Renewable and Sustainable Energy Reviews 65 (2016) 1127–1138

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Maximum power point tracking in photovoltaic (PV) systems: A review of different approaches

A. Rezaee Jordehi

Department of Electrical Engineering, Lashtenesha-Zibakenar Branch, Islamic Azad University, Lashtenesha, Iran

ARTICLE INFO

Article history:
Received 19 March 2016
Received in revised form
20 June 2016
Accepted 10 July 2016
Available online 30 July 2016

Keywords:
Solar energy
Renewable energy
Maximum power point tracking
Photovoltaic systems
Optimisation

ABSTRACT

The penetration of photovoltaics (PV's) in electric power generation is continually increasing. Tracking maximum power point in PV systems is an important task and represents a challenging problem. In maximum power point tracking (MPPT), the duty cycle of DC-DC converter is adjusted in a way that maximum achievable power is extracted from PV system. In this paper, the existing MPPT strategies are classified into two main categories and the strategies of each category are reviewed. Based on the conducted review, some directions for future research are recommended. The author strongly believes that this paper will be helpful for researchers and engineers in the field of PV systems.

Contents

E-mail address: ahmadrezaeejordehi@gmail.com

http://dx.doi.org/10.1016/j.rser.2016.07.053
1364-0321/

1. Introduction

Photovoltaic (PV) systems convert sunlight into electric energy. PV cells are the basic components of PV systems and are typically modeled either as single diode or double diode circuits [1]. The circuit of single diode model has been depicted as Fig. 1. It has five parameters; photovoltaic current (I_{PV}), diode's ideality factor (a), diode's saturation current (I_S), series resistance (R_S) and shunt resistance (R_P). Its I-V characteristic is given by Eq. (1) [2–5].

$$I = I_{PV} - I_S\left[exp\left(\frac{q(V+R_S I)}{aKT}\right)-1\right]-\frac{V+R_S I}{R_P} \tag{1}$$

where T denotes temperature in Kelvin, q denotes charge of an electron, K represents Boltzmann constant, I and V respectively denote current and voltage of PV cell.

It should be noted that the generated photovoltaic current (I_{PV}) depends on environmental conditions and can be represented by the following equation [6].

$$I_{PV}(T,G) = (I_{PV,STC} + K_I(T - T_{STC}))\frac{G}{G_{STC}} \tag{2}$$

where $I_{PV,STC}$, T_{STC} and G_{STC} denote the values of photovoltaic current, temperature and irradiation at standard test condition (STC). At STC, the temperature is 25 °C, the irradiation is 1000 W/m^2 and air mass is 1.5. The symbols T and G respectively represent temperature and irradiation at which the photocurrent is computed. Symbol K_I represents temperature coefficient of photocurrent [4]. Double diode model is also used for modeling PV cells [7]. It has seven parameters; I_{PV} , R_S , R_P , a and I_S of the first diode, a and I_S of the second diode. The circuit of double diode model has been illustrated in Fig. 2 and its I-V characteristic is given by Eq. (3) [8–10]. Based on double diode model, the I-V and P-V curves of PV cells have been depicted as Figs. 3 and 4.

The operating point of PV cell is the intersection of its I-V curve and I-V curve of load. Eqs. (2) and (3) indicate that by increase in irradiation, a negligible increase in open circuit voltage is resulted, however, short circuit current increases and therefore maximum achievable power of PV cell increases significantly. The simulations also indicate that by increase in temperature, a negligible increase in short circuit current is resulted, while open circuit voltage decreases and therefore maximum achievable power of PV cell decreases significantly.

$$I = I_{PV} - I_{S_1}\left[exp\left(\frac{q(V+R_S I)}{a_1 KT}\right)-1\right]-I_{S_2}\left[exp\left(\frac{q(V+R_S I)}{a_2 KT}\right)-1\right]-\frac{V+R_S I}{R_P} \tag{3}$$

1.1. Partial shading condition (PSC)

The situation in which different parts of a PV module receive different amount of irradiation, is referred to as "partial shading condition (PSC)." Shading may be caused by clouds, adjacent structures, trees, etc. In a PV array, when a cell is shaded and receives low insolation or no insolation, as per Eq. (2), the

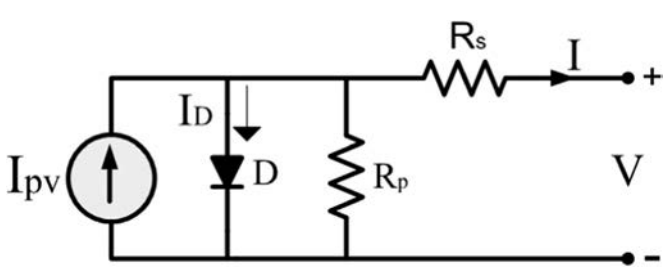

Fig. 1. Single diode R_P model [1].

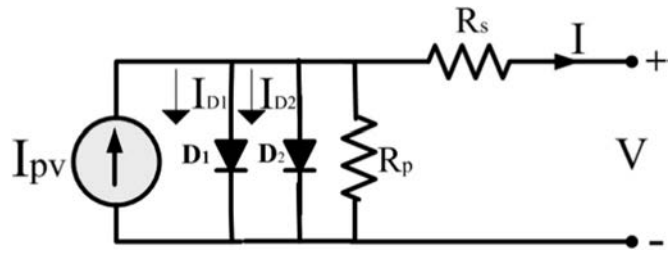

Fig. 2. Double diode model for PV cell [1].

photocurrent of that cell (I_{PV}) decreases. Since, based on kirchoff current law (KCL), the current of all series-connected PV cells must be the same, the internal diode of shaded cell goes into breakdown region to compensate the reduction of photocurrent. As a result, the shaded PV cell behaves as a load instead of a generator. Due to the absorbed power, the shaded cell heats up and damages the shaded cell . furthermore, PV array will no longer serve as a generator [11–13].

To solve the described problem, bypass diodes, as Fig. 5, are connected in parallel with PV cells. In PSC, bypass diode carries current, internal diode of shaded PV cell will not go into breakdown region and hotspot is prevented. In practice, for economical reasons, one bypass diode is used for several PV cells. Addition of bypass diodes creates stairs in I-V curve and also creates multiple optima in P-V curve of PV array. If bypass diode is not used, the stairs in I-V curve or multiple optima in P-V curve will not appear, however, the maximum achievable power is less than the case that bypass diodes are used. A blocking diode is added at the end of each string to protect it against reverse current, produced by voltage mismatch between parallel connected strings [6]. Figs. 6–11 illustrate I-V and P-V curves of a PV array for three different shading patterns [7]. In each shading pattern, the modules are put in four different groups. In shading pattern #1, the first three groups of modules receive the irradiation of 1000 W/m^2 while the fourth group of modules receive 800 W/m^2 . In shading pattern #2, the first two group of modules receive the irradiation of 1000 W/m^2 while the third and fourth group of modules receive 700 W/m^2 and 800 W/m^2 respectively. In shading pattern #3, the first group of modules receive the irradiation of 1000 W/m^2 while the other three groups receive 900 W/m^2 , 700 W/m^2 and 800 W/m^2 respectively. The Figs. 6–11 indicate that as the number of PV modules having different insolations increases, the number of stairs in I-V curve and the number of local optima in P-V curve increases.

1.2. Maximum power point tracking in PV systems

Maximum power point tracking (MPPT) aims to ensure that at any environmental condition, i.e. any irradiation or temperature, maximum achievable power is extracted from PV system [14–16]. This is done by adjusting the duty cycle of DC-DC converter, i.e. the converter's duty cycle is adjusted in a way that the operating point matches maximum point of P-V curve. MPPT is a very important problem in PV systems, since extraction of maximum achievable power from PV systems is of very high value and importance [17–19]. A MPPT system directs the operating point of PV system toward maximum power point. An efficient MPPT strategy must feature the following properties.

- It should provide high accuracy and be able to find true global maximum power point (MPP). An accurate MPPT system results in a PV system with higher efficiency.

