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Performance Evaluation of Walrus Optimization based MPPT with other Algorithms under Partial Shading Condition

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Abstract: Under partial shadowing (PS) circumstances, the solar array's photovoltaic cells become reversely biased and operate as a load. This can lead to hotspot issues, which can significantly reduce photovoltaic efficiency. In solar systems, the Perturb & Observe (MPPT) method is commonly employed; however, when both local and global maxima are present under PS circumstances, it is extremely difficult to identify the true maxima. Utilizing the Walrus optimization algorithm (WaOA), the study's innovative approach could significantly lower the solar PV system's efficiency. The suggested WaOA was used in the current study to track the GMPP under PS conditions and other meta-heuristic algorithms, including PSO, GWO, and ARO. We evaluate the performance of several solutions concerning GMPP tracking. Metaheuristic processes are evaluated in terms of their effectiveness, standard deviation (STD), rise time, mean, root mean square error (RMSE), and median. The benefits of the proposed strategy surpass the conventional P&O method when compared to the most popular metaheuristic algorithms, such as PSO, GWO, and ARO, in terms of accuracy, efficiency, and reduction in steady-state oscillations. The MPPT effectiveness of the suggested model is around 99.838%. It also has the best efficiency, a settling time of 1.83 seconds, and a mean power of roughly 662.6 W. Furthermore, the outcomes are cross-checked and verified on the prototype.

Keywords: Partial Shading; PV Systems; Metaheuristic Algorithms; Global Maximum Power Point; Walrus Optimization; Depletion of Natural Resources; Energy Sources; Maximum Power Tracking.

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1. Introduction

Over the past ten years, the need for clean and sustainable energy has grown significantly because of climatic changes and the depletion of natural resources like coal and petroleum products [1]. Humankind is forced to look for alternative sources of energy which are abundant in nature and do not harm the environment. The solution is the use of non-conventional energy sources [2]. Due to this ongoing shift towards renewable sources, several research has been conducted to optimize the energy being generated from these sources as they are intermittent and the production is significantly influenced by external factors, including

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temperature and radiation, as in the solar photovoltaic systems, which has gained popularity among the other sources like wind energy, biomass, and tidal energy [3]. Since the environmental conditions cannot be controlled, the only solution for optimism about the power being generated from these sources lies in the design of a suitable controller or control algorithm for harvesting the maximum power from the PV systems, which is commonly known as the maximum power tracking (MPPT). In the literature, numerous MPPT algorithms have been documented [3] these algorithms' main priority is not only to harvest the MPP but also accuracy, speed of tracking, and ability to reduce the oscillations near MPPT [4].

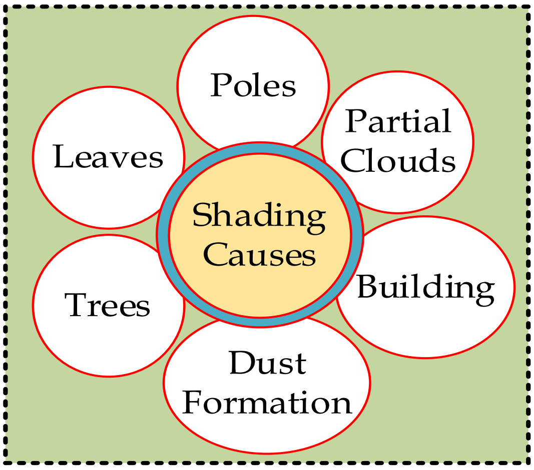


Figure 1: Causes of Partial Shading

Partially shadowing (PS) situations, where the PV systems are shadowed by trees, surrounding buildings, or poles, have emerged due to the extensive installation of PV systems on building rooftops to satisfy long-term economic expectations while lowering the overall installation cost [4]. It can be challenging to identify the appropriate global maximum power point (GMPP) for recording the maximum power since the system's power-voltage (P-V) graph shows multiple localized maximum power points (LMPPs) in addition to one GMPP peak under PS conditions [5]. Some parts of the PV get enough sunshine and work well, but the dark cells don't, drastically lowering power production. Bypass diodes are added to impacted parts to lessen impairments [6]. The major cause of the partial shading condition (PSC) is shown in Figure 1. Also, when a PV array is partially shaded, two LMPPs and one GMPP are present, as shown in Figure 2. The fact that partial obscuring of series-connected PV modules will significantly reduce or increase their capacity, either linearly or nonlinearly [7].

