

Maximum Power Point Tracking Using Machine Learning Algorithm.

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Abstract— The demand for electricity in the market is expanding, and renewable energy sources are vital to the system's management. Renewable energy is available in various ways, including solar and wind energy. The aim is to get the highest possible power point under different environmental circumstances. This article delves into the broad idea of MPPT techniques that considerably improve the efficiency of a PV system. This study compares the most common algorithms. Various MPPT algorithms were established for usage in PV systems to obtain Maximum PowerPoint; Depending on the circumstances and the application, these algorithms range from basic to complicated. In general, the most well-known MPPT methods include perturb and observe (PO), incremental conductance (INC), and artificial neural networks (ANN). In this work, we expect to detect the peak power point of a solar PV system using a machine learning approach. The training dataset may include panel input variables such as solar irradiance, temperature, etc. The data-driven MPPT algorithm will be evaluated in this work.

Keywords— MPPT; Artificial Neural Networks; P&O; INC.

I. INTRODUCTION

Recently, research has concentrated on developing renewable and environmentally friendly energy sources such as solar, wind, biomass, and water. The photovoltaic (PV) system is the largest renewable generator due to its cheap maintenance and operational costs, accessibility, and access to a free energy source. Furthermore, it turns sunlight straight into power with no noise or environmental impact.[1,2]

To define the nonlinear behaviour of PV cells, many mathematical techniques based on the Shockley diode solution have been developed. The ideal single-diode model, the most basic methodology, and the 2M7P technique, the most exact and sophisticated way, separate these models.[3]

Solar irradiation and cell temperature have an effect on the nonlinear P-V and I-V properties of PV generators. An operating point may differ from the MPP, especially when attached to the load. This decreases PV panel efficiency and

results in significant power losses. To address this issue, a DC-DC boost converter acts as a bridge between the PV generator and the load, with the maximum power point approach managing duty cycle (MPPT).[4]

To guarantee that the PV generator runs at or near the MPP, various MPPT technologies have been created. Because of their simple feedback topologies, ease of construction, and few parameters, the perturb and observe (PO) and incremental conductance (INC) algorithms are two of the most often used MPPT systems.[2] These methods, however, have significant limits when the environment is variable and changes often.[3-5]

Artificial intelligence-based MPPT solutions, such as artificial neural networks, fuzzy logic controllers, genetic algorithms, and fuzzy inference systems, are presently being proposed [6–10] to overcome these limitations and improve the stable and dynamic states. A comparison between ANN and two traditional MPPTs, PO and Inc., has been done in this research. During the tracking procedure in various weather conditions, the ANN approach proved accurate and effective.

Here we see that after adding the disturbance at the input side of the ANN algorithm, it gives better results than the PO and INC algorithm without adding any disturbance. It shows that ANN has better accuracy than P&O and INC.

II. PV SYSTEM DISCRITION

A resistive load, an MPPT controller, a boost DC/DC converter, and a solar panel that acts as the power source are all part of the system under discussion. The PV system schematic is seen in (Fig .1). The PV modules in use are four series-connected PV modules. Each module has a 300 W output, for a total nominal output of 1200 W at 1000 W/m² and 25 °C.

Electrical parameters	Values
Max. Power (P _{mpp})	300
Voltage at P _{max} (V _{mpp})	36
Current at P _{max} (I _{mpp})	8.3
Open circuit voltage (V _{oc})	44
Short circuit current (I _{sc})	8.9
Temperature coefficient P _{max}	-0.46%/°C

To match the output power to the load's power requirements, a boost DC/DC converter must be used. The MPPT is in charge of it.

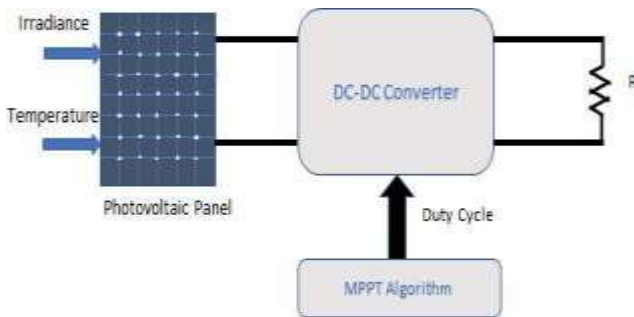


Figure 1 :PV System Scheme.

