MPPT Efficiency in PV Arrays under Partial Shading Conditions:A Comparative Analysis of PSO and P&O Algorithms

Rachid Bennia, Cherif Larbes, and Faiza Belhachat

Abstract−Global Maximum Power Point Tracking (GMPPT) presents a fundamental challenge in photovoltaic (PV) systems due to the inherent nonlinearity of PV array characteristics. Partial shading (PS) emerges as a particularly critical factor, significantly compromising overall system efficiency by inducing multiple local maxima in the Power-Voltage (P-V) characteristic curve. While conventional tracking algorithms demonstrate adequate performance under uniform irradiation conditions, their effectiveness diminishes substantially under Partial Shading Conditions (PSCs), where they frequently converge to local power peaks rather than the true Global Maximum Power Point (GMPP). To address these limitations, intelligent computational approaches have been developed as robust alternatives for reliable GMPP tracking in complex shading environments. This investigation presents a comparative analysis of two established algorithms: Particle Swarm Optimization (PSO) and Perturb and Observe (P&O), evaluating their respective capabilities in GMPP identification. Extensive simulation studies conducted across diverse shading patterns conclusively establish the superior performance of the PSO algorithm, which consistently achieves steady-state tracking efficiencies exceeding 99% in all operational scenarios. These findings strongly suggest that PSO represents the more effective solution for optimal power extraction in PV systems operating under dynamic environmental conditions.

***Keywords*−Maximum Power Point Tracking, Particle Swarm Optimization, Perturb and Observe, Partial Shading.**

NOMENCLATURE

GMPPT	Global Maximum power point tracking.
GMPP	Global Maximum power.
PV	Photovoltaic.
PSCs	Partial Shading Conditions.
P-V	Power-Voltage.
I-V	Current-Voltage.
PSO	Particle Swarm Optimization algorithm.
P&O	Perturb and Observe.
RES	Renewable Energy Sources.
SC	Soft Computing.
ANN	Artificial NeuralNetwork.
BA	Bat algorithm.

I. INTRODUCTION

The world is now experiencing an increasing need for energy, which requires the exploration of alternative energy resources to complement conventional ones[1]. Because they are year-round available and pollution-free, renewable energy sources (RES) are highly recommended [2]. One of the primary concerns for researchers today is optimizing the energy output of photovoltaic (PV) systems in different weather conditions.

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Several techniques are presented to monitor the maximum power point (MPP). Conventional maximum power point tracking (MPPT) methods can track the MPP under uniform irradiation. However, they fail under rapidly changing atmospheric conditions and PSCs [1,2]. These conventional MPPTs are unable to distinguish between global and local maxima, causing the system to be trapped at a local peak [3]. As a result, the system's performance is drastically reduced. Partial shading (PS) is a major problem that significantly influences the output power of the photovoltaic system [4]. The PV array characteristic exhibits numerous local power peaks and one global maximum due to the integration of bypass diodes to avoid the hot spots effect [5]. Soft computing (SC) methods are widely recommended as the potential solution to mitigate the concern of PS and non-uniform irradiation [6,7]. PS is a major problem that significantly decreases the overall system's efficiency [8], it is acknowledged as the primary source of energy losses in PV power systems [9,10]. Studies have indicated that PS can significantly reduce the PV system yield, ranging from 10% to 70%. To circumvent this issue, a significant interest is dedicated by researchers to the MPPT techniques based on soft computing that are considered as a potential solution to mitigate the concern of PS [11,12], particularly Particle Swarm Optimization (PSO) [13] and Cuckoo Search (CS) [14,15] which are powerful optimization techniques used to address various engineering optimization problems with several peaks and can handle effectively the partial shading issues.

