Adaptive Hybrid MPPT Using Artificial Intelligence for an Autonomous PV System

Bentrad Moutaz Bellah*, Bahi Tahar **‡, Boulassel Adel ***

* Electrical Engineering, Science and technology, Electrical Engineering Laboratory of Biskra (LGEB), University of Biskra, B.P. 145, 07000, Biskra, Algeria

** Electrical Engineering, Faculty of technology, Laboratory of Automation and Signals Laboratory of Annaba (LASA), Badji Mokhtar-Annaba University P.O Box.12, Annaba, 23000 Algeria

*** Electrical Engineering, Faculty of technology, LAM2SIN Laboratory, Badji Mokhtar-Annaba University P.O Box.12, Annaba, 23000 Algeria

(moutazbellah.bentrad@univ-biskra.dz, tahar.bahi@univ-annaba.dz, adel.boulassel@univ-annaba.dz)

‡ Corresponding Author; Second Author, Postal address, Tel: +90 312 123 4567, Fax: +90 312 123 4567,corresponding@affl.edu

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Abstract- This study compares traditional Maximum Power Point Tracking approaches, such as Perturb and Observe and Incremental Conductance, with a novel hybrid strategy incorporating Artificial Neural Networks. The hybrid algorithm synergizes the strengths of Perturb and Observe, Incremental Conductance, and Artificial Neural Networks by dynamically adjusting control parameters using historical data. The primary objective is to demonstrate the superior performance of the hybrid approach, highlighting its quick adaptation to changes in solar conditions, improved power quality and tracking accuracy, sustained stability, and a significant boost in power extraction compared to established techniques. Real-time simulations are conducted on representative solar energy systems, evaluating performance indicators under various scenarios, including rapid irradiance fluctuations and transient conditions. The results confirm that the hybrid MPPT approach, empowered by Artificial Neural Networks, outperforms traditional methods across key benchmarks such as response time, power quality, tracking precision, stability, and power extraction and even against stand -alone neural network approach. The ultimate aim is to identify the most effective hybrid MPPT technique based on comprehensive performance assessments.

Keywords: Renewable energy; MPPT; Hybrid; Neural Network; Solar Conditions.

1. Introduction

Renewable energy serves as an alternative to non-renewable sources, offering an eco-friendly solution. This type of energy is often supported by the energy coming from the sun or the one that comes from the wind. It is a free form of energy available all day long,which is supplying 1.7 percent of the worldwide demand for electricity, and by next year the production capacity should exceed 1 TW [1].

Despite the enhanced design of Renewable Energy Resources, ensuring significant Stability, Control, and Efficiency is crucial, as the control and operation of these systems pose challenges. Improving stability in renewable energy systems through control methods is a complex matter, and considerable research efforts are growing within the research community to address this issue. Solar PV Systems are widely deployed in numerous countries [2].

Solar systems are typically divided into 2 categories based on their intended applications. The 1st group includes on-grid PV systems, which encompass hybrid power systems, power plants, grid-tied systems, and various interconnected applicable scenarios. The 2nd group consists of stand-alone PV systems, which are employed to power electric vehicles (EVs), electrical pumps, streetlights, space applications and other independent devices [3–5].

Partial shading (PS) environments significantly impact the efficiency of PV energy systems, posing a prominent challenge because of the outdoor exterior installation of these systems. Temperature and irradiance levels play a crucial role in determining the characteristics of PV systems, evident in their current–voltage and power–voltage curves. The presence of a maximum power point (MPP), representing the optimal functioning point for achieving the highest output, is particularly significant. However, factors like clouds, trees, buildings, dust deposition, etc., causing partial shading can lead to its formation on PV panels, resulting in diminished performance [6-7]. To address this issue, a frequently employed approach suggests integrating bypass diodes into designated cells within the series circuit.

The term "maximum power point tracking" (MPPT) refers to the process of optimizing the power output from a PV system while accurately tracking the Global Maximum Power Point (GMPP) [8-10]. A stand-alone PV system comprises essential components such as a PV module, MPPT controller, boost converter, and load.
The boost converter functions as a medium between the PV panel and its load, enabling precise control over the MPPT process. The duty cycle, serving as the control variable, holds significant importance in accurately regulating the converter's operation [11].

