

# A Survey on Maximum Power Point Tracking for Solar PV Cells using Machine Learning Approaches

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## ABSTRACT

The classical algorithms for maximum power point tracking ensure proper operation under uniform irradiance conditions. However, when photovoltaic (PV) array is subject to partial shading conditions (PSC), several local maxima appear on the P-V characteristics curve of the PV array which are due to the use of the bypass diodes to avoid hot spots effect. The appearance of these multiple peaks on the characteristics of PV array makes the tracking more difficult under these conditions and requires the integration of a more efficient power control system which is able to discriminate between local and global maxima to harvest the maximum possible energy and therefore increase the efficiency of overall system. In addition to implementing a global maximum power point tracking strategies, the mismatch losses associated to the shading effect can further be reduced by using alternative PV arrays' configurations. This paper presents a survey on Maximum Power Point Tracking (MPPT) using Artificial Neural Networks. Prominent previous work has been cited with its salient features.

**Keywords:** Maximum Power Point Tracking (MPPT), Solar Irradiation, Artificial Neural Networks, Accuracy.

## 1. INTRODUCTION

Solar energy extracted using PV cells can be directly used as DC power supply or can be stored in batteries and converted to an AC source for future purposes. The uncertainty of our weather conditions makes it very difficult to extract maximum power hence artificial neural networks is implemented to exterminate this issue. There are two major parts in this system – DC power extraction from solar PV array and AC power transmission to the grid. The DC-AC conversion is carried out by the H-bridge inverter

system. The inverter operates only two switches at a time and the voltage across it is measured leading to the DC-AC conversion. In today's world, we need a PV system that can extract solar energy efficiently and accurately without much discrepancy. The maximum power point tracking (MPPT) using Artificial Neural Networks works by fine-tuning the array voltage and measuring the power. The measured power  $P(k)$  is compared with the preceding array power  $P(k-1)$  and if the power increases, further amendments are done. This process continues until no further changes in power are observed. These techniques find major applications in solar PV systems and wind power systems. Artificial Neural Network based approaches generally render higher accuracy of maximum power point tracking compared to conventional techniques.

A model of PV cell with current source-based circuit is depicted in this section.

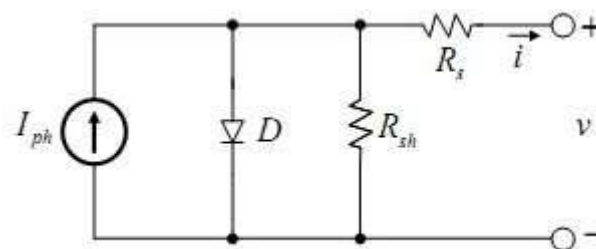


Fig.1 The equivalent circuit of a PV array.

Where,  $R_s$  denotes array series resistance in  $\Omega$ ,

$R_p$  denotes array parallel resistance in  $\Omega$ ,

$I$  and  $V$  are the output current and voltage of the array in Ampere and Volt.

$$I = N_p \times I_{ph} - N_s \times I_{rs} \left[ e^{\left( \frac{q \times V}{A \times K \times T} \right) - 1} - \left( \frac{V + I \times R_s}{R_{sh}} \right) \right] \quad (1)$$

Where,

$I_{ph}$  is photo current in Amp,

$I_{rs}$  is saturation current in Amp,

$N_s$  and  $N_p$  are the number of series and parallel modules,

$q$  is charge on electron in coulomb,

$A$  is diode ideality factor,

$T$  is cell Temperature with change in irradiation in degree kelvin.

Now,

$$I_{ph} = I_{scr} + K_i \times (T - T_r) \times S \quad (2)$$

$$I_{rs} = I_{rr} \times \left(\frac{T}{T_r}\right)^3 \times e^{\left(\frac{q \times E_g}{K \times A} \times \left(\frac{1}{T_r} - \frac{1}{T}\right)\right)} \quad (3)$$

Where,

$I_{scr}$  is Short circuit current at reference Temperature in Amp,

$I_{rr}$  is reverse saturation current in Amp,

$T_r$  is reference temperature in Kelvin,

$S$  is solar irradiance in mW/Sq. cm,

$K_i$  is S.C. current Temp. coefficient in (Amp/Kelvin),

$K$  is Boltzmann's constant,

$E_g$  is band gap energy of semiconductor used cell in joules,

Also,

$$E_g = E_{g0} - \left(\frac{\alpha \times T^2}{T + \beta}\right) \times q \quad (4)$$

