Journal of Advanced Research Design 146, Issue 1 (2026) 13-33

Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Gender Based Sea Lion Optimization Algorithm for Maximum Power Point Tracking

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ARTICLE INFO

Article history:
Received 10 March 2025
Received in revised form 23 June 2025
Accepted 14 September 2025
Available online 28 October 2025

Keywords:
Sea lion optimization algorithm; bio-inspired; metaheuristic; maximum power point tracking; photovoltaics; Matlab-Simulink

ABSTRACT

This research paper proposes an improved variant of SLnO, named the Gender Based Sea Lion Optimization (GBSLnO) algorithm. GBSLnO separates the population into two gender groups (male and female), where the search agents of different genders possess distinctive operational characteristics during the mathematical execution. Male agents are less considerate in localization, but bolder in action, consistently focused on efficiency, and capable of multitasking (variable dimension). In contrast, female agents are more considerate in positioning and actions, but work in a single task without concerning on efficiency (invariant dimensionality). GBSLnO retains the searching behavior, encircling behavior, and circle-updating behavior in the original SLnO, but its functionality has been improved with enhanced coefficient adaptation. Overall, this algorithm mainly emphasizes the interactions between two gender groups which operate in same behavioural patterns but distinctive mathematical mechanism. The proposed algorithm was simulated on a total 20 maximum power point tracking (MPPT) challenges in photovoltaic application systems to compare with standard SLnO and several existing SLnO variants. Upon evaluation, GBSLnO outperformed other comparative algorithms in terms of reliability and robustness for all test cases. Meanwhile, it achieves the highest efficiency in the MPPT process of the photovoltaic system. In addition, its output power spectrum also shows that GBSLnO has the best convergence rate and the least oscillation. All these statements prove that GBSLnO is a successfully improved variant of SLnO, offering a more superior optimization process.

1. Introduction

Optimization is the process of finding the most effective global minimum or maximum [1]. As the latest technologies always require more efficient optimizations to improve application performance, the demand for more advanced optimization approaches is on the rise. The emergence of stronger algorithms has undoubtedly inspired scholars to further develop the evolutionary optimization to provide better solutions for near-term technological applications. Upon survey, they can be implemented into upcoming potential applications, including optimal equipment diagnostics,

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https://doi.org/10.37934/ard.146.1.1333

optimal system planning, optimal equipment design, optimal decision-making with uncertainty, and optimal system operation.

Equipment diagnostics is a subfield of control engineering that focuses on system monitoring, characterizing failure types, and spotting flaws. The creation of fault classification models by optimal equipment diagnostics increases the accuracy of fault diagnosis, decreases training time, and enables equipment to recover from issues by replacing defective components. The medical industry has recently started using this technology on a regular basis as automated computer-aided diagnosis to get rid of human mistakes for more accurate early identification and treatment of chronic ailments, including breast cancer [2,3] and lung tumors [4]. Diagnostics must be completed with minimal error to avoid possible misjudgements during repeated operations.

The optimal system planning is concerned with optimizing construction, equipment layout, material procurement, facility expansion, quality assurance, and economic efficiency. It assures that all components meet or surpass user expectations by enhancing the functionality and integration of the subsystem portions. System planning optimization has recently been used in a greater variety of fields, including academia [5], medicine [6], economics [7, 8], engineering [8,9], and politics [10]. Robustness and operating speed are the things to consider when planning an optimal system to achieve reliable and fast outcomes in the recent competitive market.

The optimal equipment design is concerned with optimizing construction, minimizing quantity, and maximizing uniformity based on certain statistical criteria [11-14]. Substandard solutions in the application of optimal equipment design can lead to severe consequences, possibly even death, especially when the final design of any machine system is not optimized to completely free from failure, damage or explosion.

The optimal decision-making aims to obtain the maximum average profit with the least risk [15-19]. To be able to make the best decisions, one must consider the profitability analysis, operational efficiency, and realistic possibilities.

The optimal system operation guarantees that tasks are completed as accurately and effectively as feasible, frequently limiting publicity and boosting operational capacity. Accuracy is the primary consideration to ensure the effectiveness of the operating system, and convergence rate is a secondary prerequisite for the control system to obtain a satisfactory settling response.

It is noteworthy that the recently proposed intelligent optimization techniques typically assign a large number of search agents to execute the search mechanisms according to nature-inspired procedural rules, they are lightly referred to as nature-inspired algorithms and classified as a set of population-based algorithms. In general, nature-inspired algorithms can be divided into three main categories: chemistry-based, physics-based, and bio-inspired.

Chemistry-based algorithms imitate the principles of chemical reactions by which objects, states, and events occur in nature. The most well-known chemistry-based algorithm is the Chemical Reaction Optimization (CRO) algorithm [20]. Until now, there are still a lot of proposals for modification, improvement, transformation, adaptation, hybridization, etc. regarding CRO.

Physics-based algorithms imitate the laws of physics in the nature. Prominent physics-based algorithms include Space Gravitational Algorithm (SGA) [21], Gravitational Search Algorithm (GSA) [22], and Electromagnetism-like algorithm (EMA) [23]. Arithmetic Optimization Algorithm (AOA) [24] and Equilibrium Optimizer (EO) [25] are two state-of-the-art physics-based algorithms that have recently attracted attention.

In contrast, bio-inspired algorithms imitate the social behaviour of a group of organisms, particularly inspired by competitive or cooperative inter- and intra-species interactions in nature. Hence, most bio-inspired algorithms are classified as swarm-based intelligent algorithms. Typically, bio-inspired optimization algorithms are often named after the living organisms they mimic or the biological behavior they are inspired from. Relatively well-known swarm-based bio-inspired algorithms include Particle Swarm Optimization (PSO) [26], Artificial Bee Colony (ABC) [27], Artificial Fish Swarm Algorithm (AFSA) [28], and Ant Colony Optimization (ACO) [29]. Recently in 2019, Sunflower Optimization (SFO) algorithm [30], Artificial Coronary Circulation System (ACCS) [31], Emperor Penguins Colony (EPC) [32], Seagull Optimization Algorithm (SOA) [33], Blue Monkey (BM) algorithm [34], and Harris Hawks Optimization (HHO) algorithm [35] were proposed. In 2020, Mayfly Algorithm (MA) [36], Social Ski Driver (SSD) algorithm [37], and Black Widow Optimization (BWO) algorithm [38] were proposed. In 2021, Aquila Optimizer (AO) algorithm [39], African Vultures Optimization Algorithm (AVOA) [40], and Dingoes Optimization Algorithm (DOA) [41] were proposed. In 2022, Artificial Rabbit Optimization (ARO) [42], Chef-Based Optimization Algorithm (CBOA) [43], Dandelion Optimizer (DO) [44], Golden Jackal Optimization (GJO) [45], Honey Badger Algorithm (HBA) [46], Mountain Gazelle Optimizer (MGO) [47], Prairie Dog Optimization (PDO) [48], Red kite Optimization Algorithm (ROA) [49], Snake Optimizer (SO) [50], etc. were proposed. In 2023, Coati Optimization Algorithm (COA) [51], Alligator Optimization (AgtrO) algorithm [52], etc. were proposed.

