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# Metaheuristics-based maximum power point tracking for PV systems: a review

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**ABSTRACT**

Over the years, numerous maximum power point tracking (MPPT) methods have been developed to extract the maximum available power from PV arrays. They are generally categorized as conventional or metaheuristic methods. The most employed conventional methods include perturb and observe (P&O), hill climbing (HC), and incremental conductance (INC), due to their simplicity and ease of implementation. However, under partial shading condition (PSC), none of them can effectively locate a global maximum power point (GMPP) out of many local maximum power points (LMPPs). This results in significant power loss during PSC, prompting the development of various metaheuristic-based MPPT methods to address the problem. This paper reviews 38 existing metaheuristic-based MPPTs and 27 metaheuristic methods that have not yet been applied to any MPPT operation up to date. Metaphorically, these methods are divided into four categories: i) evolutionary-based, ii) physics-based, iii) swarm-based, and iv) human-based. The different MPPTs are compared in terms of complexity, converter topology, and PSC tracking capability. This paper is intended to serve as a one-stop resource for any researcher, practitioner, or advanced student seeking to develop a new metaheuristic-based MPPT method.



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## 1. INTRODUCTION

Photovoltaic (PV) systems are one of the most promising renewable energy sources since they are clean and environmentally friendly. A maximum power point tracking (MPPT) method is implemented into the power converter controller to manage the duty cycle in order to track the maximum power point (MPP) of the PV array. In recent years, a great variety of MPPT methods have been implemented. These methods are categorized as either conventional or artificial intelligence (AI)-based. Perturb and observe (P&O), hill climbing (HC), and incremental conductance (INC) are the most popular conventional methods due to their ease of implementation, robustness, and low cost. Under uniform irradiance, i.e., when the power–voltage (P–V) characteristic curve has a single peak, conventional methods generally function adequately.

During partial shading condition (PSC), the conventional methods are unable to identify the global MPP since the problem has become multimodal. Hence, these methods are incapable of distinguishing between many local maximum power points (LMPPs) and one global maximum power point (GMPP) [1]. This is unavoidable due to the nature of these systems, which are based on the peak detection concept; when a peak tracker identifies a perceived maximum point, it locks itself in the neighborhood of that point. If the peak is LMPP, significant PV power loss occurs.

In the last four decades, numerous metaheuristic solutions have been developed to address the aforementioned issue. These methods can be divided into four metaphorical categories: evolution-based, physics-based, swarm-based, and human-based [2], [3]. Evolution-based methods utilize genetic operators such as crossover, mutation, and selection to generate unique solutions. During an iterative search, the least fit options are removed, and the entire population will be replaced from one generation to the next. Physically-based methods are influenced by the physical and chemical laws that control natural phenomena. In the meantime, swarm-based methods were developed based on the natural behavior of animals like birds, fish, and insects. This category describes swarming behavior inside a colony. As their name suggests, human-based methods are based on human behavior, such as the interaction between people that enables the flow of new information to improve their thinking and behavior. Individuals vary in intelligence and temperament, but teamwork improves the ability to solve difficult problems.

As for PSC, metaheuristic approaches look for every conceivable peak throughout the whole P-V curve, it is quite probable that the GMPP will be identified. The authors in [4]–[6] have performed extensive reviews on the application of metaheuristic for MPPT; these include fuzzy logic controller (FLC), artificial neural network (ANN), particle swarm optimization (PSO), genetic method (GA), differential evolution (DE), ant colony optimization (ACO), Bayesian fusion (BF), and chaotic search (ChS). Particle swarm optimization (PSO) [7] appears to be the most popular approach in the literature [8]–[10] because to its simplicity and effectiveness in tracking the GMPP under PSC. Despite this, several novel metaheuristic approaches have been presented in recent years, but they have yet to be utilized in MPPT application. Thus, in this study, the metaphors of 27 novel metaheuristic procedures published in prestigious publications are addressed. Also, the metaphor, complexity, type of converter employed, and PSC tracking capability of existing metaheuristic MPPT approaches are briefly addressed. Hence, this paper may serve as a one-stop reference for any engineer or researcher interested in selecting a novel metaheuristic method for MPPT.

## 2. PARTIAL SHADING CONDITION OF PV SYSTEMS

A photovoltaic (PV) solar cell is the smallest component of a PV system, while a PV module is composed of many cells linked in series. Afterwards, these modules are linked in series or parallel to make a PV array with the necessary current and voltage. There are two PV module/array conditions: normal uniform irradiance and partial shading condition (PSC). Figure 1 illustrates the characteristics of a PV array under uniform irradiance, while Figure 2 illustrates the characteristics of partial shading caused by passing clouds.

(a)

(b)

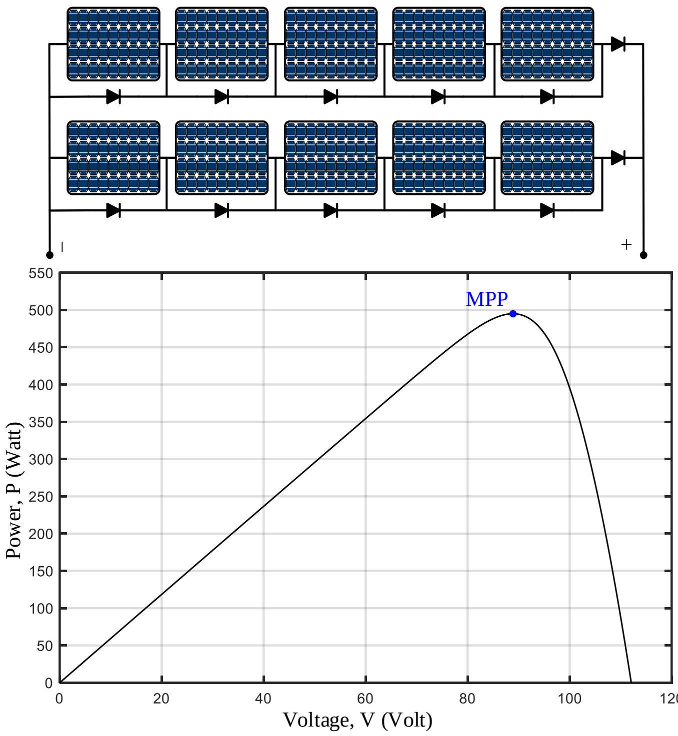


Figure 1. Characteristics of a PV array under uniform irradiance: (a) PV array configuration and (b) P-V curve

(a)

(b)

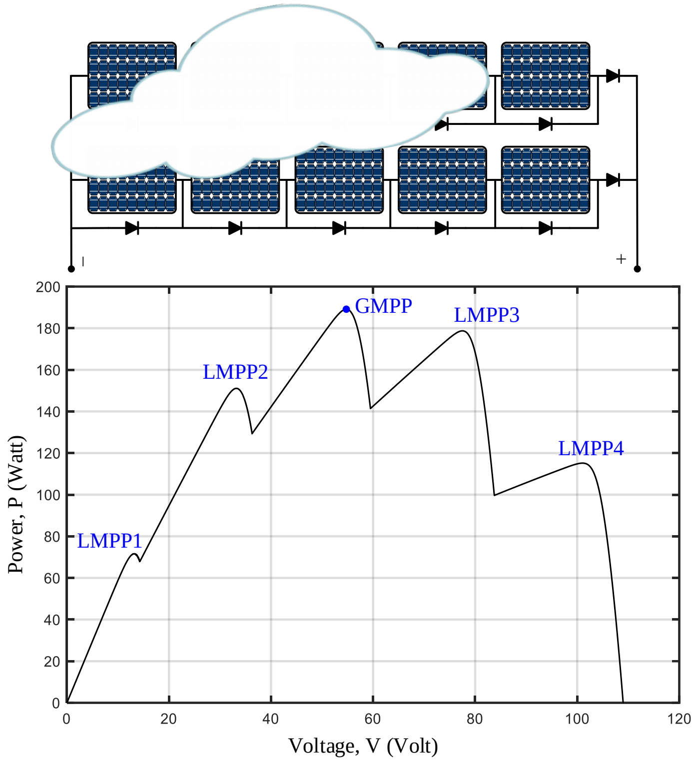


Figure 2. Characteristics of a PV array under partial shading: (a) PV array configuration and (b) P-V curve

