[1]Aditya Sharma

[2]Dheeraj Kumar Palwalia

Comparative Analysis of Gravitational Search Algorithm and Particle Swarm Optimization for Solar MPPT

JES

Journal of Electrical Systems

Abstract: - This work delves into the optimization of Maximum Power Point Tracking (MPPT) for photovoltaic (PV) systems through a comparative analysis of two advanced algorithms: the Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO). With the escalating demand for renewable energy sources, enhancing the efficiency of solar panels has become crucial. MPPT techniques are pivotal in maximizing the power output from solar panels by adjusting to varying environmental conditions. This work implements GSA and PSO within a MATLAB environment to track the MPP of a solar cell array efficiently. The study systematically evaluates the performance, convergence speed, and stability of both algorithms under diverse operational scenarios. Preliminary findings indicate that GSA exhibits faster convergence and reduced oscillatory behaviour compared to PSO, suggesting a superior efficiency in tracking the MPP. This paper aims to provide a comprehensive comparison between GSA and PSO, offering insights into their applicability and effectiveness in optimizing solar energy systems, thereby contributing to the development of more efficient renewable energy solutions.

Keywords: Gravitational Search Algorithm (GSA), Particle Swarm Optimization Algorithm (PSO), Maximum Power Point Tracking (MPPT), Photovoltic System (PV).

I. INTRODUCTION

The quest for sustainable energy solutions has, over time, been up in arms, with solar photovoltaic (PV) systems predominantly featuring as one of the cornerstones in the renewable energy sector. These convert sunlight directly into electricity and are at the core of this global transition to cleaner energy sources [1-2]. However, this decisively varies due to the variability in the environmental conditions, especially in solar irradiance and temperature. This introduces the maximization problem concerning the energy output from solar panels that must be operated at their Maximum Power Point (MPP) under variations in operating conditions [3-4]. MPP is a point at which a PV system generates its maximum available power. Good tracking of this point can significantly improve overall energy yield.

To solve this problem, the idea of maximum power point tracking (MPPT) has found extensive application. PV cells are characterized by a nonlinear characteristic curve of power versus the operating voltage and current, which contains a single peak called the maximum power point (MPP). The MPP can be affected by different environmental factors such as solar irradiance, temperature, and shading conditions; all of these change dynamically in a period of minutes throughout the day [5-7]. Therefore, working at that point commonly named MPPT constantly to extract the available maximum power from a PV system is mandatory. Traditional MPPT techniques, for example, perturb and observe (P&O) and incremental conductance (INC), are pretty famous and widely used, but they exhibit several inherent weaknesses [8]. In most the cases, they have a fast-changing behaviour, and it is challenging to adapt to changes in the environment, thus tending to oscillate about the MPP. These problems result in suboptimal power output; they can also settle at local maxima due to inefficiencies [9-11]. This has dictated the need for more advanced optimization algorithms that can quickly and accurately adapt to the new changes [12-13]. These algorithms, inspired by natural phenomena and evolutionary processes, have shown remarkable prowess in solving complex optimization problems in various domains. Two such algorithms include; the Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO) stand out for their unique approaches to optimization. GSA, based on the theory of gravity and mass interaction laws, and PSO, based on the social behavior of birds and fish, both provide new potential ways to develop the effectiveness of MPPT [14-15]. However, both these algorithms have their strengths and weaknesses, influenced by factors like convergence speed, adaptability, and computational efficiency. But on the other hand, while GSA excels in global search capabilities and offers highly efficient solutions across diversified optimization landscapes, PSO is applauded for its simplicity and the ease of implementation, coupled with its versatility across various problem

[1] *Corresponding author: Department of Electrical Engineering, Rajasthan Technical University, Kota, INDIA, asharma.phd17@rtu.ac.in
[2] Department of Electrical Engineering, Rajasthan Technical University, Kota, INDIA, dkpalwalia@rtu.ac.in

domains. However, it also has limitations, including the risk of premature convergence and sensitivity to parameter settings [16-17].