II. MAXIMUM POWER POINT ALGORITHMS

SC techniques, including Artificial Neural Network (ANN) [16], Bat algorithm (BA) [17], Cuckoo search (CS) [18,19], and Particle Swarm Optimization (PSO) [20], are commonly used in PV systems [21, 22]. PSO algorithm is a prominent MPPT approach used to track GMPP under PSCs,this technique comes with several benefits owing to its high performance, simplicity, and ease of implementation.

A. Particle Swarm Optimization Algorithm (PSO) Overview

PSO is an optimization approach inspired by the social behaviour of bird flocking, and it is designed to find the optimum solution in an n-dimensional space for an optimization issue. It is based on a swarm population called particles. Each particle follows two essential rules for finding the best solution: it follows the highest-performing particle and the best solution found by the particle itself. As a result, all particles in the swarm converge towards the optimum required solution. Particle positions and velocities are adjusted using equations (1) and (2).

$$v_i^{k+1} = w_i v_i^k + randc_1(pbest_i - d_i^k) + randc_2(gbest_i - d_i^k) \quad (1)$$

$$d_i^{k+1} = d_i^k + v_i^{k+1} \quad (2)$$

Where d_i and v_i are the particle's position and velocity, whereas w corresponds to the inertia weight and k is the iteration number, c_1 and c_2 are learning parameters, $p_{besti}$and g_{besti} are defined as the personal and global best positions, and *rand* refers to random number within the interval [0, 1].

B. Perturb and Observe (P&O)

The working principle of P&O [23] is as follows: the algorithm creates an alteration (Δ) in the operating voltage of the PV array, which results in a perturbation of the generated power. An increase in the operating power indicates that the converter is approaching the MPP. Hence, in the next sampling cycle, the same direction of alteration is kept, and the reference voltage/current is raised by the same amount (Δ). Note that the P&O algorithm will stay oscillating once the MPP is attained.

III. System Description

Fig.1 depicts the schematic diagram of the PV system. The system includes a photovoltaic array, a DC-DC boost converter, and a resistive load. The MPPT controller generates the required duty ratio to the boost converter to obtain the optimum power from the PV array. The PV model is simulated using SunPower SPR-X20-250 PV panels.

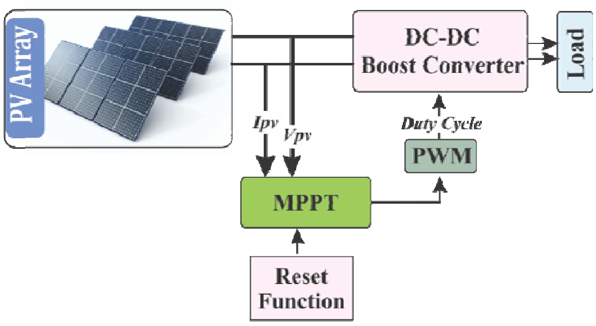

Fig. 1: Bloc diagram of a typical PV system

IV. Simulation and Discussion

The suggested approach is simulated using MATLAB/Simulink environment. The photovoltaic system is composed of four PV arrays connected in series, a DC-DC boost converter, two MPPT-based controllers (PSO and P&O), and a resistive load. The detailed profiles of the different scenarios of partial shading used in this study are illustrated in Table I whereas their corresponding (P-V) curves are shown in Fig. 2. The used PV module specifications are depicted in Table II. For optimal power efficiency, a boost converter is implemented to regulate and match the output of the PV array to the load. The converter works in continuous conduction mode. An extensive simulation analysis is performed under STC and PSCs.Several patterns with different levels of partial shadingare examined to verify the reliability of the proposed approach. For this study, the cell temperature is set constant at 25 °C for all circumstances.