Normal conditions expose the modules uniformly to solar irradiance, as shown in Figure 1(a), and the P–V characteristic curve of the PV array has a single maximum power point (MPP), as shown in Figure 1(b). Under PSC conditions, the modules may be completely or partially obscured by buildings, trees, passing clouds, bird droppings, or dirt, as shown in Figure 2(a). As shown in Figure 2(b), the P–V curve consists of multiple local maximum power points (LMPPs) but only one global maximum power point (GMPP) due to the different irradiance levels received by each module.

## 3. MAXIMUM POWER POINT TRACKING (MPPT)

The MPPT method is utilized to more precisely and efficiently determine the PV collection's maximum power. During the tracking operation, the PV's power output fluctuates due to abrupt changes in irradiance and temperature. The DC-DC converter and maximum power point tracking (MPPT) connect the PV array to the output. In addition, the DC-DC converter optimizes the peak power by modifying the load conditions and output source. The primary function of MPPT systems is to monitor the utmost output of PV panels. In the interim, the MPP manages fluctuating temperatures and solar irradiance. Consequently, the MPPT method is required to dynamically adjust the MPP as the operating point for a variety of inputs (solar irradiance and temperature). MPPT enables modules to deliver high power without adhering to a particular tracking system. On the basis of temperature and irradiance data, its methods are typically utilized to extract the most energy from the solar array. Due to variations in solar irradiance, cell temperature, and maximum power, the maximum power point (MPP) refers to the voltage at which the PV array produces the most power.

## 4. CONVENTIONAL MPPT

In actual PV inverters, the typical MPPT is frequently based on perturb and observe, hill climbing, and incremental conductance. In general, these strategies are effective under uniform irradiance conditions, i.e., when the power–voltage (P–V) and current–voltage (I–V) curves of the PV array have a single peak. During partial shading conditions (PSC), the P–V and I–V curves consist of several local maximum power points (LMPPs) and a single global maximum power point (GMPP) [10]. Unless modified appropriately, typical algorithms are incapable of discriminating between LMPP and GMPP. This is inevitable due to the nature of these algorithms, which are based on the peak detection concept, i.e., when it identifies a perceived maximum point, it locks itself in the vicinity of that point. If the peak is local, there will be severe PV power loss. The typical equations, features, and measured variables of these three approaches are summarized in Table 1.

Table 1. Summary of conventional algorithms

| Algorithms | Representative equations | Features | | Measured Variables |
|---|---|---|---|---|
| | | Advantages | Disadvantages | |
| P&O | $\begin{cases} \frac{dP}{dV} = 0, at\ MPP \\ \frac{dP}{dV} > 0, left\ of\ MPP \\ \frac{dP}{dV} < 0, right\ of\ MPP \end{cases}$ | Requires simple control structure and few measured parameters. It is not dependent on the characteristics of the PV module and can be easily applied to any PV panel. | Its disturbance increases along with the power and after the power of PV cells reaches the peak, the power will decrease and the disturbance becomes bigger. It introduces an oscillation on the steady state and the voltage variation is large. | Current (I) and voltage (V) |
| HC | $d(k) = \begin{cases} d(k) + \emptyset, if\ P(k) > P(k-1) \\ d(k) - \emptyset, if\ P(k) < P(k-1) \end{cases}$ | It is widely applied in MPPT controllers due to their simplicity and easy implementation. It does not require to study or modelling of source characteristics. | It maybe sometimes deviates from the maximum operating point under rapidly changing atmospheric conditions. It is difficult to provide good performance in dynamic and steady-state response since a constant incremental step with duty cycle is employed as the control parameter. | Perturbation step-size ($\emptyset$) |
| INC | $\frac{dP}{dV} = \frac{d(VI)}{dV} = 1 + V\frac{dI}{dV} = 0$ <br> $-\frac{I}{V} = \frac{dI}{dV} \cong \frac{\Delta I}{\Delta V}$ <br> $\begin{cases} \frac{dI}{dV} = \frac{I}{V}, \quad at\ MPP \\ \frac{dI}{dV} > -\frac{I}{V}, left\ of\ MPP \\ \frac{dI}{dV} < -\frac{I}{V}, right\ of\ MPP \end{cases}$ | It has less power loses while its tracking speed is faster than P&O. It can be really realized in simple microcontrollers. It can suppress the oscillation around MPP point. | It cannot find GMPP in local MPPs. It is impossible to achieve rapid dynamic response and good steady tracking accuracy simultaneously. | Current (I) and voltage (V). |

## 5. METAHEURSITICS-BASED MAXIMUM POWER POINT TRACKING ALGORTIHMS

To solve the drawbacks of these standard MPPT algorithms, metaheuristic-based methods are introduced. Particle swarm optimization, differential evolution, and genetic algorithm are the three most often used metaheuristics algorithms [4], [11]–[13]. As these metaheuristics algorithms search for all peaks over the whole P–V curve, it is probable that the GMPP will be identified. The algorithms in this section are those utilized in MPPT [14]. It comprises of both new and old algorithms developed during the previous two decades.

### 5.1. Evolutionary-based

#### 5.1.1. Differential evolution (DE)

In the literature on stochastic optimization, Storn and Price (1997) introduced the differential evolution (DE) method [15], which employs mutation, crossover, and selection procedures to generate candidate solutions for the subsequent iteration. The potential solution is referred to as the aim vector in this context. The DE algorithm utilizes a bio-inspired metaheuristic approach.

#### 5.1.2. Genetic algorithm (GA)

GA is a meta-heuristic approach that uses the evolution of biological behavior to determine the best solution. This technique is used to determine the ideal set parameters based on the principle of survival of the fittest. It is an adaptive meta-heuristic search technique including the production, systematic evaluation, and improvement of viable design solutions until the termination criteria are fulfilled [16].

#### 5.1.3. Hyper-spherical search algorithm (HSS)

Similar to earlier evolutionary algorithms, this technique begins with a population consisting of two groups: particles and sphere center points. In this strategy, the search is undertaken within the space of each sphere using its center and associated particles, with all particles eventually converging on the ideal location's center of the sphere. The HSS algorithm has been implemented in four steps [17].

#### 5.1.4. Monkey king evolution (MKE)

This technique is clarified by the omnipotence of the monkey king, a defining symbol from the bestselling Chinese epic novel "Journey to the West." Under stressful times, the monkey king's superpower appears, and it may turn into several little monkeys. This guy researches the solution and provides the monkey king with a report. After receiving all feedback, the monkey king selects the global best (i.e., the most appropriate response) and then acts and advances with all little monkeys [18].

### 5.2. Physics-based

#### 5.2.1. Big-bang-big-crunch (BB-BC)

In terms of the random creation of a starting population, the method is analogous to the GA. It is founded on the big bang theory and big crunch theory. In the Big Bang phase, energy dissipation leads to disorder, and randomness is the defining characteristic of this phase; nevertheless, in the big crunch phase, randomly scattered particles are brought into an order [19]. The big bang–big crunch (BB–BC) technique is an optimization algorithm that creates random points in the big bang phase and reduces them to a single representative point using a center of mass or least cost approach in the big crunch phase.

