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Research Article

Optimization of Solar Panel Deployment Using Machine Learning

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In this work, we proposed a mechanism for topology reconfiguration or optimization of photovoltaic (PV) arrays using machine learning-assisted techniques. The study takes into concern several topologies that includes series parallel topology, parallel topology, bridge link topology, honeycomb topology, and total cross tied. The artificial neural network-based topology reconfiguration strategy allows for optimal working conditions for PV arrays. With this, machine learning-assisted topology reconfiguration or optimal solar panel deployment enables the proposed mechanism to achieve higher degree of testing accuracy precision, recall, and f-measure under standard ideal condition.

1. Introduction

Researchers are working around the clock to find new ways to generate power that are safe and environmentally friendly, and this effort has global implications. Green energy, often known as renewable energy, is currently a hotly debated scientific topic [1]. Of all the sources of renewable energy, solar power is the well-known and prevalent one as it can be simply purchased and installed, with fewer restrictions on installing [2]. Advances in machine learning and signal processing models employed with the photovoltaic modules [3–6] have made it possible to effectively use data from the PV panels to enable improved control, monitoring, and optimization of power.

They are able to converse with other panels nearby. Additionally, surface mount devices have the ability to act as switching devices, allowing the connection between the panels to be altered in some way [7, 8]. The necessity for connection topology optimization can be alleviated by changing the electrical connections under partial shade situations, which can increase the overall power supplied by the panels with a significant range [3]. Conventional topologies is represented by a line graph showing power output as a function of voltage. The total cross tied topology, which offers the most power, is definitely superior to the SP topology when it comes to delivering power to the array. Therefore, the study is in need to develop a model that should learn in diverse manner from various input data consisting

of irradiance profiles that includes panel partial shadowing and forecasting the configuration for the optimal placement of robust reconfiguration of PV arrays in any type of topologies.

Therefore, the classification is conducted on using irradiance profile on partial shading condition which can be classified accurately by the machine learning model once it has been trained on a considerable amount of training data. For this application, the employment of a machine learning model generates a system that learns via training data in order of relating the irradiance profile that fits with the reconfiguration in an ideal manner. SMDs measure irradiance per panel and communicate it to a local server, where the machine learning helps in predicting the required topology using this information. The server receives the topology selected, and the SMDs are activated to complete topology reconnection.

Several machine learning models including artificial neural network designs find their operations to be successful in many applications [9–13] which can be blamed for the recent surge in supervised machine learning [14, 15]. The PV array irradiance feature is employed to train the machine learning architecture in this study. In order to maximise power output, a PV array system must be reconfigured to the labels used mostly to optimise the weights. Python scikit-learn software was used to train the neural network. The proposed technology is simple and straightforward to apply, requiring no new or external PV panels, and represents a significant advance over the current state of the art in the field.

To ensure that overall radiation on each array row is essentially constant, an irradiance equalisation [16] approach is used for connection reconfiguration. There may be mismatches in the amount of irradiance on a TCT array row that may result in a reduced current output and thus a lower output during the occurrence of the partial shadowing. Solar panels receiving less light energy are switched electronically to the ones that receive increased amount of light. Therefore, the total irradiance on each array rows is nearly identical with the sum of irradiances across every row in an entire PV array.

A simple sorting algorithm [17] may identify the array rows, which are shaded heavily in a location and add dynamic modules to those rows, which is a popular strategy. By decreasing the irradiance mismatch index (IMI) in PV arrays, the authors of [18] show considerable gains in power output when compared to the architecture with no reconfiguration. When the IMI is kept to a minimum, the array total irradiance remains constant across all of its rows, reducing the amount of current and voltage mismatches caused by shade. Based on the limits imposed on frequency inverters, an electrical system that allows the modules in array to get reconfigured and connected with different numbers of modules in each row was proposed by the authors of [19].

The series parallel topology has a variety of options for reconfiguration. In order to create an SP PV array using the SP architecture, a simple reconfiguration technique entails stringing together irradiance levels and joining the strings. Only when more than 15% of the panels are shaded, do the authors of [9] reconfigure the array, based on the current and voltage measurements from each panel.