With the ever-increasing number of optimization techniques or algorithm proposals, it is now clearly observed that most of the optimization techniques proposed in recent years are of the bio-inspired type. Hence, it can be deduced that the proliferation of bio-inspired algorithms in the field of mathematical computing could be the crucial factor that has continuously promoted the popularity of the optimization field in these years. In fact, bio-inspired optimization has indeed become a very hot topic throughout 2022. For further breakthroughs, it is highly recommended to add some evolutionary operators to the existing swarm-based variants of biomimetic optimization. Among all state-of-the-art algorithms, Sea Lion Optimization (SLnO) algorithm is currently our main research target. It was proposed in 2019 as a novel bio-inspired metaheuristic optimization algorithm. From the results and analysis obtained using SLnO, it is indeed a less promising optimization technique compared to other recently proposed algorithms, but the concise and clear mathematical formulation still leaves much room for improvement. Thus, this research work sets forth to improve SLnO through various modifications, adaptations, and additions of strategic operators inspired by deep imitation of evolutionary behaviors, primarily concerning on every single mathematical step that is beneficial to optimization efficiency. As a major finding of the research work, the Gender Based Sea Lion Optimization (GBSLnO) algorithm is proposed, where the proposed algorithm emphasizes the interactions between two gender groups (i.e., male sea lions and female sea lions) which operate in same behavioural patterns but distinctive mathematical mechanism. As the novelty is related to the major findings, the novelty lies in that GBSLnO adapts the coefficients to account for innovative shifts in the operating mechanism for agents of different genders, utilizes a partial memory-saving strategy to update all agents more reasonably, enables cross-referencing solutions of opposite genders to enhance population linkage, and keeps executable equations in the simplest format to prevent prolonged execution of algorithms.

This research paper is outlined as follows: Section 1 introduces this research work. Section 2 reviews the standard AgtrO. Section 3 explains the methodology of the proposed GBSLnO. Section 4 describes the problem definitions and simulation setups for the maximum power point tracking (MPPT) application. Section 5 compares and analyzes the collective results. At last, Section 6 concludes the study.

2. SLnO

Table 1 lists common mathematical notations used throughout the research work. This facilitates subsequent interpretation and analysis.

Table 1
Mathematical notation for algorithms [25,53]

Notation	Definition
i	Index of search agent
t	Index of iteration
n	Number of search agents or population number
$t_{\max}$	Greatest allowable iterative number
dim	Dimension
$\boldsymbol{X}$	Location point or solution
$\boldsymbol{X}_{\text{best}}$	Best solution among population
$\vec{\boldsymbol{X}}_{\text{best,m}}^{\text{t}}$	Best solution among male agents
$\vec{\boldsymbol{X}}_{\text{best,f}}^{\text{t}}$	Best solution among female agents
$f(\boldsymbol{X})$	Objective function value or fitness of $\boldsymbol{X}$
$\rightarrow$	Array vector or matrix format
$e^{(\square)}$	Exponential function
r	Random number within 0 and 1
r_{N}	Normally distributed random number
$\lvert\square\rvert$	Absolute value function
$\lfloor\square\rceil$	Round off to nearest integer
$\lceil\square\rceil$	Round up to nearest integer
$\lfloor\square\rfloor$	Round down to nearest integer
$\odot$	Element-wise multiplication
$\oslash$	Element-wise division
l	Lower bound of search space
u	Upper bound of search space

Sea Lion Optimization (SLnO) algorithm is reviewed for evolutionary reference. SLnO was first proposed in 2019, inspired by the social behavior of sea lions living in large colonies and how quickly they respond to the movement of prey [54]. In nature, sea lions perform social hunting skills by: (A) chasing, approaching and tracking prey, (B) vocalizing, (C) immobilizing and attacking. Hence, the mechanism of SLnO is divided into three main phases of operation:

2.1 Searching (Exploration)

The searching operation mimics the exploratory hunting behavior of sea lions in nature, performing random searches based on the location of allies. It is mathematically formulated as follows [54]:

$$\begin{cases} \overrightarrow{\boldsymbol{X}_i^{t+1}} = \overrightarrow{\boldsymbol{X}_j^t} - \left|2\vec{B}\overrightarrow{\boldsymbol{X}_j^t} - \overrightarrow{\boldsymbol{X}_i^t}\right| \odot \vec{A} & \text{, if } \left|\vec{A}\right| \geq 1 \\ \vec{A} = 2 - \frac{2t}{t_{\max}} & \square \\ \vec{B} = r_1 & \square \end{cases} \tag{1}$$

where $i \in \{1,2,\ldots,n\}$, $\overrightarrow{\boldsymbol{X}_j^t}$ represents the location vector from any random selected search agent. From a mathematical point of view, $\vec{A}$ and $\vec{B}$ are coefficients that determine the operating distance and direction, respectively. It can be seen from the equation that the initial value of $\vec{A}$ is 2, where it decreases linearly to 0 with iterations. Knowing that this operation can only be executed if $|\vec{A}| \geq 1$ implies that this equality is emphasized in the first half of the iteration. It is worth noting that the search agent is moving away from the reference allies to expand the search space to a wider range and avoid overlapping explorations in the same area. $\vec{B}$ is a random vector (number) between 0 and 1 used to bias the target solution for non-fixed positioning. In fact, these architectures allow the search agent to focus only on the global search, while assigning a wider range of motion to better explore unclear regions to find any possible global optimum.

2.2 Dwilding Encircling (Exploitation)

In nature, prey leave waves when they swim, and sea lions can use their whiskers to detect direction and follow prey. Typically, sea lions chase prey together while congregating prey into a narrow bait ball, as groups of sea lions hunting together increases the chances of getting more prey, especially when there are large numbers of fish. This behavior is known as encircling behavior, where it can be mathematically formulated as follows [54]:

$$\begin{cases} \overrightarrow{\boldsymbol{X}_i^{t+1}} = \overrightarrow{\boldsymbol{X}_{\text{best}}^t} - \left|2B\overrightarrow{\boldsymbol{X}_{\text{best}}^t} - \overrightarrow{\boldsymbol{X}_i^t}\right| \odot \vec{A} & \text{, if } |\vec{A}| < 1 \\ \vec{A} = 2 - \frac{2t}{t_{\max}} & \\ \vec{B} = r_2 & \end{cases} \tag{2}$$

where $\boldsymbol{X}_{\text{best}}$ is the best location vector that agents had visited so far along the iteration. Since the optimal solution in the search space is unknown a priori, SLnO recognizes that $\boldsymbol{X}_{\text{best}}$ is the target prey location close to the optimum that the i^{th} search agent is promised to approach. In order to ensure that the i^{th} search agent moves towards $\boldsymbol{X}_{\text{best}}$ without backtracking, it is necessary for the search agent to experience a coefficient $\vec{A}$ less than 1 at the current moment. Knowing that the coefficient $\vec{A}$ actually decreases linearly from 2 to 0 with the iterations, it is reasonable to infer that the search agent enforces this behavior only in the second half of the iterations. This confirms the role of encircling behavior in SLnO as an exploitative operation. From a mathematical point of view, Equation (2) closes the distance between the prey and the agent by a ratio that allows all search agents to approach the target solution $\boldsymbol{X}_{\text{best}}$ synchronously at the same interval to better surround the prey. For better flexibility to avoid agent conflicts, $\vec{B}$ has a random vector between 0 and 1 to slightly bias each agent's search direction.

