Neuro-evolutionary genetic algorithm for global MPPT under partial shading conditions: a comparative analysis with PSO

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ABSTRACT

Maximizing power extraction from photovoltaic (PV) systems is crucial for their overall efficiency. However, under partial shading conditions (PSCs), the power-voltage curve shows several points of maximum power. This phenomenon often leads to traditional maximum power point tracking (MPPT) algorithms getting stuck at suboptimal local peaks, resulting in substantial energy losses. To solve this, we introduce a novel neuro-evolutionary genetic algorithm (NEGA) for global MPPT. This hybrid algorithm integrates a neural network to intelligently guide the evolutionary search process, improving its GMPP tracking. The performance of the NEGA controller is rigorously compared against the widely used particle swarm optimization (PSO) algorithm via MATLAB/Simulink simulations across various irradiance scenarios. Results under severe PSCs demonstrate NEGA's superior tracking efficiency of 98.69%, far exceeding PSO's 76.02%. Moreover, NEGA achieves a faster convergence time of 0.1 s under dynamic irradiance, compared to 0.6s for PSO. The study concludes that NEGA is a robust and highly efficient solution for global MPPT, ensuring maximum power harvesting from PV systems under challenging operating conditions.

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1. INTRODUCTION

To mitigate climate change, countries are increasingly adopting photovoltaic (PV) systems due to their cost-effectiveness and low ecological footprint [1]. However, PV output is non-linear, depending heavily on solar irradiance and temperature [2]. Maximizing energy yield through maximum power point tracking (MPPT) is therefore essential for the economic viability of these installations [3], [4].

While the power-voltage (P-V) profile shows a single peak under uniform conditions, partial shading conditions (PSCs) create a complex, multi-modal characteristic featuring a single global maximum power point (GMPP) and multiple local maximum power points (LMPPs) [5]. Traditional algorithms like perturb & observe (P&O) and incremental conductance (Inc-Cond) often fail by trapping at LMPPs. Similarly, standard particle swarm optimization (PSO) suffers from stagnation or premature convergence in dynamic environments, especially with small swarm sizes [6], [7].

Metaheuristic techniques like PSO and genetic algorithms (GA) show promise in global peak detection [8]. Yet, these methods can still suffer from slow tracking speeds or entrapment in complex shading patterns, while Fuzzy Logic systems require extensive expert tuning [9]. To address these gaps, this paper proposes a novel neuro-evolutionary genetic algorithm (NEGA). This hybrid approach integrates the global search of a GA with an intelligent neural network to accelerate convergence and prevent entrapment.

The main contributions of this work are: i) NEGA Development: A new hybrid controller specifically for global MPPT under complex PSCs; ii) Comparative evaluation: A rigorous assessment against PSO under high, low, and non-uniform irradiance; and iii) Performance verification: Demonstrating NEGA's superior tracking efficiency, speed, and robustness. The remainder of this study covers mathematical system modeling, algorithm implementation, comparative simulation analysis, and future research directions.

2. SYSTEM MODELING AND METHODS

2.1. PV panel model

To accurately simulate the performance of the MPPT controllers, it is essential to generate an accurate mathematical model of the PV array. In this study, we chose to implement the single-diode equivalent circuit model, which is the most widely used model in the literature, and which strikes a good balance between accuracy & computational ease [10]. As shown in Figure 1, the model contains a series resistance (R_s) with a parallel circuit containing a light-generated current source (I_{ph}), a diode (D), and a shunt resistance (R_{sh}).

A PV array's terminal current (I) and voltage (V) are attached by the non-linear equation that follows:

$$I = N_p.I_{ph} - N_p.I_0.\left[exp\left(\frac{q\left(V + I.\frac{N_S}{N_p}.R_S\right)}{N_p.a.k.T}\right) - 1\right] - \frac{V + I.\frac{N_S}{N_p}.R_S}{R_{sh}} \quad (1)$$

$$I_{ph} = \left[I_{sc,n} + K_i(T - Tn)\right].\frac{S}{S_n} \quad (2)$$

$$I_0 = I_{rs}.\left(\frac{T}{T_n}\right)^3.exp\left[\frac{q.E_g}{a.k}.\left(\frac{1}{T_n} - \frac{1}{T}\right)\right] \quad (3)$$

I_{ph} is the photocurrent (A) from solar irradiance and is a function of irradiance and cell temperature, with maximum output current described by (2). The I0 term refers to the diode reverse saturation current (A), which is also a temperature-dependent value based on (3).

