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Optimizing Solar PV Array Reconfiguration for Maximum Power Extraction Using Hippopotamus Algorithm under Partial Shading

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ABSTRACT- This research paper presents an innovative approach to maximizing power extraction from solar photovoltaic (PV) arrays under partial shading conditions by employing the Hippopotamus Optimization Algorithm (HOA). Partial shading is a common issue that significantly reduces the efficiency of PV systems by creating multiple local maxima on the P-V curve, thereby challenging conventional Maximum Power Point Tracking (MPPT) methods. To address this, we propose an adaptive reconfiguration strategy for the PV array, optimized using HOA, which successfully moderates the impacts of shading and enhances overall energy yield. The Hippopotamus Optimization Algorithm, inspired by the foraging behavior of hippopotamuses, is utilized for its robust global search capabilities and fast convergence. The algorithm dynamically adjusts the arrangement of the PV module to locate and maintain operation at the global maximum power point. Our methodology involves simulating various shading scenarios and evaluating the performance of HOA-based reconfiguration against traditional MPPT techniques. Simulation results demonstrate a significant improvement in power extraction efficiency, with the HOA-based reconfiguration strategy consistently achieving higher power output compared to conventional methods. Additionally, the proposed system exhibits enhanced adaptability to changing shading patterns, ensuring reliable performance in diverse environmental conditions. The findings highlight the potential of the Hippopotamus Optimization Algorithm as a powerful tool for optimizing PV schemes, particularly in scenarios where shading is inevitable. This study contributes to the advancement of renewable energy technologies by offering a novel solution for improving the efficiency and reliability of solar PV arrays.

Keywords: Hippopotamus Optimization Algorithm (HOA); Solar PV Array; Partial Shading; Maximum Power Point Tracking (MPPT); Reconfiguration Strategy.

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1. INTRODUCTION

The increasing demand for renewable energy sources has propelled the development of efficient solar photovoltaic (PV) systems, which convert sunlight into electrical energy. However, biased shading remains a significant challenge, reducing the overall performance of PV arrays by causing multiple local maxima on the power-voltage (P-V) curve and hindering conventional MPPT techniques.

PV module reconfiguration under biased shading conditions using a genetic algorithm to maximize power extraction was focused on by [1]. The main finding was that the genetic algorithm approach was effective in optimizing the configuration of the PV array. A limitation of this study could be the reliance on simulation models rather than real-world data, potentially affecting the generalizability of the results.[2] employed particle swarm optimization for solar PV array reconfiguration beneath biased shading circumstances to maximize power extraction. The study highlighted the effectiveness of this optimization technique in improving the performance of the PV array. A limitation could be the lack of comparison with other optimization algorithms, potentially limiting the understanding of the relative effectiveness of particle swarm optimization. A review of various PV array reconfiguration techniques for maximum power extraction under partial shading conditions was provided by [3]. The main finding was the identification of different methods used in the literature for addressing partial shading issues. A limitation could be the lack of original research in the paper, potentially limiting the depth of analysis.[4] conducted a state-of-the-art review on PV array reconfiguration under partial shading conditions and proposed a new solution method. The study highlighted the advancements in the field and introduced a novel approach for optimizing PV array configurations. A limitation could be the limited empirical validation of the proposed solution method, potentially affecting its practical applicability.[5] performed an investigational assessment to obtain MPP from PV module reconfiguration during biased shading circumstances. The main finding was the successful implementation of the reconfiguration technique in a real-world

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setting. A limitation could be the specific experimental conditions used, potentially limiting the generalizability of the results to other scenarios.

The study proposed by [6] an Adaptive Evolutionary Jellyfish Search Procedure for ideal PV module reconfiguration during biased shading circumstances to increase power extraction. The main finding is the effectiveness of the proposed algorithm in improving the performance of photovoltaic arrays under shading conditions. The study focuses on the algorithm's performance in simulation settings. Real-world implementation challenges and scalability issues may arise.[7] presents a technique based on Knight's tour for reconfiguring PV modules during biased shading conditions to increase power abstraction. The main finding is the successful application of the Knight's tour technique in optimizing power output. The Knight's tour technique may have limitations in scalability and complexity when employed to substantial photovoltaic arrays or complex shading patterns.[8] discusses various PV module reconfiguration procedures for optimizing power output under partial shading conditions. The main finding is a comprehensive overview of existing reconfiguration strategies.[9] explores reconfiguration approaches to increase power abstraction from PV modules during biased shaded circumstances. The main finding is the effectiveness of certain reconfiguration strategies in improving power output. The study may not consider all possible shading scenarios or environmental factors that could affect the performance of the reconfiguration strategies.[10] discusses PV module reconfiguration procedures to obtain MPP under biased shaded situations. The main finding is the importance of reconfiguration in enhancing power output in microgrid settings. The chapter may not delve into the specific challenges or limitations of implementing reconfiguration techniques in practical microgrid systems.

