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Study of the MPP tracking algorithms: Focusing the numerical method techniques

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A B S T R A C T

A comparative review between different algorithms for maximum power point (MPP) tracking is presented, particularly focusing Numerical Method (NM) techniques. This paper presents a wide range of efficient NM schemes which have been neglected by most of the MPPT review papers. As, NM techniques are one of the simplest and fastest tracking algorithms. These techniques offer advantages of exact MPP tracking, standalone applications, flexible searching step sizes and no steady state oscillations. In addition, many different MPPT schemes are discussed and compared with the NM techniques. There are many ways of grouping and categorizing the MPPT algorithms for the Photovoltaic (PV) Array. However, evaluation of the NM schemes in comparison with other techniques is provided effectively through analog and digital classification, in terms of implementation and circuitry involved. Therefore, a comparative review majorly focusing on the importance of NM schemes to track the MPP is presented in comparison with other techniques, through analog and digital classification.

Contents

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1. Introduction

Solar energy as one of the most reliable and efficient renewable source of energy is clean, emission-free and reliable, making the harnessed energy through PV modules a common interest of research [1–6]. In addition, most of the research has been on extracting maximum output from the photovoltaic array. As, output power of the PV array depends on atmospheric conditions and shows non-linear *I–V* characteristics. A MPP exists at the knee on the PV curve, where power is maximum [7]. MPPT techniques are employed to harness maximum power from the PV source. As, MPP varies with respect to the changing atmospheric conditions, the MPPT techniques trace the PV operating voltage analogous to the MPP [8].

Moreover, many MPPT algorithms have been proposed and practically implemented, reviews on MPPT techniques are given in [9–25]. However, many review papers have either neglected to place the NM techniques in the important list [9–13] or have overlooked to even place the techniques in the review articles [14–25]. Therefore, a digital and analog classification, in terms of implementation, has been utilized to study the MPPT algorithms, majorly focusing the NM techniques.

Further, the key element of this study is to explore the application of classical root-finding optimization algorithms and other iterative techniques for MPPT. In addition, an attempt is made to discuss the working principle of different MPPT schemes and to compare their performances with NM techniques. To facilitate this comparison, the MPPT techniques have been classified into digital and analog techniques. Performance indices for evaluating the techniques are: exact MPP tracking ability, tracking speed, tuning requirement, implementation complexity, cost, PV array dependence, stability and efficiency of the system.

The objectives of the review are as follows:

1. Present a wide range of efficient NM techniques, which have been neglected by most of the MPPT review papers.
2. State different techniques for MPPT taken from the available literature, through analog and digital classification.
3. A comparative review between different algorithms for maximum power point (MPP) tracking is presented, particularly focusing the Numerical Method (NM) techniques.
4. Guide for future work on MPPT, by displaying the pros and cons of the mentioned techniques.

The paper is structured as follows: Section 2 introduces the model of a PV module. As, understanding the PV characteristics and its physical aspects supports the MPPT analysis. Section 3 investigates the digital techniques, largely focusing the root-finding algorithms and other iterative techniques for MPPT implementation. Section 4 discusses the analog methods for MPPT. Here, analog and digital classification has been utilized as it aids the understanding of NM techniques. Section 5 presents the hybrid techniques, which include features of both digital and analog methods. Section 6 offers the discussion and critical analysis of all the techniques. Areas under discussion are the convergence speed, exact MPP detection, application of the MPPT technique, circuitry involved in implementing the techniques and the PV array dependence. Finally, Section 7 presents the conclusion of this work.

2. Model of a pv module

2.1. Mathematical model of a solar cell

The Photovoltaic cell is a non-linear DC current source. Its output power depends on changing temperature and irradiation. Fig. 1 displays the equivalent circuit of an ideal PV cell.

This idealistic model is accurate enough to understand the PV characteristics and the dependence of PV cell on changing atmospheric conditions. From [27], mathematical modeling of the PV cell is presented as:

$$I = I_{pv} - I_0\left[exp\left(\frac{V - R_s I}{V_t a}\right) - 1\right] - \frac{V + R_s I}{R_p} \quad (1)$$

Where, I_{pv} is the current generated by the incident light, I_0 the reverse saturation current, $V_t = \frac{N_s kT}{q}$ the thermal voltage of the array with Ns cells connected in series. q is the electron charge $\left(1.60217646 \times 10^{-19} C\right)$, T (in Kelvin) the temperature of the p–n junction, k is the Boltzmann constant $\left(1.3806503 \times 10^{-23} J/\mathrm{K}\right)$ and a is the diode ideality constant.

2.2. Temperature and irradiation effects

Eq. (1) specifies that solar irradiance and temperature are the two main factor affecting PV cell output. Therefore, it is predictable that the PV output will vary with changing atmospheric conditions. As, irradiation depends on angle of incidence of the sunrays with respect to the panel. These factors directly affect the output, altering the *P–V* and the *I–V* characteristics. Figs. 2(a) and (b), 3(a) and (b) display the significant variation in the outputs based on a PV module with nominal parameters under standard testing condition (STC).

The non-linear *I–V* characteristic curves of Eq. (1) clearly display the variation in the output under different solar irradiance and temperature conditions. This shows that an operating power point exists for each given set of temperature and solar irradiation levels at which maximum output power can be harnessed from the PV module. This unique operating power point is known as the MPP and it is attained for the particular output voltage and current corresponding to the MPP. Moreover, MPPT techniques are required to track the optimum point of operation. The important MPPT methods discussed in this paper are classical optimization root-finding algorithms and other iterative techniques.

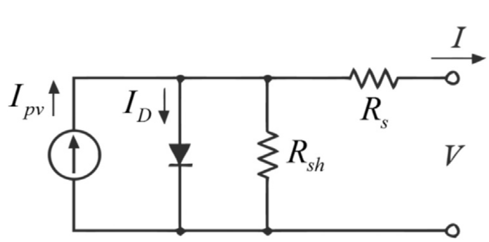


Fig. 1. Equivalent circuit of a PV cell [26].

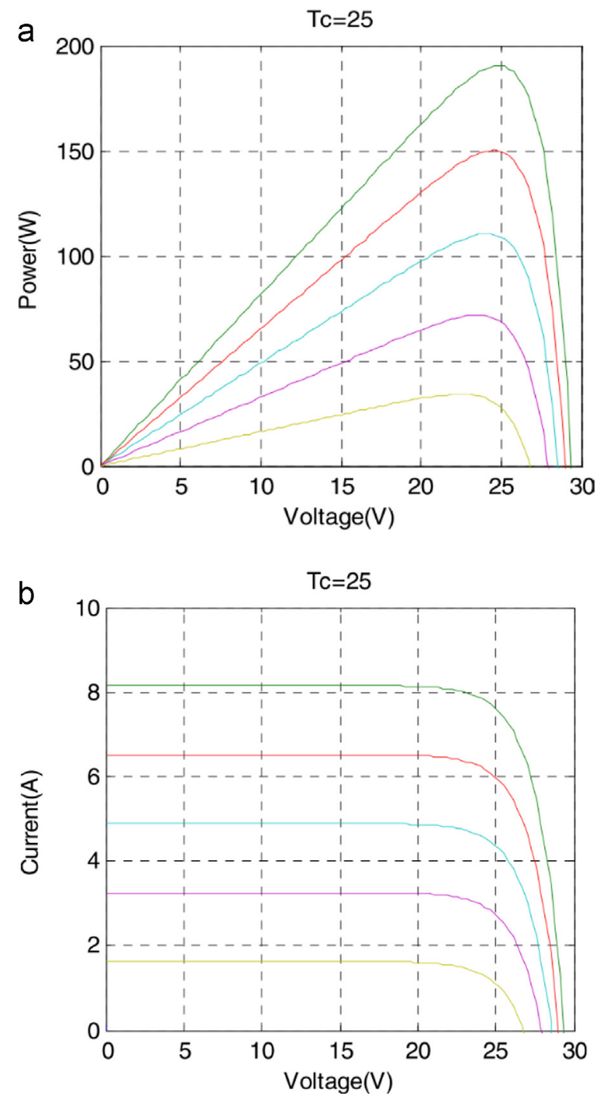


Fig. 2. (a). *P–V* curves of PV cells under the same ambient temperature and different irradiation level [8].(b). *I–V* curves of PV cells under the same ambient temperature and different irradiation level [8].

3. Digital techniques

3.1. Numerical methods (NM)

As observed analytical solutions always provide exact solutions of the problem [28]. However, when such solutions are not possible, the only way of obtaining solutions is the numerical or approximate solution. Therefore, the process of obtaining an approximate solution is possible by using repetition of same steps so that the computations become automatic [29]. Such a process is called a numerical method, providing estimates close enough to the exact solution. As, a minimal amount of error is introduced into the computation. However, the results or root findings are faster and easier, here we consider MPP as the optimum root to be tracked.

3.1.1. Root location methods to track the MPP

The value that satisfies an equation is known as the root of the equation. As, the prime concern here is to track the MPP, NMs can be used as the processes which are iterative or recursive in nature to track the exact MPP through a number of subsequent iterations. Root location methods can be divided in two types:

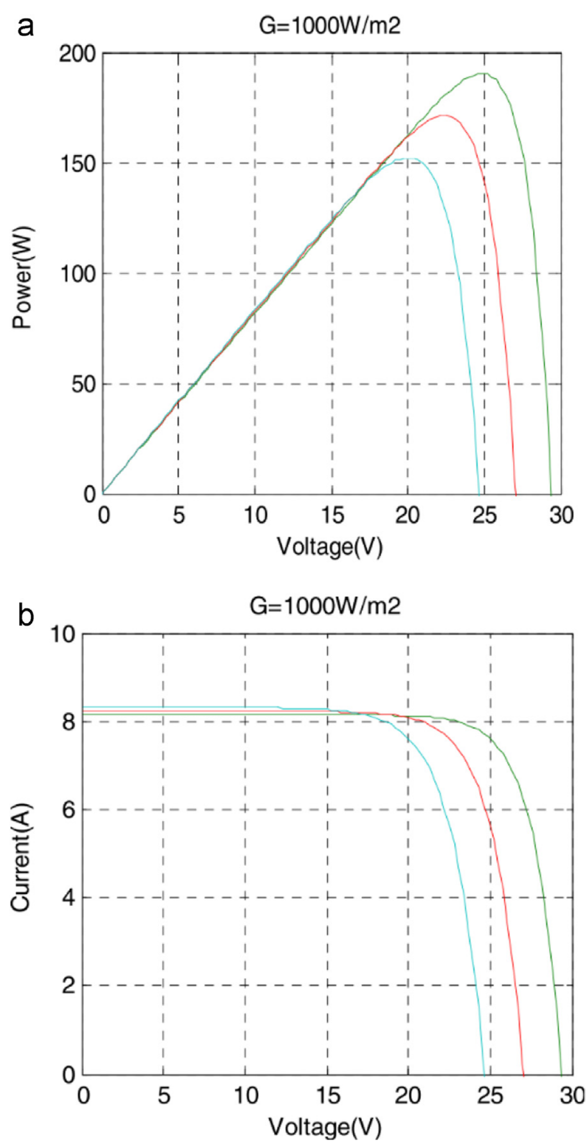


Fig. 3. (a) *P–V* curves of PV cells under the same irradiation level and different ambient temperature [8]. (b) *I–V* curves of PV cells under the same irradiation level and different ambient temperature [8].

