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A review of recent advances in metaheuristic maximum power point tracking algorithms for solar photovoltaic systems under the partial-shading conditions

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A B S T R A C T S

Several maximum power point (MPP) tracking algorithms for solar power or photovoltaic (PV) systems concerning partial-shading conditions have been studied and reviewed using conventional or advanced methods. The standard MPPT algorithms for partial-shading conditions are: (i) conventional; (ii) mathematics-based; (iii) artificial intelligence; (iv) metaheuristic. The main problems of the conventional methods are poor power harvesting and low efficiency due to many local maximum appearances and difficulty in determining the global maximum tracking. This paper presents MPPT algorithms for partial-shading conditions, mainly metaheuristics algorithms. Firstly, the four classification algorithms will be reviewed. Secondly, an in-depth review of the metaheuristic algorithms is presented. Remarkably, 40 metaheuristic algorithms are classified into four classes for a more detailed discussion; physics-based, biology-based, sociology-based, and human behavior-based are presented and evaluated comprehensively. Furthermore, the performance comparison of the 40 metaheuristic algorithms in terms of complexity level, converter type, sensor requirement, steady-state oscillation, tracking capability, cost, and grid connection are synthesized. Generally, readers can choose the most appropriate algorithms according to application necessities and system conditions. This study can be considered a valuable reference for in-depth works on current related issues.

A R T I C L E   I N F O

1. INTRODUCTION

The increase in environmental pollution, global warming, and scarcity of energy resources have increased studies on renewable power. Solar photovoltaic (PV) energy is one of the vital renewable energies obtained free and cannot be exhausted. It is also called the most auspicious new energy in technology, in contrast to conservative non-renewable bases such as fossil, petroleum, natural gas, and coal. One of the widely established renewable energy technologies utilizing solar is the photovoltaic (PV) system; therefore, several studies need to be conducted (Aziz, 2019; Bialasiewicz, 2008; Irawan *et al.*, 2021; Perdiansyah *et al.*, 2021; So *et al.*, 2007).

Currently, PV technology (Ahmad *et al.*, 2022) is indispensable and used as a source of electricity to supply demands. Therefore, it is crucial to increase the tracking maximum power point (MPP) and drag the highest power available from the PV panel without being affected by changes in light during the day. However, the power output generated is drastically reduced because of the partial-shading condition (PSC), decreasing power efficiency, and increasing configuration complexity. Under normal conditions, the PV performs significantly, with the proper functioning of almost all MPPT algorithms. However, this performance decreases per the Partial-shading condition (Bayrak *et al.*, 2017).

The technique for making effective use of PV is comprehended as a maximum power point (MPP) tracking or maximum power point tracking (MPPT). This method drags the highest energy available by operating at the most efficient output. MPPT is a solution to escalate the productivity of electric power with the DC-DC converter circuit and control algorithm as its main parts. According to various studies, this system consists of different algorithms, such as incremental conductance (INC), fuzzy logic controller (FLC), artificial neural network (ANN),

perturb-and-observe (P&O), grey wolf optimizer (GWO), firefly algorithm, ant colony optimization (ACO), and artificial bee colony (Dorigo & Birattari, 2006; Mirjalili *et al.*, 2014; Safarudin *et al.*, 2015; Soulatiantork *et al.*, 2018). MPPT is used in PV systems to maximize tracking and for continuous tracking. Meanwhile, maximum power point (MPP) is easily tracked when irradiance is constant, although this process tends to often experience perturbations due to PSC (Ishaque & Salam, 2013).

Partial-shading dramatically disturbs the power harvesting generated by the solar PV system; therefore, one problem needs to be resolved to maximize the MPPT performance. Another related problem is the strategy used to maximize the extraction generated in changing weather conditions.

Several preliminary studies focused on maximizing the energy generated by PV systems by improving MPPT performance to promote the effectiveness and efficiency generated by partial-shading (Qian, 2018). According to (Boussaïd *et al.*, 2013), metaheuristics is a widely recognized approach to MPPT performance optimization. Therefore, in this research, 40 MPPT algorithms were discussed comprehensively and thoroughly by dividing the metaheuristic algorithms into four classes based on: physics, biology, sociology, and human behaviors.

2. METHODS

Solar PV panels are usually coupled in parallel or series in large PV systems or micro-networks to escalate the voltage and power output. Furthermore, solar radiates on the large externals area of the PV module; it is not evenly operated under partial-shading conditions (PSC), thereby making it difficult to optimize the power in the PV system.
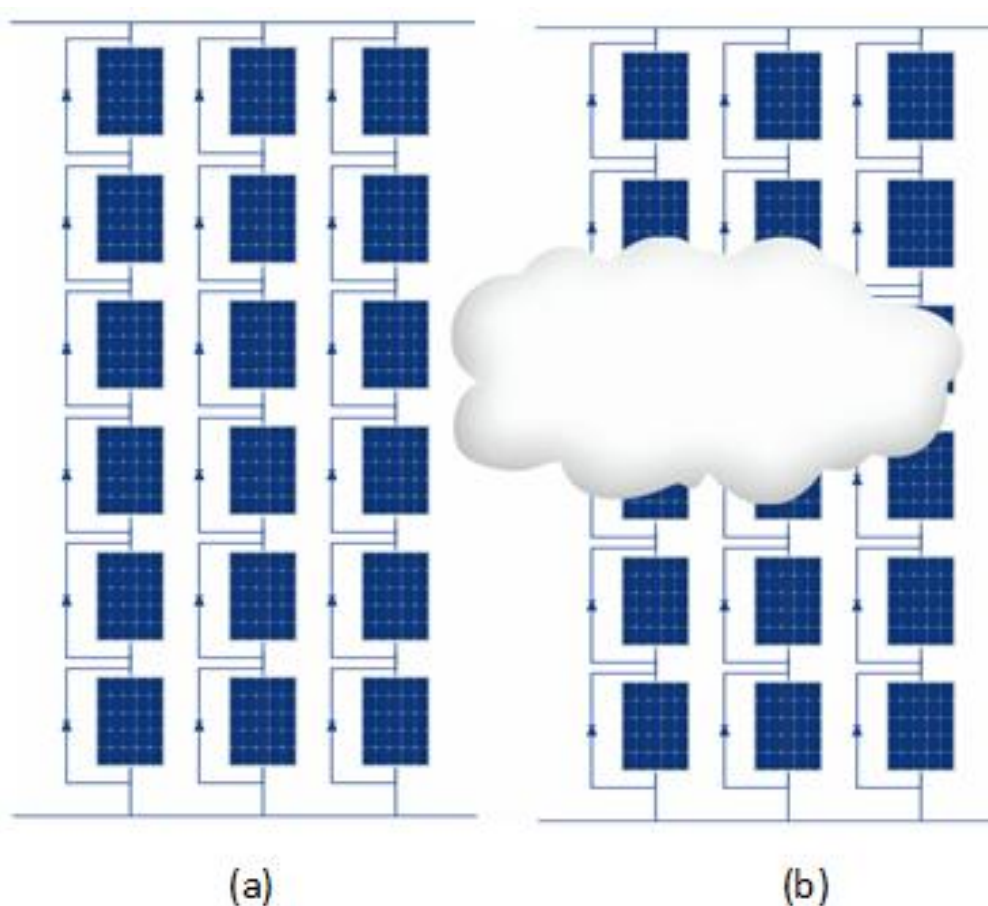
2.1. PV Normal Conditions

Figure 1 shows a PV module, where **Figure 1(a)** shows a PV system with normal conditions where all modules are evenly exposed to solar radiation. At the same time, **Figure 1(b)** shows the condition of the PV module in partial shading. However, the blockage of this module by partial shading leads to complete exposure to solar radiation; hence, the power generated becomes non-optimal. **Figure 1** describes the PV module under normal conditions and when covered by cloud shadows. PV system yields are directly affected by solar radiation and temperature; therefore, it is necessary to use an updated value of these factors to maximize power. The figure further shows that the output is directly affected by solar radiation and temperature.