#### 5.2.2. Fireworks algorithm

The algorithm Firework is classified as a metaheuristic. Based on the intelligent behavior of swarming, it is a potent universal optimization method. Multiple diode model pyrotechnics for PV modelling of MPP particle based on tracking algorithm are generated utilizing a stochastic explosion procedure for each individual firework within the examination region. At the conclusion of the explosion, the surrounding area is flooded with pyrotechnics, which represent latent explanations in the anticipated search space. Using the detonation and Gaussian mutation sparks created by the explosion and the Gaussian mutation operator, this method identifies the global optimum in the problem space. This strategy is distinguished by its ability to achieve a balance between exploration and exploitation. Exploration refers to a strategy's ability to investigate various regions of the search space in order to evaluate prospective outcomes. Exploitation, on the other hand, necessitates a thorough investigation in a smaller area in order to identify the finest result. In addition, it is capable of global investigation and a precise local examination. Sparks of Gaussian transformation are produced to enhance local research capacities and ensure swarm diversity [20].

#### 5.2.3. Gravitational search algorithm (GSA)

GSA is one of the intelligent metaheuristic strategies based on Newton's law of gravity that is used to tackle optimization-related problems. Its worldwide search capabilities offer several advantages over other intelligent systems like PSO. Using GSA has disadvantages, such as limited local investigative capacities and inadequate acceleration methods. The primary premise of the gravitational examination method relates to the optimization problem's solutions, which are seen as a collection of moving particles in space. In accordance with the law of gravity, particles interact through gravity. Thus, the gravitational force imposed on other particles increases as mass increases. Finding the optimal position when other particles shift towards the particle with the highest mass results in particle-related optimization challenges [21].

#### 5.2.4. Mine blast algorithm (MBA)

MBA is based on the observation of a mine bomb explosion in which horrific shrapnel fragments clashed and detonated around them. Consider a minefield where the objective is to reinforce the mines by identifying the mine with the most substantial combustive effect at the best location X, which is capable of inflicting the most casualties, in order to identify this condition. The location of explosive mines is exponentially determined by the direction and distance of shrapnel fragments produced by each explosion [22].

#### 5.2.5. Wind driven optimization (WDO)

The fundamental purpose of WDO is to extract from the atmosphere the horizontal air movement known as wind. In general, air pressure and density are proportional to temperature in terms of air pressure. A pressure gradient describes the movement of air from locations of high to low pressure. In the WDO method, a population of air particles is distributed at a predefined velocity and location throughout the problem area. Using a mathematical model of wind flow, the locations of air properties are analyzed repeatedly. This idea is founded on Newton's second rule, which states that air mass is pushed in the direction of the forces acting on it [23].

### 5.3. Swarm-based

#### 5.3.1. Ant colony optimization (ACO)

ACO belongs to a kind of meta-heuristics inspired by a biological strategy. It is a probabilistic technique for identifying optimal universal solutions to nonlinear problems. In order to optimize grid pathways, ACO mimics the hunting behavior of ants. In addition, the huge communal behavior of ants creates the feedback phenomenon, wherein the ants initially pick a random course and leave pheromones for others to follow [24].

#### 5.3.2. Artificial bee colony (ABC)

ABC approach is a bio-inspired optimization method created for nonlinear optimization problems, numerical functions, and standard optimization constraints. It possesses a number of qualities that make it more attractive than other bio-inspired algorithms. In addition, fewer control variables are utilized and initial state convergence is minimal. The algorithm permits the removal of the drawbacks of the standard MPPT technique. Instead, it provides a trustworthy and straightforward MPPT method. The co-simulation technique combines MATLAB/Simulink and Cadence/Spiced to assess the usefulness of the proposed method and simulate its performance under meteorological circumstances using the MPPT algorithm based on PSO. This is accomplished by utilizing MATLAB/Simulink and cadence/spiced [25].

**5.3.3. Artificial fish swarm algorithm (AFSA)**

In nature, fish can discover the most nutrient-dense location by individual search or by following other fish; the area with the most fish is often the most nutrient-dense. The fundamental concept of the AFSA is to simulate fish behaviors such as praying, swarming, and following with local search of each fish in order to obtain the global optimum [26]. The most recent version of the AFSA incorporates the search capabilities of the PSO algorithm.

**5.3.4. Bald eagle search (BES)**

The BES is a recently found intelligent meta-heuristic optimization approach [27]. It replicates bald eagles' hunting behavior. Generally, bald eagles hunt in three stages to achieve maximum success (selecting space, searching in space, and swooping). During the early phase, the eagles gather preliminary information about the search area by randomly visiting predefined locations. The ideal place is then chosen based on the collected data. Lastly, they randomly wander to several sites surrounding the optimal region in order to get new information and select the location with the highest concentration of prey. They will continue to investigate the area until the biggest concentration of prey is discovered.

**5.3.5. Bat search algorithm (BSA)**

Echolocation behavior is determined by the species of bats in close proximity to a food source [28]. It identifies the position and stability of the signal-based retrieval target. In particular, the literature developed a BSA-based MPPT method for exactly calculating GMPP for all P-V features based on local and global searches. In the majority of instances, this method was superior to 99.9% of challenges.

**5.3.6. Black widow optimization algorithm (BWOA)**

Like with prior evolutionary algorithms, the proposed technique begins with an initial population of spiders, each of which symbolizes a potential solution. These spiders of the first generation try reproduction in pairs. Black widow females eat males during or after mating. Afterwards, she releases the sperm from her sperm thecae into egg sacs. 11 days after being placed, spiderlings emerge from their egg sacs. While their residence on the maternal web for several days to one week, there have been reports of sibling cannibalism. The wind then carries them away [29].

**5.3.7. Butterfly optimization algorithm (BOA)**

In the work done by Arora and Singh (2019), a novel optimization strategy that replicates the feeding behavior of butterflies was devised. Mate and food locations are the two most significant aspects in the strategy. In this technique, there are three important butterfly behaviors: i) One butterfly must be able to attract others with its perfume; ii) The butterfly moves randomly or towards the butterfly with the strongest odour; and iii) The objective function predicts the intensity of the butterfly stimulation [30].

**5.3.8. Cat swarm optimization (CSO)**

Cat swarm optimization (CSO) is an algorithm inspired by the behavior of a colony of cats. It combines two distinct search methods for exploration & exploitation. It has been effectively applied to tackle a variety of technical issues due to its many qualities, including adaptability, global search capability, & rapid convergence [31].

**5.3.9. Chicken swarm optimization (CSO)**

CSO is a bio-inspired robust and precise algorithm that extracts the intelligence of chicken swarms to solve high-dimensional problems. This CSO is an algorithm that replicates the hierarchical structure and behavior of a chicken swarm. Each group of the chicken swarm consists of one rooster and several hens and chicks. Several chickens obey distinct rules of motion. There are competitions between various chickens based on a hierarchical structure [32].

**5.3.10. Crow search (CS)**

Crows (family Corvidae) are among the most intelligent animals, as evidenced by studies of their cognitive behavior [33]. The capacity of the crow to remember faces and the locations of concealed food up to several months later distinguishes it from other species. It is also capable of complicated communication with other corvids and the use of tools for specific tasks. In addition, a crow observes other crows and birds to identify their hidden food and steal it. Conversely, a crow changes its location to deceive other crows if it is aware of being observed.