There exist many algorithm including support vector machine, k-nearest neighbor, and Naïve Bayes to optimise the optimal configuration and placement of panels under different conditions; however, most of the methods fails as it is not supplied with rich set of data, and the proposed method was aimed at determining the solution using machine learning. According to [10], a partial reconfiguration technique employing irradiance characteristics and graph clustering is proposed to merge disparate panels and show considerable performance benefits. Using a neural network-based technique, the authors of [11, 20] have improved performance by learning the irradiance properties and translating them to the appropriate topologies. This research focuses on and elaborates on the use of neural networks to optimise topology. Before we go into the specifics of our approach, the study explains why a similar strategy is needed for photovoltaic (PV) systems [12, 13].

In this paper, we develop a mechanism that enables topology reconfiguration or optimization of photovoltaic array or PV array using a machine learning-assisted techniques. The study takes into concern several topologies that includes series parallel topology, parallel topology, bridge link topology, honeycomb topology, and total cross tied. The strategy for topology reconfiguration using artificial neural network enables optimal working conditions for the PV arrays.

The main contribution of the paper involves the following:

(i) The study takes into concern several topologies that includes series parallel topology, parallel topology, bridge link topology, honeycomb topology, and total cross tied

(ii) The strategy for topology reconfiguration using artificial neural network enables optimal working conditions for the PV arrays

2. Proposed Method

Many modern NN structures and successful applications can be ascribed to the recent rise in ML methods [16]. Learning sophisticated nonlinear mappings between input and output, learning discriminative data representations, and creating generic end-to-end systems are some of the primary advantages of employing neural networks. A model capable of learning diverse irradiance profiles includes partial shading and optimal configuration prediction and automatic reconfiguration of array into topologies.

To maximise output power, the ML model can reliably categorise an arbitrary partial shade irradiance profile once it has been trained on a considerable amount of training data. A machine learning system that helps to map irradiances to the ideal reconfiguration technique is the result of using an ML model for this application. As a result, the study makes use of the data from each and every PV panel. The irradiance feature of PV array on each panel is used to

train the NN method described in the next sections. For the NN to achieve its maximum output, a PV array system must be configured in a specific way. These labels serve as a guide for optimising NN weights.

Using NNs to achieve topology reconfiguration is discussed in length in this portion of the study. Before moving on to describe how to build a neural network model, the paper first explains how to create labelled datasets. For all of our testing, we use a 3×4 PV array. It is possible to extend our approach to work with additional types of array structures by simply scaling up our current implementation.

In Figure 1, the panels with the topology switching include series parallel topology, parallel topology, bridge link topology, honeycomb topology, and total cross tied. These topologies are provided with optimal solution from the trained neural network to reconfigure itself for optimal operation purposes. The classifier is trained with the trained data via features obtained from the panels as inputs for the topologies, and these inputs are the best solutions.

The binary mapping algorithm shown in Figure 1 was used to create synthetic irradiance values for each panel of the 3×4 array in this study. There were two 12 D-4096 irradiance profiles formed when 0 is assigned to an unshaded panel and 1 is assigned to a shaded panel in the experiment. According to the irradiance data connected with the binary integers, the following uniform distribution may be found in equations (1) and (2):

$$0 \longrightarrow \text{irr} \sim U[\alpha, 1000], \tag{1}$$

$$1 \longrightarrow \text{irr} \sim U[50, \alpha]. \tag{2}$$

In this case, the threshold used to determine whether a panel is shaded ($\alpha = 584\,\text{W/m}^2$) is indicated [4]. For a specific binary assignment, all of the panels receive the same irradiance levels, as shown.

For a wide range of partial shading irradiance profiles, the study sampled the uniform distribution for randomly chosen binary assignments and generated more than 14,000 cases. Topology reconfiguration is treated as a learning task that necessitates the use of a labelled dataset (X, y), where X represents the irradiance profile instances in dimensions $(m \times n)$, where $m = 14{,}000$ represents the total number of irradiance profile instances, $n = 12$ represents the total number of PV panels in the array, and y is the label vector that goes along with it. There are 12 irradiance features for each of the 3×4 PV panels. Therefore,

$$y_i = \text{argmax}_i P_i, \tag{3}$$

where P is the global maximum power points for all the topologies.