This research investigates into the development and evaluation of an innovative Maximum Power Point Tracking (MPPT) system for photovoltaic (PV) arrays, built upon the foundations of the Gravitational Search Algorithm (GSA). The study explores the potential of GSA, a metaheuristic optimization algorithm inspired by the laws of celestial motion and gravitational forces [18]. By harnessing the unique principles of mass interactions and gravitational attractions, GSA offers a robust and versatile approach to navigating the complex search space associated with MPPT optimization [19]. The core focus of this research lies in the detailed implementation and analysis of a GSA-based MPPT system, accurately designed to maximize power extraction from PV arrays under dynamic environmental conditions. Through simulations and comparative evaluations, the study aims to demonstrate the superiority of GSA over traditional optimization algorithms, such as PSO. GSA's inherent ability to balance exploration and exploitation, coupled with its stochastic nature, is expected to outperform PSO in terms of convergence speed, solution accuracy, and adaptability to rapidly changing conditions. Furthermore, the research delves into the computational efficiency and scalability aspects of GSA, addressing practical concerns for real-world MPPT system deployments. By comprehensively analyzing the performance metrics and characteristics of GSA in the context of MPPT, this study paves the way for more efficient and reliable solar energy harvesting systems.

II. MAXIMUM POWER POINT TRACKING

The Maximum Power Point Tracking (MPPT) system is an essential feature of photovoltaic (PV) installations, aimed at maximizing solar energy conversion efficiency. It utilizes advanced algorithms to monitor and adjust the PV modules' operating point, ensuring power extraction is optimized at all times. By dynamically identifying and following the maximum power output point on the current-voltage (I-V) curve, the MPPT system compensates for changes in environmental conditions, such as fluctuations in sunlight and temperature. Through the integration of sensors and precise control mechanisms, the system maintains peak operational efficiency, significantly boosting the electrical output and overall performance of solar power systems. This overview underscores the critical role of MPPT in improving the energy yield of PV systems.
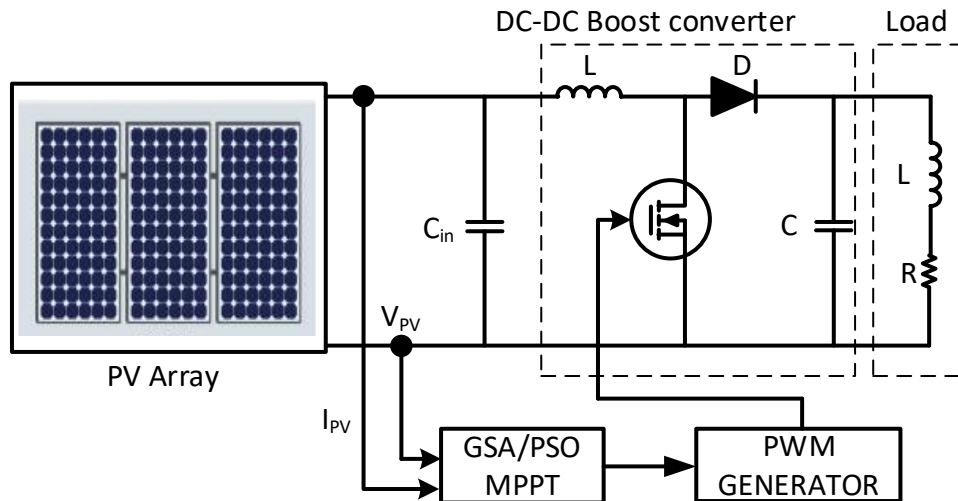

Fig. 1 Block diagram of PV system with MPPT

Through the above Fig. 1, it is demonstrated that voltage (V_{PV}) and current (I_{PV}) are extracted from the photovoltaic (PV) array, serving as critical inputs for either the Gravitational Search Algorithm (GSA) or Particle Swarm Optimization (PSO) algorithms. These sophisticated algorithms utilize the V_{PV} and I_{PV} values to determine the optimal duty cycle (D). This calculated duty cycle is subsequently used to modulate Pulse Width Modulation (PWM) signals, which govern the switching operations in a DC-DC boost converter. This converter plays a pivotal role in regulating and maintaining a stable voltage output to effectively power the connected load, which typically comprises inductance (L) and resistance (R). The converter's ability to stabilize the output voltage, despite fluctuations in solar irradiance or variations in load demand, is essential for ensuring the system's reliable performance. The parameters of the PV array system, crucial for the functioning and evaluation of the algorithms, are listed in Table 1 below.

Table 1. PV array system parameters

Parameters	Values
Max. Power	55 W
Open circuit voltage (Voc)	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 F
Inductor (L)	1.2e-3 H
Capacitor (C)	47e-6 F
Load resistance (R)	100 Ω

