Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi Sayı 7, S. 214-221, 7, 2023 © Telif hakkı IJANSER'e aittir **Araştırma Makalesi**



International Journal of Advanced Natural Sciences and Engineering Researches Volume 7, pp. 214-221, 7, 2023 Copyright © 2023 IJANSER **Research Article**

https://as-proceeding.com/index.php/ijanser ISSN: 2980-0811

Power Management of a Solar System using Hybrid Maximum Power Point Tracking Algorithm

¹Bentrad Moutaz Bellah, ²Bahi Tahar and ³Boulassel Adel

¹Electrical Engineering Department/LGEB, Mohamed Khider University, Algeria
² Electrical Engineering Department /LASA, Badji Mokhtar University, Algeria
³ Electrical Engineering /LAM2SIN, Badji Mokhtar University, Algeria

¹moutazbellah.bentrad@univ-biskra.dz

(Received: 25 August 2023, Accepted: 29 August 2023)

(1st International Conference on Recent and Innovative Results in Engineering and Technology ICRIRET 2023, August 16-18, 2023)

ATIF/REFERENCE: Bellah, B. M., Tahar, B. & Adel, B. (2023). Power Management of a Solar System using Hybrid Maximum Power Point Tracking Algorithm. *International Journal of Advanced Natural Sciences and Engineering Researches*, 7(7), 214-221.

Abstract – The integration of artificial intelligence (AI) and data analytics is a focal point of this study. Machine learning algorithms and predictive models are employed to optimize panel orientation, predict solar irradiance, and detect system faults. By leveraging real-time data, AI-based approaches enable adaptive and proactive adjustments, resulting in increased energy output and prolonged panel lifespan. This paper presents a two-phase investigation into enhancing Maximum Power Point Tracking methods for solar systems. In the first phase, an Artificial Neural Network is trained using historical data from Incremental Conductance MPPT. The ANN leverages the existing knowledge of Incrimental conductance behavior to predict optimal reference voltages, enhancing tracking efficiency. The second phase involves integrating the trained Artificial Neural Network and Incrimental conductance to create a hybrid MPPT algorithm. This hybrid approach harnesses the ANN's adaptability and IncCond's rapid response and stability. Efficiency and stability assessments are conducted, evaluating power ripples, response time, oscillation frequency, and overall stability. Results highlight the hybrid MPPT's advantages, showcasing improved performance over individual methods. The paper contributes to advancing MPPT by introducing a novel hybrid approach that combines historical data-driven ANN training with Incrimental conductance benefits. This innovation holds the potential to substantially enhance solar energy harvesting efficiency and stability, impacting the system's overall output power.

Keywords – Renewable Energy, Neutral Network, Incremental Conductance, Hybrid, MPPT.

I. INTRODUCTION

Solar energy has emerged as a viable and sustainable source of electricity generation, with photovoltaic (PV) systems playing a crucial role in harnessing this abundant renewable resource. PV systems utilize solar panels equipped with photovoltaic cells to convert sunlight directly into electrical energy. It is an attractive alternative to conventional sources of electricity for many reasons: it is safe, silent, and non-polluting, renewable, highly modular in that their capacity can be increased incrementally to match with gradual load growth, and reliable with minimal failure rates and projected service lifetimes of 20 to 30 years [1, 2]. It requires no special training to operate; it contains no moving parts; It is extremely reliable and virtually maintenance free and it can be installed almost anywhere.

Apart from harvesting the resource and decreasing the dependency on fossil fuel because they are limited, one must understand the consequences of using fossil fuels. Burning of fossil fuels for energy has an adverse effect on the environment. Further, it also causes the ozone layer to be depleted. These mentioned phenomena can cause several events to occur such as acid rain, air pollution, land pollution because of excavating operations, etc... [3].

Solar energy is the most abundant form of energy available to us. It is approximated that 10000 TW worth of solar energy is incident on earth's surface in a day (Bosshard, 2006). According to a report, the world energy consumption in 2015 was 17.4 TW altogether (Seger, 2016). There has been a minimal increase in the energy consumption every year, approximately 1-1.5% annual growth. The world's total energy consumption is expected to grow by 56% by the year 2040 (U.S Energy Information Administration, 2013). Comparing current consumption, projected growth in two decades, and the amount of solar radiation received in an hour we can just imagine the potential solar energy holds. The total energy consumed is not small fraction of what we receive in an hour [4].

Solar cells are made up of semiconductor materials, such as silicon, which is used to produce electricity. The electricity is conducted as a stream of tiny particles called electrons and the stream is called electric current. A typical solar cell has two layers of silicon, which is n-type at the top and p-type at the bottom. When sunlight strikes the solar cell, the electrons are absorbed by silicon, they flow between n and p-layers to produce electric current and the current leaves the cell through the metal contact. The electricity generated is of AC type [5].