III. DC-DC BOOST CONVERTER

DC-DC converters employ switching devices, inductors, and capacitors to convert a direct voltage by one level at the input to another at the output. Typically, the switch used here is a MOSFET or an IGBT. A PWM signal is used to turn on and off the gate. The MPPT controller controls this signal in MPPT systems. In this research, the DC-DC converter is a boost converter that transforms the input voltage to the needed voltage at the output. The input voltage of the boost equals the output voltage of the PV module. Figure 2 depicts the Simulink model of the boost converter.

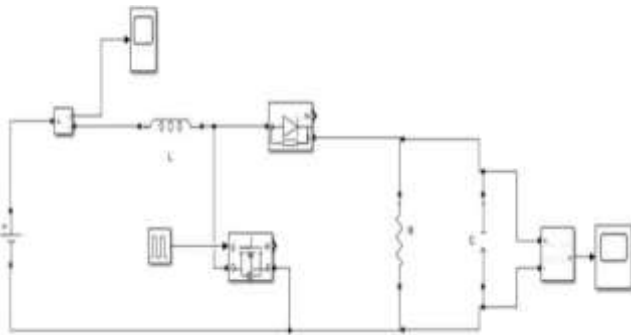


Figure 2 : DC-DC Boost Converter.

We should first establish the components of the solar PV system

to trace the MPP, such as Which type of Algorithm is used and which Algorithm Provides the best results. For this work, first we need to choose which Algorithm gives us the best results by

comparing these algorithms and which converter is best suited for tracking MPP. The Algorithm which we use must give us High-efficiency and high accuracy. For that, we need to have information about these algorithms. The most popular algorithms are as follows :

A. Perturb and observe (P&O)

The perturb and observe (P&O) approach is extensively used to regulate a PV generator's MPPT process. It has a simple structure, is reduced cost, is simple to configure, has fewer parameters, and the capacity to adapt may result in high efficiency. This method demands analyzing the link between the voltage and output power of a PV module. The following is the observed change in PV power, according to Fig. 3, which displays the behaviour of the solar panel revealing MPP and its working principle: The voltage perturbation should be small when The operational point is on the curve's left side. (P/V is positive), showing that the output power of the PV module is growing. The P&O algorithm fails to trace the MPP with changing weather patterns correctly.

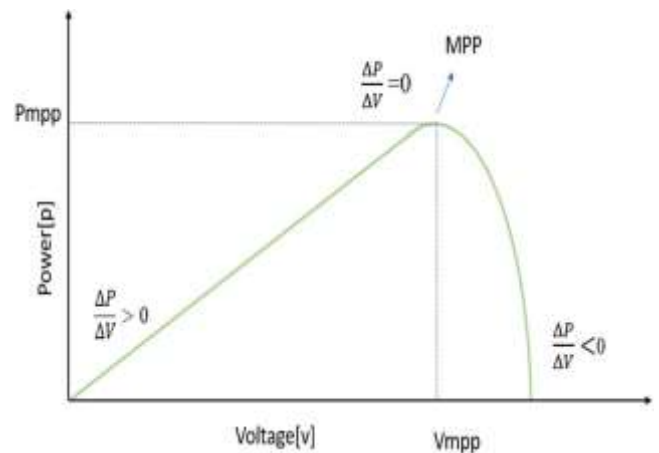


Figure 3 : Behaviour of Solar Panel Indicating MPP.

Figure 4 depicts the flowchart for developing the P&O approach. The actual current and voltage of the PV array are first measured. The product of current and voltage is then used to compute the real power of the PV module. It will then determine whether P = 0 is the current state. The operational point is at the MPP if this criterion is satisfied. If the current status is insufficient, it will try another with a P > 0. If this condition is fulfilled, it will verify that V > 0. If satisfied, The MPP's operational point is situated on the left. The operational point situated on the right V > 0 is not met.