**5.3.11. Dragonfly optimization (DFO)**

DFO is also a bio-inspired algorithm. There are 3000 unique dragonfly species in the world. Adult and nymph are the two phases of a dragonfly's life cycle. The majority of DF's time in existence is spent as a nymph. During metamorphosis, they develop into adults. The dragonfly examines the little predators that hunt all other insect species. They swarm in a striking and peculiar manner. Hunting and migration are the DF swarm's two principal activities. Migration and hunting are referred to, respectively, as dynamic and static swarms. In a static swarm, DF establishes a small group over a narrow area and hunts mosquitoes and butterflies by flying back and forth. Two crucial characteristics of static swarms are abrupt changes and local movements. In contrast, in the dynamics swarm, a vast number of DFs migrate from one site to another as a group. These are the two most essential DF technique inspiration behaviors. The similarities between these two behaviors and the two-phase meta-heuristics of exploitation and exploration are striking [34].

#### 5.3.12. Firefly algorithm (FA)

Using the notion of firefly tracking, a novel algorithm was developed and deployed. This algorithm is predicated on three key premises. First, all fireflies are unisex, and until they are all compared, advances towards a more brilliant and attractive individual are neglected. The firefly's attractiveness is related to its luminosity, which is dependent on its distance from other insects. Because to the saturation of light in the air, the allure of an object decreases with distance. The objective process value of the presented challenge ultimately determines the intensity of a firefly's light or brightness [35].

#### 5.3.13. Flower pollination algorithm (FPA)

The FPA has been widely employed in a variety of scenarios and has distinguished itself from PSO and GA [36]. Previous simulation results have demonstrated that the FPA method is favorable and can outperform both genetic algorithm and particle swarm optimization. The flower pollination algorithm (FPA) has demonstrated its superiority over particle swarm optimizer and genetic algorithm in several applications. Yang created FPA by mimicking the mechanism of plant reproduction. The FPA approach implements the biological evolution of flowers, where the primary objective is the survival of the best and reproduction at its highest level of efficiency.

#### 5.3.14. Golden eagle optimization (GEO)

GEO is a swarm-based, nature-inspired metaheuristic algorithm designed to address global optimization challenges. This algorithm's notion was inspired from the intelligence of a golden eagle's turning speed at different phases of its circular hunting path. At the first phases of the hunt, golden eagles are more inclined to cruise than to attack, however towards the final stages of the hunt, they are more likely to attack than to cruise [37].

#### 5.3.15. Grasshopper optimization (GOA)

The GOA is a novel metaheuristic algorithm based on population presented in [38]. This algorithm was inspired by the actual foraging behavior of grasshopper nymphs and adults. Similar to other metaheuristic algorithms, the grasshopper algorithm executes the target search process in two stages: exploration and exploitation. In exploration, adult grasshoppers are encouraged by random movements to discover the target (which may be avoided by trapping in LMPP), but in exploitation, nymph grasshoppers have a tendency to have minor movements around their area of residence (exact convergence).

#### 5.3.16. Grey wolf optimization (GWO)

The GWO algorithm is a highly inspired metaheuristic method that optimizes the aggressive techniques of the grey wolf when pursuing. This method effectively replicates the grey wolf's leadership structure and pursuing ability: i) alpha, ii) beta, iii) delta, and iv) omega are the most common types of grey wolves used to simulate leadership hierarchies. In the scientific application of this algorithm influenced by biology, the most significant result is designed as the second and third best options, while represents other candidates. GWO normally involves three processes: hunting, chasing, and tracking the target by establishing forces that ring it, followed by an assault on the target. This whole pursuit mechanism was incorporated into the design of the GWO in order to address MPPT optimization issues with the PV Module. The leader of the clan controls the clan's plan for hunting grey wolves. The primary responsibility of and is to protect all injured wolves [39].

#### 5.3.17. Harris hawk optimization (HH)

The Harris Hawks (HH) optimization approach is based on hawk hunting techniques. Gali *et al.* [40] suggested this Harris Hawks optimization (HHO). Typically, hawks hunt in groups, which is known as corporate hunting. This consists of two stages: seeking for and hunting prey. In quest of prey, hawks survey their surroundings for potential prey to attack. These hawks wait for extended periods of time by perching on electric poles, standing on trees, and other high perches from where they have superior vision. Once the prey has been spotted, the hawk communicates the information visually. The notion of hawks hunting is introduced to solve multi-objective functions by locating the optimal solution among all possible solutions.

#### 5.3.18. Marine predator algorithm (MPA)

The marine predator algorithm (MPA) is a meta-heuristic optimization approach [41] that has been utilized for a variety of optimization issues. Among the applications of the MPA are the estimation of the characteristics of solar PV cells and the categorization of covid-19 images, among others. During MPPT, the MPA is applied in an optimum manner to find the optimal predicted output. The defining characteristics of the MPA include (i) Lévy motion for low-concentration prey habitats, (ii) Brownian motion for high-concentration prey environments, and (iii) Good memory for recognizing hunting partners and successful hunting areas. These characteristics make the marine predator's method superior to other bio-inspired tactics.

#### 5.3.19. Meerkat algorithm (MOA)

MOA is a population-based algorithm for memetic swarm intelligence. This algorithm is based on the natural behavior of the meerkat. In general, Meerkats are regarded as a huge clan in their habitat and have the greatest swarm among mammals. MOA imitates the swarming behavior and social interaction of Meerkats when foraging for prey. Through social interaction, each leader of the search modifies their position to be more advantageous [42].

#### 5.3.20. Particle swarm optimization (PSO)

Due to its usefulness and efficacy in addressing scientific and engineering concerns, PSO is a cluster intelligence technique that has been increasingly popular for solving widespread numerical optimization problems in recent years. As with a genetic algorithm, the PSO is unsystematically initiated and population-based to identify the optimal generational updates. Objects in a genetic algorithm are referred to as "individuals" or "particles" in PSO, with each moving at a specific pace. The velocity vector provides force to a particle, with a specific amount rectified by the ways of two factors, namely cognitive behavior (memory) and present social behavior (perception). With sufficient time (repetition), the particles are anticipated to assemble at a location that best meets their demands. The aforementioned behavior, which is key to PSO, is expressed as follows [43].

#### 5.3.21. Salp swarm algorithm (SSA)

The Salp algorithm is a transparent Salp belonging to the family Salpidae with a barrel-shaped body. The movement of the salp tissue is comparable to that of a jellyfish, which advances by moving water throughout its body. In the waters, salps create swarms known as salp chains, and this algorithm determines their global optimality. In the salp chain example, the leader is followed by a subordinate who is hunting for food. The food supply is comparable to GMPP, which the salp chain pursues [44].

#### 5.3.22. Seagull optimization algorithm

Generally speaking, seagulls inhabit colonies. They employ intellect to locate and attack prey. The most prominent characteristics of seagulls are their migratory and aggressive behavior. Migration is the seasonal movement of seagulls from one location to another in search of the most nutritious and abundant food sources that will give sufficient energy [45].

#### 5.3.23. Shuffled frog leap algorithm (SFLA)

SFLA is the embodiment of both the memetic approach and the PSO process. In the approach, the population has a collection of outcomes known as frogs. In the meanwhile, the subset of solutions is known as a memeplex, and each is utilized to do a local search in the search space. Through the evolution process's memetic, ideas are transmitted across jumbled memeplexes. Additionally, the shuffle process and local search continue until optimum convergence is achieved [46].

