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Review article

A critical review and performance comparisons of swarm-based optimization algorithms in maximum power point tracking of photovoltaic systems under partial shading conditions

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ABSTRACT

This article presents a comparative analysis of the latest swarm-based optimization approaches under partial shading conditions (PSCs) for maximum power point tracking (MPPT) in photovoltaic (PV) systems. The swarm-based MPPT algorithms are stochastic meta-heuristic approaches that have become very popular recently in various applications owing to the drawbacks of conventional MPPT algorithms under different operating conditions. A comprehensive review of the recent research on these algorithms is carried out particularly focusing on the PSCs. The advantages, disadvantages, applications, computational efficiency, and stability of these algorithms are critically surveyed in detail. Moreover, to analyze the comparative performance of the swarm-based algorithms, a special case study is conducted in the MATLAB/Simulink environment for a solar-powered DC load with a boost converter. The performance of seven swarm-based MPPT techniques is evaluated in this case study in terms of their settling time, convergence speed, overshoot, and efficiency under different levels of PSCs. The statistical analysis for 30 simulation runs shows that under heavier shading conditions, the grasshopper optimization algorithm (GOA) and salp swarm algorithm (SSA) outperform other swarm-based MPPT algorithms. It is envisaged that this work will be a one-stop source of guidance for researchers working in the field of MPP optimization under PSCs.

Contents

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1. Introduction

Fossil fuels (coal, petroleum, etc.) provide a substantial amount of electrical energy, but they emit greenhouse gases that are potentially damaging to the environment (Kumar et al., 2017). The damages can be controlled by harnessing energy from renewable energy (RE) resources (Bin Wu and Moo, 2014). Solar energy (photovoltaic system (PVS)) is becoming more popular than the other RE resources due to its universal availability, zero emissions, low operational, running cost, etc. It also preserves fossil fuel resources (Gupta and Saurabh, 2017b; Moo and Bin Wu, 2014).

The maxim power point (MPP) of the PVS keeps changing due to intermittent environmental conditions. That is why it is tracked with an algorithm to maximize the benefits (Selvakumar et al., 2019). There are many MPPT algorithms available that can be classified with respect to their common working procedure or common merits and demerits (Elbarbary and Alranini, 2021). The algorithms are categorized as (i) constant parameters or offline, (ii) conventional or online (iii) soft computing or intelligent, and (iv) metaheuristic or optimization-based methods (Bollipo et al., 2021; Podder et al., 2019; Ram et al., 2017; Karami et al., 2017a; Selvan et al., 2016; Saravanan and Ramesh Babu, 2016).

Constant parameters algorithms not only need extra switches and current sensors but also include heat dissipation and more power loss (Hanzaei et al., 2020). The shortcomings of the conventional MPPT algorithms comprise oscillations around MPP and failure in convergence at the MPP. Moreover, fixed step size and trapping at the LMPP under partial shading conditions (PSCs) are also their drawbacks (Hanzaei et al., 2020; Abdullah et al., 2018; Keyrouz, 2018). The problems in soft computing techniques are the training of the neural system (artificial neural network (ANN)) which indeed requires much knowledge and time to do so (Yap et al., 2020). It is not feasible for a different kind of system once tuned, that is why it cannot be generalized for all the PVS (Singh et al., 2021). The other drawback includes the lengthy computation and large memory space to remember the tuned parameters (Ali and Arbos, 2020; Tobón et al., 2017). Weak error (power difference between two consecutive intervals) computation makes continuous oscillations around the MPP under PSCs in fuzzy logic control (FLC) algorithm. Moreover, it requires more storage volume to store look-up table values (Keyrouz, 2019).

PV output becomes nonlinear under PSCs so MPP tracking becomes extremely difficult Furthermore, the PSC also causes output power loss, hot spot impact, safety and reliability issues. Keeping in mind the drawbacks of the conventional, constant parameters and intelligence-based methods under PSCs, swarm-based algorithms are investigated in the literature due to their fast operation, free from periodic tuning, prior training, and independence from PV array configuration.

A lot of useful research to review the performance of MPPT approaches has been carried out in the literature (Elbarbary and Alranini, 2021; Bollipo et al., 2021; Podder et al., 2019; Ram et al., 2017; Karami et al., 2017a; Selvan et al., 2016; Saravanan and Ramesh Babu, 2016; Hanzaei et al., 2020; Wan et al., 2019; Mao et al., 2020a; Li et al., 2019a; Ali et al., 2020; Mnati et al., 2019; Kundu et al., 2016; Sarvi and Azadian, 2021; El-Khozondar et al., 2016; Dadkhah and Niroomand, 2021). A review for Perturb & Observe (P&O) and Incremental Conductance (INC) is presented in Elbarbary and Alranini (2021), three MPPT methods are assessed experimentally with the EN50530 dynamic test procedure in Li et al. (2021), a combination of classical and some hybrid techniques in Bollipo et al. (2021), PV array configuration based review in Yadav and Mukherjee (2021), some swarm-based techniques are reviewed in Motahhir et al. (2020) and Cheng et al. (2021), review for artificial intelligence-based algorithms is presented in Feng et al. (2021), an overview is given in Memon and Patel (2021) for optimization techniques used in the sizing of hybrid RES, review for control management of hybrid RES in Ammari et al. (2020) and many more. The majority of these reviews include all the conventional and modern methods into a single paper. The study is limited to describing the techniques' benefits and shortcomings without considering the detail and statistical analysis. Unfortunately, a comprehensive study covering most of the recent swarm-based MPPT methods in a single research reference is still missing.

This review work combines twelve swarm-based algorithms in one place and evaluates their performance for tracking speed, convergence to the MPP, and usefulness under PSCs. In addition, this study also addresses their hybrid techniques which are quite effective in overcoming the drawbacks of constant parameter methods and conventional MPPT methods under PSCs. Moreover, a case study is carried out to evaluate the functioning of seven swarm-based MPPT algorithms published in the last decade. Furthermore, a MATLAB/Simulink model is developed to assess the performance of these algorithms under different PSCs. The simulation results are compared and analyzed for settling time, convergence to MPP, overshoot, and efficiency under different PSCs. To verify the consistency of the algorithms, the simulation is run 30 times and average results are taken for statistical analysis. Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), mean, and Standard Deviation (SD) are evaluated which confirm the superiority of some algorithms over the other.

The remaining paper is arranged as follows. The effects of PSCs on PVS are described in Section 2. The third section examines and explores the swarm-based MPPT algorithms under PSCs. Section 4 is all about the case study and Sections 5 and 6 are reserved for comparative discussion and conclusion respectively.

2. Effect of PSCs on PV system

The array or even a single module may get non-uniform irradiation due to the shade of nearby buildings, dust, clouds, trees, birds littering, etc. which can cover the PV module/array fully or partially called partial shading effect as shown in Fig. 1. During cloudy days, the module/array experiences faster and dynamic irradiance change which directly affects its performance (Mansoor et al., 2020a).

Unshaded modules under PSCs receive certain solar irradiation, whereas shaded modules receive less. This imbalance irradiance level produces a hotspot on the module receiving comparatively less irradiance (Arfaoui et al., 2019). This module acts as a load to the system which may get damaged due to

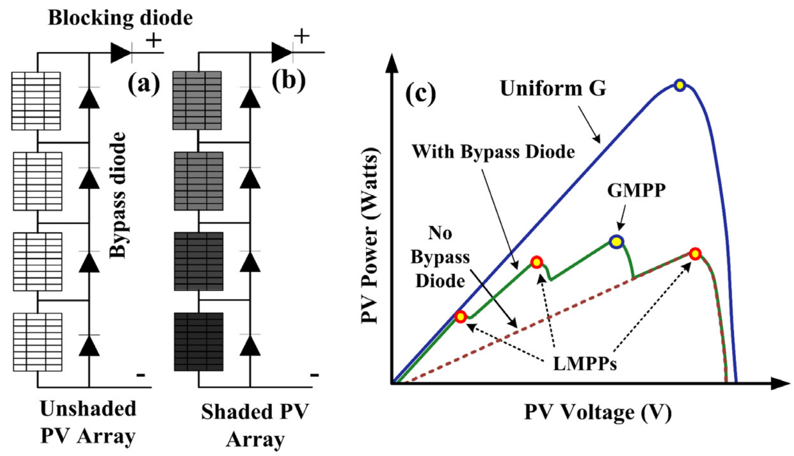

Fig. 1. PV array (a) without shading (b) under PSC (c) P–V curves.

the hotspots occurrence. The system's output power may sink up to 70% of its total installed capacity, hence dropping the efficiency (El-Khozondar et al., 2016). To protect the PV module from self-heating and to increase efficiency during PSCs, bypass diodes are coupled alongside the specific number of PV cells in a module (Huang et al., 2019). The PV characteristics are improved with the bypass diodes as they offer a different current path due to LMPPs. Each portion of the PV module under PSC has a different current, that is why a combination of local peaks and a global peak occurs in characteristics curves which are shown in Fig. 1(c). This combination is not distinguished by the constant parameters and conventional MPPT methods (Joisher et al., 2020).

Therefore, there is a need for some robust MPPT method that is capable to track the GMPP among multiple LMPPs (Kalogerakis et al., 2020). In the coming section, a review is presented on swarm-based MPPT methods which can successfully track the MPP under uniform irradiance as well as under PSCs.

3. Swarm-based algorithms

Swarm-based algorithms belong to the metaheuristic family used in modern MPPT controllers. High efficiency, resilience, and the capacity to solve the tracking issues under uniform and PSCs are the most common advantages of these algorithms (Zafar et al., 2020). Fig. 2 shows the classification of MPPT methods including swarm-based algorithms being employed in various applications. Twelve swarm-based MPPT algorithms are discussed in the coming sections.

3.1. Ant colony optimization (ACO)

The ACO duplicates the smooth movement of the ants searching for food in a search space. The ants look for food in an N-dimensional space during a search process (Sawant et al., 2017). In this procedure, they generate the pheromones (solution quality) whose density depends on the number of ants (Seyedmahmoudian et al., 2016). To find the food source, other ants follow the pheromone trail. The knowledge shared among team members facilitates the transition from a poor to a better solution. The duty cycle of the associated converter in the PV system is a critical parameter to be controlled in ACO-based MPP tracking.

The power values associated with each duty cycle are monitored once the random duty ratios are formed. The algorithm flow chart can be seen in Fig. 3. ACO can lower the traps at LMPPs as compared to PSO and conventional methods. Its convergence is also independent of the ant's initial positions. However, when ants have initialized away from the GMPP, the likelihood of being trapped at the LMPPs is increased (Mohapatra et al., 2017). Although the ACO is not widely used in individual applications, it can be hybridized with other soft computing algorithms to get beneficial results. Table 1 shows a comparative study between ACO and different MPPT approaches under PSCs. Most of the ACO-based MPPT methods are compared with conventional and PSO MPPT methods in the literature, which confirms its superiority. However, almost there is no comparison is done with the recent swarm-based MPPT algorithms. ACO has more settling time and more startup oscillations than the recent Grasshopper Optimization Algorithm (GOA) and Salp Swarm Algorithm (SSA).

3.2. Artificial bee colony (ABC)

This technique is primarily based on bees' communal nectar searching process. Employed bees, onlooker bees, and scout bees are the three sorts of bees (Bilal, 2013). Employed bees explore food sources, then share the food location with onlooker bees by a waggle dance (Minai et al., 2020). The onlooker bee's job is to select a food source based on the information received (Fanani et al., 2020). To achieve an equilibrium between exploration and exploitation, the ABC strategy combines the local search method (by employed bees) with the global search method (by onlooker and scouts). To apply this to the MPPT of the PV system, adjustments are made in the duty cycle (Gonzalez-Castano et al., 2021).

ABC algorithm is simple to implement with fewer controlled constraints and is independent of preliminary settings. It can solve both multidimensional and multimodal optimization issues with ease. Under PSCs, it tracks MPP with fine precision and efficiency. Additionally, only two control parameters are required to improve flexibility and simplicity (soufyane Benyoucef et al., 2015). The flow chart can be seen in Fig. 4. The search speed of the typical ABC algorithm is slow and has premature convergence, which limits its use in the PV system. It performs better in terms of exploration but not so well in terms of exploitation. As a result, the method is incompetent to locate the GMPP efficiently. So, some creativity is required to improve the local search ability and convergence speed (Nie et al., 2019). Table 2 organizes a comparison of ABC with other MPPT algorithms. It is observed in the literature that ABC-based MPPT methods as compared to conventional and PSO approaches show superior performance. However, almost there is no comparison is done with recent swarm-based MPPT algorithms.

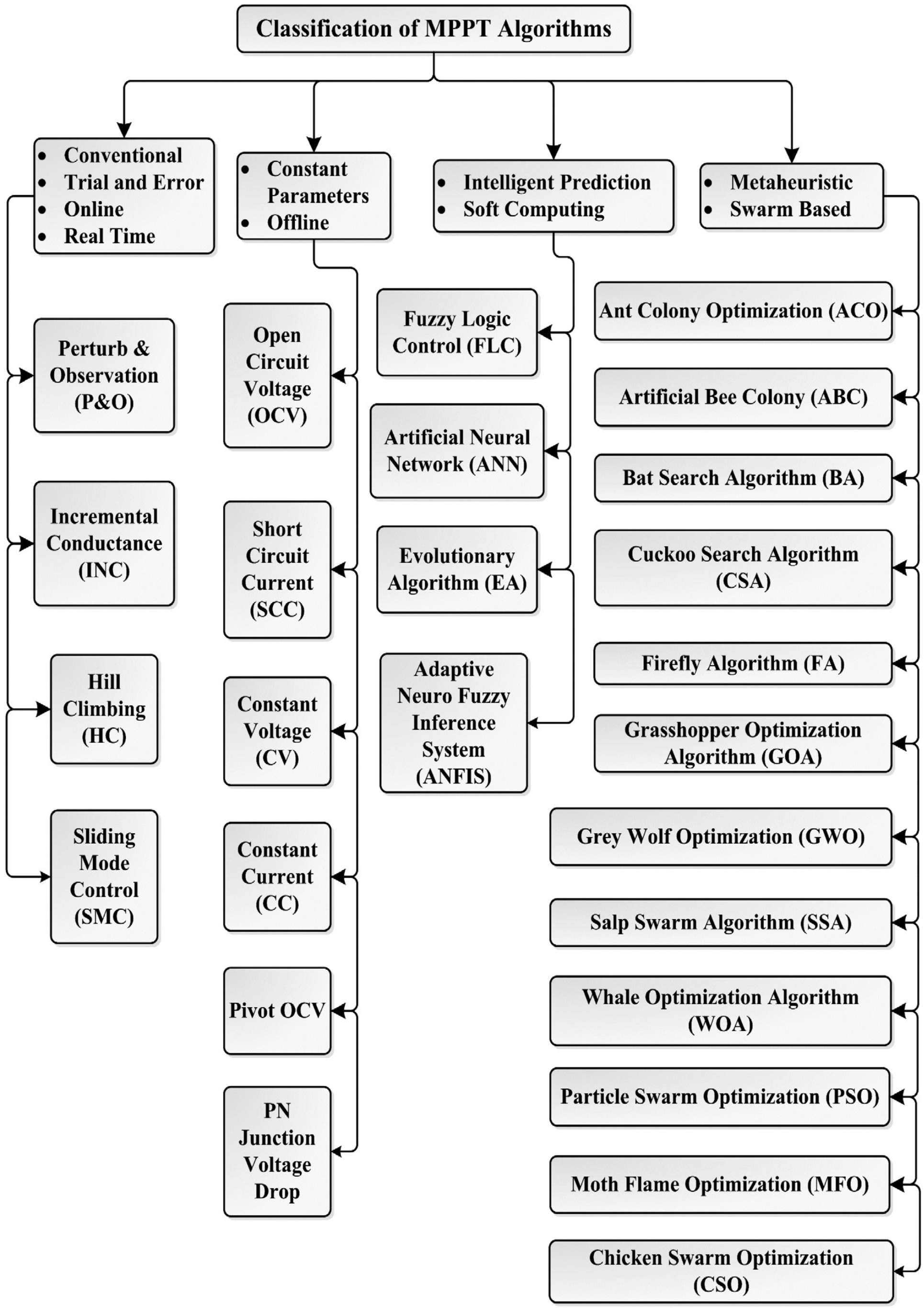

Fig. 2. Classification of MPPT methods including swarm-based algorithms.