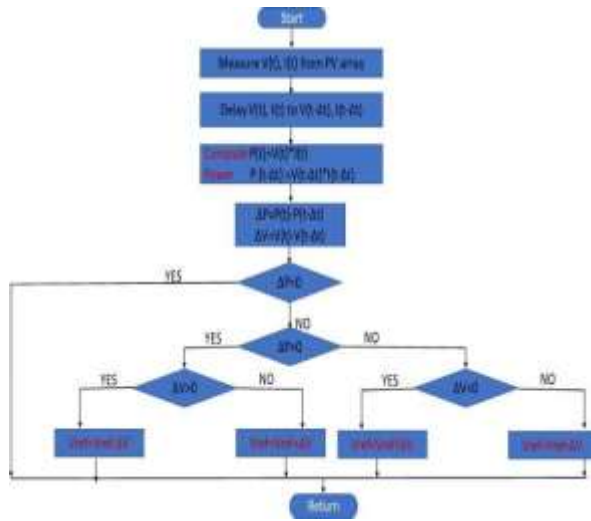


Figure 4 : : Flowchart of P & O Algorithm.

B. Incremental Conductance (INC)

The controller uses the incremental conductance (INC) approach to predict the impact of a voltage shift by studying minor variations in PV array voltage and current. This method requires the controller to perform more computations than the P&O algorithm, but it may respond to changing situations faster. It, like the P&O approach, can cause fluctuations in output power. This method calculates the direction of the variation in power concerning voltage (P/V) using the array's incremental conductance (I/V). The INC technique compares the incremental conductance with the array conductance to identify the highest power point. The output voltage is the MPP voltage whenever these two voltages are equal (I/V=I/V). The controller maintains this voltage until the irradiation changes.

In the incremental conductance approach, just current and voltage sensors are used to monitor the output current and voltage of a PV device. Figure 5 displays the flowchart for developing the INC algorithm.

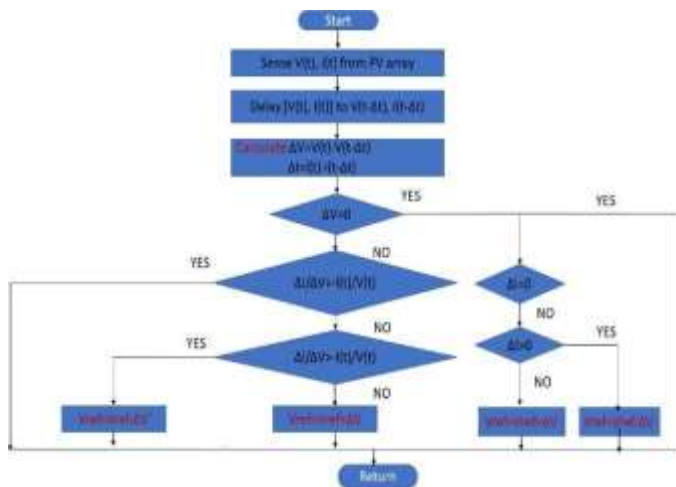


Figure 5 : Flowchart of INC Algorithm.

The incremental conductance technique requires only current and voltage sensors to monitor the voltage output of a PV device. Figure 5 depicts the flowchart for developing the INC algorithm. The INC method is officially represented by the equation below. The source's output power can be set as follows:

$$\text{Power} = \text{Voltage} * \text{Current. (1)}$$

Using the chain rule for product derivatives with respect to voltage produced:

$$\Delta P/\Delta V = I + V \Delta I/\Delta V \text{ (2)}$$

$$(I/V) \Delta P/\Delta V = (I/V) + \Delta I/\Delta V.$$

The voltage output of a source is generally positive. The main goal of this method is to calculate the operating point voltage when conductance equals incremental conductance. Eq summarises these notions (3-5). The slope of a P-V curve influences the INC algorithm. The slope will be negative on the right side of the MPP, positive on the left side of the MPP, and zero at the MPP. The essential equations for this approach are as follows :

$$\Delta P/\Delta V > 0, \text{ MPP's left side (3)}$$

$$\Delta P/\Delta V = 0, \text{ at MPP (4)}$$

$$\Delta P/\Delta V < 0, \text{ MPP's right side (5)}$$

C. Artificial neural networks (ANN)

This intelligence-based ANN will be the most effective solution to the most difficult challenges. These ANN applications will not need extensive system understanding or mathematical modeling. They can handle more complex problems by correctly mapping the system's input-output. ANN is the intelligence-based enhanced MPPT approach due to its natural learning mechanism and the biological nature of neurons. A directed chart with nodes and edges representing neurons and synapses can be used to illustrate an ANN in its most basic form. One of the simple classes of functions may be represented by radial basis function networks (RBF). This RBF network, which contains a single layer, is linked to the radial function.