2.2 PV Partial Shading Conditions

In situations whereby trees, clouds, and buildings overshadow the entire or parts of the outdoor PV system, a condition known as non-uniform insolation materializes. The module's part that receives radiation continues to operate at an optimal and efficient rate in partial-shading conditions (PSC) (Mirjalili *et al.*, 2014). Therefore, a strategy is needed to detect and track the MPP and overcome high, medium, and low voltage errors due to PSC.

In invariant circumstances, the P-V curve of the module is unimodal, which means it has only one peak. However, under partial shading, where the solar radiation is not evenly distributed, each module receives different sun rays due to shadows of buildings, trees, clouds, birds, and dirt.

(a)　　　　　　　(b)

Figure 1. PV module under (a) Photovoltaic normal condition and (b) Partial-shading condition.

2.3 MPPT Control Strategy

The MPPT management strategy is utilized to determine the maximum power of the PV collection more closely and effectively, as depicted in **Figure 2**. The power delivered from the PV is intermittent in the tracking process due to sudden changes in conditions of irradiation and temperature. The DC-DC converter and MPPT connect the PV array's power to the load. Furthermore, the DC-DC converter works by varying the changing load conditions and the output source to obtain the peak power point until the maximum amount is obtained. The primary purpose of MPPT systems is to track the maximum power of the PV panel. Meanwhile, the MPP deals with many changeable temperatures and solar radiation. Therefore, the MPPT technique is needed to dynamically set the MPP like an operating point for a vast range of inputs (solar radiation and temperature) (Haji & Genc, 2018).

MPPT allows the modules to generate high power without following any specific tracking algorithm. Its algorithms are mainly used to get highly optimized power from the solar array based on different temperature and irradiation values. Due to fluctuations in solar irradiance, temperature values of the cell, and maximum power changes repeatedly, MPP means the voltage at which the PV array produces maximum power.

2.4. Algorithm of MPPT PV System

Several preliminary studies investigated the algorithms used for MPPT on PV systems, such as the conventional, mathematical, artificial intelligence, and metaheuristic algorithms. Three adopted orthodox strategies of the MPPT are P&O, hill climbing (HC), and INC. This section discusses the algorithm used in the MPPT system to follow the highest power point generated by PV.

The use of algorithms for the MPPT PV system is supported by tracking speed, complexity, control parameters, converters used, tracking ability, and efficiency. Many algorithms are used for the MPPT system, P&O conventional algorithm, HC and INC (da Rocha *et al.,* 2020). The conventional algorithms are utilized in the MPPT system because the control structure is several, and straightforward measurable parameters do not depend on the characteristics of the PV module. However, some disadvantages are associated with the conventional algorithms, namely an increase in perturbation due to the rise in power. In addition, immediately after the PV cell power reaches its peak, the power tends to decrease, leading to a significant increase in perturbation. It also becomes challenging to offer exemplary performance in a steady and dynamic condition due to a steady, gradual step with a work process used as a management parameter and the inability to determine GMPP in MPP. Metaheuristic procedures are used for MPPT PV plans with many types of approaches. This type of algorithm is becoming attention increasingly in industrial appliances because they:

1. trust on easy-to-implement and straightforward concepts;
2. do not require gradient information;
3. can avoid the local optima;
4. are capable of a variety of glitches spanning multidiscipline.

Nature-inspired metaheuristic approaches are for solving problems in optimization by imitating physical or biological phenomena. It is categorized into three approaches, scilicet physics-based, evolution-based, and swarm-based methods, as shown in **Figure 3**. Algorithms with an evolution-based approach include (Choi *et al.,* 2015). Furthermore, examples of physics-based algorithms include (Ahmadi & Abdi, 2016; Bandyopadhyay *et al.,* 2008; Du

et al., 2006; Dutta *et al.*, 2015; Farahmandian & Hatamlou, 2015; Farrahi-Moghaddam *et al.*, 2007; Ji *et al.*, 2017; Kaveh & Khayatazad, 2012; Kumar *et al.*, 2016a; Pillai & Rajasekar, 2018; Sabri *et al.*, 2013; Sardari & Moghaddam, 2016). Then with a swarm-based approach (Chen *et al.*, 2018; Hemalatha *et al.*, 2016; Ituarte-Villarreal *et al.*, 2012; Kang *et al.*, 2018; Tirkolaee *et al.*, 2020; Titri *et al.*, 2017; Wang *et al.*, 2018).
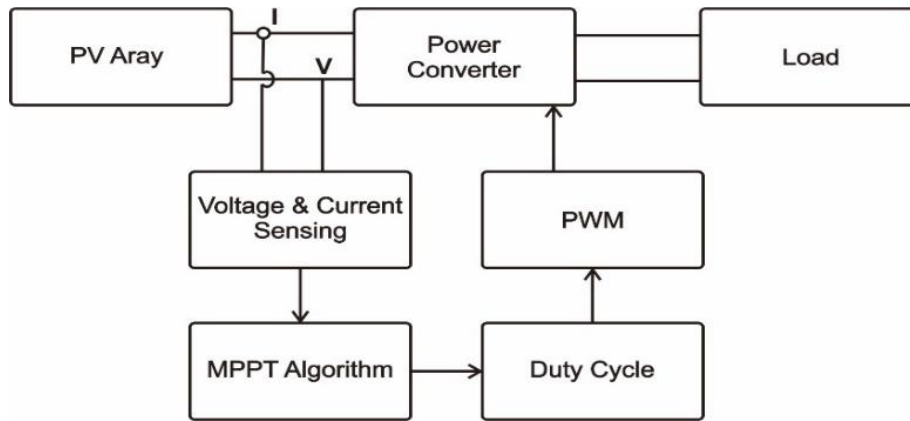
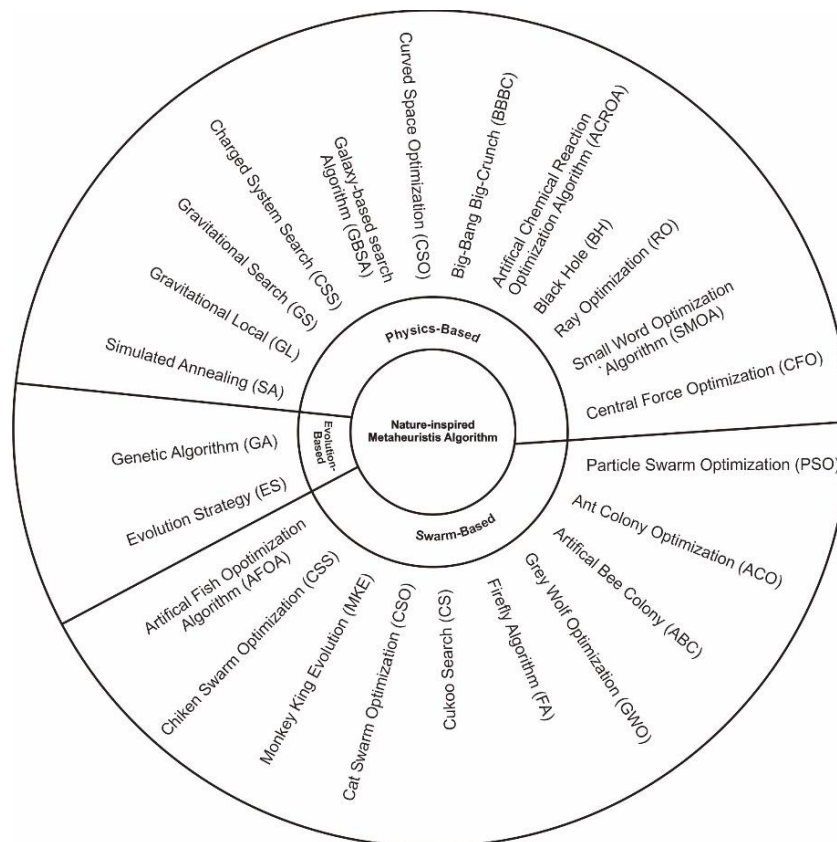