#### 5.3.24. Whale optimization algorithm (WOA)

Under dynamic PSC, the WOA algorithm effectively tracks GMPP with more precision and in less time. Consequently, based on the results, the algorithm is superior than MPPT GWO and PSO algorithms in terms of precise and timely tracking. In addition, because of the stochastic nature of the WOA, GWO, and PSO approaches, simulations Kumar and Rao (2016) were conducted for 50 experiments and statistical findings. The findings shown that the suggested standard deviation (SD) is less than that of other approaches, showing that WOA may successfully monitor GMPP. Nevertheless, the SD of PSO is exceptional since the maximum value is fixed to the local. Through GWO and PSO MPPTs, the MPPT WOA algorithm establishes its superiority based on the outcomes and statistical analysis [47]. According to research conducted by Mirjalili and Lewis (2016), the WOA employs three simulation operators of humpback whales: prey search, prey siege, and foraging behavior. Detailed research was conducted on 29 mathematical benchmarks to examine the exploitation, exploration, local optima avoidance, and convergence behavior of algorithms. The outcome shown that WOA is comparable to other metaheuristic approaches.

### 5.4. Human-based

#### 5.4.1. Athlete running algorithm

Observing an athletics race sparked the concept for this technique, which solves the challenge of locating the global MPP under partial shading effects. This competition consists of three rounds: qualifying, quarterfinals, and finals. Depending on the scale of the competition, the qualifying round will feature more or fewer groups, with 5 to 10 candidates in each group. At the starting line, competitors are numbered and positioned in a certain order. After the conclusion of the qualifying round, the contenders with the fastest times will advance to the quarterfinals. This quarterfinal is separated into subgroups as well. The ranking procedure continues in this round. After the conclusion of the quarterfinals, three to six players with the highest standings will be selected to compete in the championship round. The victor in this last round is the best competitor. The objective of this method is to locate the winner as quickly as feasible, which implies that the global MPP is determined as quickly as possible. Based on this competition, the suggested ARA technique similarly consists of three stages [48].

#### 5.4.2. Human psychology optimization (HPO)

The HPO algorithm is based on the mental and psychological characteristics of ambitious individuals. A person who is ambitious or goal-oriented is extremely strategic in nature, and regardless of the circumstances, generates good psychological energy. Four elements contribute to this good energy: enthusiasm, self-motivation, inspiration, and learning [49].

#### 5.4.3. Teaching-learning-based optimization (TLBO)

TLBO is a technique that is inspired by the teaching-and-learning process and the learning outcomes of students in a classroom. In addition, the approach mimics instructors', and students' educational and cognitive capacities in the classroom as two vital components. It also describes the two fundamental methods of teaching, through the teacher phase and through interaction with other students (the student phase) [50].

### 5.5. Analytic comparison

Table 2 is the comparative summary for the MPPT algorithm. Indirect comparisons of complexity are based on the number of included stages, the amount of processing, and the developing complexity of the structure. In the MPPT system, the converter type is utilized for conversion. In the interim, tracking capacity under PSC is used to calculate the pace at which the tracking algorithm reaches its maximum power.

Table 2. MPPT algorithm classification

| Meta-heuristic | Algorithms | Year | Complexity | Converter Type | Tracking Ability Under PSC |
|---|---|---|---|---|---|
| Evolutionary-based | Differential evolution [15] | 2018 | Moderate | Sepic | High |
| | Genetic algorithm [16] | 2013 | | Buck-boost | Moderate |
| | Hyper-spherical search algorithm [17] | 2022 | High | Boost | High |
| | Monkey king evolution [18] | 2016 | Moderate | Boost | High |
| Physics-based | Big-bang big-crunch [19] | 2016 | Moderate | Buck | High |
| | Fireworks algorithm [20] | 2016 | Moderate | Boost | Moderate |
| | Gravitational search algorithm [21] | 2019 | Low | - | Very low |
| | Mine blast algorithm [22] | 2012 | Moderate | Boost | High |
| | Wind driven optimization [23] | 2019 | High | Boost | Moderate |
| Swarm-based | Ant colony optimization [24] | 2013 | Low | Boost | Moderate |
| | Artificial bee colony [25] | 2015 | High | Boost | High |
| | Artificial fish optimization algorithm [26] | 2018 | High | Boost | High |
| | Bald eagle search [27] | 2022 | High | - | High |
| | Bat algorithm [28] | 2017 | High | Buck-boost | High |
| | Black widow optimization algorithm [29] | 2022 | High | - | High |
| | Butterfly optimization [30] | 2019 | Low | Boost | High |
| | Cat swarm optimization [31] | 2017 | High | Boost | High |
| | Chicken swarm optimization [32] | 2014 | Moderate | - | Moderate |
| | Crow search [33] | 2021 | Moderate | Boost | High |
| | Cuckoo search [51] | 2019 | Moderate | Buck-boost | Moderate |
| | Dragonfly optimization [34] | 2022 | High | Boost | Very high |
| | Firefly optimization [35] | 2020 | Moderate | Boost | High |
| | Flower pollination algorithm [36] | 2019 | High | Boost | Moderate |
| | Golden eagle optimization [37] | 2022 | High | Boost | High |
| | Grasshopper optimization [38] | 2022 | High | Boost | Very high |
| | Grey wolf optimization [39] | 2017 | High | Boost | Very high |
| | Harris hawk optimization [40] | 2021 | High | qZSC | Very high |
| | Marine predator algorithm [41] | 2022 | High | Boost | Very high |
| | Meerkat algorithm [42] | 2021 | High | Boost | High |
| | Moth flame optimization [52] | 2020 | Moderate | Boost | Moderate |
| | Particle swarm optimization [43] | 2016 | Moderate | Boost | High |
| | Salp swarm algorithm [44] | 2020 | Moderate | Boost | High |
| | Seagull optimization algorithm [45] | 2022 | High | Boost | High |
| | Shuffled frog leap algorithm [46] | 2016 | High | Boost | Moderate |
| | Whale optimization algorithm [47] | 2016 | High | Boost | High |
| Human-based | Athletics running algorithm [48] | 2022 | High | Boost | High |
| | Human psychology optimization [49] | 2017 | Low | Boost | High |
| | Teaching-learning optimization [50] | 2017 | Low | Boost | High |

## 6. NEW METAHEURISTICS ALGORITHM

The algorithm collected in this section is the new algorithm from year 2021 to 2022. The algorithms have not been used for MPPT yet. Tables 3-6 is a list of new algorithms organised by year and alphabetical order. Table 3 to Table 6 includes metaheuristics type, algorithms, author, publication year, and algorithm test applications. Table 3 is for evolutionary-based, Table 4 is for human-based, Table 5 is for physic-based and Table 6 is for swarm-based.

