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Synergistic Application of Particle Swarm Optimization and Gravitational Search Algorithm for Solar PV Performance Improvement

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Abstract

This study aims to optimize photovoltaic systems by developing a novel hybrid metaheuristic approach for maximum power point tracking (MPPT). The proposed method eclectically combines particle swarm optimization (PSO) and gravitational search algorithm (GSA) to overcome individual limitations and leverage complementary strengths. PSO, while surpassing in exploration, may suffer from premature convergence. GSA demonstrates strong exploitation capabilities but can struggle with slow convergence. A simulation model is developed to evaluate the hybrid algorithm's performance in optimizing PV systems' duty cycle. The approach utilizes the exploitation capabilities of PSO and GSA to navigate the search space effectively. Results demonstrate that the hybrid algorithm outperforms traditional techniques and standalone metaheuristics, achieving improved convergence time, faster settling time, and enhanced MPPT tracking efficiency. Under varying irradiance conditions, the proposed method consistently delivers higher power generation and improved overall PV system efficiency, offering a promising solution for optimizing PV systems and maximizing energy generation.

Keywords: gravitational search algorithm (GSA), particle swarm optimization algorithm (PSO), maximum power point tracking (MPPT), photovoltaic (PV) system

1. Introduction

In the face of escalating energy demands and growing concerns over environmental sustainability, harnessing renewable energy sources has become a global imperative. Solar photovoltaic (PV) systems, which transform sunlight into electrical energy, have been necessitated [1]. PV systems offer a clean, renewable, and sustainable source of energy, embodying their inherent importance in the transition towards a greener and environmentally-friendly future. PV systems rely on solar panels, which are composed of interconnected PV cells that absorb sunlight and generate electrical current [2]. However, the effectiveness of these schemes is influenced by various environmental factors, such as solar irradiance, temperature, and shading conditions. To maximize the power output from solar PV systems, advanced maximum power point tracking (MPPT) techniques underscore functional indispensability [3-4].

MPPT algorithms continuously adjust the operating point of the PV system to ensure the system operates at the maximum power point (MPP), thereby extracting the highest possible power from the solar panels under varying conditions [5]. Several MPPT methods are widely deployed, such as perturb and observe (P&O) and incremental conductance (IC), while effective in certain scenarios, often struggle to cope with rapidly changing environmental conditions or complex system dynamics [6]. To address these limitations, researchers have explored the application of metaheuristic optimization

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algorithms for MPPT in PV systems [7]. These algorithms, inspired by natural phenomena or biological processes, offer robust and effective solutions for complex optimization problems [8]. Two prominent algorithms, the have attracted attention in the field of MPPT, are the particle swarm optimization (PSO) and the gravitational search algorithm (GSA).

The PSO algorithm is a population-based optimization technique that emulates the collective behavior observed in bird flocking or fish schooling. Technically the PSO commences by initializing a swarm of particles, where each particle represents a potential solution to the problem [9-10]. The PSO iteratively updates the positions and velocities of the particles based on their respective best solutions and the globally optimal solution found by the entire swarm. This approach has demonstrated effective exploration capabilities, enabling the PSO to efficiently navigate the search space and identify promising regions of interest.

On the other hand, the GSA draws inspiration from the principles of Newtonian gravity and mass interactions [11]. The GSA initializes a population of agents, conceptualized as masses, and iteratively adjusts their positions based on the gravitational forces exerted by other agents within the population. The GSA has attested to its potency of optimization, offering robust exploitation capabilities and the ability to converge towards optimal solutions efficiently by capitalizing on the attractive forces between agents.

Both PSO and GSA have shown promising results in MPPT applications, each algorithm has its strengths and limitations. The PSO excels in exploration but may struggle with premature convergence or stagnation in complex search spaces [12]. Despite the effectiveness of PSO in MPPT, the algorithm can incur steady-state oscillations, thereby impacting system stability [13]. Traditional PSO algorithms might fail under partial shading conditions without significant modifications to improve accuracy and convergence speed [14]. Conventional PSO methods exhibit steady-state oscillations and slow tracking under fickle environmental conditions [15]. Classical PSO techniques have high oscillations around the MPP and slower convergence times under dynamic weather conditions [16]. The traditional PSO approach suffers from lower accuracy and speed, particularly under partial shading scenarios [17].

Conversely, GSA demonstrates strong exploitation capabilities but may suffer from slow convergence or lack of diversity in certain scenarios [18]. While implementing GSA, potential issues with convergence speed and accuracy in certain shading conditions should be considered [19]. Despite its effectiveness, the combination of GSA with other algorithms, such as the traditional P&O method, introduces complexity and potential inefficiencies in certain conditions [20]. Additionally, the integration of GSA with PSO may hinder the practicability with increased computational complexity [21-22]. To overcome these drawbacks and leverage the complementary strengths of both algorithms, a proposed hybrid metaheuristic approach that combines PSO and GSA is introduced. By integrating the exploration capabilities of PSO with the exploitation strengths of GSA, these hybrid algorithms aim to strike a balance between global search and local refinement, potentially facilitating improved performance and faster convergence toward optimal solutions.

The proposed Hybrid particle swarm optimization and gravitational search algorithm (HPSO-GSA) algorithm, which is presented in this research, integrates the principles of PSO and GSA to optimize the duty cycle solutions for PV systems. In this hybrid method, a swarm of particles is initialized to represent potential solutions. The PSO component directs the particles towards promising areas, while the GSA component calculates gravitational forces and masses to enhance the exploitation of optimal solutions. The algorithm updates the velocities and positions of particles by combining PSO and GSA equations, attaining a balanced approach between exploration and exploitation. By leveraging the strengths of both PSO and GSA, the HPSO-GSA algorithm aims to surpass the limitations of individual algorithms, furnishing a more robust and efficient optimization framework for MPPT in PV systems. This hybrid approach is expected to outperform traditional optimization techniques and single metaheuristic algorithms, resulting in higher power generation and improved efficiency under various operating conditions.