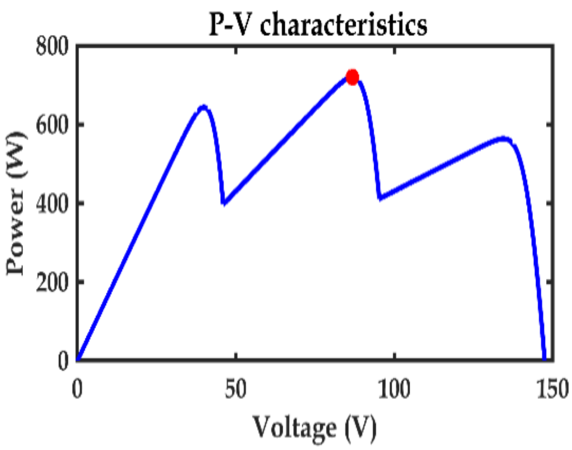


Figure 2: P-V characteristics during partial shading

The literature has numerous descriptions of MPPT techniques, most of which can be grouped into two distinct categories: conventional and metaheuristic. Perturb, observe (P&O), and incremental conductance (IC) are widely used in photovoltaic systems because of their ease of use and accuracy in tracking the MPP under uniform environmental conditions. However, they are not recommended for applications in contexts with partial shading (Figure 3).

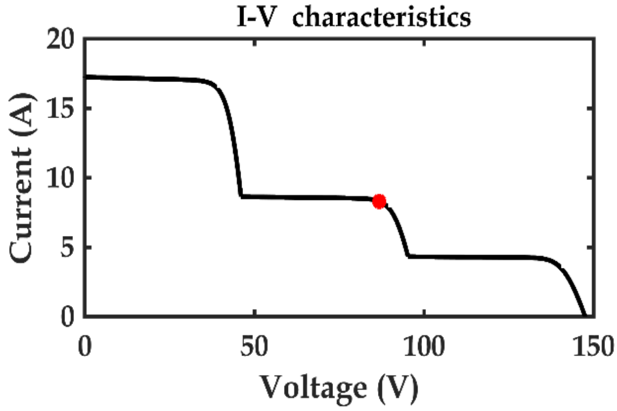


Figure 3: I-V characteristics during partial shading

Conventional approaches reduce the PV system's total efficiency, meaning it cannot track the GMPP and instead settles at an LMPP or close to it [8]. Complex optimization issues are increasingly solved with nature-inspired optimization techniques [9]–[11]. Applying optimization techniques is a very strong and efficient way to address the nonlinear MPPT issues that PS causes in photovoltaic systems. Two of the most widely used optimization techniques for MPPT problems are particle swarm optimization (PSO) and ant colony optimization (ACO), which offer several advantages, including reduced computation requirements and no need to understand the internal characteristics of the system [7]. However, they are inflexible because the PSO and ACO algorithms depend on determining control parameters [12]. Convergence of the PSO is also strongly dependent on the particle placements at initialization (Figure 4).

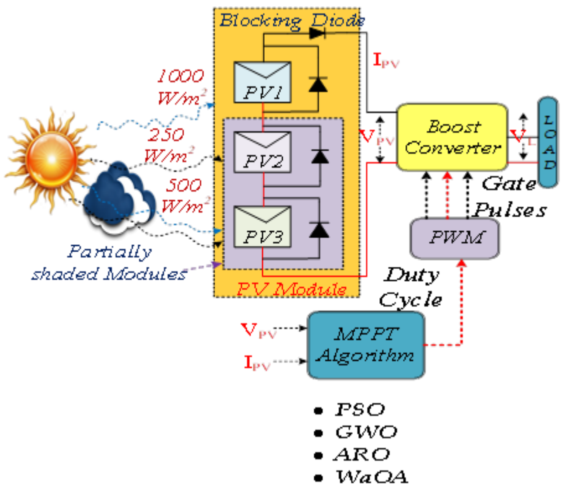


Figure 4: Proposed System

When the MPPT is recognized as a matter of optimization, metaheuristic procedures could be employed to monitor its progress. A variety of bio-inspired and swarm cognitive approaches have been investigated based on the population concept [7]; [13]; [14]–[16]. They also disclose their modifications to improve their performance. ANN [17], evolutionary algorithms, and FLC [18] are also utilized in PSCs to monitor GMPP. In the past several years, numerous hybrid approaches have also been reported. These approaches combine two or more MPPT strategies, utilizing their respective strengths [8]; [19]; [20]. At a typical efficiency of 99.92%, the authors of [21] used a combination of the traditional method and bio-inspired (INC-DFO) to demonstrate the novel idea of GMPP tracking under PSCs. TSO [22] can track GMPP with minimal power waste by precisely simulating the swarm. Using a direct control mechanism, a GWO-based MPPT [7] successfully captures the SPV array's GMPP in shading conditions. ROA [23] can also be used to determine the ideal duty cycle value to boost the power and effectiveness of the SPV system. The GWO method's leader design is incorporated into the standard SSA algorithm to enhance its ability to do global searches [31]. Due to better rates of GMPP convergence, LIPO [24] can accomplish GMPP significantly more quickly. PSO and TSA work together to create the Hybrid TSA-PSO [25] method, which increases TSA's exploitation potential while tracking GMPP. The following are the main goals of the current investigation:

- Hardware realization of the proposed system employing PSO, GWO, Walrus and ARO metaheuristic MPPT algorithms.
- Performance evaluations are conducted in real-time under PSCs under test scenarios while tracking GMPP.