Figure 2. MPPT control strategy.

Figure 3. Nature-inspired metaheuristic algorithms.

2.5. Algorithm of MPPT PV System PSC

Practically, there are problems associated with the PV system during partial shading situations. Therefore, different procedures are used to overcome the partial shading, such as conventional, mathematics-based, artificial, and metaheuristic algorithms, as shown in **Figure 4**. Furthermore, several steps are taken to choose the most suitable algorithm for dealing with partial shading conditions, such as describing it based on type and characteristics.

The approach used to discuss the MPPT is classified into four groups by the algorithm used. The first and most popular technique is the conventional method based on specific statements by employing a management indication to a power converter. This method uses various direct control systems such as P&O, HC, and INC (Kandemir *et al.*, 2017; Rezk *et al.*, 2017; Yang *et al.*, 2020). The second set is mathematical-based algorithms, by applying direct search techniques with fast search speeds. The algorithms in this second group include the Betta, the chaotic, and Fibonacci searches. The third group involves newer techniques based on a soft computing approach using PSO, FLC, ANN, and Bayesian Network algorithms. Soft computing techniques deal with imprecise representatives to deliver optimal resolutions for complicated issues.

2.5.1 Conventional algorithms

Finally, the fourth group uses an algorithm with a metaheuristic approach inspired by biological, physical, sociological, and human behavior phenomena. This algorithm has been primarily utilized in current years to design MPPT regulators or other renewable liveliness areas.

2.5.1.1 Perturb and observe algorithm (P&O)

Shifting or perturbing the operating point of solar PV based on the last increment sign of PV power is the crucial idea of the P&O algorithm. A growth or reduction in the PV power leads to a rise or decrease in the same or contrary direction perturbation, respectively. The standard P&O is one of the great commonly used algorithms for tracking the MPPT of a solar PV system due to its simple implementation and the speed and accuracy of its responses.
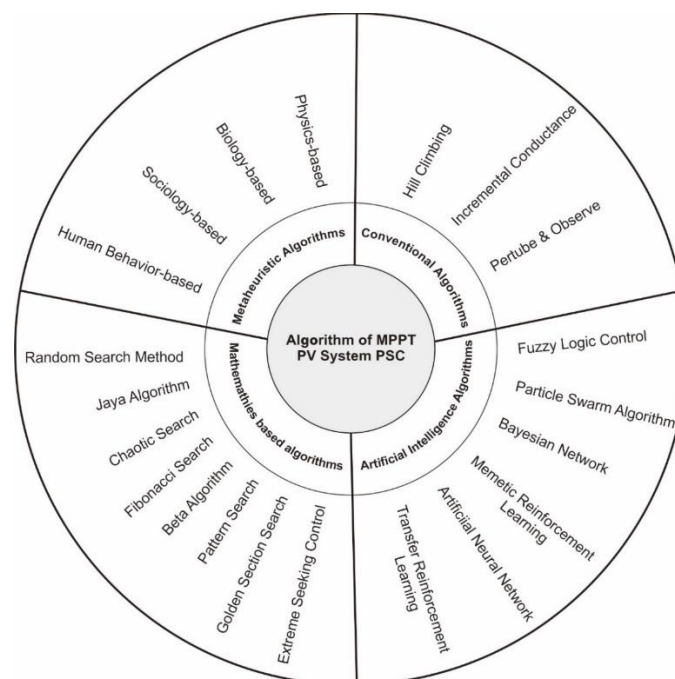
Figure 4. Algorithm of MPPT PV system PSC.

This technique is a recurrent approach, where an operational point of the solar PV swings proximate to the MPP. The principle is that the photovoltaic system's output voltages are interrupted, with changes in system power before and after the perturbation are assessed, and the system is controlled according to the principle of increasing the output power (Alik & Jusoh, 2018).

The control structure of the algorithm is simple, requires less measured parameters, does not depend on the module characteristics, and is handily applied to all PV panels. The drawbacks of this algorithm are:

1. the perturbation increases along with the power;
2. if the PV cell spans its peak, the power tends to drop;
3. the perturbation becomes more significant with steady-state oscillations at considerable voltage variation.

2.5.1.2 Hill climbing (HC)

Hill climbing is a conventional algorithm that produces a change in power by applying a specific perturbation and confirming to the controller the following action through detection. Perturbation is a duty cycle. Therefore, when the power increases after application, the control changes in its original direction with a rise in power. Meanwhile, the perturbation is controlled in the reverse track until the change is within a threshold when the power is reduced. The main problem of the algorithm is that it solely moves slope, and the derived solution quality needs to be greater than the parent as (1). Hence, it converges rapidly to local optimal is not the desired output in most matters (Burke & Bykov, 2017; Abed-alguni & Alkhateeb, 2020).

$$D(k) = D(k-1) \pm a \times Slope \qquad (1)$$

2.5.1.3 Incremental conductance (INC)

The INC MPPT algorithm is the most common method because it can carry out appropriate control under quickly altering atmospheric states without steady-state fluctuations. The method considers the reality that the pitch of the PV power value is positive/negative on the left/right of the MPP, respectively, and zero at the MPP. The algorithm is implemented as a replacement for the P&O algorithm because of its consistent performance in rapidly changing weather conditions. Furthermore, a new algorithm was introduced to provide fast-tracking of the MPP.