2.2. Modeling the DC-DC boost converter

A DC-DC converter represents a crucial connection between the PV array and the load, functioning as the actuator for the MPPT algorithm [12] [13]. This investigation employs a boost (step-up) converter, which operates, as desired, when there is a load voltage requirement that exceeds the PV array's output voltage. The schematic for the boost converter is seen in Figure 2.

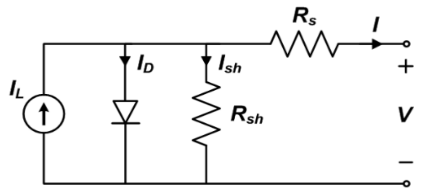

Figure 1. Diagram of the single-diode equivalent circuit [11]

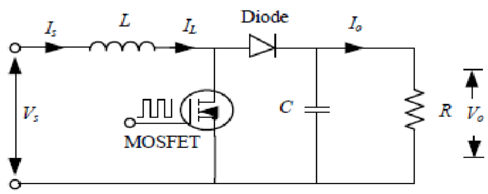

Figure 2. Boost converter schematic

The primary function of the boost converter is to vary the effective impedance of the PV array, which in turn will regulate its operating voltage V_{pv} and current I_{pv}. This is done by changing the duty cycle (D) of the pulse width modulation (PWM) signal given to the gate of the power switch (S). The optimal duty cycle that drives the PV array to operate at its maximum power point is the output from the MPPT controller [14]. For operation in continuous conduction mode (CCM), the relationship between the duty cycle D of the switch, output voltage V_o, and PV array input voltage V_{pv} can be derived by (4).

$$V_0 = \frac{V_{pv}}{1-D} \quad (4)$$

The following state-space equations for the inductor current (iL) and capacitor voltage (vC) represent the dynamic behavior of the boost converter:

$$\frac{d_{iL}}{dt} = \frac{1}{L}\left(V_{pv} - (1-D).V_0\right) \quad (5)$$

$$\frac{d_{vC}}{dt} = \frac{1}{C}\left((1-D).i_L - \frac{V_0}{R}\right) \quad (6)$$

The MPPT algorithm's duty cycle output generates the high-frequency PWM signal, which controls the energy flow to the load [15].

2.3. Simulation setup and parameters

To evaluate the performance of the benchmark PSO controllers and the proposed NEGA controllers, simulations were carried out in the MATLAB Simulink environment. The system included a PV array feeding a resistive load through a DC-DC boost converter. Table 1 has a summary of the simulation parameters for the components. The PV array included four "Advance Power API-P300" modules linked in series.

Table 1. Simulation parameters for the PV system

PV module (API-P300 at STC):	PV array configuration:	Boost converter:	System load
Maximum-power (P_{max}): 303.16 W Open-circuit voltage (V_{oc}): 44.86 V Short-circuit current (I_{sc}): 8.54 A Voltage at max power (V_{mpp}): 37.66 V Current at max power (I_{mpp}): 8.05 A	Series-connected modules (Ns): 4 Parallel strings (Np): 1	Input-inductor (L): 5 mH Output-capacitor (C): 470 µF Switching frequency (fsw): 20 kHz	Resistive load (R): 50 Ω

2.4. The particle swarm optimization (PSO) MPPT algorithm

PSO is a stochastic optimization method that mimics the social behavior of bird flocks or fish schools. In the context of MPPT, PSO is highly effective for global optimization problems like partial shading because it can locate the GMPP by searching the full search space [16] [17]. The algorithm starts by creating a swarm of particles, each representing a possible solution. For MPPT, the "position" of a particle is its corresponding duty cycle (D) [18]. Each particle's fitness is determined by its resulting PV output power. Based on its own best position (pbest) and the swarm's global best position (gbest), each particle modifies its velocity. to navigate the search space [19]. The flowchart in Figure 3 details the PSO-based MPPT controller, which functions by repeatedly updating the position and velocity of each particle in the swarm.

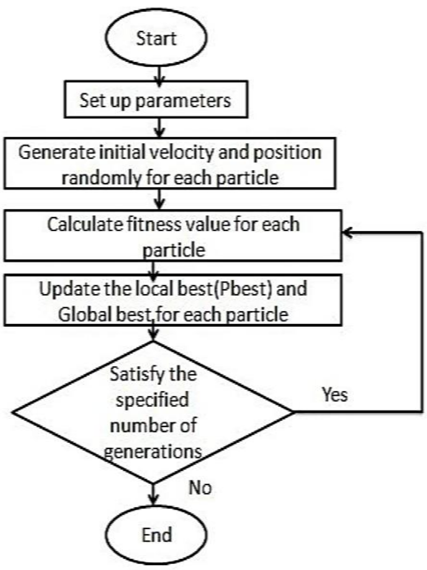

Figure 3. PSO algorithm flowchart for MPPT [20]

2.5. The proposed neuro-evolutionary genetic algorithm (NEGA) MPPT

To improve upon conventional metaheuristic methods, this paper introduces a novel NEGA. This hybrid method merges the global search strength of a GA with the adaptive learning power of an artificial neural network (ANN). The synergy between these two components allows for a faster and more reliable convergence to the GMPP, especially under challenging partial shading conditions.