3.3. Bat search algorithm (BA)

This method of optimization is established on natural bats' echolocation behavior when they are looking for prey. They find the target depending on the strength and direction of the return signal. The bats share the information within the swarm to aid others in their search for food. In the literature, MPPT methods employing the Bat search technique to precisely trace the GMPP are presented (Ge et al., 2020; Oshaba et al., 2015; Tey et al., 2018; Amalo et al., 2020).

The algorithm has a faster tracking speed than the direct techniques. Furthermore, unlike PSO, it does not depend on the initial positions of the bats which in turn makes customization easy. In comparison to evolutionary algorithms such as differential evolution (DE) and DE-PSO, it outperforms in respect of tracking and convergence speed (Seyedmahmoudian others, 2018). Another advantage is its wide local search throughout the MPPT process (Kim and Nebhen, 2021).

BA enhances the likelihood of escaping the LMPP and reduces the tracking time. Modified BA can improve dynamic tracking efficiency by 2.5 percent and about a 35 percent reduction in tracking time as compared to standard BA (Liao et al., 2020). It has been discovered that during transients, the standard BA undertakes a full scan of the PV array curves, which drops its efficiency. Hybrid techniques, such as Bat-P&O, Bat-Beta, and Bat-INC enhance the system efficiency even during transients (Eltamaly et al., 2020a; da Rocha et al., 2020).

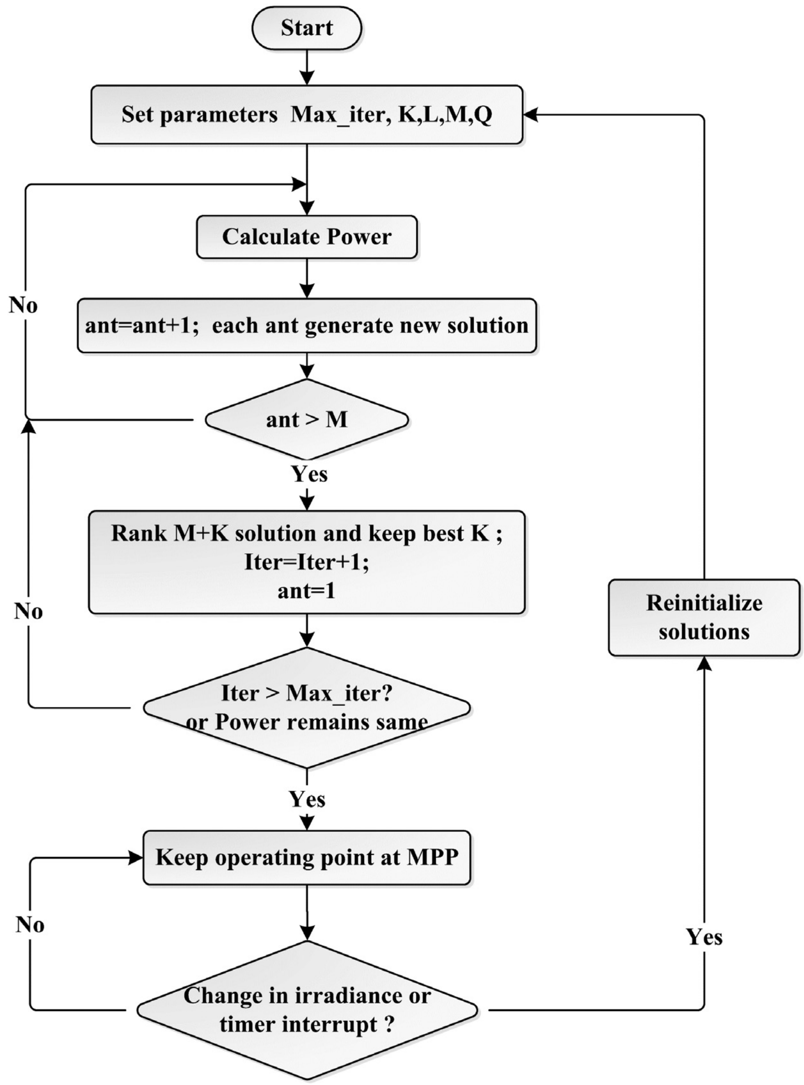

Fig. 3. Flow chart of ACO algorithm for MPPT.

Table 1
ACO algorithm for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Priyadarshi et al. (2019)	Cuk and Duty	SA Hybrid PV–Wind	A comparison of the suggested technique with PSO, artificial bee colony (ABC), and firefly algorithm (FFA) MPPT algorithms reveals that it has seven times faster convergence and tracking efficiency.
Sahoo et al. (2017)	Boost and Duty	SA	The author claims that ACO has a greater convergence rate and fewer iterations than traditional MPPT approaches. However, there is no comparison shown with any MPPT approach.
Sundareswaran et al. (2016)	Boost and Duty	GT	As compared to simple P&O, PSO and ACO, the hybrid P&O-ACO method has a faster convergence time and uses less CPU.
Jiang and Maskell (2015)	Buck and Duty	SA	ACO is implemented using evolutionary technique and successfully tracks the GMPP. However, the authors believe that there is a need for improvement in the scheme.
Besheer and Adly (2012)	Duty cycle	SA	ACO-based PI-MPPT controller combines INC and FOCV to track MPP quickly and accurately. The system's disadvantage is its increased convergence time.
Phanden et al. (2020)	Boost and Duty	SA	To reinitialize ants to examine for a new maximum point, a modified ACO method increases the tracking speed. However, there is no comparison with any MPPT approach.
Jiang et al. (2013)	Current		The system converges regardless of the initial conditions. The results are superior to P&O and PSO, but there is no comparison to any swarm-based MPPT algorithm.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, CT: Converter Type and CV: Control Variable.

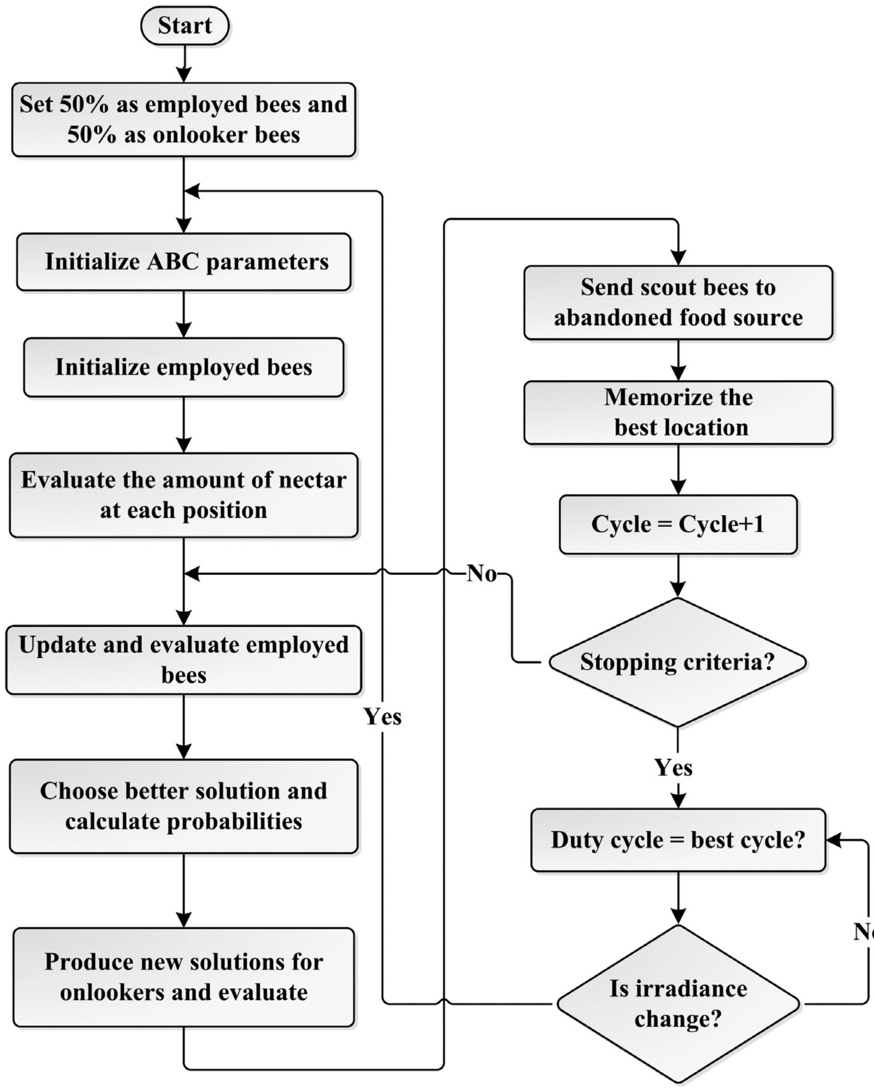

Fig. 4. Flow chart of ABC algorithm for MPPT.

Table 2
ABC algorithm for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Nie et al. (2019)	Buck-boost and Duty	SA	A modified ABC outperforms P&O, PSO, and standard ABC w.r.t. tracking time and accuracy but the oscillations are increased.
Pilakkat and Kanthalakshmi (2018)	Boost and Duty	SA	It is claimed that the proposed ABC is good in tracking the GMPP with high efficiency and fast response time, but no comparison is shown with other MPPT algorithms to prove the claim.
Sundareswaran et al. (2015)	Boost and Duty	SA	The ABC has lower output oscillations than PSO and Enhanced P&O techniques. However, tracking time is increased.
Pilakkat and Kanthalakshmi (2020)	Boost and Duty	GT	For grid-connected PV systems, an improved ABC-P&O algorithm is proposed. In a real-time implementation, the system is more complicated.
soufyane Benyoucef et al. (2015)	Boost and Duty	SA	An ABC method based on direct duty cycle control has a shorter tracking time and higher accuracy than PSO. Increased oscillations are a detriment.
Pilakkat and Kanthalakshmi (2019)	Boost and Duty	SA	The ABC-P&O algorithm is said to reduce maximum overshoot by 30% compared to the normal ABC algorithm. It has low power variations and a shorter tracking time than P&O and INC. However, the comparison is not done with any swarm-based MPPT algorithm.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, CT: Converter Type and CV: Control Variable.

Improved BA (IBA) is better than P&O, PSO, and standard BA. The output curve's stability is good. However, the IBA algorithm is a little complex and slow at times (Wu and Yu, 2018). In terms of accuracy and oscillations, the algorithm does well than P&O and

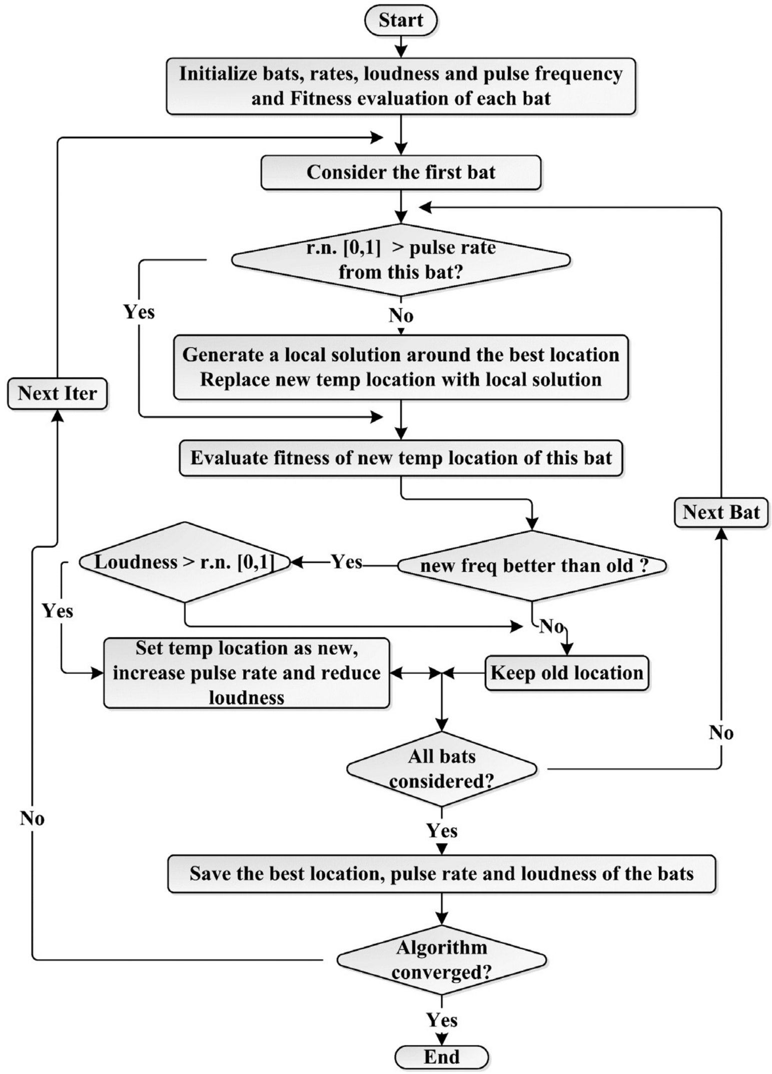

Fig. 5. Flow chart of Bat search algorithm for MPPT.

PSO approaches (Kaced et al., 2017). In most circumstances, the method's static efficiency is greater than 99.8% (Eltamaly et al., 2020a). Fig. 5 shows the flow chart of the algorithm.

The most common drawback of the BA is re-initialization and premature convergence. Improved BA and some hybrid BA solve the said issue but with large settling time and startup oscillations in the output. Table 3 presents a brief overview of the work done in MPPT under PSCs using BA. Mostly the comparison of BA is done with conventional, PSO, and GWO methods, which display good results of BA. However, no comparison is made with recent swarm-based MPPT algorithms.

3.4. Cuckoo Search Algorithm (CSA)

CSA is founded on the generation processes of cuckoo birds that lay eggs in other birds' nests. The levy flight mechanism is used in the search for a nest (Brindha et al., 2020; Goud et al., 2020). When CSA is used for MPP tracking, it allows particles to make a long jump with a large step size from their previous position, which not only reduces trapping at LMPP but also improves tracking speed (Anand et al., 2020). The flow chart is given in Fig. 6.

