Connection Topology Optimization in Photovoltaic Arrays using Neural Networks

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***Abstract*—A cyber-physical system (CPS) approach for optimizing the output power of photovoltaic (PV) energy systems is proposed. In particular, a novel connection topology reconfiguration strategy for PV arrays to maximize power output under partial shading conditions using neural networks is put forth. Depending upon an irradiance/shading profile of the panels, topologies, namely series parallel (SP), total cross tied (TCT) or bridge link (BL) produce different maximum power points (MPP). The connection topology of the PV array that provides the maximum power output is chosen using a multi-layer perceptron. The simulation results show that empirically an output power increase of 12% can be achieved through reconfiguration. The method proposed can be implemented in any CPS PV system with switching capabilities and is simple to implement.**

***Keywords*—Photovoltaic Array (PV), partial shading, neural networks, machine learning, CPS, IoT energy systems.**

I. Introduction

With the growing demand in the production of renewable energy, photovoltaic systems play an important role in meeting the energy requirements. However, the production of photovoltaic energy is affected by external conditions such as partial shading, varying temperatures and soiling of PV panels. Among these, partial shading causes a significant reduction in power [1,2]. On the other hand, the energy production can also be affected if a PV array system has faulty modules [3].

Off-the-shelf photovoltaic arrays are generally connected in a series-parallel (SP) topology, where individual PV panels are connected in series to form a PV string and several strings are connected in parallel to form the array. A typical SP topology is illustrated in Fig. 1a. In addition to the conventional SP topology, PV modules can also be connected in a cross tied manner which, although requires additional connections between the modules, provides better performance than SP under certain conditions [27]. The two types of cross tied topologies considered in this work are namely the total cross tied (TCT) and bridge link (BL) configurations. In the TCT topology shown in Fig. 1b, every PV module is connected in series and parallel with the other modules [4]. The BL topology as shown in Fig. 1c consists of half as many interconnections as the TCT topology. All the three topologies considered namely SP, TCT and BL behave similarly under perfect illumination and the generated array power is the same for all three topologies in this case. In other words, the maximum power point (P_{MP}) and the corresponding voltage (V_{MP}) are similar under no shading. However, when there are electrical

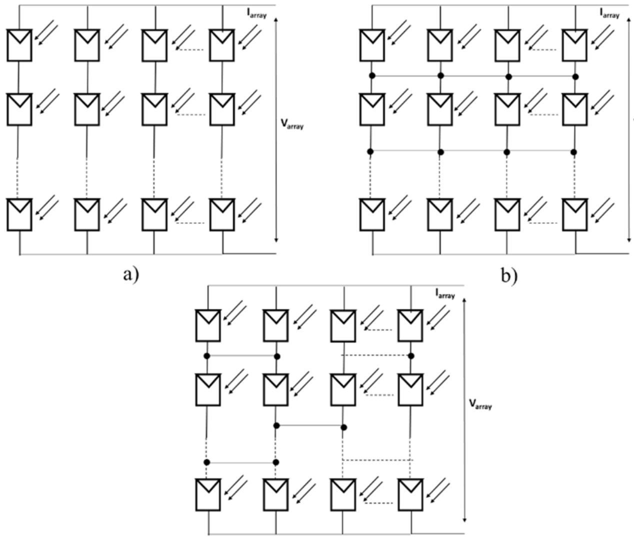

Fig.1a) Series-Parallel, b) Total Cross Tied, c) Bridge Link PV array connection topologies.

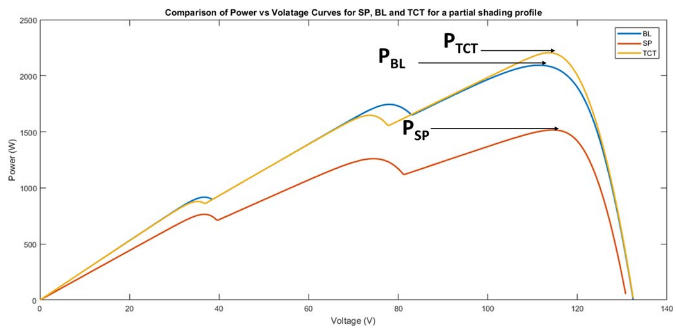

Fig.2 Comparison of maximum power for the three different configurations for a partial shading condition. As it is seen that $P_{SP}<P_{BL}<P_{TCT}$, a topology reconfiguration from SP to TCT can result in power improvement.

mismatches and partial shading, one of the topologies can outperform the others.