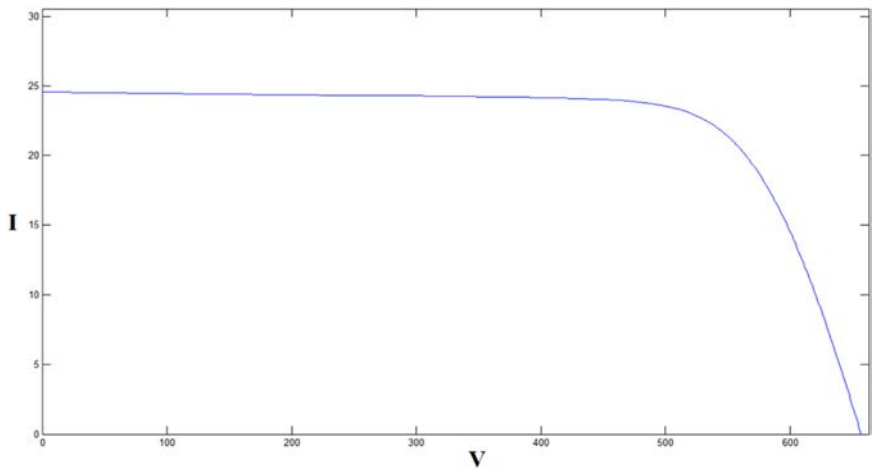

Fig. 3. Typical I-V curve of a PV array at standard test condiction with uniform solar insolation.

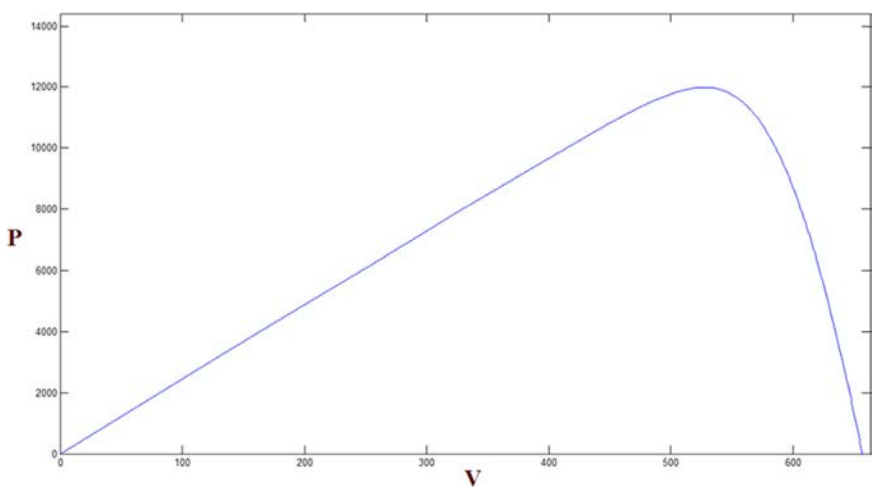

Fig. 4. Typical P-V curve of a PV array at standard test condiction with uniform solar insolation.

- It should have high tracking speed. Slow tracking speed results in reduction of extracted power and low efficiency of PV systems.
- It should be able to perform effectively both in uniform insolation conditions and partial shading conditions. In partial shading conditions, there are several local optima in P-V curve, therefore finding the true global maximum power point is a challenging task.
- It should be system-independent, i.e. it should perform effectively for different PV systems.
- It should not be too complex. Simplicity is a merit.
- It should not oscillate around maximum power point.
- It should be able to effectively track maximum power point after sudden drastic changes in environmental conditions.

The techniques for MPPT can be classified into two main categories; The first category includes classic techniques such as perturb and observe, hill climbing, fractional open circuit voltage and fractional short circuit current, while the second category includes modern MPPT techniques. Modern MPPT techniques encompass fuzzy logic-based techniques, artificial neural network (ANN)-based techniques and metaheuristic-based techniques. This paper aims to provide a comprehensive and up-to-date review of MPPT strategies and propose some directions for future research in this field. The rest of the paper is organised as follows; in Section 2, classic MPPT methods and in Section 3, modern MPPT methods are reviewed. In Section 4, an overall review of MPPT methods has been provided and few directions for future research are presented. The conclusions are drawn in Section 5.

2. Classic MPPT methods

In this section, classic MPPT strategies including perturb & observe, hill climbing, fractional open circuit voltage, fractional short circuit current are explained. It must be noted here that for a MPPT strategy, tracking efficiency is defined as below [20].

$$\eta = \frac{P_{out}}{P_{max}} \tag{4}$$

where P_{out} denotes average output power and P_{max} represents maximum available power.

2.1. Perturb δ observe

In this technique, a perturbation is applied to the voltage of PV array and the change in its output power is observed. If the perturbation leads to increase in output power, the voltage is further increased, otherwise the voltage is decreased [6]. The disadvantage of this method is that at vicinity of MPP, it oscillates around MPP and there exists an steady state error [21]. Low values of perturbation size reduces steady state error at the cost of reduction in tracking speed. For mitigating this drawback of P&O

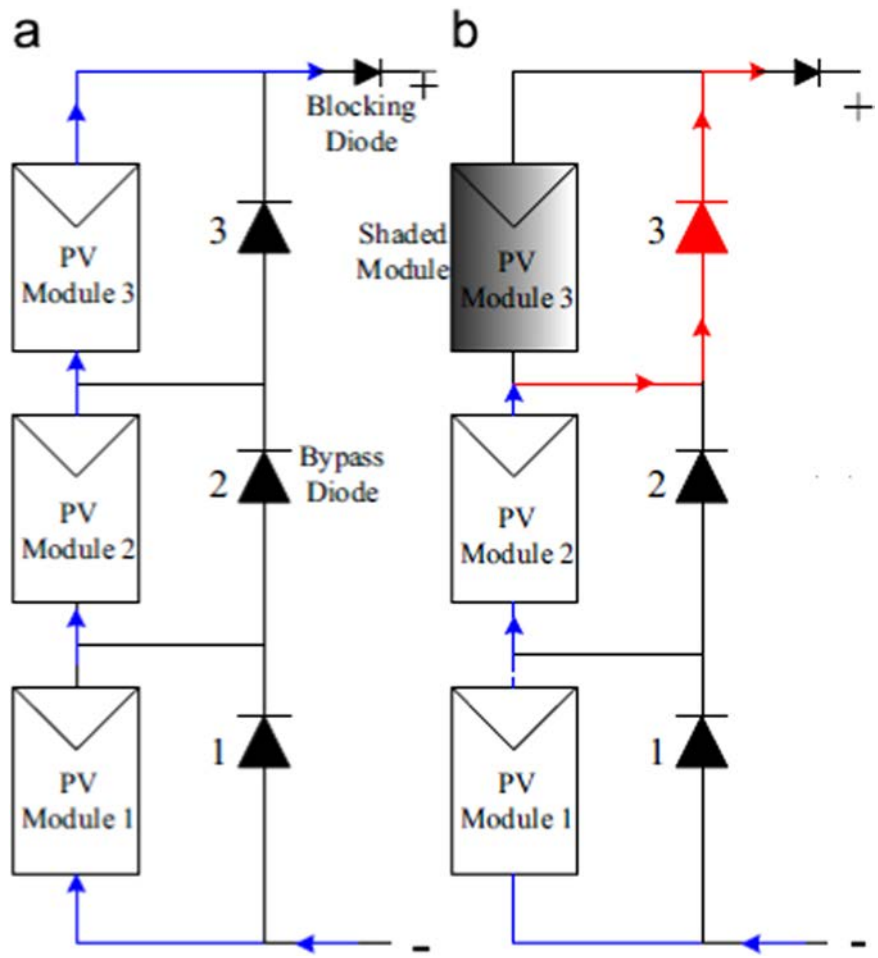

Fig. 5. PV array under uniform irradiation (a) and partial shading condition (b) [6].

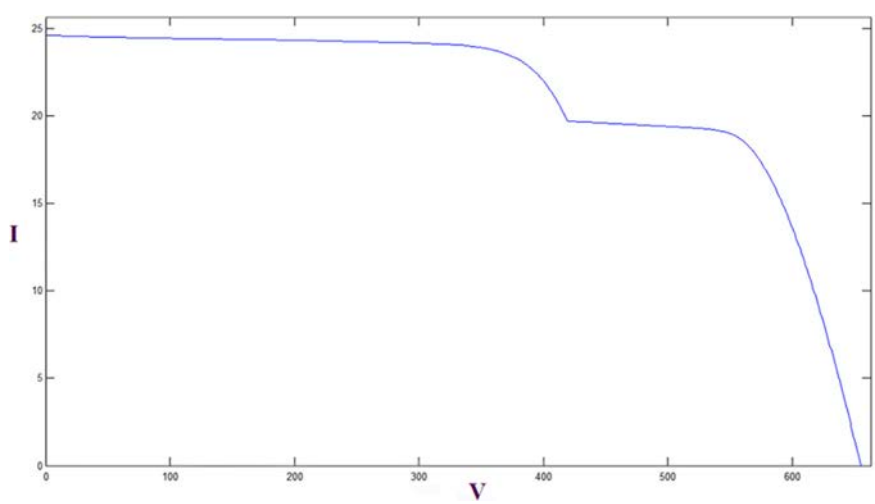

Fig. 6. I-V curve of the PV array at shading pattern #1.

technique, in [22], perturbation size is diminished during tracking process. The perturbation size is initialised with 10% of open circuit voltage and it is halved at each perturbation. In this way, the steady state oscillations around MPP are diminished. Besides [22], in attempts to mitigate the drawbacks of original P&O, in some other research works, modified versions of P&O have been developed [23–29].

