State of the art artificial intelligence-based MPPT techniques for mitigating partial shading effects on PV systems – A review

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A B S T R A C T

Given the considerable recent attention to distributed power generation and interest in sustainable energy, the integration of photovoltaic (PV) systems to grid-connected or isolated microgrids has become widespread. In order to maximize power output of PV system extensive research into control strategies for maximum power point tracking (MPPT) methods has been conducted. According to the robust, reliable, and fast performance of artificial intelligence-based MPPT methods, these approaches have been applied recently to various systems under different conditions. Given the diversity of recent advances to MPPT approaches a review focusing on the performance and reliability of these methods under diverse conditions is required. This paper reviews AI-based techniques proven to be effective and feasible to implement and very common in literature for MPPT, including their limitations and advantages. In order to support researchers in application of the reviewed techniques this study is not limited to reviewing the performance of recently adopted methods, rather discusses the background theory, application to MPPT systems, and important references relating to each method. It is envisioned that this review can be a valuable resource for researchers and engineers working with PV-based power systems to be able to access the basic theory behind each method, select the appropriate method according to project requirements, and implement MPPT systems to fulfill project objectives.

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1. Introduction

The demand for photovoltaic (PV) power generation in power systems and the distribution sector is growing significantly. Research shows that the contribution of PV systems to energy generation was approximately 14,000 MW in 2010 and is expected to be 70,000 MW in 2020 [1]. Australia is a leader in utilizing solar energy resources [2], and had a solar power generation capacity of 115 MW in 2009, which contributed an estimated 0.1–0.2% of the total electricity production. Given the hot, dry, and sunny climate, ideal for solar energy utilization, there is a projected target for 20% of total electricity supply to derive from renewable energy by 2020 [3]. Despite recent advancements in PV utilization-related factors, such as reduction in cost, cell efficiency increases, and improved structural integration to buildings [1], the low energy conversion efficiency of PV systems remains a major impediment to utilization of PV power generation and being able to accurately achieve maximum power point tracking (MPPT) is critically important. Another challenge with PV power generation is the heavy dependence on environmental factors, including solar irradiance and ambient temperature. Therefore, the control unit must be compiled through a capable MPPT technique to harvest the maximum energy from the output terminal of installed PV arrays by providing an appropriate duty cycle to operate the embedded DC-DC converter. Considering all affecting factors such as material efficiency, integration, and structural configuration, boosting the MPPT capability is the most economical way of enhancing the efficiency of the overall PV system [4].

Numerous studies have been undertaken to track the maximum power point (MPP) from the output of PV systems subject to uniform irradiance levels. The perturbation and observation (P&O) [5–9], hill climbing [10–14], incremental conductance [15–21], short-circuit current, open-circuit voltage, and ripple correlation methods are the most popular of conventional approaches to MPPT tracking. The main advantages of these methods are the use of a simple structure and fast convergence towards the MPP. These methods however are only able to provide a reliable duty cycle signal when a single MPP exists at the output of the PV system. Using bypass diodes within the circuitry of most of the current PV modules increases the possibility of partial shading conditions (PSCs). The main consequence of these conditions is the occurrence of multiple peaks at the output power-voltage locus. When multiple peaks appear at the output because of PSCs, conventional methods fail to distinguish global MPPs (GMPPs) from local MPPs. The main reason for this failure is that the aforementioned techniques are based on hill-climbing theory, where the operating point being followed shifts in the direction where the output power is maximized [22].

Considering these problems with partial shading, several studies have been performed to modify the performance of conventional methods [23,24]. These modifications however are achieved through extensive mathematical computation, which can require a powerful and expensive controller. In addition, the modified methods can only track the MPP under a limited number of PSCs. Given the unpredictability of environmental conditions, these methods can be unreliable in tracking the MPP. Different studies have been recently performed where soft computing and artificial intelligence (AI)-based methods were applied to address the detrimental effects of PSCs. The robustness, flexibility, and reliability of soft computing and AI make these methods highly suitable for PSCs. According to the growing number of studies published in this field, a thorough study of recent developments in MPPT methods is essential.

A number of valuable studies have been conducted to review the performance of MPPT methods [4,25–34]. Most of these reviews however are limited to discussing the advantages and drawbacks of the approaches without adequate detail to understand the procedures and structures of these methods. This lack of detail in the description is mainly due to the fact that the papers aim to cover all conventional and new approaches. Due to the emergence of PSC problems however, the selection of MPPT techniques requires new considerations so as to make sure they are applicable for environmental conditions typical to partial shading. Thus, most studies use AI-based MPPT methods and validate these methods under different environmental conditions. This paper first focuses on the performance evaluation of recent research relating to six commonly used AI-based techniques capable of MPPT subject to PSCs. To complement the review of these six common techniques, this paper also discusses emerging techniques which despite only having been discussed in a limited number of publications, have demonstrated very good performance in addressing the shortcomings of other MPPT methods under partial shading conditions. The procedures and structures of all the methods are described in sufficient detail to enable
researchers and engineers to select the most appropriate MPPT technique.

2. Photovoltaic system characteristics

2.1. Normal conditions

Fig. 1 presents a single-diode circuitry for a PV cell. The output of PV systems is directly affected by solar irradiance and temperature. Thus, the latest values of these factors should be employed to obtain the MPP. In addition, the mathematical model of PV changes with the short-circuit current ($I_{sc}$) and open-circuit voltage ($V_{oc}$) were obtained from the data sheet provided by the cell manufacturer.

Hence, the generated power of a single solar cell is inadequate for any convenient application. Thus, the cells in a PV system should be connected either in series or in parallel to enhance the overall capability of the system, which ensures that all cells in the PV module ($N_s$, considering the given number of cells) contribute to the output power. The module output can be obtained through the following:

$$F(I_{pv}, V_{pv}, T, G) = I_{ph} - I_{pv} - I_0 \left[ \exp \left( \frac{q(V_{pv} + I_{pv}R_s)}{N_sAKT} \right) - 1 \right] - \frac{(V_{pv} + I_{pv}R_sN_s)}{R_pN_s}$$

(1)

where $I_{pv}$ and $V_{pv}$ are the output current and output voltage, respectively, to be added through the load or network grid; $I_{ph}$ is the solar-generated current; $I_0$ is the diode saturation; $A$ is the diode ideality factor; $q$ is the electron charge constant ($q = 1.602 \times 10^{-19} \text{C}$); and $K$ is the Boltzmann constant. In Eq. (1) the parallel resistance ($R_p$) generally has a high value and sometimes assumes infinity in the PV module modeling because of the slight impression of $R_p$. By contrast, the series resistance ($R_s$) value cannot be disregarded because of the effect of $R_s$ on output power.

Fig. 2 depicts the output of the KC85T PV module in this study. This module provides a power of 87 W at a terminal voltage and current of 17.4 V and 5.02 A, respectively.

2.2. Partial shading conditions

The entire PV system or some parts of this system may be shadowed by clouds, tall trees, and high buildings in outdoor environments. This scenario causes non-uniform insolation conditions. The part of the PV modules that receive uniform irradiance continues operating at optimum efficiency during PSCs. Fig. 3 shows that shaded cells are imposed to operate with reverse bias voltage to provide the same current as the unshaded cells because the current that flows through every module in a series configuration is constant. However, the resulting reverse power polarity consumes power and reduces the extractable output power of the shaded PV system. Continuous operation of the shaded cells in excessive reverse bias voltage can result in hot spots and cause an open circuit in the entire PV array. This phenomenon is usually solved by inserting a bypass diode into a predefined number of cells in the series circuit [35].

Fig. 4 shows k-series-connected PV modules with the allocated bypass diodes of the modules in the array. The characteristics of the PV system with the bypass diodes are different from those without such diodes. Given that bypass diodes provide an alternate current path, the cells of the module do not have the same current in PSCs. Therefore, the P–V curve creates multiple maxima. This occurrence is a crucial issue, and most common MPPT techniques cannot determine the difference between local and global maxima. Therefore, a proper MPPT technique should be able to distinguish the global maximum among multiple local maxima.

Fig. 5 shows how extractable MPP differs in the shaded PV array with and without bypass diodes. In the following step, the
performance of common AI-based MPPT methods under normal and PSC conditions is evaluated.