The CSA's operating behavior is comparable to that of the HC and P&O approaches. However, because of the levy's flight procedure, the CSA step size is higher than the conventional and PSO algorithms. It has faster convergence than PSO and DE and is less dependent on initial conditions (Kumar and Lather, 2020). As the particles approach the MPP, the step size decreases until it reaches zero Peng et al. (2018). At a steady-state, the traditional CSA algorithm takes a long conversion time, more failure rate, and large oscillations (Eltamaly, 2021). A deterministic CSA improves tracking speed and accuracy by eliminating the Levy flight calculation when compared to CSA, GWO, and PSO approaches. For tracking speed, convergence time, and efficiency under PSCs, improved CSA is better than traditional CSA, BA, PSO, GWO, and ABC (Eltamaly, 2021).

A hybrid CSA–GSS method combines CSA and golden section search (GSS) to take advantage of the best aspects of both techniques. CSA prevents getting locked in at LMPP and GSS discovers the GMPP. It can maintain an accurate result with reduced tracking time in comparison to standard CSA and PSO with little complexity (Nugraha et al., 2018a,b). In terms of tracking capability, transient behavior, and convergence, CSA beats both P&O and PSO (Ahmed and Salam, 2014). It also tracks more power than INC and artificial networks (Mosaad et al., 2019). The standard CSA takes more conversion time, more failure rate, and high fluctuations at a steady-state (Eltamaly, 2021). The CSA performance can be enhanced with improved versions and hybrid

Table 3
Bat search algorithm for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Tey et al. (2018)	SEPIC and Duty	SA	The BA converges towards the GMPP. Tracking time is within 1.5 s under PSC which is high.
Amalo et al. (2020)	Boost and Duty	GT	Efficient than standard BA, but the results are highly unstable.
Seyedmahmoudian others (2018)	SEPIC and Duty	SA	More tracking and convergence speed than DE and DE-PSO. It has oscillations and more settling time than GOA.
Liao et al. (2020)	Interleaved boost and Duty	SA	A hybrid BA-CSA performs better in terms of accuracy and convergence speed than standard BA, PSO, and GWO. However, it is very slow and less efficient as compared to SSA and GOA.
Eltamaly et al. (2020a)	Boost and Duty	GT	Improved BA performs better in terms of accuracy and convergence speed than standard BA, PSO, and GWO. However, the efficiency is low.
da Rocha et al. (2020)	Boost and Duty	SA	Less efficient, very slow, and more oscillations than PSO and GWO.
Wu and Yu (2018)	Boost and Duty	SA	Efficiency is improved as compared to P&O, PSO, ABC, and standard BA. The settling time is increased. The tracking speed is slow.
Kaced et al. (2017)	Buck-boost and Duty	SA	Outperforms P&O and PSO for global search ability and dynamic performance. However, settling time needs improvements.
Eltamaly et al. (2020a)	Boost and Duty	GT	Convergence time is considerably reduced than standard BA. Output oscillations are the main drawback.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, CT: Converter Type and CV: Control Variable.

Table 4
Cuckoo search algorithm for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Eltamaly (2021)	Boost and Duty	GT	Improved performance than the standard CSA, BA, GWO, and PSO but still settling time is high.
Nugraha et al. (2018a)	Duty ratio	SA	A hybrid CSA–GSS has less tracking time than PSO and standard CSA. More settling time and oscillations are still the issue.
Ahmed and Salam (2014)	Buck-boost and Duty	SA	It outperforms P&O and PSO w.r.t. tracking and convergence time. However, startup oscillations in the output are high.
Mosaad et al. (2019)	Boost and Duty	SA	Better than INC and ANN. However, no comparison is shown with any bio-inspired method.
Anand et al. (2020)	Boost and Duty	BS	Better than P&O and INC. However, settling time is high and no comparison is done with any bio-inspired method.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, BS: Battery System. CT: Converter Type and CV: Control Variable.

algorithms. Table 4 presents a brief overview of work done in the field of MPPT in PV systems under PSCs using CSA. Most of the CSA-based MPPT methods in the literature are compared with conventional, ANN, PSO, and GWO MPPT methods, which confirms its superiority. Some improved versions are better than the bat algorithm. However, no comparison is completed with recent swarm-based MPPT methods.

3.5. Firefly algorithm (FA)

It is established on firefly behavior which consists of two processes; attraction and mobility. The primary principle of the algorithm is based on firefly attraction, with the brighter one attracting the less dazzling one (Dhivya and Kumar, 2017). In terms of maximizing, the objective function's value is comparative to the brightness of the firefly. In FA, the duty cycle denotes the location of the firefly, and output power represents the illumination of each fly (Nugraha et al., 2017). FA has fewer regulatory parameters than PSO, and its particles come closer to optimum value with fewer fluctuations. The FA outdoes the normal PSO regarding tracking speed, accuracy, and dynamic response. The fusion firefly algorithm (FFA) combines the neighborhood attraction firefly algorithm (NaFA) and the simplified firefly algorithm (SFA) to prevent trapping at LMPPs. It outperforms P&O, PSO, genetic algorithm (GA), NaFA, and SFA in terms of accuracy, tracking speed, and efficiency (Huang et al., 2020). It simplifies the process of locating GMPP and speeds up the convergence. In comparison to P&O, PSO, and SFA, FFA reveals better results than the compared algorithms (Dhivya and Kumar, 2017). A hybrid FLC-FA is more precise and efficient than P&O and normal FLC (Ajiatmo and Robandi, 2017). A modified firefly algorithm (MFA) displays faster convergence and good tracking accuracy than P&O and FA. Furthermore, a connected battery receives rapid charging, which is superior to PSO (Nugraha et al., 2017; Sundareswaran et al., 2014).

FA has better global peak power monitoring capability and low steady-state error than traditional INC. However, it has a downside in control, execution time, and implementation complexity (Yetayew et al., 2016). The MFA has less computing time, faster convergence, and efficient control to reach the GMPP than the standard FA (Teshome et al., 2017).

The adaptive MFA is superior to the traditional FA and MFA approaches with respect to tracking speed. Furthermore, it lowers the traditional FA's fluctuation under the steady-state condition (Windarko et al., 2016). The combination of SFA and P&O avoids the LMPP trap with faster convergence and tracking under PSCs (Huang et al., 2020). The SFA algorithm is simple and holds rapid convergence and tracking speed (Yanuar Mahfudz Safarudin and Mauridhi Hery Purnomo, 2016). Table 5 presents a brief overview of the work done in the field of MPPT under PSCs using FA and Fig. 7 shows its flow chart. FA algorithm is compared with conventional, GA, and PSO MPPT methods, which confirms its superiority. The shortcomings in the standard FA are improved with FFA and some hybrid techniques. However, no comparison is made with the recent swarm-based MPPT algorithms.

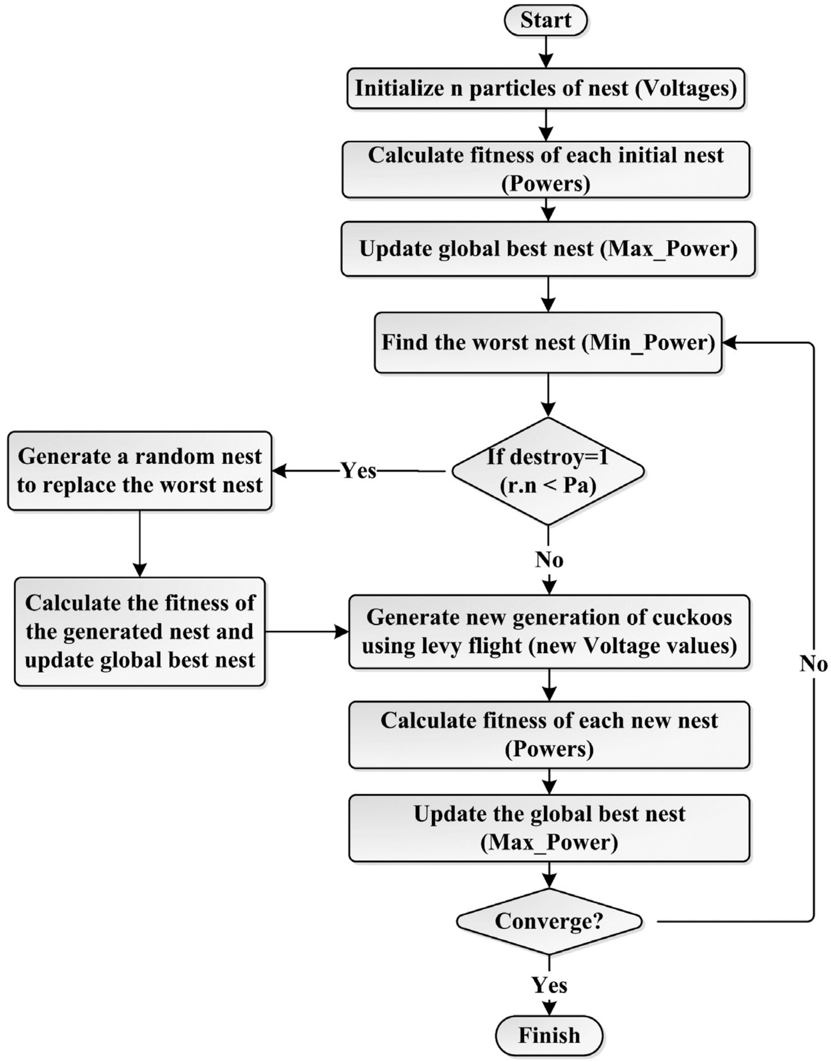

Fig. 6. Flow chart of CSA for MPPT.

Table 5
Firefly algorithm for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Nugraha et al. (2017)	Interleaved boost and Duty	SA	FA performance is better than the conventional INC method. However, a comparison should be made between bio-inspired algorithms to confirm superiority.
Huang et al. (2020)	Boost and Duty	SA	Fusion FA is more efficient and has less tracking time than standard FA. However, startup oscillations, complexity, and settling time are high.
Sundareswaran et al. (2014)	Boost and Duty	SA	Tracking speed and tracking efficiency are more than P&O and PSO. However, startup oscillations and settling time is very high.
Yetayew et al. (2016)	Boost and Duty	SA	A comparison between INC and FA confirms the better performance of FA. The comparison should be made between bio-inspired algorithms to confirm superiority.
Teshome et al. (2017)	Interleaved boost and Duty	SA	A modified FA performs better in terms of convergence speed than standard FA. However, startup oscillations and settling time is very high.
Yanuar Mahfudz Safarudin and Mauridhi Hery Purnomo (2016)	Buck and Duty	SA	Tracking speed and convergence accuracy are more than standard FA, P&O, and PSO. However, startup oscillations and settling time is very high.
Safarudin et al. (2015)	Buck and Duty	SA	A hybrid FA-P&O has a faster tracking speed and higher convergence accuracy than standard FA and P&O. However, startup oscillations and settling time is very high.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, CT: Converter Type and CV: Control Variable.

3.6. Grasshopper optimization algorithm (GOA)

GOA mimics the food searching activities of the grasshoppers. They look for food by exploration and exploitation processes (Luo et al., 2018). Three forces affect the position of each grasshopper (GH). Social interaction, gravity force, and wind effect. A comparison of GOA with P&O, PSO, and DE shows that the GOA-based MPPT method has distinct advantages in the matter of power extraction, convergence, efficiency, and fluctuations for tracking MPP under PSCs. However, the settling time of GOA needs to be improved (Sridhar et al., 2021). A hybrid GOA-INC reliably finds

Table 6
GOA for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Sridhar et al. (2021)	Buck and Duty	SA	Very efficient and smooth output curve. The settling time is high which is in seconds.
Wijaya et al. (2020)	Interleaved boost and Duty	SA	A hybrid GOA-INC outperforms the PSO and modified FA for productivity and tracking speed. But, the startup oscillations and high settling time are the main drawbacks.
Mansoor et al. (2020b)	Boost and Duty	SA	The proposed GOA method is better than P&O, PSO, PSOGS, CSA, ABC, and dragonfly optimization w.r.t. efficiency, tracking speed, and convergence time. Startup oscillations and high settling times are the main issues.
Subramanian and Raman (2020)	Boost and Duty	SA	The GOA shows good performance and convergence than P&O and PSO in tracking GMPP. The detailed analysis under PSCs to check superiority is missing.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, CT: Converter Type and CV: Control Variable.

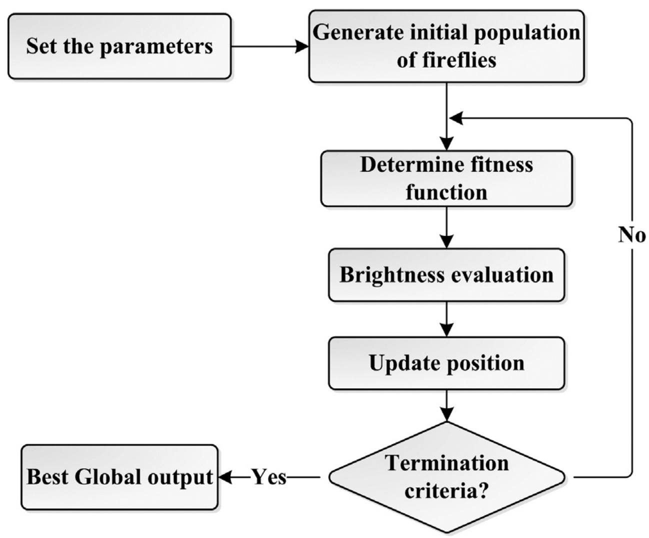

Fig. 7. Flow chart of Fire Fly Algorithm for MPPT.

the GMPP with improved tracking efficiency and short tracking time as compared to PSO and MFA. However, startup oscillations in the output need improvements (Wijaya et al., 2020). In a comparison with well-known optimization approaches such as P&O, ABC, PSO, dragonfly optimization, PSOGS, and CSA, the GOA possesses higher tracking efficiency. According to the results, fluctuation drop is nearly equal to 85% and 14%–60% quicker tracking speeds. The oscillations at the start need considerations (Mansoor et al., 2020b). A GOA-based adaptive FLC (FLC's parameters are set using a GOA) enhances efficiency, convergence speed, tracking effectiveness, and minimizes steady-state oscillations than P&O, FLC, and Fuzzy-PSO (Bhukya and Nandiraju, 2020). The GOA provides a good steady-state and dynamic response in comparison to P&O and PSO (Meraihi et al., 2021). Table 6 presents a brief overview of work done for MPPT in PV systems under PSCs using GOA. The flow chart is given in Fig. 8. GOA-based MPPT method in the literature is compared with conventional, soft computing, and recent swarm-based MPPT algorithms such as GWO, ABC, PSO, DFO, PSOGS, MFA, DE, and CSA MPPT methods which confirm its superiority. Some improved versions are better than INC, FLC, and FLC-PSO. GOA is a recent bio-inspired MPPT algorithm and is more efficient and improved tracking time. However, startup oscillations and settling times need improvements.