Fig. 2 presents a pair of curves that delineate the performance of a photovoltaic (PV) panel under varying degrees of irradiance, measured at a consistent temperature of 25°C. The upper portion of the figure, known as the I-V curve, maps the relationship between current (I) and voltage (V), illustrating a decline in the panel's electrical output as irradiance diminishes. Concurrently, the lower section showcases the P-V curve, which charts power (P) against voltage (V). Each trajectory on this graph reaches its zenith at what is termed the Maximum Power Point (MPP), signifying the panel's optimal performance under differing lighting scenarios. The distinct peak of the P-V curves is instrumental for the design of MPPT systems that strive to maintain the panel's operation at or near this peak, thereby optimizing the panel's efficiency and harnessing the maximum available power.
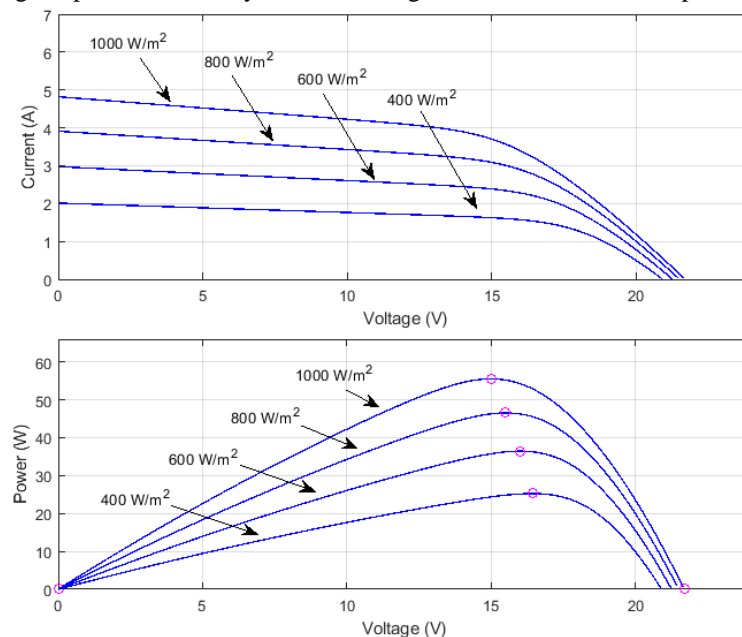

Fig. 2 PV and IV curve for solar module

Point Tracking (MPPT) algorithms, which are designed to dynamically adjust the electrical load and optimize the energy harvested from the panel throughout the day. By integrating these insights into MPPT controllers, solar energy systems can significantly improve their performance, adapting in real-time to changes in sunlight and temperature.

III. PARTICLE SWARM OPTIMIZATION

The Particle Swarm Optimization (PSO) algorithm stands out as an innovative computational strategy, adept at refining complex problem-solving by mimicking the collective social behaviors of organisms, such as birds flocking or fish schooling. For photovoltaic (PV) systems, PSO's robust methodology is harnessed to effectively locate and maintain the maximum power point (MPP), an essential aspect for optimizing solar energy conversion [20]. This lays the groundwork for understanding how PSO intelligently navigates the multidimensional search

space of power outputs, adjusting operational parameters such as voltage and current to consistently achieve peak energy efficiency under fluctuating environmental conditions.

In a solar photovoltaic system, the Particle Swarm Optimization (PSO) algorithm is employed to optimize the process of maximum power point tracking (MPPT). The PSO algorithm commences by establishing a swarm of particles, each representing a potential solution with variables that include individual and collective best-known positions 'localbest' and 'globalbest', velocity 'v', and duty cycles 'dc'. With the intent to span a broad search spectrum, the algorithm randomly assigns initial values to these duty cycles, starting the current duty cycle 'dcurrent' at a tentative optimum of 0.5. As the algorithm iterates, each particle's velocity is adjusted according to a blend of its inertia and the cognitive and social influences driving it towards personal and global optima. The velocity update is determined by the equation:

$$v_i^{(t+1)} = w.v_i^{(t)} + c_1.r_1.\left(pbest_i - \chi_i^{(t)}\right) + c_2.r_2.\left(gbest - \chi_i^{(t)}\right)$$ (1)

Where, $v_i^{(t+1)}$ is the particle velocity i at iteration $t+1$, w represents the inertia weight, c_1 and c_2 are learning factors, r_1 and r_2 are random numbers between 0 and 1, $pbest_i$ is the personal best position of the particle, and $gbest$ is the best position found by any particle.

The algorithm proceeds through each iteration, updating the power output and duty cycles. If a negligible change in power suggests a plateau, the duty cycles are reinitialized to encourage divergence. As the system continues, the new particle positions are computed with the updated velocities:

$$\chi_{i,d}^{(t+1)} = \chi_{i,d}^{(t)} + v_{i,d}^{(t+1)}$$ (2)

Where, $\chi_{i,d}^{(t+1)}$ is the new position of particle i at iteration $t+1$.