Where,  $E_{g0}$  = band gap at 0 kelvin and,

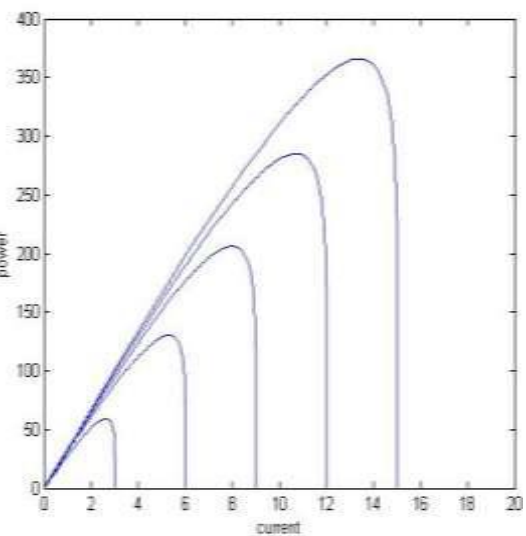
$$V_{oc} = \left(\frac{A \times K \times T}{q}\right) \times \ln\left(\frac{I_{ph}}{I_{rs}}\right) \quad (5)$$

## 2. CHARACTERISTICS OF PV CELLS

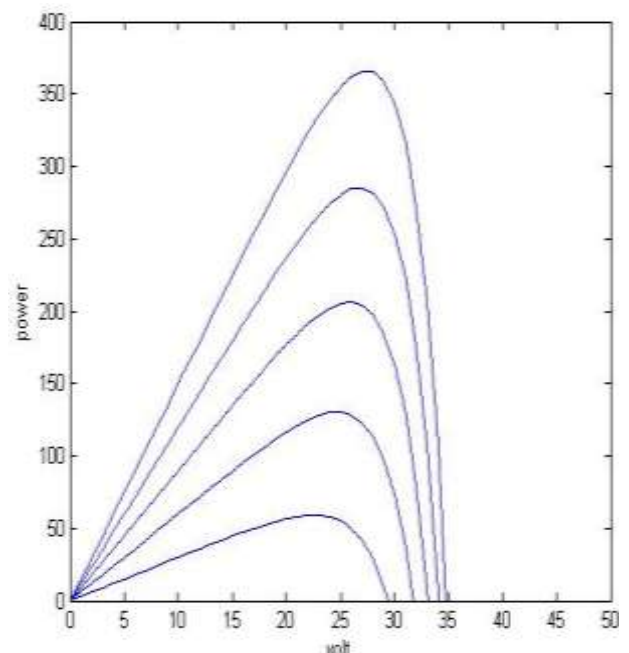
The demand for energy is increasing manifold with each continuously while the supply doesn't grow at that pace.. The renewable are at present the favorites to replace fossil-based plants due to abundance in nature and pollution free nature. Solar PV cells have a nonlinear characteristic where the output is directly dependent on the value of incident solar radiation and cell temperature.

- 1- Such systems are static devices has no moving parts make them service and maintenance free and easy to mount.
- 2- One can buy and install PV System easily and according to required specification of output.
- 3- Such systems output can easily be increased by adding more modules either in series to expand the system's voltage or in parallel to enlarge the current.

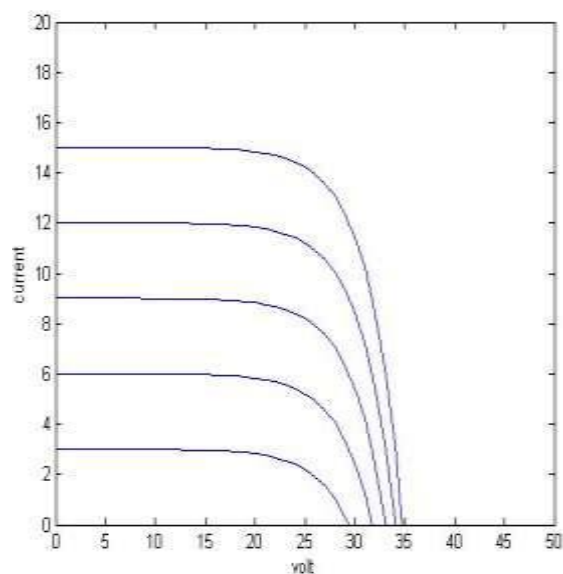
By varying the value of this two the output changes which is show in following figures.