3.1.1.1. Open bracket methods

3.1.1.1.1. Newton Raphson (NR) method. The method is commonly used because of its simplicity and great speed [28]. NR Method has been employed by many researchers either to track the MPP or find the parameters for tracking the MPP, some of the major publications include [30–46]. Where, [30–32] provide an overview of the technique, in [33–37] Extremum Seeking Control has been incorporated to tune MPPT parameters centered on the NR Method. In addition, [38–41,45,47] provide improved MPPT control through PV Array Modeling using NR and most importantly [42–44] provide Real-Time Identification of the Optimal Operating Points through the NR Root Location Method. In addition, [46] provides an auto-tuning based adaptive maximum power point tracker (ATAMPPT) for a photovoltaic (PV) system which uses NR method and can easily adjust to changing weather conditions. Basic concept of the NR method has been shown in Fig. 4. This method utilizes tangent at one point on the graph $f(Y)$ in order to approximate the graph. Therefore, it uses only one initial guess. Considering, Y_0 as the initial guess, a tangent line is produced to meet the point Y_1 on the $x-axis$ from the point of intersection, between $f(Y)$ and $f(Y_0)$. Now, solving the right

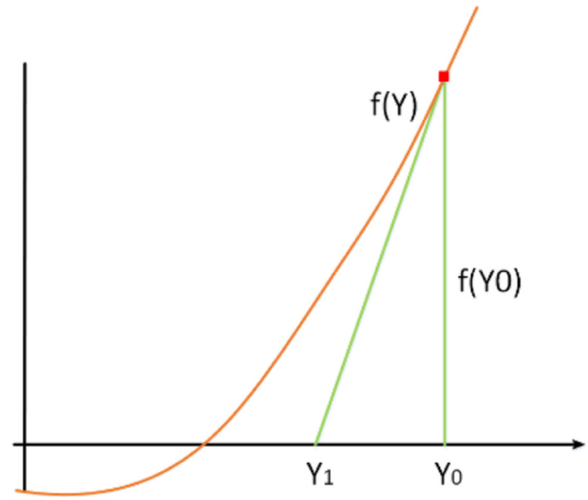


Fig. 4. Basic concept of the NR method.

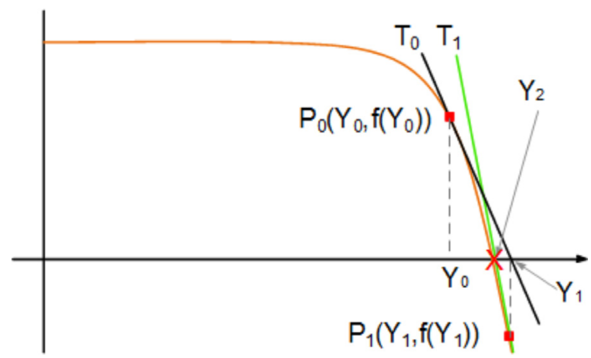


Fig. 5. NR method to track the MPP.

triangle offers Eq. (2) which is utilized for the first iterative approximation and the Eq. (3) for the subsequent approximations.

For MPP, derivatives of the change in power provide an estimation of the direction and iterations for the convergence as presented in Fig. 5. Equation utilized by the NR to either track the MPP or assist in tracking the MPP is:

$$Y_1 = Y_0 - \frac{f(Y_0)}{f^{`}(Y_0)} \tag{2}$$

Successive iterations are defined in a similar manner as:

$$Y_{n+1} = Y_n - \frac{f(Y_n)}{f^{`}(Y_n)} \tag{3}$$

where, Y_n represents the root and T_n the tangent line to the function$f(Y)$. In addition, it requires only one initial guess. In case of MPPT, Y represents the voltage V of the PV array, P the output power and $f(Y) = \frac{dP}{dV}$. This method provides fast convergence and good accuracy. However, the drawbacks of this method are that at any point of computation, if the tangent is parallel to the x-axis then this method will not work at all. As, an initial guess away from the MPP may lead to slow convergence as shown in Fig. 6.

3.1.1.1.2. Secant method (SM). SM has been used in [48–50], either to directly track the MPP through a hybrid approach [48] or assist in detecting parameters through PV Array Modeling [49,50]. NR method is very powerful, but has the disadvantage that the derivative $f^{`}$ may sometimes be a far more difficult expression than f itself. Its evaluation therefore computationally expensive. However, SM is very efficient for locating the MPP. This method requires two initial guesses. Fig. 7 displays the basic realization of

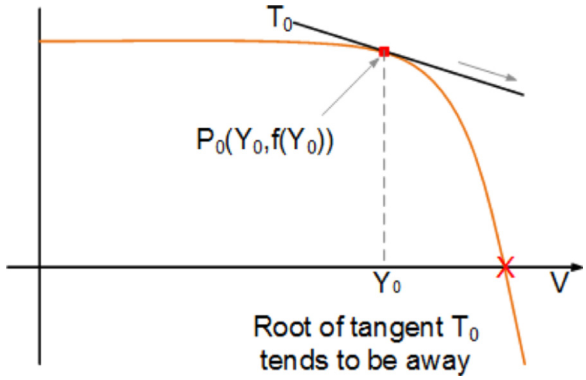


Fig. 6. NR method fails as the root tends to be farther away [30].

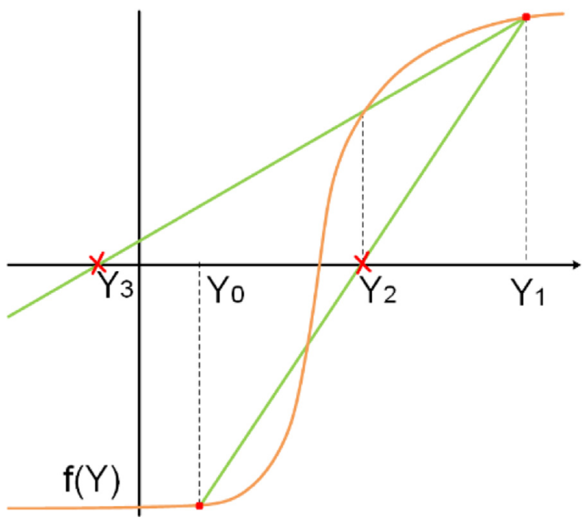


Fig. 7. Basic concept of the SM.

the secant method where the derivative has been replaced with the difference quotient. Here the green lines represent the secants. Y_0 and Y_1 the two initial guesses. A secant is constructed through the points $(Y_o,f(Y_o))$ and $(Y_1,f(Y_1))$. Finally, a point-slope derivation is utilized to derive Eq. (4) which is used to approximate the graph. The first approximation being Y_2.

Equation utilized by the secant method for successive iterations is:

$$Y_n = Y_{n-1} - f(Y_{n-1})\frac{(Y_{n-1})-(Y_{n-2})}{f(Y_{n-1})-f(Y_{n-2})} \tag{4}$$

For MPP, n is the number of iteration, Y represents the voltage of PV array, $P=VI$ output power and $f(Y)=\frac{dP}{dV}$. Fig. 8 shows a graphical presentation of the SM. Here Y_n represents the root and L_n the secant to the function$f(Y)$, not a tangent.

It is very efficient, does not require bracketed limits and even requires two initial guesses. However, drawbacks include that if the initial values are not close to the MPP, then stability and convergence are not guaranteed.

3.1.1.2. Close bracket methods

3.1.1.2.1. Bisection search method (BSM). BSM is used by researchers in [51–53] to track the MPP. Wang et al. [51] provides a clear example of utilizing the bisection search theorem to track the MPP, whereas [52] presents a modified approach of the BSM. However, [53] utilizes this method to support a MPPT scheme under partially shaded conditions. Moreover, BSM is one of the most robust and simplest of methods to track the MPP. It is

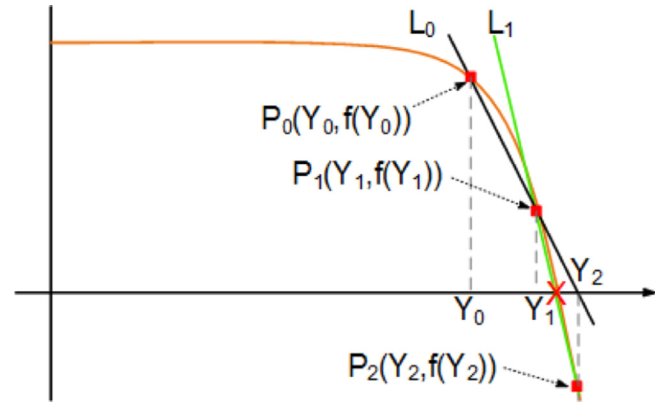


Fig. 8. SM method to track the MPP.

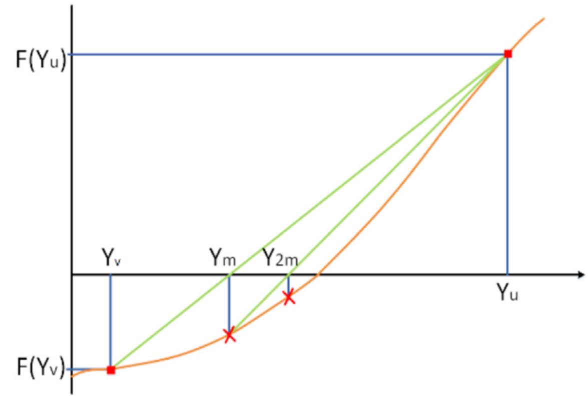


Fig. 9. Basic concept of the SM.

alternatively known as Binary Chopping, Interval Halving or Bolzano's Method and is probably the most primitive procedure for numerical approximation [29]. Fig. 9 presents the underlying idea of the BSM, as it is one type of close-bracketed incremental search method, the interval is always divided into two equal subintervals. However, for convergence the BSM utilizes the sign of the function instead of the value of the function itself. Where Y_v and Y_u are the close limits of the interval, the equation utilized by the BSM is:

$$Y_{nm} = \frac{u+v}{2} \tag{5}$$

The BSM always converges in the direction $f(Y_v)f(Y_u)<0$, utilizing sign of the function . For MPP, $\frac{dP}{dV}=0$ and a graph with function$P=f(V)$, where the root lies between the interval $[0,V_{oc}]$ (V_{oc} open circuit voltage). Eq. (5) is modified to be $Y_{nm}=\frac{0+V_{oc}}{2}$. The point $\frac{dP}{dV}=0$ can be obtained by successive iterations of the bisection equation. Where, 0 and V_{oc} are the extreme points or bracketed limits chosen. In case of MPPT, duty cycle remains the main controlling parameter to be modulated in order to attain the MPP. Further, the convergence is always directed in the path where, $f(0)f(V_{oc})<0$ is satisfied. Fig. 10 presents the graphical representation of the BSM to track the MPP.Where, the bracketed limit L1 remains the first close limit, Y_{nm} is the midpoint and n the number of iterations. Utilizing Eq. (5) the bracketed limits are subsequently bisected to L2 and then L3 close limits, to approach the MPP. This method is easy to implement and convergence is guaranteed. However, its Brute-Force approach is relatively inefficient. It is evident that the BSM makes no use of the value of the function at any point of interest, it only uses the sign of the

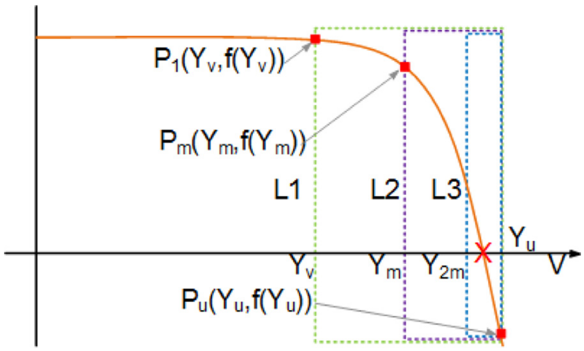


Fig. 10. BSM method to track the MPP [30].