This paper is structured to commence with an exploration of MPPT in Section 2. Section 3 discusses PSO, while Section 4 covers the GSA. A novel HPSO-GSA method is introduced in Section 5, aiming to enhance optimization efficiency. Empirical results and discussions of this method are presented in Section 6, demonstrating its comparative advantages with conclusions in Section 7 with a summary of findings.

2. Maximum Power Point Tracking

MPPT is an essential technique used in solar PV systems to optimize power output and enhance system efficiency. MPPT algorithms continuously adjust the operating point of the PV system to the MPP, ensuring maximum power extraction from the solar panels under varying conditions [23]. A solar power system, as illustrated in Fig. 1, employs a hybrid MPPT strategy using the GSA and PSO. The system's core comprises a PV array that converts solar energy into electrical power, which is characterized by its voltage (Vpv) and current (Ipv). This power is subsequently fed into a DC-DC boost converter, which increases the PV array's voltage to a suitable level for the load [24]. The boost converter consists of an inductor (L) for energy storage, a diode (D) to prevent current backflow, and a capacitor (C) to smooth the output to the load. A transistor acts as a switch, toggling on and off rapidly, controlled by a pulse width modulation (PWM) signal. This PWM signal, which is modulated by the MPPT algorithm, is crucial for the boost converter's operation.

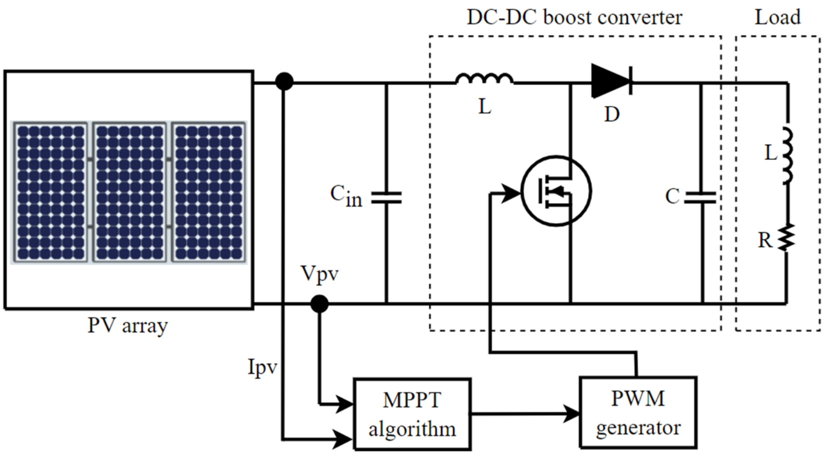


Fig. 1 Block diagram of PV system with MPPT

The duty cycle (D) of the boost converter is the ratio of the time the switch is closed (t_{on}) to the total switching cycle time (T), as shown in:

$$D = \frac{t_{on}}{T} \tag{1}$$

The output voltage (V_{out}) and input voltage (V_{in}) are defined in:

$$V_{out} = \frac{V_{in}}{1-D} \tag{2}$$

To find the duty cycle, the above equation is rearranged:

$$D = 1 - \frac{V_{in}}{V_{out}} \tag{3}$$

The system is designed to ensure that the maximum possible power is extracted from the PV array and delivered to the load efficiently, notwithstanding changes in sunlight intensity or temperature. This dynamic adjustment is key to maintaining system efficiency and is the primary function of the MPPT algorithm informed by the intelligent combination of GSA and PSO methodologies. The parameters used for this MPPT design are shown in Table 1.

Table 1 PV array system parameters

Parameters	Values
Max. power	55 W
Open circuit voltage Voc (V)	21.7 V
Short circuit current Isc (A)	4.8 A
Voltage at maximum power point Vmp (V)	15 V
Current at maximum power point Imp (A)	3.7 A
Input capacitor (C_{in})	470e-6
Inductor (L)	1.2e-3
Capacitor (C)	47e-6
Load resistance (R)	100 Ω

Fig. 2 delineates two graphs that depict the performance of a solar PV system under different levels of irradiance. The top graph is the I-V (current-voltage) curve, and the bottom graph is the P-V (power-voltage) curve. These graphs illustrate how the current and power output from a solar PV system change with voltage across various irradiance levels, ranging from 400 W/m^2 to 1000 W/m^2. As irradiance increases, both the current and voltage, at which the panel operates, also increase, facilitating higher current for a given voltage due to profuse solar energy. Similarly, higher irradiance leads to greater maximum power output, with the peak of each P-V curve representing the MPP. The MPPs, marked with circles on the P-V curves, indicate where the solar panel operates most efficiently. MPPT controllers aim to keep the panel operating at these points to maximize power extraction.