**Fig.2 Effect of temperature changes on P-V curves.**



**Fig.3 Effect of solar irradiance changes on P-V curves.**



**Fig.4 : Effect of solar irradiance changes on I-V curves.**

From above figures it can be clearly seen that output of PV cells is directly proportional to incident solar radiation and inversely to temperature. The maximum power point of any cell is the peak point of above graph whose value changes with radiation and temperature hence a DC-DC converter is used to track that point to give maximum output at any point of time.

### 3. RELATED WORK

In [1], C Robles Algarín et al. proposed the design, modeling, and implementation of a neural network inverse model controller for tracking the maximum power point of a photovoltaic (PV) module. A nonlinear autoregressive network with exogenous inputs (NARX) was implemented in a serial-parallel architecture. The PV module mathematical modeling was developed, a buck converter was designed to operate in the continuous conduction mode with a switching frequency of 20 KHz, and the dynamic neural controller was designed using the Neural Network Toolbox from Matlab/Simulink (MathWorks, Natick, MA, USA), and it was implemented on an open-hardware Arduino Mega board. To obtain the reference signals for the NARX and determine the 65 W PV module behavior, a system made of a 0.8 W PV cell, a temperature sensor, a voltage sensor and a static neural network, was used. To evaluate performance a comparison with the P&O traditional algorithm was done in terms of response time and oscillations around the operating point. Simulation results demonstrated

the superiority of neural controller over the P&O. Implementation results showed that approximately the same power is obtained with both controllers, but the P&O controller presents oscillations between 7 W and 10 W, in contrast to the inverse controller, which had oscillations between 1 W and 2 W.

In [2], Ramji Tiwari et al. presented an artificial neural network (ANN) based maximum power point tracking (MPPT) control strategy for wind energy conversion system (WECS) implemented with a DC/DC converter. The proposed topology utilizes a radial basis function network (RBFN) based neural network control strategy to extract the maximum available power from the wind velocity. The results are compared with a classical Perturb and Observe (P&O) method and Back propagation network (BPN) method. In order to achieve a high voltage rating, the system is implemented with a quadratic boost converter and the performance of the converter is validated with a boost and single ended primary inductance converter (SEPIC). The performance of the MPPT technique along with a DC/DC converter is demonstrated using MATLAB/Simulink.

In [3], Naghmasha Hammad Armghana et al. presented a non-linear backstepping controller is proposed to extract the maximum power from the PV system. A non-inverting buck-boost converter is used as an interface between the load and the PV array. Reference voltages for the controller are generated by a regression plane. Asymptotic stability of the system is verified through Lyapunov stability analysis. The performance of the proposed controller is tested under MATLAB/Simulink platform. The simulation results validate that the proposed controller offers fast and accurate tracking. Comparison with perturb & observe and fuzzy logic controller is provided to show the performance of the proposed controller under abrupt variation of the environmental conditions.

In [4], M Kermadi, EM Berkouk et al. presented a survey on the most adopted Artificial Intelligence (AI)-based MPPT techniques. The MPPT techniques which will be described are based on: Proportional-Integral-Derivative (PID), Fuzzy Logic (FL), Artificial Neural Network (ANN), Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). The developed MPPT controllers are tested under the same weather profile in the same photovoltaic system which is composed of a PV module, a DC-DC Buck-Boost converter and a DC load. Initially, Modelling and simulation of the system is performed using the MATLAB/Simulink environment. Thereafter, the

sliding mode control is applied to the converter in order to improve its performance. In a further stage, the different steps of development for each MPPT technique are presented. Simulation is performed to confirm the validity of the proposed controllers under the same variable temperature and solar irradiance conditions. Finally, a comparative study is carried out in order to evaluate the developed techniques regarding two principal criteria: the performance and the implementation cost. The performance is evaluated using comparative analysis of the tracking speed, the average tracking error, the variance and the efficiency. To estimate the implementation cost, a classification is carried out according to the type of the used sensors, the type of circuitry and the software level complexity. Recommendations that expected to be useful for researchers in the MPPT area about the validity of each MPPT technique are given in the last section.

In [5], **Dileep G. et al.** explained that Conventional maximum power point tracking (MPPT) algorithms fails to track peak power from a solar photovoltaic panel (SPV) effectively under rapidly changing atmospheric and partial shading conditions (PSC). To track peak power more effectively under these conditions, low cost, powerful soft computing (SC) have been introduced by the researchers. Due to the ability to solve non-linear problems, flexibility and adaptive nature, SC based MPPT techniques can track peak power under varying atmospheric conditions. Various SC based MPPT techniques have been proposed by researchers till date. Comprehensive studies on all these techniques are not available. This work summarizes working principle of various SC-MPPT techniques and are compared each other based on the certain parameters like accuracy, tracking efficiency, SPV array dependency, convergence time, complexity of algorithm, hardware implementation, ability to handle PSC's and variables used. The information that is gathered and summarized in this paper will help researchers for future studies in this area.