A new reconfiguration methodology to obtain maximum power from biased PV module was proposed by [11]. The main finding of this study was that the reconfiguration procedure significantly improved the output power of partially shaded PV modules. However, the limitations of this study could include the lack of real-world implementation and the need for further validation in different environmental conditions.[12] introduced the HOA as a new Bio-inspired optimization procedure. The main finding of this study was that the Hippopotamus optimization algorithm showed promising results in solving optimization problems. However, the limitations of this study could include the need for comparison with other optimization algorithms and the requirement for testing on a wider range of benchmark functions to assess its generalizability.

This research introduces an innovative approach using the Hippopotamus Optimization Algorithm (HOA) to dynamically reconfigure PV arrays and optimize power obtained under biased shading situation. Inspired by the foraging behaviour of hippopotamuses, HOA offers robust global search capabilities and rapid convergence, making it an effective solution for locating the global maximum power point. Through simulation studies, this paper demonstrates the superiority of HOA-based reconfiguration in enhancing the energy yield and reliability of PV systems compared to traditional methods, highlighting its potential to significantly advance the efficacy of PV energy harvesting in environments prone to shading.

2. SYSTEM DESCRIPTION

A PV module is formed by connecting multiple PV modules in series, parallel, or a combination of both, as the power generated by a single module is often insufficient to meet higher energy demands [13]. However, this configuration can be adversely affected by Partial Shading (PS), which is one of the primary reasons for reduced energy production from photovoltaic arrays. The presence of shade on the panels leads to panel bypassing, resulting in multiple peaks in the output characteristics. Consequently, conventional MPPT techniques may fail to extract the maximum power due to these multiple peaks, highlighting the need for intelligent algorithms [14] that can effectively navigate these complexities. Therefore, the PV array's panels may be rearranged to provide consistent shade distribution through reconfiguration. Under shadow dispersion, this approach produces consistent row current and is efficient. An in-depth study using a 9x9 TCT linked PV module before and afterward reconfiguration is provided to show the significance of PV array reconfiguration and the shade distribution process. In addition, the row current calculation corresponding to a basic TCT linked PV module has been developed for better comprehension.

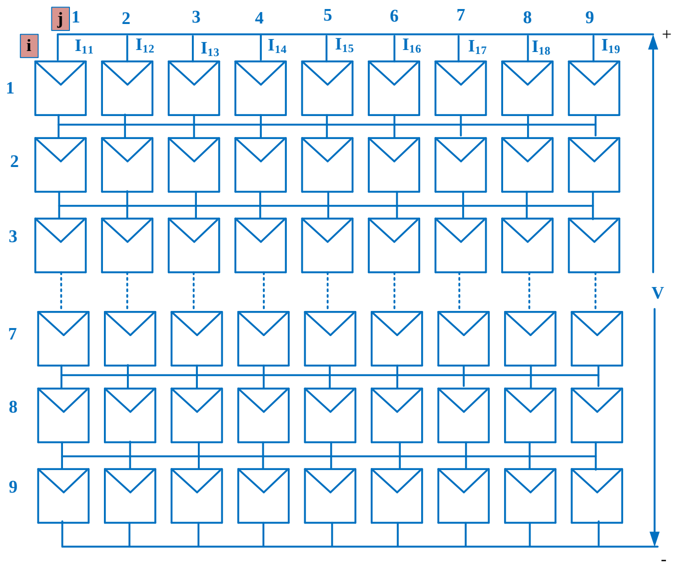

Figure 1. Representation of Interconnection of PV Array

2.1 TCT Array Configuration

Each row in the TCT connectivity technique is cross-tied in a straightforward parallel sequence. The numerous linking links will result in a greater number of loops being produced. Different current levels will therefore pass during the PV module linked in the identical string while adhering to the circuit's voltage limits. Appropriate labelling is applied to make row current identification easier to grasp. For example, the module with the number "14" designates the first row and fourth column where the panel is located. Subsequent panel numbering is done so that the array's row number is shown by the first digit and its column numbering is indicated by the second. The current bound computation for each row is determined as follows:

$$I_{Rn} = \sum_{n=1}^{9} I_{1n}^{*} g_{1n} \quad (1)$$

Where I_{1n} is the current limit at full irradiance

$g_{1n}$is the insolation level

Furthermore, determining the row currents in a TCT interconnection is crucial for determining the global peak (GP) power. The array potential of the TCT linked arrangement for the nine rows is obtained by applying Kirchhoff's Voltage Law.

$$V_{array} = \sum_{i=1}^{9} V_i \quad (2)$$

where V_i is the maximum Voltage of the modules at the i^{th} row and V_{array} is the PV array voltage. Kirchhoff's Current Law may be used to determine the current at each node in the array, and the following formula yields the overall array current:

$$I_{array} = \sum_{j=1}^{9}\left(I_{ij} - I_{(i+1)j}\right) = 0, i = 0,1,2,3..,8 \quad (3)$$

2.1 TCT during partial shaded situation:

Even though the TCT connectivity technique can extract maximum power, it has serious drawbacks such as numerous peaks and 0% shadow dispersion. Its electrical connections are still intact; hence the technique is incapable to diffuse the shadow evenly throughout the array.