With advances in signal processing and machine learning techniques used with CPS PV systems [5-8], data from the PV panels can be effectively used to provide improved monitoring, control and power output optimization. Prior work by the authors of this paper, addressed issues related to PV monitoring and solar analytics that are reported in [5-9,13-15,31,37]. The CPS PV system developed by our research group at the SenSIP Center , Arizona State University (ASU) [7] consists of 'smart-monitoring devices' (SMDs) that are connected on every PV

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panel to measure and transmit data wirelessly to a computer server. They can communicate with the neighboring panels. The SMDs also have the capabilities of switching devices that can be used to modify the electrical connection between two neighboring panels. A change in the electrical connections under partial shading conditions can be leveraged to improve the overall electrical power produced by the PV system by a considerable margin, thereby facilitating the need for connection topology optimization [5]. Figure 2 illustrates the power vs voltage curves for a partial shading profile for the three different topologies considered. It can be clearly understood that there is a significant difference in the power when the array operates under TCT topology which provides the maximum power in this case when compared to SP topology. The authors of [5,16] have reported an average 4-5% improvement in overall power output when the array is reconfigured under certain conditions.

In order to provide a generalizable, robust automatic array reconfiguration system into one of the SP, TCT or BL topologies we require a model that can learn different patterns of the irradiance profiles i.e. partial shading of the panels and predict the optimum configuration. Once the machine learning model is trained on a significantly large set of training data, it can accurately classify an arbitrary partial shading irradiance profile to that particular configuration which can maximize the output power. The use of a machine learning model for this application produces an end to end system which learns a function to map irradiances to the optimal reconfiguration strategy. This also allows us to leverage data from every PV panel. In this work, we present a novel connection topology optimization algorithm for PV arrays to change the configuration amongst series-parallel (SP), total cross tied (TCT) and bridge link (BL) topologies using a two-layer neural network architecture. Figure 3 describes a system level approach of the proposed algorithm. Here, as illustrated, the irradiance per panel is measured by the SMD and transmitted to a local server where it is fed as inputs to the neural network which predicts the required topology. The topology chosen is communicated to the server which in turn initiates the SMDs to perform topology reconnection.

The recent growth in supervised machine learning [10] in the past decade can be attributed to several modern neural network architectures and their successful applications [29, 33-36]. The neural network architecture used in this work is trained using the irradiance feature on each of the panels of the PV array. The labels which are used essentially to optimize the weights, are the particular configuration, a PV array system must be reconfigured to, to produce maximum power output. The determination of the maximum power of the three different topologies considered was performed using MATLAB^{R} Simulink [11]. The neural network training was performed using *scikit* learn package in Python[12]. In comparison with the existing work performed in this area, the method proposed is easy and simple to implement without requiring the need of new or external PV panels and provides significant improvement.

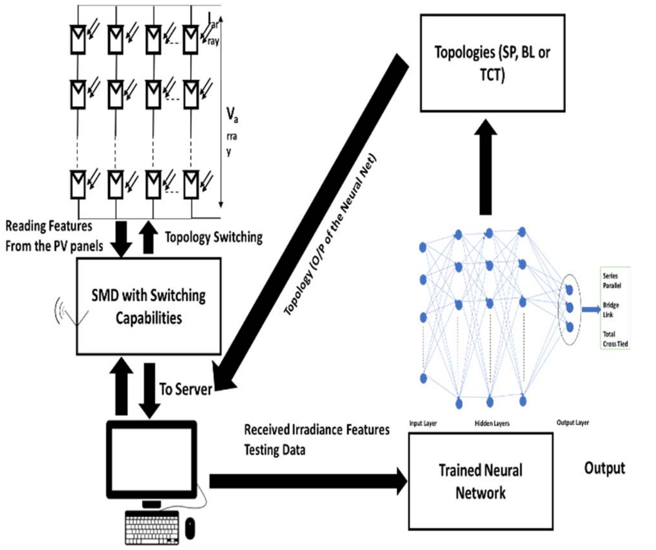

Fig.3. System level overview of the proposed algorithm. On the left, it can be seen that the SMD reads the features from the PV panels and transmits the information to the server. The server tests the received data on the trained neural network which then classifies that irradiance profile to the topology that can maximize power output. This information is communicated to the server which initiates the switching action of the SMDs.