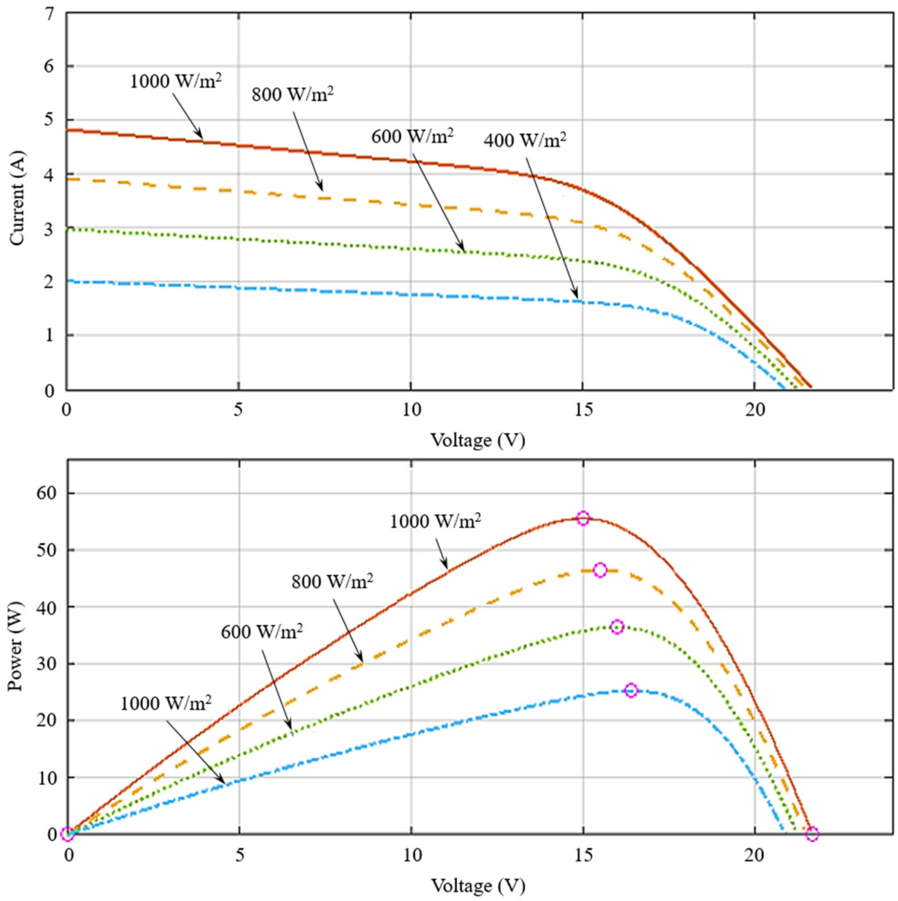


Fig. 2 PV and IV curve for solar module

3. Particle Swarm Optimization

The PSO algorithm is a robust computational method designed to optimize complex problems by simulating social behaviors observed in nature [17, 25]. The following paragraph outlines the stepwise execution of the PSO algorithm within a PV system to achieve MPPT efficiently.

(1) Initialization: The PSO algorithm commences by initializing a swarm of particles with variables for each particle's best-known position (`localbest`), the best-known position among all particles (`globalbest`), a counter (`k`), an array for best power output (`p`), an array for duty cycles (`dc`), the best power output (`Pbest`), the previous power output (`Pprev`), the current duty cycle (`dcurrent`), an index (`u`), velocity of each particle (`$\upsilon$`), and a conditional flag (`temp`). Duty cycles are randomly assigned to ensure a wide range of starting points, with `dcurrent` beginning at an assumed optimal of 0.5.

(2) Iterative loop: Within the main loop, the current duty cycle (`dcurrent`) is assigned to D, and the algorithm proceeds with sequential evaluations. If the conditional flag `temp` is negative, `temp` will be incremented for delay purposes, and the loop may exit early. Assuming the current power `P` exceeds `Pbest`, `Pbest` is updated to reflect this new maximum. Hypothesizing the iteration count (`k`) hasn't reached its threshold, the loop will continue for additional iterations. Postulating the change in power is minimal, indicating a potential plateau, the algorithm will reshuffle the duty cycles to stimulate new explorations.

(3) Particle update: The function iterates through each particle, updating personal best positions (`localbest`) based on improved power outputs (`p`). Once all particles are cycled through (`u` equals 4), the `globalbest` is updated. Particle velocities are recalculated considering the current velocity, proximate to personal and global bests, with new duty cycles computed accordingly. Particle position is updated in the following equation.

$$x_{i,d}^{(t+1)} = x_{i,d}^{(t)} + v_{i,d}^{(t+1)} \tag{4}$$

where, $x_{i,d}^{(t+1)}$ is the newly updated position of particle i at iteration $t+1$.

(4) Velocity update: Each particle's velocity is recalculated using the `updatevelocity` function, which incorporates a fraction of the particle's current velocity (inertia) and attractive forces towards personal and global bests (cognitive and social components). Stochastic elements (`c1` and `c2`) are introduced for robust search behaviors. Velocity update is governed by the following equations.

$$u_i^{(t+1)} = w.u_i^{(t)} + c_1\chi_1.\left(pbest_1 - x_i^{(t)}\right) + c_2\chi_2.\left(gbest - x_i^{(t)}\right) \tag{5}$$

where, $\upsilon_i^{(t+1)}$ is the velocity of particle i at iteration $t+1$.

(5) Duty update: The duty cycle for each particle is updated through the `updateduty` function using the newly computed velocity. This function ensures the duty cycle remains between 0 and 1. If the updated duty cycle deviates outside this range, it will be corrected to maintain the system's stability and efficiency. The duty cycle, corresponding to the best solution (`D`), is subsequently used to adjust the PV system's converter settings in search of the MPP.

Algorithm-1: Pseudo code of PSO for MPPT	
Step-1	Start
Step-2	Initialize PSO parameters and persistent variables: Define learning factors c1 and c2. Compute power (P) from Ipv and Vpv. Initialize PSO variables such as globalbest, k, dc, and pbest. Set starting points for dcurrent and dc if this is the first run.
Step-3	Set D to the current duty cycle (dcurrent)
Step-4	Increment temp if less than 0 and exit early
Step-5	Update Pbest if the current power P is greater than Pbest
Step-6	Increment iteration counter k if it is less than a threshold (3000)
Step-7	If a change in power is negligible, randomize duty cycles dc to escape local optima

Step-8	Update each particle: Update personal best if current power is higher. Update globalbest if a cycle through particles is complete. Calculate the new velocity for each particle. Update each particle's duty cycle within a valid range (0 to 1)
Step-9	Repeat steps 3 to 8 for each function call, refining the search for optimal duty cycle
Step-10	End when maximum iterations are reached or the algorithm converges
Step-11	Output the optimal duty cycle D from the best nest

4. Gravitational Search Algorithm

The GSA is a metaheuristic optimization approach that draws inspiration from the laws of Newtonian gravity and the interactions between masses. The GSA mimics the movement of objects influenced by gravitational forces, where each object represents a potential solution to the optimization problem at hand. The GSA commences by initializing a set of agents (masses) and iteratively updates their positions based on the gravitational pull exerted by other agents within the population. The gravitational force acting upon an agent is directly proportional to the product of the masses of the interacting agents and inversely pertinent to the distance separating them.