2.6. The genetic algorithm (GA) foundation

The "evolutionary" core of the NEGA framework is a standard GA, an approach to find the best solutions by mimicking natural selection [21], [22]. For the MPPT problem, each potential solution, or "chromosome" directly sets the converter's duty cycle D. The effectiveness of each duty cycle is evaluated using a fitness function defined as the resulting PV output power, f(D) = Ppv, where higher power corresponds to higher fitness [23] [24].

The GA iteratively refines its population of solutions using three primary genetic operators. First, Selection identifies parent solutions for breeding, with fitter individuals being preferentially chosen via a Roulette Wheel method [25]. Next, Crossover combines these parents to generate new offspring. Finally, Mutation introduces small, random changes to the solutions, which preserve genetic diversity and stop the algorithm from converging on a local optimum too early [26], [27].

2.7. The neural network integration (The "Neuro" Component)

The primary novelty of the NEGA lies in its "neuro" component a pre-trained ANN that intelligently guides the GA's search. The ANN, implemented as a lightweight multi-layer perceptron (MLP), functions as a search-region predictor. The system is trained offline to understand the non-linear link between observable PV characteristics (e.g., V_{oc}, I_{sc}) and the probable GMPP region. When a significant change in power triggers a new search, the ANN outputs an estimated optimal duty cycle, Dest. Instead of starting with a random population, the GA is then initialized with a set of solutions centered around this Dest. This "intelligent initialization" provides the GA with a significant head start, focusing its search on the most promising region of the P-V curve and dramatically improving both convergence speed and the reliability of finding the true GMPP.

2.8. NEGA operational flow

The NEGA-based MPPT controller's complete operational flowchart is depicted in Figure 4. The process begins when a change in conditions is detected. The ANN will provide a preliminary estimate and then the GA will refine the preliminary estimate over several generations to accurately find the GMPP solution. The specific parameters used for the NEGA implementation can be found in Table 2.

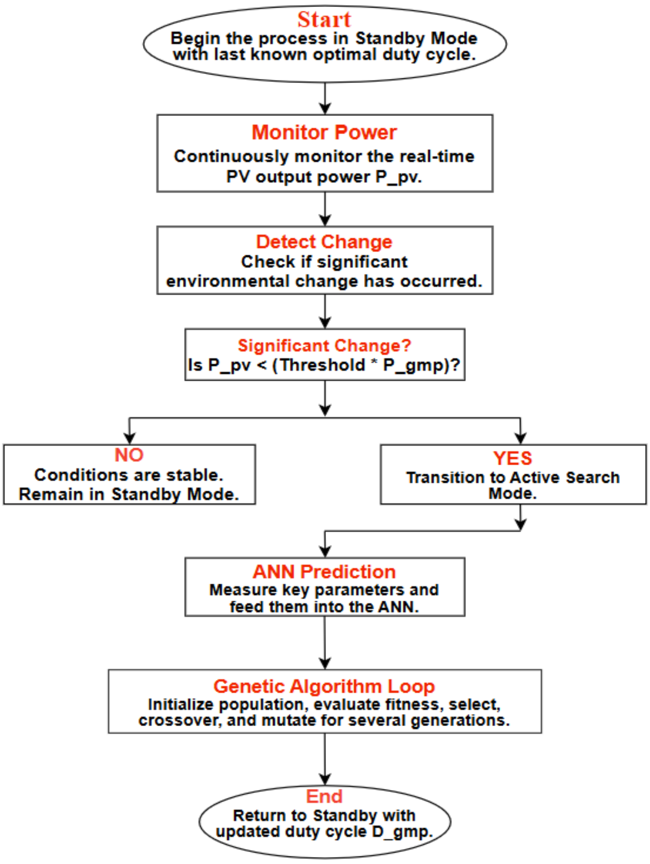

Figure 4. The proposed NEGA flowchart for global MPPT

Table 2. NEGA controller parameters

Category	Parameter	Value/method
Chromosome & fitness	Representation	Floating-point duty cycle (D)
	Fitness function	f(D) = Ppv
Genetic algorithm parameters	Population size	10
	Number of generations	5
	Selection method	Roulette Wheel
	Crossover probability (Pc)	0.8
	Mutation probability (Pm)	0.1
Neural network component	Type	Multi-layer perceptron (MLP)
	Training method	Offline (Levenberg Marquardt)
	Function	Predicts initial GMPP region

3. RESULTS AND DISCUSSION

To test the performance of our proposed NEGA and benchmark against the PSO, a variety of simulations were executed. This section will first describe the simulation environment and the test scenarios created to assess the astuteness of the controllers under many operating conditions. Then we will provide a comprehensive analysis of the results.