II. PREVIOUS WORK

Topology reconfiguration in PV arrays, first introduced by the authors of [22] and [23] has been addressed by several strategies [5,17-21,24-27]. These strategies are unique to a particular topology. For example, they can be classified into reconfiguration algorithms for TCT and SP respectively.

A. *Existing Strategies for Total Cross Tied*

In the case of TCT topology, irradiance equalization [17] is the dominant method for connection reconfiguration which ensures that the sum of irradiances falling on every row of the array to be approximately constant. Figure 4 depicts the overall idea behind the algorithm. In the case of partial shading on TCT arrays, there is a mismatch on the amount of irradiance of the panels in a particular row of the array resulting in the production of lower current and hence the overall power output of the PV array. Modules in the PV array that receive less illumination are electrically switched with those modules that receive a higher illumination such that the sum of irradiances across every row is very similar to all the rows of the array.

Topology reconfiguration in TCT arrays can also be implemented by dividing the PV system into a fixed and a dynamic part and by connecting the modules of the dynamic array to the fixed part if certain modules in the fixed part are significantly affected by partial shading. This technique is popularly referred to as adaptive banking [30] which compensates for the wastage in the power produced.

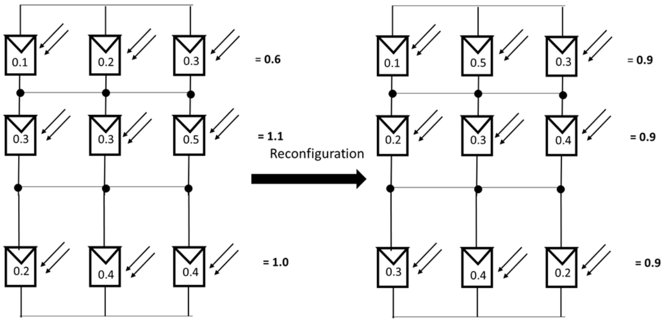

Fig. 4 Irradiance Equalization in TCT PV arrays. Note that the connection reconfigures such that the sum of irradiances is similar across the rows of the reconfigured array.

Another popular technique[18], includes a simple sorting algorithm that identifies the rows that are severely shaded in the fixed part and incorporates the modules from the dynamic part to those rows. Reference [19], optimizes the TCT topology by minimizing the irradiance mismatch index (IMI) on an array and report significant improvements in power produced. The papers considered so far utilize an array that consists of a fixed part with or without a dynamic part. Though there is reconfiguration within the same topology, it might not be the optimal topology. The authors of [20] proposed a dynamic electrical scheme where all the PV modules can be rearranged and reconnected to form a TCT array with unequal number of modules in every row with constraints imposed by the frequency inverters. Reference [21] introduce a ‘Configurations of Interest (COI)’ parameter to avoid the choice of redundant rows in the TCT array also ensuring that every row consists of the same number of PV modules.

B. *Existing Strategies for Series Parallel*

In the case of the SP topology, a basic reconfiguration strategy involves grouping PV modules with similar levels of irradiance along the same string and connecting the strings formed in parallel to obtain a SP PV array. The authors of [24] identify the conditions for SP reconfigurations based upon the current and voltage measurements from every panel and only reconfigure the array only when more than 15% of the panels are shaded. In [24], the resultant array after reconfiguration may have an unequal number of panels in a string. In [25], SP reconfiguration is performed in a manner where modules are divided into three categories based upon the received illumination and their behavior. They are namely 1) Fixed state, 2) Bi-state reconfigurable array and 3) Tri-state reconfigurable array. The authors have shown a considerable improvement in performance under the Tri-state mode of reconfiguration.