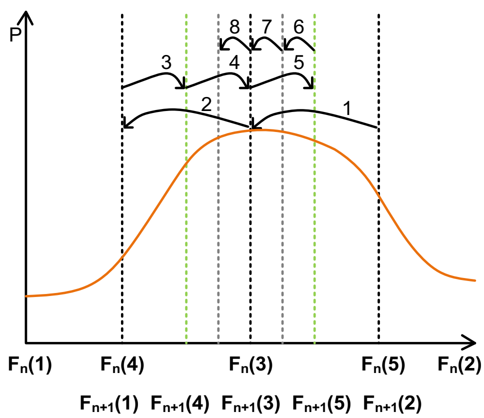


Fig. 11. CPI method to track the MPP.

function in selection of an appropriate interval containing the root. Therefore, it is quite slow.

3.1.1.2.2. Central point iterative method (CPI). Implementations of the CPI and advanced CPI methods have been presented in [54,55]. CPI method divides the entire range of the control parameters in four non-overlapped intervals providing three center points, for iterations. As, limits are constrained and bracketed, therefore it has been classified under the closed bracketing methods. For MPP, PV powers of these three center points are calculated and then compared. Further, two out of the four non-overlapped intervals (having the maximum chance for the existence of potential MPP) are selected and the rest are rejected. Then, the selected two intervals are again subsequently divided into four non-overlapped added intervals, for next power iteration. A graphical presentation of the CPI method has been given in Fig. 11.

This process makes successive iterations after continual comparisons until the MPP is attained. The principle operation of the Center Point Iterative method has been presented by the flowchart in Fig. 12.

The advantages include direct adjustment of frequency, variable perturbation, exact MPP, easy implementation and fast tracking [54].

3.1.1.2.3. False position method (FPM). FPM also known as Regula Falsi Method due its iterative formula, has been explained in [56,57], whereas an example of the Modified FPM has been presented in [58]. Researchers have utilized the FPM and Modified FPM to track the MPP in [30,59]. Further, this method is an alternative method of the SM (except that it has bracketed limits) and is more efficient than BSM at tracking the MPP as clearly presented in [30]. As, FPM takes into account the actual value of the function $f(Y)$ along with the sign of the function for appropriate interval selection. Fig. 13 displays the principle concept of the FPM.

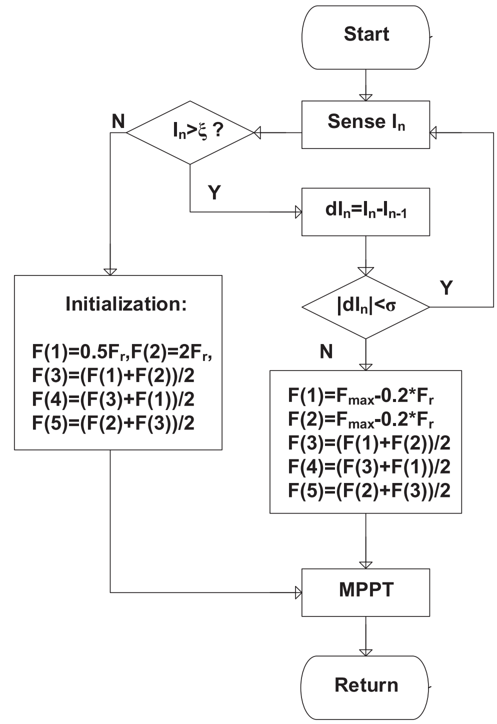


Fig. 12. Flowchart of the CPI technique to track the MPP [54].

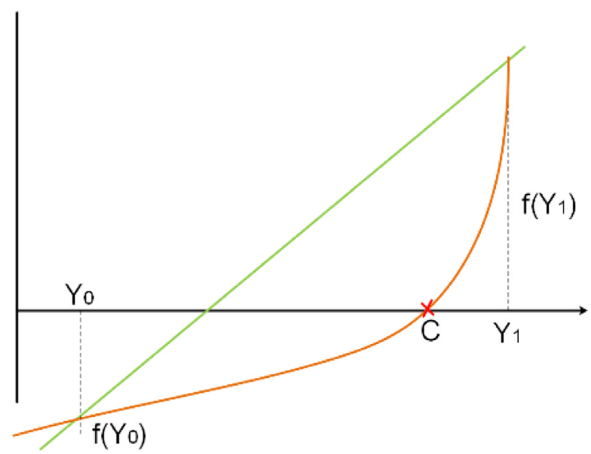


Fig. 13. Basic concept of the FPM.

Where, $[Y_0, Y_1]$ is the closed interval and C is the root. Similar to BSM, The FPM always converges in the direction where, $f(Y_0)f(Y_1) < 0$ is satisfied, but instead of halving the interval, the Regula Falsi iterative formula is used to determine a "weighted average" as:

$$C_{n+1} = \frac{Y_{n-1}f(Y_n) - Y_n f(Y_{n-1})}{f(Y_n) - f(Y_{n-1})} \tag{6}$$

For MPP, Y_v and Y_u represent the initial or extreme points taken as a close interval $[Y_v, Y_u]$, n is the number of iteration and C_{n+1} is the weighted average. In case of MPPT, the function $f(Y)$ is replaced with $\frac{dP}{dV}$ and Eq. (6) is iterated until the exact weighted average or MPP is attained, a graphical approach has been shown in the Fig. 14. Although, FPM is almost the same as BSM, it is better. As, it converges to the root faster, but is slower than NR approach.

A comparative evaluation, analyzing the open and close bracket NM technique to track the MPP has been presented in Table 1. As observed, the NR and SM offer no guarantee to converge when the

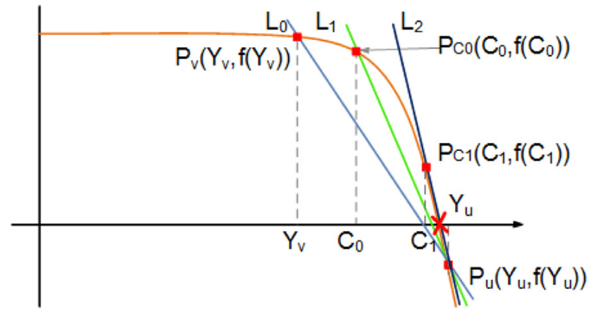


Fig. 14. FPM to track the MPP.

Table 1
Comparative evaluation of open and close bracket numerical methods for mppt.

NM	IG	SE	SY	ACC	Comments
NR	1	F	MD	G	Requires f'
SM	2	F	MD	G	Initial guess be close
BSM	2	S	A	G	Comparatively slow
CPI	2	F	A	G	Very complex
FPM	2	M	A	G	Slower than NR

Note: IG = Initial Guess, SE = Speed, SY = Stability, ACC = Accuracy, F = Fast, S = Slow, M = Medium, MD = May Diverge, A = Always and G = Good.

initial guesses are farther away from the MPP. In addition, the NR is computationally a bit more complex as it requires derivative calculation. Moreover, the BSM is quite simple and offers stability, but is quite slow in comparison to the other methods. FPM is very advantageous as it is a modified SM with accuracy and stability, but is slower than the NR method and restricts within a close interval. Lastly, CPI being very complex offers positives of every NM technique.

3.1.2. *Numerical interpolation (NI) and extrapolation methods*

PV curve is similar in shape to a parabola, in the vicinity of MPP. Therefore, a parabolic expression can be attained by the interpolation through proper point selections. Considering, a three point interpolation for MPP, as $(Y_{K-1}, X_{K-1}), (Y_K, X_K)$ and (Y_{K+1}, X_{K+1}), then the polynomial can be expressed as [60]:

$$L_n(X) = Y_{K-1}\frac{(X-X_K)(X-X_{K+1})}{(X_{K-1}-X_K)(X_{K-1}-X_{K+1})} + Y_K\frac{(X-X_{K-1})(X-X_{K+1})}{(X_K-X_{K-1})(X_K-X_{K+1})} + Y_{K+1}\frac{(X-X_{K-1})(X-X_K)}{(X_{K+1}-X_K)(X_{K+1}-X_K)} \quad (7)$$

And the quadratic function by

$$L_n(X) = aX^2 + bX + c \quad (8)$$

Where a, b and c are the interpolation constant [60–64] and the MPP is attained at $\left(-\frac{b}{2a}, \frac{4ac-b^2}{4a}\right)$.

Different NI techniques have been utilized in [60–79] to track the MPP. At prime importance, Lagrangian Quadratic Interpolation has been presented in [60–68] to track the MPP. At Secondary utilization, interpolation techniques are used for MPPT in Variable Speed PMSG Wind systems as presented in [69–71], for PV array modeling in [72–75] and for an adaptive P&O sidelined parabolic interpolation in [76,77]. Whereas, extrapolation has not been considered as a major MPPT technique, as only fewer MPPT papers with indirect implementation could be found from the literature till date [78,79].

3.1.3. *Combination of numerical methods*

3.1.3.1. Brent method (BM). Utilizing the above mentioned techniques (Close bracket, Open bracket and Interpolation) one of the most efficient methods to track the MPP is the BM, presented in

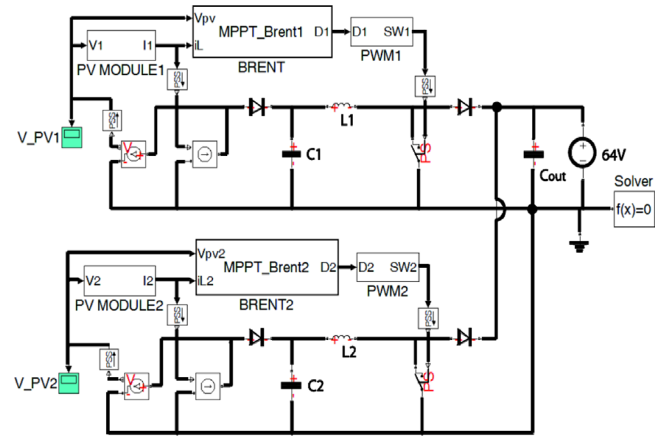


Fig. 15. Simulation model for implementation of the BM [80].

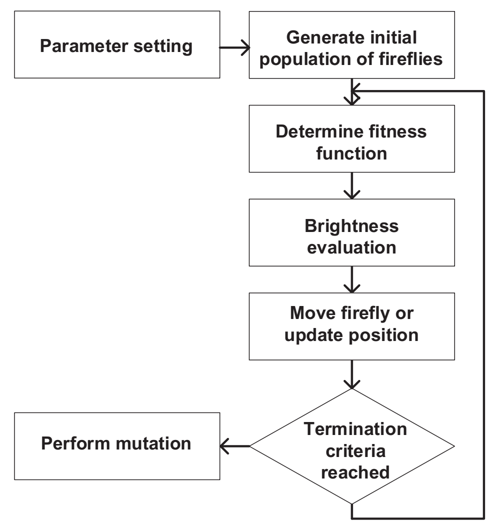


Fig. 16. FA technique flowchart to track the MPP.

[80] and explained in [81,82]. In addition, it provides fast convergence to the root, utilizing the SM and guarantees convergence to a solution by the BSM. For MPP, three voltage points and a tolerance value is required. Further, the first two points are calculated using the BM and the third by SM. All the three points are then interpolated, using inverse quadratic interpolation [80]. Amongst BM, SM or Inverse Quadratic Interpolation the best-calculated solution is provided by the BM, as the MPP. Simulation Model for the BM implementation to track the MPP is displayed in Fig. 15.

3.2. *MPPT algorithms iterative in nature (IN)*

3.2.1. *Firefly algorithm (FA)*

The firefly algorithm was first introduced in [83,84]. It is a population-based optimization technique, utilized for tracking the MPP [85]. As sensed from the word “FIREFLY” the algorithm is inspired by the movement of light illuminating flies. Equation used by firefly algorithm to track the MPP is:

$$X_p^{t+1} = X_p^t + \beta(r)(X_p - X_q) + \left(rand - \frac{1}{2}\right) \quad (9)$$

where, p and q are representing variables for two fireflies, X_p&X_q are the respective positions, with r as the distance in between, α the random movement factor and β as the degree of attractiveness. For MPPT, the position of each firefly is the duty cycle and the brightness is considered as a power generative. The principle operation of the FA has been presented by a flowchart in Fig. 16.