Table. I
Detailed Profiles of Partial Shading

Patterns	Irradiance on each PV panel (W/M^2)	GMPP (W)
STC	1000-1000-1000-1000	999.8
PSC1	1000-1000-500-200	490.5
PSC2	1000-800-500-300	411.5
PSC3	600-800-900-1000	660.0
PSC4	500-200-800-400	320.5

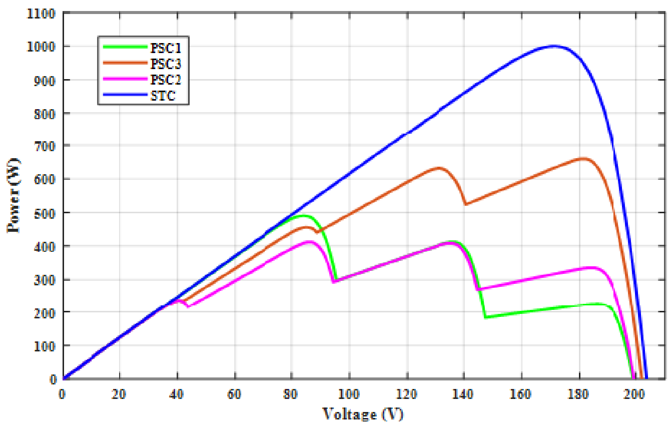

Fig. 2. Output characteristics for the simulated scenarios

Table. II
SunPower SPR-X20-250 Module Parameters

Characteristics	Value
Max-Power (W)	249.9
OC-Voltage (V)	50.93
V- $_{MPP}$ (V)	42.8
I_{mp} (A): Current at MPP	5.84
Isc (A): Short circuit current	6.2
N°. of cells	72

Dynamic and steady-stateefficiencies for each scenario are analyzed to evaluate the performance of the studied algorithms. The tracking efficiency [15]ηis defined as:

$$\eta = \frac{P_{MPPT}}{P_{max}} x\, 100\ (\%) \quad (3)$$

Where P_{MPPT}andP_{max} are, respectively, the MPPT steady-state power and the maximum delivered power by the PV system. The dynamic efficiency is defined by:

$$\zeta = \frac{\int p(t)dt}{\int P_{MPPT}\,(t)dt} x100\% \quad (4)$$

Where *p(t)* and $P_{MPPT}(t)$ are the measured power and the maximum power on the (P-V) curve at time t.

A. Tracking under uniform irradiation

The suggested system is tested under standard test conditions, where all panels receive a uniform irradiation of 1000 (W/m^2). Fig. 3 and Fig. 4 illustrate the corresponding obtained results.