2.3 Circle-Updating

During the attacking phase, sea lions capture the prey at the edge of the bait ball. SLnO models this so-called circle-updating behavior using the following mathematical formula:

$$\begin{cases} \overrightarrow{\boldsymbol{X}_i^{t+1}} = \overrightarrow{\boldsymbol{X}_{\text{best}}^t} + \left|\overrightarrow{\boldsymbol{X}_{\text{best}}^t} - \overrightarrow{\boldsymbol{X}_i^t}\right| \odot \vec{C} & \text{, if } \vec{V} \geq 0.25 \\ \vec{C} = \cos(2\pi r_3) & \\ \vec{V} = \left|\frac{(\sin\vartheta(1+\sin\emptyset))}{\sin\emptyset}\right| & \end{cases} \tag{3}$$

where $\vec{C}$ is a coefficient that determines the step size of the circle-updating behavior.

This approach first computes the distance between the i^{th} agent located at $\boldsymbol{X}_i^t$ and the prey located at $\boldsymbol{X}_{\text{best}}^t$, and then the distance is multiplied by cosine functions to create a edge-started circular motion between the i^{th} agent and the prey. In theory, this could set up a circular route in one-dimensional mathematical terms. From a mathematical point of view, the i^{th} agent is aggressively reducing the distance to the target point (prey location), intending to exploit the target point in the shortest possible time. Therefore, it can be confirmed that this mechanism plays a full role in promoting better local exploitation search.

The circle-updating behavior requires the full cooperation of a group of sea lions, therefore communication between search agents is mandatory. In fact, sea lions communicate with each other via vocalizations especially when they are chasing and hunting as a group. Thus, when a sea lion identifies the prey, it calls other agents to join in to surround and attack the prey. During mathematical modelling, search agents mimic this ability to have $\vec{V}$ playing the role as a decision coefficient impersonating the speed of vocalization of sea lion leader. When it vocalizes, the sound is reflected to the other medium which is the air and refracted at the same medium for calling agents who are under water. Thus, the first case is represented by $\sin\vartheta$ and the other by $\sin\emptyset$. For the i^{th} agent to enter the circle-updating operation, decision coefficient $\vec{V}$ must be exceeding 0.25, implying the successful reception of vocalization by the i^{th} search agent.

2.4 Mechanisms

For ease of understanding, the pseudocode of SLnO is given as follows:

```
Pseudocode for SLnO
Input parameters
Initialize population (agents)
Calculate the objective fitness values for all agents
t = 0;
X_best^t = best agent solution
WHILE (t < t_max)
    FOR i = 1 TO n
        Obtain coefficients A⃗, B⃗ and C⃗ for i^th agent
        IF V⃗ ≥ 0.25
            Execute Equation (3)
        ELSE
            IF |A⃗| ≥ 1
                Execute Equation (1)
            ELSE IF |A⃗| < 1
                Execute Equation (2)
            END IF
        END IF
        Calculate the objective fitness of i^th agent, f(X_i^(t+1))
    END FOR
    Replace X_best^t in sequence if any agent provides a better solution
    X_best^(t+1) = X_best^t
    t = t + 1
END WHILE
Global best objective fitness value = f(X_best^(t=t_max))
Output X_best^(t=t_max)
```

Output $f\left(\boldsymbol{X}_{\text{best}}^{t=t_{\max}}\right)$

From the merit point of view, each behavioral operation (i.e. Equations (1) to (3)) addresses the problem from a different optimization perspective. Despite the less-than-satisfactory step-size adaptation and object recognition, these three modes of behavior represent three distinct solutions that facilitate certain types of optimization problems that cannot be solved by a single computational approach. SLnO also follows the standard optimization regulation, to shift the emphasis from global exploration operation to local exploitation operation over the iterations. Here, $\vec{V}$ is not a controllable coefficient, hence we neglect its affection on the selection of the operational type. Instead, $\vec{A}$ plays the important role in deciding the timing of transition. Since $\vec{A}$ decreased linearly from 2 to 0 with iterations, first 50% of the iterations fall into exploration (searching behavior) and last 50% of the iterations fall into exploitation (dwindling encircling behavior). Although SLnO attempts to balance the contradiction, the fixed distribution of the decision coefficient $\vec{A}$ limits the flexibility of the algorithm, which also affects its composability to a wider range of optimization challenges.

3. Proposed GBSLnO

This research work proposes an improved variant of SLnO, called the Gender-Based Sea Lion Optimization (GBSLnO) algorithm. GBSLnO is developed on the basis of the original SLnO. It preserves but modifies 3 behaviors from the original SLnO: searching, dwindling encircling, and circle-updating operations. During evolutionary modeling, GBSLnO divides the population into two genders, where the 1st until $\left\lfloor \frac{n}{2} \right\rceil^{\text{th}}$ search agents are assigned male identities and the remaining become female search agents. The male and female groups have their own best solution (i.e., $\vec{\boldsymbol{X}}_{\text{best,m}}^{\text{t}}$ and $\vec{\boldsymbol{X}}_{\text{best,f}}^{\text{t}}$, respectively) in that particular gender. The search agents of different genders possess distinctive operational characteristics during the mathematical execution. Hence, the i^{th} search agent outputs two new solutions labeled as two different genders: male and female, namely $\vec{\boldsymbol{X}}_i^{\text{new,m}}$ and $\vec{\boldsymbol{X}}_i^{\text{new,f}}$ at the t^{th} iteration, where "m" stands for the term "male" and "f" stands for the term "female". Their mathematical expressions can be formulated as follows:

3.1 Male

$$\vec{\boldsymbol{X}}_i^{\text{new,m}} = \begin{cases} \vec{\boldsymbol{X}}_{j,\text{f}}^t - \left(\vec{B} \odot \vec{\boldsymbol{X}}_{j,\text{f}}^t - \vec{\boldsymbol{X}}_i^t\right) \odot \vec{A} & \text{, if } \vec{A} \geq 1 \text{ and } \vec{V} \geq 0.25 \\ \vec{\boldsymbol{X}}_{\text{best,f}}^t - \left(\vec{B} \odot \vec{\boldsymbol{X}}_{\text{best,f}}^t - \vec{\boldsymbol{X}}_i^t\right) \odot \vec{A} & \text{, else if } \vec{A} < 1 \text{ and } \vec{V} \geq 0.25 \\ \vec{\boldsymbol{X}}_{\text{best}}^t - \left(\vec{\boldsymbol{X}}_{\text{best}}^t - \vec{\boldsymbol{X}}_i^t\right) \odot \vec{C} & \text{, else if } \vec{V} < 0.25 \end{cases} \tag{4}$$

where $i \in \left\{1,2,\ldots,\frac{n}{2}\right\}$ and $j \in \left\{\frac{n}{2}+1,\frac{n}{2}+2,\ldots,n\right\}$ in Equation (4), $\vec{\boldsymbol{X}}_{j,\text{f}}^t$ is a randomly referenced female agent, and $\vec{\boldsymbol{X}}_{\text{best,f}}^t$ is the best solution found by female agents. The adopted coefficients in Equations (4) are formulated as follows:

$$\begin{cases} \vec{A} = 2(2\vec{r}_1 - 1)\left(\left(\frac{t}{t_{\max}}\right)^2 - \frac{2t}{t_{\max}} + 1\right) \\ \vec{B} = 1 + \overrightarrow{r_{\mathrm{N}_1}}\left(e^{-\frac{t}{t_{\max}}}\right)^4 \\ \vec{C} = e^{-\frac{f(\vec{x}^t_{\text{best}})}{f(\vec{x}^t_i)}}\cos(2\pi r_1) \\ \vec{V} = \vec{r}_2 \end{cases} \tag{5}$$