Table 3. New algorithms for evolutionary-based (alphabetical and year order)

| Metaheuristics | Algorithms | Author | Year | Application |
|---|---|---|---|---|
| Evolutionary-based | Aphid–Ant Mutualism | Eslami *et al.* [53] | 2022 | - The performance of AAM is evaluated using statistical analysis, convergence analysis, and a non-parametric Wilcoxon rank-sum test with a significance level of 5% on forty-one benchmarks selected from well-known functions of recent studies and more difficult benchmark functions known as CEC 2014, CEC 2017, and CEC-C06 2019 test suite. |
| | Lemurs Optimizer | Abasi *et al.* [54] | 2022 | - The LO is initially compared to 23 conventional optimization functions. In addition, the LO is utilized to address three real-world problems in order to assess its performance and efficacy. |

Table 4. New algorithms for human-based (alphabetical and year order)

| Metaheuristics | Algorithms | Author | Year | Application |
|---|---|---|---|---|
| Human-based | Chef-based optimization algorithm | Trojovská *et al.* [74] | 2022 | - Utilizing a collection of 52 standard objective functions, the CBOA's performance in addressing optimization issues is evaluated. Additionally, the efficacy of the CBOA in coping with real-world applications is evaluated using four engineering issues. |
| | Driving Training-Based Optimization | Dehghani *et al.* [75] | 2022 | - On a set of 53 standard objective functions of unimodal, high dimensional multimodal, fixed dimensional multimodal, and IEEE CEC2017 test function types, the efficacy of DTBO in optimization is evaluated. |
| | Sewing Training-Based Optimization | Dehghani *et al.* [76] | 2022 | - 52 benchmark functions consisting of unimodal, high-dimensional multimodal, fixed-dimensional multimodal, and the CEC 2017 test suite are used to evaluate STBO performance. The application of STBO to the solution of four engineering design problems demonstrates the proposed STBO's ability to cope with real-world applications. |
| | War Strategy Optimization Algorithm | Ayyarao *et al.* [77] | 2022 | - Tested on 50 benchmark functions and four engineering problems. |

Table 5. New algorithms for physic-based (alphabetical and year order)

| Metaheuristics | Algorithms | Author | Year | Application |
|---|---|---|---|---|
| Physic-based | Chaotic vortex search algorithm | Gharehchopogh *et al.* [78] | 2022 | - 24 UCI standard datasets were used to assess the efficacy of this method. It was also evaluated as a Feature Selection (FS) technique. |
| | Circle Search Algorithm | Qais *et al.* [55] | 2022 | - Numerous independent experiments involving 23 well-known functions and three genuine engineering issues were conducted. |
| | Ebola Optimization | Oyelade *et al.* [79] | 2022 | - An investigation was conducted into two sets of benchmark functions, consisting of forty-seven (47) classical and thirty (30) constrained IEEE-CEC benchmark functions.<br>- The algorithm was used to solve the complex problem of selecting the optimal combination of convolutional neural network (CNN) hyper parameters for digital mammography image classification. |
| | Geometric Octal Zones Distance Estimation algorithm | Kuyu *et al.* [56] | 2022 | - The search capability of the proposed algorithm is evaluated using two distinct sets of numerical benchmark problems with low and high dimensions.<br>- The developed algorithm is also applied to ten real-world constraint optimization problems.<br>- In addition, three well-known statistical metrics, Friedman, Wilcoxon rank sum, and Whisker-Box statistical tests are conducted to analyze the proposed algorithm's results further. |
| | Rain Algorithm | Rui *et al.* [58] | 2022 | - The efficacy of RNA is measured against eight standard test functions. |
| | Water wave optimization | Kaur *et al.* [59] | 2022 | - Using thirteen benchmark clustering datasets and accuracy and F-score parameters, the performance of the WWO algorithm is evaluated with respect to clustering.<br>- Additionally, a statistical test is conducted to confirm the existence of the proposed WWO algorithm. |
| | Integrated optimization algorithm | Li *et al.* [57] | 2021 | - Test on 27 representative functions. IOA has also been utilized to address unit commitment issues in the power system with positive outcomes. |

Table 6. New algorithms for swarm-based (alphabetical and year order)

| Metaheuristics | Algorithms | Author | Year | Application |
|---|---|---|---|---|
| Swarm-based | Beluga whale optimization | Zhong *et al.* [61] | 2022 | - The effectiveness of the proposed BWO is assessed using 30 benchmark functions, with qualitative, quantitative, and scalability analysis, and the statistical results are compared to those of 15 other metaheuristic algorithms. |
| | Cheetah optimizer | Akbari *et al.* [62] | 2022 | - Conduct exhaustive testing on fourteen shifted rotated CEC2005 benchmark functions in order to compare the performance of the proposed CO to that of state-of-the-art algorithms.<br>- In addition, the CEC2010 and CEC2013 benchmarks are considered to evaluate the efficacy of the proposed CO algorithm for largescale optimization problems.<br>-The proposed algorithm is also applied to one of the most well-known and difficult engineering problems, the economic load dispatch problem. |
| | Coati Optimization Algorithm | Dehghani *et al.* [63] | 2022 | - The evaluation of OA performance is based on fifty-one objective functions, including twenty-nine functions from the IEEE CEC-2017 test suite and twenty-two real-world applications from the IEEE CEC-2011 test suite. To evaluate the effectiveness of the COA in real-world applications, the proposed method is applied to the IEEE CEC-2011 test functions and four real-world optimization problems. |
| Swarm-based | Dandelion Optimizer | Zhao *et al.* [64] | 2022 | - CEC2017 benchmark functions are used to evaluate the performance of DO, including optimization accuracy, stability, convergence, and scalability, by comparing it to nine well-known nature-inspired metaheuristic algorithms.<br>- In conclusion, the applicability of DO is validated by solving four actual optimization problems. |
| | Fire Hawk Optimizer | Azizi *et al.* [65] | 2022 | - For optimization purposes, a numerical investigation was conducted on 233 mathematical test functions with dimensions between 2 and 100, and 150,000 function evaluations were performed.<br>- Standard statistical analyses, including Kolmogorov–Smirnov, Wilcoxon, Mann–Whitney, Kruskal–Wallis, and Post-Hoc analysis, were also performed. |
| | Gannet optimization algorithm | Pan *et al.* [66] | 2022 | - Validate the GOA's ability to locate the optimal solution in multiple dimensions for 28 benchmark functions. |
| | Giant Trevally Optimizer | Sadeeq *et al* [67] | 2022 | - On a set of forty benchmark functions with varying characteristics and five complex engineering problems, the performance of GTO is compared to that of cutting-edge metaheuristics for global optimization. |
| | Mountain Gazelle Optimizer | Abdollahzadeh *et al.* [68] | 2022 | - Using fifty-two standard benchmark functions and seven distinct engineering problems, the MGO algorithm is evaluated and tested. |
| | Predator–prey optimization | Mohammad Hasani Zade *et al.* [69] | 2022 | - Three evaluation phases are used to assess the proposed algorithm. The predator–prey optimization (PPO) algorithm is evaluated as an optimizer utilizing a set of sixteen mathematical functions. Second, it is evaluated as a feature selection problem solver using seven datasets.<br>- The proposed global optimizer algorithm was compared to other metaheuristic algorithms. |
| | Search in forest optimizer | Ahwazian *et al.* [70] | 2022 | - Four well-known standardized examinations, including traditional unimodal and multimodal functions, CEC2014 unimodal and multimodal functions, and CEC2014 combined functions. |
| | Tasmanian Devil Optimization | Dehghani *et al.* [71] | 2022 | - Twenty-three standard objective functions are used to evaluate the efficacy of DO in optimization. Unimodal benchmark functions evaluated the TDO exploitation capability, whereas high-dimensional multimodal and fixed-exploitation multimodal benchmark functions tested the TDO exploration capability. TDO is evaluated further by optimizing four engineering design problems. |
| | Tree optimization algorithm | Mahmoodabadi *et al.* [72] | 2022 | - In testing the efficacy of optimization algorithms, multimodal test functions are extensively used. In order to further evaluate the proposed optimization method, a classic mechanical engineering issue initially introduced by Golinski is formulated and solved as a speed reducer optimization problem. |
| | Archerfish Hunting Optimizer | Zitouni *et al.* [60] | 2021 | - First, AHO is contrasted to 12 recent metaheuristic algorithms for unconstrained optimization using ten test functions from the CEC 2020 benchmark. Using the Wilcoxon signed-rank test, the experimental results are analyzed.<br>- Second, the performance of AHO and three recent metaheuristic algorithms for non-convex constrained optimization is evaluated using five engineering design problems drawn from the CEC 2020 benchmark.<br>- Finally, the efficacy of AHO in solving five engineering design problems is evaluated and compared to a number of well-established, cutting-edge algorithms. |
| | Trees Social Relations Optimization Algorithm | Alimoradi *et al.* [73] | 2021 | - Tests for discrete problems and algorithms that serve as comparison standards. These investigations were conducted on the knapsack (KN) and travelling salesman (TS) problems (TSP).<br>- Benchmark functions and comparison algorithms for continuous problems. These investigations are conducted on unimodal and multimodal functions, as well as a succession of multimodal functions with fixed dimensions.<br>- Robot path planning issue, Feature selection issue, Image color clustering cost issue, and Speed reducer design issue. |

### 6.1. Evolutionary-based
#### 6.1.1. Aphid–ant mutualism (AMM)
The primary phases of AMM include the generation of an initial population, the formation of colonies, mutualism, the development of ants, and the flight of aphids. Similar to other evolutionary algorithms, AMM begins its search with randomly produced solutions that are classified as aphids or ants (candidate solutions and their counterparts). In the AAM, the population of ants is lower than the population of aphids because ants require the faeces of many aphids to get the necessary energy for long migrations in nature [53].