3. Common SC based MPPT techniques

3.1. Artificial neural network

3.1.1. Theory

Artificial neural network (ANN) is one of the most reputed methods among all soft computing methods that model the operations of biological neural systems. Basically, neural networks are collections of interconnected processing units called neurons, through which signals and information pass. ANN can be considered a mathematical model of a brain-like system that functions as a parallel processing network. This system should undergo an extensive and careful training process to learn how to reflect the input patterns in the actual system. Notably, any ANN system is normally trained to function in predetermined systems and conditions because ANN neurons are trained to process and respond based on the in-out pattern relationship of the system. Therefore, for any system change, the designed ANN should undergo a retraining process to avoid producing unreliable and inaccurate responses [4,37].

An ANN does not require complex mathematical functions and physical models when managing a system. An ANN can create predictive functions from multidimensional data resources. Nowadays, ANN is used in a wide range of engineering applications, such as pattern identification, environmental factor forecasting, energy production estimation, and electrical load prediction. An ANN system is favorable for complex and ill-defined problems, where fuzzy or incomplete information are involved and a decision is normally made based on intuition. However, such a system normally cannot handle problems that require high accuracy and precision [38].

The basic structure of an ANN comprises the following three layers: input, hidden, and output. The schematic diagram of a multilayer feed forward structure is presented in Fig. 6. As shown in this figure, the neurons in each layer are connected through synaptic weights of the other neurons in the previous layers. Knowledge is usually stored as a set of connection weights (which presumably correspond to synapse efficacy in biological neural systems). Training is the process of modifying the connection weights methodically by using a suitable learning method. A network uses a learning mode, where an input is presented to the network along with the desired output, and the weights are adjusted for the network to attempt to produce the desired output. After training, the weights contain meaningful information, whereas the weights are random and meaningless before training [38].

3.1.2. ANN based MPPT

In ANN-based MPPT, the input variables are normally selected as PV system parameters, such as short-circuit current, open-circuit voltage, terminal voltage, output current, or environmental factors, which include irradiance level, module temperature, and wind speed [39,40]. These variables are received in the input
layers, processed in the hidden layers, and provide the required signals in the output layer. Selecting the input variables and the number of nodes significantly depend on system complexity, designer knowledge, and data availability.

The capability and accuracy of ANN-based MPPT largely depend on the functionality of the algorithm in the hidden layers and training process. Several months or even years are required for training procedures to boost the functionality of ANN-based MPPT under various environmental conditions. To monitor MPP with high accuracy and precision, the associated weights of the neurons should be obtained through an intensive and comprehensive training process. During this process, neurons are weighted in accordance to the input–output relation of the targeted PV system. Therefore, the trained ANN for this PV system, which has a particular specification, might not respond properly in other types of PV systems. The output variable is normally the signals by which the operation point approaches the MPP region. The most common output signal selected in literature to provide control signals for a DC–DC controller is the duty cycle or voltage Ref. [4].

The performance of the ANN method in identifying solutions according to unknown parameters motivates researchers to employ this method when monitoring the MPP while considering environmental factors. Hiyama et al. [41] used the ANN approach in the MPP to track the system under normal conditions. In the proposed method of the authors, open circuit voltage is considered the input, while the required operating voltage serves as the output signal. Authors in [42] used a radial basis function network to predict the MPP of a PV system. According to the authors, in contrast to conventional MPPT methods, the proposed method can track MPP without searching around the optimal power point. In [43], the authors propose the ANN peak power tracking of a PV that supplies a DC motor that drives two different load torques. In this study, gradient descent algorithm is used to train the proposed ANN-based MPPT controller. Bahgat et al. proposed an ANN-based MPP tracking approach, as presented in [44], which can transmit around 97% of the actual maximum generated power of the PV system under a uniform insulation level. In [45–48], the ANN method is used to track the MPP using back-propagation neural network. In such systems, more nodes are used in the hidden layer, thereby possibly producing more accurate results. However, a controller cannot respond properly to fast irradiance change conditions (FICCs) when using numerous nodes [44,49].

The application of ANN-based MPPT under FICCs has been presented in some research recently [40,50]. In [40], Liu et al. developed and proposed neural network to obtain the parameters of an emulated MPP locus. According to the authors, the main advantages of the developed method are fast tracking speed and high dynamic and static efficiency to track the MPP under FICCs. However, the proposed method cannot work under PSCs. Laudani et al. [50] proposed an MPPT algorithm based on neural networks embedded in a low-cost microcontroller. The output results confirm the accurate performance of the proposed method under abrupt changes in environmental parameters. However, the validation results are limited to the simulation investigations. Some references used ANN is used in order to improve the performance of P&O method by detecting the variation in environmental conditions [51–53]. However, the proposed methods cannot monitor the MPP if the PV system operates under PSCs. This drawback is mainly caused by the uncertain behavior of the PV system under PSCs and the dependency of the ANN training process on previous data.

Given this problem, various researchers utilized the advantageous characteristics of the ANN method to optimize or tune the parameters of other established MPPT methods. For instance, Punitha et al. [54] presented an ANN-based modified incremental conductance method as the main approach to monitor the MPP of a PV system under PSCs. This proposed method is validated by simulating a field-programmable gate array-based experimental verifications. The performance of the algorithm is compared with that of P&O and fuzzy-based modified hill climbing algorithms. The results show the effectivity of the proposed approach in tracking the MPP under PSCs. However, the accuracy and precision of the output signal is still dependent on the ANN training process. Furthermore, the back-propagation learning rule is used to adjust the network weights. Thus, the system may not function properly under abrupt climatological changes. Xu et al. [55] employed a two-stage algorithm, where ANN uses the results of the traditional incremental conductance method as the training data. The system performs satisfactorily under normal conditions and FICCs. However, the system has not yet been tested under PSCs. In addition, the validation is limited to the simulation results. Ramaprabha et al. [56] developed a method based on genetic algorithm (GA)-optimized ANN to enable a controller to operate under PSCs. This method is validated under several simulated PSCs. However, the system cost increases when insulation and temperature data are used for the training process. A brief summary of studies employed ANN method for MPPT unit is presented in Table 1.

![Schematic diagram of the multilayer feed forward structure.](image-url)
3.2. Fuzzy logic control

3.2.1. Theory

Fuzzy logic control is one of the most commonly used techniques in different engineering challenges because of its multi-rule-based characteristics [57]. Fuzzy logic control has a simple and clear procedure because exact mathematical modeling and technical quantities of a system are not required for this controller [58]. In this technique, the variables manage some non-numeric and linguistic actual values that range between completely true and completely false values, such as high, low, medium, and often [59]. In fuzzy logic controller optimization, everything is defined according to the matter of degree, exact reasoning is replaced by approximate reasoning, the mathematical model of this system is not required, and decision is based on estimated values [37,60].

The technique comprises three different steps: fuzzification, rule interference diagram, and defuzzification. A block diagram of this technique is shown in Fig. 7. The input variables of a fuzzy logic controller highly depend on the controller design, but these variables are generally known as error “e” and variation in error “Δe.” The definition of these input variables, given the fuzzification steps and the output signals received from the defuzzification step, is determined by the requirements of the targeted problem. The three main stages in the fuzzy logic process are described as follows:

3.2.1.1. Fuzzification. The input values in this stage are fuzzified by some predefined membership functions. The main task of fuzzification is to convert crisp values to linguistic values via membership functions. Different membership functions exist, such as trapezoidal, Gaussian, and triangular. However, the triangular membership is the most popular, as shown in Fig. 8. The acronyms “NB,” “NS,” “Z,” “PS,” and “PB” in this figure represent negative big, negative small, zero error, positive small, and positive big, respectively [61,62]. In general, the quantity of membership functions is more effective than the type and shape in terms of system speed and accuracy. More membership functions, which are recommended for more complex engineering problems, result in higher accuracy and longer processing time. By contrast, fewer designed membership functions result in faster processing time and higher possibility of diversity.

3.2.1.2. Rule interference. This stage is designed to control the output variables according to an inference engine. The inference engine applies rules to membership functions using a rule base table. Five rule-based inferences are shown in Table 2. The design of these rules is based on the “if-then” concept and requires designer knowledge about the systems. Mamdani’s inference method is the most common method that uses the max–min operation approach.