3.1. Simulation setup

We are going to use MATLAB-Simulink software to model and simulate the entire photovoltaic power system. The simulation model shows three main subsystems, which are illustrated in Figure 5. The PV array block is used to express the mathematical model presented in section 2.1; The boost-converter, which is the MPPT actuator; and the MPPT Controller block, which is either the PSO or proposed NEGA algorithm. The system will be connected to a 50 Ω resistive load. Specific parameters for the PV array and converter can be found in Table 1.

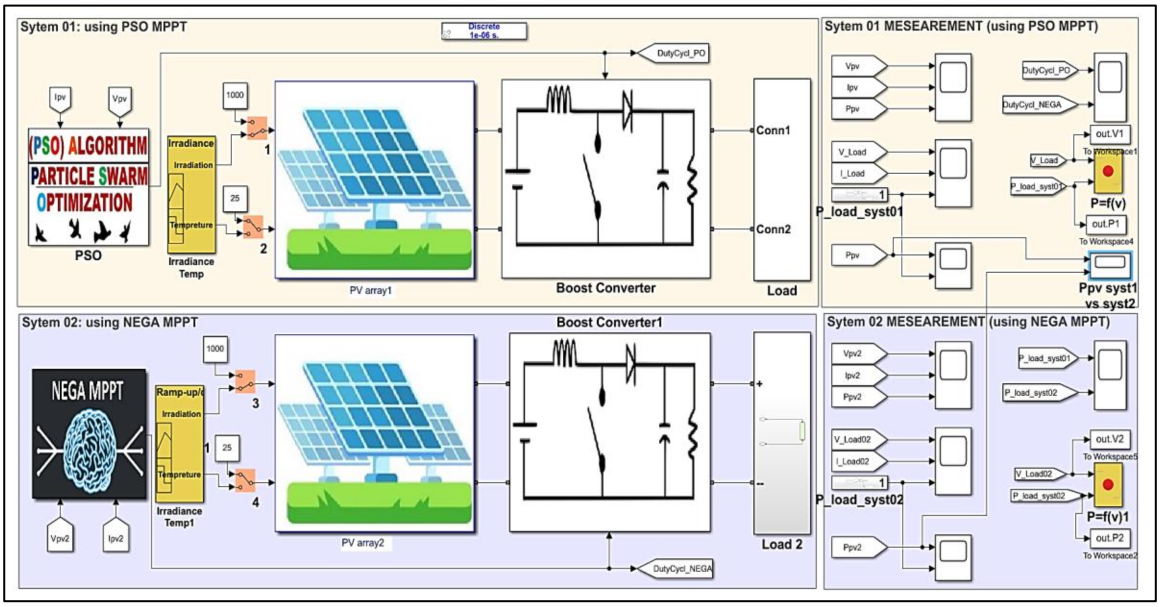

Figure 5. Simplified block diagram of the simulated PV system with MPPT controllers

3.2. Test scenarios

In order to deliver a complete analysis, the performance of the MPPT algorithms was tested under three distinct cases. For all tests, the temperature was constant at 25 °C:

- Case 1 - High uniform irradiance: The standard test case to measure an efficiency baseline of tracking speed and efficiency, uniformly at 1000 W/m².
- Case 2 - Partial shading condition (PSC): The most critical test, designed to evaluate global search capability. To create a multi-peaked P-V curve, the PV array was modelled as two series-connected sub-strings receiving non-uniform irradiances of 800 W/m² and 300 W/m², respectively.
- Case 3 - Low uniform irradiance: A low-light test with uniform irradiance of 500 W/m² to assess performance under less ideal power conditions.

The controllers' performance was analyzed based on their tracking efficiency, response time, and steady-state stability across these dynamic cases. The specific Simulink model for implementing the PSC is detailed in Figure 6.