2.2. Incremental conductance (IC)

At maximum power point, the derivative of power with respect to voltage is zero [30].

$$\frac{dP}{dV} = \frac{d(VI)}{dV} = V\frac{dI}{dV} + I = 0 \tag{5}$$

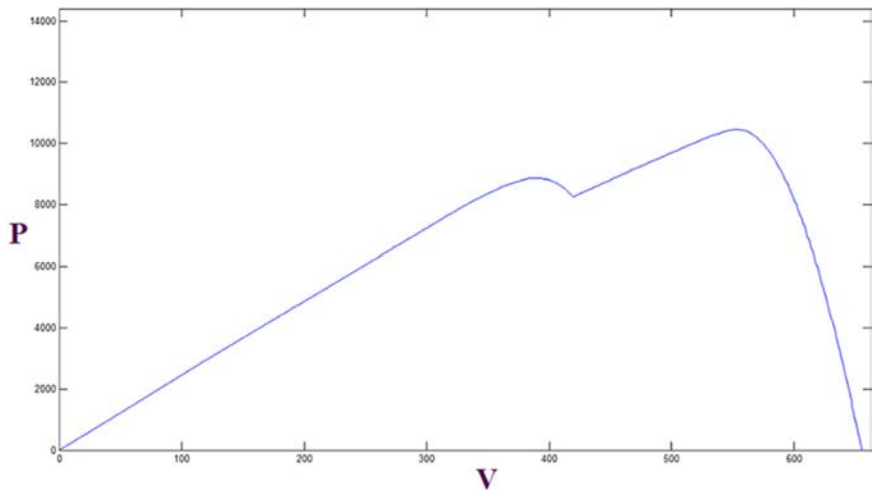

Fig. 7. P-V curve of the PV array at shading pattern #1.

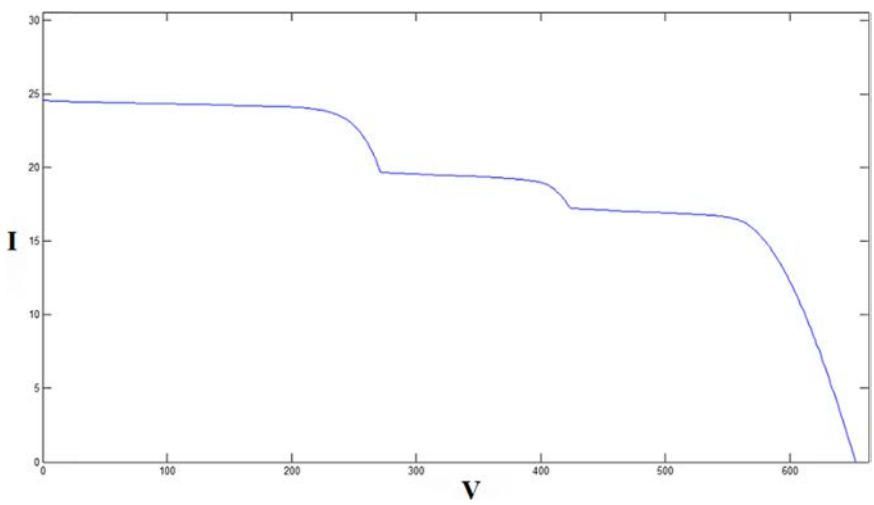

Fig. 8. I-V curve of the PV array at shading pattern #2.

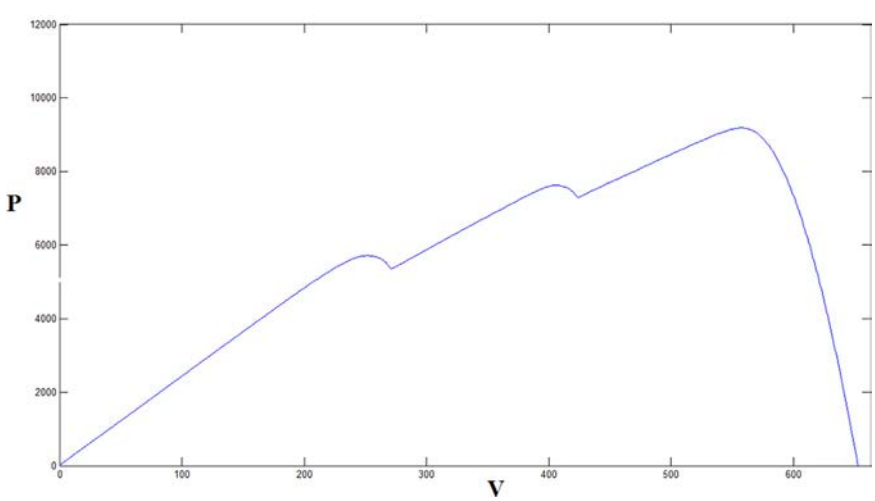

Fig. 9. P-V curve of the PV array at shading pattern #2.

Eq. (5) implies that at MPP, (6) is met.

$$\frac{dI}{dV} = -\frac{I}{V} \tag{6}$$

At the left of MPP, $\frac{dP}{dV}$ is positive, therefore, the following inequality is met.

$$\frac{dI}{dV} > -\frac{I}{V} \tag{7}$$

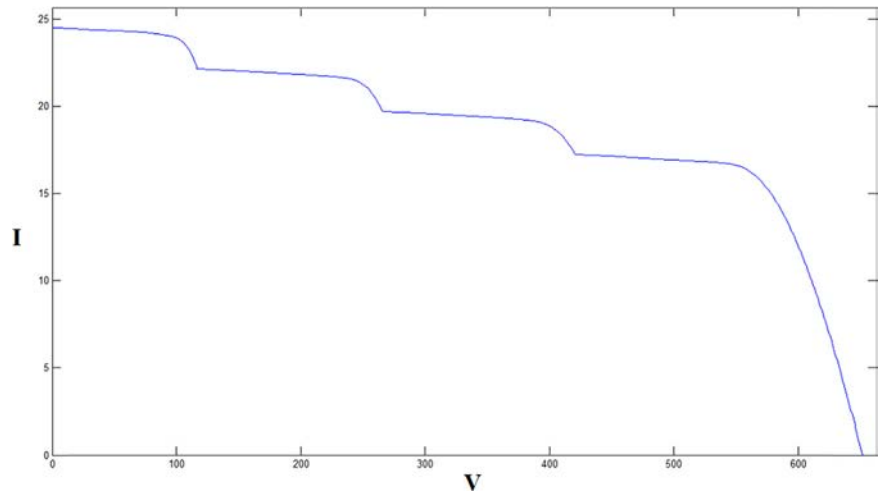

Fig. 10. I-V curve of the PV array at shading pattern #3.

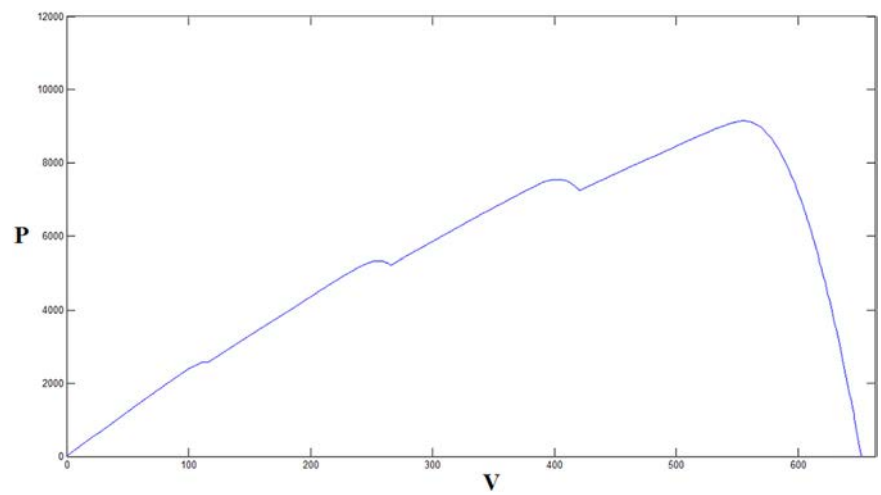

Fig. 11. P-V curve of the PV array at shading pattern #3.