PSO, WaOA, and ARO performance evaluations are conducted using different parameters. The Walrus optimization that has been proposed tracks the GMPP with fewer iterations, thereby minimizing oscillations near the GMPP and minimizing tracking time. The findings of the proposed technique have been evaluated with those of the traditional P&O MPPT technique along with the metaheuristic algorithms. The proposed technique was developed in the MATLAB/Simulink environment, and the results were validated on the hardware.

2. Methodology

An SPV array comprises several PV modules, which are made up of parallel and series-connected solar cells. DDM and SDM, two equivalent circuits, can be used to simulate these cells. Because SDM involves less computing overhead and fewer parameters for precise simulation, it is used in the design and analysis of SPV systems. Figure 5 represents the equivalent circuit of PV using a single diode. The equivalent PV system current is calculated using the basic equations derived from the Kirchhoff current rule.

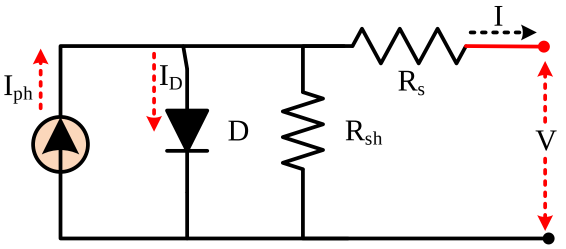


Figure 5: Equivalent Circuit diagram of single diode model

$$I = I_{ph} - I_o\left[e^{\frac{q(V+IR_S)}{KTA}} - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{1}$$

Where I represents the output current, V represents the voltage across the PV, while I_{ph}, K, T, A denotes the photocurrent, Boltzmann constant, temperature and ideality factor. R_S And R_{sh} denotes the series and shunt resistance.

$$I_{ph} = \left(I_{sc} + k_i \Delta T\right)\frac{G}{G_{STC}} \tag{2}$$

$$I_o = I_{oSTC}\left(\frac{T_{STC}}{T}\right)^3 e\left[\frac{qE_g}{AK}\left(\frac{1}{T_{STC}} - \frac{1}{T}\right)\right] \tag{3}$$

$$I_{oSTC} = \frac{I_{sc}}{e\left(\frac{qV_{oc}}{AKT_{STC}}\right) - 1} \tag{4}$$

Reduced FF and power loss are two of the factors that contribute to variance in incidence irradiations (PSCs) on different modules inside the SPV array, as shown in Figure 6. PSCs cause hotspots and unbalanced circumstances throughout the system because they cause a few of the array's modules to have a sharp decline in yield power. Bypass diodes are the solution to this issue. The PV modules create the PS condition by employing three PV modules with 60 solar photovoltaic cells, each having 20 cells. With a bypass diode in each of these three models, which are connected in series, the irradiance of each model may be changed to a set value, such as 1000 W/m2 for panel 1, 300 W/m2 for panel 2, and 600 W/m2 for panel 3. The equivalent model of the connected solar PV system is shown in Figure 6. Simultaneously, the P-V and I-V characteristics during the PS conditions are depicted in Figure 2 and Figure 3, respectively.

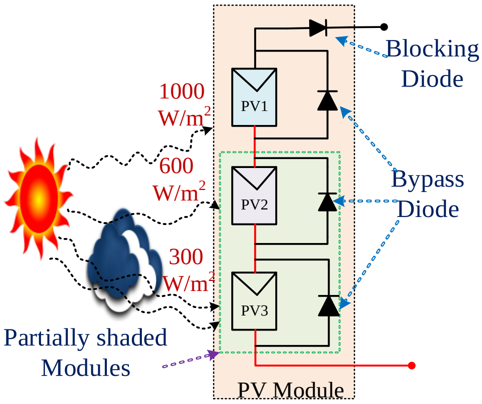


Figure 6: Configuration of Partially shaded PV module

As illustrated in Figure 6, this experimental investigation uses a 2 x 2 SPV array arrangement with four SPV modules.