3.2 Female

$$\vec{\boldsymbol{X}}_i^{\text{new,f}} = \begin{cases} \vec{\boldsymbol{X}}^t_{j,\text{m}} - \left(\vec{B} \odot \vec{\boldsymbol{X}}^t_{j,\text{m}} - \vec{\boldsymbol{X}}^t_i\right) \odot \vec{A} & \text{, if } \vec{A} \geq 1 \text{ and } \vec{V} \geq 0.25 \\ \vec{\boldsymbol{X}}^t_{\text{best,m}} - \left(\vec{B} \odot \vec{\boldsymbol{X}}^t_{\text{best,m}} - \vec{\boldsymbol{X}}^t_i\right) \odot \vec{A} & \text{, else if } \vec{A} < 1 \text{ and } \vec{V} \geq 0.25 \\ \vec{\boldsymbol{X}}^t_{\text{best}} - \left(\vec{\boldsymbol{X}}^t_{\text{best}} - \vec{\boldsymbol{X}}^t_i\right) \odot \vec{C} & \text{, else if } \vec{V} < 0.25 \end{cases} \tag{6}$$

where $i \in \left\{\frac{n}{2}+1, \frac{n}{2}+2, \dots, n\right\}$ and $j \in \left\{1,2,\dots,\frac{n}{2}\right\}$ in Equation (6), $\vec{\boldsymbol{X}}^t_{j,\text{m}}$ is a randomly referenced male agent, and $\vec{\boldsymbol{X}}^t_{\text{best,m}}$ is the best solution found by male agents. The adopted coefficients in Equation (6) are formulated as follows:

$$\begin{cases} \vec{A} = 2\,\text{In}\left(\frac{1}{r_1}\right)\left(1 - \frac{t}{t_{\max}}\right)\left(\text{sign}(r_2 - 0.5)\right) \\ \vec{B} = 1 + \frac{t_{\max} - t + 1}{t_{\max}} r_{\mathrm{N}_1} \\ \vec{C} = \left(e^1 - e^{\frac{t-1}{t_{\max}}}\right)\sin(2\pi r_3)\cos(2\pi r_4) \\ \vec{V} = r_5 \end{cases} \tag{7}$$

3.3 Mechanisms

It is worth noting from the mathematics of Equations (4) and (6) that the i^{th} search agent has three executable operations corresponding to its conditions. Though having refined modification, the first line of expression still mimics the searching behavior that operates as global exploration, second line of expression mimics the dwindling encircling behavior that operates as local exploitation, and third line of expression mimic the circle-updating behavior that operates as supportive local exploitation. As a qualified exploration operation, searching behavior slightly shifts the overall updated position point by $\vec{A} - 1$ values, away from its target point referenced to the current position point of another randomly chosen search agent of opposite genders. To strengthen the exploitation, dwindling encircling behavior brings the i^{th} agent $1 - \vec{A}$ steps closer to the vague prey location (best solution) found by its allies of opposite genders. To further promote the exploitation capability, the circle updating behavior brings the i^{th} agent $1 - \vec{C}$ steps closer to the exact prey location (best solution) found by the whole population. It is worth noticing that three operations refer to different target solutions when executing. This is one of the main concerns in this proposed algorithm to distinctly extend the search space for better exploration in the early stage, and strength the ability of escaping local optima in the later stage of iteration.

Not only mimicking the fact that sea lions have two genders in nature, the separation of population (entire search agents) into two different genders also specifies a series of new regulations to the mathematical mechanism. First, in searching behavior, a search agent can only refer to an ally of opposite genders. Second, in dwindling encircling behavior, a search agent can only refer to the best solution found by opposite genders. Third, in circle-updating behavior, a search agent can refer to the best solution of population (which is shared between all agents without caring the gender). It is explainable that each agent refers to the position and best solution of the opposite gender for sustainable interaction, while referring to the same global best solution in circle-updating behavior for detailed clustering of two gender groups. Every search agent executing under these protocols is destined to experience both intra- and inter-specific interdependence, directly or indirectly benefiting from two groups of different genders with distinctive organizational search strategies. Upon in-depth interpretation, the architecture superimposes the patterns of combinatorial searches to diversify operations, thereby increasing applicability to wider types of optimization challenges. In fact, the inter-dependence relationship between two gender groups provides more variation to the search direction, without frequently trapping all search agents within a small search space. This arrangement increases the flexibility of the algorithm while providing additional opportunities for the search agent to escape local optima and increase attempts to explore new search spaces for better global optima. From a mimetic standpoint, it mimics a creature's natural instinct to be fascinated by an ally of the opposite gender.

It is worth noting that the different coefficient adaptation methods for male agents in Equation (5) and female agents in Equation (7) reflect their individual characteristics in specific genders. Observing all the coefficients in both equations: $\vec{A}$, $\vec{B}$, and $\vec{C}$ coefficients adopted in Equations (5) and (7) have distinct mathematical structures to distinguish two genders by characteristics. $\vec{A}$ denotes the step range to be adopted in the searching and dwindling encircling behaviors. The original formulation of $\vec{A}$ in SLnO is simply a linear declination from 2 to 0 along the iteration, which lack of flexibility and potential to be compatible to wider optimization challenges. Hence, it is proposed that $\vec{A}$ for female agents has linear declined slope but is set to always have a chance of assigning a high multiplier with the longitude function, which in turn provided the female agent with the ability to make up any flaws caused by prior actions for a more heedful search. Instead, male agents have its random variable $\vec{A}$ declining from 2 to 0 in slightly increasing rate to accelerate the search process with iterations to speed up the transition from global exploration to local exploitation for better trade-offs of contradiction. These adaptive approaches hint at how female organisms are more thoughtful and careful than male agents in responding to challenges, and how male organisms are bolder in training themselves to work faster. But it should be noted that only male agents can move toward the target point with different step lengths in each dimension due to the inclusion of random arrays.

$\vec{B}$ plays the role in offsetting the target point to enhance the orientation deviation for better global and local identifications. Note that the original formula for $\vec{B}$ in SLnO is just a random value from 0 to 2, without any complex provisions. However, the simplest approach may severely bias a vast distant away from the real target point, bringing the search agent to an unknown and non-promising position after updating. Hence, it is proposed that $\vec{B}$ in Equation (5) for male search agents gradually converges to a value close to 1 at an increasing rate, while $\vec{B}$ in Equation (7) for female search agents converges linearly to the real number 1. From an imitation point of view, it simulates the truth that male agents are poor at remembering exact reference target points (where $\vec{B}$ does not really converge to the true 1 until the end of the iteration), but this strategy dares to promote the male search agent to be strengthened in the global search ability and endowed with the ability to get rid of the local optima. On the contrary, female search agents are better at locating precise reference target points to promote female search agents to be strengthened in terms of local search ability (where $\vec{B}$ converges to a real number 1 along iterations), which is endowed with the ability to exploit the global optimal region to obtain any possibility of true optimality.

$\vec{C}$ represents the step range for circle-updating behavior. It was originally the multiplier of the cosine function in SLnO, and it did approach the target point, but the convergence was very slow and limited. To accelerate the searching pace, it is modified so that male agents compare the fitness they currently have with the global best fitness when performing a circle-updating behavior. This emphasizes the nature of male creatures to always seek the highest efficient method of solution for higher motivation to be less concern on searching accuracy. In contrast, female agents place more emphasis on a gradual process as they make appropriate assignments to approach the desired goal by adjusting the coefficient $\vec{C}$ in the random variable from a value higher than 1 to 0.