This force determines the movement and positioning of agents within the search space as the algorithm progresses. Agents with better fitness values (solutions) are assigned higher masses, enabling them to exert stronger gravitational forces and attract other agents towards their positions. This exploitation mechanism enables GSA to efficiently refine solutions and converge towards optimal regions of the search space. Applied to MPPT in solar PV systems, the GSA leverages the metaphorical gravitational pull among candidate solutions to steer the search towards the MPP with smart precision [26-27]. Below is the systematic process of GSA, where each solution is weighted by its fitness, orchestrating a delicate balance between attraction towards the best solution and repulsion from the least efficient, thereby ensuring a continuous evolution towards the system's optimal performance.

(1) Initialization: The GSA commences by setting up agents randomly within the solution space, laying a foundation for a comprehensive search across potential solutions.

(2) Iterative loop: During each iteration, the algorithm assesses the power output of each agent, comparing it to their respective bests and updating records for continual performance enhancement.

(3) Mass calculation: The algorithm calculates the mass of each agent based on their fitness, using the relative mass strength variable q, to translate fitness into gravitational mass.

$$M_i^{(t)} = \frac{fitness^{(t)} - worst^{(t)}}{best^{(t)} - worst^{(t)}} \tag{6}$$

where, $M_i^{(t)}$ is the mass of agent i and j at time t. Meanwhile, $fitness^{(t)}$ is the fitness value of agent i and j at time t. $best^{(t)}$ and $worst^{(t)}$ are the best and worst fitness values among all agents at time t.

(4) Force calculation: Forces between agents are computed considering an exponentially decaying gravitational constant G and a stochastic element, which enables the algorithm to avoid local optima and navigate the search space effectively.

$$F_{ij}^{(t)} = G(t)\frac{M_i^{(t)} M_j^{(t)}}{R_{ij}^{(t)} + e}.rand_{ij} \tag{7}$$

where, $F_{ij}^{(t)}$ is the gravitational force between agent i and j at time t. $G(t)$ is the gravitational constant at time t. $M_i^{(t)} M_j^{(t)}$ are the masses of agents i and j at time t. $R_{ij}^{(t)}$ is the Euclidean distance between agent i and j at time t. $rand_{ij}$ is a random number between 0 and 1.

(5) Position update: The positions of agents, which are conceptualized as duty cycles, are updated and influenced by both the calculated gravitational forces and an element of randomness that includes a portion of their previous velocity.

$$X_{ij}^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \tag{8}$$

where $X_i^{(t+1)}$ and $V_i^{(t+1)}$ is the new position and velocity agent i at time t.

(6) Distance function: The function, which is essential for the movement dynamics of the algorithm, calculates the Euclidean distance between two agents, influencing the gravitational force calculations.

(7) Velocity update: The velocities of agents are updated by introducing variability through a random multiplier, combined with the new acceleration from the gravitational force, resulting in the final velocity.

$$V_{ij}^{(t+1)} = V_{ij}^{(t)} + F_{ij}^{(t)}.rand_{ij}.X_j^{(t)} - X_i^{(t)} \tag{9}$$

where $V_{ij}^{(t+1)}$ is the velocity of agent i towards agent j at time $t+1$. $V_{ij}^{(t)}$ is the current velocity of agent i at time t. $X_j^{(t)}$and $X_i^{(t)}$ are the positions of agent i and j at time t.

(8) Duty update: Finally, the algorithm ensures that the updated positions (duty cycles) of agents remain within the operational bounds of the system, thereby maintaining the physical feasibility of the PV system.

Algorithm-2: Pseudo code of GSA for MPPT	
Step-1	Start
Step-2	Initialize GSA variables, including dcurrent, pbest, force, acceleration, mass, q, p, p_current, p_min, worse, dc, v, and gbest. Set dcurrent and gbest to 0.5, and initialize dc randomly if it's the start of the GSA process.
Step-3	If the counter is within operational limits (less than 3000), proceed with the current duty cycle
Step-4	For each particle (u = 1 to 3), update p_current, improve p and pbest if possible, and adjust p_min and worse if necessary.
Step-5	Increment the particle index (u), resetting after cycling through all particles
Step-6	If within the iteration limit, refine D for ongoing exploration or finalize it.
Step-7	Calculate each particle's mass (q) based on their performance relative to the group's best and worst, affecting their gravitational pull
Step-8	Determine the total strength of mass and individual masses, informing the force calculation
Step-9	Adjust the gravitational constant over iterations to ensure convergence, calculate forces incorporating stochastic elements for robust search behavior
Step-10	Update acceleration based on calculated forces proportionate to the mass
Step-11	For each particle, update velocity and subsequently, the duty cycle (dc) ensuring exploration guided by gravitational forces
Step-12	If the final iteration is reached, solidify the duty cycle (D) to prevent further adjustments
Step-13	Conclude the process once the maximum iterations are reached or the algorithm converges on a solution, outputting the optimal duty cycle (D)
Step-14	End

5. HPSO-GSA Algorithm

The HPSO-GSA algorithm is a novel approach that synergistically combines the principles of PSO and GSA for optimizing the duty cycle of solar PV systems. This hybrid metaheuristic technique aims to leverage the complementary strengths of both algorithms, balancing the exploration capabilities of PSO with the exploitation strengths of GSA, to efficiently navigate the search space and converge towards optimal duty cycle values that maximize the power output of the PV system.

The objective function for an optimization algorithm in PV systems aims to maximize the power output or, equivalently, to minimize the negative power output. For the given HPSO-GSA approach, an appropriate objective function would be:

$$Maximize \rightarrow P = V_{PV} \times I_{PV} \tag{10}$$

where P is the power output of the PV system, V_{PV} is the voltage, and I_{PV} is the current. The algorithm seeks to adjust the duty cycle (D) to find the MPP.