2.1. Neural Network Optimization. Machine learning approaches use neural networks. Like biological brain networks, they are composed of nodes and connections. There are countless numbers of neuronal connections. Neural networks like the one shown in Figure 1 are an excellent illustration of this. Neurons are shown by the white circles, and

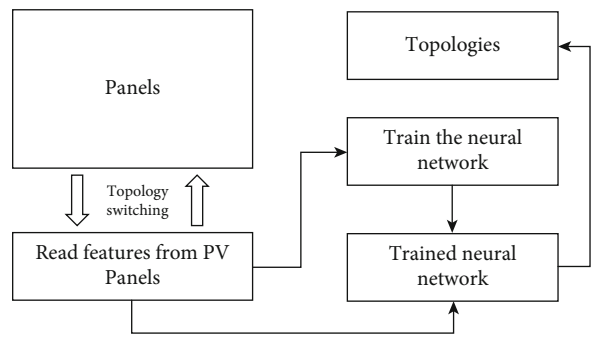

Figure 1: Proposed algorithm.

the arrows show the connections between them. Because the links are directed, arrows are used to symbolise them in the study. The neural network will be explained in this section of the study.

To begin with, researchers need to understand what a neuron is. Inputs, thresholds, and outputs are all defined in biology. The neuron is triggered, and a signal is sent to the output if the input voltage exceeds the threshold. One thing to keep in mind is that even if the neuron has multiple inputs, there is only one signal output from it. Neuron models in machine learning are remarkably similar to those found in biology. The inputs and outputs are also included. Even though there are numerous neurons connecting to the neuron output, the output values are the same. There are, of course, certain differences between the two. The neuron in machine learning uses a function instead of a threshold to convert inputs to outputs. The activation function is available in a variety of ways. It is frequently used as the sigmoid function in research $\sigma(x)$.

$$\sigma(x) = \frac{1}{1 + e^{-x}}. \tag{4}$$

Thresholding in this paper is achieved using a fitness function named sigmoid function that resembles step function. The output of sigmoid function is close to 1 when x is a big positive value. It is impossible to get an output larger than zero when x is 0. The two things are also different in terms of how much they weigh. The weights indicate how much a neuron is affected by a certain stimulus. In other words, the research will not just activate every input. The input value of the activation function is equal to the sum of its inputs, multiplied by a linear formula. The following is a mathematical representation:

$$\sigma(w_1 x_1 + w_2 x_2 + \cdots + w_N x_N), \tag{5}$$

where N is the total inputs, w_i is the weights of x_i, and $\sigma(x)$ is the activation function.

Using only one input and varying the weight, researchers were able to observe the effect of different weightings on the final output. In this example, it is clear that 0 can be used as a threshold to assess if the output is close to 0 or close to 1. A bias is added to the study in order to shift the sigmoid function in this scenario. As a result, the new relationship is as

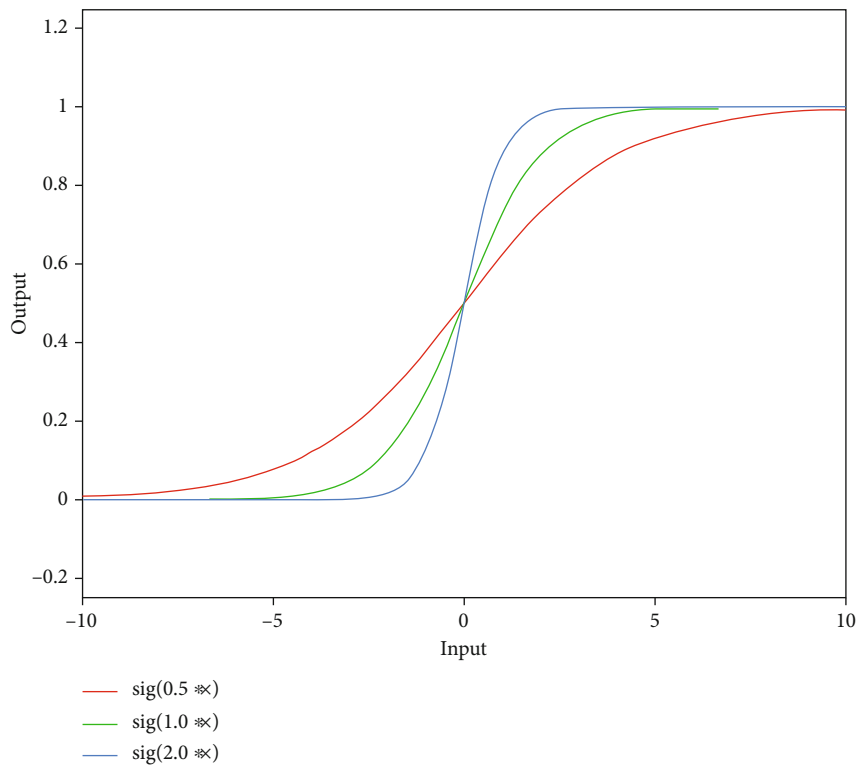

Figure 2: The sigmoid function result with various input weights without bias.