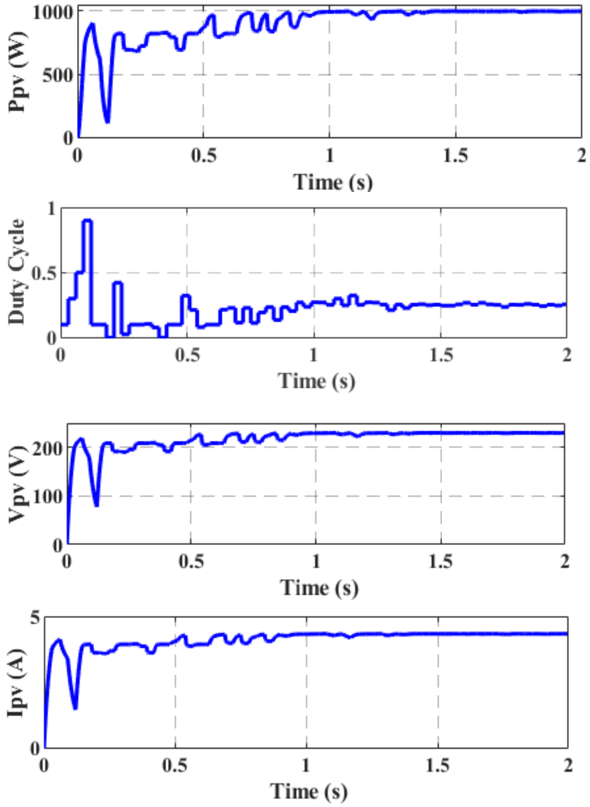

Fig. 3: Tracking performance under STC using the PSO algorithm

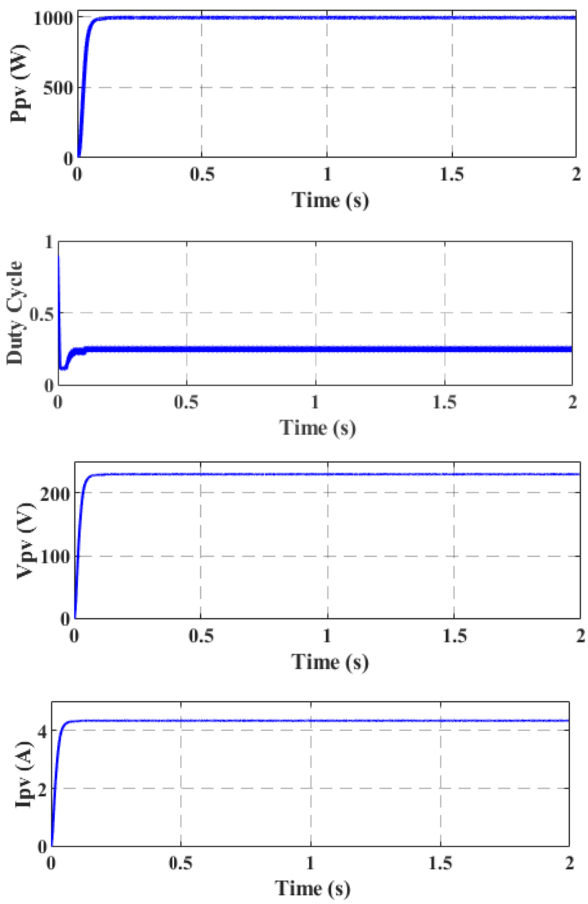

Fig. 4: Tracking performance under STC using the P&O algorithm

Fig. 3 and Fig. 4 illustrate that both algorithms can converge to the global maximum power point at 999.8 W. The P&O algorithm converges faster than PSO since, under this case, the PV characteristic shown in Fig. 2 is characterized by only one peak; in contrast, the PSO approach takes more time to converge due to the search process that covers the whole search space, however, it demonstrates higher steady state efficiency than the P&O algorithm.

B. Tracking under PSC1

The system is tested against the first partial shading scenario (PSC1) where the PV panels receive the first set of solar irradiations (1000-1000-500-200 W/m²) as shown in Table. I the corresponding output curves are illustrated in Fig.5. and Fig. 6.

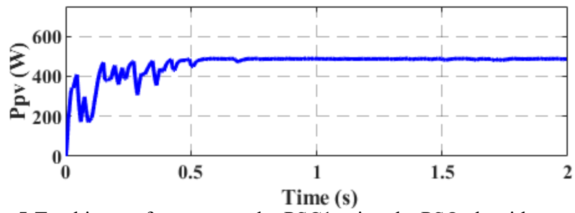

Fig. 5: Tracking performance under PSC1 using the PSO algorithm

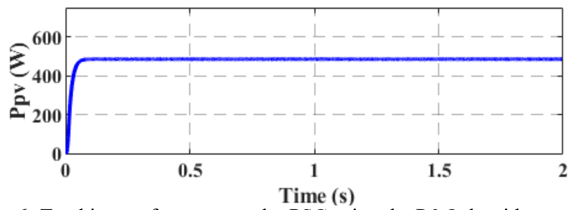

Fig. 6: Tracking performance under PSC using the P&Oalgorithm

As shown in Fig. 2, the PV output characteristic presents three peaks: 490.4 W, 411.7 W, and 226 W, where the first peak is the GMPP at 490.5 W. In this case, both algorithms also converge to the real GMPP with high efficiency more than 99 %. The P&O algorithm was able to recognize the global peak since it comes first in the PV output curve.