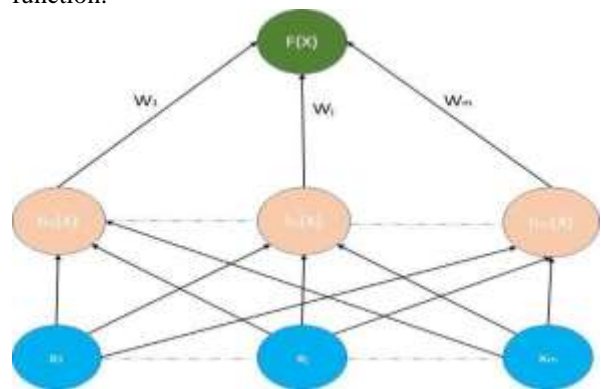


Figure 6 : Formulation Of ANN.

The ANN algorithm is much more efficient and has fewer oscillations around the MPP than the P&O and INC methods. It can adequately track the MPP under quickly changing weather conditions.

(AF) is provided by the

$$f(X) = \sum w_j * h_j = 1(X)$$

Furthermore, x_1, x_2, \dots, x_n are the n incoming signals, whereas w_1, w_2, \dots, w_m are the weights of the corresponding synapses, and $h_j(X)$ represents the network's hidden layers. Generally, AF is a nonlinear function that turns a linear function into a nonlinear function by combining a hyperbolic tangent and a log-sigmoid. Figure 6 depicts the ANN formulation. The ANN is the essential building component of a multi-layer feed-forward system, which comprises three levels of input, hidden, and output layers. The PV module's attributes, such as VOC and ISC, as well as environmental data, such as temperature and irradiance, or any combination of the two, can be utilized as input to this approach. The output will also be the VMPP, V_{ref} , or GMPP. The procedure is carried out at the critical hidden layer by adjusting the weights and bias to estimate the best-targeted value or GMPP with the available input sets. It will generate the D signal that will power the converter depending on the MPP.

The learning process and the structure of Ann affect how successfully this technology (ANN) can detect genuine GMPP. The number of data sets (VPV, IPV) at which the P-V curve is examined increases the likelihood that it will reach the GMPP. ANN neurons, unlike prior methods, may process input in parallel. Weights are adjusted based on the function utilized in the hidden layers. Furthermore, all weights are reset, resulting in speedier reactions (faster in the process). The accuracy of the approach, however, is dependent on the amount of data employed. Figure 7 depicts the detailed implementation of ANN.

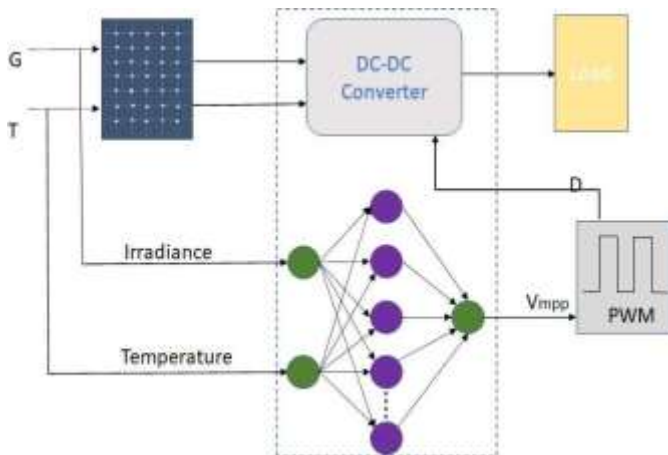


Figure 7 : Detailed Implementation Of ANN.

IV. COMPARISON OF ANN, PO & INC METHOD

A. Under changing irradiation

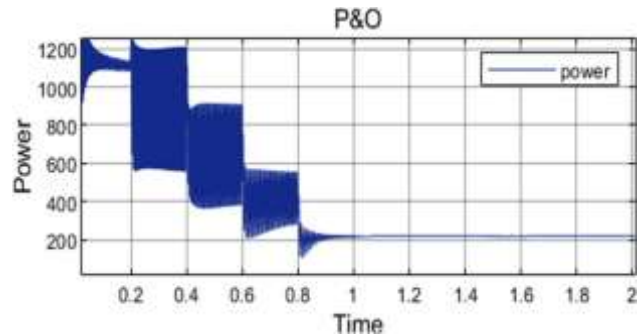


Figure 8 : P&O Output Power as Irradiation Changes.