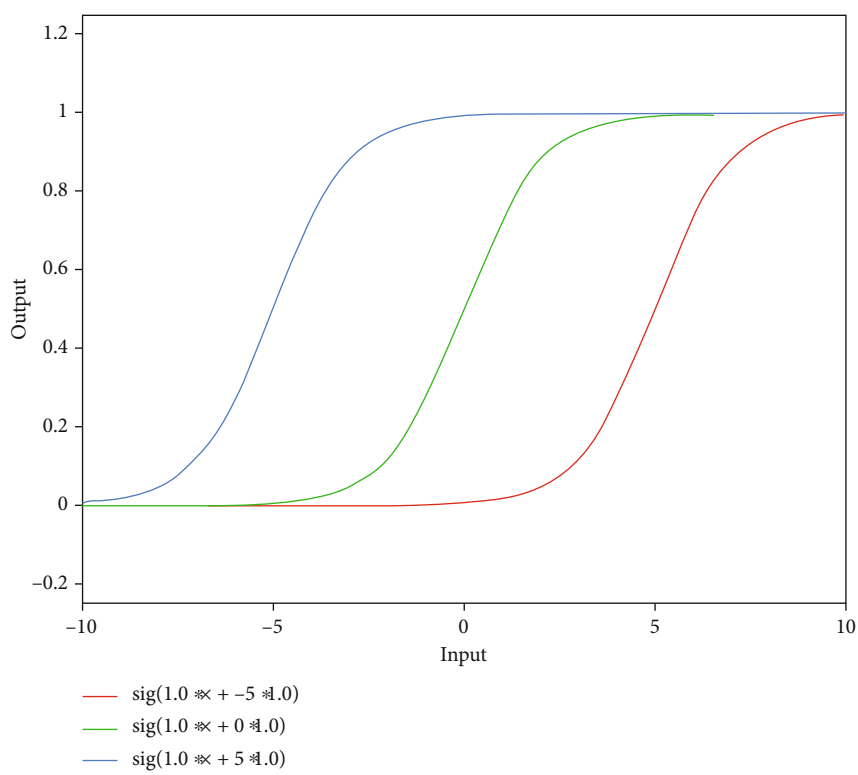

Figure 3: The sigmoid function result with various input weights with bias.

Table 1: Accuracy.

Accuracy	KNN	NB	SVM	ANN
Series parallel	0.9296	0.9421	0.9443	0.9569
Parallel	0.9294	0.9420	0.9436	0.9568
Bridge link	0.9285	0.9412	0.9436	0.9568
Honeycomb	0.9284	0.9409	0.9429	0.9566
Total cross tied	0.9282	0.9337	0.9428	0.9564

Table 2: Precision.

Precision	KNN	NB	SVM	ANN
Series parallel	0.7771	0.8725	0.8731	0.8941
Parallel	0.7703	0.8590	0.8628	0.8920
Bridge link	0.7595	0.8586	0.8628	0.8870
Honeycomb	0.7543	0.8392	0.8417	0.8862
Total cross tied	0.7530	0.8380	0.8415	0.8711

Table 3: Recall.

Recall	KNN	NB	SVM	ANN
Series parallel	0.7843	0.7834	0.8390	0.9438
Parallel	0.8266	0.8300	0.8405	0.9443
Bridge link	0.8270	0.8398	0.8407	0.9536
Honeycomb	0.8609	0.8597	0.8520	0.9558
Total cross tied	0.8648	0.8693	0.9061	0.9564

Table 4: f-measure.

f-measure	KNN	NB	SVM	ANN
Series parallel	0.8291	0.9545	0.9012	0.9412
Parallel	0.7346	0.9517	0.8938	0.9346
Bridge link	0.7078	0.9459	0.8925	0.9328
Honeycomb	0.6801	0.9349	0.8844	0.9318
Total cross tied	0.6663	0.8686	0.8844	0.8967

Table 5: MAPE.