At the right of MPP, $\frac{dP}{dV}$ is negative, therefore, the following inequality is met.

$$\frac{dI}{dV} < -\frac{I}{V} \tag{8}$$

In incremental conductance (IC) method, a perturbation ΔV in voltage is applied and the change in current ΔI is sensed. Since ΔV and ΔI are small, $\frac{dI}{dV}$ and $\frac{\Delta I}{\Delta V}$ are assumed the same. Then, if $\frac{\Delta I}{\Delta V} > -\frac{I}{V}$, the voltage is increased and if $\frac{\Delta I}{\Delta V} < -\frac{I}{V}$, the voltage is decreased [30]. Similar to P&O, IC oscillates around maximum power point.

In [31], as an attempt for mitigating the oscillations around MPP, based on a tradeoff between accuracy and allowable oscillations around MPP, a value ε is selected. If $\frac{\Delta I}{\Delta V} + \frac{I}{V} > \varepsilon$, the voltage is increased and if $\frac{\Delta I}{\Delta V} + \frac{I}{V} < \varepsilon$, the voltage is decreased [31]. In this way, the oscillations around MPP will significantly decrease. In [32], IC with adaptive perturbation step size as (9) is used.

$$s = M\left|\frac{P(K) - P(K-1)}{V(K) - V(K-1)}\right| \tag{9}$$

Where s is perturbation step size, M is a constant which is found by trial and error, $P(K)$ and $P(K-1)$ respectively denote power values at Kth and $(K-1)$th perturbation, $V(K)$ and $V(K-1)$ respectively represent voltage values at Kth and $(K-1)$th perturbation.

2.3. Hill climbing (HC)

HC is analogous to P&O, but instead of perturbation in voltage/current, duty cycle of DC-DC converter is perturbed. If the increase in duty cycle leads to increase in output power, duty cycle will be further increased, otherwise duty cycle will be decreased [33]. The same as P&O and IC methods, HC suffers from oscillations around MPP which significantly decreases efficiency of PV systems. In [34], HC with adaptive perturbation size has been introduced in order to diminish the oscillations around MPP. During the course of tracking, perturbation size is adapted as per following equation [34].

$$s = \frac{\Delta P / \Delta d}{P / d} \tag{10}$$

where s denotes perturbation step size, ΔP and Δd respectively denote the difference between power values and duty cycle values of two previous perturbations.

In some other research works, adaptive versions of HC have been developed [35,36].

2.4. Fractional open circuit voltage/short circuit current

In fractional open circuit voltage method (FOV), operating point is simply pushed toward a fraction of open circuit voltage as

suggested by Eq. (11) [37,38].

$$V_{mp} = K_1 V_{OC} \tag{11}$$

where K_1 is a constant in the interval [0.71, 0.78], V_{mp} denotes the voltage of MPP and V_{OC} represents open circuit voltage.

The main advantage of this method is its simplicity. It only requires a voltage sensor, however, its accuracy is not high.

In fractional short circuit current method (FSC), operating point is simply pushed toward a fraction of short circuit current as characterised by Eq. (12) [39].

$$I_{mp} = K_2 I_{SC} \tag{12}$$

where K_2 is a constant in the interval [0.78, 0.92], I_{mp} denotes the current of MPP and I_{SC} represents short circuit current.

The same as fractional open circuit voltage method, the salient advantage of this method is its simplicity. It only needs a current sensor, however it does not provide high accuracy.

A drawback of FOV and FSC methods is that open circuit voltage/short circuit current must be periodically measured and this interrupts supply to the loads and decreases MPPT efficiency.

2.5. Other MPPT methods

Besides the above-mentioned MPPT strategies, some other strategies have been proposed in the literature. Ripple Correlation Control [40,41], current sweep strategy [42] and linear current control strategy [43] are some examples of those methods.

2.6. Modification of classic MPPT methods for partial shading conditions

The most important disadvantage of basic variants of P&O, IC and HC is that they are not able to achieve global MPP in partial shading conditions. In PSC, there exist multiple local optima in P-V curve and these MPPT strategies converge into local optima instead of the global one. In attempts to solve this problem, some researchers have developed modified variants of these strategies. In [44], the following steps are proposed.

1. The voltage is initialised from $0.85V_{OC,all}$, where $V_{OC,all}$ represents open circuit voltage of the whole PV array.
2. Conventional P&O or IC is applied and the local MPP is found and memorised.
3. Voltage perturbation is applied with perturbation step size of $0.6-0.7V_{OC,one}$, where $V_{OC,one}$ denotes open circuit voltage of a single module. Then, conventional P&O or IC is applied to find the next local MPP.
4. Among the found local MPP's, the one giving the highest output power, will be the global MPP.

In [45], first a global search is done to find the interval containing global MPP, then conventional P&O or IC is applied to find the global MPP in that interval. The perturbation step size of global search and local search are quite different. In this method, in selecting the perturbation step size of global search, the tradeoff between accuracy and tracking speed must be considered. If it is set too high, the global MPP may be missed and if it set too low, tracking speed is diminished.

3. Modern MPPT methods

Modern MPPT techniques encompass artificial neural network (ANN)-based techniques, fuzzy logic-based techniques and metaheuristic-based techniques. In this section, modern MPPT techniques are reviewed.

3.1. Artificial neural network (ANN)-based MPPT methods

Artificial neural networks may be used for MPPT [46–53]. The typical inputs of ANN include parameters of PV array (open circuit voltage, short circuit current, etc.) and environmental parameters (irradiation and temperature) and shading pattern of PV array. The output may be the voltage or duty cycle which leads to MPP. In ANN, higher number of hidden layers increases tracking efficiency, but decreases tracking speed. A challenge in application of ANN to MPPT is that finding reliable data as training set is formidable [6]. Another challenge is that the developed MPPT strategy is system-dependent. In some cases, ANN is hybridised with classic MPPT techniques in order to achieve a more efficient MPPT strategy. In [54], it has been hybridised with IC and in [55], it has been hybridised with P&O.

3.2. Fuzzy logic controller (FLC)-based MPPT methods

Fuzzy logic controllers (FLC's) have been frequently used for MPPT [56–63]. Every FLC encompasses three parts; fuzzification, inference rules and defuzzification. For MPPT, the inputs of FLC are error e and the change in error Δe that are defined as below [56–63].

$$e(K) = \frac{P(K) - P(K-1)}{V(K) - V(K-1)} \tag{13}$$

$$\Delta e = e(K) - e(K-1) \tag{14}$$

The output of FLC is the change in voltage ΔV or the change in duty cycle Δd .

Since FLC-based MPPT functions based on $\frac{dP}{dV}$ information, in partial shading conditions (PSC's) it can not distinguish between local MPP's and global MPP, therefore, it must be modified to effectively track global MPP in PSC's [64]. In some cases, FLC's are incorporated into classic MPPT techniques. For instance, in [65], FLC has been incorporated into HC. In [66], the performance of ANN and FLC in MPPT systems have been compared and it is concluded that FLC provides higher tracking efficiency than ANN. A salient disadvantage of FLC-based MPPT strategies is their dependency to system. Moreover, their design requires prior knowledge of the behavior and characteristics of PV array.

3.3. Metaheuristic-based MPPT methods

Finding maximum power point in PV systems represents an optimisation problem. For uniform insolation, it represents a unimodal optimisation problem with single optimum, whereas for partial shading conditions, it represents a multimodal optimisation problem with multiple local optima. In the last three decades, metaheuristics have proved to be efficient techniques for solving difficult optimisation problems. They are even efficient in cases where a clear mathematical formulation of objective function versus decision variables does not exist. They are equipped with exploration capability, so unlike P&O, IC and HC, they may find global MPP in partial shading conditions. Unlike classic MPPT techniques, metaheuristic-based MPPT strategies do not oscillate around MPP. In this section, applications of different metaheuristic optimisation techniques in maximum power point tracking of PV system are reviewed.

3.3.1. PSO applications in MPPT

Particle swarm optimisation (PSO) is the most popular metaheuristic optimisation algorithm for MPPT in PV systems. It takes inspiration from flocking behavior of birds [67–69]. It searches within search space with N_P particles. The particles are randomly initialised. The position of ith particle is denoted by X_i

$(i=1,2,\ldots,N_P)$ and its velocity is denoted by V_i. The best position found by each particle is called its personal best. For ith particle, the position vector of personal best is denoted by P_i and its corresponding objective value is denoted by P_{best} . The best position achieved by the whole swarm is called global best. It is denoted by P_g and its corresponding objective value is denoted by g_{best}. PSO memorises the personal bests of all particles as well as global best [69,70].