3.2.1.3. Defuzzification. Membership functions are once again employed to convert output linguistic values into relevant crisp and numerical values. However, the range of the membership functions used in this section may vary based on designer knowledge. Several defuzzification techniques exist, such as center of area and mean of maxima; the latter is more common in control Table 1
The brief summary of some of the applied ANN-MPPT in the literature.

<table>
<thead>
<tr>
<th>Method</th>
<th>References</th>
<th>Remarks</th>
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<tbody>
<tr>
<td>ANN</td>
<td>[41–44]</td>
<td>The standard ANN method is employed for the MPPT of the PV system under normal conditions, but the tracking fails under FICC.</td>
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<tr>
<td></td>
<td>[45–48]</td>
<td>Back-propagation neural network is used to increase the accuracy of the system.</td>
</tr>
<tr>
<td></td>
<td>[40,50]</td>
<td>The modified ANN is employed to track the MPP under FICC.</td>
</tr>
<tr>
<td></td>
<td>[31–33]</td>
<td>ANN method is employed in order to improve P&amp;O functionality.</td>
</tr>
<tr>
<td></td>
<td>[34]</td>
<td>The ANN method is proposed to modify the incremental conductance method to track MPP under PSCs.</td>
</tr>
<tr>
<td></td>
<td>[55]</td>
<td>A two-stage algorithm is employed. Satisfactory results are obtained under normal conditions and FICC, but the verification fails under PSCs.</td>
</tr>
<tr>
<td></td>
<td>[56]</td>
<td>An ANN method is developed to optimize the GA technique to track the MPP under PSCs.</td>
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Fig. 7. FLC block diagram.

Fig. 8. Membership function of FLC.

Table 2
Rule base table of FLC.

<table>
<thead>
<tr>
<th>ΔE</th>
<th>E</th>
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<tbody>
<tr>
<td></td>
<td>NB</td>
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<tr>
<td>NB</td>
<td>ZE</td>
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<tr>
<td>NS</td>
<td>ZE</td>
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<td>Z</td>
<td>NS</td>
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<td>PS</td>
<td>PS</td>
</tr>
<tr>
<td>PB</td>
<td>PB</td>
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applications [63].

### 3.2.2. FLC-based MPPT

In MPPT applications, the input variables of the fuzzification step in an FLC system can be calculated by using the following equations:

\[
e(t) = \frac{\Delta P(t)}{\Delta V} = \frac{P(t) - P(t-1)}{V(t) - V(t-1)}
\]

where \( t \) is the sampling time; \( P(t) \) and \( V(t) \) are the power and voltage values at the operating point, respectively; \( \Delta e(t) \) defines the direction of the operating point in the next movement of the operation; and \( e(t) \) is the position of the operation point in the \( P-V \) locus with respect to the maximum power point.

In the next section, the fuzzy rules, as mentioned in Table 2, are used to determine the MPP based on “THEN Changes applied AND power increased THEN continue the direction” to define the required change in duty cycle of a DC–DC converter. Finally, defuzzification converts the output of the rule base section into non-fuzzy values. In MPPT applications, only the centroid method is used to define the proper duty!ycle variation as the output of the MPPT controller based on fuzzy logic scheme.

### 3.2.2.1. Early research

According to literature, different researchers have tested the fuzzy logic-based MPPT method in various PV systems and under different environmental conditions [64,65]. In early studies, the authors in [66] introduced the fuzzy logic controller as MPPT, where \( \Delta P_p / \Delta I_p \) and its change [67] are considered fuzzy controller inputs. The main problem of the proposed method is the inefficiency of the dynamic response under FICCs. Simon et al. [67] improved the dynamic response of fuzzy controller through duty cycle and power variations (\( \Delta D_k \) and \( \Delta P_p \)) as inputs for the system. However, the accuracy of the system is still limited under varying irradiance and temperature conditions. Methods of improving fuzzy logic controller for better dynamic characteristics and accuracy have been introduced by the authors in [63] and [68]. In [63], the authors selected three input variables, namely, \( \Delta P_p / \Delta I_p \), \( \Delta I \) \( \Delta P_p / \Delta I_p \), and duty cycle variation (\( \Delta D_k \)), whereas temperature and irradiance values are the inputs in [68]. Both systems show an accurate dynamic response under environmental parameter variations. In [69], the authors considered the instantaneous values of voltage and power at the output of the PV system as the input of the FLC system and verified the efficiency of the proposed method for a stand-alone PV water pumping system. Liu et al. [70] designed an FLC-based MPPT method according to an asymmetrical membership function concept. The final results show improvements of 42.8% and 0.06% in transient time and higher MPPT tracking accuracy, respectively, compared with the symmetrical FLC-based MPPT approach. However, similar to previous references, the proposed methods have the following significant drawbacks [71]: first, these methods largely depend on the shape of membership functions and the rule base interference. Second, the designers of these methods require a comprehensive knowledge of the PV system operation; insufficient knowledge would usually cause an inefficient and slow system.

#### 3.2.2.2. Reduction of designer dependency via the optimized FLC

To reduce the effects of the aforementioned drawbacks, some researchers have attempted to optimize or combine normal fuzzy logic controller with other methods. In [72] and [73], the authors optimized the performance of fuzzy logic controller through GA and particle swarm optimization (PSO) approaches, respectively. In [65], the authors improved the performance of normal fuzzy logic controller together with the fuzzy cognitive network. In such a system, different nodes exist, which represent the operational and control variable of a PV system. Node interconnection weights are determined by using data to cover the PV system under different environmental conditions. When the system is trained, the system can be mounted in any PV system. The method has a fast tracking speed under normal conditions. In [74–79] the FLC in combination with other methods has been used in order to increase the system independency of MPPT unit. In [80] authors used a single input fuzzy logic controller to reduce the complexity and hence achieved a faster and easier implementation. Authors in [81] used an adaptive neuro-fuzzy solar cell model to estimate the function of the array junction current in order to improve the efficiency of array power and reduce the hardware setup. However, like methods presented in [65,72–80], it cannot, or at least have not been verified, to track the MPP under PSCs.

#### 3.2.2.3. Performance under partial shading conditions

Recently, several researchers have used the FLC approach to improve the performance of MPPT controller under PSCs. In [82], fuzzy logic is applied to define the perturbation size in a proposed P&O technique. In [64], fuzzy logic controller is used to enhance the performance of the hill climbing method by scanning and storing the MPP during the P&O procedures. The proposed methods in both references perform satisfactorily in determining the GMPP under certain PSCs. The authors in [83] optimized normal fuzzy logic controller by using the GA approach, which has been successfully tested under PSCs. In [59], FLC with ANN is employed to track the GMPP. In this method, irradiance level and cell temperatures are the main inputs to train the ANN process to determine the MPP. However, this information cannot be acquired in some shading conditions. However, these methods require extensive computations, which make them too complex for commercial use. In addition, this method requires extensive computations in the fuzzification, rule base, and defuzzification stages. The highlights of studies employed FLC-MPPT have been presented in Table 3.

### 3.3. Particle swarm optimization

#### 3.3.1. Theory

PSO is one of the metaheuristic search tools that receive considerable attention in engineering applications. PSO was first introduced in 1995 by Kennedy and Ebrahat; this method is inspired by the natural behavior of birds flocking [84–86]. This theory

<table>
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<th>Method</th>
<th>References</th>
<th>Remarks</th>
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<tr>
<td>FLC [63,66–71]</td>
<td>Standard FLC was for MPPT application. These methods were significantly dependent on the designer knowledge about PV system and also the membership functions. In addition the methods were unable to track MPP under PSCs.</td>
<td></td>
</tr>
<tr>
<td>[72–79,65]</td>
<td>Optimized FLC was employed. The methods were more independent and very fast, however unable to operate under PSCs.</td>
<td></td>
</tr>
<tr>
<td>[64,83,54,59]</td>
<td>Hybrid methods including FLC and other methods such as P&amp;O, ANN and GA were designed and tested. The ability to operate under some PSCs is improved. The complexity increased.</td>
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basically explores a specific area called the solution space, where each location has a possibility degree for the solution of problems. The PSO moves each particle throughout the solution space to determine the optimum solution according to the individual and neighboring particle experiences of the PSO during optimization. Therefore, particles involved in optimization use the memory of the particles to modify the particle fitness by following the behavior of the successful particles in the swarm.