The MPPT techniques are classified based on various criteria, including the practical implementation difficulty, algorithmic structure, and resource requirements. Traditional MPPT algorithms have been widely used to maximize the generated output power of solar systems. These encompass perturb and observe (P&O), incremental conductance (INC), fractional short-circuit current (FSCC), hill climbing (HC) and fractional open-circuit voltage (FOCV) [12-16]. P&O, INC, and FOCV algorithms are favored in MPPT applications thanks to their simplicity. However, P&O and INC algorithms have two notable drawbacks. Firstly, they exhibit suboptimal tracking performance in sudden changing weather conditions. Secondly, these algorithms can result in increased power loss due to significant oscillations. The FOCV algorithm bases its operation on the open-circuit voltage of the PV panel, but this approach may lead to temporary generated power loss during variations in solar irradiance.

In contemporary times, Artificial Neural Networks (ANN) are extensively employed in various applications within PV systems, primarily due to the non-linear nature of meteorological data. ANN finds utility in prediction applications, forecasting, and optimizing the power output of PV systems. It proves to be more fitting compared to statistical methods when dealing with non-linear and intricate relationships in data without requiring any prior assumptions. An ANN-based MPPT method [17] has also been introduced to consistently maintain the overall Maximum Power Point (MPP) across diverse weather conditions in stand-alone PV systems.

The fusion of the advantages offered by Fuzzy Logic (FL) and ANN can enhance the performance of optimization methods. ANFIS serves as a hybridation of neuro-fuzzy controller that combines FL and ANN. In [18], the authors demonstrate the superior performance of ANFIS control in comparison to a heuristic INC command for optimizing the conversion efficiency of a solar system. The results reveal that the intelligent control exhibits a response time of approximately 2.4 seconds and achieves an efficiency of 99%, outperforming the 94% efficiency obtained with INC control. ANN, known for modeling complex relationships in nonlinear systems, has been widely utilized to optimize the efficiency of solar systems. In [19], the authors describe the utilization of ANFIS to enhance the solar power output of an on-grid system.

In this work, implementing two separate Artificial Neural Networks (ANNs) based on historical gathered data obtained from the P&O and INC techniques. The results from these ANN models will be compared with those obtained from the INC and P&O algorithms, and later on, a hybrid approach will be employed, combining both the INC and P&O techniques. The behavior of this hybrid system will be monitored, specifically focusing on the generated output power. Results will be studied and compared to extract information regarding response time , power quality, tracking ability , stability, and the amount of extracted power from the photovoltaïque generator, in the aim of choosing the best MPPT with the best performance under various solar conditions.

The novel approach represents a departure from its predecessors, distinguishing itself by deviating from the conventional use of time intervals that encapsulate the robust performance of individual Maximum Power Point Tracking (MPPT) techniques. In contrast to prior methods, this innovative approach involves the integration of both conventional MPPT and neural network outputs through a unique mathematical calculation. This simultaneous utilization of outputs is then subjected to a filter, enhancing stability and maximizing power extraction efficiency. Unlike existing methodologies, our approach not only combines the strengths of traditional and neural network-based MPPT techniques but also employs a refined filtering process, ensuring optimal and stable power extraction.

2. Modelization

2.1. Photovoltaic Model

The examined setup consists of solar panels and a capacitor positioned at the boost converter's input, along with a MPPT, a capacitor for DC input, an inductive filter, and the DC load.

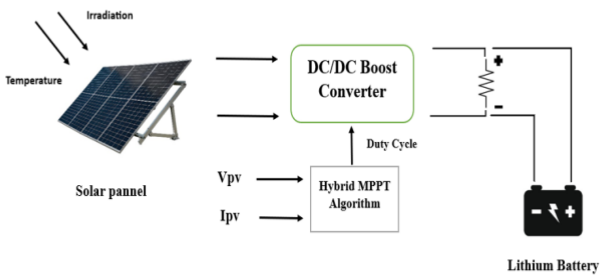

Fig 1 .Configuration of the PV system

The schematic representation of a solar cell's equivalent circuit is illustrated in “Fig. 2”. The source of current (I_{ph}) symbolizes the photocurrent generated by the cell. The intrinsic shunt resistance (R_{sh}) and series resistance (R_s) of the cell are denoted. Typically, R_{sh} has a significantly large value, and R_s is very small, allowing them to be disregarded for the sake of simplifying the analysis [20].