As a result, the row current, which is influenced by varying irradiation levels, experiences significant fluctuations. To prevent damage, panels with lower row current values are often skipped, leading to inefficiencies. Consequently, panel bypassing in the TCT technique produces stepped I-V characteristics, which increases the system's mismatch losses. Therefore, rearranging the panels to disperse shadows becomes essential to minimize the number of bypasses and optimize energy production in the TCT-linked PV array.

To address this issue, it is important to note that while the physical locations of the panels must remain unchanged, their electrical connections can be adjusted. By swapping any panel within the column, it is possible to achieve better shadow distribution and maintain nearly equal row current. However, a significant challenge of this approach is finding the optimal combination of connections in the shortest amount of time, which can hinder the efficiency of the rearrangement process and impact overall energy production. When the HOA approach is used, this weakness may be fixed because it begins with a random starting guess and uses an optimization process to arrive at the best option. For any shade pattern, shade spreading in conjunction with the HOA approach can thus be successful. The next section explains the specific procedural procedures needed to apply the HOA approach to the array reconfiguration problem.

3. HIPPOPOTAMUS OPTIMIZATION ALGORITHM

Hippopotamuses are used as search agents in a population-cantered optimization method known as the Hippopotamus Optimization Algorithm (HOA). The placement of each hippo in the hunt space indicates the quantity of the decision variables, and every hippopotamus in the HOA signifies a possible outcome to the optimization process. A matrix represents the hippo population, and each hippo is represented as a vector. During the initialization stage, the HOA produces random beginning solutions, just like conventional optimization methods. The choice variable vector is created using the formula below:

$$X_i : x_{ij} = lb_j + r.\left(ub_j - lb_j\right), i = 1,2, \dots N, j = 1,2, \dots., m \quad (4)$$

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_i \\ \vdots \\ x_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & v_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \cdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \ddots & \cdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \quad (5)$$

Phase 1: Hippopotamuses update their position in their natural habitat—a river or pond (Exploration)

A herd consists of a dominant male who leads the group, many adult females, calves, and several adult males. The dominant man is identified by using the objective function value, which is highest for issues involving maximizing and lowest for jobs involving minimization. Hippos usually gather in small groups, with the dominant male guarding the group's territory. The adult females surround the males. men must either entice females or outcompete other men to establish supremacy after being banished by the dominant male when they reach adulthood. The mathematical location of the male hippopotamuses in the lake or pond is represented by *equation (6).*

$$X_i^{Mhippo} : x_{ij}^{Mhippo} = x_{ij} + y_1.\left(D_{hippo} - I_1 x_{ij}\right) \quad (6)$$

For i=1,2….,[N/2] and$_j = 1,2 \dots.m$

The location of a male hippopotamus is represented by x_{ij}^{Mhippo} while the position of the dominating hippopotamus, which has the lowest cost in the current repetition, is represented by D_hippo. Equation (6) illustrates that the vector $\vec{r_1}$ *to* r_5 is a random vector between 0 and 1.I_1 and $I_2$are values between 1 and 2, and $MG_i$is the average of a small sample of randomly selected hippos, which include the hippos (xi) that are being considered equally likely. While y_1 is an extra random number between 0 and 1, integer random values q_1 and q_2 can both be zero or one.

$$h = \begin{cases} I_2 \times \vec{r_1} + (\sim q_1) \\ 2 \times \overrightarrow{r_2 - 1} \\ \vec{r_3} \\ I_1 \times \vec{r_4} + (\sim q_2) \\ r_5 \end{cases} \quad (7)$$

$$T = \exp\left(-\frac{t}{T}\right) \tag{8}$$

$$x_i^{FBhippo} : x_{i,j}^{FBhippo} = \begin{cases} x_{i,j} + h_1(D_{hippo} - I_2 MG_i) T > 0.6 \\ [I] \quad else \end{cases} \tag{9}$$

$$[I] = \begin{cases} x_{i,j} + h_2(MG_i - D_{hippo}) r_6 > 0.5 \\ lb_j + r_7(ub_j - lb_j) else \end{cases} \tag{10}$$

For i=1,2….,[N/2] and$_j = 1,2 \ldots . m$

The placements of female and immature hippopotamuses ($x_i^{FBhippo}$) in the herd are modeled by *equations (9)* and *equation (10)*. Although they often stick close to their moms, young hippo sometimes wanders due to curiosity. The young hippo has migrated away from its parent if T is greater than 0.6. Despite being far from its mother, the young hippopotamus remains close to the herd if r_6(which ranges from 0 to 1) is greater than 0.5.