The PSO procedure starts with a random particle (initialization), continues by searching for optimal solutions within the past iterations (movement), and then evaluating the particle quality according to the fitness function (evaluation) [87]. The main steps of this algorithm are described as follows.

### 3.3.1.1. Initialization

In this step, PSO defines the population size by randomly selecting the participant particles during optimization. The particle are selected from D-dimensional solution space, where D is determined based on the number of variables for optimization. Given the unavailability of information about the system operation, the particles in the initialization step are randomly selected and optimized through the succeeding steps of the algorithm.

### 3.3.1.2. Movement

The current position ($X_i$) of each particle is left with the speed of ($V_i$) to stochastically explore the search space and determine a better solution. The movements of the particles are in accordance with the best ($P_{bi}$) position and global best ($G_b$) position of the particles. Particularly, $P_{bi}$ is the best position experienced by the $i$-th particle throughout all previous iterations, while $G_b$ is the best position experienced by the sum of all the particles within all the past iterations.

During optimization, the particles adopt the values of the objective function, while the $G_b$ and $P_{bi}$ of the particles are recorded. The basic PSO algorithm that defines the next position of the candidate solution is as follows:

$$\begin{align*}
V_{i}^{k+1} & = w \times V_{i}^{k} + r_1 \times c_1 \times (P_{bi} - X_{i}^{k}) + r_2 \times c_2 \times (G_b - X_{i}^{k}) \\
X_{i}^{k+1} & = X_{i}^{k} + V_{i}^{k}
\end{align*}$$

where $i$ represents the optimization vector variable, $k$ is the number of iterations, $V_{i}^{k}$ and $X_{i}^{k}$ are the respective velocity and position of the $i$-th variable within $k$ iterations, $w$ is the inertia weight factor, $c_1$ is the cognitive coefficient of the individual particles, $c_2$ is the social coefficient of all the particles, and $r_1$ and $r_2$ are the random selected variables in the range $[0, 1]$. These random parameters mainly aim to maintain stochastic movement within the iterations. To maintain the search space in a certain area, the velocity values are set to the range of $[0, V_{max}]$.

In PSO, the parameters $w$, $c_1$, and $c_2$ are highly mutable. A slight change in the values of these parameters may affect the speed and accuracy of the algorithm. The optimization may involve the local maximum through any poor design for $c_2$, and the optimization accuracy can be diminished by the inappropriate value of $c_1$. Similarly, the influence of inertia weight on the speed and convergence of PSO is substantial; a large value for this parameter causes slower convergence, whereas a small value produces a narrower search space range. In conclusion, a shift in the values of inertia weight encourages the particles at the initial stages to diffuse before gradually limiting the search space in the final iterations. The behavior of the inertia weight values is shown in Fig. 9.

### 3.3.1.3. Evaluation

The fitness of the particles in the new location is evaluated and saved to improve the particle movements in the succeeding iterations. The best self-experienced location ($P_{bi}$), which records the best position experienced by the $i$-th particle up to the current iteration, is updated once Eq. (4) is satisfied. In addition, the variable ($G_b$) records the $G_b$ experienced location met by all contributed particles throughout the past iterations and is compared with the $P_{bi}$ in each iteration. The update condition of $G_b$ and $P_{bi}$ is presented in Eq. (7) and Eq. (8). These equations indicate that $G_b$ is only recorded as $P_{bi}$ if the conditions below are satisfied.

$$\begin{align*}
P_{bi} & = X_{i}^{k} \quad \text{if} \quad F(X_{i}^{k}) \geq F(P_{bi}). \\
G_b & = P_{bi} \quad \text{if} \quad F(P_{bi}) \geq F(G_b).
\end{align*}$$

The particles continue to operate until the stopping conditions are met. This condition is designed based on the complexity of the system, required accuracy, and time limitation of the control process. The flowchart of described steps of PSO is presented in Fig. 10.

#### 3.3.2. PSO-based MPPT

In the MPPT application, the search space depends on the configuration of the PV system. For example, if an MPPT controller is designed to control D number of converters, the search space would be D-dimensional, where each dimension represents a voltage value as a solution to the problem. The evaluation of the particles is based on the output power of the PV panel, which is denoted by $F$ as the fitness evaluator. Eq. (8) shows the location matrix of the particles as a solution to the MPPT problem in the D-dimensional search space.

$$X_{i}^{k} = \left[ X_{i1}^{k}, X_{i2}^{k}, X_{i3}^{k}, \ldots, X_{i1}^{k}, \ldots, X_{iN_{-1}}^{k}, X_{iN}^{k} \right].$$

where $X_{i}$ is the location of the $i$-th particle at the $k$th iteration. Practically, the generated power fluctuates because of variations in the insolation levels and partial shading degrees. Therefore, the algorithm should be initialized when Eq. (9) is satisfied. If this step is neglected, the actual values of the acquired $P_{bi}$ and $G_b$ values should not be considered.

$$\left| \frac{F(X_{i+1}) - F(X_{i})}{F(X_{i})} \right| > \Delta P$$

#### 3.3.3. Discussion and previous studies

The idea of using PSO approach as a tool for tracking the MPP initially emerged to improve the efficiency of MPPT controller under PSCs. Tracking the global MPP by using the PSO method makes the controller system independent, fast, and robust in PSCs. The PSO-based MPPT approach has been presented in several studies [22,26,88–90].
3.3.3.1. Early studies. A highly efficient PSO-based MPPT was employed by adding repulsive force to the PSO algorithm to track the MPP under climatological changes [88]. The study proves the reliability of the proposed technique under frequent environmental changes. The PSO approach has been proposed to track the global maximum from the output characteristic of a modular PV system [22,89]. The system cost has been significantly reduced as the number of sensors is reduced in the experimental implementations. However, using standard PSO imposes several limitations on the control system. In the standard PSO, high velocity must be used for a particle whose position is too far from the position of the best particles (Gbest), which is defined as the best experienced position of all particles. In addition, the trajectory of the particles is limited by designed acceleration. Low acceleration results in a smooth trajectory for particles but slow convergence. By contrast, high acceleration may accelerate computation but may lead the particles toward infinity [91]. In addition, a random coefficient in the cognitive and social parameters of the PSO component significantly affected the performance of the algorithm, which requires intensive knowledge for optimum parameter tuning. The low-valued random coefficients result in slight movement of the particles. Therefore, more iterations are required to find the optimum values. On the other hand, large-valued random coefficients increase the step size of particle movement, which can lead them out of the search space margin or in the local MPP. In addition, the initial location of the particles significantly affects the convergence quality and speed of the algorithm.

3.3.3.2. Improved version. Some studies have modified the standard PSO technique [92–94]. Chowdhury et al. [92] modified the perception radius and search direction of each agent in accordance with its performance improvement throughout algorithm iterations. In the adaptive perceptive PSO method, all agents should scan their own range of the search space. The modification significantly increases the accuracy of the algorithm to find the global maximum. However, in this method, the additional dimensional search space leads to an assignment of a higher number of particles and consequently boosts the computational burden and complexity of implementation. Ishaque comprehensively studied the improvement of the PSO technique in [93] and [94]. In [66], steady-state oscillation was reduced by using the PSO method in conjunction with the direct duty cycle method. In [94], a fast and accurate global tracking method was achieved by using a proposed deterministic PSO method. In this method, the convergence and the accuracy of the PSO-based method to find the global MPP was enhanced by eliminating random numbers. However, the removal might reduce the reliability of the method under intensive mismatching condition as the algorithm loses the main advantage of evolutionary algorithms and cannot track the global maximum point in all partial shading patterns. In [95], a P&O method was employed to improve the convergence speed of PSO. In this method, the first P&O identifies the nearest local MPP and then the PSO starts searching to find the global MPP. As a result of using this combination, the search space exploration is reduced in early iterations. In [36] hybrid method called DEPSO, a combination of PSO and DE, is used in order to reduce the impacts of random coefficients and enhance the system independency of standard PSO method. The proposed technique showed a satisfactory performance under PSCs. However, the problem of this method is the oscillation during tracking period. Table 4 presents a brief summary of studies applied PSO-MPPT in the literature.