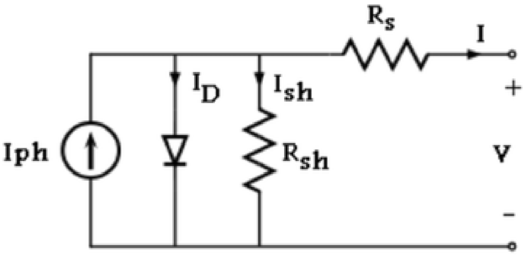

Fig 2 .PV Cell schematic circuit

$$I_{ph} = [I_{sc} + \frac{K_i}{T-298}] \times \frac{I_r}{1000} \quad (1)$$

I_{ph}: represents the photo-current in amperes (A); I_{sc}: denotes the short-circuit current in amperes (A); $K_{i:}$ signifies the short-circuit current of the cell at 25 °C and 1000 W/m²; T: operational temperature level (K); I_r: irradiation (W/m2). Module reverse saturation current I_{rs}:

$$I_{rs} = I_{sc}/(e^{\frac{qVOC}{NSknT}} - 1) \quad (2)$$

q= 1.6 × 10^{-19}C: electron load; $V_{oc:}$ represents open circuit voltage (V); N_s: depicts totality of cells that are connected in series; n: the diode's ideality factor; k: constant of Boltzmann, = 1.3805 × 10^{-23} J/K

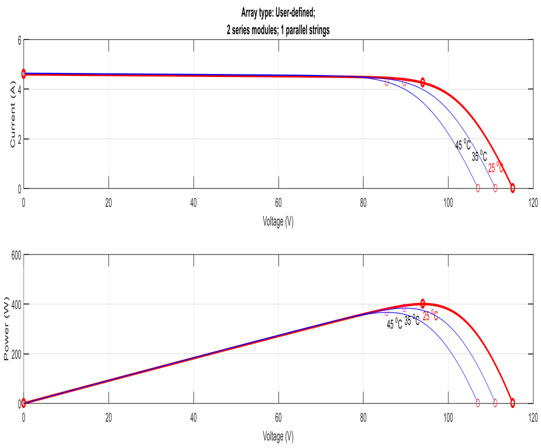

Fig 3 .I-V and P-V characteristics under fixed irradiance and variable temperature

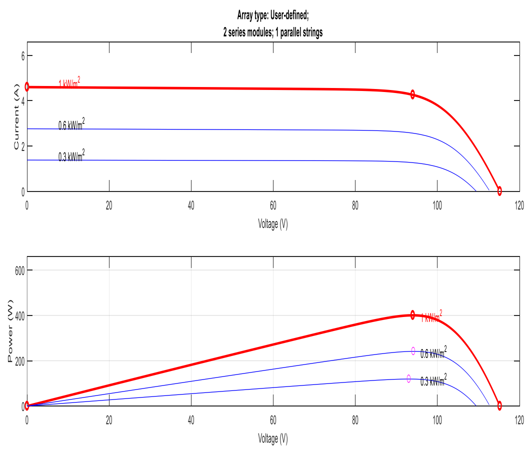

Fig 4 .I-V and P-V Curve under fixed temperature and variable irradiance

Table 1. PV Module Parameters

Parameter	Value
cells per module	60
Maximum power	200(W)
Open circuit voltage (V_{oc})	57(V)
Short-circuit current (I_{sc})	4(A)
Voltage at maximum power point (V_{mp})	47(V)
Current at maximum power point (I_{mp})	4.26(A)
Light-generated current (I_L)	4.609(A)
Diode saturation current (I_0)	1.287e-10(A)
Diode ideality factor	1.53
Shunt resistance (R_{sh})	412.70(ohms)
Series resistance (R_s)	0.827(ohms)

2.2.Maximum Power Point Tracker

The P&O algorithm facilitates the adjustment of the PV panel's output voltage to reach the MPP [21]. In this method, the module voltage is periodically perturbed [22]. As depicted in Fig. 5, when the voltage increases (or drops), the power simultaneously increases (or decreases). Therefore, to achieve the MPP, the power should be increased while keeping the perturbation constant. Conversely, when the power decreases, the perturbation is proportionally reversed [23].