Other than adaptive step range, the coefficient $\vec{A}$ also remains the role as decision coefficient to decide which operation to enter for the i^{th} search agent. $\vec{A} > 1$ allows the search agents to execute the searching behaviour (entering global exploration phase), while $\vec{A} \leq 1$ allows the search agents to execute the dwindling encircling behaviour (entering local exploitation phase). Note that the maximum generated value of coefficient $\vec{A}$ is linearly declined to zero along the iterations, this reasonably emphasizes exploration at the early stage of iterations, and exploitation at the later stage of iterations, so as to balance the contradiction or trade-offs between the global and local searches. $\vec{V}$ is another decision coefficient representing the vocalization factor. In fact, the vocalizing-based decision selection in the original SLnO seems slightly complicated but still unsatisfactory, so we propose an inverse modification on the decision coefficient $\vec{V}$. Instead of being vocalized by a leader solution, we grant every search agent simpler way of defining with random array for male agents and with random number for female agents. This trains the search agents for being more independent when making the execution decision, proving room for maneuver to secure the diversity of operations. The search agent first checks whether the condition of $\vec{V} < 0.25$ is met to enter the circle-updating mechanism, which is the priority. It is set to such a low comparison value of 0.25 to keep the execution of circle-updating behaviors to its minimal required counts just to act as the intermediate in clustering the agents of both genders together. This is also to share out more proportion for emphasizing the interaction between genders, where one agent should refer more to the ally or (temporarily optimal) solution of different gender for more interdependent optimization.

It is also worth noting that decision coefficients $\vec{A}$ and $\vec{V}$ for male search agents utilize the random vectors, while those for female search agents utilize only random number. This is another implication that the male agents are assigned random vectors in decision coefficients to confer multitasking capabilities to perform different behaviors in variable dimensions. In contrast, the female agent is not assigned a random vector, but a random number in the decision coefficient, so for the invariant dimension, the female agent can only perform one behavior per execution.

The pseudocode of the proposed GBSLnO is given as follows to comprehend its overall mechanism:

Pseudocode for SLnO
Define problem definition.
Input parameters.
Initialize population.
Initialize $\vec{\boldsymbol{X}}^t_{\text{best,m}}$ and $\vec{\boldsymbol{X}}^t_{\text{best,f}}$.
FOR $t = 1$ TO $t_{\max}$
FOR $i = 1$ TO $\left\lfloor \frac{n}{2} \right\rfloor$
Obtain coefficients $\vec{A}$, $\vec{B}$, $\vec{C}$ and V from Equation (5).
Execute Equation (4).
Boundary check $[l, u]$ on $\vec{\boldsymbol{X}}_i^{\text{new,m}}$.

Define: $r = \text{rand}[0,1]$
IF $f\left(\vec{\boldsymbol{X}}_i^{\text{new,m}}\right)$ is better than $f\left(\vec{\boldsymbol{X}}_i^{\text{t}}\right)$ OR $r < 0.34\left(e^{-t/T}\right)^4$ THEN
Update $\vec{\boldsymbol{X}}_i^{\text{t}}$ to $\vec{\boldsymbol{X}}_i^{\text{new,m}}$.
END IF
Update $\vec{\boldsymbol{X}}_{\text{best,m}}^{t}$ if $\vec{\boldsymbol{X}}_i^{t}$ provides a better solution.
Update $\vec{\boldsymbol{X}}_{\text{best}}^{t}$ if $\vec{\boldsymbol{X}}_i^{t}$ provides a better solution.
END FOR
FOR $i = \left\lfloor \frac{n}{2} \right\rfloor + 1$ TO n
Obtain coefficients $\vec{A}$, $\vec{B}$, $\vec{C}$ and V from Equation (7).
Execute Equation (6).
Boundary check $[l, u]$ on $\vec{\boldsymbol{X}}_i^{\text{new,f}}$.
Define: $r = \text{rand}[0,1]$
IF $f\left(\vec{\boldsymbol{X}}_i^{\text{new,f}}\right)$ is better than $f\left(\vec{\boldsymbol{X}}_i^{\text{t}}\right)$ OR $r < R_{\text{ps}}\left(e^{-t/T}\right)^4$ THEN
Update $\vec{\boldsymbol{X}}_i^{\text{t}}$ to $\vec{\boldsymbol{X}}_i^{\text{new,f}}$.
END IF
Update $\vec{\boldsymbol{X}}_{\text{best,f}}^{t}$ if $\vec{\boldsymbol{X}}_i^{t}$ provides a better solution.
Update $\vec{\boldsymbol{X}}_{\text{best}}^{t}$ if $\vec{\boldsymbol{X}}_i^{t}$ provides a better solution.
END FOR
Inherit: $\vec{\boldsymbol{X}}^{t+1} = \vec{\boldsymbol{X}}^{t}$.
END FOR
Output optimal result.

GBSLnO attempts to update $\vec{\boldsymbol{X}}_i^{\text{t}}$, $\vec{\boldsymbol{X}}_{\text{best,m}}^{t}$, $\vec{\boldsymbol{X}}_{\text{best,f}}^{t}$ and $\vec{\boldsymbol{X}}_{\text{best}}^{t}$ immediately after each search agent executes its operation. From a mathematical point of view, this strategy enables the algorithm to accelerate the overall progress of the optimal tracking process among population. However, it may cause a slight mismatch in the optimal region due to the excessive acceleration of early exploration. As a solution, GBSLnO then proposes a partial memory saving strategy. The option by chance not to update $\vec{\boldsymbol{X}}_i^{\text{t}}$ during the hunting stage if the newly generated solution is worse compared to the current fitness can prevent the agent from being guided into an unpromising search space. It significantly reduces the probability of the agent being bootstrapped to the local optima, increasing the reliability of the algorithm to achieve the global optimum. It, in other words, also grants the proposed algorithm with excellent clustering properties, as it rationally controls the movement of search agents to reduce divergence.

4. MPPT Application

A PV system is composed of three major electro-devices: PV panel, boost converter and controller. A full layout of the PV system, including the internal devices, is shown in Figure 1. These devices interact with each other, where the PV panel generates a PV output to the controller, the controller receives reference PV data to tune the duty ratio while generating the desired PWM signal to the boost converter, and the boost converter receives the PWM signal to toggle the switching for optimizing PV output regulation from the PV panel [55]. Note that the output terminal of the boost converter is connected to the user equipment to provide stable PV power for the user end.