<table>
<thead>
<tr>
<th>Method</th>
<th>References</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>[22,88–90]</td>
<td>Standard PSO was employed in the different PV system configurations and under various partial shading patterns.</td>
</tr>
<tr>
<td></td>
<td>[92]</td>
<td>Convergence and accuracy was improved by modifying the search direction of agents in a proposed adaptive perceptive PSO method.</td>
</tr>
<tr>
<td></td>
<td>[93]</td>
<td>Steady-state oscillation was reduced by using the PSO in conjunction with the direct duty cycle method.</td>
</tr>
<tr>
<td></td>
<td>[94]</td>
<td>DPSO was used. Convergence speed and accuracy was improved.</td>
</tr>
<tr>
<td></td>
<td>[95]</td>
<td>Combination of P&amp;O and PSO was used. Convergence speed was improved.</td>
</tr>
</tbody>
</table>

![Fig. 10. Flowchart of PSO.](image-url)
3.4. Ant colony optimization

3.4.1. Theory

Ant colony optimization (ACO) is a probabilistic algorithm used for global solution search in a stochastic problem. The algorithm was first introduced by Dorigo and Gambardella in 1997 based on the foraging behavior of actual ants to find the best path toward food [96]. Shen et al. [97] and Dorigo et al. [98] modified the algorithm and presented it in the form of an optimization method. Basically, ACO mimics the social behavior of ants searching for a food source. First, all individuals search for the food. Once any of the ants finds food, it estimates the size of the food. If the food is too large, it takes a small portion and brings it to the nest. The ant leaves pheromones in its path as it moves toward the nest. These pheromones constitute a pheromone trail, which is used by other ants to find the source. The density of the pheromones in the path is directly related to the number of the ants that travel the path. As more ants pass along the mentioned path, more pheromones are deposited [99]. Given that the pheromones are vaporized over time, the density of the pheromones would be reduced if other ants do not travel the same path. Therefore, the shorter path is more preferred by ants. This methodology leads the ants to find the shortest possible route from the nest toward the food source by exchanging such information among team members. In general, the ACO trail will be selected and updated if it represents the good problem solution [100]. Fig. 11 illustrates the behavior of ants when finding food. The figure is divided into six sections and shows the procedure of selecting the best trail between nests and food sources.

Two ant colony schemes have been defined in the literature. The application of ACO for discrete optimization problem has been discussed in [102,103] and the continuous problem in [104,105]. In continuous ACO, the pheromone density (τ) is intensified around the best objective that is found during the algorithm operation. This density then leads the ants to converge toward the best possible path obtained in the solution space. Eq. (10) defines the location of the ant in the search space.

\[ x_{t+1}^k = x_{gbest}^k + \alpha x \text{ where } \quad (t = 12, 3, ... T) \]  

(10)

in which \( T \) represents the predefined number of iteration, \( t \) represents the current iteration number, \( x_{gbest}^k \) represents the best objective location value that has been found by the algorithm up to the current iteration, and \( \alpha x \) is the randomly elected vector in the area of \([-\alpha, \alpha]\), which denotes the variation allowance of the ant from the best objective value (\( x_{gbest}^k \)). Following the studies in [106,107], the length and direction of variation in accordance to the best objective value can be defined by Eqs. (11) and (12), respectively, after termination of \( \sqrt{T} \) iteration. The direction of the ant is

\[ \alpha_{t+1} = 0.1 \times \alpha_t \]  

(11)

\[ x_{gbest} = x_{gbest} + (x_{gbest} \times 0.01) \rightarrow \begin{cases} f(x_{gbest}) - f(x_{gbest}) & \text{if } f(x_{gbest}) \leq 0 \\ f(x_{gbest}) - f(x_{gbest}) & \text{if } f(x_{gbest}) \leq 0 \end{cases} \]  

(12)

The deposited pheromone then vaporizes. The simulation of the vaporization is shown by Eq. (13), while the pheromone increment around the best objective is presented in Eq. (14).

\[ n = 0.1 \times n_{-1} \]  

(13)

\[ n_t = n_{t-1} + (0.01 \times f(x_{gbest})) \]  

(14)

A brief and simplified description of ACO is presented step by step in Fig. 12.

3.4.2. ACO-based MPPT techniques

In the ACO-based MPPT technique, each location represents the voltage value of PV array. In addition, f(x) objective function is the output power of PV array by which the fitness of each ant is evaluated according to its respective voltage value. Assuming that N ants participate in the optimization, the following Eq. (15) shows the location matrix for ants in rth iteration.

\[ X_r = [X_r^1, X_r^2, ..., X_r^N] \]  

(15)

The variable environmental conditions and changes in shading patterns must be considered by using the optimization procedure. Consequently, the condition presented in Eq. (16) results in re-initialization of the algorithm once it has been satisfied.

\[ \frac{|F(X_{r+1}) - F(X_r)|}{F(X_r)} > \Delta P \]  

(16)

ACO has recently been used to solve problems in different renewable energy sectors [101,104]. In [108], ACO is applied to find the global MPP from the output of a modular PV system. The method was tested under four predefined shading conditions and showed satisfactory results under these conditions. The proposed method was fast and has a low system cost. It has the ability to track global MPP by using a single current sensor at the output of the PV system. In addition, unlike PSO, the convergence speed of ACO is independent of the initial conditions. However, the verification part was limited to simulations, and the experimental feasibility of the system under real conditions was not demonstrated. In addition to the sole application of ACO for the MPPT problem, some researchers used the advantages of the ACO approach to design hybridized methods in which ACO is employed to optimize the performance of other methods. For instance, in [109], ACO is employed to optimize the parameters of an adaptive FLC-based MPPT controller to improve the dynamic response of the

Fig. 11. Ants behavior in six steps [101].
system, as well as reduce steady-state errors. The satisfactory dynamic and steady-state performance of the simulated PV system even under variable irradiance levels reflects the superiority of the proposed control technique under any environmental condition. In [110] ACO was used to design the FLC gains in an ant adaptive fuzzy logic MPPT technique. The proposed method achieved a good response even under extreme irradiance variations. However, the simulated results were verified based only on the performance of the system under uniform insolation levels. The highlights related to the ACO-MPPT techniques, presented in the literature, are listed in Table 5.

3.5. Genetic algorithm

3.5.1. Theory

GA is a meta-heuristic optimization method for finding solutions based on evolution biological behavior. This method was introduced by Holland in 1975 through the principle of survival of the fittest [111]. In general, GA models the candidates’ solutions, known as chromosomes, in the problem search space through fixed-length strings. A chromosome consists of a constant population of genes that can be presented either as real or binary codes. In the algorithm procedure, the population of chromosomes evolves gradually over generations through competition [37]. This evolution is achieved through the following applications of genetic operators: selection, crossover, and mutation. The evolution process helps the best fitness chromosome to survive and mate from one generation to the next [37]. In other words, the GA is an iterative method through which a population of chromosomes evolve and improve through generations affected by GA operators. In each generation, parents are selected from the existing population and used to generate children in the next generation. The objective function is the main evaluative factor for improving population fitness over time. The procedure and life cycle of the population are shown in Fig. 13, and the following steps are the implementation procedure of GA optimization.

3.5.1.1. Initialization. First, the objective function is defined as the main tool for ranking the candidate solutions’ fitness throughout the algorithm procedure. The selection and formation of an objective function is based on the requirements and complexity of the targeted system. Then, the first population of chromosomes is defined through random selection. The convergence speed of the algorithm largely depends on the population size. Similar to any metaheuristic method, a large population is recommended for a complex optimization problem; however, it dramatically reduces the convergence speed of the algorithm.

3.5.1.2. Selection. Initially, the fitness values of the chromosomes in the initial population are evaluated by defining an objective function. Then, based on the fitness evaluation results, the chromosomes are included in the current population. In general, the chromosomes with the higher fitness value will have an increased chance to be considered for the next generation.

3.5.1.3. Crossover. Two selected chromosomes are combined in this step. The application depends on how the genes in the chromosomes are coded. The normal crossover technique can be used if

Table 5
The brief summary of some of the applied ACO-MPPT in the literature.