3.7. gray wolf optimization (GWO)

The GWO algorithm is centered on the natural chasing activity of gray wolves in search of prey. Alpha, beta, delta, and omega are the four categories of a wolf shown (Ali and Ouassaid, 2019). The alpha wolf is regarded as the decision-maker as it is thought to be the best answer. The beta and delta wolves are considered at the number two and three respectively as they are also in wolves' decision-making process (Singh et al., 2021). Finally, the lowest ranking gray wolf omega is always utilized as a scapegoat. When used for MPP tracking, gray wolves represent the converter duty cycle and MPP is the prey being chased (Seyedmahmoudian et al., 2016). The traditional GWO can follow the GMPP, but with several iterations and significant power losses. It can converge to the GMPP with fewer power fluctuations than P&O and PSO (Jing et al., 2020).

GWO-GSO combines GWO and golden search optimization (GSO) in which a modified GWO ensures global search and GSO does indigenous hunt. It reduces tracking time as it avoids needless searches (Belhachat and Larbes, 2019). In the majority of circumstances, the improved GWO algorithm knocks the P&O, PSO, ABC, salp–PSO, SSA-GWO, and enhanced GWO, particularly w.r.t tracking time and efficiency (Guo et al., 2020). In comparison to P&O and FLC, the GWO produces better results but it is less efficient than enhanced GWO (Jegha et al., 2020).

GWO has a better MPPT performance than P&O and PSO (Mohanty et al., 2017b, 2016). Comparing the GWO-P&O hybrid algorithm to other fast converging algorithms, it offers faster tracking and convergence speed (Mohanty et al., 2017a). The upgraded GWO enhances tracking efficiency and the problem of large voltage variations during the search process is overcome (Almutairi et al., 2020; Xiang et al., 2018). Table 7 presents a brief overview of work done in the field of MPPT in PV systems under PSCs using GWO. Fig. 9 represents the flow chart of the algorithm. GWO and its improved versions are compared with conventional, soft computing and some swarm-based MPPT algorithm such as ABC, PSO, salp-swarm base GWO, and salp-swarm based PSO which confirms its superiority. However, startup oscillations and settling times need improvements.

3.8. Salp swarm algorithm

Salp is a marine invertebrate with a transparent and barrel-shaped body. It owns a jellyfish-like body and moves in a jellyfish-like manner (Mao et al., 2020c). To propel themselves ahead, salps pump water through their tubular bodies. The foraging and coordinate adjustments to find the ideal position for food is the fundamental factor in salp swarm behavior (Fathy et al., 2021). Only one salp is the leader that is at the head of the chain, while other salps are called followers (Mao et al., 2020b).

Memetic SSA (MSSA) uses numerous separate slap chains to force exploration and exploitation at the same time to quickly find a high-quality optimal solution that tracks more power (Belhachat and Larbes, 2019). A hybrid SSA-P&O outperforms P&O, hybrid whale optimization algorithm (WOA), and hybrid GWO for tracking speed, accuracy, and efficiency under PSCs (Premkumar et al., 2021). The integrated SSA-GWO method outdoes the PSO and basic SSA algorithms with less power fluctuation (Wan et al., 2019).

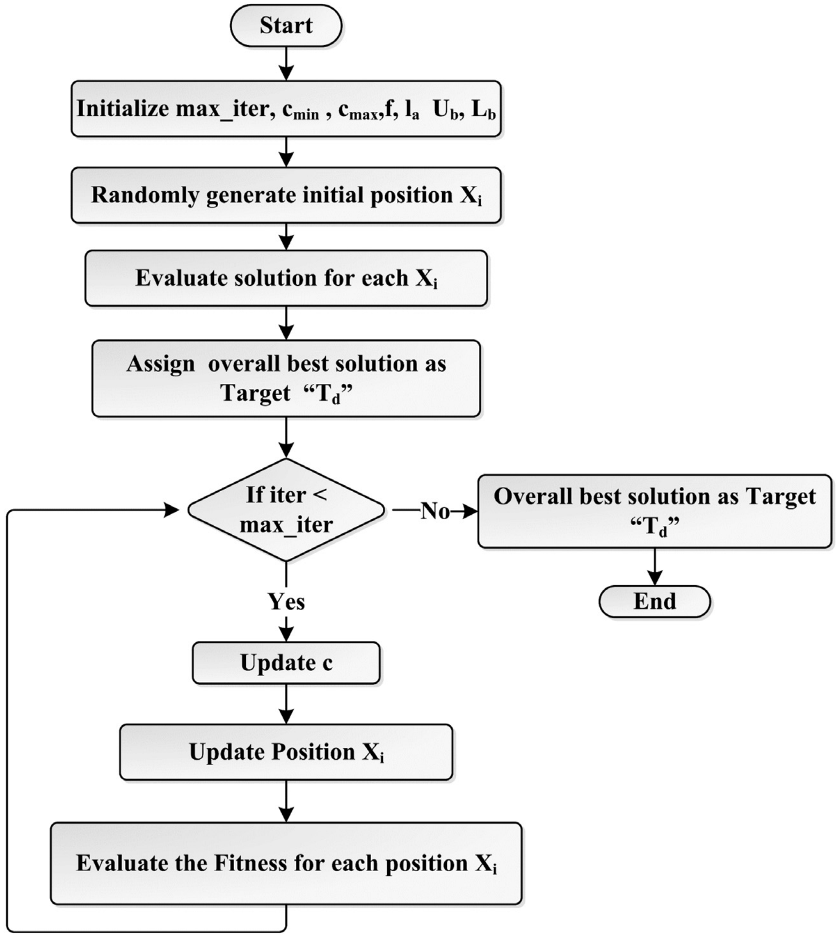

Fig. 8. Flow chart of GOA for MPPT.

Table 7
GWO algorithm for MPPT in PVS under PSCs.

Ref.	CT and CV	Application	Remarks
Guo et al. (2020)	Boost full-bridge isolated converter and Duty	DC to AC	Improved GWO has high tracking speed and fast convergence than P&O, ABC, SSA-GWO, EGWO, and PSO. There are startup oscillations and a high settling time.
Laxman et al. (2021)	Boost and Duty	MG	A GWO-FLC is more efficient than P&O and FLC. A trade-off is made among tracking speed and fluctuations. However, a comparison should be done with the algorithm having the same characteristics i.e. bio-inspired.
Mohanty et al. (2017b)	Boost and Duty	SA	A GWO outperforms P&O and PSO. However, settling time is more than GOA and SSA.
Mohanty et al. (2017a)	Boost and Duty	SA	A hybrid GWO-P&O has high pursuing speed and fast convergence relative to P&O and PSO.
Mohanty et al. (2016)	Boost and Duty	SA	Proposed GWO has high tracing speed and fast convergence relative to P&O and improved PSO.
Almutairi et al. (2020)	Boost and Duty	GT	More efficient than P&O. However, the comparison be done with the algorithm having the same characteristics.
Xiang et al. (2018)	Boost and Duty	GT	Improved GWO performs better than standard GWO in terms of efficiency. High startup oscillations and more settling time are the drawbacks.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, MG: Micro Grid. CT: Converter Type and CV: Control Variable.

In all respects, the SSA algorithm beats the HC and other common metaheuristic methods such as PSO, butterfly algorithm, GWO, and moth flame optimization (MFO) (Jamaludin et al., 2021b). It also has fewer oscillations in the vicinity of the MPP (Mostafa and Ibrahim, 2019). It is 20%–30% faster in tracking and average power generation than other bio-inspired algorithms and 8%–46% faster than traditional P&O. Complex PSCs, on the other hand, are a scenario in which much more research is needed in the future (Mirza et al., 2020). Table 8 presents a brief overview of the work done in the field of MPPT in PV systems under PSCs using SSA. Its flow chart is accessible in Fig. 10.

3.9. Whale optimization algorithm (WOA)

WOA mimics the bubble-net feeding mechanism used by humpback whales in their hunting process (Haridy, 2019). "Herder", one of the two WOA family groups pursue prey and the pursued prey is seized by the "catchers" (Qais et al., 2020).

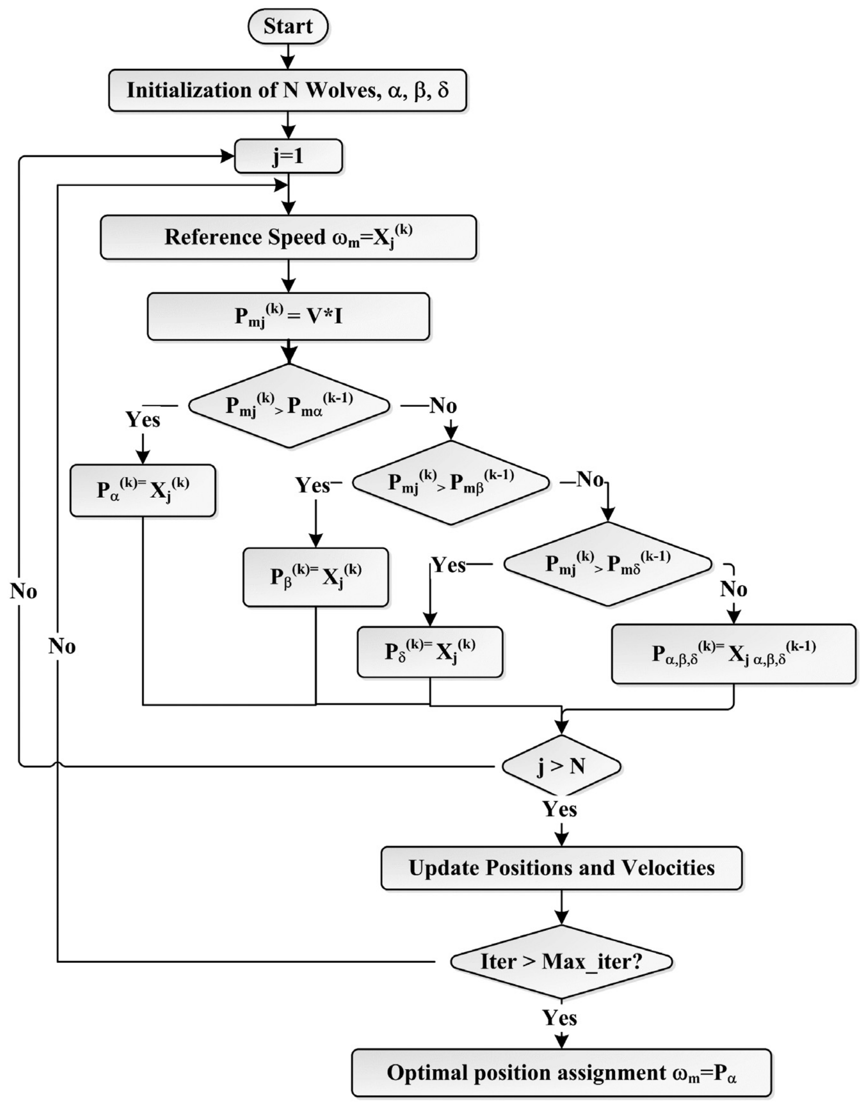

Fig. 9. Flow chart of GWO algorithm for MPPT.

Table 8
SSA for MPPT under PSCs.

Ref.	CT and CV	Application	Remarks
Mao et al. (2020c)	Cuk and Duty	SA	The proposed system has fast-tracking and convergence speed than SSA, SSA-GWO, and SSA-PSO. However, there is a drop in efficiency.
Premkumar et al. (2021)	Boost and Duty	SA	A hybrid SSA-P&O outperforms P&O, hybrid WOA, and GWO in terms of tracking and convergence speed. However, the proposed algorithm is less efficient than GOA. Moreover, the system is more complex.
Wan et al. (2019)	Buck-boost and Duty	SA	A hybrid SSA-GWO is more efficient than PSO and standard SSA. However, the system becomes more complex. The settling and tracking time are increased with more startup oscillations.
Jamaludin et al. (2021b)	Buck-boost and Duty	SA	The proposed system has a fast-tracking and convergence speed than HC, GWO, butterfly optimization algorithm (BOA), PSO, and GOA.
Mirza et al. (2020)	Boost and Duty	SA	Shows better performance w.r.t tracking time and convergence speed than ABC, PSO, PSOGS, DFO, and CSA. However, settling time still needs to be reduced and the startup oscillations are also present.

Ref.: Reference, SA: Standalone, GT: Grid-Tied, CT: Converter Type and CV: Control Variable.

Prey is the power acquired from the PVS and the duty cycle is the location of the "herders" in a modified artificial killer whale optimization MAKWO algorithm (Gupta and Saurabh, 2017a). A simple WOA demonstrates satisfactory accuracy under dynamic conditions, but with a longer tracking time. It outperforms the modified artificial wolf pack, ABC, and PSO approach in terms of tracking speed. Not only does it take less time to converge, but also eliminates the issue of excessive output power fluctuations.

WOA is used to increase the functioning of a 400-kW grid-tied PVS to modify the PI control parameters (Ebrahim et al., 2019). INC is tuned using the hybrid WOA and pattern search method which enhances tracking efficiency (Tao et al., 2021).

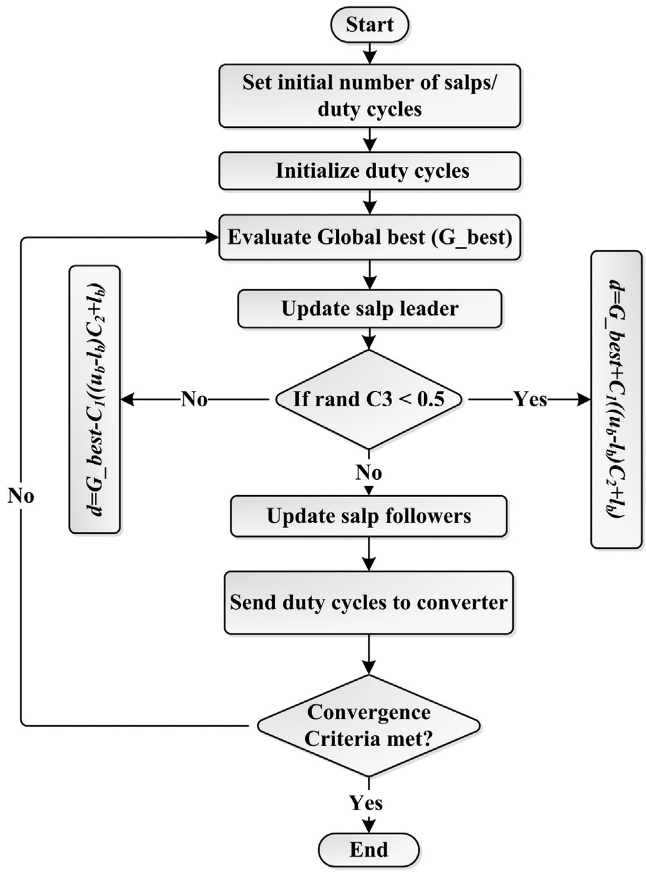

Fig. 10. Flow chart of SSA for MPPT.