3. MPPT Metaheuristics Techniques

3.1. Particle Swarm Optimization Technique

PSO's quick computation speed and excellent accuracy make it the most effective way to track MPP compared to other MPPT techniques. Fish in pools or birds' flocks together serve as models for the basic principles of PSO execution [26]. According to this optimization strategy, certain particles form a swarm and fly across the search region like wasps to get the optimal answer. With its extensive flying experience, every particle tries to change its moving velocity. There are two distinguishing features of every particle. This position in the search space could be a potential answer. Typically, the following equations determine each particle's velocity and position updates. The particle's velocity in the search space indicates its direction and rate of motion.

$$P_i^{t+1} = wP_i^t + c_1 r_1 (P_{best_i} - Y_i^t) + c_2 r_2 (G_{best} - Y_i^t) \quad (5)$$

$$Y_i^{t+1} = Y_i^t + P_i^{t+1} \quad (6)$$

Where P_i^t is the velocity of particle i, Y_i^t is the position of the particle at iteration t, P_{best_i} is the best-known position and G_{best} is the best-known position, w is inertia weight, c_1 and c_2 are acceleration coefficients, while r_1 and r_2 are random values between $[0,1]$. Figure 7 shows the particles' updated velocity and position using the PSO. By defining position as the current duty cycle and velocity as the deviation from that value, we can derive an equation describing the converter's duty cycle.

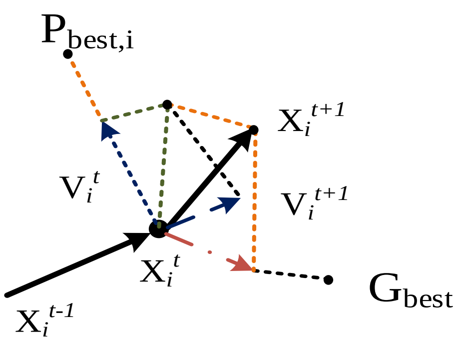


Figure 7: Velocity and position update in PSO

$$d_i^{t+1} = d_i^t + V_i^{t+1} \quad (7)$$

İt is evident from Eq.7 that the duty cycle depends on the P_{best_i} and G_{best}.

3.2. Artificial Rabbit Optimization

The actual survival strategies adopted by rabbits are described mathematically by the ARO's effective optimization model. Thus, two often imitated strategies—detour eating and unintentional concealment are investigated. An initial model of the detour foraging approach is executed. This tactic prompts the rabbit to nibble the grass around nearby nests [27]. Following each iteration, the positions of the rabbits are changed in compliance with the guidelines of the proposed approach, and they are then evaluated concerning the objective function. The agents will get increasingly adept at locating the bunnies' hiding spots, which serve as a stand-in for the answers as the procedure proceeds. A randomly selected location inside the search space is assigned to each member of the initial population based on equations 11 through 14.

$$Rb_i = X_b + rand(1, dim) * [Y_b - X_b], i = 1 : N_{rb} \quad (8)$$

$$NRb_k(itr+1) = Pb_i + (Pb_k - Pb_j) * X_m + Nds * rand\left(\frac{1}{2}\left(\frac{5}{100} + r_1\right)\right) \quad (9)$$

$$X_m = c\left(e - e^{\left(\frac{iter-1}{iter_{max}}\right)^2}\right)\sin(2\pi r_2) \quad (10)$$

NDS stands for the normal distribution standard function, where iter indicates the current iteration and the kth rabbit's previous and current positions. In a subsequent phase, reducing the possibility that an opponent will successfully capture a rabbit using the randomized concealment technique is feasible. Rabbits may endure a lack of energy when they reach the third stage, which could lead to the discontinuation of their strategy in favour of an unpredictable, evading approach. The positions of the rabbits are modified following each iteration. Eq.8 can be used to represent the rabbits' detour foraging mathematically. A rabbit typically excavates many tunnels closer to its nest to protect itself from predators. The following formula is shown.

$$b_{j,k}(iter) = Pb_k(itr) * (1 + C.T) \quad (11)$$

$$k = 1 : N_{Rb} \;\&\; j = 1 : dim \quad (12)$$

$$C = r_4 \frac{itr_{max} - (itr+1)}{itr_{max}} \quad (13)$$

$$C(j) = \begin{cases} 1, j = k, j = 1 : dim \\ 0, else \end{cases} \quad (14)$$

The energy factor can be defined using the following factors (AF).

$$AF(iter) = 4 * \ln\frac{1}{r}\left(1 - \frac{iter}{iter_{max}}\right) \quad (15)$$

3.3. Grey Wolf Optimization

The GWO algorithm aligns the proposal of grey wolf leadership and hunting mechanisms. As apex predators, grey wolves prefer packs to simulate leadership responsibilities [28]. To quantitatively model wolf social hierarchy in GWO design, the fittest solution is used as alpha (α). As a result, beta (β) and delta (δ) rank second and third, respectively. Other possible solutions are considered to be omega (ω). There are three steps to the GWO algorithm: pursuit, wrapping around, and assaulting prey. During the hunt, grey wolves encircle their prey, which can be roughly represented by Equations 16–17.