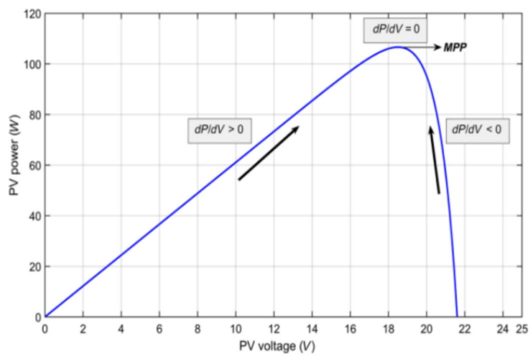

Fig 5. P-V curve for (P&O) algorithm

This approach involves examining the fluctuation in power (dP) of the PV system in response to a change in PV cell voltage (dV). When dP/dV is observed to be positive, the actual point is situated in the left half of the Maximum Power point . This calculation carries on to the point where (dP/dV) reaches zero, as illustrated below.

dP/dV=0 at (MPP) (3)

dP/dV>0 at left side of (MPP) (4)

dP/dV<0 at right side of (MPP) (5)

Incremental conductance (INC) approach operates by adjusting the photovoltaic power relative to its voltage. The

MPP is achieved when the division of the differentiation result is zero [24, 25].

$$\frac{dP}{dV} = \frac{d(VI)}{dV} = I + V\left(\frac{dI}{dV}\right) = 0 \quad (6)$$

$$\left(\frac{I}{V}\right) + \left(\frac{dI}{dV}\right) = 0 \quad (7)$$

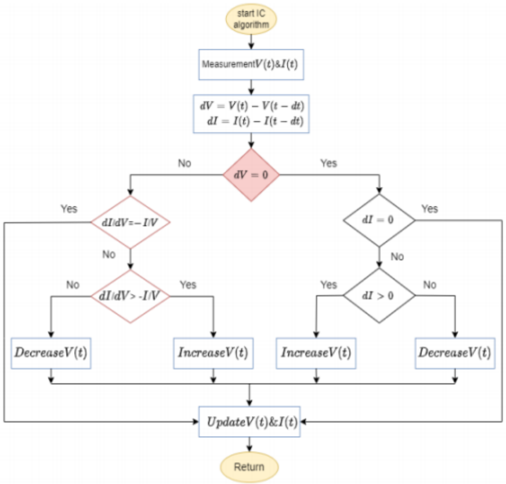

Fig 6. Flowchart of INC algorithm

3. Artificial Intelligence Algorithm

ANN are extensively applied in addressing nonlinear problems, particularly in the context of solar systems. These systems possess the capability to extract information from examples and handle disconnected data. Once trained, the algorithm can quickly perform tasks such as prediction [26, 27], optimization [28,29], and system modeling [30,31]. The utilization of ANN eliminates the need to solve intricate mathematical models of systems, and it does not necessitate prior knowledge of the input/output relationships.

The non-linear characteristics of photovoltaic systems, represented by P-V or I-V curves, are influenced by key variables such as solar temperature and radiation. In this study, an ANN is employed to optimize the power output of a photovoltaic system. Specifically, a multilayer perceptron (MLP) is utilized, as it is well-suited for handling non-linear systems [32]. In MLP, the neurons that are connected across different layers, and signals flow from the input to the output layers, with no interconnections between neurons within the same layer. The ANN structure comprises three layers: an input layer determined by the number of inputs, a hidden layer situated in between, and an output layer determined by the number of outputs. For a more in-depth understanding of the theory behind modeling an ANN, additional details can be found in other studies [33, 34].

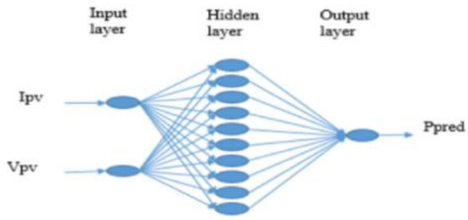

Fig 7. Designated ANN for MPPT implementation

In order to perform an evaluation of the performance of the chosen machine learning algorithm, a mathematical calculation will be conducted to calculate the gap between the predicted values and the real ones, and the error will be optimized through some metrics the chosen metric in this operation is Mean Squared Error (MSE).