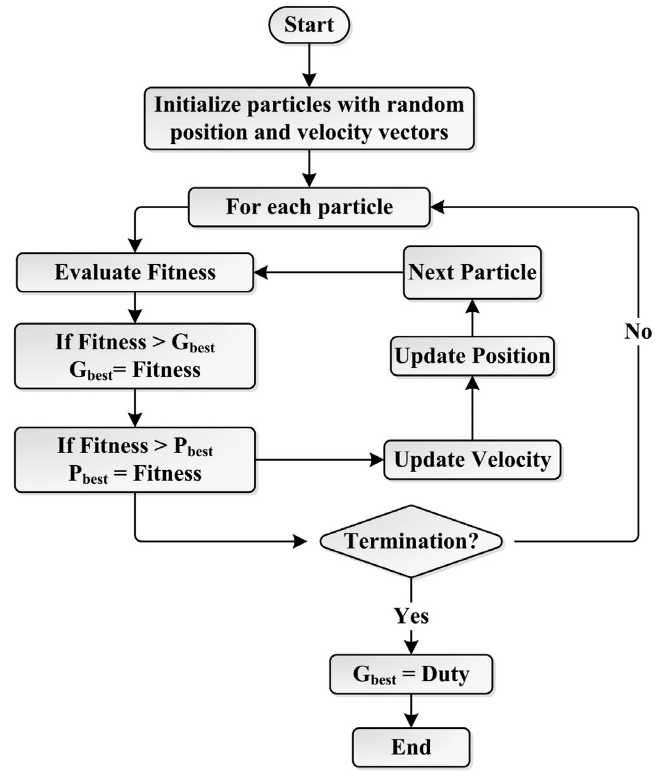

Fig. 11. Flow chart of PSO for MPPT.

WOA based MPPT method in the literature is compared with ABC and PSO methods which confirm its superiority. However, no comparison is made with the recent swarm-based MPPT approaches. WOA has more settling time, less efficiency, and more startup oscillations than GOA and SSA.

3.10. Particle swarm optimization (PSO)

PSO is grounded on flocking birds' natural performance and focuses on a precise area known as solution space, in which every position gives a degree of problem-solving possibility (Eltamaly et al., 2020b). The PSO transports every particle through the solution space in search of the best solution based on its own and neighboring particle knowledge (Makhloufi and Mekhilef, 2021). As a result, particles participating in optimization, use their memories to adapt fitness by copying successful swarm particles' behavior (Obukhov et al., 2020).

The traditional PSO has several parameters whose values are determined from a set of options in a certain range (Kalaiarasi et al., 2018). It also uses random integers in the velocity equation, which makes the outcomes irregular. Even after tracking the GMPP, PSO performance is sometimes vulnerable because of particles' random initialization. Typical PSO has limitations such as slow convergence, poor local search capabilities, more parameters to tweak, and oscillations around the MPP. Moreover, the particles may explore the areas which were previously scanned by the other particles. The flow chart is given in Fig. 11.

Many modifications of the original PSO were created to improve its performance, e.g. deterministic (D-PSO), modified particle velocity-based (MPV-PSO) (Sen et al., 2018), overall distribution (OD-PSO) (Li et al., 2019b), artificial neural network (ANN-PSO) (Farayola et al., 2018). PSO with one cycle control (PSO-OCC) (Anoop and Nandakumar, 2018), PSO gravitational search algorithm (PSO-GSA) (Mohamed et al., 2019), enhanced leader (EL-PSO) (Gavhane et al., 2017), levy flight (LF-PSO) (Charin et al., 2021), improved PSO (Dileep and Singh, 2017; Hayder et al., 2020; Samir et al., 2021; Hu et al., 2019), adaptive neuro-fuzzy inference system (ANFIS–PSO) (Priyadarshi et al., 2020), simulated annealing (SA-PSO) (Guan and Zhuo, 2017), PSO-P&O (Alshareef et al., 2019; Manickam et al., 2016), leader (L-PSO) (Prasanth Ram and Rajasekar, 2017), FLC-PSO (Cheng et al., 2015) and terminal sliding mode controller based (PSO-TSMC) (Lamzouri et al., 2020) are proposed.

3.11. Moth flame optimization (MFO)

It is established on a population of moths and flames traveling around the search space. The goal of the MFO is to obtain the finest gain to reduce the error. It performs better than the INC, FLC, and PSO when a comparison is made for tracking time, effectiveness, and stability (Aouchiche et al., 2018). A hybrid INC-MFO (INC works in uniform irradiance conditions and MFO acts in non-uniform scenarios) shows good performance in dynamic and steady-state conditions (Rezk et al., 2019). Its flow chart is given in Fig. 12. MFO-based MPPT shows good performance relative to conventional, FLC, and PSO methods which confirm its superiority. However, no comparison is made with the recent swarm-based MPPT algorithms. MFO has more settling time, less efficiency, and more startup oscillations than GOA and SSA.

3.12. Chicken swarm optimization (CSO)

CSO mimics the chicken's search behavior (Meng et al., 2014). An improved (ICSO) technique is presented in the literature, in which adaptive inertial weight is used to renew hen directions.

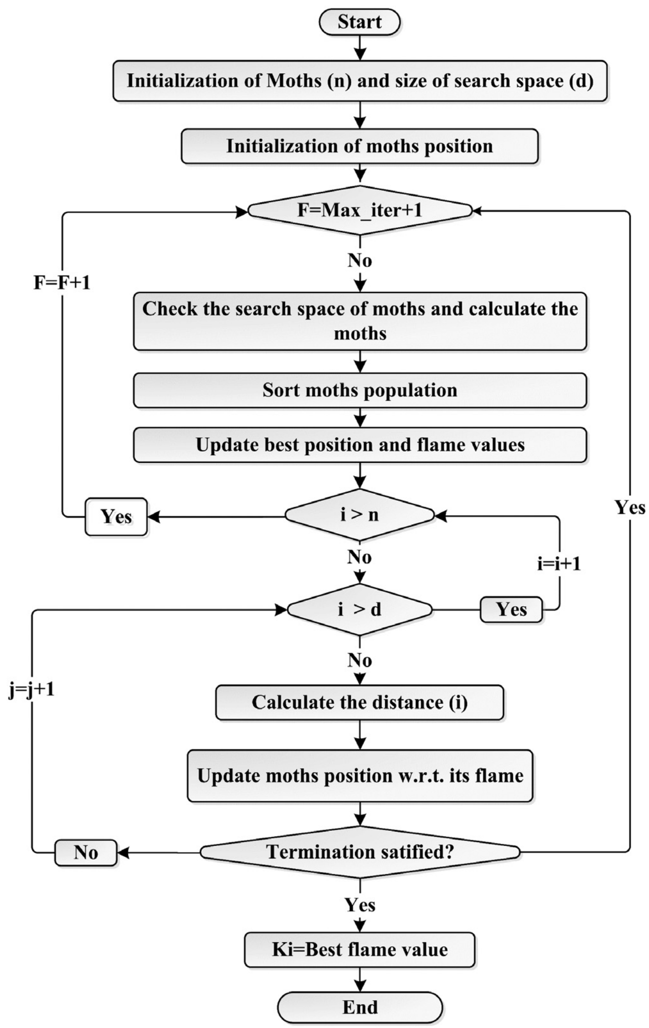

Fig. 12. Flow chart of MFO for MPPT.

Furthermore, the actual implementation of ICSO is demonstrated by several tests, which show that the swarm's uniformity is much improved when compared to standard CSO (Wu et al., 2018). It can also provide a healthy mix of local exploitation and global exploration. The authors claim better performance of the ICSO method than PSO and Bat algorithms for tracking and convergence speed (Irsalinda et al., 2017). CSO-based MPPT method performs well as compared to Bat and PSO algorithms which confirm its supremacy. However, no comparison is shown with the recent swarm-based MPPT approaches. CSO has more settling time, is less efficient, and has more startup oscillations than GOA and SSA.

4. Case study: A comparative analysis of swarm-based MPPT algorithms under PSCs

Today's world is looking for alternative green energy resources such as PV energy to cope with the issue of energy crisis in every field. However, the intermittent environmental behavior and PSCs create a hindrance in getting optimal power from the PV system. To solve the said issue, various swarm-based approaches which have been employed in getting maximum power from the PV system under PSCs are summarized in the previous sections. In this section, a case study to evaluate the performance of these swarm-based MPPT algorithms published in the last decade is carried out. The voltage and current of the PV array are the input variables to the MPPT algorithm. The main objective is to get maximum power from the PV system by tracking a GMPP among different LMPPs. Therefore, the duty ratio '*d*' of the MOSFET (of boost converter) is controlled by the algorithm. Hence, the objective function is defined as

Table 9
Irradiance patterns on each PV module under PSCs.

Case study	Irradiance on each PV module (W/m^2)				GMMP (W)
	PV-1	PV-2	PV-3	PV-4	
Case 1	800	250	700	400	450
Case 2	500	800	1000	900	796

$$\boldsymbol{P}\left(\boldsymbol{d}_i^{(k)}\right) > \boldsymbol{P}\left(\boldsymbol{d}_i^{(k-1)}\right) \tag{1}$$

where P is the power received at a specific duty ratio d and iteration number k for the ith particle (candidate solutions) in the swarm. In this case study, three particles and hundreds of iterations are considered in each case.

4.1. Simulation setup

A simple model is designed to test the feasibility of the algorithms under PSCs using Simulink whose block diagram is shown in Fig. 13. The visible light spectrum hits the PV array with various irradiance (G) and produces current and hence the power. The produced power flows into a boost converter which adjusts the output voltage per required voltage level. A small capacitor (C) is added between the PV array and the boost converter is used to provide the ripple current required by opening and closing the MOSFET of the converter. Swarm-based MPPT control algorithms are employed one by one to track the MPP of the system by monitoring PV current and voltage. This then ultimately controls the duty ratio '*d*' of the MOSFET in the boost converter. The specification of the PV module used in this study is given in Table 10. Four such modules are connected in series to make 1260 W in full capacity (when the irradiance is 1000 W/m^2 and temperature is 298 K on all PV modules). Two PSCs are considered which are taken from Mansoor et al. (2020b) and are given in Table 9. The results are compared w.r.t

i. Efficiency
ii. Startup oscillations
iii. Convergence time, settling time, and peak time
iv. Relative error, mean absolute error and root mean square error

Seven swarm-based MPPT algorithms are selected for the case study. Their equations and the value of variables used are listed in Table 11.

4.2. Results for Case-1

There are three LMPPs and one GMMP at 450 W in this scenario. How the system should behave i.e. the P–V and I–V characteristic curves are shown in Fig. 14, whereas Table 10 depicts the irradiance pattern for the case. Conventional MPPT algorithms get trapped at LMMPs therefore, to break this trap, swarm-based MPPT approaches randomly select their particles. Extreme randomness can be found in CSA and WOA which causes unwanted fluctuations in the duty cycle. For each swarm-based MPPT algorithm, a comparison of the duty cycle is depicted in Fig. 15.

Fig. 16 shows a comparison between powers obtained by GOA, SSA, WOA, MFO, GWO, CSA, and PSO. The efficiency and

Table 10
Specifications of 315W Sun-power PV module (SPR-315E-WHT-D).

Attributes			Values	Units
Maximum power at STC (P_{max})			315.072	W
Optimal working voltage (V_{mp})			54.7	V
Optimal working current (I_{mp})			5.76	Å
Open circuit voltage (V_{oc})			64.6	V
Short circuit current (I_{sc})			6.14	Å
Temperature constants	For V_{oc}	β	−0.27269	%/°C
	For I_{sc}	α	0.061694	%/°C

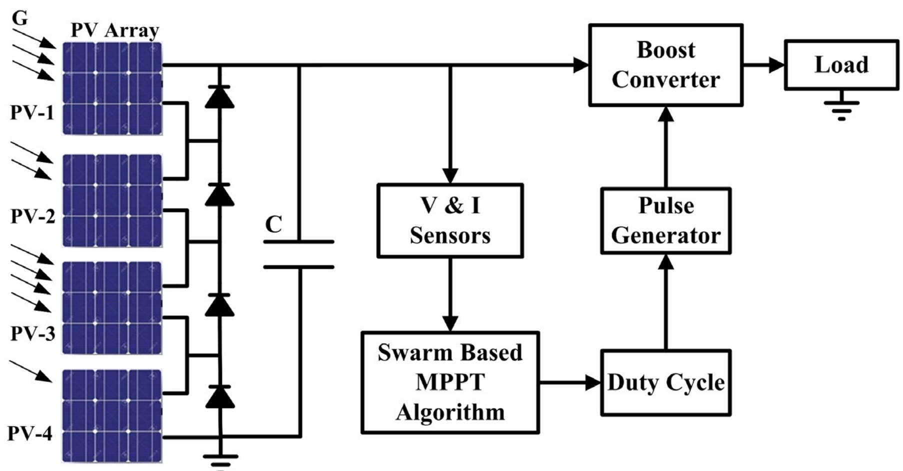

Fig. 13. Block diagram of PV system under PSCs for case study.

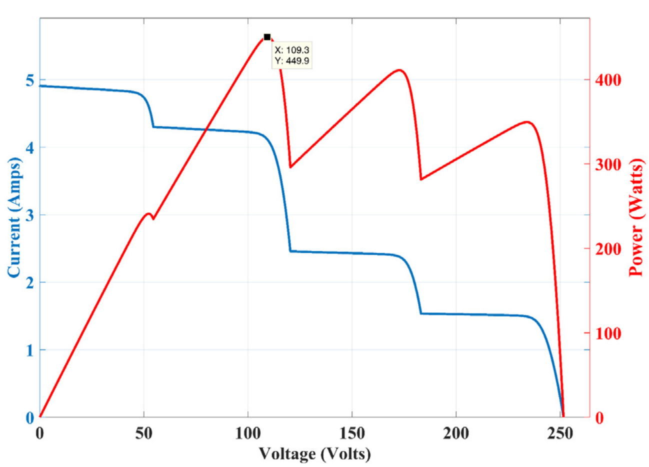

Fig. 14. Case 1, PV array characteristics curves (blue: I–V and red: P–V) under PSCs. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

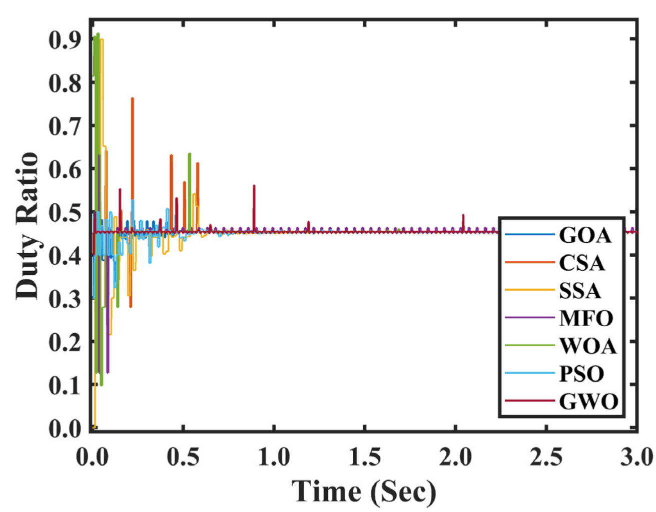

Fig. 15. Case 1, Duty ratio comparison under PSCs.

power are determined based on a 450 W GMPP for case 1. GOA, SSA, WOA, MFO, GWO, CSA, and PSO produce average power 448.61 W, 447.30 W, 445.137 W, 445.39 W, 445.71 W, 444.67 W, and 444.08 W respectively with GOA being the most efficient. GOA with a 99.69 percent average efficiency, followed by SSA with 99.40%, GWO with 99.05%, MFO with 98.97%, WOA with 98.92%, CSA with 98.81%, and PSO with a 98.68%, efficiency.