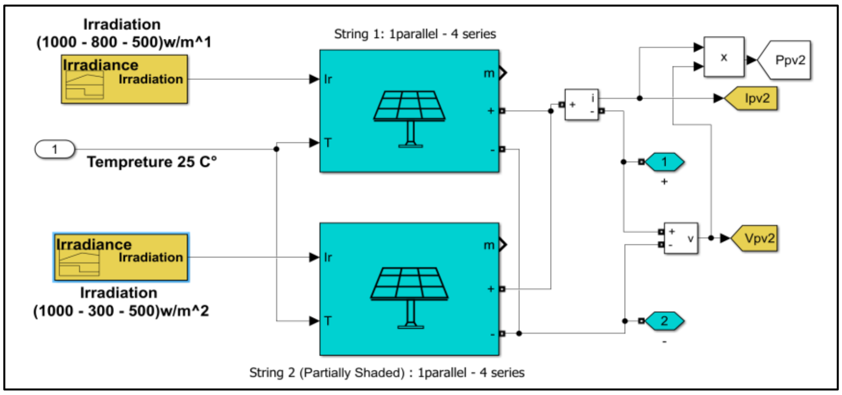

Figure 6. Simulink implementation model for creating the PSC by applying different irradiance levels to series-connected sub-strings of the PV array

3.3. Performance analysis under varied irradiance conditions

The performance of the proposed NEGA and the benchmark PSO controllers was evaluated across the three defined test scenarios. The PV array's I-V and P-V curves under uniform illumination (1000, 800, and 500 W/m²) are depicted in Figure 7. These curves establish the theoretical maximum power available under each condition.

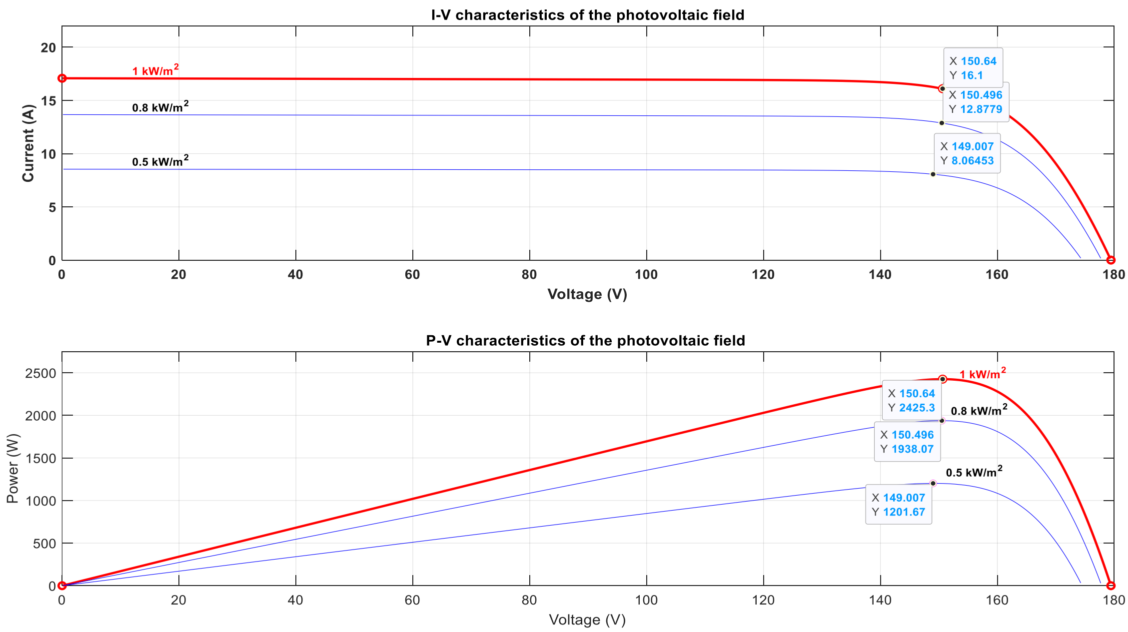

Figure 7. Characteristics of the PV array (I-V and P-V) under uniform irradiance

The dynamic response of the system under step changes in irradiance is presented in Figures 8, 9, and 10. The system transitions through all three test cases during these conditions. These figures provide a comprehensive view of the tracking behavior of the algorithms.

- Case 1 - High and uniform irradiance (0–2s): As observed in the initial phase (0 to 2 s) of the simulation in Figure 10, both controllers attempt to track the MPP of approximately 2425.3 W. The NEGA controller demonstrates rapid convergence, settling in about 0.1 s, while the PSO controller takes longer (0.6 s) but achieves a slightly higher steady-state power in this specific uniform case.