$$G = | C.Y_p(t) - Y(t) | \tag{16}$$

$$Y(t+1) = Y_p(t) - A.G \tag{17}$$

Where $\vec{A}$ [?] and[?] denote the coefficient vectors, which represent the position vector of prey while [?] represents the position vector of the prey. The best solution is updated using the mathematical Eq.18- Eq.21.

$$\left.\begin{aligned} G_\alpha &= | \vec{C}_1.Y_\alpha - Y | \\ G_\beta &= | \vec{C}_1.Y_\beta - Y | \\ G_\delta &= | \vec{C}_1.Y_\delta - Y | \end{aligned}\right\} \tag{18}$$

$$\left.\begin{aligned} Y_1 &= Y_\alpha - A_1.(G_\alpha) \\ Y_2 &= Y_\beta - \vec{A}_1.(G_\beta) \\ Y_3 &= Y_\delta - \vec{A}_1.(G_\delta) \end{aligned}\right\} \tag{19}$$

$$Y(t+1) = \frac{Y_1 + Y_2 + Y_3}{3} \tag{20}$$

The converter duty cycle is represented by the Eq.21.

$$D_i(t+1) = D_i(t) - A.D \tag{21}$$

3.4. Walrus Optimization

The proposed Walrus Optimization Algorithm (WaOA) is a population-based approach where walruses are the explorers in this population [29]. Every walrus in WaOA represents a possible solution to the optimization issue. Thus, each walrus's position in the search space determines the potential values of the identified variables. Therefore, Each walrus is a vector, and the population can be statistically represented using the so-called population matrix. When WaOA is first implemented, walrus herds are initialized at random. Equation 22 is used to determine this WaOA population matrix.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N \times m},$$

X is the walrus population, Xi is the ith possible solution, while Xi,j is the jth value of the variable Table 2. The Pseudo code of POA is given in Table 1.

Table 1: Pseudo Code of WaOA algorithm

Start	
	Input all the parameters of optimization.
	Set the number of walruses and the total number of iterations.

	Initialization of the position of and calculate the objective function
	For t = 1:T
	Update the strongest position based on objective function criterion. For I = 1:N Phase 1: Feeding strategy (exploration). Calculate the new location of the jth walrus using equation 3. Update the ith location using Equation (4). Phase 2: Migration Choose an immigration destination for the ith walrus. Calculate new status of the ith walrus using Equation (5). Phase 3: Escaping and fighting against predators (exploration) Calculate a new position in the neighbourhood. Update the ith walrus location using equation 9 End Save the best solution so far End End

Table 2: Converter specifications

Parameters	Values
C_{in}	100μF
C_{out}	100μF
L	3mH
R_{Load}	30Ω
f_{sw}	10kHz

4. Results & Discussion

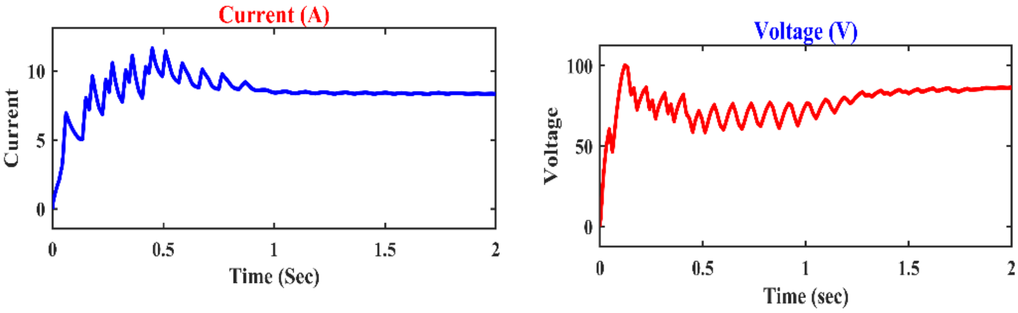
The reliability of the suggested WaOA MPPT algorithm was assessed through comprehensive simulation studies and hardware validations (Figure 13). P&O, PSO, ARO, and GWO-based MPPT algorithms are used to compare the outcomes, depending on several attributes, under the PS conditions shown in Figure 7 and a constant temperature of 25 °C. The first is the GMPPT's capacity to converge to the appropriate GMPP. This criterion is the most crucial since it determines the method's robustness and dependability (Figure 12). The optimum duration, or the entire time required to reach the GMPP, is the second (Figure 10). At the third point, it meets to its maximum power (Figure 11). The MPPT efficiency during the change from one shade pattern to another is the transient efficiency, which comes in at number four. Table 2 lists all the data, including the maximum power and numerical values of the assessment criteria for each GMPPT approach pertinent to the significant discoveries. Figure 4 depicts the PV system that was used in this investigation (Figure 14). The different system parameters are listed in Table 3.