2.5.2 Mathematics-based Algorithms
2.5.2.1 Beta algorithm

The main advantages of the beta algorithm are (i) easy implementation, (ii) steady-state sans fluctuation, and (iii) high tracking speed. Therefore, to improve the precision and reach zero fluctuations under steady-state conditions, an enhanced beta procedure (2) is created to get the GMPP position beneath PSC.

$$\beta = ln\left(\frac{i_{pv}}{v_{pv}}\right) - C \times v_{pv} \qquad (2)$$

2.5.2.2 Chaotic search

Chaos is a general nonlinear phenomenon with complex, random, and inherent behavior. Due to ergodicity, the chaos variable is used to carry out an optimal search, which is superior to a blindfolded random search. The essential features of chaos search are regularity, ergodicity, sensitivity, and randomness (Zhou *et al.*, 2011). The chaos word is defined as the randomness of the responsive nature of the system for a slight change in initial conditions. Therefore, this predefined attribute is applied for the MPPT optimization in the photovoltaic generation system (PGS).

2.5.2.3 Fibonacci search

The Fibonacci search technique is used to sort an array using the conquer and divide algorithm that narrows down appropriate positions with the help of Fibonacci numbers. It continuously determines the optimal point by narrowing the range (Ramaprabha *et al.,* 2012). This method is based on search area reduction in each iteration with the complete search area and two middle points initially assigned using the Fibonacci search (Pati & Sahoo, 2016).

2.5.2.4 Random search method

RSM is a straight search, accessible ramp method first proposed by Anderson and associated with the fundamental mathematical analysis developed by Rastrigin. RSM selects a random value within the specified limits to analyze global optimizations. In the MPPT method, the generated random value is the duty cycle value, updated until the MPP is reached (Ram *et al.,* 2017).

2.5.2.5 Pattern search

The pattern search algorithm is a straightforward search approach that uses a mesh to compute a series of iterations which continues to decrease the value of the objective function until convergence is achieved. It purposes to complete the optimization of the unconstrained non-linear problems and is also aimed as a general pattern search. This approach requires fewer voltage samples to identify global maxima (GM) under PSC, improving tracking capability and dynamic efficiency (Javed *et al.,* 2016).

2.5.2.6 Golden section search (GSS)

The GSS technique is integrated into the proposed multi-stage MPPT as a straightforward variable step size that optimizes the algorithm. It provides an initial bracketing interval in which the MPP is located with the GSS algorithm converging to

the MPP by repeatedly narrowing the width of the interval with the rate of the golden ratio.

2.5.2.7 Extreme seeking control

The SMESC develops from the combination of SMC and ESC, which further improve the output response of WECS. Compared with ESC, the SMESC method not only enhances the robustness of MPPT but also enhances the efficiency of WECS (Hu *et al.,* 2019).

2.5.2.8 Jaya algorithm

Jaya was presented by Rao (2016). It is a new solution based on population to get prime solutions for unconstrained and constrained optimization cases. Dissimilar to other heuristic algorithms based on population, Jaya has no exact controlling parameter and involves only the candidate solutions (namely, the population dimension (m)) and the total iterations (number of generations (Gn)). The optimization procedure of this method is idea-based elicited, and the established solution for a typical case has to move toward the best solution to avoid the inferior. The Jaya algorithm is one of the modest optimization techniques due to having only one phase.

2.5.3 Artificial intelligence algorithms
2.5.3.1 Fuzzy logic control (FLC)

FLC falls into the usually employed methods in many engineering tasks. It has an easy and straightforward methodology because technical quantities and proper mathematical modeling of a plan are not essential for this approach (Seyedmahmoudian *et al.,* 2016).

2.5.3.2 Particle swarm optimization (PSO)

PSO is an algorithm that works by adjusting the path by manipulating each coordinate. Some of the algorithm's success at real-number functions is because it "surpasses" known local optima, traveling further afield or between the two. However,

questions are asked to determine the meaning of trajectory, velocity, and intermediate concepts in discrete space.

$$\vec{v_i}(j+1) = w(j)\vec{v_i}(j) + \varphi_1(j)(\overrightarrow{pbest_i}(j) - \vec{x_i}(j)) + \varphi_2(j))(\overrightarrow{gbest_i}(j) - \vec{x_i}(j)) \qquad (3)$$

$$\varphi_1(j) = c_1 r_1(j), \ \varphi_2(j) = c_2 r_2(j) \qquad (4)$$

$$\vec{x_i}(j+1) = \vec{x_i}(j) + \vec{v_i}(j+1) \qquad (5)$$

2.5.3.3 Bayesian network

A Bayesian network is an approach of a combined probability distribution modeling of numerous random parameters and a powerful instrument for information fusion (Keyrouz, 2018).

2.5.3.4 Artificial neural network (ANN)

ANN is a parallel and distributed processing system consisting of many simple and massively connected elements called neurons. The multilayer perceptron architecture is the most commonly used paradigm of ANNs (Punitha *et al.*, 2013).

2.5.3.5 Memetic reinforcement learning

Memetic computing is a broad topic that examines complicated configurations arranged of interactive memes, which efficiently accomplish a precise optimization via uninterrupted evolutions and exchanges (Zhang *et al.*, 2019).

2.5.3.6 Transfer reinforcement learning (TRL)

Compared with the other meta-heuristic procedures, TRL is capable of knowledge transfer and online learning. This system can transport positive information from previous optimization duties, thereby maximizing the matrices of the new optimization duty and efficiently harvesting an optimum of high quality. Furthermore, TRL continually discovers further information from environmental connections, which quickly acclimate to MPPT beneath different temperatures, solar irradiation, and PSC.

2.5.3.7 Metaheuristic algorithms

Metaheuristic approaches are characterized by nature (based on some philosophies from biology, physics, or ethology). Stochastic factors relating to random variables do not use the ramp or Hessian matrix of the objective function and have several limitations that need to be adjusted to the existing problem. The optimizer needs to include an operator to discover the investigation area globally in this stage, where activities, such as design variable perturbations, need to be randomized.

The utilization step pursues the exploration one, and it is described as the procedure of analyzing a promising area in the investigation area. Exploitation relates to local examination capabilities in promising space design areas discovered in the exploration phase. However, one of the most challenging tasks is determining the right balance between exploration and exploitation in metaheuristic algorithm development due to the stochastic essence of the optimization stage.

Numerous surveys on metaheuristics have been proposed over time, although none covers all aspects. For example, much research focuses on one side of metaheuristics, especially biology or nature, without discussing more variants. Metaheuristic algorithms offer suitable algorithm structures and metaheuristic capabilities (Elshaer & Awad, 2020): such as (1) Depend on easy-to-apply and straightforward concepts, (2) Do not demand gradient data, (3) Can pass local optimum, and (4) used in a variety of problems spanning various disciplines.

Furthermore, they offered suitable algorithm structures applied to various optimization problems with only minor modifications suitable for a given problem. The metaheuristic algorithm successfully solves a specified optimization problem,

assuming it can provide a proportion between diversification (exploration) and intensification (exploitation). Exploitation is needed to find the part of the intensification space with superior solutions. Increasing the search in several capable areas is essential, including the gathered historical values. The critical difference between the current metaheuristics is related to the strategies used to achieve this balance.

Furthermore, judging the best ranking among the existing algorithms is not easy. Therefore, based on the indicators and parameters measured, by making a fair comparison, it was concluded that the metaheuristic algorithm has a better capability than others based on the measured parameters. The following section comprehensively discusses 40 metaheuristic algorithms grouped into four categories in the situation of partial shading.