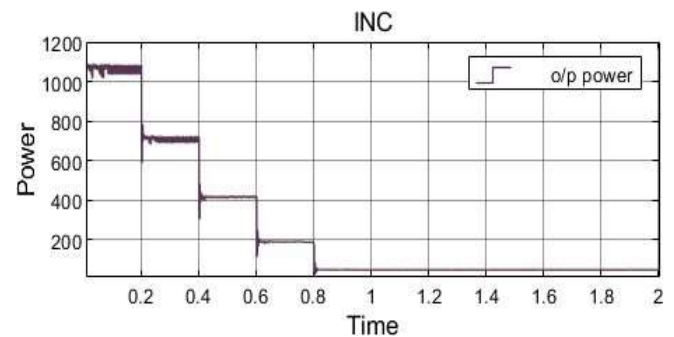


Figure 9 : INC Output Power as Irradiation Changes.

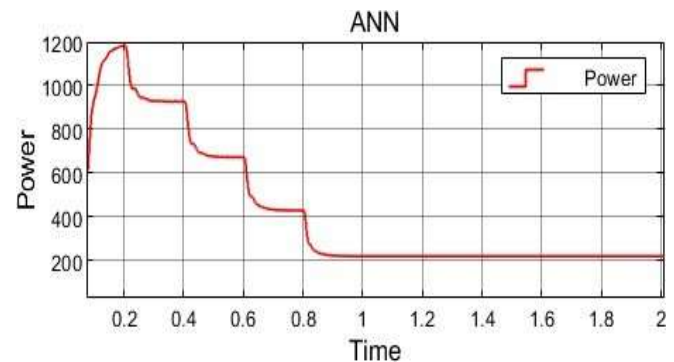


Figure 10 : ANN P&O Output Power as Irradiation Changes.

Figure 8,9&10 respectively displays the simulation outcomes for the PO, INC, and ANN techniques at a constant temperature of 25° C & changing irradiation. Comparing Figure 8,9&10, the ANN approach can swiftly track the MPP when the irradiation changes. However, the PO method cannot track the MPP, and the INC method is superior to PO. Additionally, INC oscillation is lower than PO oscillation, but PO oscillation is very strong and results in power loss in a steady-state. Even after it hits MPP, on the other hand, oscillations in ANN are negligible..

B. Under constant irradiation

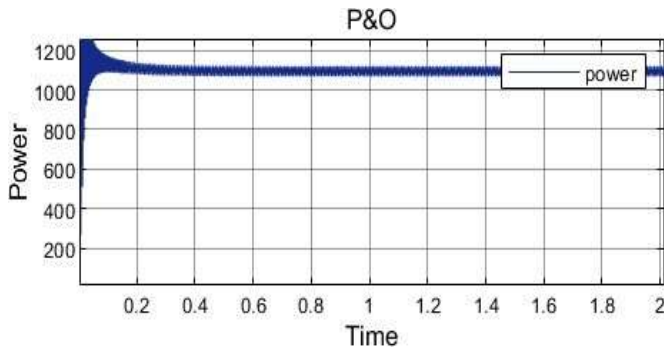


Figure 11 : P&O Output Power Under Constant Irradiation.

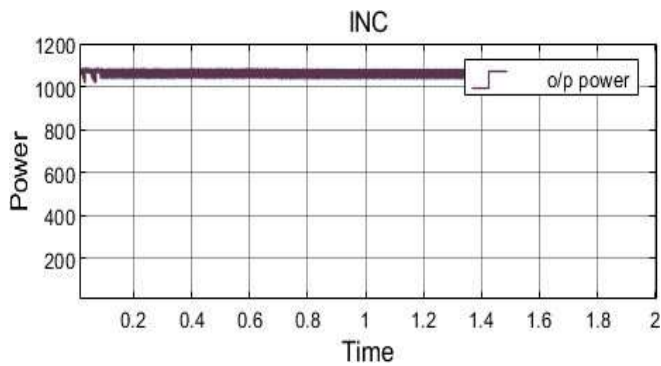


Figure 12 : INC Output Power Under Constant Irradiation.