Otherwise, it is no longer part of the herd. The integers or vectors h_1 and h_2 in the h equation are selected at random from the five states. The value of r_7 can be any integer between 0 and 1. *Equations (11)* and *equation (12)* provide the most recent locations of the immature, female, and male hippopotamuses in the herd. F_i is the representation of the objective function.

$$x_i = \begin{cases} x_i^{Mhippo} F_i^{Mhippo} < F_i \\ x_i \quad else \end{cases} \tag{11}$$

$$x_i = \begin{cases} x_i^{FBhippo} F_i^{FBhippo} < F_i \\ x_i \quad else \end{cases} \tag{12}$$

By employing h vectors, the I_1 and I_2 scenarios in the proposed method expand exploration and the global search. It improves the exploration phase of the proposed procedure and produces a more effective global hunt.

Phase 2: Hippo defense beside predators

Hippopotamuses live in herds primarily for security and stability. Potential predators are discouraged from pursuing these enormous, huge beasts. Young hippopotamuses, however, may occasionally stray from the herd out of curiosity since they are not as strong as adults, putting them at risk of being devoured by predators like lions, hyenas, and crocodiles. They are similarly vulnerable to predators because to hippocampal diseases. The two main defence mechanisms used by hippos are sudden turns toward predators and loud noises used to scare them away. Hippopotamus may potentially approach the predator during this period and force it to retreat to effectively ward off the danger. *Equation (13)* displays the predator's location in the search space.

$$Predator_j = lb_j + \overrightarrow{r_8} \cdot (ub_j - lb_j), j = 1,2, \ldots . m. \tag{13}$$

where r_8 signifies an arbitrary vector extending from 0 to 1.

$$\vec{D} = |Predator_j - x_{i,j}| \tag{14}$$

The distance between the i^{th} hippopotamus and the predator is shown by *equation (14)*. A protective response is elicited by the $Predator_j$ factor in the hippopotamus. The hippopotamus quickly turns and moves forward to force the predator to retreat if $Predator_j$is less than Fi, indicating that the predator is close. The hippopotamus turns toward the predator or intruder with restricted mobility to indicate its presence within its territory if $Predator_j$ is larger, suggesting the predator or intruder is farther away.

x_i^{hippoR} represents the hippopotamus's location when it faces the predator. When there are sudden changes in the predator's position, the Lévy-distributed random vector RL→ is used. The Lévy random motion is calculated in eq. (15). Equation (16) is utilized to get σ_w, where A is a fixed value ($\vartheta = 1.5$) and Γ is the Gamma function. Random values between [0,1] make up W and v.

$$Levy(v) = 0.05 \times \frac{w \times \sigma_w}{|v|^{\frac{1}{v}}} \tag{15}$$

$$\sigma_w = \left[\frac{\Gamma(1+v) \sin\left(\frac{\pi v}{2}\right)}{\Gamma\left(\frac{(1+v)}{2}\right) v 2^{\frac{(v-1)}{2}}} \right]^{\frac{1}{v}} \tag{16}$$

A uniform arbitrary number falls between two and four (f), one between one and one-half (c), and three between two and three (d). A uniform arbitrary number between -1 and 1 is represented by g. An arbitrary vector having dimensions of 1×m is called r_9. A hippopotamus has been slaughtered and will be replaced in the herd by another if F_i^{hippoR} is bigger than F. If not, the hunter will be able to get away, and the hippo will rejoin the herd. During the second phase, notable improvements were seen in the global search procedure. The first and second stages work in tandem to minimize the likelihood of being stuck in local minima.

$$x_i = \begin{cases} x_i^{hippoR} F_i^{hippoR} < F_i \\ x_i F_i^{hippoR} \geq F_i \end{cases} \tag{17}$$

Phase 3: Hippo Escapes from the Predator (Exploitation)

Because lions and hyenas, for example, steer clear of places containing bodies of water, a hippopotamus seeking sanctuary will often head toward the nearest lake or pond when it comes across a group of predators or is unable to fend them off. The third phase of the HO process significantly models this behaviour to enhance local search capabilities. To imitate this, a random place around the hippopotamus's current location is generated. If the hippopotamus' new location results in a higher cost function value, it has successfully determined a safer site and modified its position. *t* indicates the current repetition, while *T* denotes the MaxIter.

$$lb_j^{local} = \frac{lb_j}{t}, ub_j^{local} = \frac{ub_j}{t}, t = 1,2,,,,,, T \tag{18}$$

$$x_i^{hippoe} : x_{i,j}^{hippoe} = x_{i,j} + r_{10}(lb_j^{local} + s_1(ub_j^{local} - lb_j^{local})) \tag{19}$$

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x_i^{hippoe} denotes the position of a hippopotamus that searches for the nearest safe location. s_1 are an arbitrary vector or number chosen arbitrarily from three possible situations, these scenarios enhance local search effectiveness, improving the algorithm's exploitation quality.

$$s = \begin{cases} 2 \times r_{11} - 1 \\ r_{12} \\ r_{13} \end{cases} \tag{20}$$

r_{11} denotes an arbitrary vector ranging from 0 to 1. $r10$ and $r11$ are arbitrary values generated within the choice of 0 to 1. r_{12} is also included as a normally distributed arbitrary number.

$$x_i = \begin{cases} x_i^{hippoe} F_i^{hippoe} < F_i \\ x_i F_i^{hippoe} \geq F_i \end{cases} \tag{21}$$

It would have been better to mimic the nature of hippos if the population had been divided into different categories of immature, female, and male hippos; nevertheless, this would have had an adverse effect on the optimization algorithm's performance.