3. RESULTS AND DISCUSSION

3.1. Metaheuristic MPPT algorithms for partial shading

This section aims to cover all relevant metaheuristic aspects to help new authors briefly overview all existing taxonomies and variants. Furthermore, several metaheuristics are widely used for partial shading conditions and classified into four groups, as shown in **Figure 5**. The metaheuristic algorithm relies on an easy-to-implement and straightforward concept, which does not require gradient information, can pass local optima, and is used to solve various problems spanning multiple disciplines (Mirjalili & Lewis, 2016). Metaheuristics are broadly known as a practical approach to various complex optimization problems. The algorithm is divided into four main parts, namely biology-based, physics-based, sociology-based, and human behaviors. Furthermore, this approach is used to accomplish the partial shading thing experienced by the PV system on the MPPT.
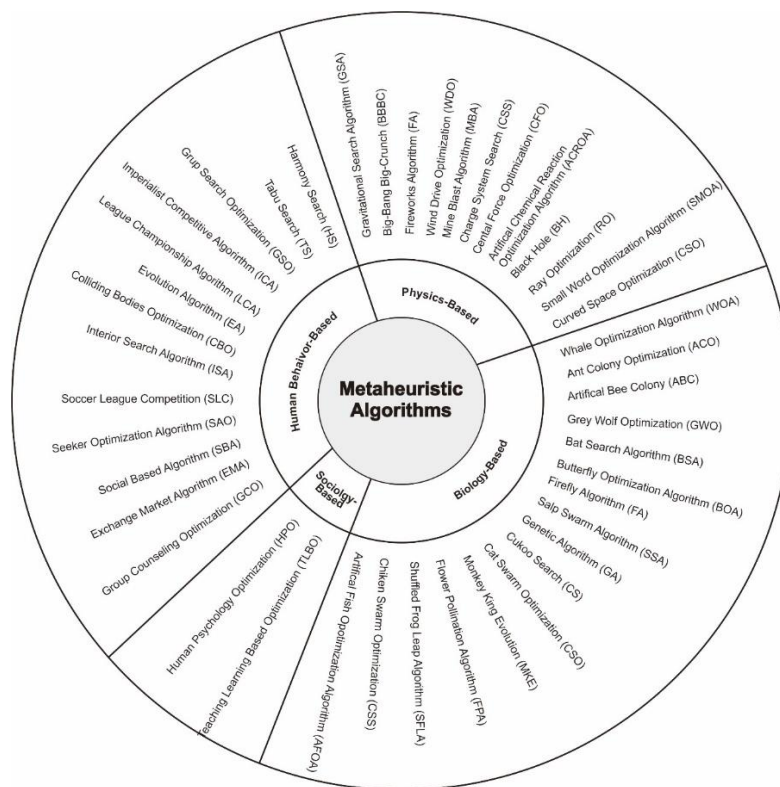

Figure 5. Taxonomy algorithm metaheuristic.

3.1.1 Biology-based algorithms
3.1.1.1 Genetic Algorithm (GA)

GA is a meta-heuristic method used to determine the right solution based on the biological behavior evolution (Seyedmahmoudian *et al.*, 2016). This technique is used to determine the survival of fittest-based optimum set parameters (Caraka *et al.*, 2021). It is an adaptive meta-heuristic search method that comprises the creation, methodical evaluation, and improvement of possible design solutions until the termination criteria are fulfilled (Shaiek *et al.*, 2013).

3.1.1.2 Artificial bee colony (ABC)

ABC approach is a bio-inspired optimization technique developed for nonlinear optimization problems, numerical functions, and classic optimization constraints (Karaboga & Basturk, 2007a). It comprises numerous features that cause it to be further attractive than other bio-inspired algorithms. Furthermore, this algorithm uses fewer control variables and convergence negligible of the initial states. The algorithm makes it possible to resolve the common disadvantages of the traditional MPPT technique. Instead, it also provides a robust and straightforward MPPT procedure. The co-simulation process combines Matlab/SimulinkTM and Cadence/PspiceTM to confirm the usefulness of the suggested procedure and resemble its performance, in weather situations, with the MPPT algorithm based on PSO is conducted in (Benyoucef *et al.*, 2015).

3.1.1.3 Ant colony optimization (ACO)

ACO is included in a meta-heuristic class inspired by a biological approach. It is a probabilistic technique used to determine the universal optimal solutions to nonlinear problems. ACO imitates the hunting behavior of ants to reach path optimization in the grid. Furthermore, the communal behavior of ants in huge numbers forms the feedback phenomenon, in which the ants initially look for a random path and place pheromones for others to follow (Dorigo & Birattari, 2006).

3.1.1.4 Grey wolf optimization (GWO)

The GWO algorithm is a highly inspired metaheuristic approach that optimizes the offensive techniques used by the grey wolf when pursuing. This method is proficient in duplicating the hierarchical order of leadership and the grey wolf's pursuing abilities. There are mainly four types of grey wolf used to simulate leadership hierarchies, namely properly: (i) alpha (α), (ii) beta (β), (iii) delta (δ), and (iv) omega (ω). In the scientific instance of this bio-inspired algorithm, the most relevant result is α. Furthermore, β and δ are devised as the second and third best solutions, while ω represents other candidates. There usually are three steps for GWO: hunting, chasing, and tracking the target by establishing groups, which is surrounded, and finally attacking the target. This whole pursuing mechanism was applied when designing the GWO to execute optimization issues in the MPPT for the PV Module. The grey wolf hunting method is guided by the α clan known as a leader, trailed by the β clan. The critical task of δ and ω is to guard all the injured wolves (Mirjalili *et al.*, 2014; Mohanty *et al.*, 2015). The following equations are used to model the strategies used by the grey wolf to surround the prey during hunting and siege behavior.

$$\vec{D} = |\vec{C} \cdot \vec{X}_p(t) - \vec{X}_p(t)| \qquad (7)$$

$$\vec{X}(t + 1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \qquad (8)$$

where t represents the present iteration, D, A, and C are the coefficient vectors, Xp is the location vector of the target, and X presents the location vector of the grey wolf. D and C Vectors are calculated as follows.

$$\vec{D} = 2_{\vec{a}} \cdot \vec{r}_1 - \vec{a} \qquad (9)$$

$$\vec{C} = 2 \cdot \vec{r}_2 \qquad (10)$$

3.1.1.5 Bat search algorithm (BSA)

Echolocation behavior is based on the nature of the bats at the nutrition site. It locates the movement and soundness of the retrieval signal-based target. In particular, the literature designed an MPPT technique using BSA to accurately determine GMPP for all P-V features based on local and global searches. Furthermore, this method was more additional than 99.9% in most problems.

3.1.1.6 Butterfly optimization algorithm (BOA)

In the research carried out by (Arora & Singh, 2019), a new optimization technique was proposed, which imitates the foraging behavior of butterflies. The two critical variables of the method are mate and food locations. There are three key behaviors of butterflies in this approach, namely: (i) one butterfly must be able to pull others by its aroma; (ii) the butterfly changes its place randomly or towards the one with the most pungent smell, and (iii) the prospect of the objective function assigns the strength of the butterfly stimulus (Aygül *et al.*, 2019).