In [6], **F Belhachat et al.** proposed a technique with the main aim to design an intelligent MPPT controller that allows predicting and extracting the global maximum power point (GMPP) from PV array under partial shading conditions (PSC) whatever is the used configuration or its size. This intelligent MPPT controller is based on adaptive neuro-fuzzy inference system (ANFIS). The adopted ANFIS network has two inputs and one output. The two inputs of the proposed ANFIS consist of voltage and current while, the output is the output power of each configuration. The ANFIS

network is trained using the data derived from performances analysis of different PV array configurations. Furthermore, the ANFIS network uses a hybrid learning algorithm that combines the least-squares estimator and the gradient method.

In [7], **S. SAaravanan et al.** presented a comprehensive review on various maximum power point tracking (MPPT) algorithms based on Perturb and Observe, Incremental Conductance, Soft Computing and other techniques along with the real time hardware implementation of photovoltaic (PV) system. In this review, the complete procedure, the implementation methodology and their effects in the PV output were discussed in detail for each algorithm. Further, MPPT algorithms for PV systems with partial shading condition were reviewed and reported. This paper is intended to serve as a suitable reference for future work in PV based power generation and its related research.

In [8], **L. Liu et al.** presented a review of different MPPT methods. Firstly, the main methods at uniform radiation that will be deliberated are Hill-Climbing (HC), Incremental Conductance (IncCond), Perturbation and Observation (P&O), Fuzzy-Logic (FL), and Neural Network (NN). However, these existing methods have several drawbacks such as slow tracking speed, low tracking efficiency, which fail to extract maximum power at complex partial shading. Then, the more recent MPPT methods at partial shading are discussed to find the best MPPT control strategy, such as the particle swarm optimization (PSO) algorithm, Cuckoo Search (CS) method, and Fibonacci line search scheme, etc. The advantages and shortcomings of abovementioned MPPT methods are compared to find the optimal MPPT during partial shading conditions. It is imagined that this article will be a source of valuable information for PV professionals to keep abreast with the latest progress in the PV power area, as well as for new researchers to get started on MPPT.

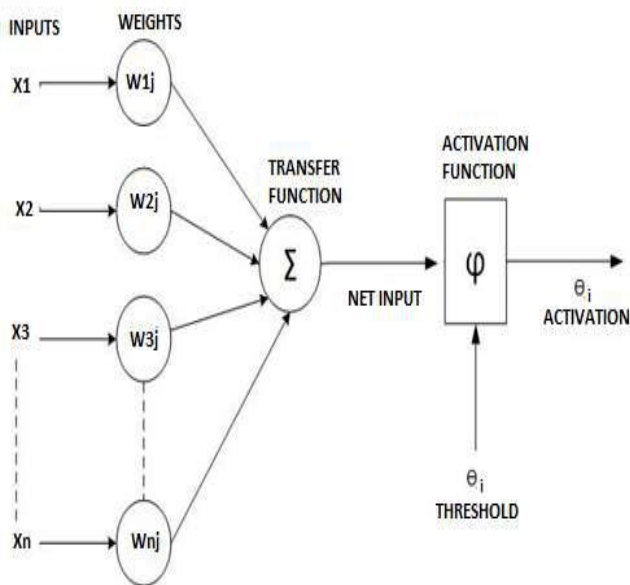
#### 4. Artificial Neural Networks

Artificial neural networks are a practical way of implementing artificial intelligence with an aim to solve fitting problems generally needing herculean efforts due to the data size and complexity.

The artificial neural architecture tries to imitate the human thought process in the following ways:

- Process data as a parallel stream independently
- Identifying patterns and correlating them.
- Evolving and updating the experiences (called weights) as per the changes in the data received. Neural networks work on training and testing mechanism.
- Finally rendering an output and further storing it as an experience.

ANN basically tries to inherit this capability of human brain to self-train itself for tasks which are never been performed by it that too very efficiently. Human brain's structure consists of neurons which are interconnected with each other and there by forming a very large network which is well connected thereby helps in performing very complex task like voice and image recognition very easily. The same task when performed using normal computer won't give accurate result. Hence ANN mimics neurons structure of human brain to discover link between input and targets. Neurons have this ability to save previous experimental data. The speed of human brain is several thousand times faster than traditional computer because in brain unlike traditional computer as whole information is not passed from neuron to neuron they are rather encoded in the neuron network. This is reason why neural network is also named as connectionism.