This equation ensures that each particle explores the search space for the most efficient power output. The duty cycle (dc) is modified accordingly through the 'updateduty' function, keeping it within the 0 to 1 range for operational stability. Once the algorithm surpasses a defined iteration count or reaches convergence, indicated by the global best solution (D), this optimized duty cycle is applied to the power converter within the PV system. This methodical adjustment aims to continuously capture the maximum power point, despite variations in environmental conditions, ensuring the system's performance is optimized.

Algorithm-1 *Pseudo code for PSO for MPPT*

I	*Start*
II	*Initialize PSO parameters and persistent variables:*
	- c1, c2: learning factors
	*- P: power calculated from voltage and current (Ipv * Vpv)*
	- Initialize globalbest, k, dc, p, localbest, v, Pbest, Pprev, dcurrent, u, temp
	- If globalbest is empty:
	- Set k to 0
	- Initialize duty cycles dc with random values within specific ranges
	- Set Pbest to initial power
	- Set dcurrent to an initial guess (0.5) and assign it to globalbest
III	*Set D to the current duty cycle (dcurrent)*
IV	*Increment temp if less than 0 and exit early*
V	*Update Pbest if the current power P is greater than Pbest*
VI	*Increment iteration counter k if it is less than a threshold (3000)*
VII	*If change in power is negligible, randomize duty cycles dc to escape local optima*
VIII	*Update particles:*
	- For each particle:
	- Update personal best if current power is higher
	- Update globalbest if a cycle through particles is complete
	- Calculate new velocity for each particle
	- Update each particle's duty cycle within valid range (0 to 1)
IX	*Repeat steps 3 to 8 for each function call, refining the search for optimal duty cycle*
X	*End when maximum iterations are reached or the algorithm converges*
XI	*Output the optimal duty cycle D from the best nest*

IV. GRAVITATIONAL SEARCH ALGORITHM

In the pursuit of optimizing photovoltaic systems for maximal energy harvest, the Gravitational Search Algorithm (GSA) emerges as a pivotal tool. Mimicking the cosmic dance of gravitational forces, GSA navigates the intricate landscape of possible solutions [21]. The ensuing sections delineate the core processes that underpin this innovative optimization technique.

The Gravitational Search Algorithm (GSA) initiates its process by distributing agents randomly within the solution space, setting the stage for an extensive exploration of potential solutions. As the algorithm iterates, it evaluates the power output of each agent, comparing it to their recorded personal bests to continuously refine their performance. A crucial step in the GSA is the calculation of each agent's mass, which is determined by their fitness. This relationship is expressed through the equation given below as:

$$M_i^{(t)} = \frac{fitness^{(t)} - worst^{(t)}}{best^{(t)} - worst^{(t)}} \tag{3}$$

Where, $M_i^{(t)}$ represent the mass of agent i at time t, $best^{(t)}$ and $worst^{(t)}$ denote the best and worst fitness values among all agents at time t respectively.

Subsequently, the forces exerted between agents are calculated, taking into account an exponentially decaying gravitational constant G and a random factor, enabling the algorithm to steer clear of local optima and efficiently traverse the solution space. The force equation is given as:

$$F_{ij}^{(t)} = G(t) \frac{M_i^{(t)} M_j^{(t)}}{R_{ij}^{(t)} + e} . rand_{ij} \tag{4}$$

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.

The positions of the agents, conceptualized as duty cycles, are updated based on the gravitational forces and a degree of randomness that incorporates elements of their previous velocity, shown as:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \tag{5}$$

Where $X_i^{(t+1)}$ and $V_i^{(t+1)}$ is the new position and velocity agent i at time t. This update mechanism ensures that agents move towards more promising areas of the search space while maintaining variability in their trajectory.

The algorithm also employs a distance function to calculate the Euclidean distance between two agents, an essential component in determining the gravitational forces that drive the algorithm's dynamics. The velocities of agents are then updated by combining the calculated forces with randomness, resulting in a final velocity equation:

$$V_{ij}^{(t+1)} = V_{ij}^{(t)} + F_{ij}^{(t)} . rand_{ij} . X_j^{(t)} - X_i^{(t)} \tag{6}$$

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

In the final stage, the GSA ensures that the newly updated positions, or duty cycles, of agents remain within the operational boundaries of the system, thereby preserving the physical and practical applicability of the solutions generated for the PV system. This comprehensive approach allows the GSA to effectively navigate the complex solution landscape in search of the optimal setting for maximum power output.