Utilizing Eq. (9) firefly having the maximum illumination stays still at the same position whereas, remaining of the fireflies change their positions through number of iterations, to approach the MPP.

3.2.2. Steepest-descent technique (SD)

This technique is an iterative optimization technique as presented in [43,86]. The equation used by the SD method for tracking the MPP is provided as:

$$V(K+1)=V(K)\frac{f(V)}{K_\varepsilon} \tag{10}$$

where, $K_\varepsilon$represents step size corrector, V represents the PV array voltage and $f(V)=\frac{dP}{dV}$. In SD, K_ε is utilized in order to choose the steepness and step size of each step, in the gradient direction.

3.2.3. Predictor method (PM)

The MPP is calculated from the interpolation technique quadratic functions and parabolic convex, as provided in the previous NI technique. However, the approach of predictor method is different, so it is considered as a different iterative technique. As, the optimal region and concavity of the considered approximate parabola is attuned for ensuring an iterative convergence [64,87], instead of simple NI. In order to approximate the objective function f(X), PM utilizes a parametrically controlled parabolic function Q(X) as:

$$Q(X)=aX^2+bX+c \tag{11}$$

As shown in Fig. 17 (a) and (b) three points (X_0,X_1,X_2) are present in zone of maximum value of objective function f(X)

$$Q(X)=f(X_0)\frac{(X-X_1)(X-X_2)}{\Delta X_{01}\Delta X_{02}}+f(X_1)\frac{(X-X_0)(X-X_2)}{\Delta X_{10}\Delta X_{12}} +f(X_2)\frac{(X-X_0)(X-X_1)}{\Delta X_{20}\Delta X_{21}} \tag{12}$$

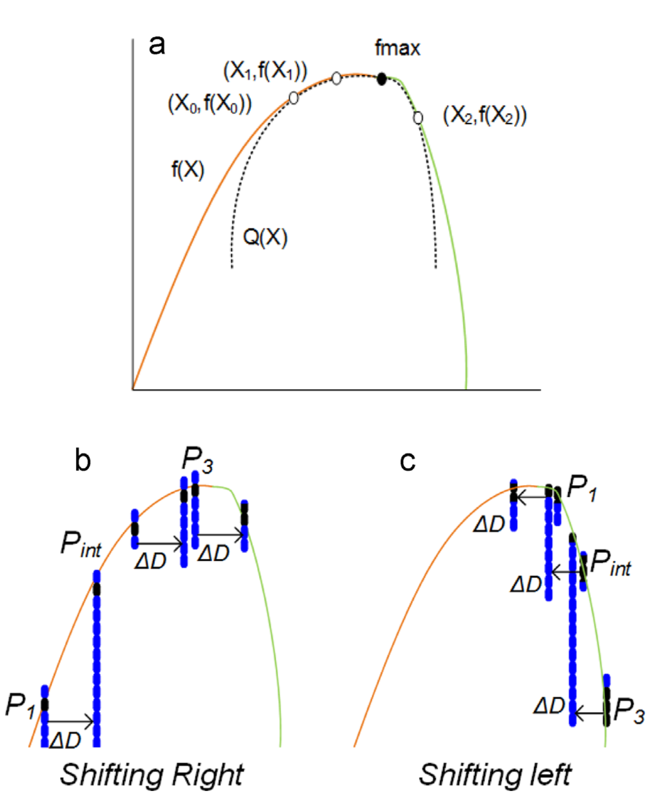


Fig. 17. (a) PM to track the MPP [64,87] and (b) shifting right and left using PM to track the MPP [87].

Using (12) through continuous iterations the PM tracks the MPP by reaching the f_{max} value. Moreover, an easy way to represent value of Q(x) is offered by the parabolic function, near its optimum point. In addition, this provides an elevated view for the MPPT algorithm using three point results. However, the drawback of the PM include that such a method is not suitable or applicable under partial shading condition, as predictor function is unable to constitute multiple peaks. Therefore, no work has been reported on the implementation of the predictor under the partial shading condition. In addition, PM gets trapped and stops tracking the MPP, once optimum point of the predictor curve overlaps the local maxima.

3.2.4. Chaos optimization search (COS)

This method has been explained in [88,89] and the MPP tracking using chaos optimization search method has been presented in [90–92]. Essentially, it is employed to solve optimization difficulties confronted for nonlinear multimodal function, considering the boundary constraints through chaos variables. Equation for tracking the MPP with chaos optimization search is:

$$f=f(X_i^*)=\max f(X_i)X_i\in[A,B] \tag{13}$$

Where, X_i represents the optimization variable, indicating the output voltage of PV array and $i=1,2,3,\ldots,n$. A and B define the range of initial seeking zone. With subsequent iterations, search zone starts turning smaller and eventually halts – when its value decreases the specified threshold value – tracking the exact MPP. In addition, if the output power of PV array is dependent on the continuous objective function, $f(X_i^*)$ is the P_{max} or the fitness function. Further, there are single and dual carrier search implemented for MPPT. In dual carrier, two chaotic mappings are utilized. Fig. 18 displays the schematic diagram of two stage COS circuit.

3.2.5. Ant colony optimization (ACO)

Regurgitating the phenomenal path-searching quest of ants for food, ACO is entirely based on this incredible behavior. Where, an individual ant initially hunts for the path randomly and then lays down pheromone for the other ants to follow, forming a positive feedback as presented and explained in [93]. Higher the ant following of a certain path, higher is the density of the pheromone. Fig. 19 (a) presents the behavior of the ants when the shortest path is being followed and Fig. 19 (b) when initially the paths are randomly chosen. Here, the main strategy remains at converging the random paths into the shortest path.

In the case of MPPT, the density responsible for transition probability of ants is taken into consideration. Where, the control variable turns out to be current of each of the PV string. Further, ACO possesses the capability to search for the global MPP with

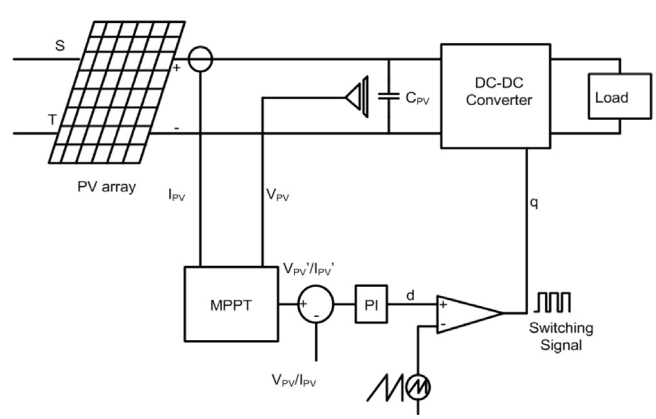


Fig. 18. Two stage COS circuit [92].

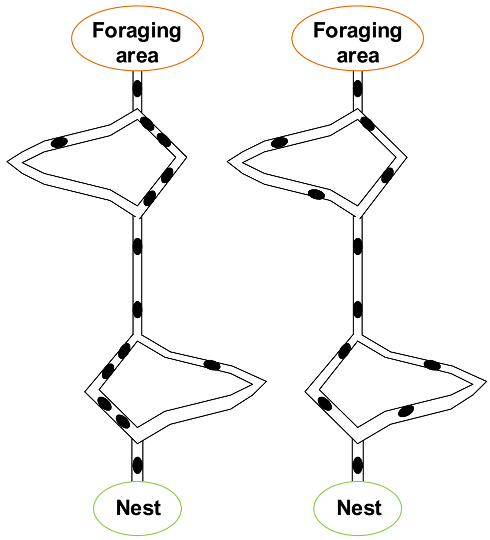


Fig. 19. (a) Shortest path followed and (b) random paths followed [21].

respect to changing weather conditions utilizing the equation:

$$\frac{|I(s_{i+1}) - I(s_i)|}{I(s_i)} > \Delta I \tag{14}$$

where, I represents the current control value and S the current vector. Depending upon the stronger value of current, ACO acts and iterates to force the S in the direction of a stronger current density. In addition, once the specified period set by the timer is touched or Eq. (14) is satisfied, the search process executes once again. Ensuring that the global MPP can be tracked under different environmental conditions. Various implementations of the ACO for MPPT have been presented in [94–97].

3.2.6. *Genetic algorithm & differential evolution (G&D)*

Both GA & DE are categorized under the optimizer evolutionary methods. Principle operation of both the techniques is almost similar. However, DE algorithm offers creating and sustaining a population of candidate solutions to attain optimization at a problem, using the mutation operation. Whereas, GA stands to be a problem troubleshooting technique inspired by principles of biological evolution, majorly relying on crossover. Moreover, the processes start with initialization and selection of chromosomes for GA and a candidate solution for DE. Followed by the implementation of genetic operators. Finally, the algorithms track an optimum solution by random recombination. These optimizations are tested under a predefined fitness function. In case of MPPT, initially chromosome (GA) or searching parameter (DE) can be either duty cycle or voltage. Where, PV equation is treated as the fitness function and the chromosomes can be defined through a binary code or combination of real numbers. Fig. 20 (a) presents the operation of the GA process and Fig. 20 (b) presents the operation of the DE process by a flowchart.

Implementations of GA are presented in [98–101], whereas DE method for tracking the MPP has been utilized in [102–104].

3.2.7. *Particle swarm optimization method (PSO)*

An iterative method based on the attempt to improve a particle's position (candidate solution). The basic principle is that on the search space, the best position of every particle and the best-known positions, effect the particle positions. As, Fig. 21 illustrates the particle movement in PSO based on Eq. (15)

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{15}$$

where, v is the velocity and x denotes particle position.

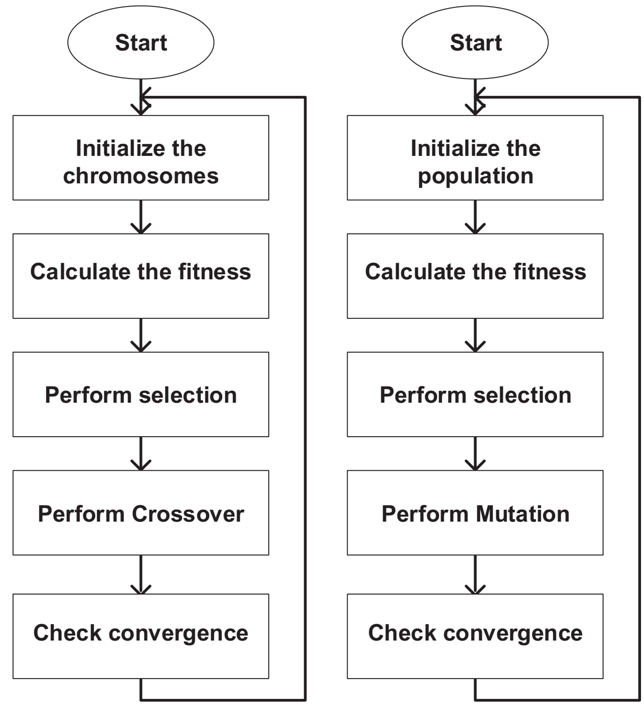


Fig. 20. (a) GA Flowchart and (b) DE Flowchart.