C. Tracking under PSC2

A more complicated shading pattern is presented to the system to verify its robustness under complex PSCs. As illustrated in Fig. 2, for the second case (PSC2), the PV output curve demonstrates four peaks; moreover, there is only a slight difference between the GMPP and the other local peaks. The obtained results are illustrated in Fig. 7 and Fig. 8.

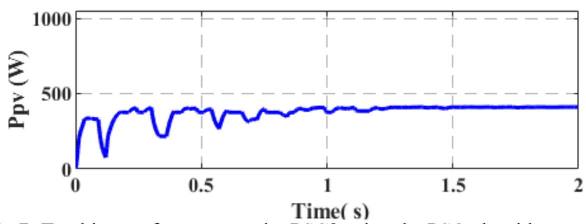

Fig.7: Tracking performance under PSC2 using the PSO algorithm

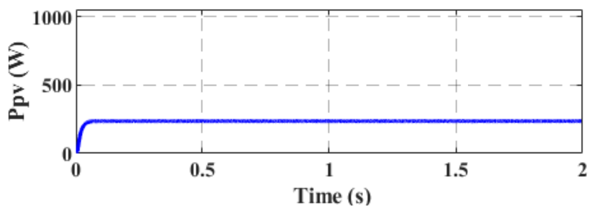

Fig. 8: Tracking performance under PSC2 using theP&O algorithm

This scenario is more complicated since the PV output characteristic presents four peaks, where the GMPP is at 411.5 W and is located at the second peak of the (P-V) output curve. As a result, the P&Oalgorithm was trapped in a local maximum; however, the PSO was able to escape this trap and converge to real GMMP despite there being another local maximum at 408.8 W in the vicinity of the GMPP.

D. Tracking under PSC3

As a third test, a set of solar irradiations is presented to the system. In this case, the PV output characteristic also shows four peaks, where the GMPP is found at the last position of the curve, as shown in Fig. 2. The obtained resultsare illustrated in Fig. 9 and Fig. 10.

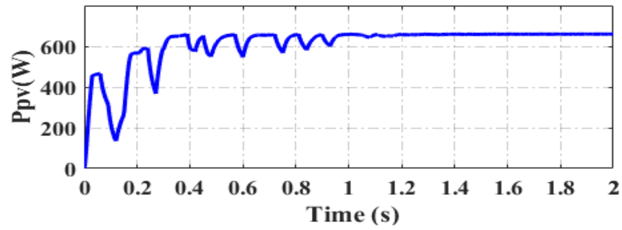

Fig. 9: Tracking performance under PSC3 using the PSO algorithm

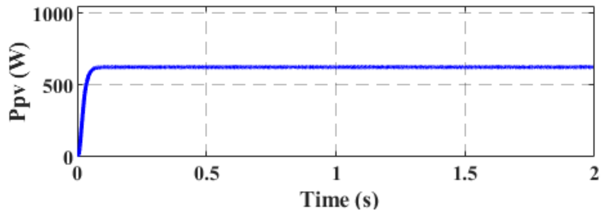

Fig.10: Tracking performance under PSC3 using the P&O algorithm

Both algorithms are tested against the third scenario to confirm their suitability to monitor partial shading situations. In this case, the PV output characteristic presents three local maxima and one global maximum at 660 W shifted to the end of the PV output characteristic. As illustrated in Fig. 9, the PSO algorithm converges effectively to the real GMPP, whereas the P&Ois trapped in a local peak 623 W.

E. Tracking under PSC4

To confirm the efficiency of these algorithms in monitoring the optimum power under various weather circumstances, the proposed system is tested against PSC4 (500 – 200- 800 – 400 W/M²) which simulates a real daily variations of solar irradiation, where the values are chosen to vary in both ascending and descending order. The corresponding P-V curve for this scenario is shownin Fig. 11whereas the dynamic responses are illustrated in Fig. 12 and Fig. 13.