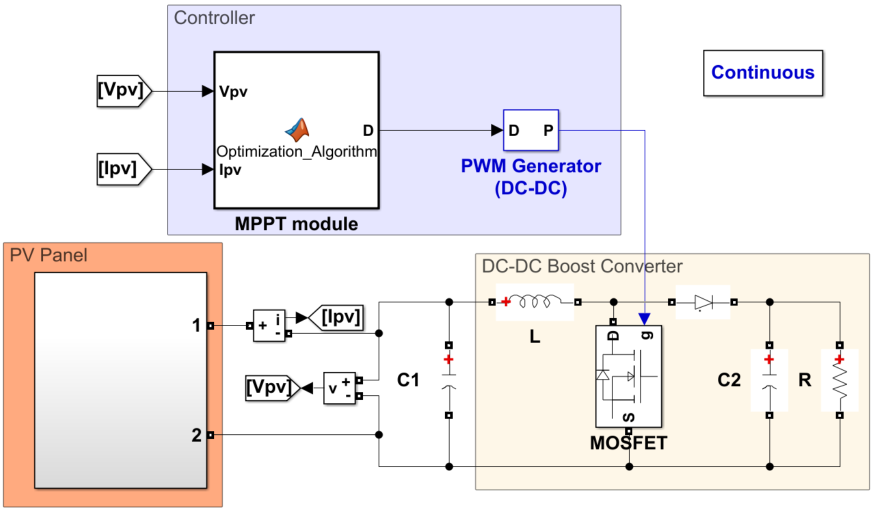

Fig. 1. Simulated PV system for MPPT application in Matlab-Simulink

MPPT is defined as the process of regulating a system to attain maximum power point (MPP) in the P-V characteristics of a PV panel, where any optimization or intelligence algorithm for reaching, searching, and tracking P_{mp} is recognized as an MPPT technique. In actuality, the MPPT module in the controller plays the most important role for MPPT. It installs specified MPPT technique to tune vital parameters while iteratively running to find a better solution to extract more power from the PV panel [56]. Normally, it optimizes the duty cycle D when referring to the environment data (i.e., irradiance G and temperature T) and the PV data (i.e., photovoltaic current I_{PV} and photovoltaic voltage V_{PV}), where D ranges from 0 to 1 to represent the proportion of the PWM signal continuously "ON" within a time period.

It is important to note that the boost converter's ability to collect and stabilize solar power P_{pv} is indirectly controlled by the controller. Generally speaking, the main contribution of a MPPT technique is to assist the PV systems in achieving P_{max} that is, ideally, close to or equal to P_{mp}. In fact, the tracking efficiency of the MPPT technique can be expressed as:

$$\eta = \left(1 - \frac{P_{\text{mp}} - P_{\text{max}}}{P_{\text{max}}}\right) \times 100\% \tag{8}$$

where P_{mp} is the power value at MPP on the P-V curve, P_{max} is the maximum available power obtained by the load R in the converter. In fact, the higher the efficiency, the more satisfactory power supply to the end-user [57].

After verifying the applicability of the optimization algorithms to MPPT for photovoltaic systems, it is convincing to apply the proposed GBSLnO to address the challenge. To test the superiority of GBSLnO against all other existing SLnO variants, the comparative algorithms are selected as AFSA-SLnO-F [58], AFSA-SLnO-S [58], AFSA-SLnO-SF [58], and SLnO (original) [54]. All the adopted SLnO variants have the same parameter settings as in the proposed GBSLnO for fair performance comparison.

4.1 Problem Definitions

The PV array configuration is one of the factors affecting the maximum power efficiency in a centralized topology. Many researchers have endeavored to explore the prospects of different PV array configurations to achieve more stable, robust and efficient PV module power generation. In this research work, 4 PV array configurations (i.e., series-parallel (SP), bridge-link (BL), honey-comb (HC), and triple-tied (TT) configurations) were selected for simulation. Figure 2 documents the physical layout of these 4 PV array configurations. To escalate the difficulty of the optimization challenge, we also simulated different partial shading patterns (i.e., center, bottom, L-shaped, random, and diagonal) in the PV model. It is a hardware setting that defines the level of irradiance each PV array receives at the installation position. Table 2 collects the numerical setups of the 5 partial shading patterns, where the array counts from 1st to 25th vertically from top left to bottom right, referring to any PV layout in Figure 2.

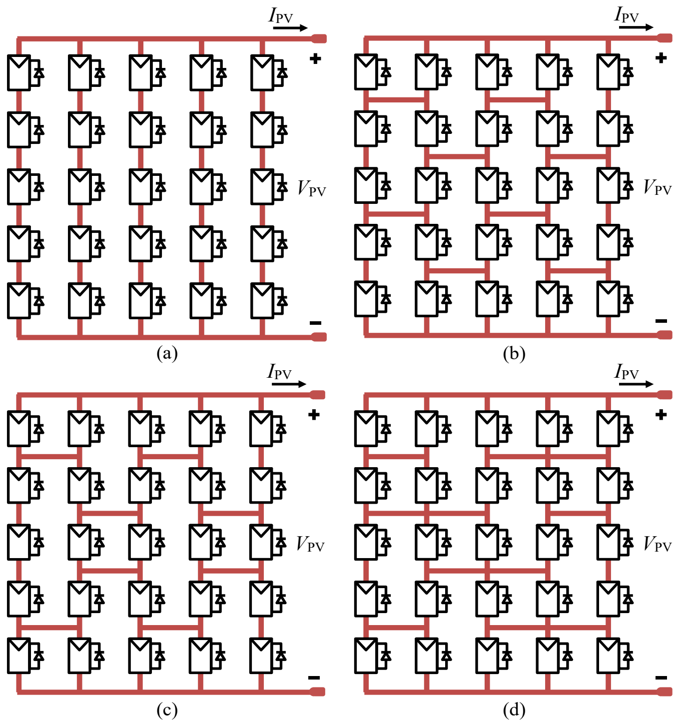

Fig. 2. PV array configuration models: (a) series-parallel (SP), (b) bridge-link (BL), (c) honey-comb (HC), (d) triple-tied (TT)

Table 2
The values of Reynolds number and velocity

Shading pattern	Irradiance (kW/m^2)												
	PV array												
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th	11th	12th	13th
Center	1.0	1.0	1.0	1.0	1.0	1.0	0.2	0.5	0.8	1.0	1.0	0.2	0.5
Bottom	1.0	1.0	1.0	0.9	0.9	1.0	1.0	1.0	0.7	0.7	1.0	1.0	1.0
L-shaped	1.0	1.0	1.0	1.0	0.1	1.0	1.0	1.0	1.0	0.3	1.0	1.0	1.0
Random	1.0	1.0	0.3	0.6	0.7	0.8	0.5	0.2	1.0	0.4	1.0	1.0	1.0
Diagonal	0.1	0.1	1.0	1.0	1.0	1.0	0.3	0.3	1.0	1.0	1.0	1.0	0.5
Center	0.8	1.0	1.0	0.2	0.5	0.8	1.0	1.0	1.0	1.0	1.0	1.0	Center
Bottom	0.5	0.5	1.0	1.0	1.0	0.3	0.3	1.0	1.0	1.0	0.1	0.1	Bottom
L-shaped	1.0	0.5	1.0	1.0	1.0	1.0	0.7	0.1	0.3	0.5	0.7	0.9	L-shaped
Random	0.7	0.3	0.5	0.4	1.0	0.2	1.0	1.0	0.3	1.0	0.5	0.3	Random
Diagonal	0.5	1.0	1.0	1.0	1.0	0.7	0.7	1.0	1.0	1.0	1.0	0.9	Diagonal

Combined with 4 PV array configurations and 5 shading pattern, we will have $4 \times 5 = 20$ MPPT challenges to be solved by the optimization algorithms. As an initial insight, we collected the power-voltage output characteristics of individual array configurations under various partial shading patterns.

4.2 Configuration settings

The model is simulated via Matlab−Simulink R2022b, where its configuration is shown in Table 3. The maximum iterative number and population number allocated to all applied algorithms were set as $t_{\max} = 10$ and $n = 5$. Reliably, they were run only 10 times due to the extremely long duration taken to complete a single simulation run.