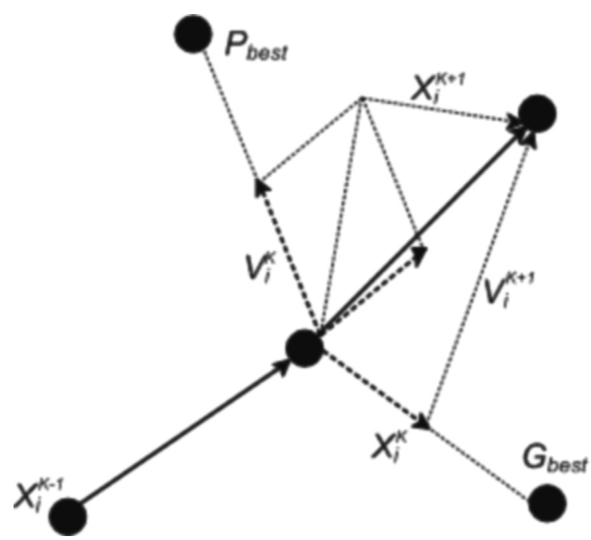


Fig. 21. Particle movement in PSO [23].

For MPP, x is considered as duty cycles, which act as initial particles for the first iteration. Every particle is directed towards the local best position. After successive iterations, a best fitness value is attained known as the Global best position. Recent researches on PSO and modified PSO include [105–116]. Drawbacks include that the principle method confronts the problem of oscillations, which has been addressed in [110,116], many reviews consider the PSO algorithm to be complex and the choice of its parameters has some impacts on the optimization performance. Based on various multi-peak curve characteristics weights in conventional PSO must be readjusted appropriately. As, tracking failure results due to excessive high and low weights when some modules are shaded.

3.2.8. Shuffled frog leaping algorithm (SFLA) technique

This method has been presented in [117,118]. In [117] SFLA is used for PV array modeling so as to attain unknown parameters, specifically of the single diode model PV of a module, but not for the MPPT itself. This mimetic technique is inspired by the principle of 'survival of the most experienced and genetically fittest'. Where, the position of frog (search parameter) with worst fitness can be updated using the equations:

$$D_i = Rand \times (X_b - X_w) \tag{16}$$

$$X_w^{new} = X_w^{old} + D_i(D_{imin} \le D_i \le D_{imax}) \tag{17}$$

where, X_b, X_w and X_g are the best, worst and global best frog positions. D_i represents variation in the frog position, *Rand* is a notation for random numbers between [0, 1] & D_{imin} and D_{imax} symbolize minimum and maximum step sizes permissible for the position of the frog. In addition, SFLA offers the pros of both the GA and PSO approaches offering high speed of GA and the social behavior of the PSO.

3.2.9. Bayesian network (BN)

Simple directed acyclic graphs, where conditional probability is applied on the nodes. The nodes represent different parameters or random variables. In case of tracking the MPP, [119] presents BN approach with twenty nodes, used along with Incremental conductance and Particle swam optimization methods, both with ten equal nodes. As shown in Fig. 22. Presenting that the right and left sectors are compared in order to compute the matching entries.

Further, the information is directly converted to an on state "1" once a matching node is detected. After subsequent iterations, it provides a final vector consisting the fusion of matching nodes utilizing conditional probability. Following these iteration the optimum value is attained.

3.2.10. Artificial bee colony (ABC)

The ABC algorithm for the MPPT is inspired by the model presented in [120]. It depicts the foraging pattern of the honeybee colonies. ABC technique is typically a swarm based meta-heuristic scheme. It was initially introduced for solving multimodal and multidimensional optimization problems. Further, artificial bees are categorized into three groups: employed, onlooker and scouts. Here, a candidate solution of optimization issue represents location of a food source and nectar amount of the food source represents quality of associated solution. Here, the duty cycle value *d* of DC converter is considered as candidate solution, so optimization problem has only one parameter to optimize (D=1). The fittest solution can be found out as [121]:

$$d_i = d_{min} + rand[0,1](d_{max} - d_{min}) \tag{18}$$

$$new\, d_i = d_i + Ø_i(d_i - d_k) \tag{19}$$

Fitness of each solution (duty cycle) is selected as the generated power Ppt [121]:

$$P_i = \frac{P_{pvi}}{\sum_{n=1}^{SN} P_{pvi}} \tag{20}$$

where, *SN* is the number of randomly distributed initial population solutions, P_{pvi} is the corresponding power of each duty cycle d_i. At the culmination of each search cycle, ABC algorithm stores best solution attained and iterates the process from employed bees phase until maximum cycle number is touched or until power value remains unchanged within specified number of cycles.

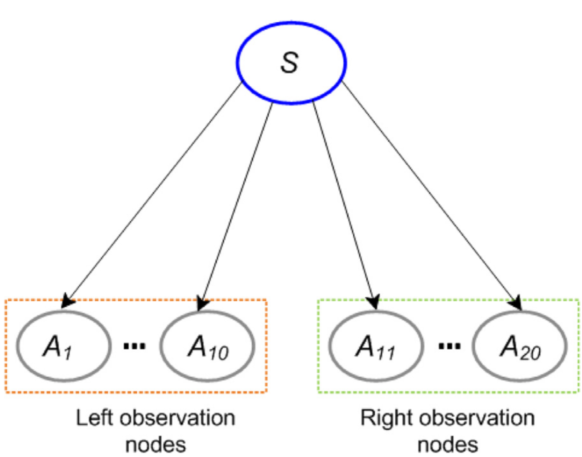


Fig. 22. BN nodes to track the MPP [119].

3.2.11. Gray wolf optimization technique (GWO)

GWO is based on the hunting mechanism and principle of leadership hierarchy of the gray wolves as presented in [122]. For GWO, four types of gray wolves are considered, which are represented by Greek letters α, β, δ, and ω. Here, α is taken as the candidate solution having better understanding about location of the prey. For GWO based MPPT number of gray wolves, is considered as the duty ratio. Further, once the wolves detect MPP, the correlated vectors become almost equal to zero. Moreover, this technique minimizes the steady-state oscillations, resulting into higher efficiency. The Duty-Cycle D is found as [123]:

$$D_i(k+1) = D_i(k) - A \bullet D \tag{21}$$

And, fitness function is determined as:

$$P\left(d_i^k\right) > P(d_i^{k-1}) \tag{22}$$

3.2.12. Cuckoo search method (CuS)

CuS algorithm is an optimization technique based on parasitic reproduction approach of the cuckoo birds [124]. In addition, in laying cuckoo eggs in the nests of other birds, numerous species of the cuckoo birds perform brood parasitism [125]. Thus, integral phase of cuckoo bird reproduction approach is seeking for appropriate nests. Generally, seeking a nest is alike searching for food. While hunting for food, all the animals take different paths that can be mathematically modeled. Further, Lévy flight is one of most common model of such a trajectory. Here, the Lévy flight is utilized to characterize the nest searching steps of the cuckoo birds. For mathematical modeling, Lévy flight simply represents an arbitrary walk with step-sizes, these step-sizes can be determined by the Lévy distribution, which can be measured according to a power law as:

$$\text{Lévy}(\lambda) \approx \mathrm{u} = l^{-\lambda}, (1 < \lambda < 3) \tag{23}$$

For CuS based MPPT, suitable variables are to be chosen for search. First, samples of the PV voltages are taken into consideration, as Vi($i = 1, 2 \ldots$n). Second, step size denoted by α. Here, value of PV power at MPP is considered as the fitness function (J). As, J is dependent on PV voltage, So, $J = f(\mathrm{V})$. Moreover, all generated samples are supplied to PV modules and power is established as initial fitness value. P_{max} provided by its corresponding voltage is associated as current best sample. Then, Lévy flight is executed, subsequently new voltage samples are produced based on following equation:

$$\mathrm{V}_i^{(t+1)} = \mathrm{V}_i^t + \alpha \oplus \text{Lévy}(\lambda) \tag{24}$$

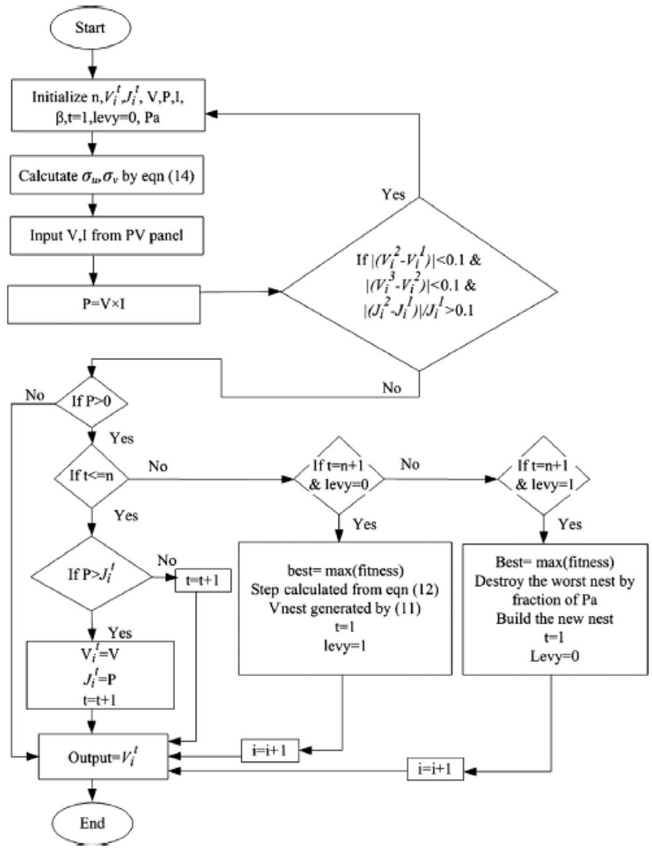


Fig. 23. Flow chart of searching mechanism by CuS [126].

Fig. 23 displays the flowchart for CuS. For MPP tracking, CuS is similar to the HC methods. There are several features that make the CuS more robust in comparison to HC [126–129]:

1. CuS exhibits elitism in selection procedure. However, similar to GA and PSO it is a population-inspired technique.
2. Faster convergence due to larger step-sizes and efficient randomization because of the Lévy flight.
3. Two parameters required for tuning CuS, whereas, three for GA and PSO.
4. Contrasting from PSO, CuS is not sample initialization dependent.

3.3. Artificial intelligence (AI)

3.3.1. Neural networks (NN)

Recent researches utilizing the NN technique to track the MPP include [130–144]. NN is an intelligent technique, as it possess the ability to optimize a given parameter through probabilistic control, intelligent training and an algorithm in the hidden layer or layers, as NN technique offers more than one layer for optimization as shown in Fig. 24. The input parameters may include irradiance, temperature, Voc and Isc. The output being a signal to operate the converter at MPP. The MPP is attained majorly due to the intelligent training process, where the weighted links between different nodes are adjusted to match the optimization pattern. As, tracking depends on the training of the Neural Networks and the algorithm utilized by the hidden layer, NN remains PV array dependent in order to determine the probabilistic relation of Voltage at the MPP with respect to the irradiance and temperature. However, unlike few of the previous review papers the NN method has been consider as a cost effective method, as digital implementation has

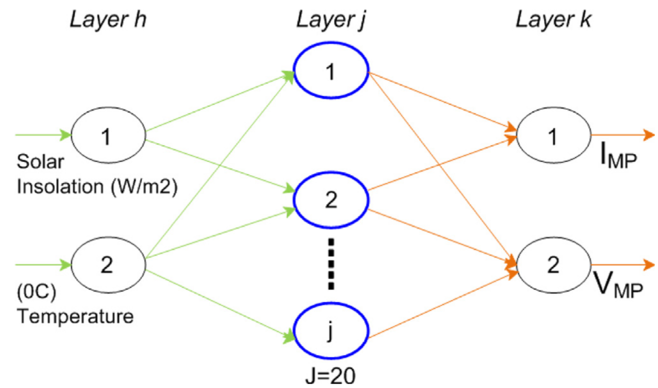


Fig. 24. NN layers to track the MPP.