<table>
<thead>
<tr>
<th>Method</th>
<th>Reference</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACO</td>
<td>[107]</td>
<td>ACO method was applied for a modular PV system. Its capability under PS was verified by using a single sensor.</td>
</tr>
<tr>
<td></td>
<td>[108]</td>
<td>ACO was employed to optimize the FLC parameters. Steady-state errors and dynamic response were improved compared with normal FLC. Its capability under PS conditions was verified. Its complexity was increased.</td>
</tr>
<tr>
<td></td>
<td>[106,108,110,115]</td>
<td>ACO was employed to FLC gains in the AAF_MPPT method. Its tracking capability under FICC is verified. The complexity was increased. Its capability under PS was not verified. Experimental verifications were lacking.</td>
</tr>
</tbody>
</table>

Fig. 12. Flowchart of ACO method.
the genes are in binary format. The random integer number, which is smaller than the number of genes in the chromosome, is used to split parent chromosomes and generate offspring, as shown in Fig. 13 [37,112,113]. If the chromosomes are coded in continuous numbers, and $\alpha$ is considered as crossover rate, the offspring will be crossed over as below.

\[
\text{Offspring}_1 = \alpha \times \text{parent}_1 + (1 - \alpha) \times \text{parent}_2 \\
\text{Offspring}_2 = (1 - \alpha) \times \text{parent}_1 + \alpha \times \text{parent}_2
\]

(17)

3.5.1.4. Mutation. The mutation operator maintains the stochastic nature of the algorithm by maintaining the genetic diversity of current generation to the next one. The mutation operator provides chances for candidate solutions that cannot be obtained only by using the crossover operator application in the binary format. This operator randomly manipulates the chromosome with a specific rate called mutation rate ($\beta$). For the continuous coded chromosomes, the mutation follows the statement below [114]

\[
\text{Offspring} = \pm \beta \cdot \text{Offspring} + \text{Offspring}
\]

(18)

The algorithm continues to work until the stoppage condition is met. This condition can be set in regards to the requirement and the complexity rate of the optimization problem. The brief procedure of GA algorithm is shown in Fig. 14.

3.5.2. GA-based MPPT

GA optimization has been used in different optimization problems faced by the renewable energy sector, such as MPPT. GA has a rapid convergence speed in different optimization problems. In addition, the method showed satisfactory performance in reducing the chance of being trapped in the local optimum. However, this method is not recommended for optimizing very large or excessively complex problems. In the application of GA for MPPT system, the initial parent population is shown as:

![Flowchart of GA method.](image)
where \( n \) is the population size, and each parent represents initial voltage values in which the algorithm starts the evaluation process. The objective function \( f(x^n) \) is the generated power at the output of the PV system. The fitness values of each position are evaluated by the objective function and are used to evolve the population and improve the population fitness through the generations. In the MPPT application, the algorithm must be re-initialized because of sudden changes in load, solar irradiance, or partial shading patterns. Therefore, the following conditions re-initialize the GA-based MPPT algorithm once they have been satisfied:

\[
|V(k + 1) - V| < \Delta V
\]

\[
\frac{P(k + 1) - P(k)}{P(k)} > \Delta P
\]

3.6. Differential evolution

3.6.1. Theory

Another particle-based optimization method is the differential evolutionary (DE) algorithm, which is used for global optimization applications. The algorithm has a similar concept to GA and was first introduced by Storn and Price [120,121]. Owing to its simplicity, DE is one of the most powerful population-based optimizers. The problem is optimized by creating new candidate solutions based on different formulas for each of the different techniques while maintaining the population size. In this algorithm, existing particles with the best fitness records remain in the population, while the others are replaced by new particles. The algorithm is suitable for problems with many local optimum solutions [122–124]. The algorithm consists of the following four sections:

3.6.2. Initialization

The algorithm must be initialized by assigning the initial locations to the target vector. The parameters in the initialized vector are recommended to be selected randomly to enhance the stochastic nature of the method and cover the entire search space [125]. Assuming the \( NP \) as the total population size, Eq. (22) describes \( X_G \) as the target vector of the \( i \)th particle in the \( G \)th iteration.

\[
X_G; \quad i \in (1, 2, 3, \ldots NP)
\]  

3.6.3. Mutation

The \( x_{iG} \), which is the mutant or donor vector of the \( i \)th particle in iteration \( G \), is formed by mutating each particle of the target vector by using the equation below

\[
x_{iG+1} = x_{iG} + k(x_{iG} - x_{iG}) + F(x_{iG} - x_{iG}) \tag{23}
\]

where \( r_1, r_2, \) and \( r_3 \) are the random numbers in the range of \((1, 2, \ldots, NP)\), and \( n_p \) denotes the number of particles. \( K \) and \( F \) are the scaling and combination factors, respectively, which are ranged in \([0, 2]\).

The DE parameters, like other metaheuristic methods, affect the performance of the system significantly. Parameter selection is an important responsibility for a designer, especially when the engineering problem is significantly critical, such as MPP tracking from the nonlinear output of partially shaded PV system. The most common parameter selection method is rule of thumb by Storn [126].

3.6.4. Crossover

After generations of mutant vectors in the mutation section, combining the target vectors and mutant vector generates the trial vectors through a non-uniform crossover operation as shown in Eq. (24). The crossover enables the algorithm to propose better solutions by shuffling the data of successful combinations. In this equation, \( j \in (1, 2, \ldots, D) \), \( \text{rand}_j \) is a random value between 0 and 1, and \( \text{rand}_j \) is a random number chosen from the domain of \( j \). The

\[
x_{iG+2} = \begin{cases} x_{iG} & \text{if } \text{rand} < \text{rand}_j \\ x_{iG} + \text{rand}_j & \text{otherwise} \end{cases}
\]  

Table 6 presents a brief summary of studies employed GA technique as a main strategy of MPPT unit.

<table>
<thead>
<tr>
<th>Method</th>
<th>Reference</th>
<th>Remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA</td>
<td>[115,116]</td>
<td>GA approach is applied to address the MPPT problem. It performs well under some PS conditions. However, it lacks experimental verification.</td>
</tr>
<tr>
<td></td>
<td>[112]</td>
<td>GA performance is compared with the performance of conventional methods. It demonstrated tracking capability under PSCs. However, it lacks experimental verification.</td>
</tr>
<tr>
<td></td>
<td>[117]</td>
<td>A modified GA method is integrated with a P&amp;A approach. Its capability under PSC is experimentally proven.</td>
</tr>
<tr>
<td></td>
<td>[118]</td>
<td>GA used to tune FLC parameters. Its performance is experimentally verified under UIL. However, its capability under PSC is not verified.</td>
</tr>
<tr>
<td></td>
<td>[119]</td>
<td>GA used to train the ANN parameters. Its performance under UIL is experimentally verified. However, its capability under PSC is not verified.</td>
</tr>
</tbody>
</table>

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**Table 6**

The brief summary of some of the applied GA-MPPT in the literature.
maximum dimension of the search space is denoted by $D$. CR is the so-called crossover constant in the range of $[0,1]$, which is used in the condition statement of the crossover section. If this value is greater than the random number, the value of the trial value follows the mutant value. If not, it follows the target value. In the DE-based MPPT, the output power will be evaluated when the crossover sections are completed and the trial components of trial vectors are generated.

$$
U_{i,G+1} = \begin{cases} 
V_{i,G} & \text{if } (rmd) \leq CR \quad \text{or} \quad j = n_i \\
x_{i,G} & \text{if } (rmd) > CR \quad \text{or} \quad j \neq n_i 
\end{cases}
$$

(24)

3.6.5. Selection

$$
x_{i,G+1} = \begin{cases} 
u_{i,G} & \text{if } f(U_{i,G}) \geq f(x_{i,G}) \\
x_{i,G} & \text{if } f(U_{i,G}) < f(x_{i,G}) 
\end{cases}
$$

(25)

In the final step, the selection operation defines the next movement of the particle toward the prospective region of the search space. The selection of the parent target vectors is independent of the fitness values. However, the produced children (offspring) in the mutation and crossover must be evaluated by the fitness function and compared with the parents. The selection operator compares the fitness values of obtained trial vectors with target vectors. The parents remain in the population if they have better fitness values than their children. If not, the selection operator will replace them with a trial vector that has better fitness.