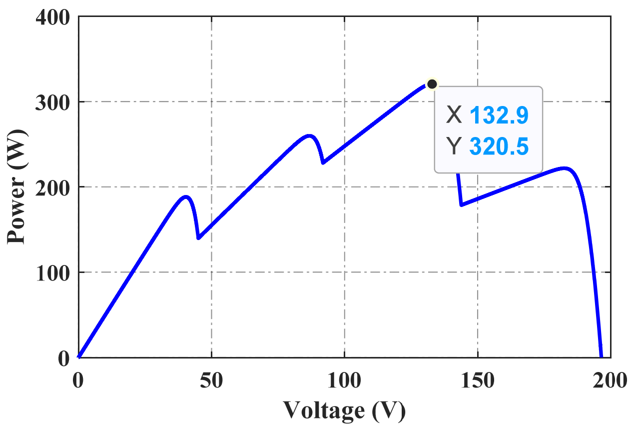

Fig. 11: Output characteristic under PSC4

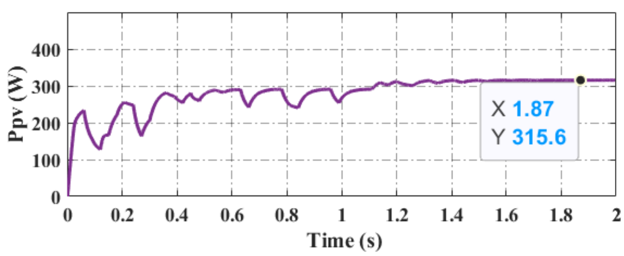

Fig. 12: Tracking performance under PSC4 using the PSO algorithm

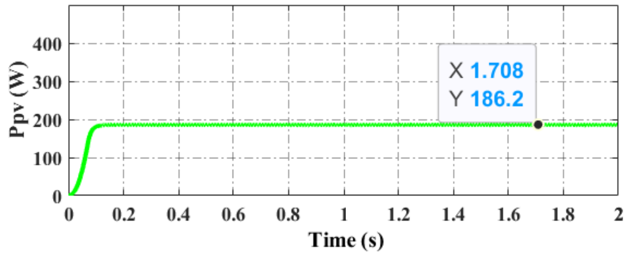

Fig. 13: Tracking performance under PSC4 using theP&O algorithm

The dynamic responses corresponding to this scenario illustrate the outperformance of the PSO under a real life change in irradiation. The PSO could converge to the GMPP. In contrast, the P&O algorithm was trapped in a local maximum leading to important power losses. Table. III illustrates the performance comparison of the two algorithms for the different scenarios.

Table. III
PERFORMANCE EVALUATION BETWEEN PSO AND P&O

Scena -rios	MPPT TECHNIQUE	GMPP (W)	Pmax(W)	Static Eff. (%)	Dynamic Eff.(%)
STC	PSO	999.6	999.8	99.98	90.3
	P&O	995.2		99.53	98.1
PSC1	PSO	488	490.5	99.49	94
	P&O	486.4		99.16	98
PSC2	PSO	408.5	411.5	99.27	90.91
	P&O	232.6		56.52	55.97
PSC3	PSO	658	660	99.69	96.89
	P&O	623		94.39	93.25

F. Tracking under rapid change in irradiance

To confirm the robustness of the proposed system in tracking the GMPP under a more challenging scenario, the system is tested against a rapid change in irradiance every three seconds. As shown in the dynamic response in Fig.14, Fig. 15, Fig. 16 and Fig. 17, the proposed algorithm successfully tracks the real power as the shading profiles change from PSC1 to PSC3. This change in irradiation is instantly detected by the reset function, which restarts the search process for the new GMPP.