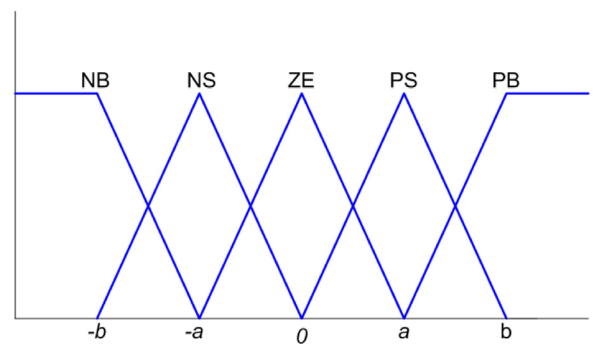


Fig. 25. Membership function for FL.

been found in previous literature using quite economical circuitry involving microcontrollers [141].

3.3.2. Fuzzy logic (FL)

Similarly, FL has been considered as an economical technique, as cost effective implementation has been found in the previous literature [141,145]. Moreover, this technique utilizes fuzzification and defuzzification stages for the artificially intelligent computation. Further, the process of fuzzification is utilized to convert the input parameters or numerical variables to linguistic notations which are completely based on a membership function as presented in Fig. 25. Where, error (E) and small change in error (ΔE) are taken as input parameters. A rule based lookup table is set in between the two stages for assigning a specific output with respect to different combinations of the inputs. Once, the numerical input variables are measured and changed to linguistic variables, the rule base table as presented in Table 2 can be utilized to look up the change in duty ratio or FL output. Fuzzy rules displayed in Table 2 are employed for controlling the DC converter such as the maximum power of the PV generator is reached.

As an example,

IF E is NS & ΔE is ZE THEN ΔD is NS. Inferring that “if operating point is distant from maximum power point towards left hand side and the change of slope in P–I characteristic is about zero, increase duty ratio largely“. This paper presents Max-Min inference method of Mamdani [146].

By contrast, for defuzzification, change in the duty ratio or FL output, is again converted into numerical variable from linguistic variable utilizing similar membership functions displayed by Fig. 25. The FL technique finally offers an analog signal that is used to attain operation at the MPP for the power converter. Advantages of the FL include that an accurate mathematical model is not required, offers fast responses without an overshoot, manages nonlinearity, less noise due to atmospheric changes, reliable

Table 2
Rule based lookup table utilized by fuzzy logic [146,147].

E \ ΔE	NB	NS	ZE	PS	PB
NB	ZE	ZE	NB	NB	NB
NS	ZE	ZE	NS	NS	NS
ZE	NS	ZE	ZE	ZE	PS
PS	PS	PS	PS	ZE	ZE
PB	PB	PB	PB	ZE	ZE

providing exact MPP, handles imprecise inputs and offers efficient performance. Recent MPPT research on Fuzzy logic include [145,148–157]. Where, [156] includes a new tracking loop grounded on FL along with a scanning and storing algorithm.

3.4. Hill climbing (HC)

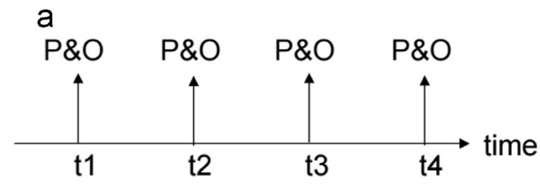
Few of the commendable researches on Hill climbing technique include [152,158–160]. Unlike previous review papers, both INC and P&O have been considered as adaptive forms of the Hill Climbing Technique and are classified under digital category [110,161]. Initially, earliest of the INC algorithm was proposed in the research paper [162]. Where, the harmonic component of PV array was utilized to compute the term dI/dV offering an analog implementation. By contrast, [163] computed the dI/dV term by tracker perturbations, offering a discrete implementation. Practically, both the P&O and INC are generally implemented in discrete time [164,165]. Therefore, according to the extensive discrete implementation of both the methods, they have been classified as digital, ignoring the fewer analog implementations. Hill climbing method utilizes periodical sampling of voltage and current. This technique outputs a duty cycle in response to the difference in power of the present and previous sample, process continues till MPP is attained [166]. Advantages include that these techniques need no information about the PV array, are easy to implement on digital controller and apt for any PV array. Hill climbing technique can fail under rapidly changing atmospheric conditions, resulting either into divergence of the optimal operating point or reverse in the perturbation.

3.4.1. Perturb and observe (P&O)

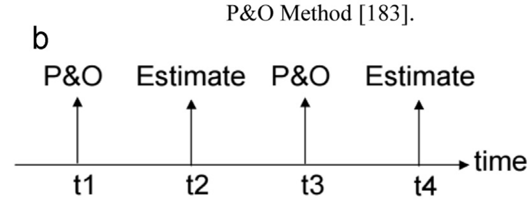
P & O is employed by many researchers to track the MPP [76,101,167–175]. In P & O, difference in the power in response to the voltage is zero “0” at the corresponding MPP. In addition, the perturbation tends to direct the operating point in the MPP direction. When, $dP > 0$ and the operating voltage is perturbed in the direction of the MPP, the P & O algorithm would perturb the voltage in the same direction continuously. By contrast, this technique directs the perturbation in the opposite direction, if $dP < 0$. Drawbacks include, poor tracking under changing atmospheric conditions & irradiance and oscillations around MPP, under the steady-state conditions [14,16,169]. Methods to confront such shortcomings have been presented in [76,176–179]. As, observed most of the research implementations, implying the P & O algorithm are digital. Therefore, this technique has been considered as a digital adaptation of the HC method.

3.4.2. Modified P&O (MP&O) techniques

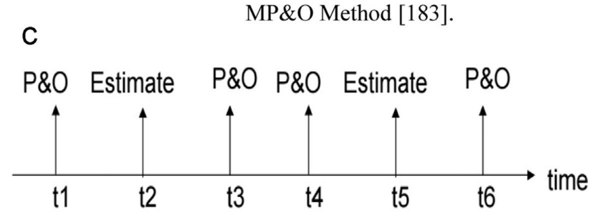
Similarly, the MP&O, dP-P&O, 3 Point and Estimated–Perturb–Perturb (EPP) techniques are extensions to the P & O method, few have been presented in Fig. 26 (a), (b) & (c). As, implementation of the P & O algorithm has been considered digital, unlike previous review papers [9] the M P&O, dP-P&O, 3 Point and EPP MPPT algorithms have been considered as a purely digital techniques, with discrete implementation and digital circuitry involved. In



P&O Method [183].



MP&O Method [183].



EPP Method [183].

Fig. 26. (a) P&O Method [183], (b) MP&O Method [183] and (c) EPP Method [183].

[180,181], the dP-P&O offers an additional acquisition of the power (change in power *dP*) during the MPPT sampling period, without making any perturbation. This additional acquisition is utilized for improvement. Further, 3 Point MPPT technique in [182], which uses 3 Points, namely previous, present and next power points for perturbation. Moreover, [183–185] presents MP&O as a control algorithm which offers one estimate mode in every perturb mode and EPP technique which provides estimate mode one, between two consecutive perturb modes. Implementations of these techniques and the circuitry involved can clearly render these techniques as digital.

For MPP the MP&O methods, have two modes. In the first, power fluctuation are produced, utilizing the previous voltage value and environmental change calculations. Further, PV voltage constant is sustained within this mode for the next control cycle. The second mode entirely dependents on the previous and present power variations, determines power fluctuations and regulates the new PV voltage. These techniques are certainly complex, but tracking is faster and accurate than the principle P & O algorithm [180,183].

3.4.3. Incremental conductance method (INC)

Recent researches on INC method include [186–198]. Here, INC is treated as a specific implementation of the P & O [161]. Basic INC [163], simply replaces change of the power with respect to change of voltage $\frac{dP}{dV}$, with comparison of PV array instantaneous $\frac{I}{V}$. Making the incremental $\frac{dI}{dV}$ conductance.

3.4.4. Global MPPT techniques (GMPPT)

As the name suggests, these techniques trace the Global MPP. GMPPT techniques have been placed under the HC category as these algorithms directly or indirectly employ P&O or INC methods for tracing the GMPP. Moreover, due to many irregularities the *P–V* curve shows many peak power points. One of these points is the global MPP (GMPP), whereas, rest are considered local MPPs (LMPPs). Conventional MPPT schemes overlooking the difference between GMPP and LMPPs, not only reduce the tracking speed, but also, minimize efficiency.

This paper provides a brief overview of six GMPPT methods. First, VWS-GMPPT is one of the efficient method, which tracks the GMPP by restricting the voltage window (VW) search range, as proposed in [199]. However, the VW method ignores characteristics of the PV string, resulting that its MPP tracking speed remains mediocre. Second, a constant power operation global MPPT (CPO-GMPPT) technique is presented in [200], it traces the GMPP by employing the CPO algorithm. However, it requires a constant input power DC converter and offers slow performance. Third, convention global MPPT (C-GMPPT) traces the GMPP by regularly scanning the entire voltage range starting from initial point of operation till the end, employing the conventional IncCond method [200]. C-GMPPT is simple and effective, but offers slower tracking speed. Fourth, modified global INC (M-GMPPT) method, it has been presented and explained in [201]. M-GMPPT also utilizes the INC method for tracing the GMPP but scans a limited range of points, it offers exceptional performance with respect to speed and accuracy. Fifth, is the Searching Skipping and Judging Global MPP (SSJ-GMPPT) tracking technique [202]. SSJ-GMPPT possess the ability to trace the GMPP regardless of partial shading, offering a commendable tracking speed. Fig. 27 displays the flowchart of the SSJ-GMPPT technique. As, observed this method does not require additional sensors. Thus, its implementation can be considered simple. It searches for the real GMPP, skips the vicinity of LMPPs and traces the GMPP by judging the optimum output. However, in case of long PV strings where the GMPP is high, SSJ-GMPP remain insufficient, as it requires longer scanning time.

Sixth, is the rapid global MPP (R-GMPPT) which possess the ability to address the shortcomings of the SSJ-GMPPT offering a very fast response [202]. This is attained by pre-estimating the voltage and current values corresponding to the GMPP. However, this technique requires additional sensors for its operation, comparatively making it an expensive technique. Table 3 summarizes all the six GMPPT techniques presented in this paper.

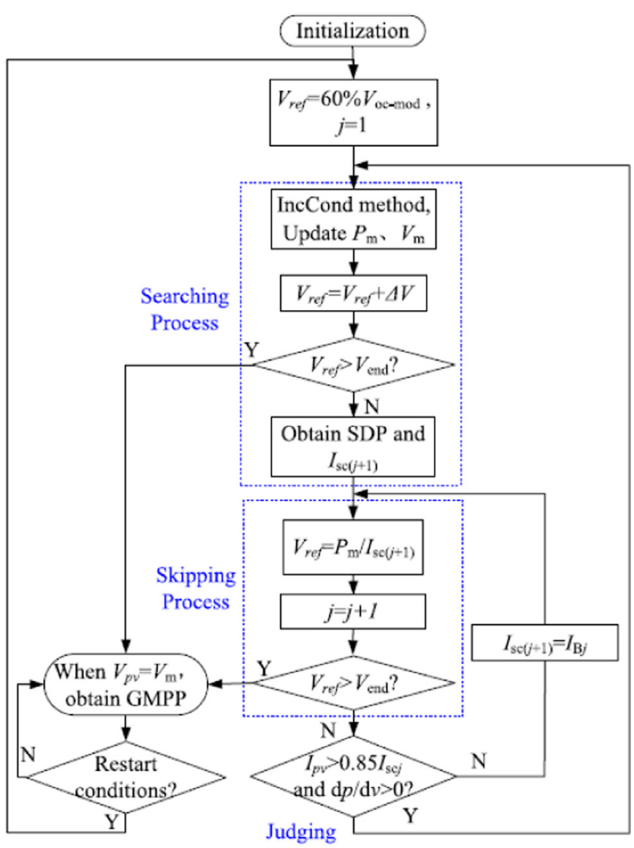


Fig. 27. Complete algorithm flowchart of SSJ-GMPPT [202].