Upon initiating the HPSO-GSA function, the algorithm checks for the existence of '*globalbest*' as a marker indicating whether the algorithm has run before. If absent, the algorithm initializes the parameters for PSO, such as the particles' duty cycles '*dc*', personal bests '*localbest*', velocities '*v*', and the global best condition '*globalbest*'. Duty cycles, which determine the operating state of the power converter in the PV system, are initialized with random values within specified ranges. This randomness is essential for the broad search capabilities of the algorithm. The core of the algorithm revolves around two key equations. First, in the PSO component, the velocity of each particle is updated using the formula:

$$v_{final} = w.v + c_1.rand().\left(pbest - d\right) + c_2.rand().\left(gbest - d\right) \tag{11}$$

where, w is the inertia weight, c_1 and c_2 are the cognitive and social coefficients, respectively, $rand()$ is a random number between 0 and 1, *pbest* is the personal best position, *gbest* is the global best position, and d is the current position. This equation ensures each particle is influenced by its own best position and that of the swarm.

Second, the GSA part calculates the force exerted on each mass (particle), simulating a gravitational attraction. The force is given by:

$$f = G.\frac{m_i.m_j}{distance + e}.rand() \tag{12}$$

where G is the gravitational constant, m_i and m_j are the active and passive masses, *distance* is the Euclidean distance between two particles, e is a small constant to prevent division by zero, and $rand()$ introduces a stochastic element. Subsequently, the force determines the acceleration and, ultimately, the updated velocity of the particle.

By alternating between these two mechanisms, the algorithm adeptly balances exploration and exploitation. Furthermore, the algorithm continuously updates the positions of particles, i.e., the different duty cycle values, and converges on the MPP. The optimal duty cycle D, which is found when the algorithm satisfies its convergence criteria, is subsequently applied to the PV system to effectuate its very efficient point, despite the variability of solar irradiance and environmental factors. The pseudo-code for this hybrid approach is given as follows in Table 2.

Table 2 Parameters values for the HPSO-GSA algorithm

Parameter	Description	Value
'c1'	The cognitive coefficient for PSO	2
'c2'	The social coefficient for PSO	2
'max_iter'	Maximum number of iterations	3000
'dcurrent' (Initial)	Initial guess for the duty cycle	0.5
'dc range'	The range for initializing duty cycle positions	0.005 to 0.995
'Iteration'	Iteration counter	Initialized to 1, increments
'alpha'	Coefficient for gravitational constant decay in GSA	200
'G0'	Initial gravitational constant in GSA	1
'e'	Small constant to prevent division by zero in GSA	2.2204×10^{-16}

This table indicates an overview of key parameters utilized in a hybrid optimization algorithm combining PSO and GSA. A direct impact lying in each parameter reflects on the performance and convergence of the HPSO-GSA function. Notably, the values for the dc range are extrapolated from the '*randi*' function with the division by 1000 in the code and reflect the initial setup. Actual values of '*dc*' during algorithm execution will vary as they are updated by the PSO and GSA procedures.

Algorithm-3: Pseudo code of HPSO-GSA for MPPT	
Step-1	Start
Step-2	Initialize Parameters: Initialize persistent variables for PSO and GSA parameters. Set PSO coefficients (c1, c2) and maximum iterations (max_iter).
Step-3	Check Initialization If globalbest is empty, initialize PSO and GSA parameters.
Step-4	Calculate the power (P) using the given voltage (Vpv) and current (Ipv).
Step-5	Update Personal and Global Best (PSO) Update the personal best (Pbest) if the current power is better. Check if the maximum iterations are reached and reset the iteration counter (k) if necessary. If the power change is small and far from the best, reinitialize PSO parameters.
Step-6	Update Local Best and Worst (GSA) Update the personal best (localbest) and worst (worse) solutions for each particle.
Step-7	HPSO-GSA Update If all particles have been updated (u == 4): Find the index of the maximum personal best and update the global best (globalbest). Calculate the strength of mass (q), mass, and force (GSA). Update acceleration (GSA). -For each dimension: Update velocity using a hybrid of PSO and GSA equations. Update position (duty cycle) using the updated velocity. Increment the iteration counter. -Update the previous power (Pprev). Otherwise, update the duty cycle (D) and current duty cycle (dcurrent) with the current particle's values.
Step-8	Return Result. Return the optimized duty cycle (D)
Step-9	End

Several complexity challenges emerge as the proposed HPSO-GSA algorithm is primarily driven by the initialization and iterative update processes. During initialization, parameters for both PSO and GSA are set up, entailing a linear time complexity pertinent to the number of particles. Each iteration, which can reach a maximum number of iterations, involves evaluating the fitness of each particle, updating personal and global bests, and computing new velocities and positions using both PSO and GSA equations. These steps collectively contribute to a linear time complexity per iteration, resulting in an overall complexity that scales linearly with the number of particles and iterations. Regarding scalability, the HPSO-GSA algorithm is designed to handle larger datasets and more extensive PV systems effectively. Both exploration and exploitation are maintained in an equilibrium, thereby adapting efficiently to various problem sizes. The performance of the algorithm, demonstrated in the results section, exhibits superior efficiency and effectiveness, compared to traditional optimization techniques, highlighting its robustness and suitability for large-scale applications.

6. Results and Discussions

In a MATLAB Simulink simulation environment, the models depicted in Fig. 1 were utilized to evaluate the efficiency of MPPT algorithms at a uniform temperature of 25 °C and irradiance of 1000 W/m^2. Fig. 3 captures the performance of the PSO algorithm, which demonstrated initial power oscillations before stabilizing at a power output of 54.32 W and a load voltage of 15.29 V. Fig. 4 exhibits the results for the GSA algorithm, yielding a more consistent power output of 55.1 W and a load voltage of 56.39 V, thereby indicating its robust capacity. The HPSO-GSA approach is represented in Fig. 5, where it outstripped the standalone algorithms by achieving the highest power output of 55.4 W and load voltage of 56.41 V. Hence, the HPSO-GSA effectively and rapidly secures the MPP. These representations in Figs. 3, 4, and 5 provide a clear comparative insight into the progressive optimization capabilities of the algorithms in enhancing solar PV system performance.