Fast-tracking of GMPP and efficient settling time at GMPP demonstrate the robustness of an MPPT approach. Table 12 gives a comparison between convergence time and settling time of the employed algorithms. The average convergence time of the GOA, SSA, WOA, MFO, GWO, CSA, and PSO is 0.09 s, 0.10 s, 0.18 s, 0.11 s, 0.09 s, 0.15, and 0.13 s, respectively. It can be seen that GOA settles in 0.21 s, SSA 0.63 s, WOA 0.59 s, MFO 0.29 s, GWO 0.92 s, CSA 0.62 s, and PSO 0.48 s according to simulations. GOA settles faster than the other compared algorithms due to reduced oscillations. So, it reduces power loss and improves efficiency. Figs. 17 and 18 illustrate the voltage and current comparison of the algorithms for this case. A graphical representation of average convergence time, average settling time, and average peak time is given in Fig. 19.

4.3. Results for Case 2

Table 10 shows the irradiance pattern of each module under PSCs and Fig. 20 shows the related I–V and P–V curves. There are three LMPPs and one GMMP at 796 W. Fig. 21 shows the control given by the duty cycle.

Table 11
Algorithms with their values of variables for case study.

Algorithm and Reference	Equation used	Variable values
CSA (Nugraha et al., 2018b)	$d_{i+1}^{k} = d_i^k + \alpha * \frac{\lvert u \rvert}{v^{\frac{1}{\beta}}} * \left(d_{best} - d_i^k\right)$ $u \approx N\left(0, \sigma_u^2\right)$ $v \approx N\left(0, \sigma_v^2\right)$ $\sigma_u = \left(\frac{\Gamma(1+\beta) * sin\left(\pi * \frac{\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) * \beta * 2^{\left(\frac{\beta-1}{2}\right)}}\right)$ $\sigma_v = 1$	$\beta = 1.5$; $\alpha = 0.8$; N = 4; L = 90
GOA (Mansoor et al., 2020b)	$X_i = c\sum_{j=1}^{N} c\left(\frac{ub_d - lb_d}{2} s\left(\lvert x_j^d - x_i^d \rvert\right) \frac{x_j - x_i}{d_{ij}}\right) + \hat{T}_d$ $s(r) = fe^{\frac{-r}{l}} - e^{-r}$ $c = c_{max} - l\frac{c_{max} - c_{min}}{L}$	$N = 3$; $L = 90$ $c_{max} = 1$; $c_{min} = 0.00004$ $f = 0.845$; $l = 3.015$;
GWO (Guo et al., 2020)	$\vec{D} = \left\lvert \vec{C}.\overrightarrow{X_{p(t)}} - \overrightarrow{X_{(t)}} \right\rvert$ $\overrightarrow{X_{(t+1)}} = \overrightarrow{X_{p(t)}} - \vec{A}.\vec{D}$ $a = a_{in} - \left(a_{in} - a_f\right) * tan\left(\frac{1}{\varepsilon}.\frac{l}{L}\pi\right)$ $A = 2a * random - a$ $C = 2 * random$	$N = 3$; $L = 120$; $a_{in} = 2$ $a_f = 0.5$; $\varepsilon = 4$;
MFO (Aouchiche et al., 2018)	$Flame_{no.} = round\left(N_f - l * \frac{N-1}{L}\right)$ $b = 1$ $t = (a-1) * random + 1$ $M = (ub - lb) * random(n, d) + lb$ $a = -3.15 + \left(\frac{-l}{L}\right)$ $S(M, F) = D.e^{bt}.\cos(2\pi t) + F$	$N = 4$; $L = 120$; $ub = 0.9$ $lb = 0.1$
PSO (Charin et al., 2021)	$\mathrm{v_{ij}}(t+1) = \mathrm{w} * \mathrm{v_{ij}}(t) + \mathrm{r_1 c_1}\{\mathrm{P_i}(t) - \mathrm{x_i}(t)\}$ $+ \mathrm{r_2 c_2}\{\mathrm{g_j}(t) - \mathrm{x_{ij}}(t)\}$ $\mathrm{x_{ij}}(t+1) = \mathrm{x_{ij}}(t) + \mathrm{v_{ij}}(t+1)$	$N = 9$; $L = 120$; $w = 0.4$; $c_1 = 1.4$; $c_2 = 1.8$; $r_1, r_2 = $ random
SSA (Jamaludin et al., 2021b)	$x_j^1 = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right), & c_3 \geq 0.5 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right), & c_3 < 0.5 \end{cases}$ $c_1 = 2.e^{-\left(\frac{4l}{L}\right)^2}$ $x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right)$	$N = 7$; $L = 120$; $ub = 0.8$; $lb = 0.1$; $c_2 = $ random
WOA (Tao et al., 2021)	$D = \left\lvert \vec{C}.X * (t) - X(t) \right\rvert$ $X_{(t+1)} = X * (t) - A * D$ $A = 2a.r - a$ $C = 2r$ $a = 2 - l * \left(\frac{2}{L}\right)$	$N = 7$; $L = 120$; $r = $ random

Table 12
Case 1, Simulink results parameters comparison.

GMPP = 450 W	Swarm-based algorithm for PV MPPT under PSCs						
Attributes	GOA	SSA	WOA	MFO	GWO	CSA	PSO
Avg. convergence time (s)	0.09	0.1	0.18	0.11	0.09	0.15	0.13
Avg. settling time (s)	0.21	0.63	0.59	0.29	0.92	0.62	0.48
Avg. overshoot (W)	0.36	2.06	2.19	0.31	0.42	2.01	1.69
Avg. max power (W)	448.61	447.30	445.13	445.39	445.71	444.67	444.08
Avg. peak time (s)	0.33	0.21	0.14	0.9	0.7	0.2	0.32
Avg. efficiency (%)	99.69	99.40	98.92	98.97	99.05	98.81	98.68

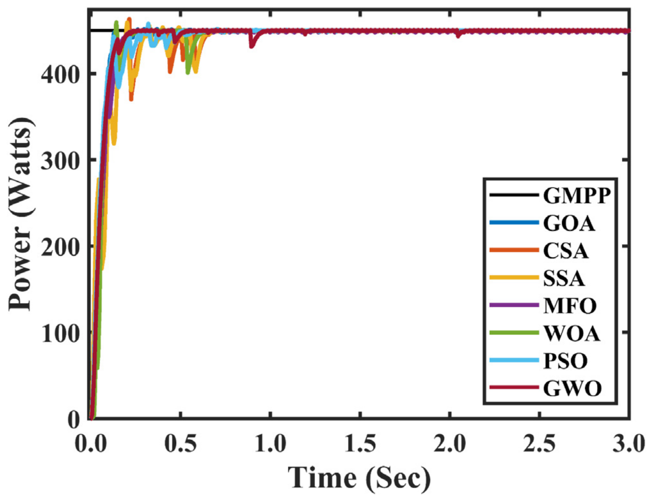

Fig. 16. Case 1, Output power comparison.

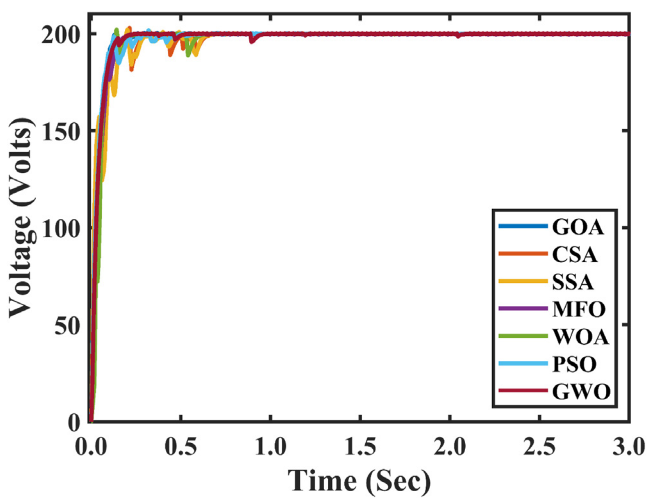

Fig. 17. Case1, Output voltage comparison under PSCs.

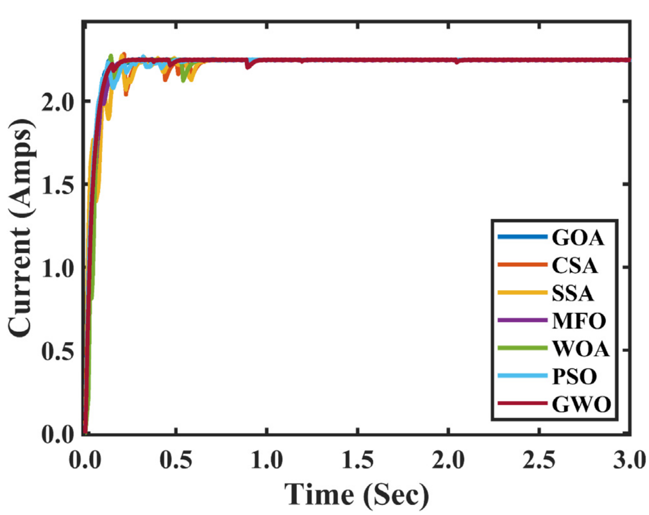

Fig. 18. Case1. Output current comparison under PSCs.

Fig. 22 shows a comparison between powers obtained by GOA, SSA, WOA, MFO, GWO, CSA, and PSO. The efficiency and power are determined based on a 796 W GMPP for case 2. GOA, SSA, WOA, MFO, GWO, CSA, and PSO produce 794.69 W, 793.06 W, 788.01 W, 788.37 W, 789.75 W, 785.47 W, and 785.31 W respectively with GOA being the most efficient. GOA with a 99.84 percent efficiency, followed by SSA with 99.63%, GWO with 99.21%, MFO with 99.04%, WOA with 99%, CSA with 98.68%, and PSO with a 98.66% efficiency. It is observed that when the irradiance goes near STC, the efficiency of the algorithms approves.

Faster tracking improves the robustness of the system and eliminates unwanted oscillations. Table 13 gives a comparison between convergence time and settling time of the employed algorithms. The convergence time of the GOA, SSA, WOA, MFO, GWO, CSA, and PSO is 0.12 s, 0.11 s, 0.19 s, 0.18 s, 0.41 s, 0.15, and 0.16 s, respectively. It can be seen that GOA settles in 0.19, SSA 0.67 s, WOA 2.4 s, MFO 0.25 s, GWO 0.48 s, CSA 0.25 s, and PSO 0.31 s according to simulations. GOA settles faster than the other compared algorithms due to the reduced oscillations. So, it reduces power loss and improves efficiency. Figs. 23 and 24 illustrate the voltage and current comparison of the algorithms. Even though GWO, WOA, and CSA have an efficiency of more than 98%, high startup oscillations in voltage and current can still be seen. With ripples of less than 1 W, GOA and SSA improve startup oscillations and lower steady-state oscillations to zero in the later stages of iterative cycles with stable output. Convergence time, settling time, and peak time are represented in Fig. 25 for case 2. A graphical representation of the efficiency for both cases is given in Fig. 26.

The mean absolute error (MAE) Eq. (2), and root means square error (RMSE) Eq. (3) are used to assess the sensitivity of MPPT approaches.

$$E_{MAE} = \frac{\sum_{j=1}^{m}(P_{stc} - P_t)}{m} \tag{2}$$

$$E_{RMSE} = \sqrt{\frac{\sum_{j=1}^{m}(P_{stc} - P_t)^2}{m}} \tag{3}$$

The output power at STC is P_{stc}, the power tracked by the MPPT algorithm is P_t, and the total number of simulation runs is m. In this case study, total numbers of runs are 30. In Figs. 27 and 28, the statistical data for average MAE, and RMSE are graphically depicted for case 1 and case 2, respectively. It is observed that the GOA has the lowest average MAE (error from the GMPP on average) than rest of the algorithms, following SSA, GWO, MFO, WOA, CSA and PSO respectively. Average RMSE (how focused the data is around the GMPP) of the GOA and WOA is less than the rest of the algorithms which means that the power tracked by these algorithms is dense around the GMPP. PSO shows more RMSE clearly states the more scattered data around the maximum. The mean/average powers for both the cases are graphically shown which depicts the consistency in output of the algorithms. It can be seen that the output of the algorithms is tracked very well for both cases for larger number of runs (see Fig. 29).

The standard deviation (SD) is shown in Fig. 30. It is observed that the SD for case 1 is more as compared to case 2 which specifies that when the irradiance level is lower (more shadings on PV array) then the SD is high and vice versa. It means that the output of the algorithms is more prone to deviate from the mean value under high PSCs. As the irradiance goes towards STC, the SD starts decreasing. Careful observation reveals that the GOA and SSA are less effected by the high PSCs as compared to other algorithms. Therefore, their performance is more stable than the remaining MPPT algorithms employed in this case study.

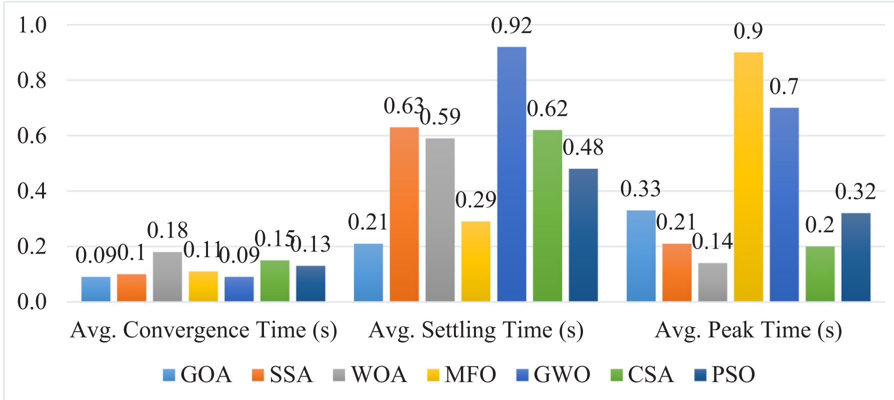

Fig. 19. Case 1. Graphs for avg. convergence, settling and peak times.

Table 13
Case 2, Simulink results parameters comparison.