At each iteration t, the velocities and positions of all particles are updated via Eqs. (15) and (16) which are called update equations or flight equations [71].

$$V_i(t+1)=\omega V_i\,(t)+C_1\,r_1(P_i-X_i)+C_2 r_2\left(P_g-X_i\right)\quad (i=1,2,\ldots,\ N_P) \tag{15}$$

$$X_i(t+1)=X_i\,(t)+V_i\,(t+1)\quad (i=1,2,\ldots,N_P) \tag{16}$$

The flight equations show that the new position of each particle is affected by three terms; The first term weighted by inertia weight (ω), is the current velocity of the particle. The second term weighted by cognitive acceleration coefficient (C_1), prompts the attraction of the particle towards its own personal best and the third term weighted by social acceleration coefficient (C_2), prompts the attraction of the particle towards global best. Symbols r_1 and r_2 represent two random numbers in [0,1].

After applying update equations, the objective values for all particles are computed and their personal bests and global best are updated. The described processes are repeated until the termination criterion is satisfied. After termination, the position and objective value of global best are given out respectively as optimal decision vector and optimal objective value of the optimisation problem in hand [69]. It must be noted that any metaheuristic optimisation algorithm must explore search space at initial iterations to find the region containing global optimum (exploration phase) and after finding that region, must try to fine tune global optimum (exploitation phase). An appropriate tradeoff between exploration and exploitation capabilities is critical.

Despite the advantages such as simplicity, strong exploitation capability and low number of control parameters, PSO lacks strong exploration capability to find global optimum in highly multimodal optimisation problems with many local optima [72]. In such problems, PSO due to its weak exploration capability, gets trapped in false local optima, therefore for MPPT in partial shading conditions, conventional PSO can not give out global optimum and it has rarely been used for solving this problem. As a result, a lat of research effort is being put in order to enhance PSO's exploration capability and enable it to successfully deal with MPPT in partial shading conditions.

In [20], in an attempt to enhance exploration capability of PSO, a modified PSO variant was developed wherein during the course of run, cognitive acceleration coefficient is linearly decreased and social acceleration coefficient is linearly increased. The proposed PSO variant has been used for MPPT in PV systems. In [20], PSO terminates If the velocity of particles falls below a threshold or the maximum number of iteration is met. The proposed MPPT strategy can be implemented using a low-cost digital controller. In [20], it has been implemented by a 500 W prototype. The tracking efficiency in all test cases were higher than 99.5%. and the average tracking efficiency was higher than 99.9%. Three different shading patterns were used for simulation. At the first shading pattern, the global MPP was located at right hand side of P-V curve, while at the second shading pattern, the global MPP was located at middle of P-V curve and at the third shading pattern, the global MPP was located at left hand side of P-V curve. Among the compared MPPT strategies, only the proposed modified PSO variant was capable of successfully tracking global MPP in all 1000 test cases.

In [73], a modified PSO variant is proposed for MPPT, wherein random numbers and acceleration coefficients in cognitive and social terms of PSO's update equation are removed and following equations are used for updating velocities of particles [73].

$$V_i(t+1)=\omega V_i(t)+(P_i-X_i)+\left(P_g-X_i\right) \tag{17}$$

or

$$V_i(t+1)=\omega V_i(t)+P_i+P_g-2X_i \tag{18}$$

As Eqs. (17)–(18) indicate, the probabilistic characteristic of PSO has been removed and the effects of personal best and global best on new position of particles are the same. In the proposed deterministic PSO, inertia weight is the sole parameter to be tuned. In experiments, it has been set as 0.4. Number of particles has been set as three. The simulation and implementation results show that for both uniform insolation and partial shading conditions, the proposed deterministic PSO outperforms conventional PSO and IC in both terms of tracking speed and tracking efficiency. It offers average tracking efficiency of 99.5%.

In [74], in order to enhance the exploration capability of PSO, it has been hybridised with DE. In this hybrid PSO-DE algorithm, PSO works in half of iterations and DE works in the other half of iterations, i.e. one iteration is done by PSO and the next iteration is done by DE and this continues till termination criterion is met. Simulations have been done for different shading patterns. The findings show that the hybrid PSO-DE outperforms IC, FLC and PSO in terms of efficiency, tracking speed, simplicity and low oscillations around MPP.

In [75], a hybrid of dormant PSO and IC has been proposed for MPPT. In dormant PSO, the random numbers of update equation are replaced by unity and during search process, the particles are categorised into active particles and dormant particles. First, dormant PSO is used to find the best hill (exploration phase), then IC is used to find MPP via a local search. (exploration phase). The simulation results testify that the proposed hybrid of dormant PSO and IC outperforms hybrid of conventional PSO and IC.

In [76] , PSO with the following new update equation has been proposed for MPPT in PV systems.

$$V_i(t+1)=\frac{2}{\pi}\sin^{-1}\left(\omega V_i(t)+C_1 r_1(P_i-X_i)+C_2 r_2\left(P_g-X_i\right)\right) \tag{19}$$

The simulation results show that the proposed modified PSO, characterised by (19), is superior to conventional PSO, both in terms of tracking efficiency and tracking speed.

In [77], a modified PSO variant was developed wherein a new update equation for particles has been proposed. The proposed algorithm enhances exploration capability of PSO in a way that it is able to track global MPP for partial shading conditions, even in extreme environmental conditions and large fluctuations of insolation. The implementation may be done using a low-cost microcontroller. The results in uniform insolation and partial shading conditions show that the proposed methodology outperforms HC both in terms of tracking speed and tracking efficiency.

In [78], a new PSO variant is put forward wherein random initialisation is replaced by deterministic initialisation. For uniform insolation and for ten different partial shading patterns, the proposed PSO variant outperforms conventional PSO, IC and HC in terms of tracking efficiency and tracking speed. In [79], PSO with multiple clusters was applied to MPPT. The simulation results indicate that for partial shading conditions, cluster-based PSO outperforms P&O. It leads to 13.3% increase in output energy with respect to P&O. In [80], hybrid of PSO and P&O is proposed for MPPT. In the proposed methodology, PSO works at initial stages of tracking process in order to find the promising regions of search space, then P&O is applied to fine tune the global MPP. Simulations

for two different PV configurations under varying shading patterns indicate that the proposed MPPT technique results in higher tracking efficiency and lower oscillations around MPP than PSO and P&O.

3.3.2. ABC applications in MPPT

Artificial bee colony (ABC) is inspired from food foraging behavior of bees and is known as a powerful optimisation algorithm with only one control parameter. In [81], ABC has been applied for MPPT. Simulations, done for two different PV configurations and for four different shading patterns, testify that ABC outperforms PSO and an enhanced version of P&O, both in terms of tracking efficiency and tracking speed. In [82], ABC has been used for MPPT. The simulations done for different patterns of partial shading conditions indicate the superiority of ABC over PSO.

3.3.3. GA applications in MPPT

Genetic algorithm (GA) is a well known metaheuristic optimisation algorithm which is inspired from natural evolution, mutation, crossover and selection [83]. In GA, a population of search agents (chromosomes) try to find global optimum. At each generation, new chromosomes are generated by reproductive operators such as crossover and mutation, then, based on objective values, selection operator selects the chromosomes of next generation. These stages continue until termination criterion is met. The best chromosome of the last generation is given out as global optimum of the problem in hand. In [84], GA has been used for MPPT. Simulations for PSC and for changes in different irradiations/temperatures/loads confirm that GA outperforms P&O and IC. In [85], P&O is integrated into GA in order to add to the exploitation capability of MPPT strategy. The findings for partial shading conditions indicate that the proposed hybrid GA-P&O outperforms GA.

3.3.4. Applications of other metaheuristics in MPPT

Other than PSO, ABC and GA, some other metaheuristic optimisation algorithms have also been used for MPPT. In [86], Cuckoo search optimisation (CSO) has been used for MPPT. CSO takes inspiration from obligate brood parasitism of some cuckoo species that lay their eggs in nests of other birds [87]. The findings for both uniform insolation and partial shading conditions confirm the outperformance of cuckoo search optimisation algorithm over P&O and PSO. Simulations have been done for gradual and sudden changes in irradiation and temperature. In [88], Firefly optimisation algorithm has been used for MPPT in partial shading conditions. Firefly algorithm is a metaheuristic inspired from flashing behavior of fireflies. The findings indicate that for two different used shading patterns, firefly optimisation algorithm outperforms P&O and PSO in terms of tracking efficiency and tracking speed.