Table 3
Configuration settings for simulated PV model

Indicator	Configuration
Stop time	5s
Type	Variable-step
Solver	ode15s
Maximum step time	1E-06s
Minimum step time	Auto
Number of consecutive minimum steps	1
Relative tolerance	1E-06s
Absolute tolerance	Auto
Zero-crossing control	Use local settings
Time tolerance	10*128*eps
Number of consecutive zero crossings	1000
Shape preservation	Disable
Tasking and sample time options	Disable
Data import/ export	Enable

5. Results and Discussion

GBSLnO was evaluated on maximum power point tracking from different evaluated matrices. Table 4 collects the statistical results of the final photovoltaic power (P_{pv}) obtained by each algorithm in the 20 MPPT challenges. Optimization algorithms seek to maximize the best and mean results, but minimize the standard deviation (SD) value, where the evaluation in terms of best, mean and SD respectively determines the accuracy, compatibility (or reliability) and robustness of the algorithm to achieve MPP in PV systems.

In the statistical best and mean results, GBSLnO ranked first in all 20 MPPT challenges, confirming the superior accuracy and compatibility of GBSLnO relative to other algorithms in solving MPPT applications. In the statistical SD results, GBSLnO outperforms other comparative algorithms in all MPPT test cases except for the model of the SP array configuration under the L-shaped shading pattern. The fact that GBSLnO yielded better SD results than other algorithms in 19 out of 20 MPPT test cases demonstrates the highest robustness in MPPT applications. Overall, it is worth noting that the optimization performance of GBSLnO outperforms other existing SLnO variants. The fact that all algorithms output the same optimal P_{pv} values on BL, HC and TT array configurations is attributed to array characteristics, mainly their sensitivity to mismatch power losses and high stability against power changes.

In contrast, Figure 3 plots the efficiency of individual algorithms in MPPT applications. As shown, GBSLnO achieves an overall efficiency of 97.99% across 20 MPPT challenges, with average efficiencies of 99.71%, 97.42%, 97.14%, and 97.71% on the corresponding array configurations, respectively. In fact, except for the SP array configuration, the MPPT results for the other array configurations are slightly less than ideal, with a relative percentage error of about 2~3%, which is mainly due to power mismatch in the wiring layout. However, GBSLnO still outperforms AFSA-SLnO-F, AFSA-SLnO-S, AFSA-SLnO-FS, and SLnO whose efficiencies reached only 97.58%, 97.30%, 97.75%, and 96.86%, respectively. The efficiency of GBSLnO is at least 0.25% higher compared to other existing SLnO variants, indicating the superior performance of GBSLnO in the MPPT process.

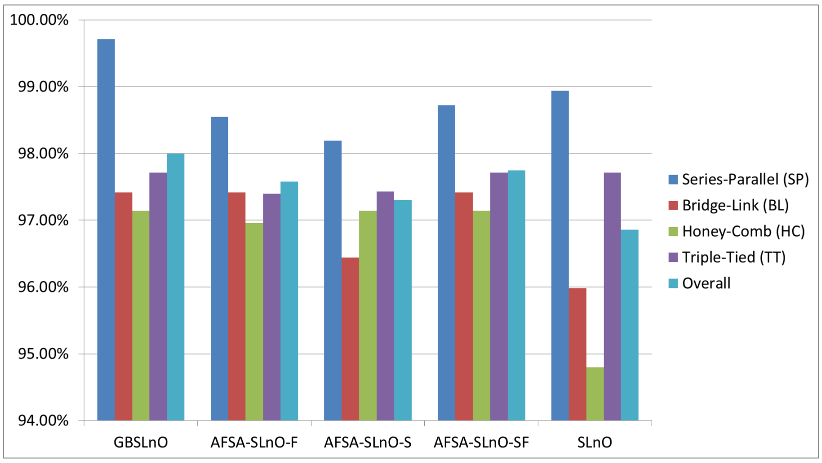

Fig. 3. Efficiency chart of SLnO variants

To gather additional assessment data, we capture the power spectrum at the boost converter during simulation runs in which the PV panel is mounted in an SP array configuration and is subjected to various shading patterns. Figure 4 depicts the outcomes. It is evident from Figures 4(b) and 4(d) in particular that GBSLnO oscillates very little and only does so when the input signal deviates. It is also noteworthy that upon reaching a steady state, the power spectrum induced by GBSLnO does not exhibit oscillations. Additionally, GBSLnO has the best convergence as it delivers power spectra that peak at the earliest duration. Not to mention the convergence speed, AFSA-SLnO-F, AFSA-SLnO-SF, and SLnO encounter apparent oscillation issues during simulation. Though the power spectrum yielded by AFSA-SLnO-S has competitive convergence and less oscillations, it is still not as efficient as GBSLnO. All these statements demonstrate the superior ability of GBSLnO to monitor MPPs with minimal delay and spectral oscillations.

Overall, SLnO is proven to outperform other existing SLnO variants in terms of accuracy, reliability, robustness, tracking efficiency, convergence rate, and oscillation avoidance. Based on these claims, GBSLnO appears to be a successful improved SLnO variant.

6. Conclusion

This research work proposes an improved Sea Lion Optimization (SLnO) variant, named Gender Based Sea Lion Optimization (GBSLnO) algorithm. In a more innovative way, GBSLnO separates the population into two gender groups: males and females, to mimic the fact that sea lions have both genders in nature. In terms of mathematical modeling, GBSLnO preserves the original SLnO's searching behavior, dwindling encircling behavior, and circle-updating behavior, but their functionality is improved with enhanced coefficient (also decision coefficient) adaptation. Note, however, that both genders experience different coefficient adaptations to reflect their individual characteristics in a particular gender. Hence, search agents of different genders have different operational characteristics during mathematical execution. Male agents are less considerate in localization, but bolder in action, consistently focused on efficiency, and capable of multitasking (variable dimension). In contrast, female agents are more considerate in positioning and actions, but work in a single task without concerning on efficiency (invariant dimensionality). During behavioral operations, an agent references the position and best solution of the opposite-gender group, mimicking the natural instinct of a creature to be attracted to an ally of the opposite gender. From a mathematical point of view, this approach is advantageous for bringing the two gender groups together for efficient clustering while maintaining the interaction between the two hunting groups. The inter-dependence relationship between two gender groups also provides more variation to the search direction, without frequently trapping all search agents within a small search space. This arrangement increases the flexibility of the algorithm, meanwhile giving additional chance for the search agents to escape from the local optima to increase the attempts of exploring the new search space for possible better global optimality. Overall speaking, this algorithm mainly emphasizes the interactions between two gender groups which operate in same behavioural patterns but distinctive mathematical mechanism. Additional features such as partial memory saving strategies can occasionally restore agent positions corresponding to improved fitness to further refine performance capabilities of GBSLnO.

GBSLnO was evaluated on 20 maximum power point tracking (MPPT) application challenges. Upon applications, GBSLnO achieved the best statistical mean and SD results compared to other comparative algorithms (including standard SLnO). This confirms the fact that GBSLnO outperforms others in the reliability of global optimal acquisition and the robustness of the algorithm. Furthermore, GBSLnO achieved optimal tracking efficiency in MPPT applications, supported by data recorded in extensive analytical charts. According to the output power spectrum, it can also be observed that GBSLnO exhibited the best convergence and the least oscillation. All these statements revealed the excellent performance of GBSLnO in MPPT applications, thereby proving the utility of GBSLnO in a wide range of optimization fields. Likewise, they demonstrated successful improvements over SLnO in this research work.