The proposed neural network utilizes historical data that includes Ipv and Vpv as inputs, along with the duty cycle controlling the closing duration of the Mosfet embedded in the Pulse Width Modulation (PWM). The PWM, in turn, regulates the DC/DC converter to render power output at its maximum point. Our ANN employs the Backpropagation technique and consists of one hidden layer, comprising 10 hidden neurons. The learning process undergoes multiple epochs, often in the thousands, to optimize the performance of the ANN and minimize the resulting error, utilizing the mean square error (MSE) technique.

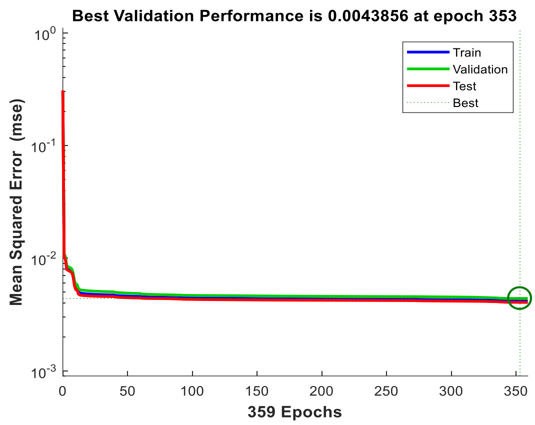

Fig 8. MSE performance Curve.

4. Simulation Results

The simulation process consists of two major steps. The first step involves implementing two separate ANNs based on the collected data obtained from the INC and Perturb and Observe methods. The results from these ANN models will be compared with those gathered from the INC and P&O algorithms.

In the second step, a hybrid approach will be employed, combining both the INC and P&O techniques. The behavior of this hybrid system will be monitored, specifically focusing on the generated output power. The simulation process will be conducted under different solar conditions outlined as follows:

- 1st Scenario:

- Maintain a constant temperature of 25 °C.

- Vary the irradiation levels at three hundred, six hundred, and 1000 W/m²;

- observe the overall PV performance.

- 2nd Scenario:

- Fix irradiance at 1000 W/m²;

- Vary the temperature levels at twenty-five, thirty-five, and fourty-five °C.

- Observe the generated PV signals.

- Analyze the results to determine how changes in temperature influence the general performance of the PV system and its effects on the load.

These scenarios aim to provide an overall insight of the adaptability and performance of the solar system under changing meteorological conditions, helping to optimize its operation.

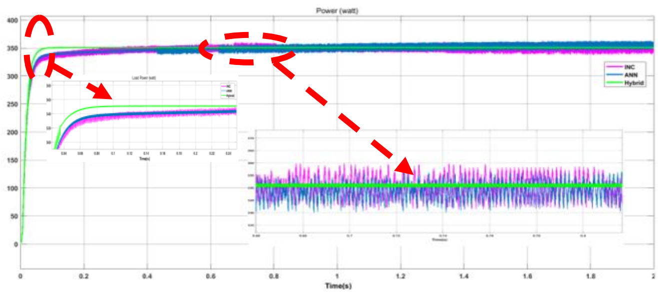

Fig 9. Load power under Hybridation of INC,ANN, in optimal solar conditions

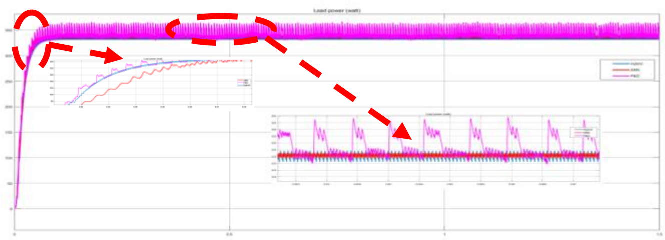

Fig 10. Load power under Hybridation of P&O,ANN, in optimal solar conditions

- 1st scenario:

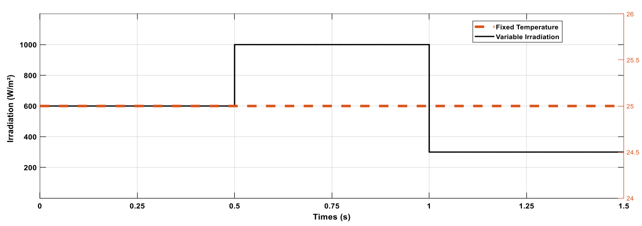

Fig 11. Temperature and irradiation profile

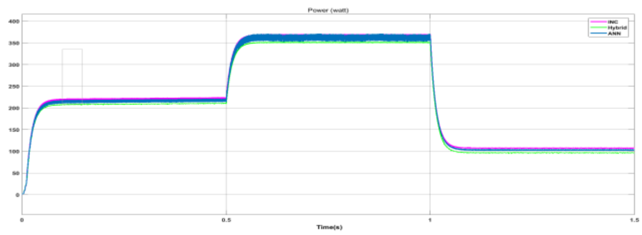

Fig 12. Load power with INC, ANN under variable irradiation conditions

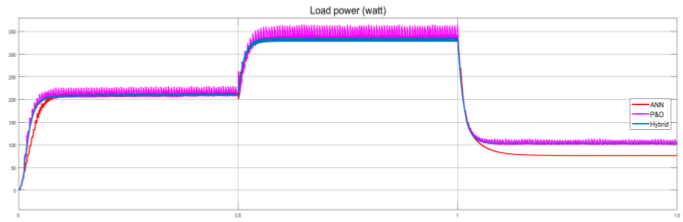

Fig 13 . Load power Hybrid P&O,ANN, in under variable irradiation conditions

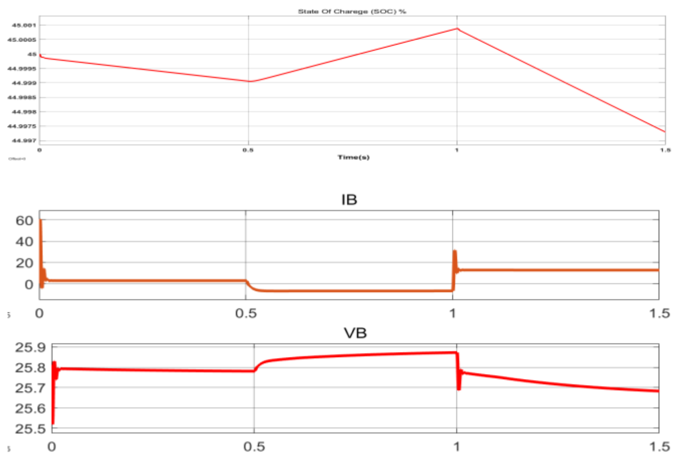

Fig 14 .Battery Performance : SOC ,Current and Voltage

- 2nd Scenario :

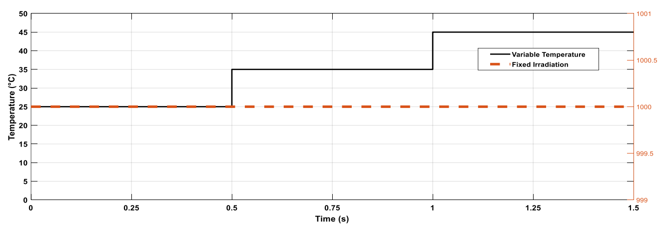

Fig 15 .Temperature and irradiation profile

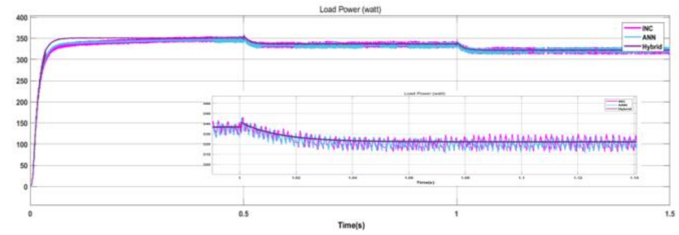

Fig 16 . power under Hybrid algorithm of ANN,INC under variable temperature conditions.