In [89], a modified variant of differential evolution (DE) with deterministic mutation operator has been proposed for MPPT. DE is known as a well-established and popular algorithm for solving Engineering optimisation problems. The findings testify that the proposed modified DE outperforms PSO and leads to 99.5% tracking efficiency. It performs successfully in tracking global MPP of a PV system for a typical day in Malaysia, from 9 am to 5 pm. In [90], ant colony optimisation (ACO) has been used for MPPT. ACO is a metaheuristic inspired from the behavior of ants seeking a path between their colony and a source of food. Four ants have been used as population. The simulation done for four different shading patterns confirm the outperformance of ACO over P&O, PSO and fractional open circuit voltage (FOV). In [91], Chaos optimisation algorithm with logistic map function has been used for MPPT. The simulation results indicate that chaos optimisation algorithm outperforms conventional HC and variable step size HC. In [92], artificial immune system (AIS) optimisation algorithm has been used for MPPT. AIS is inspired from immune systems of the body of human beings. However, the performance of the proposed AIS has not been validated by comparison with state of the art MPPT methodologies. Table 1 has tabulated the characteristics of different metaheuristic-based MPPT techniques. In overall, due to the following reasons, metaheuristics are appropriate candidates for MPPT and are superior to classic MPPT strategies, FLC-based MPPT strategies and ANN-based MPPT strategies.

- Unlike classic methods such as P&O, IC and HC, metaheuristics are able to conduct global search and find global optimum in multimodal landscapes. Therefore, in partial shading conditions, where multiple local optima exist, metaheuristics are able to find global maximum power point, while classic methods may easily be trapped in false local optima.
- Unlike FLC-based MPPT strategies and ANN-based MPPT strategies which are designed based on a specific PV system, metaheuristic-based MPPT strategies are not system-dependent and perform effectively for different PV systems.
- Unlike classic MPPT methods such as P&O, IC and HC, metaheuristic-based MPPT strategies do not oscillate around maximum power point.

4. Overall review on MPPT methods and some directions for future research

After reviewing the existing research works on MPPT strategies in PV systems, the following directions are proposed for future research.

- Although, a couple of metaheuristic optimisation algorithms have already been used for MPPT, application of other metaheuristics such as teaching-learning based optimisation (TLBO), imperialistic competitive algorithm (ICA), brainstorm optimisation algorithm (BSOA), bat swarm optimisation (BSO) algorithm, evolutionary programming (EP), invasive weed optimisation (IWO), grey wolf optimisation (GWO) algorithm, gravitational search algorithm (GSA), seeker optimisation algorithm (SOA), water cycle algorithm (WCA), evolution strategy (ES), harmony search (HS) and krill herd optimisation (KHO) to MPPT, may lead to better results and is recommended for future research.
- Control parameters of metaheuristic optimisation algorithms significantly affect their computational behavior. The suitable values of control parameters are different from problem to problem. For each optimisation problem, the suitable values of control parameters must be found. However, in none of the existing research works on MPPT, the control parameters of metaheuristics have been tuned.
- A detailed comparison between classic, FLC-based, ANN-based and metaheuristic-based MPPT strategies from different points of view is recommended.
- Comparing the performance of a diverse set of metaheuristics on MPPT from the viewpoint of tracking efficiency and tracking speed and identifying the most suitable metaheuristic(s) for MPPT is recommended.
- Finding ways for easier and cheaper implementation of MPPT strategies is recommended.
- Finding the most appropriate MPPT strategy for each specific application of PV systems is recommended.

5. Conclusions

Tracking maximum power point in photovoltaic systems is an important task and represents a formidable problem. In maximum

Table 1
Different metaheuristic-based MPPT methods.

Ref	optimisation algorithm	Simulation/ implementation	Remarks
[20]	PSO with linearly decreasing cognitive acceleration coefficient and linearly increasing social acceleration coefficient.	Both	It is implemented using a low cost digital controller. The tracking efficiency in all test cases is above 99.5% and the average tracking efficiency is above 99.9%. Only the proposed modified PSO was capable of successfully tracking global MPP in all 1000 test cases.
[73]	A deterministic PSO wherein the random numbers and acceleration coefficients in cognitive and social terms of update equation are eliminated.	Both	For both uniform insolation and partial shading conditions, deterministic PSO outperforms conventional PSO and IC in both terms of tracking speed and tracking efficiency.
[74]	Hybrid PSO-DE	Both	The findings show that hybrid PSO-DE outperforms IC, FLC and PSO in terms of efficiency, tracking speed, simplicity and low oscillations around MPP.
[75]	Hybrid of dormant PSO and IC.	Both	The hybrid of dormant PSO and IC outperforms hybrid of conventional PSO and IC.
[76]	PSO with a new update equation as (19)	Both	The findings show that the proposed modified PSO outperforms conventional PSO in terms of tracking efficiency and tracking speed.
[77]	A new update equation for particles has been proposed.	Both	The proposed algorithm enhances exploration capability of PSO in a way that it is able to track global MPP for partial shading conditions. The results show that the proposed methodology outperforms HC in both terms of tracking speed and tracking efficiency.
[78]	PSO with deterministic initialisation	Both	For uniform insolation and for ten different partial shading patterns, the proposed PSO variant outperforms conventional PSO, IC and HC in terms of tracking efficiency and tracking speed.
[79]	PSO with multiple clusters	Both	For partial shading conditions, it outperforms P&O. It leads to 13.3% increase in output energy with respect to P&O.
[80]	Hybrid of PSO and P&O	Only simulation	The findings indicate that the proposed MPPT technique results in higher tracking efficiency and lower oscillations around MPP than PSO and conventional P&O.
[81]	ABC	Both	Simulations show the superiority of ABC over PSO and an enhanced version of P&O in terms of tracking efficiency and tracking speed.
[82]	ABC	Both	The simulations done for different patterns of partial shading conditions testify that ABC outperforms PSO.
[91]	Chaos optimisation algorithm	Both	Chaos optimisation algorithm outperforms conventional HC and variable step size HC.
[86]	Cuckoo search optimisation	Both	The findings confirm the outperformance of cuckoo search optimisation algorithm over P&O and PSO.
[88]	Firefly optimisation algorithm	Simulation only	Under PSC, firefly optimisation algorithm outperforms P&O and PSO in terms of tracking efficiency and tracking speed.
[84]	GA	Simulation only	Simulations confirm that GA outperforms P&O and IC.
[89]	DE with deterministic mutation operator	Both	The proposed DE outperforms PSO and leads to 99.5% tracking efficiency. It performs successfully in tracking global MPP of a PV system for a typical day.
[85]	Hybrid of GA and P&O	Both	The findings for partial shading conditions indicate that the proposed hybrid GA-P&O outperforms GA.
[90]	ACO	Simulation only	The simulations done for four different shading patterns confirm the outperformance of ACO over P&O, PSO and fractional open circuit voltage.

power point tracking (MPPT) systems, the duty cycle of DC-DC converter is adjusted in a way that maximum achievable power is extracted. In this paper, the existing MPPT methods have been categorised into two main categories and the methods of each category have been reviewed. The findings of this review indicate that metaheuristic optimisation algorithms, due to merits such as system independency, effective performance in partial shading conditions and absence of oscillations around maximum power point, are the best candidates for MPPT. They are superior to classic MPPT strategies, FLC-based MPPT strategies and ANN-based MPPT strategies.

References

[1] Jordehi AR. Parameter estimation of solar photovoltaic (PV) cells: a review. Renew Sustain Energy Rev 2016;61:354–71.

[2] Chin VJ, Salam Z, Ishaque K. Cell modelling and model parameters estimation techniques for photovoltaic simulator application: a review. Appl Energy 2015;154:500–19.

[3] Ishaque K, Salam Z, Mekhilef S, Shamsudin A. Parameter extraction of solar photovoltaic modules using penalty-based differential evolution. Appl Energy 2012;99:297–308.

[4] Ishaque K, Salam Z. An improved modeling method to determine the model parameters of photovoltaic (PV) modules using differential evolution (DE). Sol Energy 2011;85:2349–59.

[5] Bendib B, Belmili H, Krim F. A survey of the most used MPPT methods: conventional and advanced algorithms applied for photovoltaic systems. Renew Sustain Energy Rev 2015;45:637–48.

[6] Ishaque K, Salam Z. A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition. Renew Sustain Energy Rev 2013;19:475–88.

[7] Ishaque K, Salam Z. A comprehensive MATLAB Simulink PV system simulator with partial shading capability based on two-diode model. Sol Energy 2011;85:2217–27.

[8] Gow J, Manning C. Development of a model for photovoltaic arrays suitable for use in simulation studies of solar energy conversion systems; 1996.

[9] Chowdhury S, Taylor G, Chowdhury S, Saha A, Song Y. Modelling, simulation and performance analysis of a PV array in an embedded environment. In: Proceedings of the 42nd international universities power engineering conference, 2007. UPEC 2007, IEEE; 2007, p. 781–85.

[10] Gupta S, Tiwari H, Fozdar M, Chandna V. Development of a two diode model for photovoltaic modules suitable for use in simulation studies. In: Proceedings of the power and energy engineering conference (APPEEC), 2012 Asia-Pacific, IEEE, 2012, pp. 1–4.