3.1.1.7 Whale optimization algorithm (WOA)

The proposed WOA algorithm effectively tracks GMPP with high precision and less time under dynamic PSC. Therefore, based /on the results, the algorithm is excellent in precise and time tracking compared to the MPPT GWO and PSO algorithms. Furthermore, due to the stochastic nature of the WOA, GWO, and PSO methods, simulations (Kumar & Rao, 2016) were performed for 50 experiments and statistical results. The result showed that the proposed standard deviation (SD) is smaller than other methods, indicating that WOA can effectively track GMPP. However, the SD of PSO is excellent because the maximum value is stuck to the local. Based on the results and statistical analysis, the MPPT WOA algorithm

proves its superiority through GWO and PSO MPPTs (Kumar & Rao, 2016). A study carried out by Mirjalili & Lewis (2016) stated that the WOA uses three simulation operators of humpback whales, namely prey search, prey siege, and foraging behavior. A comprehensive study was carried out on 29 mathematical benchmarks to investigate the algorithms' exploitation, exploration, local optima prevention, and convergence behavior (Mirjalili & Lewis, 2016). The result proved that WOA is competitive with other metaheuristic methods.

3.1.1.8 Firefly algorithm (FA)

An algorithm using the tracking principle of fireflies was developed and introduced. This algorithm has three basic assumptions. Firstly, all fireflies are unisex and overlook progress towards a brighter and better stunning one until they have all been compared. Secondly, the firefly's attractiveness is related to its brightness, which depends on the distance between itself and other flies. However, due to the saturation of light in the air, its comeliness decreases with increasing distance. Finally, the light or brightness intensity of a firefly is decided by the objective procedure value of the given problem. The following three equations mathematically express the FA algorithm.

$$\beta(r) = \beta_0 \exp(-\gamma r^m), m \geq 1, \tag{11}$$

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{d}(x_{i,k} - x_{j,k})^2} \tag{12}$$

3.1.1.9. Particle swarm optimization (PSO)

PSO is a cluster intelligence approach commonly applied to increase widespread numerical optimization problems in current years due to its effectiveness and efficiency in dealing with science and engineering challenges. The PSO is unsystematically initialized population-based and used to determine the best generational updates like a genetic algorithm. Meanwhile, the objects in a genetic algorithm are called "individuals"

or "particles" in PSO, with each moving at a particular speed. The rapidity vector assigns drive to a particle, with a distinct quantity corrected by the manners of two parameters, namely cognitive behavior (memory) and current social behavior (perception). With sufficient time (iteration), the particles are expected to gather in a place that optimally suits their needs. The behavior mentioned above, fundamental to PSO, is formulated as follows (Tsai & Lin, 2011):

$$v_i^{t+1} = v_i^t + \alpha\, \varepsilon_1 [pbest_i^t - x_i^t] + \alpha\, \varepsilon_2 [gbest^t - x_i^t] \qquad (13)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \qquad (14)$$

3.1.1.10 Salp swarm algorithm (SSA)

The Salp algorithm is a barrel-shaped Salp that belongs to the Salpidae family and has a transparent body. The salp tissue's movement is similar to a jellyfish that moves onward by propelling water throughout the body. In the oceans, salps form swarms called salp chains, and this algorithm is used to determine its global optima. In the salp chain instance, the chief is followed by the subordinate searching for food. The food source is likened to GMPP, which is chased by the salp chain (Krishnan & Sathiyasekar, 2020).

3.1.1.11 Shuffled frog leap algorithm (SFLA)

SFLA is the personification of the memetic method and the PSO procedure. The population contains a set of results known as frogs in the method. Meanwhile, the solution subset is called a memeplex, with each used to perform a local search in the search space. Ideas are communicated between the shuffled memeplexes through the memetic of the evolution process. Furthermore, the shuffle process and local search stay until optimal convergence (Sridhar *et al.*, 2016).

3.1.1.12 Artificial fish swarm algorithm (AFSA)

AFSA is a new swarm modeling technique consisting mainly of seeking, swarming, and following a behavior (Tsai & Lin, 2011). An improved AFSA was current, and it combines the capabilities of the PSO algorithm search system.

3.1.1.13 Chicken swarm optimization (CSO)

CSO is a bio-inspired robust and accurate algorithm that extracts chicken swarm intelligence to solve high-dimensional problems. This CSO is an algorithm that replicates the hierarchy and behavior of the chicken with the swarm approach used when tracking (Meng *et al.*, 2014).

3.1.1.14 Flower pollination algorithm (FPA)

The FPA was broadly used in numerous contexts and has indicated its distinction from PSO and GA (Yousri *et al.*, 2019). Simulation results from previous studies have shown that the FPA approach is advantageous and can outperform both genetic algorithm and particle swarm optimization.

3.1.1.15 Monkey king evolution

This algorithm is elucidated by the superpower of the monkey king, a supreme symbol of a well-known Chinese mythological best-seller whose names are "Journey to the West." The superpower of the monkey king arises in a challenging case, and it can convert into several small monkeys. The latter researches the solution and reports to the monkey king. After acquiring all feedback, the monkey king establishes the global best (i.e., the most appropriate solution) and then takes action and drives forward with all small monkeys (Kumar *et al.*, 2016a).

3.1.1.16 Cat swarm optimization

This approach models the behavior of a cat at rest. It keeps alert while trying to seek a 185 better position. After carefully observing its neighborhood circumstances, it moves 186 slowly to a new position (Guo *et al.,* 2018).

3.1.1.17 Cuckoo search (CS)

The CS method is one of the meta-heuristics based on population. It emulates both the breeding conduct of some cuckoos and the Lévy flight manners of some bird species to overwhelm both continuous and discrete optimization issues (Abed-alguni & Alkhateeb, 2020).

3.1.2 Physics-based algorithms
3.1.2.1 Gravitational search algorithm (GSA)

GSA is one of the intelligent meta-heuristic methods based on Newton's law of gravity to overcome optimization-related problems. Its global search capabilities have several advantages over other clever solutions such as PSO. However, some disadvantages are associated with using GSA, such as inadequate local investigation capacities and weak acceleration mechanisms (Li & Zhou, 2011).

The basic principle of the gravitational examination method is associated with the solutions to the optimization problem, which is regarded as a group of particles running in space. According to the law of gravity, particles are involved with each other by gravity. Therefore, the more extensive the mass, the greater the gravitational force on the other particles. The optimization problems associated with particles are obtained by determining the optimal position when other particles change towards the one with the highest mass (Li *et al.,* 2018).

3.1.2.2 Fireworks algorithm

The Firework algorithm belonging to the meta-heuristic algorithm category. It is an effective universal optimization method based on the intelligent behavior of swarms. Several diode model fireworks for PV modeling of MPP particle based on tracking algorithm are produced in the examination area with a stochastic burst procedure for apiece firework. After the detonation procedure is complete, the generated sparks of the fireworks fill the local space and represent latent explanations in the anticipated search space. The approach uses the detonation and Gaussian mutation sparks produced by the explosion and the Gaussian mutation operator to determine the global optimal in the problem space. The main characteristic of this approach is its capability to strike an equilibrium between probe and exploitation. Exploration refers to the capability of a technique to discover different areas of the seeking space to analyze promising results. Meanwhile, exploitation is characteristic of performing an in-depth search in a smaller area to find the best result. Furthermore, it is signed by a global investigation ability and an accurate local examination at the end. Gaussian transformation sparks are produced to improve local research capabilities and ensure swarm diversity.