4.1. Performance Evaluation in MATLAB/SIMULINK Environment

According to Table 3, the Walrus-based MPPT approach surpasses all other MPPT techniques while monitoring the GMPP of 719 watts (Figure 15). Concerning certain performance measures, it has a mean of 662.6, a median of 714.1, and a standard deviation of 671.6. With a settling time of 1.83 seconds and an efficiency of 99.39%, it can be deemed an effective means to handle PS conditions in PV systems (Figure 9). Figure 8 displays the simulation results for each algorithm discussed regarding GMPP tracking, PV voltage and current, and duty cycle control.

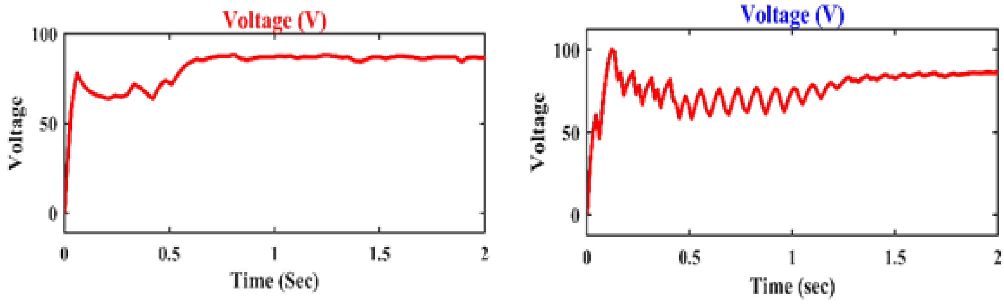
Table 3: Performance evaluations of MPPT techniques

MPPT Technique	Parameters							
	Pmax (W)	Mean	Median	Standard deviation (std)	Root Mean Square (RMS)	Rise time (ms)	Settling time (s)	Efficiency (%)
WaOA	719.0	662.6	714.1	671.6	0.484	-	1.83	99.839
ARO	717.7	654.1	710.4	664.2	0.542	-	1.99	99.659
GWO	717.4	653.8	679.6	661.1	0.123	2.57	0.36	99.617
PSO	717.8	702.2	717.6	705.4	0.163	.083	3.148	99.672



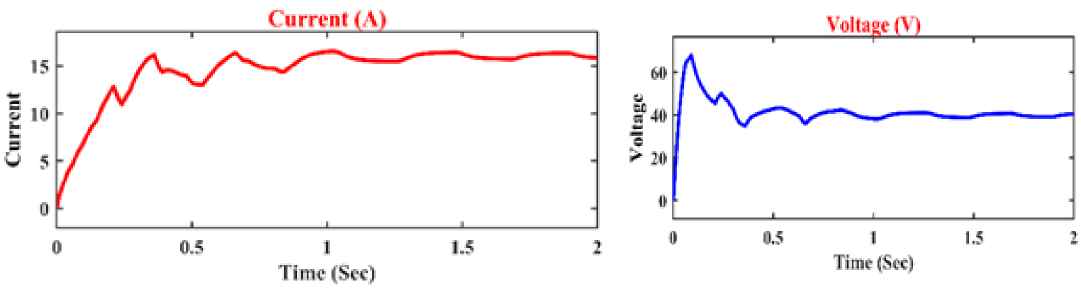
(a) (b)

Figure 8: (a) Current & (b) Voltage graphs of GWO MPPT



(a) (b)

Figure 9: (a) Voltage & (b) Current of ARO MPPT



(a) (b)