[11] Liu Y-H, Chen J-H, Huang J-W. A review of maximum power point tracking techniques for use in partially shaded conditions. Renew Sustain Energy Rev 2015;41:436–53.

[12] Logeswaran T, SenthilKumar A. A review of maximum power point tracking algorithms for photovoltaic systems under uniform and non-uniform irradiances. Energy Procedia 2014;54:228–35.

[13] Lyden S, Haque M. Maximum Power Point Tracking techniques for photovoltaic systems: a comprehensive review and comparative analysis. Renew Sustain Energy Rev 2015;52:1504–18.
[14] Bizon N. Global Maximum Power Point Tracking (GMPPT) of Photovoltaic array using the Extremum Seeking Control (ESC): a review and a new GMPPT ESC scheme. Renew Sustain Energy Rev 2016;57:524–39.
[15] Kheldoun A, Bradai R, Boukenoui R, Mellit A. A new golden section method-based maximum power point tracking algorithm for photovoltaic systems. Energy Convers Manag 2016;111:125–36.
[16] Sundareswaran K, Peddapati S, Palani S. Application of random search method for maximum power point tracking in partially shaded photovoltaic systems. IET Renew Power Gener 2014;8:670–8.
[17] Amir A, Selvaraj J, Rahim N. Study of the MPP tracking algorithms: Focusing the numerical method techniques. Renew Sustain Energy Rev 2016;62:350–71.
[18] Dadjé A, Djongyang N, Kana JD, Tchinda R. Maximum power point tracking methods for photovoltaic systems operating under partially shaded or rapidly variable insolation conditions: a review paper. Int J Sustain Eng 2016:1–16.
[19] Abdul-Kalaam R, Muyeen S, Al-Durra A. Review of maximum power point tracking techniques for photovoltaic system. Glob J Control Eng Technol 2016;2:8–18.
[20] Liu Y-H, Huang S-C, Huang J-W, Liang W-C. A particle swarm optimization-based maximum power point tracking algorithm for PV systems operating under partially shaded conditions. IEEE Trans Energy Convers 2012;27:1027–35.
[21] Elgendy MA, Zahawi B, Atkinson DJ. Assessment of perturb and observe MPPT algorithm implementation techniques for PV pumping applications. IEEE Trans Sustain Energy 2012;3:21–33.
[22] Al-Amoudi A, Zhang L. Optimal control of a grid-connected PV system for maximum power point tracking and unity power factor. In: Proceedings of the seventh international conference on power electronics and variable speed drives, 1998. (Conf. Publ. No. 456), IET; 1998, p. 80–85.
[23] Abdelsalam AK, Massoud AM, Ahmed S, Enjeti P. High-performance adaptive perturb and observe MPPT technique for photovoltaic-based microgrids. IEEE Trans Power Electron 2011;26:1010–21.
[24] Fermia N, Granozio D, Petrone G, Vitelli M. Predictive & adaptive MPPT perturb and observe method. IEEE Trans Aerosp Electron Syst 2007;43:934–50.
[25] Piegari L, Rizzo R. Adaptive perturb and observe algorithm for photovoltaic maximum power point tracking. IET Renew Power Gener 2010;4:317–28.
[26] Petrone G, Spagnuolo G, Vitelli M. A multivariable perturb-and-observe maximum power point tracking technique applied to a single-stage photovoltaic inverter. IEEE Trans Ind Electron 2011;58:76–84.
[27] De Brito MAG, Galotto Jr L, Sampaio LP, de Azevedo e Melo G, Canesin CA. Evaluation of the main MPPT techniques for photovoltaic applications. IEEE Trans Ind Electron 2013;60:1156–67.
[28] Ahmed J, Salam Z. An improved perturb and observe (P&O) maximum power point tracking (MPPT) algorithm for higher efficiency. Appl Energy 2015;150:97–108.
[29] Saravanan S, Babu NR. Maximum power point tracking algorithms for photovoltaic system–a review. Renew Sustain Energy Rev 2016;57:192–204.
[30] Sera D, Mathe L, Kerekes T, Spataru SV, Teodorescu R. On the perturb-and-observe and incremental conductance MPPT methods for PV systems. IEEE J Photovolt 2013;3:1070–8.
[31] Wu W, Pongratananukul N, Qiu W, Rustom K, Kasparis T, Batarseh I. DSP-based multiple peak power tracking for expandable power system. In: Proceedings of the eighteenth annu. IEEE appl. power electron. conf. expo; 2003, p. 525–30.
[32] Li J, Wang H. A novel stand-alone PV generation system based on variable step size INC MPPT and SVPWM control. In: Proceedings of the IEEE 6th international power electronics and motion control conference, 2009. IPEMC'09, IEEE, 2009, p. 2155–60.
[33] Liu F, Kang Y, Zhang Y, Duan S. Comparison of P&O and hill climbing MPPT methods for grid-connected PV converter. In: Proceedings of the 3rd IEEE conference on industrial electronics and applications, 2008. ICIEA 2008, IEEE; 2008, p. 804–807.
[34] Chiang ML, Hua CC, Lin JR. Direct power control for distributed PV power system. In: Proceedings of the IEEE power conversion conference, 2002. PCC-Osaka 2002; 2002, p. 311–15.
[35] Xiao W, Dunford WG. A modified adaptive hill climbing MPPT method for photovoltaic power systems. In: Proceedings of the 2004 IEEE 35th annual power electronics specialists conference, 2004. PESC 04; 2004, p. 1957–63.
[36] Xiao W. A modified adaptive hill climbing maximum power point tracking (MPPT) control method for photovoltaic power systems. In: University of British Columbia, 2003.
[37] Kobayashi K, Matsuo H, Sekine Y. A novel optimum operating point tracker of the solar cell power supply system. In: Proceedings of the 2004 IEEE 35th annual power electronics specialists conference, 2004. PESC 04; 2004, p. 2147–2151.
[38] Patterson DJ. Electrical system design for a solar powered vehicle. In: Proceedings of the 21st annual IEEE power electronics specialists conference, 1990. PESC'90 Record; 1990, p. 618–22.
[39] Noguchi T, Togashi S, Nakamoto R. Short-current pulse based adaptive maximum-power-point tracking for photovoltaic power generation system. In: Proceedings of the 2000 IEEE international symposium on industrial electronics, 2000. ISIE 2000; 2000, p. 157–62.
[40] Lim YH, Hamill D. Simple maximum power point tracker for photovoltaic arrays. Electron Lett 2000;36:1.
[41] Lim YH, Hamill DC. Synthesis, simulation and experimental verification of a maximum power point tracker from nonlinear dynamics. In: Proceedings of the 2001 IEEE 32nd annual power electronics specialists conference, 2001. PESC; 2001, p. 199–204.
[42] Bodur M, Ermiş M. Maximum power point tracking for low power photovoltaic solar panels. In: Proceedings of the IEEE 7th mediterranean electrotechnical conference, 1994; 1994, p. 758–61.
[43] Pan CT, Chen JY, Chu CP, Huang YS. A fast maximum power point tracker for photovoltaic power systems. In: Proceedings of the 25th annual conference of the IEEE industrial electronics society, 1999. IECON'99 Proceedings; 1999, p. 390–93.
[44] Patel H, Agarwal V. Maximum power point tracking scheme for PV systems operating under partially shaded conditions. IEEE Trans Ind Electron 2008;55:1689–98.
[45] Renaudineau H, Houari A, Martin J-P, Pierfederici S, Meibody-Tabar F, Gerardin B. A new approach in tracking maximum power under partially shaded conditions with consideration of converter losses. Sol Energy 2011;85:2580–8.
[46] Islam MA, Kabir MA. Neural network based maximum power point tracking of photovoltaic arrays. In: TENCON 2011-2011 IEEE Region 10 Conference, IEEE, 2011, p. 79–82.
[47] Veerachary M, Yadaiah N. ANN based peak power tracking for PV supplied DC motors. Sol Energy 2000;69:343–50.
[48] Khanaki R, Radzi M, Marhaban MH, Comparison of ANN and P&O MPPT methods for PV Applications under Changing Solar Irradiation. In: Proceedings of the 2013 IEEE conference on clean energy and technology (CEAT); 2013, p. 287–92.
[49] Rai AK, Kaushika N, Singh B, Agarwal N. Simulation model of ANN based maximum power point tracking controller for solar PV system. Sol Energy Mater Sol Cells 2011;95:773–8.
[50] Ocran TA, Cao J, Cao B, Sun X. Artificial neural network maximum power point tracker for solar electric vehicle. Tsinghua Sci Technol 2005;10:204–8.
[51] Kaliamoorthy M, Sekar R, Raj I. Solar powered single stage boost inverter with ANN based MPPT algorithm. In: Proceedings of the 2010 IEEE international conference on communication control and computing technologies (ICCCCT), IEEE; 2010, p. 165–170.
[52] Vasarevicius D, Martavicius R, Pikutis M. Application of artificial neural networks for maximum power point tracking of photovoltaic panels. Elektron Elektrotech 2012;18:65–8.
[53] Rizzo SA, Scelba G. ANN based MPPT method for rapidly variable shading conditions. Appl Energy 2015;145:124–32.
[54] Xu J, Shen A, Yang C, Rao W, Yang X. ANN based on IncCond algorithm for MPP tracker. In: Proceedings of the 2011 sixth international conference on bio-inspired computing: theories and applications (BIC-TA), IEEE; 2011, p. 129–34.
[55] Amrouche B, Belhamel M, Guessoum A. Artificial intelligence based P&O MPPT method for photovoltaic systems, Revue des Energies Renouvelables ICRESD-07 Tlemcen; 2007. p. 11–16.
[56] Mahmoud A, Mashaly H, Kandil S, El Khashab H, Nashed M. Fuzzy logic implementation for photovoltaic maximum power tracking. In: Proceedings of the 26th annual conference of the IEEE industrial electronics society, 2000. IECON 2000; 2000, p. 735–40.
[57] Khaehintung N, Pramotung K, Tuvirat B, Sirisuk P., RISC-microcontroller built-in fuzzy logic controller of maximum power point tracking for solar-powered light-flasher applications. In: Proceedings of the IEEE 30th annual conference of IEEE industrial electronics society, 2004. IECON 2004; 2004, pp. 2673–78.
[58] Won CY, Kim DH, Kim SC, Kim WS, Kim HS. A new maximum power point tracker of photovoltaic arrays using fuzzy controller. In: Proceedings of the 25th annual IEEE power electronics specialists conference, PESC'94 Record. IEEE; 1994, p. 396–403.
[59] Gounden NA, Peter SA, Nallandula H, Krithiga S. Fuzzy logic controller with MPPT using line-commutated inverter for three-phase grid-connected photovoltaic systems. Renew Energy 2009;34:909–15.
[60] Altas I, Sharaf A. A novel maximum power fuzzy logic controller for photovoltaic solar energy systems. Renew Energy 2008;33:388–99.
[61] Patcharaprakiti N, Premrudeepreechacharn S. Maximum power point tracking using adaptive fuzzy logic control for grid-connected photovoltaic system. In: Proceedings of the IEEE power engineering society winter meeting, 2002. IEEE; 2002, p. 372–77.
[62] Messai A, Mellit A, Pavan AM, Guessoum A, Mekki H. FPGA-based implementation of a fuzzy controller (MPPT) for photovoltaic module. Energy Convers Manag 2011;52:2695–704.
[63] Chen Y-T, Jhang Y-C, Liang R-H. A fuzzy-logic based auto-scaling variable step-size MPPT method for PV systems. Sol Energy 2016;126:53–63.
[64] Alajmi BN, Ahmed KH, Finney SJ, Williams BW. A maximum power point tracking technique for partially shaded photovoltaic systems in microgrids. IEEE Trans Ind Electron 2013;60:1596–606.
[65] Alajmi BN, Ahmed KH, Finney SJ, Williams BW. Fuzzy-logic-control approach of a modified hill-climbing method for maximum power point in microgrid standalone photovoltaic system. IEEE Trans Power Electron 2011;26:1022–30.
[66] Salah CB, Ouali M. Comparison of fuzzy logic and neural network in maximum power point tracker for PV systems. Electr Power Syst Res 2011;81:43–50.
[67] Kennedy J, Eberhart R, Particle swarm optimization. In: Proceedings of the IEEE international conference on neural networks, Perth, Australia; 1995, p. 1942–48.
[68] Eberhart RC, Shi Y, Kennedy J. Swarm intelligence. Elsevier; 2001.