Fig. 15, shows the process of obtaining a new proposal in the DE algorithm. Locations 1 and 2 in the search space denote two members whose difference vector is used to move a third population member (3). The obtained location, denoted by (4), is subjected to crossover with the replacement candidate, denoted by (5), to generate a new proposal (6). Afterward, if the proposal has a better fitness value than the candidate, the candidate is updated by the proposal. In the MPPT scheme, $U_{i,G}$ represents the duty cycle value in the trial vectors; therefore, $f(U_{i,G})$ represents the output power at this duty cycle. The measured power for the duty cycles in the trial vectors is compared with duty cycles in the target vector. The result of this comparison will update the duty cycle at which the higher output power was achieved. Fig. 16, shows a flowchart of the process.

3.7. DE-based MPPT

The DE method was recently applied in different extents to solve the control issues of renewable energy systems, including the problem of global MPP tracing in PSCs. In the DE-based MPP tracking method, the target vector is normally considered the duty cycle of the designed DC-DC converter. The DE approach in the MPPT problem was first presented in [127,128] where a standard DE algorithm was used. However, the method is based on static objective function in which the P-V curve must be predetermined, which makes the method impractical for real-time MPPT application [122]. The DE method was used in MPP tracking of the PSCs [94,123]. The search time was reduced by avoiding the additional measurement from the output of the converter setup. As mentioned in the crossover step, the value of the trial vector components might be the same with the target value depending on the crossover condition. Thus, the processing time was reduced by avoiding the measurement of the power for those duty cycles that remained the same after the crossover step. Moreover, the proposed DE method was compared with the conventional HC method. The standard DE algorithm was modified to suit the nature of a dynamic tracking system. According to the author’s investigations, the proposed DE algorithm has the following significant features:

a) Simple and straightforward implementation.

b) The ability to search the global maximum point regardless of the initial parameter values.

c) Fast convergence.

d) Requires only a few control parameters.

The final results proved that unlike the conventional method, the proposed DE techniques have fast and reliable tracking performance under PSC without any oscillation at the output waveform. However, the performance of the method was verified only through simulations and experiments. Therefore, the response time and the complexity of an actual experimental setup have not been considered in the final verification of the method. In [129], a two-stage MPPT technique based on the combination of DE and ANN is proposed for a simulated PV system under PSCs. In the first stage, the DE method is used to find the area in which the MPP existed. In the second stage, the ANN method is employed to track the exact MPP at the output Ipv-Ppv characteristics. The method performance was promising under different PSCs. However, the use of a two-stage technique results in further complication in the overall systems. In addition, as in previous studies, the proposed method was evaluated under simulated conditions only. Highlights and main points of studies, which used DE-MPPT in the literature, are summarized in Table 7.

3.8. Emerging methods

This paper has thus far reviewed 6 popular AI-based MPPT techniques including their ability to perform subject to partial shading conditions. Aside from these techniques, there are emerging approaches for MPPT subject to partial shading which have only very recently been proposed and discussed in a limited number of publications. Despite not having been extensively investigated in the literature, these emerging approaches do present strong approaches to global MPP tracking, and are likely to be the focus of future research attention. As such, in order to present a comprehensive review of AI-based methods for MPPT, these emerging approaches are reviewed in this section.

3.8.1. Radial movement optimization (RMO)

RMO is a swarm-based stochastic optimization technique [130]
One of the main differences between the RMO and PSO techniques is that for RMO the location and velocity of all particles are not transferred across iterations [130]. Rather particles begin to move from a new updated point at each iteration and as a result, less memory is required. Furthermore, using RMO the presence of a global best vector prevents the algorithm from being trapped at a local optimum. In [131], the RMO technique was employed for GMPP tracking for a partially shaded PV system. Compared with other techniques including PSO, the technique demonstrated under different partial shading conditions to be faster and provide more stable tracking performance. This demonstrated performance however was limited to simulation only. To fully evaluate the RMO-MPPT technique, experimental verification is required including considering all partial shading conditions.

3.8.2. Cuckoo search method (CS)

The Cuckoo search (CS) method is based on the reproduction strategy of some species of Cuckoo bird which are reported to lay their eggs in the nests of other birds. This parasitic reproduction approach is the basis of the CS optimization method. In this approach, seeking the right host nest is a key step. This is similar to searching for food, which is a random process and can be modeled using mathematical functions. One of the common methods for modeling an animal’s food seeking trajectory is the Lévy flight model. In the CS algorithm, the Lévy flight model is used in order to characterise the nest seeking steps of a Cuckoo bird’s reproduction process. The Lévy flight model represents a random walk where step sizes are defined using Lévy distribution, which is determined by the power law, as shown in the following equation [132–134].

\[ \text{Lévy}(\lambda) \approx u = t^{-\lambda}, \quad (1 < \lambda < 3) \]  

For each iteration, in order to determine the new solution, the Lévy flight is performed using the following expression

\[ x_{t+1}^i = x_t^i + \alpha \oplus \text{Lévy}(\lambda) \]  

where \( i \) is the number of samples or eggs, \( t \) is the iteration number, the product indicates entry-wise multiplication, and \( \alpha \) is the step size which needs to be tuned properly according to the constraints of the optimization problem. The value of \( \alpha \) is often defined using the initial step \( \alpha_0 \), and the difference between two samples (\( x_t^i \) and \( x_t^j \)), as shown by the following expression

\[ x_{t+1}^i = x_t^i + \alpha \oplus \text{Lévy}(\lambda) \]
\[ a = a_0(x_0^i - x_i^p) \] (31)

The operational behavior of the CS technique is similar to the HC and P&O methods. Unlike these methods however, the step size of the CS is based on Lévy flight and is a population-based algorithm. Due to Lévy flight, compared with standard PSO and DE techniques, the CS method, has more efficient randomization and faster convergence. Also compared with PSO method it has fewer parameters needing to be tuned and is more independent from initial conditions. The CS-based MPPT technique was developed in [132] and was verified under certain partial shading conditions. The final experimental results demonstrated the ability of the method to outperform the standard PSO and conventional P&O methods.

3.8.3. Grey wolf optimization (GWO)

Grey wolf optimization (GWO) is another population-based optimization technique, based on the hierarchical leadership and the hunting behavior of the grey wolf and recently presented in [135]. Grey wolves live in packs and have a strict social hierarchy as shown by Fig. 17. When seeking prey, grey wolves can be classified into four types; \( \alpha, \beta, \delta, \) and \( \omega \), based on the fitness evaluation of each type where \( \alpha \) type possesses the highest fitness and \( \omega \) the worst. Grey wolves have three main steps in their hunting behavior: a) searching, tracking and approaching prey; b) pursuing and encircling prey; and c) attacking prey.

Circling behavior by the wolves is a key step in the hunting procedure and for the purpose of designing the GWO algorithm is mathematically represented by Eq. (33),

\[
\vec{D} = \left| \vec{X}_q(t) - \vec{X}(t) \right| 
\] (32)

\[
\vec{X}(t + 1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} 
\] (33)

where \( t \) is the number of the iteration, \( \vec{X}_p \) and \( \vec{X} \) are the positions vectors of the prey and the grey wolf, respectively; and \( \vec{A}, \vec{C} \) and \( \vec{D} \) are the coefficient vectors calculated by Eqs. (32), (34) and (35).

\[
\vec{A} = 2 \cdot \vec{r}_1 \cdot \vec{r}_1 - \vec{a} 
\] (34)

\[
\vec{C} = 2 \cdot \vec{r}_2 
\] (35)

where components of \( a \) are linearly decrease from 2 to 0 across iterations and \( r_1, r_2 \) are random vectors in \( [0, 1] \). The GWO method is applied to MPPT where the number of participating grey wolves represent the converter’s duty cycles and the MPP is prey being hunted [136].