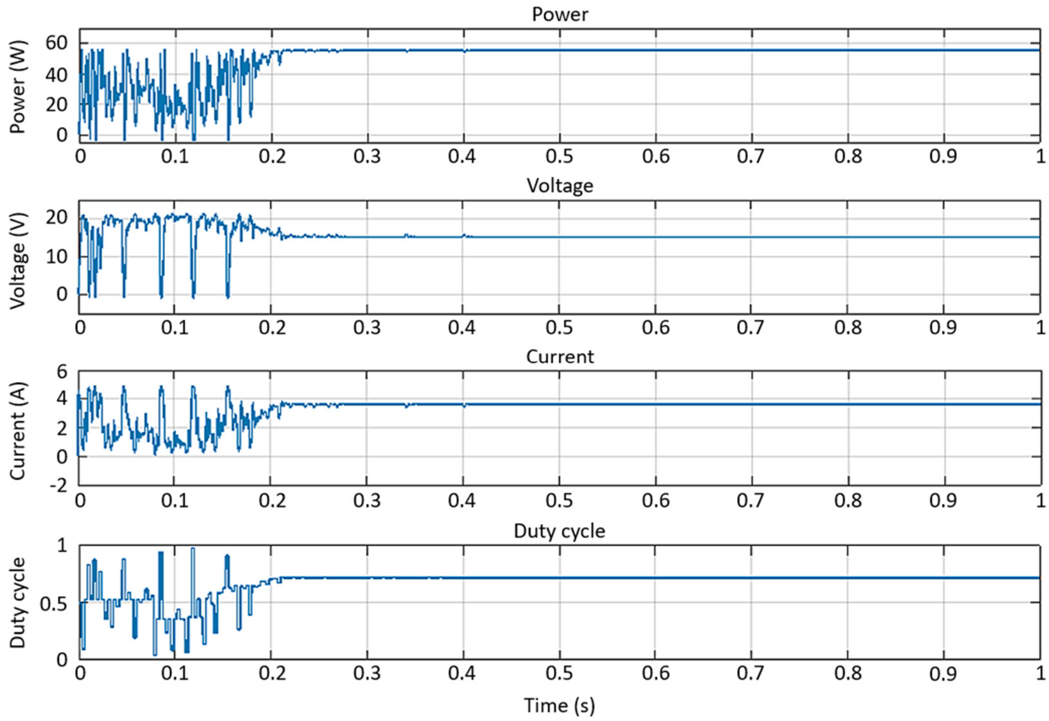


Fig. 3 MPPT output with PSO algorithm for 1000 W/m^2

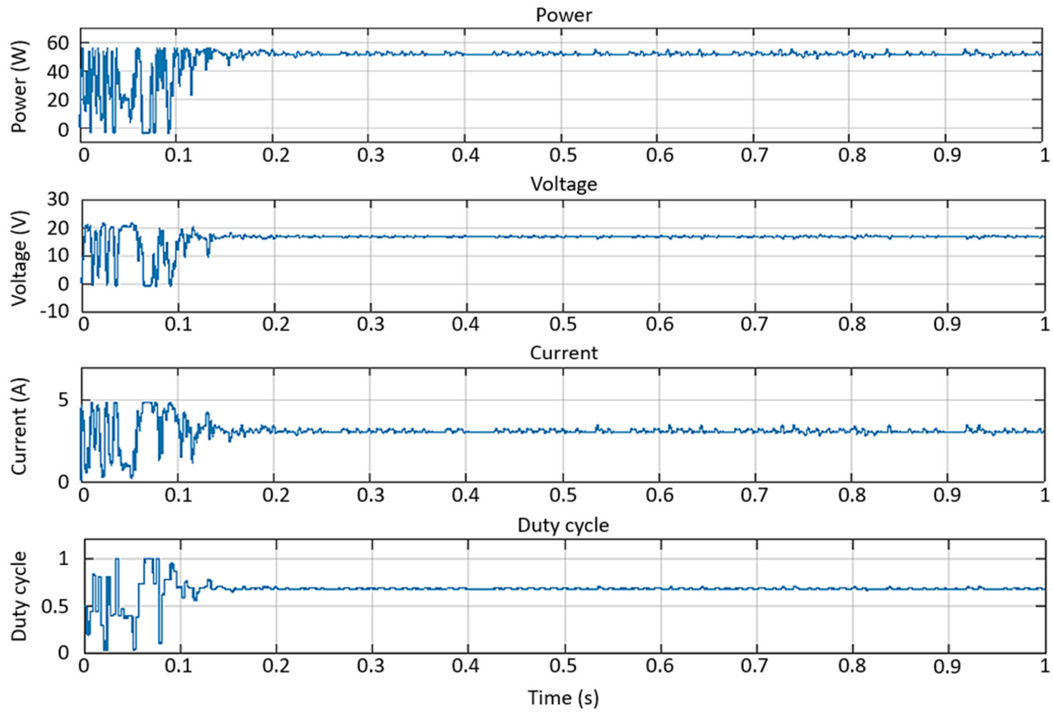


Fig. 4 MPPT output with GSA algorithm for 1000 W/m^2

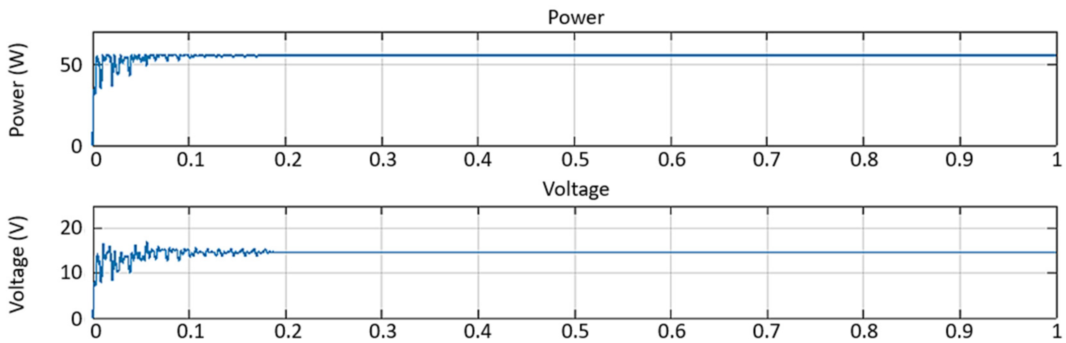


Fig. 5 MPPT output with HPSO-GSA algorithm for 1000 W/m^2

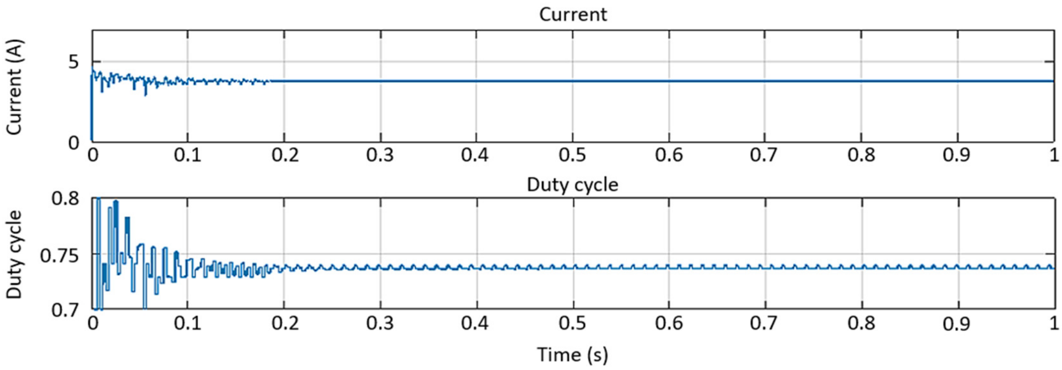
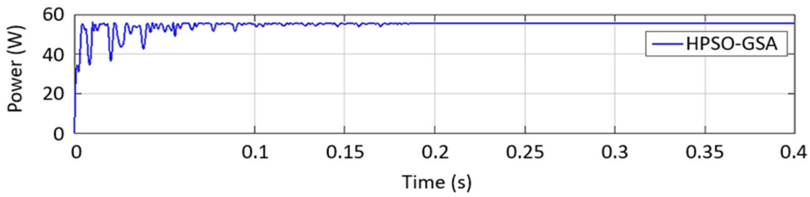
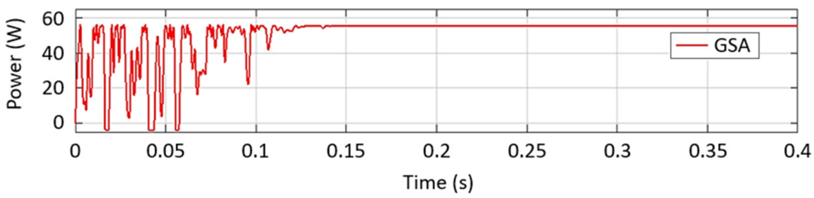


Fig. 5 MPPT output with HPSO-GSA algorithm for 1000 W/m^2 (continued)

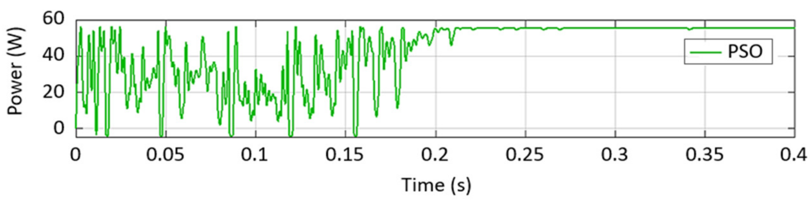
Fig. 6 to Fig. 8 compares the performance of the PSO, GSA, and HPSO-GSA algorithms in maintaining power output over time under specific testing conditions, as mentioned in Table 1, at different irradiance levels of 1000 W/m^2, 800 W/m^2, and 600 W/m^2. Specifically, comparative results concern tracking efficiency, settling time, convergence time, and oscillations. Moreover, these results highlight that the HPSO-GSA algorithm outperforms both PSO and GSA, thereby attesting to its effectiveness in achieving and maintaining a stable power output under varying irradiance levels.



