Low cost ANN based MPPT for the mismatched PV modules

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Abstract. Due to manufacturing dispersal, the photovoltaic (PV) panels of similar rating and manufacturer have distinctive characteristics in practical. As the maximum power point tracking (MPPT) becomes essential to optimally utilize the solar PV panel, distributed maximum power point tracking (DMPPT) is considered in this paper to follow the MPP of each panel. As the common MPP value is used in the existing DMPPT method to control all the panels, it fails to consider the uniqueness of each panel. By considering the uniqueness of each panel, the ANN based MPPT is implemented in this paper. As the ANN is trained using the actual characteristics of each panel based on the operating current, voltage and temperature, it is able to track the actual MPP. Due to the solar irradiance free MPPT, the costly pyranometer is not required in the actual PV system for MPPT. It reduces the cost of the system and also provides the interruption free tracking due to its independent nature on \( V_{oc} \) and \( I_{sc} \) values. Also, because of the looping free behaviour of the proposed algorithm, it is capable of following the MPP at rapidly varying condition. The proposed technique and the verified outcomes are discussed here in detail.

Keywords: Artificial neural network, DC-DC converter, Distributed maximum power point tracking, Mismatched panels, Photovoltaic panels

1. Introduction

The increase in energy requirement due to the high life style pulled the people and government towards the renewable energy sources. As the solar photovoltaic panels are able to directly convert the solar energy into electricity without any noise and rotating element, it is widely availed to meet the commercial and industrial energy requirement among the other renewable energy sources. Also, the various government schemes in supporting the solar energy production and continuous reduction of PV panel prices attracted many towards the standalone and grid tied photovoltaic (PV) system. As the solar panels have a less life span of 25 years, the investors are expecting the maximum utilization of the PV plants. For the maximum power generation through the optimal utilization, the operation of the PV system should be around the maximum power point (MPP) and it is attained through maximum power point tracking (MPPT). But due to the nonlinear behaviour of PV panel (PVM) at quickly fluctuating surroundings and the iterative nature of the existing conventional MPPT schemes [1]-[4], the tracking is ineffective to track the MPP at faster rate though they are not dependent of the type or model of the panel. Also, the disparities in the serially connected PV panels due to the differences if the manufacturing process and the partial shading cause huge power reduction in the string [5]-[6].

Though, the researchers proposed different MPPT procedures to find the global maxima under the mismatched or partial shaded condition, it resulted in interruption in the power output to measure \( V_{oc} \).
and $I_{sc}$. As the mismatches are unavoidable, the MPP tracking of individual panel becomes essential instead of common MPP tracking for an array. The distributed panel level MPPT (DMPPT) [7]-[9] is considered in this paper due to its nature of maintaining the actual MPP across each panel and proven efficiency due to reduced mismatch losses. Even in DMPPT, the conventional MPPT algorithms fail due to its iterative nature at rapidly changing environment. So, by considering the tracking ability, the Artificial Neural Network (ANN) based MPP procedure is implemented here. Though, there are different ANN based MPPT procedures in the literature [10]-[13], the proposed procedure in this paper is pyranometer free in the PV farm. Also, the proposed method is able to easily track the MPP depending on the panel voltage, panel current and the rear side panel temperature of the PV panel during that instant. As, the proposed methodology does not seek the insolation profile for MPP tracking, it is free from the costly pyranometer. The proposed methodology and its validation are given in section 2 and section 3 respectively.

2. Proposed ANN based MPPT

In solar PV systems, the array consists of many strings in parallel and each of these strings is made up of many PV panels of same rating. Though, the series connected panels of same string are from the same manufacturer, each PV panel has unique characteristics due to manufacturing dispersion. It resulted in poor MPP tracking, when the same maximum voltage $V_{MPP}$ is used to control all the panels through DMMPT. By considering this, the proposed ANN controlled methodology is utilized to identify the MPP of individual panel using its own operating voltage, current and the rear side temperature as shown in figure 1.

To track the MPP using ANN, initially the ANN is trained based on the individual panel characteristics. To train ANN, around 85 sets of $P-V$ and $V-I$ characteristics of each panel which are measured at different environmental conditions are used. Each characteristic consists of 50 equally spaced values. In ANN, the artificial neurons are interconnected to resemble the human brain. Like human brain, the ANN acquires expertise via the learning process and stores the knowledge in the interneuron connection weights or synaptic.

