most applications utilize the MLP-BP algorithm. This paper shows the utilization of radial basis function networks for solar PV modeling to mitigate the dust from the panel. Through wide-ranging computer based versions we concluded that the RBFNN based models ought to attain finer recital than the conformist neural models as multilayer perceptron (MLP). It has demonstrated that a RBFNN model can be takes lesser time in preparation as compared to MLP and has no nearby minima issue.

The trained networks are sufficiently accurate in representing solar PV characteristics with all the data measured from the panel and require less computational time in predicting the dust when compared with other conventional modeling like perturb and observe (PO), etc. Because of their low computational intricacy, the RBFNNs are presently favored in demonstrating of complex and non-linear phenomena like solar cell attributes. It has also been shown that the proposed RBFNN model results in prediction of dust data with accuracy of 99% that further generates the control signal to the wiper motor and wipes the dust with the water ejected from the water ejector.

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