#### 6.1.2. Lemurs optimizer (LO)
The lemur optimizer (LO) [54] is an innovative algorithm inspired by nature. This method is primarily motivated by two aspects of lemur behavior: leap up and dancing hub. In the domain of optimization, these two ideas are mathematically modelled to handle local search, exploitation, and exploration search concepts.

### 6.2. Physics-based
#### 6.2.1. Circle search algorithm (CSA)
Geometry is the study of the attributes of figures in space, including their dimensions, relative location, distance, shape, and size. Due to its distinctive qualities, such as a diameter, a perimeter, a centre point, and a tangent line, the circle is the most often employed geometric form. The radius that crosses the tangent point is perpendicular to the tangent line, and the ratio of the radius to the perpendicular tangent line is the orthogonal function. The orthogonal function varies dramatically with a little change of angle, which may accelerate the CSA phase of exploration [55].

#### 6.2.2. Geometric octal zones distance estimation algorithm (GOZDE)
The GOZDE utilizes a search technique in which information is shared across zones based on their distance using median values. Population as a whole reflects the eight zones that are the mixture of several search tactics that direct the transmission of knowledge from one zone to the others in the search area. The best solution discovered thus far is a central, and zone1, which contains the best candidate solutions, is a reference area. The distances between zones and zone1 are computed using the median fitness values of the respective zones [56].

#### 6.2.3. Integrated optimization algorithm (IOA)
The IOA is comprised of five sub-algorithms: follower search, leader search, wanderer search, crossover search, and role learning. Identifying superior solutions by locating the influencers is the objective of the follower search. The leader search refines existing optimal solutions by approaching or departing from the center of the population, and then performs a single-round coordinate descent. The wandering search significantly broadens the search space. The cross-breeding search yields offspring with superior solutions inherited from their parents. Role learning automates the process by which a search agent decides whether to follow or wander [57]

#### 6.2.4. Rain algorithm (RA)
According to the description [58], when raindrops reach a certain density, they will begin to descend to the earth. Then, each raindrop collides with the ground and fragments into smaller droplets, which coalesce into a new raindrop. Finally, the new droplets combine to create rain water and flow downwards. the rain algorithm consists of four steps: creating initial rain drops, breaking them into smaller rain drops, merging them into larger rain drops, and making streaming rainfall.

#### 6.2.5. Water wave optimization (WWO)
WWO is a metaheuristic approach for tackling global optimization problems [59] that is influenced by water wave theory. WWO compares solution space to a seabed region, where each solution represents a "wave" by combining its height and wavelength. The seabed depth is used to quantify the fitness of each wave, with a shorter distance to the level of still water indicating more fitness.

### 6.3. Swarm-based
#### 6.3.1. Archerfish hunting optimizer (AHO)
The archerfish constitute a single-species family known as Toxotes chatareus. They predominantly inhabit mangrove regions of the Indo-Pacific. They hunt aerial insects by shooting them with water droplets spit from their jaws, which is one of the most complex and thrilling feeding behaviors. Archerfish capture insects in one of two ways: i) by dislodging the target with a forceful water jet (left archerfish), or ii) by leaping

at the prey if it is near enough (right archerfish). Two parameters (the swapping angle and the attractiveness rate) must be specified for the AHO algorithm [60].

#### 6.3.2. Beluga whale optimization (BWO)

The BWO algorithm imitates beluga whale behaviors such as swimming, hunting, and falling. BWO, like other metaheuristics, consists of the exploration and exploitation phases [61]. The exploration phase ensures the capacity for global searching in the design space through the random selection of beluga whales, while the exploitation phase governs local searching. To describe the beluga whales' behaviors, they are considered search agents that may move in search space by modifying their position vectors. In addition, the likelihood of whale fall is included in BWO, which alters beluga whale locations.

#### 6.3.3. Cheetah optimizer (CO)

Prey can be detected while a cheetah is roaming or monitoring its surroundings. When the cheetah spots its prey, it may stay still and wait for the prey to approach before launching an assault. The attack mode consists of two phases: rushing and capturing. The cheetah may abandon the hunt for a variety of reasons, including its limited energy reserves, the swift flight of its prey, etc. Then, they may return home to recover before continuing their quest. The cheetah may select one of these techniques based on its evaluation of the prey's condition, location, and distance. The CO algorithm is built on employing various hunting techniques intelligently throughout hunting seasons (iterations) [62].

#### 6.3.4. Coati optimization algorithm (COA)

Coati optimization algorithm (COA), which imitates the behavior of coatis in the wild. The core concept of COA is the simulation of two natural coati behaviors: i) Their behavior when assaulting and pursuing iguanas, and (ii) Their behavior when escaping from predators. The steps of COA implementation are defined and mathematically characterized as two phases: exploration and exploitation [63].

#### 6.3.5. Dandelion optimizer (DO)

DO replicates the three-stage process of dandelion seed long-distance flight, which is dependent on the wind. During the rising phase, seeds rise in a spiral pattern as a result of updrafts from above or drift locally in communities based on varying weather conditions. In the falling phase, seeds alter their orientation in global space in order to descend gradually. In the landing phase, seeds are placed at random in order to germinate [64].

#### 6.3.6. Fire hawk optimizer (FWO)

A metaheuristic algorithm based on the behavior of whistling kites, black kites, and brown falcons while foraging. These birds are known as Fire Hawks. As a method for controlling and capturing their prey, birds gather up burning sticks and drop them in unburned areas to start small fires. These small fires frighten the prey, including rodents, snakes, and other animals, and cause them to flee in a panicked and hasty manner, making it simpler for the hawks to capture them [65].

#### 6.3.7. Gannet optimization algorithm (GOA)

The optimization procedure for gannet (GOA). The GOA quantifies the distinctive foraging behaviors of gannets and is used to facilitate exploration and exploitation. The U-shaped and V-shaped dive patterns of GOA are responsible for exploring the optimal region of the search space, with abrupt turns and random walks guaranteeing that better solutions are located in this region [66].

#### 6.3.8. Giant trevally optimizer (GTO)

Giant trevally feeds on a variety of creatures in the wild, including fish, cephalopods, and seabirds (sooty terns) [67]. The distinctive techniques of giant trevally when hunting seabirds have been quantitatively modelled and categorized into three categories. The first phase simulates the foraging movement patterns of gigantic trevallies. In the second stage, the gigantic trevallies select a hunting region that is optimal in terms of food availability. In the last phase, the trevally begins to pursue the seabird (prey). When the victim is close enough, the trevally rushes out of the water and attacks it in the air or even snatches it off the water's surface.