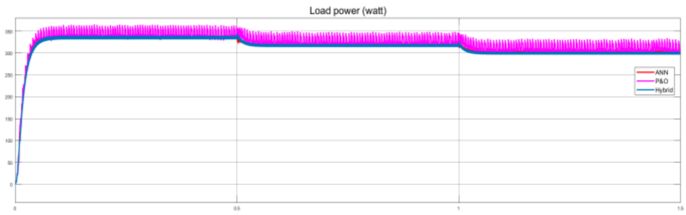

Fig 17. Load power under Hybrid algorithm of ANN, P&O under variable temperature conditions

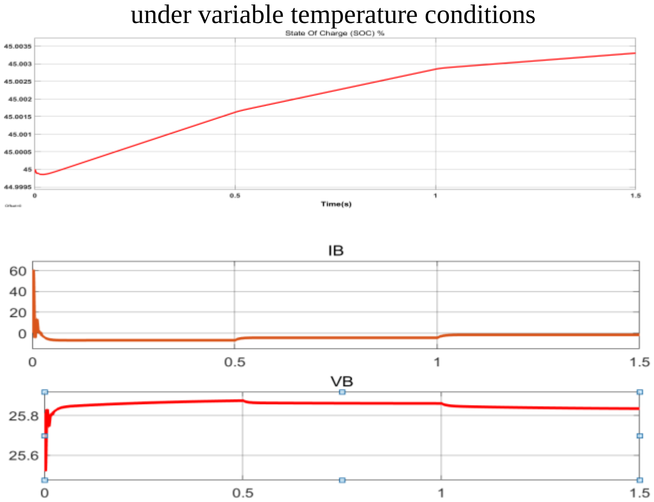

Fig 18. Battery Performnce : SOC , Cuurent and Voltage.

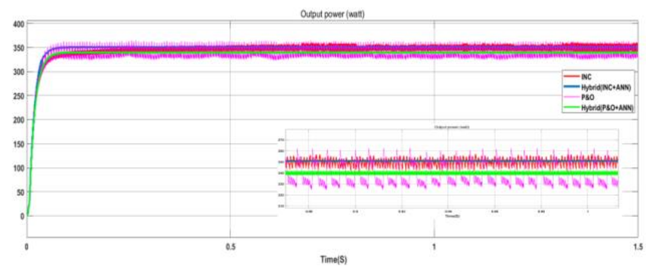

Fig 19 .Overall MPPT comparison

Table 2. Tracker Performance Evaluation

MPPT Algorithm	Efficiency (%)	Response time(s)
INC	88.4	0.38
ANN	88.57	0.48
Hybrid(INC+ANN)	87.62	0.066
P&O	82.51	0.068
ANN	87.86	0.08
Hybrid(P&O+ANN)	89.94	0.074

Table 3. MPPT Overall Performances Evaluation

MPPT Algorithm	Tracking	Power quality	Stability	Power extraction	Response time
INC	-	+	-	+	-
ANN	-	-	+	-	-
Hybrid (INC+ANN)	+	+	+	+	+
P&O	-	-	-	+	+
ANN	-	+	+	-	-
Hybrid(P&O+ANN)	+	+	+	-	+

It is clear that during optimal solar conditions , the Solar system is able to supply the DC load and the surplus in energy will be stored in the battery as shown in figure 14 and 18 (SOC levels), however during changes in these conditions the battery will become the primary supply source for the load .

As the irradiation level increases, the generated power by the photovoltaic system also tends to increase.

On the other hand, temperature exhibits an inverse proportionality with power generation. Higher temperatures often lead to a decrease in the efficiency of photovoltaic cells, resulting in a reduction in power output. This is due to the fact that elevated temperatures can cause an increase in the semiconductor's intrinsic carrier concentration, causing a decrease in the cell's open-circuit voltage.

Thanks to the proposed technique in this work, which incorporates a limiter designed to filter the output signal of the duty cycle, preventing signal overshooting and simultaneously enhancing response time, the hybrid approach has demonstrated reliability and efficiency compared to other approaches, including the conventional MPPTs and the stand-alone ANN approaches.

5. Conclusion

The hybrid Maximum Power Point Tracking algorithm’s implementation, which combines conventional techniques with Artificial Neural Network-based learning, demonstrates a clear advantage in terms of response time, power quality, tracking accuracy, stability, and energy extraction. This study offers valuable insights for choosing the most effective MPPT solution in photovoltaic systems, especially when faced with dynamic and uncertain operating conditions. The hybrid approach presented in this research showcases enhanced performance across various critical factors, contributing to the optimization of MPPT in the context of solar energy systems.

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