- Case 2 - Partial shading condition (2–5 s): This scenario represents the most critical test of the algorithms' global search capabilities. At t = 2 s, the irradiance changes to a non-uniform profile (800 W/m² and 300 W/m²), creating a complex P-V curve with a GMPP at 1938.07 W. The PSO controller (Figure 8) fails to locate the GMPP. It becomes trapped in a local maximum, achieving a steady-state power of only 1473.42 W. This represents a significant power loss and highlights the primary weakness of standard PSO in complex shading landscapes. In stark contrast, the NEGA controller (Figure 9) successfully identifies and converges to the true GMPP. As shown in the comparative plot (Figure 10), it rapidly escapes the local peak and settles at a power of 1912.52 W. This demonstrates the effectiveness of the neuro-evolutionary approach in navigating multi-modal search spaces. The convergence is swift, occurring within 0.2 s of the irradiance change.

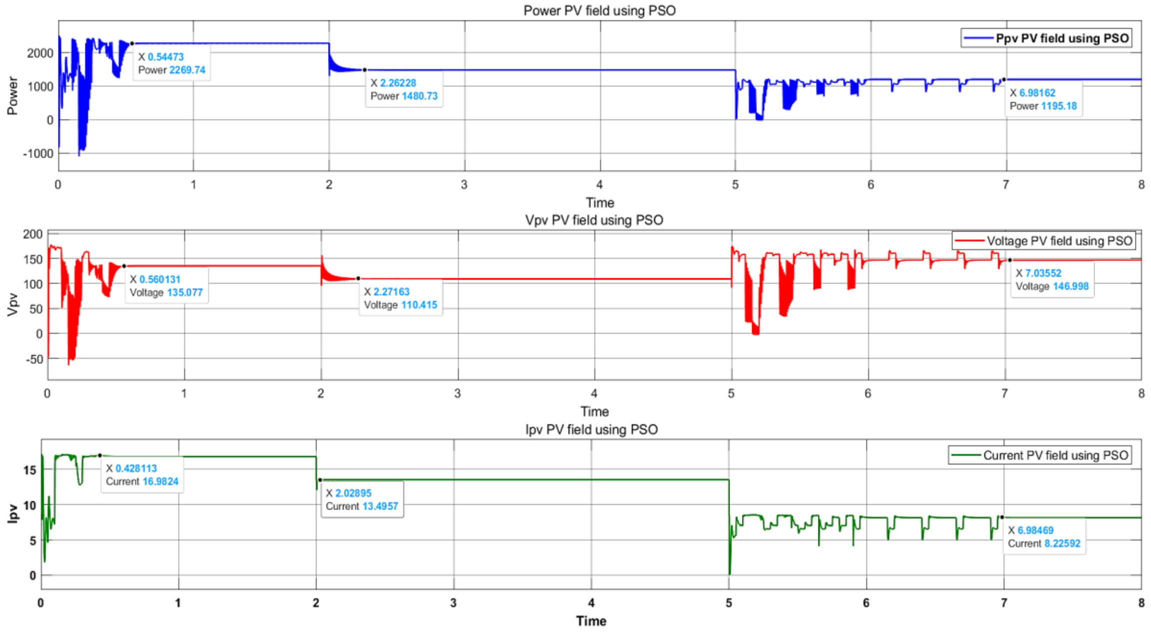

Figure 8. PSO controller's reaction to abrupt shifts in solar irradiance

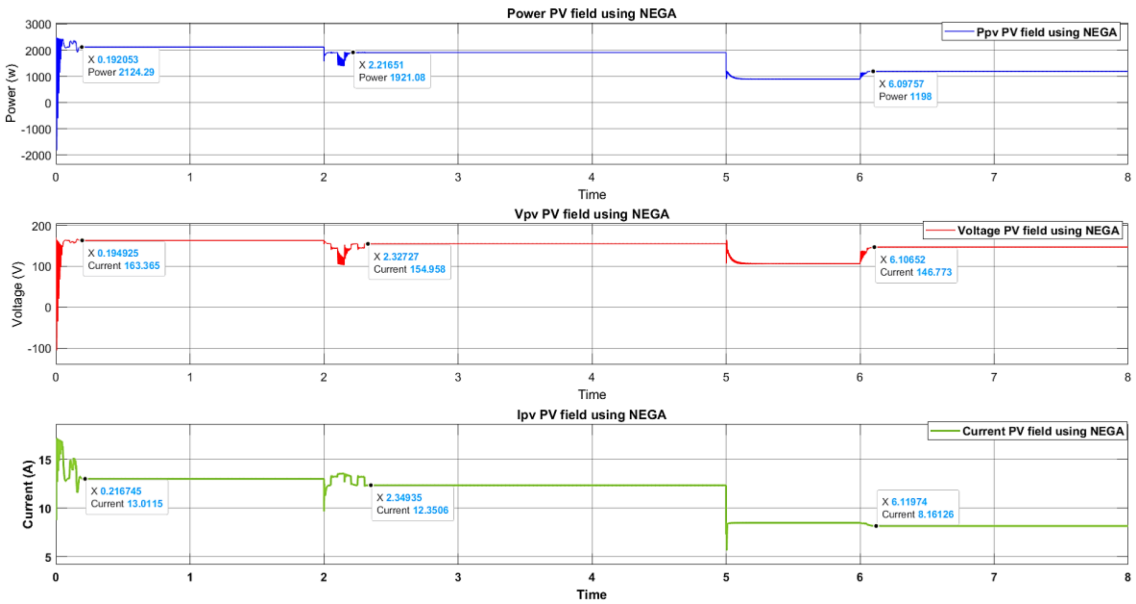