#Algorithm of HOA-implemented PV Array Reconfiguration

Start*: Define 'm x n' PV modules.*

Initialization Phase*: Initialize constants for HOA, such as social and cognitive factors and inertia weight.*

Generate Velocity Matrix*: Generate initial velocities for the hippopotamuses.*

Calculate Row Current and Voltage*: Calculate current and voltage for each row in the PV module.*

Fitness Evaluation*: Evaluate the fitness of each hippopotamus.*

Reconfiguration Phase*: Update the positions of the hippopotamuses and reconfigure the PV array based on the best-known positions.*

Iterate*: Increment the iteration counter and repeat the process if the termination criterion is not met.*

4. SIMULATION RESULTS & DISCUSSIONS

The proposed HOA method is evaluated on a 9×9 TCT-configured PV array under different shading patterns, Short Wide and Long Narrow, Diagonal shading, and Short Narrow shading Patterns. A 213W PV module with an open-circuit voltage (V_{oc}) of 36.3V and a short-circuit current (I_{sc}) of 7.84A and V_{max} =29V & I_{max} =7.35A is used in this study. The performance of the HOA method is compared with TCT configuration and Genetic algorithm-based reconfiguration techniques. The analysis is conducted on a laptop with 12 GB RAM, a Core i5 processor running at 2.40 GHz, and MATLAB 2021a. The four shading patterns analysed are described as follows:

4.1 Case 1: Short Wide (SW) Shading Pattern

In the SW shading pattern, a broad, short shadow partially covers the PV array. Assuming constant temperature and focusing solely on irradiation as the variable, the levels range from 900 to 200 W/m². The modules are exposed to irradiation levels of 900 W/m², 800 W/m², 600 W/m², 400 W/m², and 200 W/m². *Figure 2* illustrates the shading pattern used in Case 1, while *figure 3* shows the modified PV pattern obtained using the HOA method under these shading conditions. The most notable features of the HOA results are: (1) a uniform distribution of shade and (2) improved current regulation for each row of the array. As shown in the I-V and P-V curves in *figure 4,* the HOA method maintains a smoother curve and higher MPP voltage compared to its counterpart. This leads to higher power output, as higher voltage at greater current boosts performance. The maximum power achieved with the HOA method is 12,284 W, while the GA method reaches 11,336 W.

900 W/m2 | 800 W/m2 | 600 W/m2 | 400 W/m2 | 200 W/m2

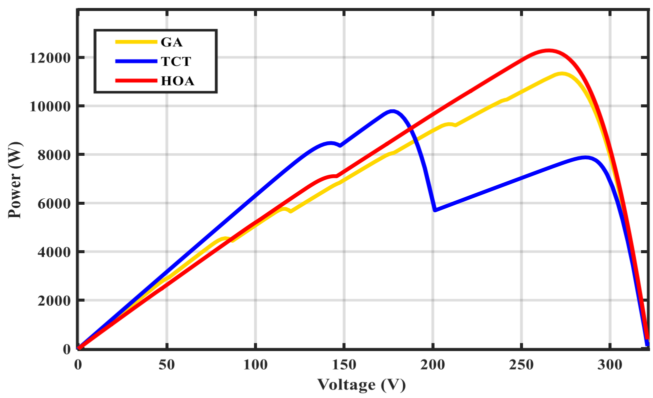
11	12	13	14	15	16	17	18	19
21	22	23	24	25	26	27	28	29
31	32	33	34	35	36	37	38	39
41	42	43	44	45	46	47	48	49
51	52	53	54	55	56	57	58	59
61	62	63	64	65	66	67	68	69
71	72	73	74	75	76	77	78	79
81	82	83	84	85	86	87	88	89
91	92	93	94	95	96	97	98	99

Figure 2. Shading pattern of Case-1

900 W/m2 | 800 W/m2 | 600 W/m2 | 400 W/m2 | 200 W/m2

11	12	13	14	15	16	17	18	19
21	22	23	24	25	26	27	28	29
31	32	33	34	35	36	37	38	39
41	42	43	44	45	46	47	48	49
51	52	53	54	55	56	57	58	59
61	62	63	64	65	66	67	68	69
71	72	73	74	75	76	77	78	79
81	82	83	84	85	86	87	88	89
91	92	93	94	95	96	97	98	99

Figure 3. Reconfigured pattern of Case-1



(a)