From the solid results, GBSLnO appears ready to face future challenges to be applied to a wider range of real-world optimization problems. The future challenge should be to increase processing speed and efficiency according to current application trends.

Acknowledgement

This research is supported by the Ministry of Higher Education (MOHE) Malaysia under the Fundamental Research Grant Scheme (Grant no. FRGS/1/2021/TK0/USM/02/14).

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Table 4
Statistical P_{pv} results obtained by each algorithm for 20 MPPT challenges

Array conf.	Shading pattern	Ind.	Algorithm				
			GBSLnO	AFSA-SLnO_F	AFSA-SLnO_S	AFSA-SLnO_SF	SLnO
Series-parallel (SP)	Center	Best	230.530386	223.745888	230.128425	225.711738	230.211148
		Mean	230.449791	220.291374	219.389875	224.532228	228.228428
		SD	0.129771	5.562296	9.242273	1.015161	1.368206
	Bottom	Best	232.468343	231.377502	232.445252	232.451541	232.240666
		Mean	232.372799	231.123570	232.260332	232.263476	232.098643
		SD	0.100712	0.267668	0.194923	0.198238	0.149705
	L-shaped	Best	267.019109	267.017139	266.692002	267.016815	267.017845
		Mean	267.018963	267.017113	265.927032	266.854409	267.016258
		SD	0.000154	0.000028	0.806350	0.171192	0.001673
	Random	Best	154.752331	154.403941	152.256935	152.258121	152.083468
		Mean	154.578136	153.193865	151.217330	151.217923	151.547889
		SD	0.076349	1.011306	0.970224	0.971063	0.257423
	Diagonal	Best	233.651963	233.651514	233.649490	233.417063	232.453661
		Mean	233.643227	233.640007	233.159361	233.348003	231.670419
		SD	0.006354	0.011274	0.193147	0.047665	0.707671
Bridge-link (BL)	Center	Best	217.432078	217.432078	217.432078	217.432078	217.432078
		Mean	217.432078	217.432078	217.432078	217.432078	217.432078
		SD	0	0	0	0	0
	Bottom	Best	232.381126	232.381126	232.381126	232.381126	232.381126
		Mean	232.381126	232.381126	232.381126	232.381126	232.381126
		SD	0	0	0	0	0
	L-shaped	Best	248.064630	248.064630	248.064630	248.064630	248.064630
		Mean	248.064630	248.064630	248.064630	248.064630	248.064630
		SD	0	0	0	0	0
	Random	Best	165.677568	165.677568	165.677568	165.677568	165.677568
		Mean	165.677568	165.677568	157.495806	165.677568	153.608058
		SD	0	0	4.076278	0	7.574384
	Diagonal	Best	249.416670	249.416670	249.416670	249.416670	249.416670
		Mean	249.416670	249.416670	249.416670	249.416670	249.416670
		SD	0	0	0	0	0
Honey-comb (HC)	Center	Best	218.245376	218.245376	218.245376	218.245376	218.245376
		Mean	218.245376	218.245376	218.245376	218.245376	212.623086
		SD	0	0	0	0	1.058770
	Bottom	Best	232.381127	232.381127	232.381127	232.381127	232.381127
		Mean	232.381127	232.381127	232.381127	232.381127	213.364927
		SD	0	0	0	0	11.865345
	L-shaped	Best	246.893796	246.893796	246.893796	246.893796	246.893796
		Mean	246.893796	246.893796	246.893796	246.893796	246.893796
		SD	0	0	0	0	0
	Random	Best	159.570689	159.570689	159.570689	159.570689	159.570689
		Mean	159.570689	158.093724	159.570689	159.570689	157.847171
		SD	0	1.273196	0	0	1.299450
	Diagonal	Best	248.478276	248.478276	248.478276	248.478276	248.478276
		Mean	248.478276	248.478276	248.478276	248.478276	248.478276
		SD	0	0	0	0	0
Triple-tied (TT)	Center	Best	216.329244	216.329244	216.329244	216.329244	216.329244
		Mean	216.329244	216.329244	216.329244	216.329244	216.329244
		SD	0	0	0	0	0
	Bottom	Best	232.381127	232.381127	232.381127	232.381127	232.381127
		Mean	232.381127	232.381127	232.381127	232.381127	232.381127
		SD	0	0	0	0	0

L-shaped	Best	248.362326	248.362326	248.362326	248.362326	248.362326
	Mean	248.362326	248.362326	248.362326	248.362326	248.362326
	SD	0	0	0	0	0
Random	Best	174.558879	174.558879	174.558879	174.558879	174.558879
	Mean	174.558879	171.726010	174.558879	174.558879	174.558879
	SD	0	1.429706	0	0	0
Diagonal	Best	269.230207	269.230207	269.230207	269.230207	269.230207
	Mean	269.230207	269.230207	265.426266	269.230207	269.230207
	SD	0	0	2.793165	0	0

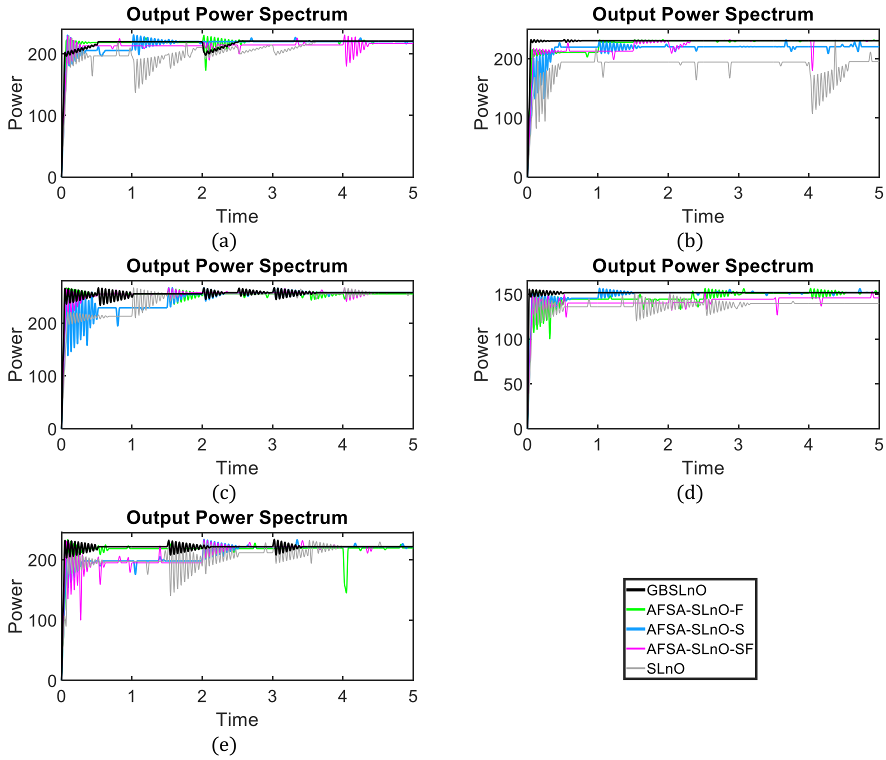

Fig. 4. Power spectra of SLnO variants during MPPT for SP array configuration under (a) center (b) bottom (c) L-shaped (d) random (e) diagonal shading patterns