3.1.2.3 Mine blast algorithm (MBA)

The idea of the MBA is based on the remark of a mine bomb bang, in which the terrifying sections of shrapnel collided and exploded others in the surrounding area. To recognize this state, consider a minefield where the purpose is to strengthen the mines by determining the one with the most significant combustive consequence found at the best point X^*, which is capable of causing most casualties $(min\ or\ max\ f(x)\ per\ X^*)$ (Sadollah *et al.,* 2012).

3.1.2.4 Wind driven optimization (WDO)

The main idea of WDO is to extract horizontal air movement known as the wind from the atmosphere. Usually, the air pressure and density depend on the

temperature relying on the air pressure. The air movement from high to low-pressure areas is known as a pressure gradient. In the WDO method, a population of air pieces is unsystematically dispensed through issue space within a certain velocity and position. The places of air properties are appraised based on the wind movement mathematical model per iteration. Such a model is Newton's second law-based, which states that the forces subjected to air mass urge it to hurry in the direction (Abdalla *et al.*, 2019).

3.1.2.5 Big-bang big-crunch

The method is similar to the GA regarding the random creation of an initial population known as the Big Bang phase, which is spread all over the search space in a uniform manner (Erol & Eksin, 2006).

3.1.2.6 Charge system search (CSS)

CSS is an efficient optimization algorithm created using Coulomb and motion laws governing physics and Newtonian mechanics (Kaveh & Talatahari, 2010).

3.1.2.7 Central force optimization (CFO)

CFO is an algorithm based on deterministic multi-dimensional search. In (Rashedi *et al.*, 2009) has been developed a model that probes the search space under the influence of gravity based on CFO.

3.1.2.8 Artificial chemical reaction optimization algorithm (ACRO)

ACRO algorithm is based on the chemical reaction process where molecules undergo a sequence of reactions with each other. Furthermore, the CRO has a good searching ability that shows an excellent operation of strengthening and divergence, two crucial characteristics of the evolutionary algorithm (Dutta *et al.*, 2015).

3.1.2.9 Black hole (BH)

The BH algorithm is a population-based method comprising some standard features. Like other population-based algorithms, a population of nominee resolutions to a specified issue is generated and spread unsystematically in the examination area, which evolves the created population towards the best solution (Hatamlou, 2013). In the BH, a randomly produced population of nominee solutions is located in the search space to determine the problem or function. After initializing the black hole, it starts absorbing the surrounding stars.

3.1.2.10 Ray optimization (RO)

Like other meta-heuristic methods, RO also has an agent number containing design problem variables. Although ray-tracing, as the primary basis of RO, has been addressed in two and three-dimensional spaces, it is necessary to introduce procedures to perform algorithmic steps in higher-dimensional spaces (Kaveh & Khayatazad, 2012).

3.1.2.11 Galaxy-based search algorithm (GbSA)

This metaheuristic and nature-inspired method are founded on an adjustable neighborhood examination technique. GbSA is based on a Spiral chaotic movement, which uses a spiral undertaking to determine the current best solution, which it uses to update the existing one (Kumar et al., 2016b).

3.1.2.12 Curved space optimization (CSO)

CSO is a simple probabilistic optimization method strengthened by the concept of general relativity theory. This new method is designed based on the transformation of a random search space into a new search space and is used to overcome global optimization challenges such as performance and convergence using the general relativity theory.

3.1.3 Sociology-based algorithm

3.1.3.1 Teaching-Learning-Based Optimization (TLBO)

TLBO is a method motivated by the teaching-and-learning process based on the inspiration of a teacher on student learning outcomes in a class. The procedure also imitates teachers' and students' education and understanding abilities in the classroom as two essential elements of the method. It also explains the two elementary ways of education, through the instructor step and interacting with other students (student phase) (Rao *et al.*, 2011; Rao & Patel, 2013).

3.1.3.1 Human psychology optimization (HPO)

The HPO algorithm is based on a pretentious and goal-oriented person's mental and psychological condition. This category of persons is very strategic and able to create some positive energy out of the worst situation on a psychological level (Kumar *et al*., 2017a).

3.1.4 Human behaviors in the literature
3.1.4.1 Harmony search algorithm (HSA)

The HSA is one of the newest metaheuristic population search algorithms that depend mainly on the musical process for a pleasing harmony. The musicians are the decision variables of the function to be optimized, and their notes represent values. The harmony is considered the optimal solution vector, and unlike the gradient optimization techniques, the HSA is a stochastic search free from a derivative algorithm. Furthermore, it has a simple mathematical model and is easier to implement in engineering problems than other metaheuristic techniques (Ambia *et al.*, 2015).

3.1.4.1 Tabu search algorithm (TSA)

TSA is a global optimization algorithm and a simulation of human intelligence. It avoids circuity search by introducing a flexible storage structure and relevant tabu rule. Furthermore, it releases some tabooed superior states to assure diversification.

3.1.4.2 Group search optimization (GSO)

GSO is a method motivated by foraging (animal searching) behavior. Research carried out by He *et al.*, (2009) proposed GSO primarily for continuous optimization problems.

3.1.4.3 Imperialist competitive algorithm (ICA)

The algorithm is inspired by the concept of the imperialism competition process. It starts by dividing the initial population of countries into two groups. The first is called imperialist, which has the best fitness function values, while the second is known as colonies. According to studies, the colonies in the initial population share the imperialists according to their powers. Furthermore, they also change cultures based on their imperialism, which is stimulated by the process of moving colonies toward their imperialist country, known as assimilation. In this process, the colony with considerable power replaces the imperialist and vice versa. During the imperialistic competition, the most and less powerful empires try to increase and crumble their powers, respectively. At the end of the ICA algorithm, the solution is concentrated in the most powerful empire (Fathy & Rezk, 2017).

3.1.4.4 League championship algorithm (LGA)

This algorithm is stimulated by the struggle of sports squads in an artificial competition league for some weeks and over several seasons. The approach has been used in the Algerian power system network for some objectives. In LCA, the individuals considered as teams strive in an artificial league for some weeks and seasons (Bouchekara *et al.*, 2014).

3.1.4.5 Social-based algorithm

This technique begins by producing a collection of unexpected nominee results in the examination area of the optimization issue. The delivered arbitrary points are anointed the initial population, including persons who serve as the equivalent of chromosomes in GA and particles in PSO, i.e., a collection of nominee solutions. Classes of individuals construct a society and are contained in its growth (Ramezani & Lotfi, 2012).

3.1.4.6 Exchange market algorithm

This algorithm is inspired by human intelligence and the experience of elite individuals in the stock market. It comprises two absorbent operators, which absorb the individuals toward elite members of the second and third groups in balanced market conditions, and two searching operators in the second and third groups in oscillated market conditions.

3.1.4.7 Group counseling optimization (GCO)

The GCO is a search algorithm inspired by the group counseling approach to solving problems. The algorithm requires some parameters to be set, namely the number of group members representing the population size (m), group members number applied as counselors (c), counseling probability (cp), the maximum value of modification (mdf_max), and rate of exploration to exploitation transition (tr). The significance of these variables becomes apparent in future studies.