Algorithm-2 *Pseudo code for GSA for MPPT*

I	*Start*
II	*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.*
III	*If the counter is within operational limits (less than 3000), proceed with the current duty cycle*
IV	*For each particle (u from 1 to 3):*
	a. Update current power (p_current) based on the product of Vpv and Ipv
	b. If the current power is an improvement, update p and pbest accordingly
	c. If the current power is less than the worst recorded, update p_min and worse
V	*Increment the particle index (u), resetting after cycling through all particles*

VI	In the main operation loop:
	- If iteration is ongoing and under the limit, adjust D for exploration or finalize if concluding
	- Upon reaching the updating phase (u==4), enhance gbest based on max power output identified
VII	Calculate each particle's mass (q) based on their performance relative to the group's best and worst, affecting their gravitational pull
VIII	Determine the total strength of mass and individual masses, informing the force calculation
IX	Adjust the gravitational constant over iterations to ensure convergence, calculate forces incorporating stochastic elements for robust search behavior
X	Update acceleration based on calculated forces, proportionate to mass
XI	For each particle, update velocity and subsequently, the duty cycle (dc) ensuring exploration guided by gravitational forces
XII	If the final iteration is reached, solidify the duty cycle (D) to prevent further adjustments
XIII	Conclude the process once the maximum iterations are reached or the algorithm converges on a solution, outputting the optimal duty cycle (D)
XIV	End

V. RESULTS AND DISCUSSIONS

In the simulation environment of MATLAB Simulink, as presented in Figure 1, a comprehensive model of a solar PV system with Maximum Power Point Tracking (MPPT) is created. The Particle Swarm Optimization (PSO) algorithm is initially employed to optimize the system's performance, and the resulting data is captured in Fig. 3. This visualization corresponds to a scenario where the PV array is subjected to a consistent temperature of 25°C and an irradiance level of 1000 W/m². In such conditions, the PV module reliably delivers a voltage output of 15.25V, and the subsequent voltage measured at the load stands at 56.39V. The power generated by this setup is quantified to be 55.12 W, showcasing the potential of the PSO method in extracting energy from the solar cells. However, it is observed that the PSO algorithm demonstrates a tendency towards more frequent oscillations and experiences a comparatively slower rate of convergence to the maximum power point. These initial outcomes provide a benchmark for assessing the effectiveness of the PSO algorithm in MPPT applications and establish a basis for comparison with GSA optimization technique.
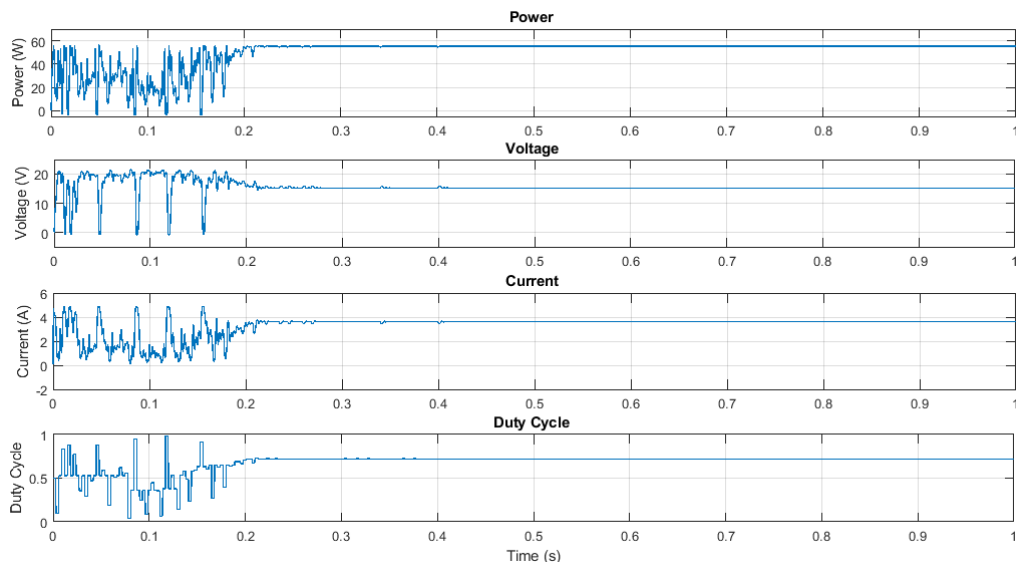