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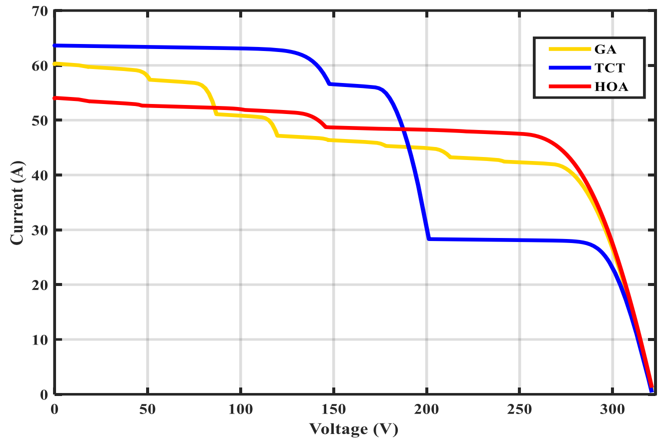


(b)

Figure 4. Comparison of reconfigured results with GA & HOA during case-1

4.2 Case 2: Long Narrow (LN) Shading Pattern

The LN shading pattern creates a long, narrow shadow across the PV array. This pattern results in the array experiencing five distinct levels of insolation: 900 W/m², 800 W/m², 700 W/m², 400 W/m², and 300 W/m², in that order. Unlike the short-wide shadow, only the panels in the column grouping are affected by shading, resulting in reduced impact from shade dispersion. *Figure 5* depicts the shading pattern for *case 2*, while *figure 6* shows the reconfigured pattern for this case. In *case 2*, the maximum power obtained after reconfiguration using the HOA method is 13,268 W, compared to only 12,107 W achieved with the GA method. This demonstrates that the proposed HOA method outperforms the GA approach, yielding superior results in PV array configuration.

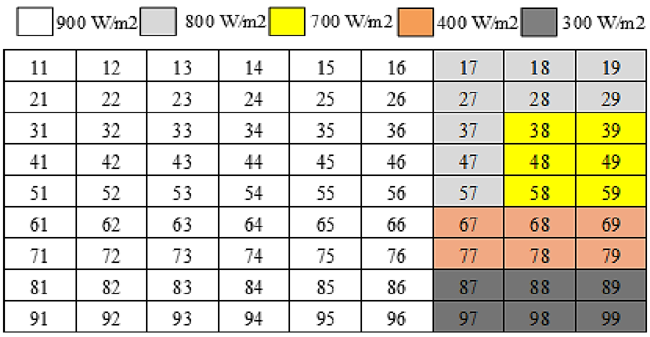


Figure 5. Shading pattern of Case-2

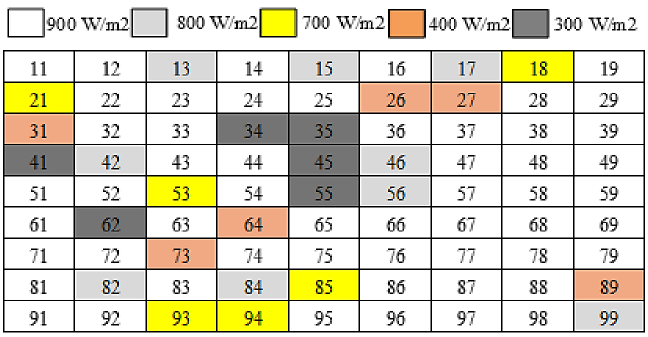
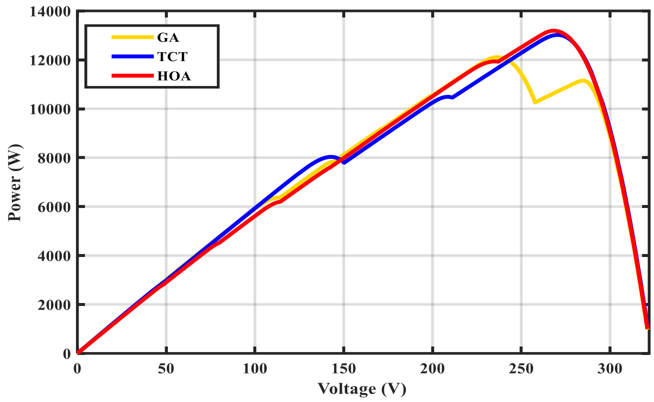
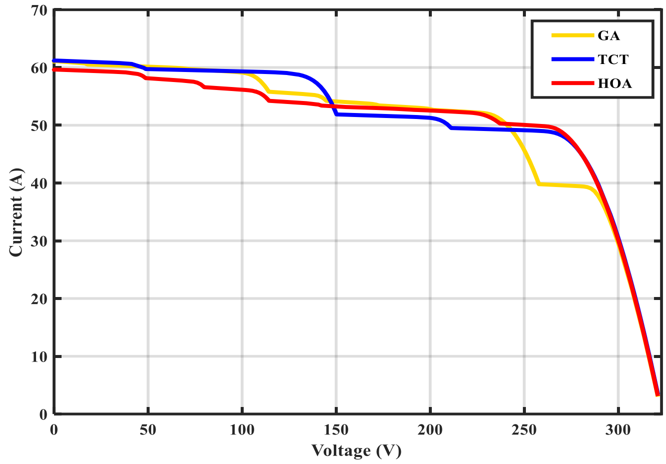


Figure 6. Reconfigured pattern of Case-2



(a)



(b)

Figure 7. Comparison of reconfigured results with GA & HOA during case-2

4.3 Case 3: Diagonal Shading Pattern

Diagonal shading is a typical pattern caused by nearby tall structures such as towers or high-rise buildings. *Figure 8* illustrates the shading pattern for *Case 3*, while *figure 9* displays the reconfigured pattern. In *case 3*, the maximum power output after reconfiguration using the HOA method is 12,723 W, compared to only 12,298 W achieved with the GA method. As shown in *figure 10*, the proposed array configuration produces smoother characteristic curves compared to other configurations.