![Figure 1. Schematic diagram of ANN based DMPPT scheme.](image)

Though, there are different types of ANN like multilayer perceptron, multilayer feed forward network (MFFN), radial basis function network (RBFN), etc., the back propagation type network (BPNN) is utilized here for maximum power point tracking because of its powerful learning algorithms. The back propagation network structure which is used in the proposed methodology is given in figure 2.
The network is made up of one input, output layer and two hidden layers. To track or identify the MPP, the input layer is having three neurons for accepting the input data corresponding to the panel voltage $V$, panel current $I$ and the back side panel temperature $T_p$. The output layer consists of two neurons to provide the predicted maximum power and the respective voltage $V_{MPP}$ as outputs. The number of hidden layer neurons in the first and the second layer are 30 and 10 respectively. These network neurons are interrelated through the adjustable synaptic weights. Firstly, the training data set with input and output pairs are given to train the network. Through the selection of appropriate network learning method, the weights of the network are improved to work with better accuracy. This will help in predicting the output with more accuracy. From the literature on the different training algorithms used in ANN, the Levenberg–Marquardt (LM) is considered in this paper due to its high speed. During the learning phase, the network receives the training data set with input and output pair to regulate the interconnection weight to produce an accurate output. The transfer function which is used for the different layers of the ANN are, ‘tansig’ for the hidden layers and ‘purelin’ for the output layer. The gradient descent method is used as bias learning function with momentum weight in this selected ANN structure. This attempts to reduce the error or increase the accuracy by adjusting the connection weights. The efficiency of the neural network in accurate prediction is evaluated by the root-mean-square error (RMSE) value. The error value is calculated by

$$RMSE = \frac{1}{2} \left( \sum_p \sum_i [t_{ip} - O_{ip}]^2 \right)^{1/2}$$

(1)

Where $p$ specify the input sets, $i$ specify the node, $t$ specify the desired output and $O$ specify the actual predicted output of the neural network. The inter-connection weights are altered to have a lesser difference between the predicted output and the actual output by calculating the error derivative of the network weights in BPNN. In this way, the chosen ANN is trained and prepared for the specific application.

3. Validation of the ANN based DMPPT scheme

For validation of the proposed methodology, the PV panel used in a 2X2 array is of KSL025 from USL with 34 crystalline silicon type solar cells connected in series. The size of the PV panel is 665 mm X 345 mm X 38 mm. The panel parameters utilized from the data sheet which is provided by the manufacturer for all the four selected PV panels at standard testing condition are given in table 1.

| $V_{OC}$ | $I_{SC}$ | $V_{MPP}$ | $I_{MPP}$ | $\alpha$ | $\beta$ | NOCT |
|-------|--------|--------|--------|--------|--------|------|
| (V)   | (A)    | (V)    | (A)    | (%/K)  | (%/K)  | (ºC) |
| 21.5  | 1.64   | 17.1   | 1.47   | 0.06   | -0.36  | 45   |
Though, the manufacturer claim that there are same output for the panels of same rating, the actual output varies among the same rating panels even at same solar irradiation $G$ and ambient temperature $T$. In table 2, the real maximum power $P_{\text{max}}$ of all the panels of array at different environmental conditions are provided.

### Table 2. Output of 25W solar panels at different environmental conditions.

| Temp. $T_p$ ($^\circ\text{C}$) | Irrad. $G$ (W/m$^2$) | $P_{\text{max}}$ of Panel (1,1) (W) | $P_{\text{max}}$ of Panel (1,2) (W) | $P_{\text{max}}$ of Panel (2,1) (W) | $P_{\text{max}}$ of Panel (2,2) (W) |
|-----------------------------|----------------------|------------------------------------|------------------------------------|------------------------------------|------------------------------------|
| 31.67                       | 578.64               | 10.298                             | 10.302                             | 10.301                             | 10.249                             |
| 42.458                      | 741.46               | 15.653                             | 15.855                             | 15.851                             | 15.624                             |
| 34.845                      | 804.98               | 17.104                             | 17.347                             | 17.341                             | 17.005                             |