Fig. 3 MPPT output with PSO algorithm

In the illustrated Fig. 4, the implementation of the Gravitational Search Algorithm (GSA) on a Maximum Power Point Tracking (MPPT) model is portrayed, where the inputs are maintained at a constant temperature of 25°C and an irradiance level of 1000 W/m². The application of the GSA method has yielded a consistent power output of 55.4 W, demonstrating the algorithm's effectiveness in stabilizing the power generation of the PV module. Furthermore, the figure shows that the PV module outputs a voltage of 15.6 V, which, through the MPPT process, contributes to achieving a load voltage of 56.41 V. This is indicative of the MPPT system's capacity to regulate and adapt the output from solar array.
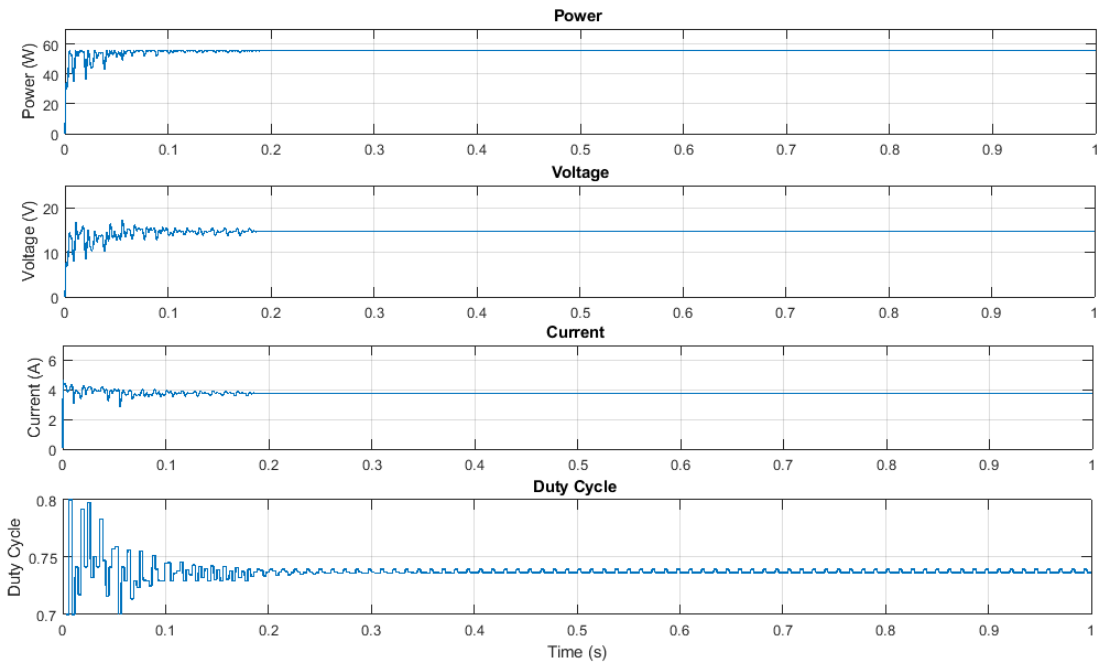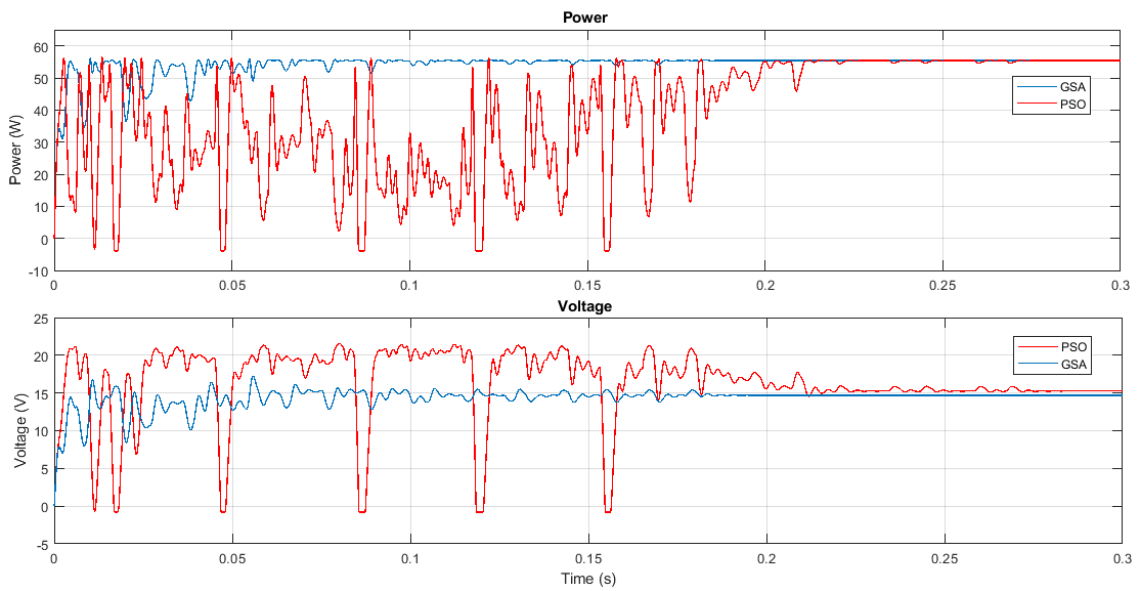
Fig. 4 MPPT output with GSA algorithm
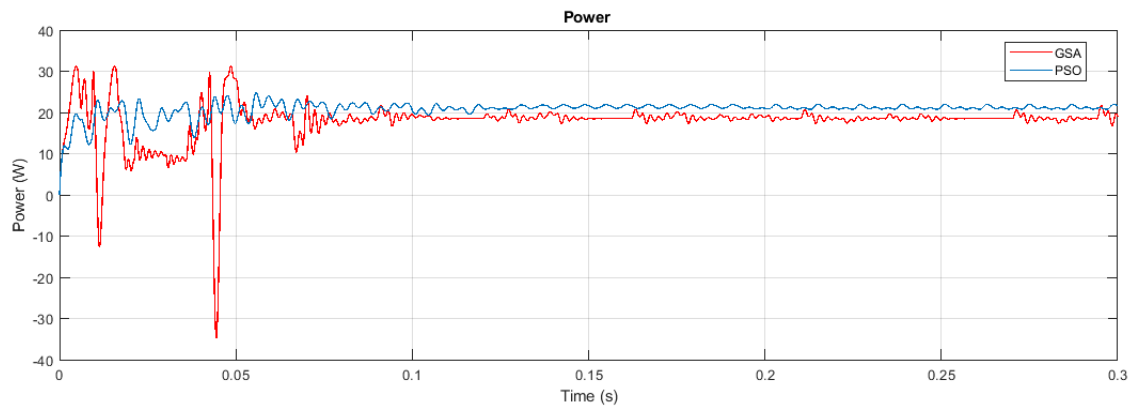