The most widely used algorithms are perturb and observe (P&O) [6,7] and incremental conductance (InC) [8]. However, they may suffer from certain limitations, including slow tracking speed. sensitivity to partial shading, and oscillations around the MPP. In contrast, implementing an Artificial Neural Network (ANN) using Incrimental conductance (Inc) historical data can significantly enhance the efficiency of the MPPT algorithm. P&O is a widely used method for MPPT, but it may suffer from oscillations or slow tracking in rapidly changing environmental conditions. By leveraging historical data collected over time during different solar conditions, an ANN can learn the patterns and relationships between PV panel parameters, irradiance levels, and optimal operating points. This learned knowledge enables the ANN to make accurate predictions and adapt quickly to varying conditions.

In the next phase, a hybrid MPPT technique is forged by combining both Incrimental conductance and ANN. The goal is to leverage the strengths of each method to overcome their individual limitations, resulting in a more efficient and stable MPPT algorithm. During normal operation, the ANN predicts the reference voltage (V_{ref}) based on the real-time measurements and historical data, providing a smoother and more accurate tracking of the MPP.

II. MODELIZATION

The studied system is composed of photovoltaic panels and a capacitor at the input of the boost converter with a "tracker" of the maximum power point (MPPT), a DC input capacitor, of an inductive filter, and the non-linear load.

A. Photovoltaic generator



Fig. 1. Hybrid MPPT implimentation in PV generator

1) Photovoltaic model

The equivalent circuit of a photovoltaic (PV) cell is shown in Fig. 2. The current source I_{ph} represents the cell photocurrent. R_{sh} and R_s are the intrinsic shunt and series resistances of the cell, respectively. Usually, the value of R_{sh} is very large and that of R_s is very small, hence they may be neglected to simplify the analysis [9].



Fig. 2.PV cell equivalent circuit

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

Here, I_{ph} : photo-current (A); I_{sc} : short circuit current (A); K_i : short-circuit current of cell at 25 °C and 1000 W/m2; T: operating temperature (K); I_r : solar irradiation (W/m2). Module reverse saturation current I_{rs} :

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

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



Fig. 3. Equivalent circuit of solar array

Tab 1. Parameters of the Pv module

cells per module	60
Maximum power	200.22(W)
Open circuit voltage (Voc)	57.6(V)
Short-circuit current (Isc)	4.6(A)
Voltage at maximum	47(V)
power point (Vmp)	
Current at maximum power	4.26(A)
point (Imp)	
Light-generated current	4.6092(A)
(IL)	
Diode saturation current	1.2872e-10(A)
(I0)	
Diode ideality factor	1.5395
Shunt resistance (Rsh)	412.7019(ohms)
Series resistance (Rs)	0.82756(ohms)
Current at maximum powerpoint (Imp)Light-generatedcurrent(IL)Diodesaturationcurrent(IO)Diode ideality factorShunt resistance (Rsh)Series resistance (Rs)	4.6092(A) 1.2872e-10(A) 1.5395 412.7019(ohms) 0.82756(ohms)

For the photovoltaic generator we chose the following profile for the temperature and the irradiation:



Fig. 4.I-V and P-V characteristics at 1000 W/m² and variable temperature of a user defined Module



Fig. 5.I-V and P-V characteristics at 25°C and variable irradiance of a user defined Module



Fig. 6. Current-voltage characteristic at ideal envirenmental conditions



Fig. 7.Current-voltage characteristic at ideal envirenmental conditions

B. Boost converter

A boost converter is a device that converts a DC voltage into another DC voltage of higher value. This type of converter can be used as a load source adapter when the load needs a higher voltage than the PV generator. It is essentially composed of an inductance (L), a capacitor (C), a switch (K) which can take two states 1 and 0 (like IGBT or MOSFET) and a diode (D) [10], the theoretical transfer function of the boost converter is: $\frac{Vout}{Vin} = \frac{1}{1-\alpha}$ (3)

Where, is α is the duty cycle ; V_{out} : output voltage and V_{in} is input voltage.



Fig. 8. Boost converter circuit

C. Maximum power point tracking

There are many MPPT algorithm which can be used for implementation via. Incremental conductance method, constant voltage method, Fuzzy logic based method etc. different MPPT algorithms are briefed about their features and limitations as follows [11]. $dp_{pv} = 0$



Fig. 9. Maximum power point of a PV array

1) Incrimental conductance algorithm

The incremental conductance algorithm depends on the slope of the P–V curve, which is affected by the solar irradiation level and load resistance. As the algorithm uses the current and voltage of the PV module in the calculation, the effect of solar irradiation and load changes on the current and voltage of the PV module must be considered in the algorithm[12].