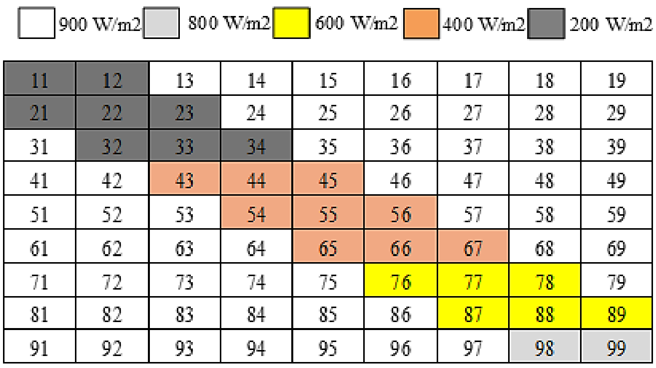


Figure 8. Shading pattern of Case-3

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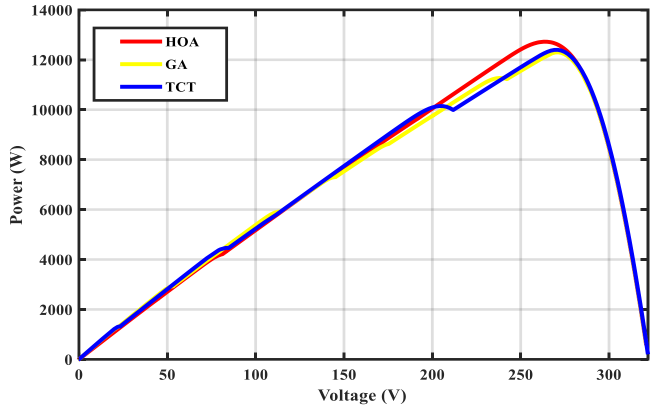
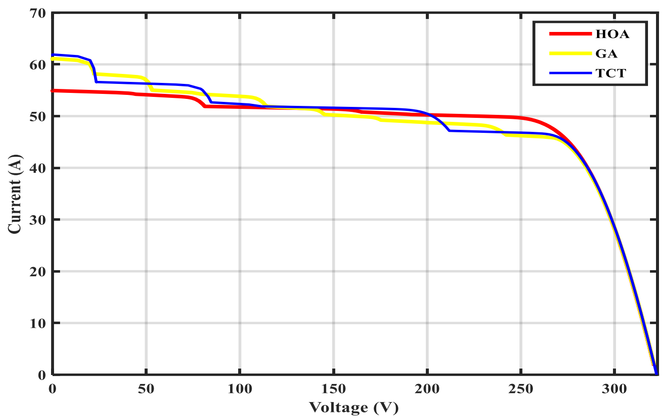
900 W/m2 800 W/m2 600 W/m2 400 W/m2 200 W/m2

11	12	13	14	15	16	17	18	19
21	22	23	24	25	26	27	28	29
31	32	33	34	35	36	37	38	39
41	42	43	44	45	46	47	48	49
51	52	53	54	55	56	57	58	59
61	62	63	64	65	66	67	68	69
71	72	73	74	75	76	77	78	79
81	82	83	84	85	86	87	88	89
91	92	93	94	95	96	97	98	99

Figure 9. Reconfigured pattern of Case-3



(a)



(b)

Figure 10. Comparison of reconfigured results with GA & HOA during case-3

4.4 Case 4: Short Narrow shading Pattern

The short and narrow (SN) shading pattern is often caused by nearby objects such as trees or buildings and can affect any part of the PV array from any direction. *Figure 11* depicts the shading pattern for Case 4, while *figure 12* shows the reconfigured pattern. After reconfiguration using the HOA method, the maximum power output achieved is 14,125 W, whereas the GA method only reaches 13,483 W. This demonstrates that the proposed HOA method outperforms the GA method, yielding superior results in PV array configuration. *Figure 13* highlights that the HOA configuration scheme results in a smoother curve without local maximum power points, whereas other configuration schemes show multiple local maxima on their curves.