MAPE	KNN	NB	SVM	ANN
Series parallel	0.1878	0.0857	0.0137	0.0031
Parallel	0.1936	0.1803	0.0210	0.0020
Bridge link	0.2194	0.2070	0.0223	0.0019
Honeycomb	0.2628	0.2486	0.0462	0.0030
Total cross tied	0.2334	0.2347	0.0409	0.0030

follows:

$$\sigma(\theta + w_1x_1 + w_2x_2 + \cdots + w_Nx_N), \tag{6}$$

where θ is the bias and the other notations are the same as before.

$\theta, w_1, \cdots, w_n$ is the parameter.

It appears that neural networks exist when several neurons are connected together in a single experiment. Many neurons make up the coloured rectangles, which the study calls rectangle layers. One or more neurons can be found in the layer, but these neurons will not be connected. For the purpose of reconfiguring the network architecture, we provide a six-layered feedforward ANN model with completely linked nodes. These parameters were discovered through a hyperparameter search with the purpose of increasing overall accuracy. Each panel irradiance is represented by an n-dimensional feature vector ($n = 12$) that is fed into the neural network. Figures 2 and 3 display the sigmoid function result with various input weights without bias and with bias.

3. Results and Discussions

Simulink model was used to acquire simulated data for the generation of maximum power points (MPPs). For the Simulink model, Sandia performance model for PV modules was used. There are several topologies available in MATLAB for setting up parameters for the Sandia model, including short-circuit current (I_{SC}), open circuit voltage (V_{OC}), irradiance, and temperature over various topologies like series parallel, parallel, honeycomb, bridge link, and total cross tied. Using the Simulink model, a single PV module may be generated.

Class-wise performance scores provided by the confusion matrix are used to gauge how well NN classifies the test dataset. Generalizability is demonstrated by the fact that more cases are correctly classified than are incorrectly labelled. Then, we ran the algorithm on 10 distinct test splits and found that the average test accuracy was 95%. These methods can simply be incorporated into cyberphysical solar monitoring systems as indicated in the introduction.

Table 1 shows the results of accuracy of predicting the topology configuration of various topologies like series parallel, parallel, honeycomb, bridge link, and total cross tied associated with I_{SC} and V_{OC}, irradiance, and temperature. The results of simulation shows that the proposed ANN achieves higher rate of classification accuracy than the other existing support vector machine (SVM), Naïve Bayes (NB), and k-nearest neighbor (K-NN).

Table 2 shows the results of precision of predicting the topology configuration of various topologies like series parallel, parallel, honeycomb, bridge link, and total cross tied associated with I_{SC} and V_{OC}, irradiance, and temperature. The results of simulation shows that the proposed ANN achieves higher rate of precision than the other existing SVM, NB, and K-NN.

Recall is indeed a criterion of how well our model identifies true positives. Table 3 shows the results of recall of predicting the topology configuration of various topologies like series parallel, parallel, honeycomb, bridge link, and total cross tied associated with I_{SC} and V_{OC}, irradiance, and temperature. The results of simulation shows that the proposed ANN achieves higher rate of recall than the other existing SVM, NB, and K-NN.

Table 4 shows the results of f-measure of predicting the topology configuration of various topologies like series parallel, parallel, honeycomb, bridge link, and total cross tied

associated with I_{SC} and V_{OC}, irradiance, and temperature. The results of simulation shows that the proposed ANN achieves higher rate of f-measure than the other existing SVM, NB, and K-NN.

Table 5 shows the results of MAPE of predicting the topology configuration of various topologies like series parallel, parallel, honeycomb, bridge link, and total cross tied associated with I_{SC} and V_{OC}, irradiance, and temperature. The results of simulation shows that the proposed ANN achieves reduced mean of the absolute percentage errors than the other existing SVM, NB, and K-NN.

4. Conclusions

In this paper, a topology reconfiguration strategy for PV arrays using ANNs is proposed. Using such an approach, we achieve a high test accuracy under ideal conditions. The algorithm can be easily integrated into any cyberphysical system with switching capabilities on every panel. The topologies including series parallel topology, parallel topology, bridge link topology, honeycomb topology, and total cross tied. The strategy for topology reconfiguration using artificial neural network enables optimal working conditions for the PV arrays. The results of simulation show that the proposed mechanism achieves higher degree of accuracy (98%) in finding the optimal topologies to deploy the PV panels under standard conditions. In the future, the method should focus on considering minimal cost consideration while reconfiguring the topology of the panels.

Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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