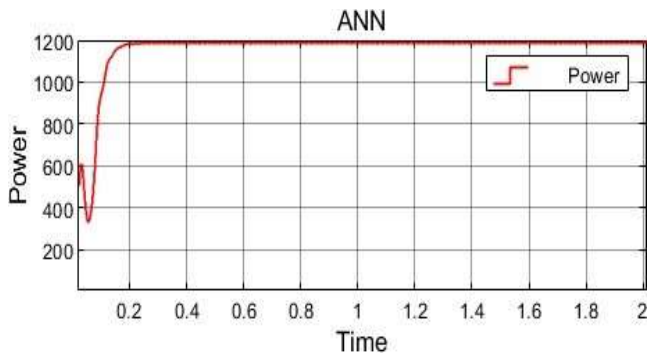


Figure 13 : ANN Output Power Under Constant Irradiation.

Figure 11,12 &13 shows the performance of PO, INC, and ANN methods, respectively, under constant irradiation. In contrast to the PO approach, which exhibits considerable oscillation and substantial power loss in the situation of constant solar irradiation, the ANN method exhibits very little oscillation under constant irradiation. INC algorithm still has oscillations around the MPP.

V. ADDING DISTURBANCE AT THE INPUT SIDE OF ANN ALGORITHM.

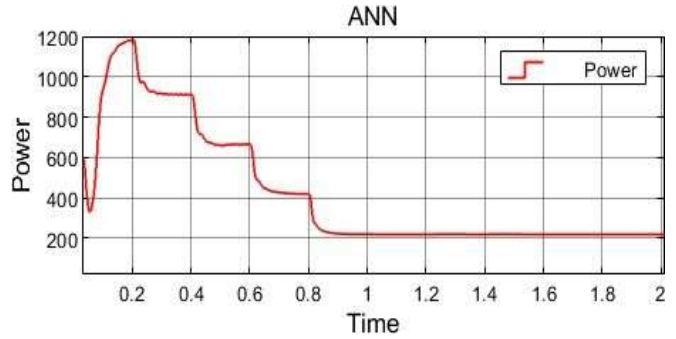


Figure 14 : ANN Output Power Under Changing Irradiation & adding disturbance at the input side.

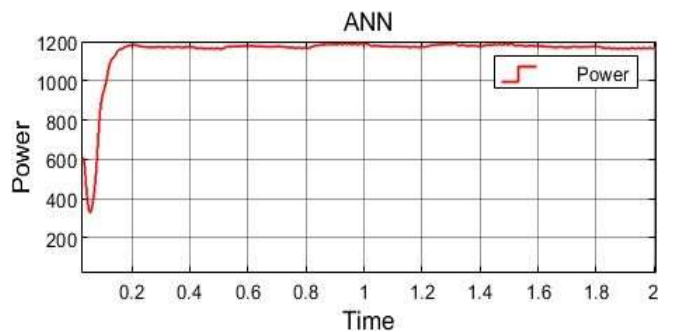


Figure 15 : ANN Output Power Under Constant Irradiation & adding disturbance at the input side.

According to the data above, ANN outperforms the P&O and INC algorithms regarding results. After adding a slight disturbance to the input side of the ANN, we see the outcomes as shown in figure.14&15. By comparing all the above figure.8,9&10 and figure.11,12&13 with figure 14&15, we see that after adding disturbance at the input side, there are small oscillations in the ANN algorithm, but still very small as compared to other algorithms, so ANN can Effectively track MPP. From this, The ANN approach is more exact and accurate than the P&O and INC algorithms.

VI. CONCLUSION

The simulations for several MPPTs in this work show that the ANN approach detects and tracks the MPP exceptionally quickly and accurately in the presence of rapidly changing solar irradiation. Furthermore, this approach can consistently extract the maximum power point despite gradually changing sun irradiation. However, when the irradiation varies, the P&O approach fails to follow the MPP because MPP changes fast over a short period. Furthermore, with constant sunlight, this method exhibits high fluctuation around the MPP, leading to significant power loss over time. Again, in the INC algorithm. The oscillations are significant, causing some power loss.

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