Figure 9. Dynamic response of the NEGA controller under step changes in irradiance

- Case 3 - Low and uniform irradiance (5 s onwards): At t = 5 s, the irradiance is uniformly reduced to 500 W/m² across the array, with a theoretical MPP of 1201.67 W. Both algorithms successfully track this new MPP. The NEGA controller again shows a faster response time of 0.2 s compared to the PSO's 1.0 s. Both algorithms achieve excellent steady-state efficiency in this low-light condition.

To further analyze the operational dynamics, the behavior of the output duty cycle for both algorithms is presented in Figure 11. Figure 11 highlights the contrasting search behaviors of the two controllers. While the PSO exhibits high volatility and wide duty cycle oscillations during search phases (0–2 s and 5 s+), NEGA provides a stable, decisive response with smooth transitions. Notably, during partial shading (2–5 s), the PSO duty cycle remains trapped in a local optimum, whereas NEGA successfully initiates a smooth search to locate the true Global MPP duty cycle.

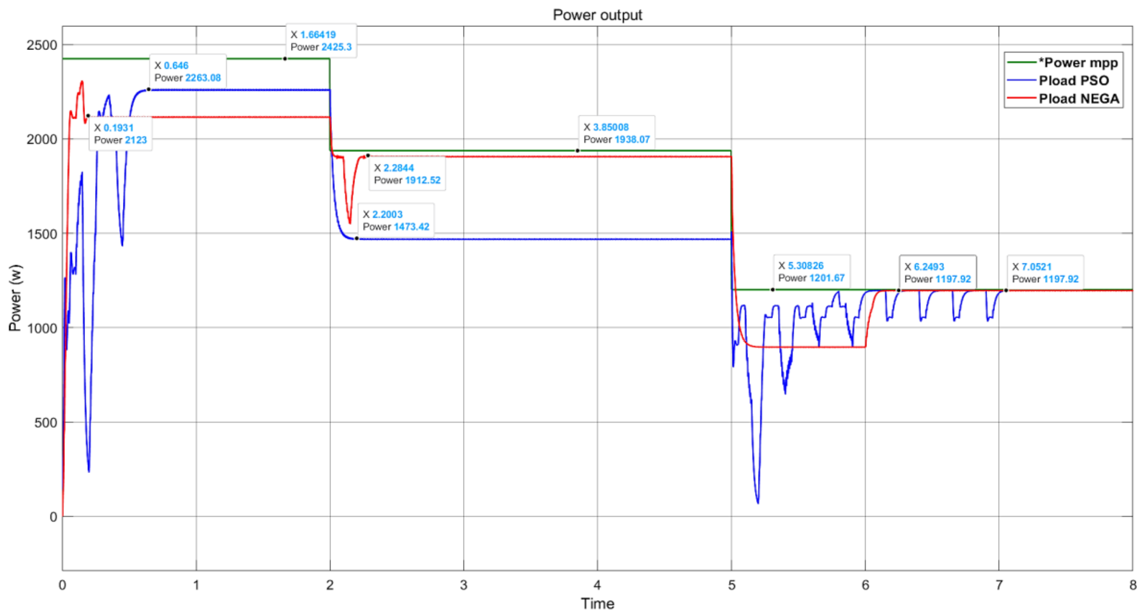

Figure 10. Comparative tracking performance of NEGA and PSO controllers under irradiance changes