Figure 10: (a) Current & (b) Voltage of WaOA MPPT

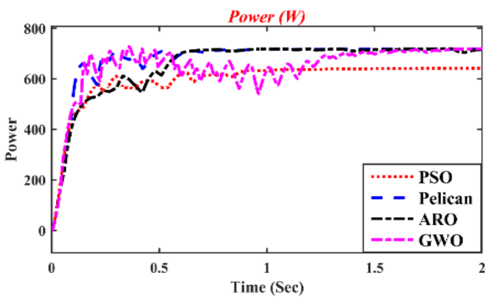


Figure 9: Comparative analysis of Metaheuristic MPPT

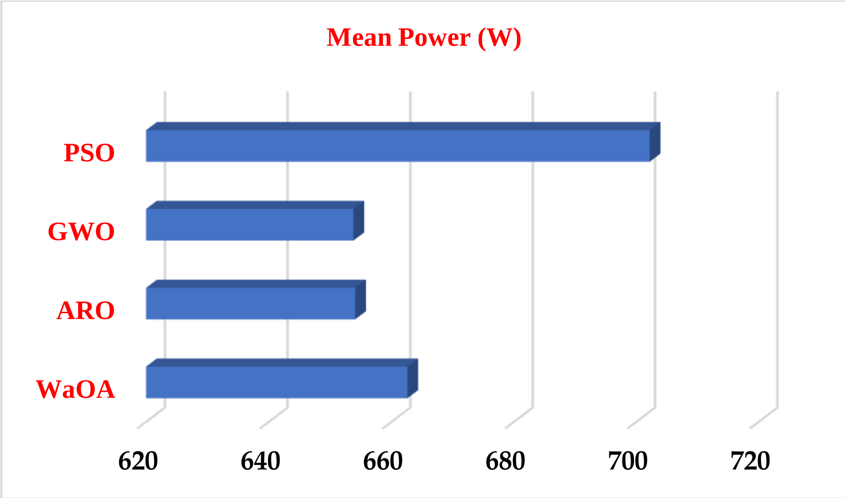


Figure 10: Comparative analysis of Mean Power

Figure 11: Comparative Analysis of Power

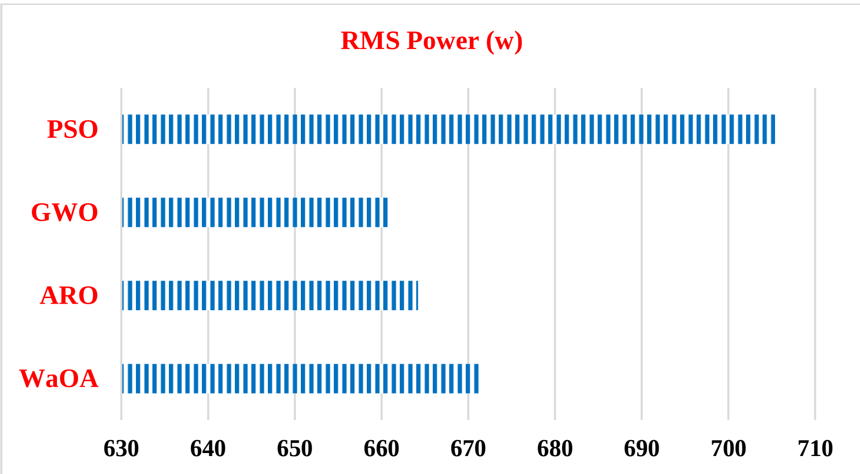


Figure 12: Comparative analysis of RMS Power

Figure 13: Comparative analysis of Rise time and settling time

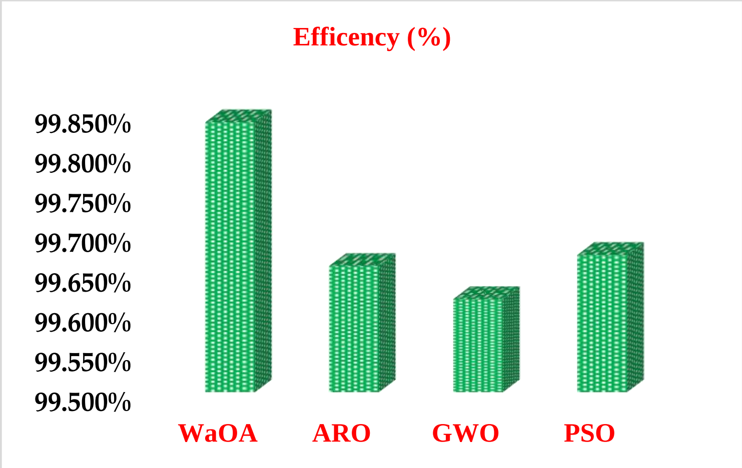


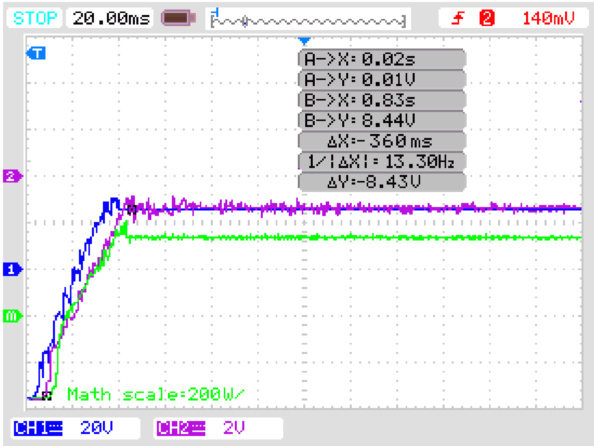
Figure 14: Comparative Analysis of Efficiency