3.4.5. *β method (β)*

In this method, solar PV operates near to the value β rather than the MPP. β is a variable which is utilized to track the MPP [22,203,204]. This variable is provided by a non-linear *I–V* curve, which is determined using voltage and current of the PV array as,

$$\beta = ln\frac{I_{pv}}{V_{pv}} - \left(\frac{q}{k \times T \times \eta}\right) \times V_{pv} \tag{25}$$

where, q is the electron charge$\left(1.60217646 \times 10^{-19}C\right)$, T (in Kelvin) the temperature of the p–n junction, k is the Boltzmann constant $\left(1.3806503 \times 10^{-23}J/K\right)$ and η is the diode quality factor. A range of β values ranging from βmax to βmin are provided in [204] for a particular PV system, where this technique offers an appropriate solution. As, observed β is independent of isolation, therefore the variations in the MPP are the slightest at fixed temperatures. The method fetches the operating point close to the value of beta in few iterations thereafter P&O methods with finer steps can be used to trace exact MPP. Fig. 28 displays flow chart of this method. However, Beta method can also be used along with another method such as incremental conductance as reported in literature. Finally, compared with a reference value in order to assess the error and utilize the error to track the MPP.

3.5. *Different digital methods (DDM)*

3.5.1. *Current sweep method (CS)*

This technique is entirely dependent on the fact that the function for the sweep waveform offers a direct proportionality to the derivative as presented in [205]:

$$f(T) = ks\frac{df(T)}{dt} \tag{26}$$

Where, ks represent the proportionality constant. As, Current-Voltage curve is obtained using the current sweep waveform through periodical repetitions of the sweep. This method is complex, slow and delivers power losses. However, tracks the exact MPP.

3.5.2. *Linearization method (LM)*

A technique largely exploiting the linear relationship between voltage and current. This method is fairly simple and inexpensive. Linearization of current and power equations thorough algebraic equations are utilized to estimate the MPP [177,206]. Higher irradiation conditions are considered for linearization of this method. Finally, this V-I linearization is utilized to track the MPP, specifically at the point of intersection.

Table 3
Performance comparison of six gmppt methods.

MPPT method	Tracking speed	Tracking efficiency	Implementing complexity	Additional sensors
CGMPPT	SLOW	HIGH	SIMPLE	NONE
MGMPPT	FAST	HIGH	SIMPLE	NONE
SSJGMPPT	MEDIUM	HIGH	SIMPLE	NONE
RGMPPT	V FAST	HIGH	SIMPLE	CURRENT
VWSGMPPT	MEDIUM	HIGH	SIMPLE	NONE
CPOGMPPT	SLOW	HIGH	SIMPLE	NONE

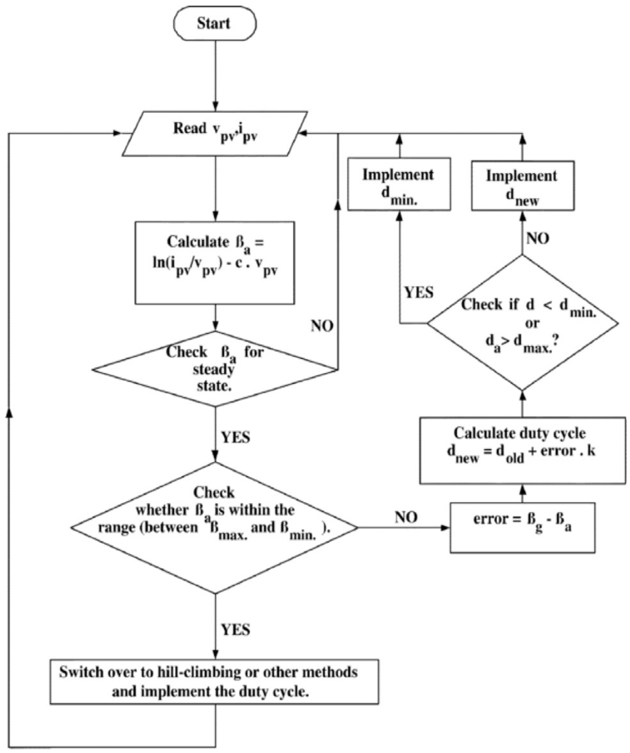


Fig. 28. Flowchart of the *β Method* [204].

3.5.3. Slide mode control technique (SMC)

The SMC operation has two modes [207]. First is the approaching stance, whereas, the second is sliding mode. In the sliding mode, state of the system is restricted to sliding surface and is focused towards origin. In SMC, opting for sliding surface as$\frac{\delta P_{pv}}{\delta I_{pv}} = 0$, there remains a surety that the system state will strike the surface and attain the MPP as:

$$\frac{\delta P_{pv}}{\delta I_{pv}} = \frac{\delta I_{pv}^2 R_{pv}}{\delta I_{pv}} = I_{pv}\left(2R_{pv} + I_{pv}\frac{\delta R_{pv}}{\delta I_{pv}}\right) = 0 \tag{27}$$

where, $R_{pv} = V_{pv}/I_{pv}$ is equivalent load.

In SMC the duty cycle output control is selected based on the observation of duty cycle as:

$$\delta_{update} = \begin{cases} \delta + \Delta\delta & for \quad \sigma > 0 \\ \delta - \Delta\delta & for \quad \sigma < 0 \end{cases} \tag{28}$$

Drawbacks include power and voltage output fluctuations with the increase in switching [208–210]. Few of the recent publications on SMC include [45,211–213].

3.5.4. Curve-fitting technique (CFT)

To determine the voltage at the MPP (V_{mpp}), this technique employs a third order polynomial function for PV Curve-Fitting as [214]:

$$P = aV^3 + bV^2 + cV + d \tag{29}$$

Where, a, b, c&d are constant coefficients and V_{mpp} can be found as:

$$V_{mpp} = \frac{-b \pm \sqrt{b^2 - 3ac}}{3a} \tag{30}$$

Which are derived by mathematical modeling as presented in [73].

3.5.5. Parasitic capacitance technique (PCT)

Here, the prime thought remains that in the PCT if the parasitic capacitance turns to be zero, the technique shall entirely resemble the INC. Therefore, the basic idea remains to focus on the effect of the parasitic junction capacitance, which is taken into consideration in order to track the MPP. Parasitic junction capacitance includes the stray capacitance and storage charges in the PV junction cell [19]. Further, considering the effects of capacitance on voltage, first and second derivatives of voltage are finally utilized to track the MPP.

3.5.6. Look up Table (LuT) method

LuT method requires information of the PV panel and its characteristics at varying atmospheric conditions. This information is stored and retained, to compare it with the instantaneous output voltage or current of the PV panel. Moreover, these comparisons are then used to track MPP [141,215–221]. LuT technique's drawbacks include large stored data, large memory, level of complexity, number of sensors and slow speed to track the MPP.

3.5.7. Array reconfiguration (AR)

This method utilizes the fact that series and parallel cascading of PV array increments in the voltage and current, respectively. MPP at a specific load can be attained by different combinations of PV array. It certainly suits heavy loads. However, it is complex and less efficient [222].

3.5.8. Temperature method (TM)

The TM utilizes temperature sensors to track the MPP. This algorithm using a temperature function tracks the MPP as it varies with respect to temperature by using V_{oc} and I_{sc}, representing the open circuit voltage and short circuit current, respectively. As, V_{oc} fluctuates with cell temperature and the I_{sc} with irradiance levels [223,224].

4. Analog techniques

4.1. Load current or voltage (LCLV) maximization

Output current and voltage are utilized for controlling and tracking the MPP. Moreover, for the implementation of the LCLV Maximization only one output parameters is required and so only one sensor is needed which results into a cheap analog implementation circuitry. For LCLV method, in order to attain optimization for current source load, voltage at load should be optimized to reach MPP and vice versa for voltage source. Further, for different other type of loads, either of the two parameters can be utilized or maximized. This axiom is generally applicable, regardless of load nature [225–227]. However, exact MPP is never attained, as the method is principled on assumptions.

4.2. Ripple correlation control (RCC)

The RCC technique has been presented in [228,229] which tracks the MPP at a faster rate and does not depend on the PV Array. Using array voltage and current ripples, the RCC method asymptotically converges to the MPP. As, these ripples are intrinsic in the system itself. Further, for RCC if a switching converter is used, the rate of change in power with respect to rate of change in current or voltage is utilized. Basic principle here is to utilize oscillations in current and voltage occurring due to the pulsations of instantaneous power. Further, these oscillations are used to track the MPP as they provide information about the power gradient. Advantages of RCC include that no artificial perturbation is needed to measure the gradient information, no assumptions are required, offers a faster response and is PV array independent [230–234].

4.3. System oscillation technique (SOT)

Researches on SOT include [235–237], in order to track the MPP, the system is made to self-oscillations using a tracker controller, to inherently modulate the duty cycle of the main switch. Principle of operation, is based on comparing the mean value of input voltage with ac component (due to variations in the duty cycle), to determine quiescent duty cycle for proper operation. It is advantageous as it can track the global MPP without any mere approximations [237]. However, small variations in the duty cycle are offered by the SOT.

5. Hybrid (A/D implemented) techniques

5.1. DC-link capacitor (DCL) droop control MPPT

Implementation of this technique is simple and easy as it requires output power calculation and few analog operational amplifiers for designing decision-making logic circuits. Moreover, the duty factor command is digital [238]. Therefore, this technique has been categorized under "HYBRID" (Both). Here, the system can operate at MPP if and only if duty ratio (d) of the chopper maximizes the amplitude value(I^*_{peak}). Where * represents the maximum value. This technique is limited to systems that are in parallel connection with an AC system line [239]. The duty factor command (d) is represented as:

$$d = 1 - \frac{V}{V_{link}} \tag{31}$$

where, V_{link} represents voltage across the DC Link and V the voltage of the system. Moreover, if the output power tends to be smaller than the maximum power P_{max}, V_{link}can be retained as a constant value.

However, if output power exceeds P_{max}, DC Link voltage instantaneously decays. As, input and output power balance is disturbed at the DC Link. The word "DROOP" here suggests this prompt decay in the DC Link.

Further, in order to once again maintain the DC link voltage constant the load current (I_L) is chosen as the feedback parameter, to operate the system at MPP. Fig. 29 presents a graphical view of this technique, which is explained in Table 4 to understand the principle working. As observed Table 4 provides different orientations used by the DCL technique to track the MPP.

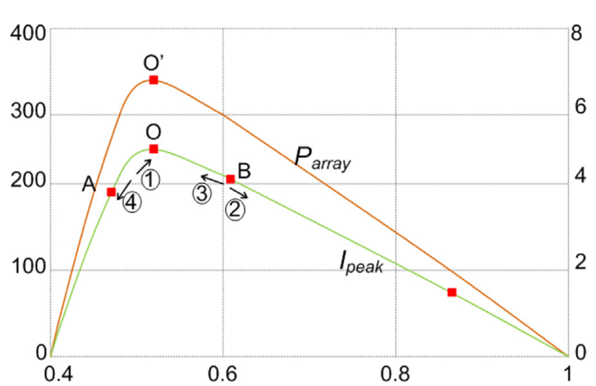


Fig. 29. DCL to track the MPP [238,239].

Table 4
Operating direction of d in the dcl mppt control

Operating points in Fig. 29	Current states		Operating direction of d^*
	I^*_{peak}	d^*	
1	P	I	H
2	N	I	R
3	P	D	H
4	N	D	R

Note: P=Positive, N=Negative, I=Increasing, D=Decreasing, H=Hold on, R=Reverse.