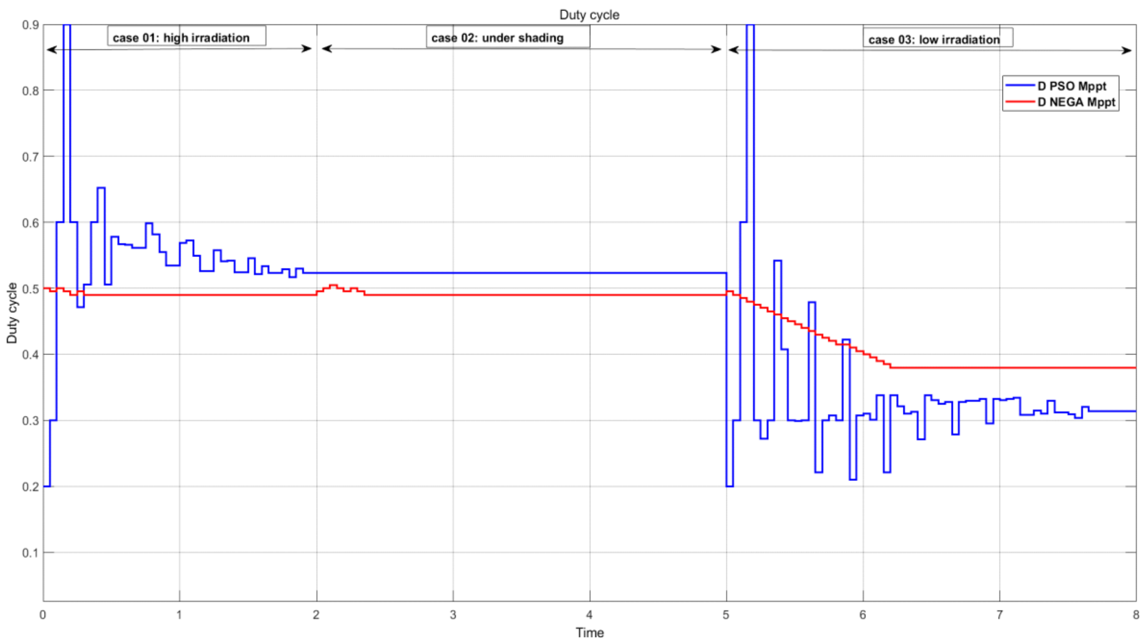

Figure 11. Comparative duty cycle evolution for NEGA and PSO controllers under dynamic conditions

3.4. Comparative analysis and discussion

For a numerical comparison of the controllers' performance, the response time and MPPT tracking efficiency (ηMPPT) were calculated in each case. The efficiency is calculated by dividing the actual power extracted by the controller by the PV array's available theoretical maximum power, as given by (7):

$$\eta MPPT(\%) = \frac{P_{MPPT}}{P_{max}} \times 100 \quad (7)$$

Table 3 summarizes the key performance metrics. NEGA demonstrates a clear performance advantage under partial shading (Case 2), achieving 98.69% efficiency compared to PSO's 76.02%, which failed to locate the GMPP. Beyond increased energy yield, NEGA's superior stability and minimal oscillation produce a cleaner current waveform through the Boost converter. By reducing dynamic error and off-peak operation, the controller minimizes RMS current, effectively lowering thermal stress and conduction losses in the MOSFET and inductor. This enhances both energy extraction and the long-term reliability of the power electronic components.

Table 3. Performance comparison of PSO and NEGA controllers

Performance Parameters	Irradiation: String01: 1000 w/ m^2 String02: 1000 w/ m^2	response - time (s)	Irr (partial shading): String01: 800 w/ m^2 String02: 300 w/ m^2	response – time (s)	Irradiation: String01: 500 w/m^2 String02: 500 w/m^2	response - time (s)
Power system 01 PSO algorithm (W)	2263.08	0.6	1473.42	0.2	1197.92	1
Power system 02 NEGA algorithm (W)	2123	0.1	1912.52	0.2	1197.92	0.2
PV field max Power (W)	2425.3		1938.07		1201.67	
ηMPPT Efficiency system 01 (%)	93.31		76.02		99.69	
ηMPPT Efficiency system 02 (%)	87.53		98.69		99.69	

4. CONCLUSION

This research introduces the NEGA for PV maximum power point tracking. MATLAB/Simulink simulations under varied irradiance and PSC confirm NEGA's superiority over the standard PSO algorithm. While both perform well under uniform light, NEGA excels in complex PSC scenarios-achieving 98.69% tracking efficiency, whereas PSO is trapped in local optima at only 76.02%. Furthermore, NEGA's hybrid GA-NN architecture ensures faster response times and minimal power loss during dynamic transitions, providing a robust solution for global MPPT. Future work will focus on the experimental validation of the NEGA controller through hardware implementation on a DSP or FPGA. Testing on physical PV arrays will verify their performance against real-world noise and component non-idealities, paving the way for commercial application.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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So : **So**ftware
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

All data necessary to reproduce the findings presented in this study are available from the corresponding author upon reasonable request.

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