**Fig 1: Mathematical Model of ANN**

The mathematical conversion of the ANN can be done by analyzing the biological structure of ANN. In the

above example, the enunciated properties of the ANN that have been emphasized upon are:

1. Strength to process information in parallel way.
2. The power to grasp and learn from weights
3. Searching for patterned sets in complex models of data.

Consider a signal  $S_1$  travelling through a path  $p_1$  from dendrites with weight  $W_1$  to the neuron. Then the value of signal reaching the neuron will be  $S_1 \cdot W_1$ . If there are "n" such signals travelling through n different paths with weights ranging from  $W_1$  to  $W_n$  and the neuron has an internal firing threshold value of  $\theta_n$ , then the total activation function of the neuron is given by:

$$Y = \sum_{i=1}^n X_i \cdot W_i + \theta_i \quad (1)$$

$X_i$  represents the signals arriving through various paths,  
 $W_i$  represents the weight corresponding to the various paths and  
 $\theta$  is the bias.

The entire mathematical model of the neuron or the neural network can be visualized pictorially or the pictorial model can be mathematically modelled. The design of the neural network can be modeled mathematically and the more complex the neural design, more is the complexity of the tasks that can be accomplished by the neural network. The soul of the above model lies in the fact that the system so developed tries to mimic the working of human brain in terms of the following:

- It works in a complex parallel computation manner
- High speed of performance due to the parallel architecture.
- It learning and adapt according to the modified link weights.

## 5. CONCLUSION

It can be concluded from the previous discussions that photovoltaic (PV) array is subject to partial shading conditions (PSC), several local maxima appear on the P-V characteristics curve of the PV array which are due to the use of the bypass diodes to avoid hot spots effect. The appearance of these multiple peaks on the characteristics of PV array makes the tracking more difficult under these conditions and requires the integration of a more efficient power control system which is able to discriminate between local and global

maxima to harvest the maximum possible energy and therefore increase the efficiency of overall system. In addition to implementing a global maximum power point tracking strategies, the mismatch losses associated to the shading effect can further be reduced by using alternative PV arrays' configurations. The survey is expected to pave the path for further research in the field.

## 6. REFERENCES

- [1] C Robles Algarín, D Sevilla Hernández, Diego Restrepo Leal, "A Low-Cost Maximum Power Point Tracking System Based on Neural Network Inverse Model Controller", MDPI 2018
- [2] Ramji Tiwari, Kumar Krishnamurthy, Ramesh Babu Neelakandan, Sanjeevikumar Padmanaban, Patrick William Wheeler, "Neural Network Based Maximum Power Point Tracking Control with Quadratic Boost Converter for PMSG—Wind Energy Conversion System", MDPI 2018
- [3] Naghmasha Hammad Armghana, Iftikhar Ahmad, Ammar Armghan, Saud Khan, Muhammad Arsalan, "Backstepping based non-linear control for maximum power point tracking in photovoltaic system", Elsevier 2018.
- [4] M Kermadi, EM Berkouk, "Artificial intelligence-based maximum power point tracking controllers for Photovoltaic systems: Comparative study", Elsevier 2017
- [5] Dileep G., S.N. Singh, "Application of soft computing techniques for maximum power point tracking of SPV system", Elsevier 2017
- [6] F Belhachat, C Larbes, "Global maximum power point tracking based on ANFIS approach for PV array configurations under partial shading conditions", Elsevier 2017
- [7] S Saravanan, NR Babu, "Maximum power point tracking algorithms for photovoltaic system—A review", Elsevier 2016
- [8] L Liu, X Meng, C Liu, "A review of maximum power point tracking methods of PV power system at uniform and partial shading", Elsevier 2016
- [9] L Gil-Antonio, MB Saldivar-Marquez, "Maximum power point tracking techniques in photovoltaic systems: A brief review", IEEE 2016
- [10] S Messalti, AG Harrag, "A new neural networks MPPT controller for PV systems", IEEE 2015
- [11] RK Kharb, SL Shimi, S Chatterji, MF Ansari, "Modeling of solar PV module and maximum power point tracking using ANFIS", Elsevier 2014
- [12] MR Vinchek, A Kargar, GA Markadeh, "A hybrid control method for maximum power point tracking (MPPT) in photovoltaic systems", Springer 2014