Tab 2.Changes in PV voltage and current during changes in solar irradiation and load resistance

		dV	dI
Solar	Increase	Increase	/
Irradiation	Decrease	Decrease	/
Load	Increase	Increase	Decrease
Resistance	Decrease	Decrease	Increase



Fig. 10. Incremental conductance Mppt algorithm organizational chart

D. ANN algorithm



Fig. 11. Neural network structure

The suggested neural network uses historical data containig Ipv, Vpv as inputs and the duty cycle that controls the closing duration of the Mosfet embedded in the PWM which also controls the boost converter to generate maximized power in the output, our ANN uses Backpropagation technique and contains one hidden layer, the latter contains 10 hidden neurones, and each learning process passess by thousand epochs to optimize the performance of the ANN and reduce the resulted error using mean square error (MSE) technique.



Fig. 12. MSE performance curve





III. RESULTS AND DISCUSSION

The simulation process passes through two major steps : the first one will be dedicated for implimenting the ANN based on the historicl data gathered from the INC technique and compare the results with the ones gathered from the INC algorithm, and the second phase will combine both techniques and monitoring the behaviour of the hybridation on the generated output power, it is worth to mention that the simulation process will pass through different solar conditions as follows :

In the first scenario, we maintain a constant temperature of 25 °C and vary the irradiation levels at 300, 600, and 1000 W/m². We monitor and record the generated current, voltage, and power of the PV array and the connected load for each irradiation level. By analyzing these results, we aim to understand how the PV system adapts to different light intensities while the temperature remains unchanged.

In the second scenario, we keep the irradiation level constant at 1000 W/m^2 and vary the

temperature levels at 25, 35, and 45°C. Similarly, we observe and record the generated current, voltage, and power for both the PV array and the load at each temperature level. This analysis allows us to explore how changes in temperature impact the overall performance of the PV system and how it affects the load.

The obtained results are as follows:





Fig. 14. Temperature and irradiation profile



Fig. 15. PV and Load Power under INC control



Fig. 16. PV and Load Power under ANN control





Fig. 17. Temperature and irradiation profile



Fig. 18. PV and Load Power under INC control



Fig. 19. PV and Load Power under ANN control

Hybrid MPPT implimentation :



Fig. 20. Output load power using INC,ANN,Hybrid under standard solar conditions



Fig. 21. Response time comparison





Fig. 22. Load power under ANN,INC and Hybrid MPPT during variable temperature conditions.

Variable irradiation and fixed temperature



Fig. 23. Tracking the MPP during sudden changes of irrdiations conditions





Fig. 24. Effeciency and stability curve

Tab 3. MPPT performance table

MPPT	Effeciency (%)	Response
Algorithm		time(s)
Inc	88.11	0.38
ANN	88.57	0.48
Hybrid	87.62	0.08

The impact of implimenting the hybrid MPPT over stand-alone ANN based algorithm, showed promising results, that appear in :

Reduced Power Ripples: The hybrid MPPT algorithm showed remarkable efficiency in reducing power ripples in the generated power output. Standalone ANN-based algorithms tend to exhibit some degree of fluctuation in the power output.In contrast, the hybrid MPPT approach algorithm utilizes the Inc during transient conditions, which rapidly responds to environmental changes and smoothly guides the photovoltaic system towards the optimal operating point.

Stability and precision: The hybrid MPPT method demonstrated a reduced oscillation frequency compared to ANN-based algorithms. The inherent nature of Inc to converge quickly towards the maximum power point, especially during rapid changes in solar conditions, enables the hybrid MPPT algorithm to maintain a stable and steady tracking behavior. As a result, the

photovoltaic system experiences fewer oscillations and attains the maximum_power point more efficiently, leading to enhanced energy harvesting capabilities.

Fast Response Time: The hybrid MPPT algorithm exhibited a remarkable reduction in response time compared to the other MPPT's algorithms. The ANN, while capable of accurate predictions, may suffer from a slower response during sudden changes in solar conditions due to its dependence on historical data and learning process. However, the integration of the Inc algorithm, with its rapid and direct convergence towards the maximum power point, significantly improved the overall response time of the hybrid MPPT system.

IV. CONCLUSION

The implementation of the hybrid MPPT algorithm by integrating Artificial Neural Network and Inc strategies has proven to be a highly effective and efficient approach for solar energy harvesting. The hybrid algorithm combines the predictive capabilities of Artificial Neural Network with the rapid response and stability of Inc, resulting in reduced power ripples, faster response time, and enhanced stability compared to standalone ANN-based algorithms. The synergistic combination of these methods optimizes power extraction from photovoltaic systems, paving the way for improved energy efficiency and reliability in real-world solar applications.

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