[69] Jordehi AR. Particle swarm optimisation (PSO) for allocation of FACTS devices in electric transmission systems: a review. Renew Sustain Energy Rev 2015;52:1260–7.
[70] Rezaee Jordehi A, Jasni J. Parameter selection in particle swarm optimisation: a survey. J Exp Theor Artif Intell 2013;25:527–42.
[71] Shi Y, Eberhart R. A modified particle swarm optimizer. In: Proceedings of the 1998 IEEE international conference on IEEE world congress on computational intelligence, evolutionary computation proceedings, 1998, IEEE; 1998, p. 69–73.
[72] Jordehi AR. Enhanced leader PSO (ELPSO): a new PSO variant for solving global optimisation problems. Appl Soft Comput 2015;26:401–17.
[73] Ishaque K, Salam Z. A deterministic particle swarm optimization maximum power point tracker for photovoltaic system under partial shading condition. IEEE Trans Ind Electron 2013;60:3195–206.
[74] Seyedmahmoudian M, Rahmani R, Mekhilef S, Maung Than Oo A, Stojcevski A, Soon TK, Ghandhari AS. Simulation and hardware implementation of new maximum power point tracking technique for partially shaded PV system using hybrid DEPSO method. IEEE Trans Sustain Energy 2015;6:850–62.
[75] Shi J, Zhang W, Zhang Y, Xue F, Yang T. MPPT for PV systems based on a dormant PSO algorithm. Electr Power Syst Res 2015;123:100–7.
[76] Mirhassani SM, Golroodbari SZM, Golroodbari SMM, Mekhilef S. An improved particle swarm optimization based maximum power point tracking strategy with variable sampling time. Int J Electr Power Energy Syst 2015;64:761–70.
[77] Ishaque K, Salam Z, Amjad M, Mekhilef S. An improved particle swarm optimization (PSO)–Based MPPT for PV with reduced steady-state oscillation. IEEE Trans Power Electron 2012;27:3627–38.
[78] Babu TS, Rajasekar N, Sangeetha K. Modified particle swarm optimization technique based maximum power point tracking for uniform and under partial shading condition. Appl Soft Comput 2015;34:613–24.
[79] Chen WR, Chen LR, Wu CH, Lai CM. Multicluster-based particle swarm optimization algorithm for photovoltaic maximum power point tracking. In: Proceedings of the 2015 IEEE 2nd International future energy electronics conference (IFEEC); 2015, p. 1–6.
[80] Sundareswaran K, Palani S. Application of a combined particle swarm optimization and perturb and observe method for MPPT in PV systems under partial shading conditions. Renew Energy 2015;75:308–17.
[81] Sundareswaran K, Sankar P, Nayak P, Simon SP, Palani S. Enhanced energy output from a PV system under partial shaded conditions through artificial bee colony. IEEE Trans Sustain Energy 2015;6:198–209.
[82] Benyoucef A soufyane, Chouder A, Kara K, Silvestre S. Artificial bee colony based algorithm for maximum power point tracking (MPPT) for PV systems operating under partial shaded conditions. Appl Soft Comput 2015;32:38–48.
[83] Goldberg DE, Holland JH. Genetic algorithms and machine learning. Machine Learn 1988;3:95–9.
[84] Shaiek Y, Smida MB, Sakly A, Mimouni MF. Comparison between conventional methods and GA approach for maximum power point tracking of shaded solar PV generators. Sol Energy 2013;90:107–22.
[85] Daraban S, Petreus D, Morel C. A novel MPPT (maximum power point tracking) algorithm based on a modified genetic algorithm specialized on tracking the global maximum power point in photovoltaic systems affected by partial shading. Energy 2014;74:374–88.
[86] Ahmed J, Salam Z. A Maximum Power Point Tracking (MPPT) for PV system using Cuckoo Search with partial shading capability. Appl Energy 2014;119:118–30.
[87] Yang X-S, Deb S. Engineering optimisation by cuckoo search. Int J Math Model Numer Optim 2010;1:330–43.
[88] Sundareswaran K, Peddapati S, Palani S. MPPT of PV systems under partial shaded conditions through a colony of flashing fireflies. IEEE Trans Energy Convers 2014;29:463–72.
[89] Ramli MA, Ishaque K, Jawaid F, Al-Turki YA, Salam Z. A modified differential evolution based maximum power point tracker for photovoltaic system under partial shading condition. Energy Build 2015;103:175–84.
[90] Jiang LL, Maskell DL, Patra JC. A novel ant colony optimization-based maximum power point tracking for photovoltaic systems under partially shaded conditions. Energy Build 2013;58:227–36.
[91] Zhou L, Chen Y, Guo K, Jia F. New approach for MPPT control of photovoltaic system with mutative-scale dual-carrier chaotic search. IEEE Trans Power Electron 2011;26:1038–48.
[92] Xu R, Sun X, Liu H. PV array model with maximum power point tracking based on immunity optimization algorithm. In: Electrical engineering and control, Springer; 2011, p. 535–42.