#### 6.3.9. Mountain gazelle optimizer (MGO)

The Mountain Gazelle Optimizer (MGO) is a metaheuristic algorithm inspired by the social structure and behavior of mountain gazelles in the wild. In this algorithm, the hierarchical and social life of gazelles is mathematically articulated and used to the development of an optimization algorithm. The MGO optimization algorithm executes optimization operations based on four major factors in the existence of mountain gazelles: bachelor male herds, maternity herds, solitary, territorial males, and migration to find food [68].

#### 6.3.10. Predator–prey optimization (PPO)

Two random populations are considered in the Predator-prey optimization. The energy gain is determined for both predators and prey based on their body mass and the interaction between predators and mutual prey. The most effective predator (i.e., the predator with the greatest energy gain) conducts a local search (exploitation). The other members of the prey population aid the search space exploration [69].

#### 6.3.11. Search in forest optimizer (SIFO)

The algorithm is based on the systematic behavior of search teams searching a forest for missing individuals [70]. According to the SIFO optimizer, a number of teams comprised of numerous professionals in the search field are dispersed across the forest and progressively advance in the same direction by discovering evidence from the target until the missing person is located. This search structure was built using a mathematical framework consisting of intragroup search operators and the transfer of the expert member to the leading team.

#### 6.3.12. Tasmanian devil optimization (TDO)

Tasmanian Devil optimization (TDO) is a new bio-inspired metaheuristic algorithm that replicates Tasmanian devil behavior in the wild. The primary source of inspiration for TDO is the eating behavior of the Tasmanian devil, which has two feeding strategies. In the first strategy, if a Tasmanian demon encounters carrion, it will consume it. In the second strategy, the animal pursues and feeds by attacking its prey [71].

#### 6.3.13. Tree optimization algorithm (TOA)

This method, which is inspired by the growth of trees, begins with a random beginning population and increases their performance based on the pattern of tree growth. In fact, the objective of this novel optimization technique is to identify the tallest leaf of a tree by employing the location of the best leaf and replacing yellow, wilted leaves with new, randomly selected, fresh green ones. These techniques prevent the algorithm from prematurely converging and becoming trapped in local minimums [72].

#### 6.3.14. Trees social relations optimization algorithm (TSR)

TSR influenced by the hierarchical and communal existence of trees in the rainforest. The primary concern of the collective awareness of trees is the preservation of the forest. The trees attempt to mitigate the harm in a variety of ways so that the forest can flourish. Organizing trees, preserving new seedlings, and their communication mechanism produce a complex structure based on swarm intelligence that serves as inspiration for the development of an algorithm to handle current issues. In TSR, each response is represented as a tree, and a group of solutions is represented by a sub jungle. Sub-jungles are interrelated and aid one another in reaching the correct conclusion. Utilizing parallel and synchronized sub-jungles with their own dedicated operators will boost accuracy and decrease the time required to achieve a satisfactory answer [73].

### 6.4. Human-based

#### 6.4.1. Chef-based optimization algorithm (CBOA)

The algorithm for optimization based on chefs (CBOA) [74]. The process of learning cooking abilities through training classes serves as the primary influence for CBOA's design. Various steps of the culinary training process are mathematically described in an effort to improve the global search capacity in exploration and the local search ability in exploitation.

#### 6.4.2. Driving training-based optimization (DTBO)

Driving training-based optimization (DTBO) is an algorithm that simulates the human activity of driver training. The primary motivation for the DTBO design was the process of learning to drive in a driving school and the education of the driving teacher. The mathematical model of DTBO consists of three phases: (1) teaching by the driving instructor, (2) patterning of pupils from instructor skills, and (3) practice [75].

#### 6.4.3. Sewing training-based optimization (STBO)

STBO is a swarm-based metaheuristic algorithm whose members are novice tailors and trainers. Each member of the STBO population corresponds to a possible solution to the issue, whose suggested values for the decision variables are represented by the STBO population. Therefore, each STBO member may be mathematically represented by a vector, and the STBO population can be represented by a matrix [76].

#### 6.4.4. War strategy optimization algorithm (WSO)

The war strategy optimization (WSO) relies on the strategic movement of army units during battle [77]. The strategy of warfare is modelled as an optimization procedure in which each soldier advances dynamically toward the optimal value. The program mimics two prevalent military methods, assault and defense. The placements of soldiers on the battlefield are updated based on the adopted plan. To enhance the algorithm's convergence and resilience, a weight update mechanism and a relocation technique for weak soldiers are implemented. The algorithm for military strategy strikes a balance between the exploration and exploitation phases.

## 7. BENCHMARK OPTIMIZATION METHOD

The manner in which metaheuristic approaches optimize the solution can be categorized into four primary steps based on observation [80]: initialization, reproduction, selection, and stopping criterion. Figure 3 shows the benchmark flow diagram for the metaheuristic methods during the optimization process. Usually, the initial population (known as the parent) of search agents is formed during the initialization at random. In the context of MPPT, the search agents can be the voltage or duty cycle of the power converter [9], [81], [82] whereas the optimal solution is the PV array's maximum output power. In reproduction, a new population (termed offspring) is generated from the parent population by use of a uniquely formed equation, in accordance with many metaphorical metaheuristic methods. In the meantime, the selection process is a discriminating method for selecting the best search agents that will survive for the following generation (or iteration). It is based on the fitness function's predetermined criteria. There are numerous selection techniques presented in the literature, with the roulette wheel, tournament, ranking, and steady state selection being the most prevalent. The details of these techniques can be found in [83], [84]. The reproduction and selection procedures are repeated iteratively until a predetermined stopping criterion is fulfilled. Concurrently, the best search agent across all generations is selected as the method's optimal solution. The stopping criterion varies according to the precise needs of various problem areas. The most typical stopping criterion are as follows [80]:

a) Generation number: The algorithm stops the iteration after carrying out a certain number of prescribed threshold value.
b) Best fitness threshold: This stops the iteration when the maximum value of objective function is less than the set value.
c) Population convergence: This stops the iteration when the difference between the maximum and minimum values of all individuals in the population is less than the prescribed tolerance.
d) Fitness convergence: This stops the iteration when the difference between the maximum and minimum values of objective function for all search agents is less than the prescribed tolerance.

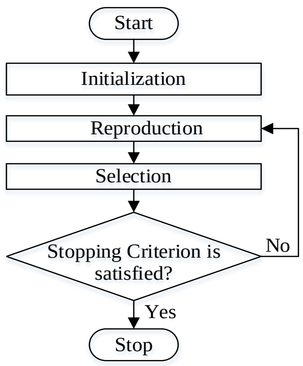


Figure 3. Benchmark methodology for metaheuristics methods.

## 8. CONCLUSION

The main problem with conventional MPPT methods is their poor efficiency during PSC due to their inability to locate a single GMPP out of many LMPPs. Various metaheuristic methods have been proposed to solve the problem. Since these metaheuristic methods search for all the peaks over the entire P–V curve, finding the GMPP is very likely. These methods can be metaphorically divided into four categories: i) evolutionary-based, ii) physics-based, iii) swarm-based, and iv) human-based. This paper reviews the metaphors of 38 existing metaheuristic-based MPPTs and 27 recent metaheuristic methods that have the potential to be applied to MPPT applications. In addition to describing the fundamental concepts and criteria, this study compares the performance of metaheuristic-based MPPT in terms of complexity level, converter type, sensor requirements, and tracking abilities. This article can therefore serve as a one-stop resource for any engineer or researcher interested in selecting a new metaheuristic approach for MPPT.

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