3.8.4. Firefly optimization algorithm (FOA)

The FOA is a population-based optimization method and similar to PSO. The FOA is inspired by illuminated bugs, and is mathematically presented in [137] and [138]. Unlike PSO the FOA has less parameters to be tuned and the particles in FOA aggregate more closely around each optima, without rapid fluctuation like PSO. Flashing light is a key component of the population-based behavior of fireflies and is used to attract mating partners and potential prey, as well as a mechanism for protective warning. As such, brightness is important and used to determine the new position for particles in the search space [137,139]. For example, if the firefly \( p \) has lower brightness than firefly \( q \), the new position for firefly \( p \) is determined by following expression

\[
x_{p}^{t+1} = x_{p}^{t} + \beta(t)(x_{p} - x_{q}) + \left( \text{rand} - \frac{1}{2} \right) 
\] (36)

where, \( x_p \) and \( x_q \) represent the positions of two fireflies, \( r \) is the distance between these two fireflies, \( \beta \) is the level of attractiveness, and \( \alpha \) is a random movement factor and is constant value in the range of \([0, 1]\). As explained in [137], it is important to mention that a large value of \( \alpha \) makes it possible to search for the solution through a large search space whereas a smaller value of \( \alpha \) tends to facilitate local search [28]. The degree of attractiveness (\( \beta \)) in Eq. (37), can be calculated using the following expression

\[
\beta(t) = \beta_0 e^{-\gamma t q^y}, \quad n \geq 1; 
\] (37)

where, \( \gamma \) is the absorption coefficient and controls the light intensity and \( \beta_0 \) is initial attractiveness.

Using the FOA-based MPPT method, the converter duty cycle represents the position of the firefly and the output generated power of PV system is the brightness of each butterfly. The performance analysis of FOA-MPPT technique is carried out in [139], and it is shown that this technique outperforms the standard PSO technique in terms of tracking speed, tracking accuracy and dynamic response.

4. Analytical comparison

Published research in this field indicates the difficulty of evaluating and comparing the best MPPT approaches and techniques. In general, the final MPPT technique is selected based on the application requirements and preferences. Therefore, knowledge about the nature of the project and the limitations is an essential prerequisite. In addition, the test benches, applications, and environmental conditions used to verify the performance of the designed MPPT techniques are not similar. Therefore, a comparison among these methods should be fair. Compared with the conventional MPPT techniques, the intelligent approaches commonly have lower oscillation around MPPT and higher reliability for sudden changes in irradiance levels. In addition, they mostly show better performance in the most significant criteria. However, their behavior with regard to the main criteria, such as efficiency, reliability under PSCs, convergence speed, system independence, and steady-state oscillation, might be different. The performance of these techniques in accordance to the accredited literature is discussed and presented in Table 8 and Fig. 18. In Fig. 18, the axes \( A, B, C, D, E, F \) refer to periodic tuning and parameter dependency, simplicity, efficiency, reliability under PSCs, system independency and convergence speed, respectively.

According to the reviewed studies, the FLC and ANN methods in their original forms are incapable of tracking the global maximum points under PSCs. However, they obtain satisfactory results under normal conditions. The most significant advantage of the ANN method is its independence from detailed information of the PV
system. However, its reliability is largely affected by the training process, which makes the system exclusive for each PV system. Therefore, the ANN method cannot operate for another PV system unless it undergoes a new training process. This problem may also occur when the characteristics of the array change due to aging or degradation. The main advantages of FLC are its system independence, ease of implementation, and satisfactory performance under FICC. However, the computational cost of the system for designing the fuzzification rule base and defuzzification process increases. Compared with other AI-based MPP techniques, the FLC requires more perception and comprehension of the PV system by the designer to design the different FLC parameters, such as rules and membership functions. Therefore, this method can be considered more system dependent than others. System independence,
speed, and decision making based on approximate values make the fuzzy logic controller one of the most suitable techniques for complex engineering challenges. Thus, this method can be considered one of the more reliable options for finding the MPP in the nonlinear characteristics of PV systems under normal conditions and some PSCs. However, this technique highly depends on designer knowledge in the different steps of the algorithms. In addition, the method needs extensive computation in the fuzzification, rule base, and defuzzification stages.

All the PSO-based methods, both original and modified versions, are suitable to operate under PSC. The methods are mainly related to their heuristic behavior for exploring the search space that comprise multiple maximum power points. The main problems of the PSO method are implementation complexity, poor dynamic response due to the interruption for measurement process, long tracking process as a result of undefined initial points, and significant dependency on the coefficient designs and initial conditions. The modified version of the PSO method solved the initialization problems; however, it does not guarantee that the MPP under any PSCs can be tracked, and the initial points are set close the global MPPs. Overall, PSO has a fast convergence speed, high sensitivity atmospheric change, low hardware implementation cost, and high efficiency with no oscillation around MPP.

ACO can also track the MPP under both normal and PSC. Unlike PSO, ACO is not dependent on the design of the initial location of the particles. In addition, it is capable of tracking MPP in a system with minimized sensors, which results in a more cost-effective system. However, theoretically, this condition can be similar for all the metaheuristic approaches, such as PSO, DE, and GA. In general, ACO comprises three factors: the positive feedback mechanism that increases the probability of detecting optimal solutions in initial iterations, the distributed computation to ensure that the algorithm is not involved in the local optimum, and the greedy search that helps the algorithm find the optimal solution with higher convergence speed [108]. Overall, the most significant advantages of the ACO over other AI-based methods are system independence, high convergence speed, and initial location independence of particles. However, these advantages might increase the computational burden because of complex calculations. In addition, due to the lack of research in this area, the reliability and robustness of the technique under different PSCs have not been experimentally verified.

The GA and DE techniques, which have almost similar concepts, can track the global MPP under PSCs because of their ability to solve multi-objective problems. Both algorithms are system independent, efficient, have no need for periodic tuning, and have no oscillation around MPP. Moreover, the advantages of the DE algorithm are simplicity because of the few required control parameters, fast convergence speed, and initial location independence. However, experimental verifications for purely using either of these methods under PSC conditions are lacking. Unlike the PSO and ACO theories, the methods do not remember previous movements and locations that the particles have experienced throughout the program. Therefore, the algorithm is more likely to be stuck in the local optimum.

Of the four emerging techniques, RMO and CS appear to have similar functionality and address similar limitations of the standard PSO technique. In RMO particles explore a fraction of main search space therefore achieving faster convergence speed compared to other MPPT methods. The CS MPPT technique also has a very fast convergence speed compared to other MPPT techniques, achieved using Lévy flight during its operation. Both techniques require only a few parameters to be tuned however the CS technique has fairly complex operation compared with other soft computing based MPPT methods and RMO has not been experimentally tested. GWO and FAO techniques have demonstrated similar performance under partial shading conditions. The convergence speed towards the GMPP for both algorithms is an improvement upon common AI-techniques, and they have less complex structure compared with RMO and CS algorithms. However, GWO or FAO based MPPT unit results in output oscillation during tracking period compared with RMO and CS algorithms. Therefore, in the applications which are very sensitive to output power fluctuations, RMO or CS technique are preferred.

5. Conclusion

In view of the importance of control strategies in the overall efficiency of the PV systems, this paper focused on the different approaches in tracking the MPP of PV systems. Given the drawbacks of conventional MPPT methods, such as system independence, high oscillation around MPP, and deficiency under PSCs, six common and four emerging AI-based MPPT approaches were reviewed in this paper. The concept, structure, sequential steps, and the state of the art of each method of tracking the MPP under PSCs have been thoroughly presented. To comprehend the significance of the environmental conditions on the performance of the PV system, an extensive analysis on the behavior of PV systems under normal and PSCs was carried out in advance. In addition, the latest studies that conducted performance analyses of each method under different conditions were discussed and analyzed. This paper also presented the different hybrid methods that used one of the covered AI methods.

The final evaluation was carried out to evaluate the complexity, ability to track GMPP under PSC, sensitivity to atmospheric changes, convergence speed, cost, system independence, efficiency, periodic training or coefficient tuning process, and oscillation around each method of MPP. The comparison was conducted mainly according to the concept of the method, as the validations reported in the studies were performed on different systems and under different conditions. This study is not limited to reviewing the performance of the recent methods and the step-by-step procedures and structures of each method; it also comprehensively covered the required references. The findings of this paper will help researchers and engineers who work with PV-based power systems to understand the basics of each method and select the appropriate one according to project requirements to be implemented in their MPPT systems to fulfill project objectives.

References

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