GMPP = 796 W	Swarm-based algorithm for PV MPPT under PSCs						
Attributes	GOA	SSA	WOA	MFO	GWO	CSA	PSO
Avg. convergence time (s)	0.12	0.11	0.19	0.18	0.41	0.15	0.16
Avg. settling time (s)	0.19	0.67	2.4	0.25	0.48	0.25	0.31
Avg. overshoot (W)	0.13	0.25	14.46	0.16	0.41	0.37	0.22
Avg. max power (W)	794.69	793.06	788.01	788.37	789.75	785.47	785.31
Avg. peak time (s)	0.28	2.32	2.12	0.86	1.03	0.37	1.55
Avg. efficiency (%)	99.84	99.63	99.00	99.04	99.21	98.68	98.66

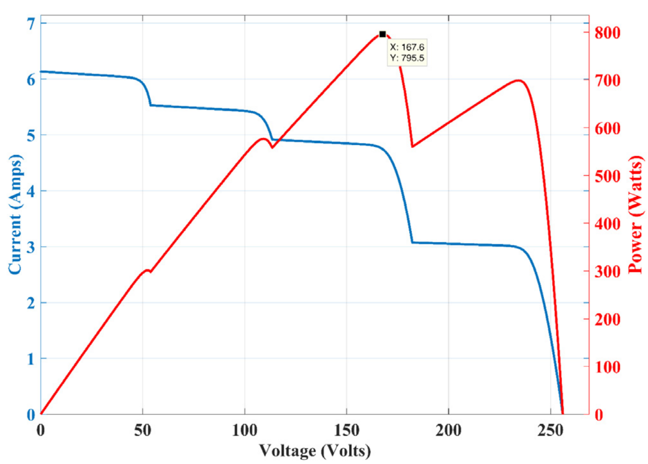

Fig. 20. Case 2, PV array characteristics curves (blue: I–V and red: P–V).. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

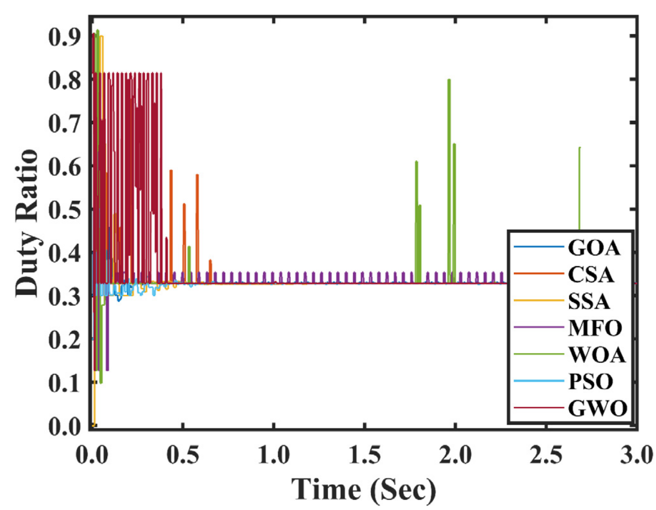

Fig. 21. Case 2, Duty ratio comparison.

5. Comparison and discussion

The advantages and disadvantages of swarm-based MPPT approaches under PSCs were classified and reviewed in the previous sections (see Table 14). The following observations can be drawn from the review.

ACO can lower the traps at LMPPs compared to PSO and conventional methods. Compared to simple P&O, PSO and ACO, a hybrid ACO- P&O algorithm has a fast convergence.

ABC exhibits energy savings and more revenue production relative to PSO and Enhanced P&O techniques with slow tracking speed. The hybrid ABC-HC method offers a quick convergence speed and low cost in comparison to HC and ABC methods.

Hybrid Bat-P&O, Bat-INC, and Bat-Beta techniques have shown the ability to enhance system efficiency even during transients than PSO and simple Bat method.

Improved CSO and modified CSO methods possess good performance as compared to the PSO and Bat algorithms.

Improved and deterministic CSA is more efficient than regular CSA, BA, PSO, GWO, and ABC for tracking speed, convergence time, and efficiency.

Fusion FA outperforms the P&O, PSO, and standard FA. A hybrid FLC-FA is more correct and efficient than P&O and normal FLC. A MFA displays faster convergence to MPP and good tracking accuracy than P&O and FA.

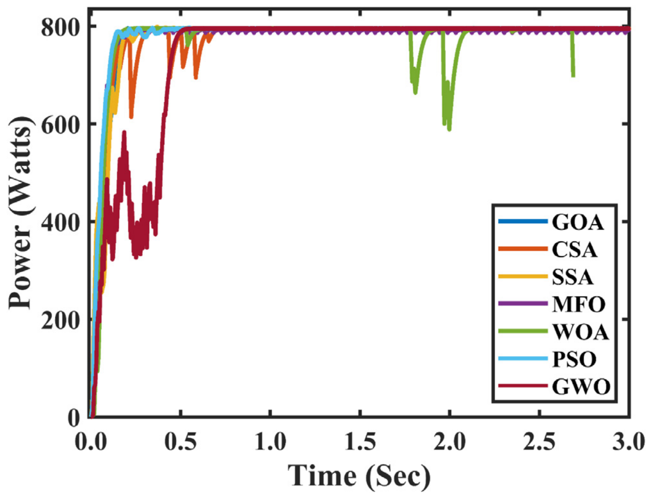

Fig. 22. Case 2, Output power comparison under PSCs.

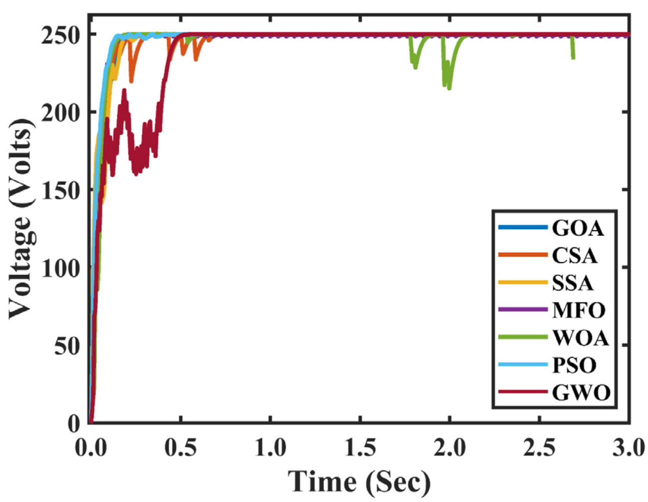

Fig. 23. Case 2, Output voltage comparison under PSCs.

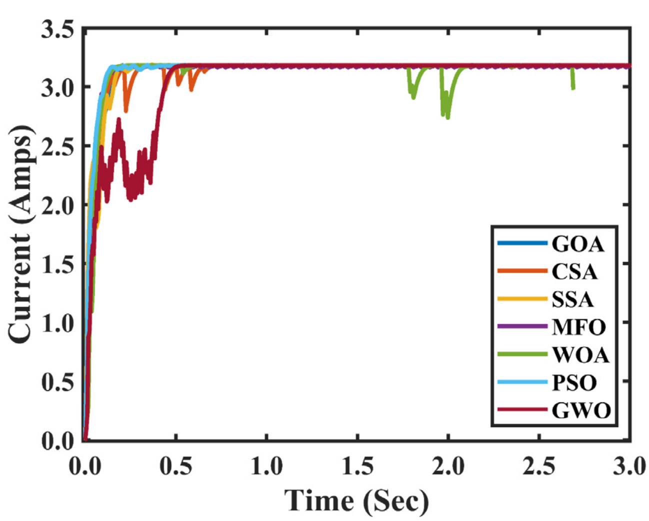

Fig. 24. Case 2, Output current comparison.

The GOA is highly resilient with enhanced tracking efficiency than P&O, ABC, PSO, DFO, PSOGS, GOA, and CSA. GOA-FLC enhances efficiency, convergence speed, tracking efficiency, and minimizes steady-state oscillations.

Improved GWO algorithm is better than the P&O, PSO, ABC, Salp-swarm-GWO, Salp-swarm-PSO, and enhanced GWO, particularly w.r.t tracking time and efficiency but less efficient than enhanced GWO. The GWO-Beta displays small power fluctuations at steady-state and better-tracing effectiveness. The GWO-GSO outperforms the P&O, PSO, GWO, and GWO-P&O for tracking time and output power.

SSA is considerably more efficient than the HC and other common metaheuristics such as PSO, butterfly algorithm, GWO, MFO, ABC, PSO-GS, PSO, and CSA.

The MAKWO outperforms the modified artificial wolf pack, ABC, and PSO approaches in terms of tracking speed. Not only does it take less time to converge, but also eliminates the issue of excessive output power fluctuations.

The OD-PSO works better than FA and P&O-PSO regarding tracking speed, dynamic performance, and output power. The PSO-OCC tracks the GMPP with greater accuracy and speed than the traditional PSO method.

6. Conclusion

The recent literature on modern swarm-based MPPT approaches is reviewed in this paper mainly focusing on PSCs. The benefits and drawbacks of each strategy are discussed and tabulated. A comparative summary was created and presented which provides an overview of the findings with the help of a case study and appropriate research reviews. The summary compares the system's efficiency, tracking speeds, converters used, experimental work, and applications. It is seen that in contrast to the standard algorithms, the hybrid swarm-based algorithms produce better outcomes. All swarm-based algorithms achieve better results when compared to PSO. The advantageous part of these strategies is that they may be used on any PV system without any prior knowledge of its nature. Some hybrid approaches, on the other hand, add complexity and the computational burden to the algorithm. The effect of irradiance and the statistical analysis of the algorithm performance is compared by testing them on a case study for 30 simulations runs. The results showed stable performance of GOA and SSA over the traditional MPPT algorithms under all weather conditions. They also ensure a high level of efficiency, rapid tracking, and minimal oscillations in the vicinity of MPP. At the end of each category, a tabular comparison is provided, which can be a useful tool in determining the most productive and ideal type of MPPT to meet the user's needs. This review is considered to be a valuable resource for all researchers working on PV systems under PSCs. Given the importance of MPPT in PSCs, it can be stated that there is a lot of room for study to develop a viable strategy for improving the algorithms' performance. Future MPPT research regarding swarm-based algorithms for PV systems can concentrate on the following aspects:

i. The detection of PSC is one area of modeling that still looks to be inadequate and requires improvement.
ii. The hybrid swarm-based MPPT algorithms have a lot of room for development.
iii. The 'weighting' parameters of the algorithms need to be optimized more carefully.
iv. The hardware implementations of these approaches are rarely covered in the existing literature. Most MPPT algorithms are tested solely through simulation. To further test the MPPT performance of various algorithms, hardware experiments should be conducted.

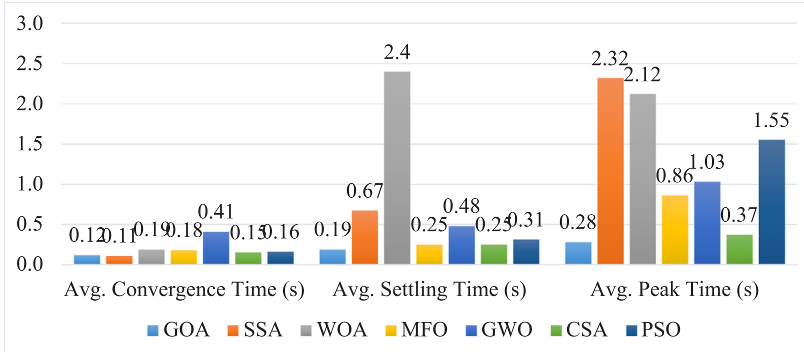

Fig. 25. Case 2. Graphical depiction of avg. convergence, settling, and peak times.

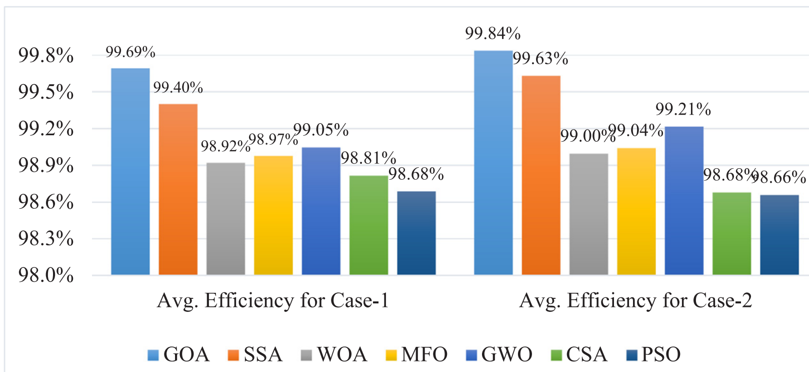

Fig. 26. Graphical representation of efficiency (%).

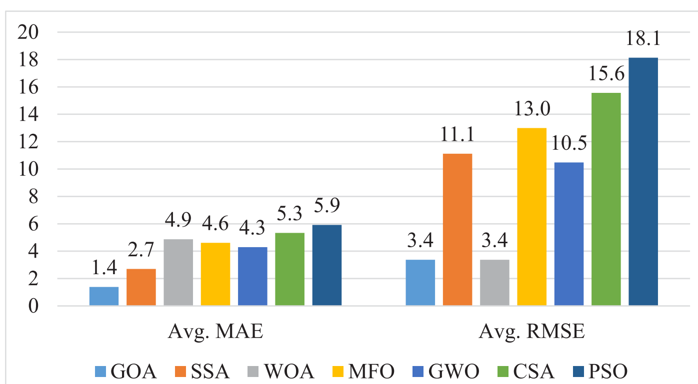

Fig. 27. Case 1, Graphical representation of avg. MAE, and RMSE.

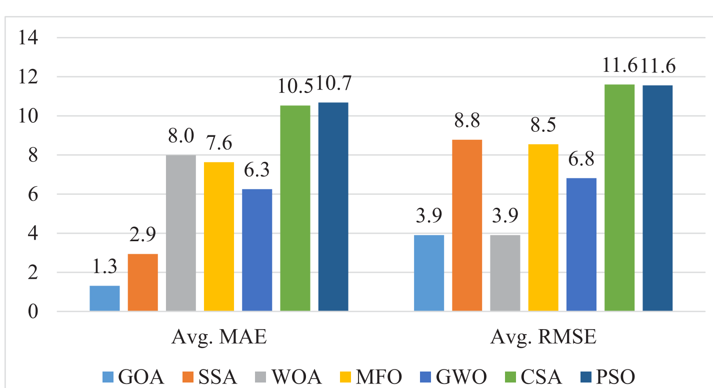

Fig. 28. Case 2, Graphical representation of avg. MAE, and RMSE.

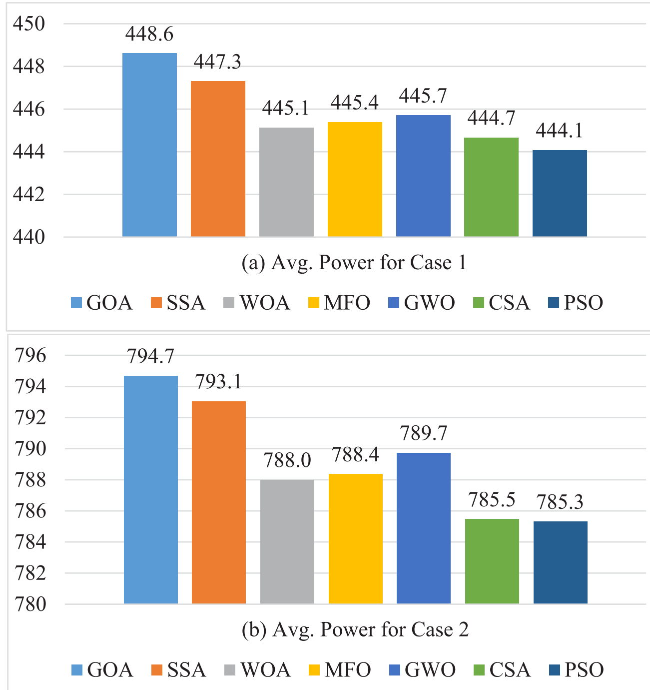

Fig. 29. Graphical representation of avg. powers for both cases.