900 W/m2 600 W/m2 400 W/m2

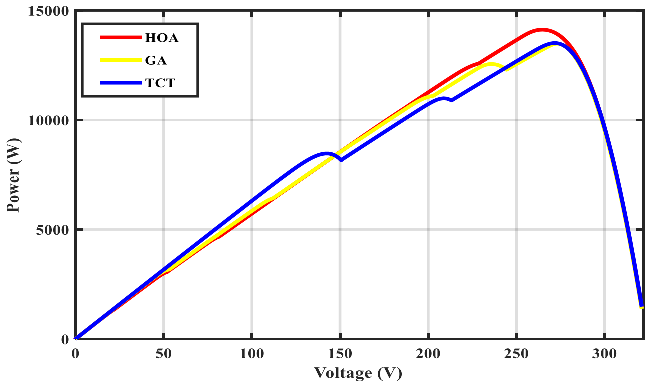
11	12	13	14	15	16	17	18	19
21	22	23	24	25	26	27	28	29
31	32	33	34	35	36	37	38	39
41	42	43	44	45	46	47	48	49
51	52	53	54	55	56	57	58	59
61	62	63	64	65	66	67	68	69
71	72	73	74	75	76	77	78	79
81	82	83	84	85	86	87	88	89
91	92	93	94	95	96	97	98	99

Figure 11. Shading pattern of Case-4

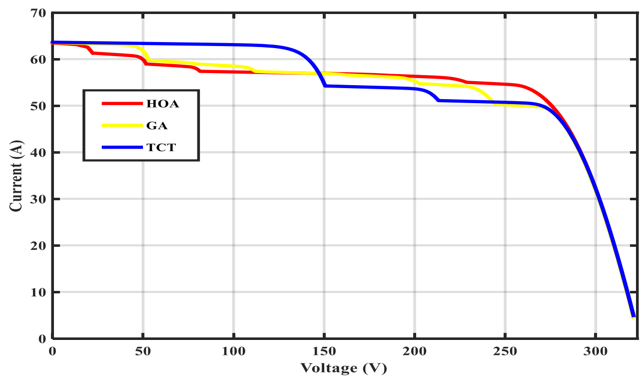
900 W/m2 600 W/m2 400 W/m2

11	12	13	14	15	16	17	18	19
21	22	23	24	25	26	27	28	29
31	32	33	34	35	36	37	38	39
41	42	43	44	45	46	47	48	49
51	52	53	54	55	56	57	58	59
61	62	63	64	65	66	67	68	69
71	72	73	74	75	76	77	78	79
81	82	83	84	85	86	87	88	89
91	92	93	94	95	96	97	98	99

Figure 12. Reconfigured pattern of Case-4



(a)



(b)

Figure 13. Comparison of reconfigured results with GA & HOA during case-4

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Consistency in obtaining solutions is a key consideration when selecting optimization techniques for a given problem. To assess solution quality, the best, worst of the objective function and computational time were documented over 25 trials for both HOA and GA methods. The results were compared for all the cases and are shown in *table 1*. In all the scenarios described, it was observed that the power generated by the HOA method was higher than that produced by the GA method and the TCT arrangement. Additionally, the proposed method proved to be effective under various shading conditions.

Table 1. Comparison of Objective Function Metrics for HOA and GA Methods

Case	Method	Best Value	Worst Value	Computational Time (sec)
Case 1	HOA	12284 W	12194 W	1.02 sec
	GA	11336 W	10292 W	3.5 sec
Case 2	HOA	13268 W	13218 W	1.01 sec
	GA	12107 W	11473 W	4.3 sec
Case 3	HOA	12723 W	12564 W	0.94 sec
	GA	12298 W	10965 W	4.6 sec
Case 4	HOA	14125 W	14093 W	0.9 sec
	GA	13483 W	12242 W	3.3 sec

5. CONCLUSIONS

In this work, we proposed a reconfiguration strategy for PV arrays using the Hippopotamus Optimization Algorithm (HOA). The primary objective was to improve the working of PV modules during partial shading situations, a common issue that significantly reduces the efficiency of PV structures. Through comprehensive analysis and comparison, HOA demonstrated a marked improvement over the Genetic Algorithm (GA), a commonly used optimization technique in this domain. HOA's ability to maintain higher current levels across a broader range of voltages is particularly noteworthy. This feature ensures that the PV arrays can operate more efficiently even when parts of the array are shaded, thereby maximizing power output. The power curves generated by HOA are not only smoother but also higher compared to those produced by the original configuration and the GA-reconfigured array. This smoothness indicates more stable and reliable power generation, which is crucial for the consistent operation of solar energy systems. The superior performance of HOA is largely attributed to its robust optimization capabilities. Unlike GA, which may struggle with local optima and convergence issues, HOA effectively navigates the solution space to find optimal configurations that mitigate the effects of partial shading. This makes HOA a promising tool for advancing both the efficiency and reliability of solar energy systems, as it can adapt to changing environmental conditions more effectively than traditional methods. Moreover, the substantial improvements in power extraction observed with HOA highlight its potential for broader application. Future research should focus on further refining HOA to enhance its performance and exploring its applicability in larger, more complex PV systems. This could involve integrating HOA with other advanced algorithms or adapting it to work in conjunction with real-time monitoring systems for dynamic reconfiguration.

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