Fig. 5 Power comparison of PSO and GSA at 1000 W/m2

Fig. 6 Power comparison of PSO and GSA at 500 W/m2

Table 2 below describes the performance analysis between PSO and GSA based solar MPPT on irradiance of 1000 W/m2.

Table 2. Performance of PSO and GSA

Algorithm	PSO	GSA
Power (W)	54.12 W	55.4 W
Efficiency	97.87%	99.27%
Convergence Time	0.21 sec	0.17 sec
Settling Time	0.21 sec	0.15 sec
Oscillations	More	Less
Conversion	Slower	Faster

A comparison of PSO and GSA based MPPT at 1000W/m2 and 500W/m2 irradiance is shown in the Fig. 5 and Fig. 6. The results show that the Gravitational Search Algorithm (GSA) quickly finds the most efficient setting, or maximum power point, for the solar panel system. It keeps the power output stable after finding this setting, which is great for solar power systems. On the other hand, Particle Swarm Optimization (PSO) takes longer to find this efficient setting because it moves back and forth around the best point before it settles. The study found that GSA is about 19.05% better than PSO in finding this setting quickly (convergence time) and about 28.57% better in keeping the power output stable (settling time). Both algorithms tracked a rated power of 55.5 W, with PSO achieving an efficiency of 97.87% and GSA achieving 99.27%.

VI. CONCLUSION

This study has comprehensively explored the application of two advanced optimization algorithms, the Gravitational Search Algorithm (GSA) and Particle Swarm Optimization (PSO), for the task of Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems. Through experimentation and analysis within a MATLAB environment, this research has systematically evaluated the performance, convergence speed, and stability of both GSA and PSO in tracking the Maximum Power Point (MPP) of a solar cell array under diverse operational scenarios. The findings have revealed that the GSA exhibits notable advantages over PSO, demonstrating faster convergence and reduced oscillatory behavior in its search for the optimal operating point. Specifically, GSA showed a convergence time improvement of approximately 19.05% and a settling time improvement of around 28.57% over PSO. These enhancements in time-related performance metrics significantly contribute to the algorithm's efficiency, especially in fluctuating irradiance conditions common in solar applications. The Gravitational Search Algorithm (GSA) shines in optimizing MPPT challenges, based on its physics-inspired exploration and exploitation methods, which adeptly handle the dynamic optimization landscape. Its stochastic approach and fine-tuned balance offer superior solution accuracy and adaptability, surpassing Particle Swarm Optimization (PSO) in responding to environmental changes.