3.1.4.8 Evolutionary algorithms

It is a population-based metaheuristic optimization method. This approach employs biologically inspired means such as transformation, crossover, natural choosing, and the existence of the fittest to iterate over a series of candidate solutions. It comprises many EAs, and all share the same idea based on the existence of the fittest, which leads to a rise in population fitness in different generations. Some of the better nominees are selected and pit for the next generation by utilizing recombination and mutation based on the fitness function. Furthermore, this operator's implementation oversees a new set of nominees.

3.2 Analytic comparison of different MPPT algorithms

This paper reviews and compares various MPPT metaheuristic algorithms from PV systems. It was thoroughly evaluated and used to compare several MPPT strategies, such as complexity, type of conversion, sensors utilized, level of steady-state oscillation, the ability to track under PSC, cost, and application. **Table 1** summarizes the comparison of the MPPT algorithms. The algorithm's complexity is used to determine the algorithm with the MPPT method based on complexity. Indirect comparisons are based on the number of steps comprised, the amount of computation, and the complexity that develops in the structure. The converter type is used in the MPPT system for conversion. Furthermore, parameter control is used to measure the parameters used. An oscillation Sensor is a change under steady-state conditions. Meanwhile, tracking capability under PSC is used to measure the speed of the tracking algorithm in achieving maximum power.

Table 1. Classification of MPPT algorithm.

Classification	Algorithms	Complexity	Converter Type	Control Parameter	Sensor	Oscillation	Tracking Ability under PSC	Cost	Application
Conventional	Perturb & Observe (Otong & Bajuri, 2016)	low	buck-boost	-	I, V	high	very low	very high	SA/GA
	Hill Climbing (Hu *et al.*, 2019)	low	buck-boost	-	I, V	very high	very low	very high	SA/GA
	Incremental Conductance (Li *et al.*, 2018) (Tey *et al.*, 2014)	moderate	buck-boost	duty cycle	I, V	high	very low	very high	SA/GA
Physics-based algorithms	Gravitational search algorithm (Pervez *et al.*, 2019)	moderate	boost	-	I, V	low	high	high	GA
	Fireworks algorithm (Rajsekar *et al.*, 2016)	moderate	boost	-	I, V	low	moderate	moderate	SA
	Mine blast algorithm (Sadollah *et al.*, 2012)	moderate	boost	-	I, V	low	high	moderate	SA
	Wind-driven optimization (Abdalla *et al.*, 2019)	high	boost	duty cycle	I, V, P	high	moderate	high	SA
	Big-Bang Big-Crunch (Ahmadi & Abdi, 2016)	moderate	buck	current	I, V	low	high	high	SA
	Black Hole (Hatamlou, 2013)	moderate	buck	-	I, V	low	high	high	GA
	Ray Optimization (Kaveh & Khayatazad, 2012)	moderate	boost	-	I, V	low	low	high	GA
	Small-World Optimization Algorithm (Du *et al.*, 2006)	low	boost	-	I, V	low	high	high	GA
	Galaxy-based Search Algorithm (Kumar *et al.*, 2016b)	moderate	boost	-	I, V	low	low	high	GA
	Curved Space Optimization	moderate	buck	current	I, V	low	high	high	GA
Sociology-based algorithms	Teaching-learning-based optimization (Rezk & Fathy, 2017)	low	boost	duty cycle	I, V	low	high	high	GA
	Human psychology optimization (Kumar *et al.*, 2017a)	low	boost	duty cycle	I	low	high	high	GA

Table 1 (Continue). Classification of MPPT algorithm.

Classification	Algorithms	Complexity	Converter Type	Control Parameter	Sensor	Oscillation	Tracking Ability under PSC	Cost	Application
Meta-heuristic Biology-based algorithm	Genetic Algorithm (Shaiek *et al.*, 2013)(Savage *et al.*, 2013)		buck-boost	-	I, V	high	moderate	high	SA
	Differential evolution (Tey *et al.*, 2018)	moderate	sepic	duty cycle	I, V, P	moderate	high	high	SA
	Artificial bee colony (Pilakkat & Kanthalakshmi, 2019)(Benyoucef *et al.*, 2015)	high	boost	duty cycle	I, V, P	moderate	high	moderate	SA
	Ant Colony Optimization (Lian *et al.*, 2013)	low	boost	duty cycle	I, V	moderate	moderate	moderate	SA
	Grey wolf optimization (Mohanty *et al.*, 2015) (Mohapatra *et al.*, 2017)	**high**	**boost**	**duty cycle**	**I, V, P**	**very low**	**very high**	**high**	**SA**
	Bat search algorithm (Kaced *et al.*, 2017)	high	buck-boost	duty cycle	I, V	low	high	high	SA
	Butterfly optimization algorithm (Aygül *et al.*, 2019)	low	boost	duty cycle	I, V	low	high	moderate	SA
	Moth-flame optimization (Bouakkaz *et al.*, 2020)	moderate	boost	-	I, V	low	moderate	moderate	GA
	Whale optimization algorithm (Krishnan & Sathiyasekar, 2020) (Premkumar & Sowmya, 2019)	high	boost	duty cycle	I,V,P	low	high	high	GA
	Firefly Algorithm (Teshome *et al.*, 2016) (Huang *et al.*, 2020)	moderate	boost	-	I, V	low	high	high	SA
	Salp Swarm Algorithm (Mirza *et al.*, 2020)	moderate	boost	duty cycle	I, V	low	high	high	SA
	Shuffled frog leap algorithm (Sridhar *et al.*, 2016)	high	boost	-	I, V	low	moderate	high	SA
	Artificial fish swarm algorithm (Mao *et al.*, 2018)	high	boost	-	I, V	low	high	high	SA
	Chicken swarm optimization (Meng *et al.*, 2014)	moderate	boost	-	I, V	low	moderate	high	SA
	Flower pollination algorithm (Yousri *et al.*, 2019)	high	boost	duty cycle	I, V	low	moderate	high	GA
	Monkey king evolution (Kumar *et al.*, 2016a)	moderate	boost	-	I, V	low	high	moderate	GA
	Cat swarm optimization (Nie *et al.*, 2017)	high	boost	-	I, V	very low	high	high	GA
	Cuckoo search (Ahmed & Salam, 2014)(Mirza *et al.*, 2019)	moderate	buck-boost	duty cycle	I, V	low	moderate	moderate	GA

4. CONCLUSION

The main problems of the MPPT conventional methods are poor power harvesting and low efficiency due to several local maximum appearances and difficulty determining the global maximum tracking. The standard MPPT algorithms for partial shading conditions are (i) conventional, (ii) mathematics-based, (iii) artificial intelligence, and (iv) metaheuristic algorithms. This research presented a comprehensive review of 40 MPPT algorithms for partial shading conditions, mainly metaheuristics. In addition to the basic principles and specifications, the performance comparison of the 40 metaheuristic algorithms in terms of complexity level, converter type, sensor requirement, steady-state oscillation, tracking capability, cost, and grid connection has been explained fairly thoroughly in this research. Swarm-based biology algorithms provide fast convergence and accurate tracking in partial shading conditions. Therefore, based on the analyzed parameters, it is concluded that a swarm-based metaheuristic algorithm can be used as an algorithm to handle the partial shading problem in MPPT. The strategy, especially swarm, offers a suitable algorithm structure for various optimization problems with only minor modifications to suit the given problem. In general, we can choose the most appropriate solutions matching the necessities of the system's application and specifications. This result can be a valuable reference for advanced works in related fields.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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