4.2. Experimental Validation

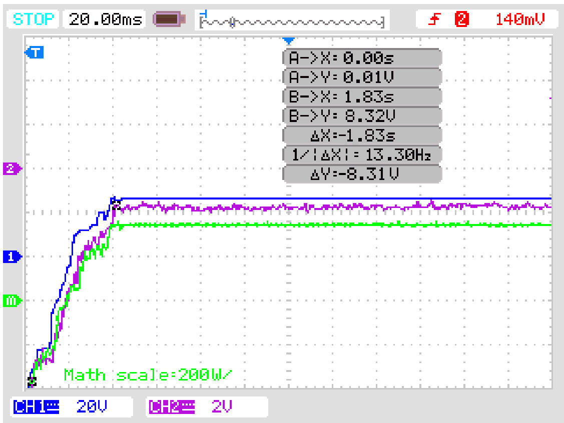
Both MPPT methods are tested on 50W PV modules to demonstrate their practicality. A standalone PV system with a resistive load and DC-DC converter has been developed in real-time for investigation (Figure 16). The experimental configuration shows a PV module (Pm=183.97W, Vm=43.38V, Im=4.24A) coupled with an MPPT system. All three MPPT approaches are explored when solar irradiation increases from 0W/m2 to 1000W/m2, as illustrated in Figure 17.

Figure 17: Experimental setup for MPPT-assisted PV system

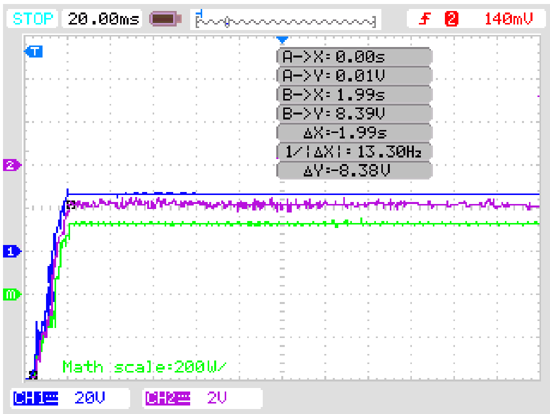
As illustrated in Figure 18 (a) - (b), digital storage oscilloscope (DSO) screens indicate the transient response of both MPPT approaches when the PV system gradually changes irradiance from 0W/m2 to 1000W/m2. Conventional MPPT's transient response under this scenario reveals that when the PV module is lighted at 1000 W/m2, ARO achieves electrical performance of 725.49W, 86.67V, and 8.38A, as shown in Figure 18(a). Furthermore, the existing GWO-based MPPT's transient response under this scenario reveals that when the PV module is lighted at 1000 W/m2, it achieved electrical performance as 720.22W, 86.67V, and 8.31A as shown in Figure 18(b). Figure 18(c) demonstrates that the based MPPT approach shows a transient response when the PV system is exposed during the irradiation level of 1000W/m2. Thus, the PV system output power increases to 730.62W. It was superior to conventional ARO and GWO-based MPPT techniques concerning less tracking time. Table 4 shows that the based MPPT technique outperformed in a shorter tracking time.



(a)



(b)



(c)

Figure 18: Transient response of (a) ARO (b) GWO (c) WAOA

Table 4: Performance assessment for MPPT integrated PV system

MPPT Techniques	Channel	Parameters	Scale	Performance at MPP
ARO	1	Voltage(v)	50	86.67 V
	2	Current (Amp)	2	8.38 A
	Math Scale (green)	Power(watt)	50	725.49 W
GWO	1	Voltage(v)	50	86.67 V
	2	Current (Amp)	2	8.31 A
	Math Scale (green)	Power(watt)	50	720.22 W
WaoA	1	Voltage(v)	50	86.67V
	2	Current (Amp)	2	8.43A
	Math Scale (green)	Power(watt)	50	730.62W

Moreover, compared to traditional ARO (726.29W) and GWO (720.22W) based MPPT approaches, WAoA is computationally simpler, exhibits excellent accuracy, has a cheap implementation cost, and can maintain a high power output of 730.62W.

5. Conclusion

To maximize power extraction from PV arrays operating under PSCs, a novel MPPT controller based on the WaOA metaheuristic algorithm is proposed and discussed in this study. The MATLAB/SIMULINK platform has been used to implement and present the suggested WaOA-based MPPT approach for a 719 W PV system. Additionally, the performance comparison between the suggested MPPT method and well-known MPPT techniques such as GWO, PSO, and ARO was evaluated. Regarding tracking reliability, rate of convergence to GMPP, and other metrics, the simulation results under different partial shade situations show the new Pelican-based MPPT method's notable benefits over the current techniques (GWO, PSO, and ARO).

5.1. Nomenclature

PV	Photovoltaic
GMPP	Global maximum power point
LMPP	Local maximum power point
PS	Partial shading
P&O	Perturb and observe
FPA	Flower pollination algorithm
WaOA	Walrus Optimization algorithm
ARO	Artificial rabbit optimization
GWO	Grey wolf optimization

PSO	Particle swarm optimization
IC	Incremental conductance
MPP	Maximum power point
CS	Cuckoo Search
G	Irradiation
T	Temperature
MPPT GMPPT	Maximum power tracking Global Maximum point tracking

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