REFERENCES

[1] Nwaigwe, K. N., Philemon Mutabilwa, and Edward Dintwa. "An overview of solar power (PV systems) integration into electricity grids." Materials Science for Energy Technologies 2.3 (2019): 629-633.

[2] Kumar, Raj, and S. K. Singh. "Solar photovoltaic modeling and simulation: As a renewable energy solution." Energy Reports 4 (2018): 701-712.

[3] Jayaswal, Kuldeep, D. K. Palwalia, and Aditya Sharma. "Renewable Energy in India and World for Sustainable Development." Power Electronics for Green Energy Conversion (2022): 67-89.

[4] Jayaswal, Kuldeep, et al. "Global solar insolation estimation and investigation: A case study of various nations and cities." IEEE Access 9 (2021): 88069-88084.

[5] Podder, Amit Kumer, Naruttam Kumar Roy, and Hemanshu Roy Pota. "MPPT methods for solar PV systems: a critical review based on tracking nature." IET Renewable Power Generation 13.10 (2019): 1615-1632.

[6] Verma, Deepak, et al. "Maximum power point tracking (MPPT) techniques: Recapitulation in solar photovoltaic systems." Renewable and Sustainable Energy Reviews 54 (2016): 1018-1034.

[7] Mao, Mingxuan, et al. "Classification and summarization of solar photovoltaic MPPT techniques: A review based on traditional and intelligent control strategies." Energy Reports 6 (2020): 1312-1327.

[8] Motahhir, Saad, Aboubakr El Hammoumi, and Abdelaziz El Ghzizal. "Photovoltaic system with quantitative comparative between an improved MPPT and existing INC and P&O methods under fast varying of solar irradiation." Energy Reports 4 (2018): 341-350.

[9] Yap, Kah Yung, Charles R. Sarimuthu, and Joanne Mun-Yee Lim. "Artificial intelligence based MPPT techniques for solar power system: A review." Journal of Modern Power Systems and Clean Energy 8.6 (2020): 1043-1059.

[10] Ali, Amjad, et al. "Investigation of MPPT techniques under uniform and non-uniform solar irradiation condition–a retrospection." IEEE Access 8 (2020): 127368-127392.

[11] Sharma A, Palwalia DK. (2024) "Small Signal Modelling and Stability Analysis of a Grid Connected Inverted Based Microgrid." Indian Journal of Science and Technology. 17(19): 2024-2037.

[12] Kermadi, Mostefa, et al. "Recent developments of MPPT techniques for PV systems under partial shading conditions: a critical review and performance evaluation." IET Renewable Power Generation 14.17 (2020): 3401-3417.

[13] Bollipo, Ratnakar Babu, Suresh Mikkili, and Praveen Kumar Bonthagorla. "Critical review on PV MPPT techniques: classical, intelligent and optimisation." IET Renewable Power Generation 14.9 (2020): 1433-1452.

[14] Hayder, Wafa, et al. "Improved PSO: a comparative study in MPPT algorithm for PV system control under partial shading conditions." Energies 13.8 (2020): 2035.

[15] Javed, Saba, and Kashif Ishaque. "A comprehensive analyses with new findings of different PSO variants for MPPT problem under partial shading." Ain Shams Engineering Journal 13.5 (2022): 101680.

[16] Eltamaly, Ali M., Hassan MH Farh, and Ahmed G. Abokhalil. "A novel PSO strategy for improving dynamic change partial shading photovoltaic maximum power point tracker." Energy sources, part a: recovery, utilization, and environmental effects (2020): 1-15.

[17] Xu, Libin, et al. "Improved particle swarm optimization (PSO)-based MPPT method for PV string under partially shading and uniform irradiance condition." 2020 Asia Energy and Electrical Engineering Symposium (AEEES). IEEE, 2020.

[18] Pattnayak, Sangram Keshari, et al. "Maximum power tracking & harmonic reduction on grid PV system using chaotic gravitational search algorithm based MPPT controller." 2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE). IEEE, 2020.

[19] Alkhalaf, Salem, Ziad M. Ali, and Hitoshi Oikawa. "A novel hybrid gravitational and pattern search algorithm based MPPT controller with ANN and perturb and observe for photovoltaic system." Soft Computing 26.15 (2022): 7293-7315.

[20] Tharwat, Alaa, and Wolfram Schenck. "A conceptual and practical comparison of PSO-style optimization algorithms." Expert Systems with Applications 167 (2021): 114430.

[21] Hashemi, Amin, Mohammad Bagher Dowlatshahi, and Hossein Nezamabadi-Pour. "Gravitational Search Algorithm: Theory, Literature Review, and Applications." Handbook of AI-based Metaheuristics (2021): 119-150.