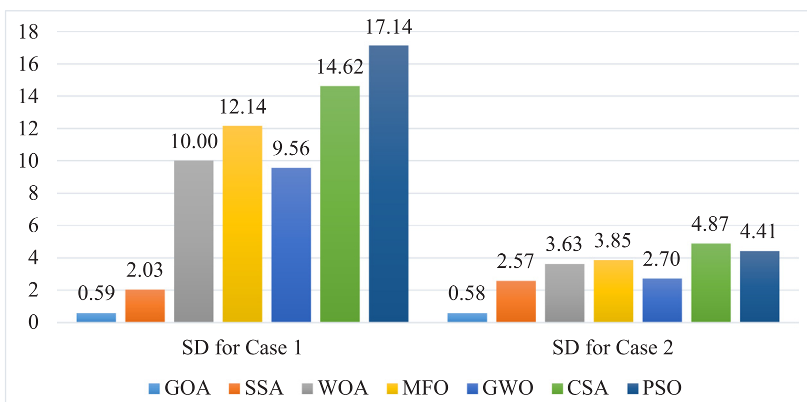

Fig. 30. Graphical representation of standard deviation (SD) for both cases.

Table 14
Comparison of different swarm-based algorithms for MPPT under PSCs.

Ref.	MPPT Method	CT/CV	App	TS (s)	Eff. (%)	Inputs	Exp.	Remarks
Goswami and Kumar Sadhu (2021)	SFA	Boost/Duty	HEV charging	–	–	V, I	Yes	EV charging station is designed with a 100 kW solar power plant. Stochastic firefly (SFA) is implemented, financial estimation, and cost estimation is presented. The proposed EV substation generates an overall gross profit of 51.85% during its lifetime, with a 12-year payback period. However, there is no comparison with other such schemes.
Prasetyono et al. (2020)	ACO & CV methods	Cuk/Duty	Street Lightning Charging	–	–	V, I	Yes	The ACO and constant voltage methods are employed for charging function of street lighting. However, there is no comparison with other such schemes, and no statics for efficiency and speed are shown after comparison.

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Table 14 (*continued*).

Ref.	MPPT Method	CT/CV	App	TS (s)	Eff. (%)	Inputs	Exp.	Remarks
Ferahtia et al. (2022)	SSA	Boost/Duty	EMS for Micro gird	–	–	V, I	Yes	An energy management system for a DC microgrid system is designed and SSA is employed to track the MPP from the solar system.
Jegha et al. (2020)	GWO	LUO/Duty	BLDC Motor drive	–	97.8	V, I	Yes	A PV system for a water pumping application with the help of LUO converter and BLDC motor drive is designed which shows better results as compared to FLC and P&O. The authors suggest extending the project for a 3-phase BLDC pumping motor.
Brindha et al. (2020)	CSA	Zeta/Duty	BLDC Motor drive	–	–	V, I	No	A CSA is used for the BLDC motor to drive a centrifugal pump.
Manickam et al. (2016)	Hybrid PSO-P&O	Boost/Duty	To reduce oscillations	8.14		V, I	Yes	A hybrid PSO-P&O algorithm is used to reduce power oscillation in string inverters and works better than P&O and PSO. However, The settling time is very high.
Ajiatmo and Robandi (2017)	FLC-FA	Boost/Duty	Solar Car	0.14	99.98	V, I	No	A hybrid FLC-FA algorithm is used to extract MP from PV system for solar car application. It works better than P&O and FLC.
Laxman et al. (2021)	GWO-FLC	Boost/Duty	Micro Grid	0.046	99.95	V, I	Yes	A GWO-FLC is proposed for microgrid applications which is more efficient than P&O and FLC. A trade-off is made among tracking speed and fluctuations. However, a comparison should be done with the algorithm having the same characteristics i.e. bio-inspired.
Khan et al. (2022)	IMFO	Boost/Duty	SA	0.34	99.89	V, I	Yes	The performance of improved MFO is tested for non-uniform temperature distribution and compared PSO, CSO, ABC, and dragonfly optimization algorithms. It is observed that the IMFO shows better performance than the competing techniques.
Eltamaly et al. (2020a)	MBA	Boost/Duty	GT	–	–	V, I	Yes	The modified BA (MBA) with re-initialization is compared with the PSO and GWO algorithms. A number of swarm vs convergence time comparison is also done which shows the superiority of MBA over the competing methods. However, no statics for efficiency and speed are shown after comparison.
Moghassemi et al. (2022)	Hybrid WOADE	Boost/Duty	GT	0.23	99.74	V, I	Yes	A hybrid WOA and differential evolution algorithm (WOADE) is compared with the WOA and DE separately and shows good efficiency and tracking speed than the two.
Mirza et al. (2021)	ISSA	Boost/Duty	SA	–	–	V, I	No	An improved SSA (ISSA) is compared with the standard SSA, CSA, PSO, and P&O and shows good efficiency and tracking speed. However, there is no comparison with the other high efficient swarm-based MPPT schemes.
Jamaludin et al. (2021a)	Hybrid SSA-HC	Buck-boost/Duty	SA	0.25	99.8	V, I	No	A hybrid SSA and hill-climbing algorithm (SSA-HC) is compared with the SSA and shows good efficiency and tracking speed than SSA. However, there is no comparison with other such schemes, and no statics for efficiency and speed are shown after comparison.
Chai et al. (2021)	Hybrid PS-FW	Boost/Duty	SA	61	99.19	V, I	Yes	A hybrid PSO with a fireworks algorithm (PS-FW) shows better performance as compared to FW and PSO alone. Though the system obtained high efficacy but the tracking time is very high even in minutes. Moreover, the startup oscillations are very high.
Sundareswaran et al. (2016)	ACO-P&O	Boost/Duty	GT	3.45	99.93	V, I	Yes	As compared to simple P&O, PSO, and ACO, a hybrid P&O-ACO approach has a faster convergence time and uses less CPU. The tracking time is increased to seconds.
Jiang and Maskell (2015)	ACO with EA	2-Buck/Duty	SA	7.3	94.1	V, I	Yes	ACO is implemented using evolutionary technique and successfully tracks the GMPP. However, the authors believe that there is a need for improvement in the scheme.

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Table 14 (*continued*).

Ref.	MPPT Method	CT/CV	App	TS (s)	Eff. (%)	Inputs	Exp.	Remarks
Jiang et al. (2013)	ACO_NPU	Boost/Duty	SA	1.2	99.1	V, I	No	The ACO with a new pheromones updating (ACO_NPU) strategy outperforms P&O, soft computing, PSO, and standard ACO when the comparison is made for tracking quickness and efficacy. There are startup oscillations in the output.
Bilal (2013)	ACO	–/Duty	SA	0.6	98.87	V, I	Yes	The system converges regardless of the initial conditions. The results are superior to P&O and PSO, but there is no comparison to any swarm-based MPPT algorithm.
Priyadarshi et al. (2019)	ACO	Cuk/Duty	SA	0.38	–	V, I	Yes	A comparison of the suggested technique with PSO, ABC, and FFA MPPT algorithms reveals that it has seven times faster convergence and tracking efficiency.
Nie et al. (2019)	MABC	Buck-boost/Duty	SA	0.39	99.91	V, I	No	A modified ABC outperforms P&O, PSO, and standard ABC w.r.t. tracking time and accuracy. However, there is no detailed comparison and the startup oscillations are increased.
Pilakkat and Kanthalakshmi (2018)	ABC	Boost/Duty	SA	–	97.75	V,I	No	It is claimed that the suggested ABC effectively tracks the GMPP with high efficiency and fast response time, but no comparison is shown with other MPPT algorithms to demonstrate superiority.
Sundareswaran et al. (2015)	ABC	Boost/Duty	SA	4.78	99.93	V,I,T	Yes	The ABC has lower output oscillations than PSO and Enhanced P&O techniques. However, the tracking time is increased.
Pilakkat and Kanthalakshmi (2020)	ABC-P&O	Boost/Duty	GT	0.1	99.59	V, I	No	For grid-connected PV systems, an improved ABC-P&O algorithm is proposed with good convergence as compared to P&O, INC, and standard ABC. In a real-time implementation, the system is more complicated and highly complex.
soufyane Benyoucef et al. (2015)	ABC	Boost/Duty	SA	3	99.35	V,I	Yes	An ABC method based on direct duty cycle control has a shorter tracking time and higher accuracy than PSO. Increased oscillations are a detriment.
Pilakkat and Kanthalakshmi (2019)	ABC-P&O	Boost/Duty	SA	0.1	99.59	V, I	No	ABC-P&O algorithm reduces maximum overshoot by 30% compared to the normal ABC algorithm. It has low power variations and a shorter tracking time as compared to P&O and INC. However, the comparison is not done with any swarm-based MPPT algorithm. Moreover, only two PV modules are considered for PSCs.
Amalo et al. (2020)	CABAT _Ns	Boost/Duty	GT	–	98.4	V,I	No	Efficient than standard BA, but the results are highly unstable.
Seyedmahmoudian others (2018)	BA	SEPIC/Duty	SA	1.4	99.8	V, I	No	More tracking and convergence speed than P&O, PSO, DE, and DEPSO. It has oscillations and more settling time than GOA.
Liao et al. (2020)	MBA	Interleaved Boost/Duty	SA	3.6	99.85	V, I	Yes	A modified bat algorithm (MBA) performs better in terms of accuracy and convergence speed than standard BA, PSO, and GWO. However, it is very slow and less efficient as compared to SSA and GOA.
da Rocha et al. (2020)	Bat-P&O	Boost/ Duty	SA	5.6	99.8	V, I	Yes	Very slow and more oscillations than PSO and GWO.
Kaced et al. (2017)	BA	Buck Boost/Duty	SA	1.6	99.9	V, I	Yes	It possesses good global search ability and dynamic performance than &O and PSO. However, settling time needs improvements.
Eltamaly (2021)	ICSA	Boost/Duty	GT	0.4	99.97	V, I	Yes	An improved performance than the standard CSA, BA, GWO, and PSO but still startup oscillations need improvements.
Nugraha et al. (2018a)	CSA–GSS	–/Duty	SA	3.3	99.87	V, I	Yes	A hybrid CSA–GSS has less tracking time than PSO and standard CSA. More settling time and oscillations are still the issues.
Huang et al. (2020)	Fusion FA	Boost/Duty	SA	2.5	89.6	V, I	No	Fusion FA is more efficient and has less tracking time than standard FA. However, startup oscillations, complexity, and settling time are high.

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Table 14 (*continued*).

Ref.	MPPT Method	CT/CV	App	TS (s)	Eff. (%)	Inputs	Exp.	Remarks
Sundareswaran et al. (2014)	Flashing FA	Boost/Duty	SA	2.1	99.97	V, I	Yes	Tracking speed and tracking efficiency are more than P&O and PSO. However, startup oscillations and settling time is very high.
Teshome et al. (2017)	MFA	Interleaved Boost/Duty	SA	1.6	98.8	V, I	Yes	A modified FA performs better in terms of convergence speed but is less efficient than standard FA. However, startup oscillations and settling time is high.
Yanuar Mahfudz Safarudin and Mauridhi Hery Purnomo (2016)	Beta FA	Buck/Duty	SA	2.18	99.4	V, I	No	Tracking speed and convergence accuracy are more than standard FA, P&O, and PSO. However, startup oscillations and settling time is very high.
Safarudin et al. (2015)	FA-P&O	Buck/Duty	SA	1.8	99.67	V,I,T	No	A hybrid FA-P&O has tracking rapidity and convergence precision more than standard FA and P&O. However, startup oscillations and settling time is very high.
Sridhar et al. (2021)	GOA	Buck/Duty	SA	3.05	99.66	V, I	No	Very efficient and smooth output curve. The settling time is high.
Wijaya et al. (2020)	GOA-INC	Interleaved Boost/Duty	SA	2.385	99.9	V, I	Yes	A hybrid GOA-INC outperforms the PSO and modified FA for productivity and tracking effectiveness. However, the startup oscillations and high settling time are the main drawbacks.
Mansoor et al. (2020b)	GOA	Boost/Duty	SA	0.298	99.85	V, I	No	The proposed GOA method is better than P&O, PSO, PSOGS, CSA, ABC, and dragonfly optimization w.r.t. efficiency, tracking speed, and convergence time. Startup oscillations and high settling times are the main issues.
Guo et al. (2020)	IGWO	BFBIC/Duty	AC	0.35	98.54	V, I	No	Improved GWO has high tracking speed and fast convergence than P&O, ABC, SSA-GWO, EGWO, and PSO. There are startup oscillations and a high settling time.
Mohanty et al. (2017b)	GWO	Boost/Duty	SA	–	99.8	V,I	Yes	A GWO outperforms P&O and PSO. Smooth output curves. However, the comparison is done with the algorithm having the same characteristics.
Mohanty et al. (2017a)	GWO-P&O	Boost/Duty	SA	2.4	99.9	V, I	Yes	A hybrid GWO-P&O has a low tracking time and fast convergence than P&O and PSO.
Mohanty et al. (2016)	GWO	Boost/Duty	SA	3.18	99.81	V, I	Yes	Proposed GWO has low tracking time and fast convergence than P&O and improved PSO.
Xiang et al. (2018)	IGWO	Boost/Duty	GT	0.83	99.88	V, I	Yes	Improved GWO performs better than standard GWO in terms of efficiency. High startup oscillations and more settling time are the drawbacks.
Wan et al. (2019)	SSA-GWO	Buck-boost/Duty	SA	0.82	99.82	V, I	No	A hybrid SSA-GWO is more efficient than PSO and standard SSA. However, the system becomes complex. The settling and tracking time are increased with more startup oscillations.
Jamaludin et al. (2021b)	SSA	Buck-boost/Duty	SA	0.22	99.87	V, I	Yes	The proposed system has a fast-tracking and convergence speed than HC, GWO, BOA, PSO, and GOA.
Mirza et al. (2020)	MSSA	Boost/Duty	SA	0.25	99.32	V, I	Yes	Shows better performance w.r.t. tracking time and convergence speed than ABC, PSO, PSOGS, DFO, and CSA. However, settling time still needs to be reduced and the startup oscillations are also present.
Mao et al. (2020c)	DWSSA	Cuk/Duty	SA	0.04	98.93	V, I	Yes	The proposed system has fast-tracking and convergence speed than SSA, SSAGWO, and SSAPSO. However, there is a drop in efficiency.

Ref: References **CT:** Converter Type **CV:** Control Variable **App:** Applications **SA:** Standalone **GC:** Grid-Tied **MG** = Micro grid,
V, I: Voltage, Current **Exp:** Experimental setup included? **TS**: Tracking Speed.
ACO_NPU = ACO with new pheromones updating, BFBIC = Boost full bridge isolated converter, AC = Alternating Current.
OGWO = opposition-based learning gray wolf optimization, DWSSA = dynamic nonlinear w factor SSA.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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