The authors of [26] have shown that in an array with two shaded modules, a 4% increase in the array power under shading conditions can be achieved by reconfiguring the conventional SP topology to bridge link (BL) and total cross-tied (TCT) topologies. TCT and BL are shown to be more tolerant to losses caused due to aging and manufacturing processes as in [27]. However, under partial shading or fault conditions, it is not guaranteed that the TCT or BL would outperform all the existing topologies for any shading pattern in the array. The authors of [5,16] have proposed a topology reconfiguration algorithm among SP, TCT and BL configurations similar to the one proposed in this work. In the paper, the authors first perform panel fault detection [7], [13] to classify the healthy and faulty modules and perform reconfiguration based upon which topology namely SP, TCT or BL under a particular irradiance profile produces the maximum operating power. The required reconfiguration is chosen after attempting different topologies and heuristically comparing the

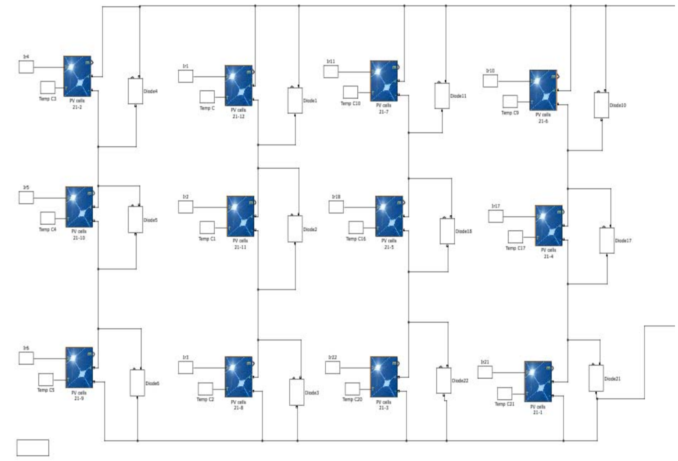

Fig. 5. MATLAB Simulink Series Parallel Topology model. Here the inputs to the PV module (‘blue’) are irradiance (‘Top’) and cell temperature (‘bottom’). Similar to SP topology, Simulink models for TCT and BL are also constructed.

maximum power produced. However, the authors have considered specific partial shading conditions only and not a general profile of irradiances on the overall array. Moreover, the determination of the best topology in this case will require a significantly higher amount of switching and time when implemented in a real-time scenario. The irradiance profile on the PV array may also vary within the period of determination.

Most of the aforementioned papers, do not use machine learning models to learn the function of mapping the irradiance profile to the best configuration among the three topologies considered. In this work, we propose a learning strategy to solve the topology optimization problem.

III. Proposed Approach

A. *Data Generation and Preprocessing*

In this work, data has been generated through simulated models. Figure 5 shows the MATLAB-Simulink SP PV array model which was used in the experiments where the inputs to the PV module (‘blue’) are irradiance and cell temperature. Similar to Fig. 5 Simulink models for TCT and BL PV arrays were used to extract the data for the respective configurations. A module which is partially shaded is denoted by a value of 1 and assigned a very low irradiance compared to an unshaded module which is denoted by a value of 0. The irradiance assigned to a shaded module is a value drawn from a uniform distribution between $50 W/m^2$ and $500 W/m^2$ whereas the irradiance assigned to an unshaded module is a value drawn from a uniform distribution between 500W/m^2 and 1000W/m^2 for that particular irradiance profile. In this simulation, each and every panel is given irradiance and temperature as inputs. The temperature considered is a constant of 27 degrees centigrade for all the simulations. In order to generate a comprehensive training set, 10500 instances of irradiance profiles were generated and fed as inputs to the Simulink model. The irradiance profiles theoretically cover a wide range of partial shading scenarios. Each instance of irradiance consists of 12 values corresponding to the irradiance given per panel. The SP, TCT and BL Simulink models are executed for the different irradiance profiles and the overall maximum power is computed. The label k for each irradiance profile is obtained as

$$k = \underset{i}{argmax}\ P_i \qquad (1)$$

where $P_1=P_{SP}$, $P_2=P_{BL}$ and $P_3=P_{TCT}$ are the MPPs of SP, BL and TCT topologies. The set consisting of the irradiances along with the respective labels forms the training and test dataset to be fed into the neural network classifier. It was ensured that a similar number of samples per class were used as inputs to the network to prevent sample biases. This work assumes ideal conditions and does not include the inverter downtime and associated losses.