(a) HPSO-GSA

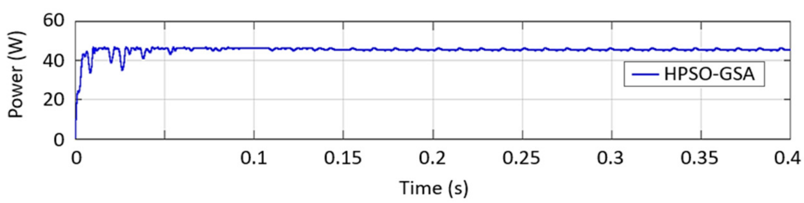


(b) GSA

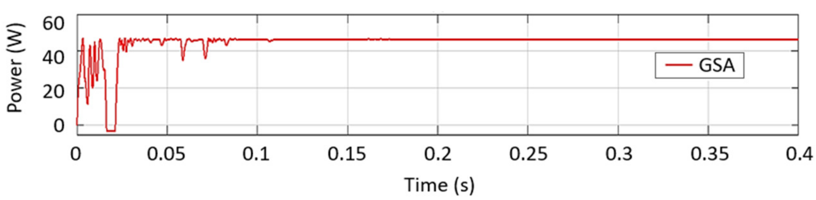


(c) PSO

Fig. 6 Power comparison of all at 1000 W/m^2

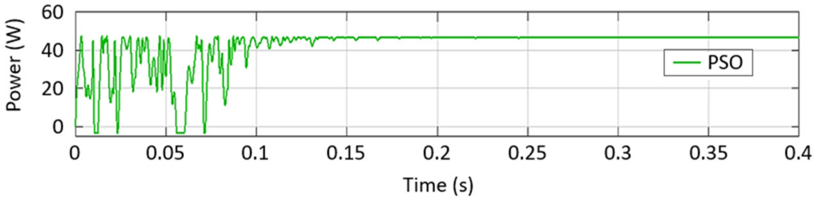


(a) HPSO-GSA



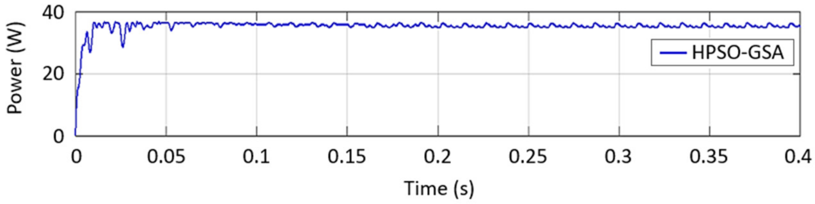
(b) GSA

Fig. 7 Power comparison of all at 800 W/m^2

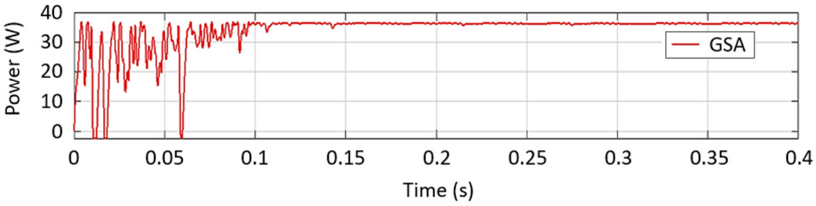


(c) PSO

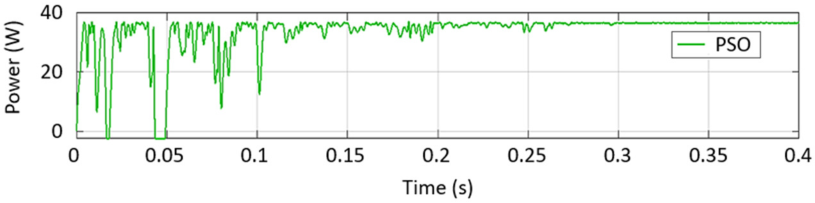
Fig. 7 Power comparison of all at 800 W/m^2 (continued)



(a) HPSO-GSA



(b) GSA



(c) PSO

Fig. 8 Power comparison of all at 600 W/m^2

From Fig. 6 to Fig. 8, as listed above, a performance comparison of PSO, GSA, and HPSO-GSA approach for MPPT at 1000 W/m^2, 800 W/m^2, and 600 W/m^2, respectively, is demonstrated. The PSO line seemingly exhibits more fluctuations initially before stabilizing, while the GSA line also displays variability in power output, with less intensity than PSO. The HPSO-GSA line, in contrast, expeditiously reaches a stable power output and maintains this stability over time, indicating quicker convergence and less oscillatory behavior. Table 3 below summarizes and shows quantified data for the above results.

Table 3 Performance analysis of PSO and GSA and HPSO-GSA

Algorithm	Irradiance (W/m^2)	PSO	GSA	HPSO-GSA
Power (W)	1000	54.32 W	55.1 W	55.4 W
	800	45.7 W	46.1 W	46.4 W
	600	35.2	35.8 W	36.2 W
Efficiency	1000	97.87%	99.27%	99.81%
	800	98.2%	99.13%	99.78%
	600	96.96%	98.62%	99.72%
Settling time	1000	0.21 sec	0.15 sec	0.11 sec
	800	0.16 sec	0.12 sec	0.09 sec
	600	0.19 sec	0.13 sec	0.10 sec
Convergence time	1000	0.21 sec	0.17 sec	0.06 sec
	800	0.14 sec	0.09 sec	0.05 sec
	600	0.19 sec	0.10 sec	0.04 sec
Oscillations	1000-600	More	Less	Least
Conversion	1000-600	Slower	Faster	Fastest

Table 3 summarizes the performance of the PSO, GSA, and HPSO-GSA approaches for MPPT in PV systems across varying irradiance levels. The hybrid approach outperforms the individual PSO and GSA in several metrics, including power output, efficiency, convergence time, and settling time. Notably, concerning convergence time across irradiance levels of 1000, 800, and 600 W/m^2, the hybrid algorithm is on average 56.38%, which is better than GSA and 71.55% better than PSO. Apropos settling time, the hybrid method shows an average improvement of 24.91% over GSA and 46.24% over PSO, underscoring its ability to rapidly stabilize at the optimal operating point. The hybrid algorithm excels in tracking the MPPT power with efficiency ratings peaking at 99.81%, 99.78%, and 99.72% for all irradiance levels. Overall, the HPSO-GSA algorithm accentuates its rapid response and high efficiency, marking it as a significant enhancement in the optimization of solar PV systems.

7. Conclusions

The study presents a novel hybrid metaheuristic approach, i.e., HPSO-GSA, combining PSO and GSA for optimizing solar PV systems. Based on simulations under various solar irradiance conditions, the following conclusions can be drawn:

(1) The proposed HPSO-GSA algorithm demonstrates potential as an intelligent and robust solution for maximizing power generation in solar PV systems, contributing to enhanced efficiency and reliability in renewable energy systems.

(2) The HPSO-GSA consistently outperforms individual PSO and GSA algorithms across all measured metrics, including power output, convergence speed, settling time, and overall efficiency.

(3) The hybrid approach demonstrates significant enhancements in convergence time, with an average improvement of 56.38% over GSA and 71.55% over PSO across irradiance levels of 1000, 800, and 600 W/m^2.

(4) The HPSO-GSA exhibits an average improvement of 24.91% over GSA and 46.24% over PSO in settling time, indicating a superior ability to quickly stabilize at the optimal operating point.

(5) The hybrid algorithm excels in tracking the MPP with efficiency ratings peaking at 99.81%, 99.78%, and 99.72% for all tested irradiance levels.

(6) By integrating the exploration capabilities of PSO with GSA's exploitation strengths, HPSO-GSA effectively explores the search space and converges towards optimal duty cycle values, maximizing power generation from PV systems.

(7) The HPSO-GSA successfully addresses the limitations of both PSO and GSA, mitigating the tendency of PSO for premature convergence and overcoming GSA's potential for slow convergence or lack of diversity.

The aforementioned findings underscore the efficacy of the HPSO-GSA approach in optimizing solar PV systems and highlight its potential for broader applications in renewable energy optimization.

Conflicts of Interest

The authors declare no conflict of interest.

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