### 3.1. Characteristic Measurement of PV Panel

As the practical output varies among the panels of same rating and manufacturer as shown in table 2, the DMPPT using the ANN is implemented here for the actual MPPT. Using the current and voltage sensor, the complete characteristics of the PV panel is measured for different environmental conditions along with the temperature sensor PT100 output. From each one of the measured characteristics, the maximum power $P_{\text{max}}$ and the corresponding voltage $V_{\text{max}}$ are selected. The $V_{\text{max}}$ is selected to generate the gate control signal for the DC-DC converter which is connected across the same PV panel for maintaining the panel voltage at $V_{\text{max}}$. By regulating the PV panel voltage at $V_{\text{max}}$, the PV panel is forced to operate at $P_{\text{max}}$ and provide maximum output. Through this same procedure, around 100 data sets corresponding to the characteristics are measured for each PV panel. Also, for each characteristic 50 samples are observed. Among the 100 sets, 85 sets are used for training the ANN of each panel using the complete voltage, current, temperature, $P_{\text{max}}$ and $V_{\text{max}}$ values and the remaining 15 sets are used for testing the performance of ANN for the prediction of desired outputs. The performance of ANN for the prediction of MPP is given in Table 3. The performance of the network is evaluated using the MSE value. It shows that the prediction capability of the ANN with more accuracy without any iteration and interruption. Also, the interrupt free tracking resulted in an increased energy output.

### Table 3. Predicted MPP of 25W solar panel at different environmental condition through ANN.

| Temp. $T_p$ ($^\circ\text{C}$) | Irrad. $G$ (W/m$^2$) | $P_{\text{max}}$ of Panel (1,1) (W) | $P_{\text{max}}$ of Panel (1,2) (W) | $P_{\text{max}}$ of Panel (2,1) (W) | $P_{\text{max}}$ of Panel (2,2) (W) |
|-----------------------------|----------------------|------------------------------------|------------------------------------|------------------------------------|------------------------------------|
| 43.368                      | 786.642              | 14.436                             | 14.397                             | 3.02E-03                           | 14.469                             |
| 43.786                      | 593.261              | 12.664                             | 12.625                             | 12.681                             | 12.685                             |
| 41.40                       | 505.07               | 11.235                             | 11.231                             | 11.252                             | 11.247                             |
Figure 3. Simulation diagram of DMMT scheme through ANN based MPPT for a 2x2 array.

Figure 4. Maximum voltage maintained across the different panels of an array using ANN based DMPPT.
3.2. Simulation of ANN Based DMPPT

For the validation of ANN based DMPPT, the simulation was completed with a 2×2 solar PV array using PSIM9.0.3 simulation tool. The PSIM software is selected due to the availability of detailed physical model of a solar panel. This is used to analyse the performance of PV panel in the mismatched condition. The chosen solar array which is rated for 100W consists of two parallel paths and each parallel path of array consists of 2 panels in series as shown in figure 3. So, two such 25 W panels of the same model are connected. Each panel is connected in parallel with the respective DC-DC converter. Here, the boost converter is used as a DC-DC converter. The boost converters are designed for 30 W. The gate signal for the primary side MOSFET is generated based on the reference voltage $V_{ref}$ produced by the ANN procedure written in a MATLAB function file using MATLAB R2010a. Using the Sim Coupler panel, the required signals are transferred between the PSIM and MATLAB environment. To study the performance of mismatched array, the physical model parameters of PSIM solar panel are selected based on the actual performance of each panel at same environmental condition. Based on the estimated $V_{MPP}$ of each panel using the ANN, the gate pulse is generated for triggering the switch of the boost converter so as to regulate the panel output at its own MPP. So, the output voltage of the boost converter is matching the panel’s own $V_{MPP}$. The results given in figure 4 obtained at mismatched condition shows that the maximum voltage $V_{max}$ corresponding to the $P_{max}$ is maintained by the dedicated converter based on the ANN output. So, this ANN based DMPPT procedure maintains the actual MPP of each panel even at mismatched condition. This results in optimal extraction of power from the PV array with reduced losses. The performance of the proposed method is compared with the unified decoupled MPPT algorithm which is implemented for the shaded modules [14]. The comparison is presented in Table 4. It shows that the proposed method is efficient due to the lesser complexity and the high speed performance.

| MPPT method          | Complexity | Speed | Efficiency % |
|----------------------|------------|-------|--------------|
| Proposed method      | Low        | High  | 72.337       |
| Unified decoupled MPPT [14] | More        | Low   | 68.349       |

4. Conclusion

The ANN based distributed MPPT was employed in this paper to maintain the actual MPP of each panel of an array even under mismatched condition due to the manufacturing dispersion. It also resulted in iteration and interrupt free MPP tracking in the output of array. The DMPPT was also validated through the PSIM based simulation using the ANN. The prediction ability of the ANN, based on the operating voltage, current and the back side temperature of the PV panel resulted in pyranometer free MPPT in the customer site.

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