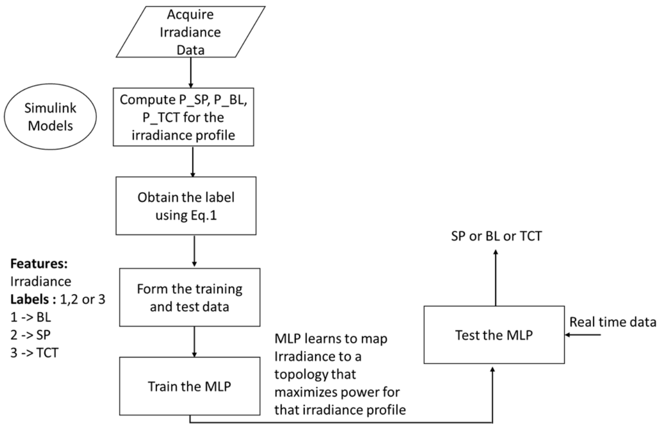

Fig. 6. Flowchart describing the overall algorithm. The diagram illustrates the overall methodology which involves pre-processing, training and classification.

B. MLP Architecture

The multi-layer perceptron is a feedforward neural network architecture consisting of several layers with a number of neurons in each layer. In this work, an MLP with 2 hidden layers is considered. The input to every neuron in an MLP is a weighted sum of the inputs from the previous layer. The weighted sum at every neuron is passed through an activation function which introduces non- linearities in the network. The activation function used in this work is 'tanh' (Hyperbolic tangent).The weighted sum propagates through the network and the error between the output and actual output label is computed and intended to minimize an overall loss function. The projected error is back- propagated and through the network based upon which the weights at every layer is updated. The training is carried out for a certain number of epochs and is expected to provide satisfactory classification results. The ADAM optimizer was used to minimize the overall log loss function of the network. A neural network at its most basic can be considered to be an adaptive filter [28] whose filter coefficients are updated with the number of iterations.

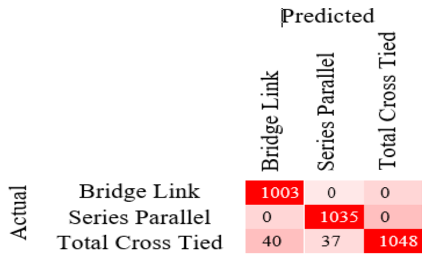

Fig. 7. Confusion Matrix. The neural network produces a classification accuracy of 96.2% with synthetic data.

IV. Experiments and Results

The overall algorithm is depicted in a flow chart as shown in Fig. 6. In the work, the multi-layer perceptron is trained with the irradiance instances along with the label for that configuration which provides the maximum power among the possible configurations considered for that irradiance profile. The entire dataset is divided into the training and test set with a ratio of 70:30 respectively. The MLP is trained for a maximum of 500 epochs where the network is completely exposed to the entire training data. The trained MLP is used to provide the classification accuracy on the test dataset. The neural network architecture was simulated in Python using the *scikit learn* toolbox.

The confusion matrix as shown in Fig. 7 provides the number of examples that are correctly or incorrectly classified into the respective classes and hence can provide a measure of test accuracy. It can be clearly understood from the matrix that the examples that are true positive are significantly more in number than the false positives and negatives depicting the performance of the algorithm. The overall average test accuracy was found to be 96.2% after simulating the algorithm with synthetic data for 10 Monte-Carlo iterations.

901	901	901	901
901	446	901	446
446	446	446	901

Default - Series Parallel

Before Reconfiguration (SP)	MPP : 1830.9W
After Reconfiguration (TCT)	MPP : 2124.3 W

% Power Increase : 16.0243 %

Fig. 8. The matrix on the left represents a series parallel PV array with a partial shading irradiance profile. The percentage of power increase after reconfiguration to TCT is depicted on the right.

Figure 8 illustrates a single example of power improvement with connection reconfiguration from series parallel to total cross tied. It was also found that the overall average power increase was 12 % for different irradiance profiles indicating the effect and importance of topology reconfiguration.

V. CONCLUSION

A PV array topology reconfiguration algorithm that maximizes the power output using neural networks is proposed in this work. The network chooses one among the three topologies namely SP, BL and TCT that will optimally maximize power for a given irradiance profile falling on the PV panels. The use of neural nets allows the process of learning to map irradiance inputs to the topology that maximizes power. An overall classification accuracy of 96.2% was obtained from the simulated model indicating that a machine learning model can be used for topology reconfiguration. An average power improvement of 12% was computed illustrating the importance of PV array reconfiguration using machine learning techniques.

Ongoing and future work involves testing the algorithm with real-time data obtained from the ASU SenSIP CPS Solar Facility [7]. We also want to investigate the effectiveness of the algorithm taking into account of the mismatch, heating losses and inverter transient effects.

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