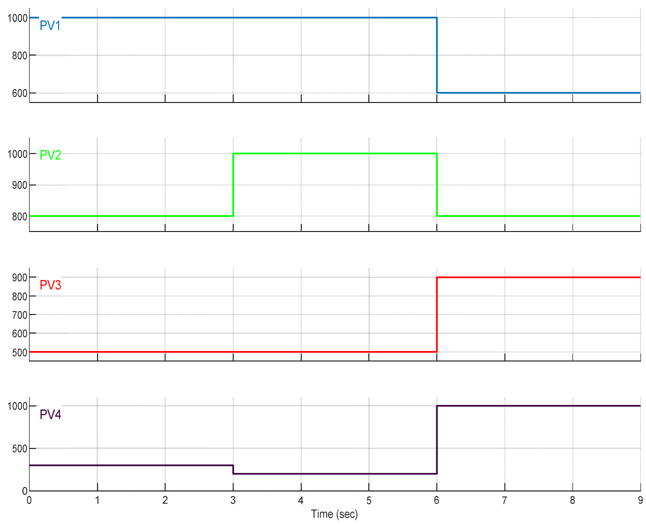

Fig. 14: Irradiance Scenarios

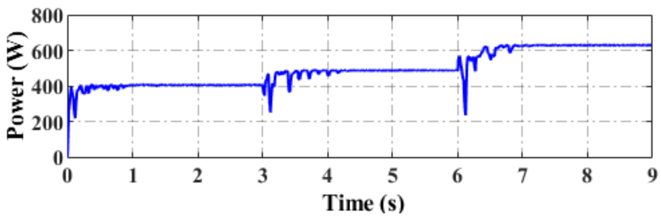

Fig. 15: Tracking performance under rapid change of irradiance

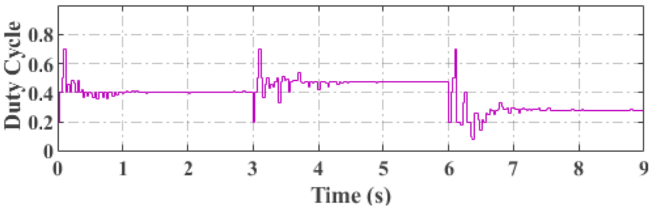

Fig. 16: Duty Cycle

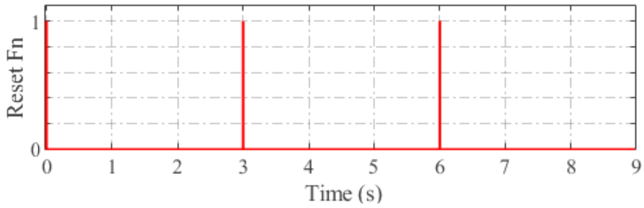

Fig. 17: Reset Function

As illustrated in the dynamic response under this complex scenario, the proposed system tracks successfully the real GMPP demonstrating an outstanding robustness and stability against complex dynamic weather circumstances. This performance is achieved since the system integrates a reset function that initiates the algorithm upon irradiation change detection.

V. Conclusion

To investigate the performance of maximum power point tracking (MPPT) under partial shading conditions (PSCs), two distinct optimization techniques are evaluated and compared: the conventional Perturb and Observe (P&O) method and a swarm intelligence-based approach, namely Particle Swarm Optimization (PSO). The comparative analysis is conducted under varying environmental conditions, including uniform irradiance, complex partial shading scenarios, and rapid irradiance changes. As evidenced by the results presented in Table III, the PSO algorithm exhibits superior performance in accurately identifying and tracking the GMPP, achieving a steady-state efficiency exceeding 99% across all test cases. This enhanced efficacy stems from PSO's global search mechanism, which systematically explores the entire solution space to avoid suboptimal convergence. In contrast, the P&O technique, relying on a localized search strategy, is prone to convergence at local maxima, as demonstrated in Scenario 2, where its efficiency declines to 56.52%, resulting in significant power losses. Consequently, the findings suggest that PSO is a more robust and reliable solution for GMPP tracking under both uniform and complex partial shading conditions, making it a preferable choice for photovoltaic systems operating in varying environmental conditions.

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