5.2. Different both – A/D circuitry – methods (DBM)

Fig. 30 offers a tree diagram completely summarizing all the evaluated techniques.

5.2.1. State space based method (SS)

SS is primarily focused on the mathematical modeling of PV system, with the DC converter and it can be considered as a dynamic system. The system in SS is represented by state space equation:

$$\dot{x}(t) = Ax(t) + B(t)u(t) + D\varepsilon(t) \tag{32}$$

where: x is the state variable vector, u is the switch duty ratio, ε is the disturbance and t, is an independent time variable. SS assures a globally asymptotically stable system. In addition, SS is also applicable to fast changing environmental condition [240].

5.2.2. Fractional V_{oc} and I_{sc} (FVI)

Based on the V–I characteristics, a direct proportionality exists between Voltage at the MPP (V_{mpp}) and Open Circuit voltage value (V_{oc}) which is expressed as [241]:

$$V_{mpp} = K_{oc}V_{oc} \tag{33}$$

where K is the constant of proportionality. V_{oc} can be determined by open circuiting the PV system instantaneously and measuring value of K after analyzing the system. V_{oc} technique is inexpensive and easy to implement. However, it never offers an exact operation at MPP with increased power losses and the constant K remains invalid at partial shading. Similarly, current at the MPP (I_{mpp}) offers a direct proportionality with the Short Circuit current value *(Isc)* of the array thus [241,242]:

$$I_{mpp} = K_{sc}I_{sc} \tag{34}$$

This method is very cheap and simple. However, it never offers an exact MPP as it is a mere approximation.

5.2.3. Feedback control technique (FCT)

In the FCT technique reference voltage or current values which remain pre calculated, are compared with feedback panel voltage or current, so it is denoted as the Feedback Current or Voltage Technique, where operation close to the MPP is offered when duty ratio of the converter is constantly attuned [243].

5.2.4. Best fixed voltage (BFV) technique

Another method based on approximations, as it never provides exact MPP, offers less efficiency and relies on the statistical collection of data. A specified period is set for data collection about temperature and irradiance, which is used by BFV to approximate the MPP [244].

5.2.5. One-cycle control (OCC) method

In the OCC methods, for tracking the MPP and DC to AC conversion a single stage inverter is employed. OCC operates on two control loops. The inner dealing with the conversion, whereas the

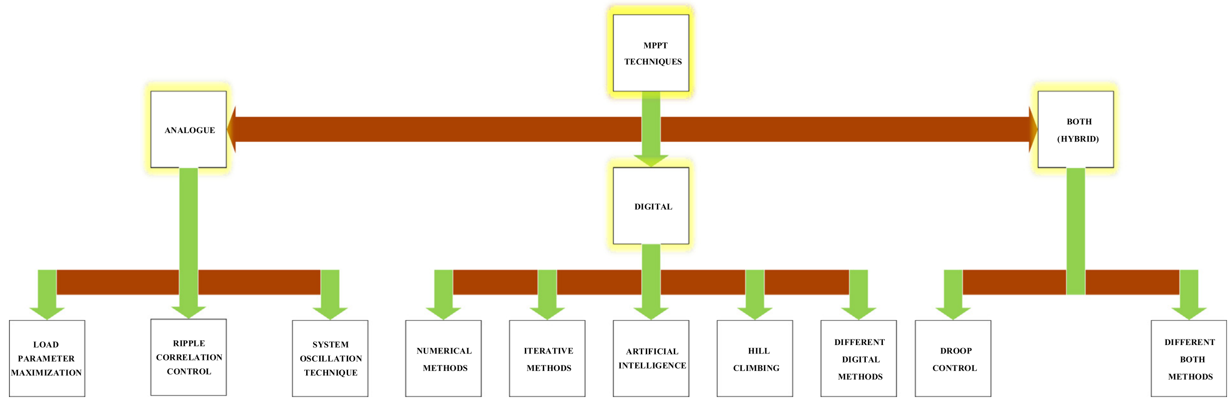


Fig. 30. Tree diagram for summarizing the evaluated techniques.

outer fulfills the MPP tracking. Inner loop being the PWM loop which is required to generate a duty cycle and the outer loop being the MPPT loop is entirely utilized for the MPPT, and to adjust parameters so as to attain the MPP. The advantages of this method include that the power might not be measured or required, it is economical with less complexity and fairly reliable at tracking the MPP. However, if the parameters are fixed the OCC method cannot be rendered as an exact MPPT technique [245]. Different implementations have been presented in [6,215,245–252].

6. Discussion

In order to track the MPP, many different MPPT schemes have been presented. Every technique employed offers certain pros and cons. Generally, P&O and INC are the mostly widely reported MPPT techniques. P&O is slow in rapidly changing conditions and confronts a problem of oscillations around the MPP. β method shows irregularities with variations in temperature. In addition, methods with simpler implementation are less accurate as FVI and FCT. Complex mathematical algorithms as SS, SD and SMC are accurate but very complex with implementation. Soft computing techniques as GA and PSO are fast and efficient, but require expensive implementation. Moreover, intelligent techniques as NN and FL require pre-estimated values. Further, INC technique even after GMPPT modification confronts problem of slow tracking and less efficiency as these techniques become insufficient, when large PV strings are employed.

NM techniques address most of the above mentioned shortcomings, as this scheme offers an iterative approach along with speed, accuracy, stand-alone application, feasible circuitry involved, no steady state oscillations, adjustability with rapid changing atmospheric conditions, does not require pre-estimated value for operation and PV array independence. Further, the aim of this paper has been to ponder on these iterative approaches, which offer heavy merits, but remain unnoticed. The following subsections highlight these merits.

6.1. Convergence speed

The NM techniques offer one of the fastest approaches to track the MPP [44]. BSM is the only technique, which offers an average tracking speed in comparison to the other NM schemes. Considering BSM, this technique provides an approach, which is faster than many of the analog or both classified techniques and offers an exact MPP. These advantages can render the NM techniques favorable for application where high speed controlling or tracking is required, as solar vehicles.

6.2. Exact MPP

Every iterative scheme, specifically the NM techniques offer accuracy, as they track the true MPP. Avoiding the oscillations about the MPP, which are offered by many of the HC techniques or the mere approximation techniques which can never be utilized for the exact MPP as FVI and other DBM techniques.

6.3. Application

Presently, major applications demand accuracy and reliability instead of Cost and Complexity. The NM techniques suit the applications where fast continuous tracking of the exact MPP is required without PV array information, avoiding periodic tuning and the issue of oscillating about the MPP. Therefore, the applications where nil oscillations are required, as solar powered satellites, the NM techniques are preferable options instead of the HC schemes. In case, where the PV information is unavailable for the training of the intelligent systems the NM techniques offer the best stand-alone applications. However, almost all of the iterative techniques are not suitable for low cost or the simplest applications.

6.4. Circuitry involved

This paper is entirely dependent on the implementation and circuitry involved for the MPPT application, utilizing a particular MPPT scheme. Implementation circuitry is utilized here for the digital and analog classification. As observed, analog schemes are mostly cost-effective and provide simple approaches to track the MPP. Whereas, digital schemes are quite expensive and a bit complex in comparison to the analog techniques. This perspective is the main aim of this presentation and has been tabulated in Table 5. The highly reliable digital circuitry involved for implementing the NM techniques makes the NM scheme an obvious choice for many industrial applications.

6.5. PV array dependence

Along with other merits, NM techniques offer reliability, as these methods do not depend on the PV array and numerically track the MPP through successive iterations. This PV array independence offers an edge to all the methods involving an iterative approach over the intelligent MPPT methods as the NN or FL, most of the approximation techniques as the AR or DBM and the pre-calculated value approaches as the LuT or BFV.

Table 5
Comparative evaluation of the mppt techniques: focusing numerical methods for mppt.

A/D	MPPT techniques		Exact MPP	Speed	Complexity	Cost	Application	Control parameters	PV array dependence
Digital	**NM**	NR	YES	F	Si	E	SA	*V*, *I*	NO
		SM	YES	F	Si	E	SA	*V*, *I*	NO
		BSM	YES	M	M	CE	SA	*V*, *I*	NO
		CPI	YES	F	C	E	SA	*I*	NO
		FPM	YES	M	M	E	SA	*V*, *I*	NO
		NI	YES	F	M	CE	SA	*V*	NO
		BM	YES	F	C	E	SA	*V*, *I*	NO
	IN	FA	YES	F	M	CE	SA	V, *I*	NO
		SD	YES	M	M	E	SA	*V*, *I*	NO
		PM	YES	M	C	CE	SA	*V*, *I*	NO
		COS	YES	F	C	E	SA	*V*	NO
		ACO	YES	F	C	E	SA	*V*, *I*	NO
		G&D	YES	F	C	E	SA	*V*, *I*	NO
		PSO	YES	F	C	E	SA	*V*, *I*	NO
		SFLA	-	-	C	E	SA	*V*, *I*	–
		BN	YES	M	C	E	SA	*V*, *I*	NO
		ABC	YES	S	C	E	SA	*V*,*I*	NO
		GWO	YES	F	C	E	SA	*V*,*I*	NO
		CuS	YES	M	C	CE	SA	*V*,*I*	NO
	AI	NN	YES	F	C	CE	G	*V*, *I*	YES
		FL	YES	F	C	CE	B	*V*, *I*	YES
	HC	P&O	YES	M	Si	E	B	*V*, *I*	NO
		MP&O	YES	F	M	E	B	*V*, *I*	NO
		INC	YES	F	M	E	B	*V*, *I*	NO
		GMPPT*	YES	M	Si	CE	SA	*V*	NO
		β	YES	F	C	E	G	*V*, *I*	NO
	DDM	CS	YES	S	C	CE	SA	*V*, *I*	YES
		LM	YES	F	Si	E	SA	*V*, *I*	YES
		SMC	YES	F	M	E	B	*V*, *I*	NO
		CFT	NO	S	Si	CE	SA	*V*	YES
		PCT	YES	M	C	E	SA	*V*, *I*	NO
		LuT	YES	F	M	CE	SA	*V*, *I*	YES
		AR	NO	S	C	E	SA	*V*, *I*	YES
		TM	YES	M	C	E	SA	*V*	NO
Analog	**LCLV**	LCLV	NO	F	Si	CE	SA	*V*, *I*	NO
	RCC	RCC	YES	F	Si	E	G	*V*, *I*	NO
	SOT	SOT	YES	–	Si	E	SA	*V*	NO
Both	**DCL**	DCL	NO	M	C	CE	B	*V*, *I*	NO
	DBM	SS	YES	F	C	E	SA	*V*,*I*	YES
		FVI	NO	M	Si	CE	SA	*V*, *I*	YES
		FCT	YES	M	Si	CE	SA	*V*, *I*	YES
		BFV	NO	–	Si	CE	B	–	YES
		OCC	NO	F	M	CE	SA	*I*	YES

Note: Si=Simple, C=Complex, E=Expensive, CE=Cost-Effective, SA=Stand-Alone, G=Grid Connected, B=Both (SA & G), *V*=Voltage, *I*=Current. GMPPT* is the overall evaluation of the provided six GMPPT techniques.

7. Conclusion

A study presenting MPPT algorithms, majorly focusing the NM techniques taken from the literature are discussed. An attempt has been made to analyze the hits and drawbacks of each method. In the concluding discussion, it is clearly shown that many of the NM techniques have been utilized by researchers to track the MPP which have either been ignored in many review papers or have been given a secondary importance. This paper aimed at presenting the NM techniques as one of the effective algorithms, amongst other technique. In addition, most of the MPPT techniques have been touched through analog and digital classification, which might help researchers in selecting and implementing the accurate MPPT technique for a specific PV systems.

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References

[1] Rahim NA, Chaniago K, Selvaraj J. Single-phase seven-level grid-connected inverter for photovoltaic system. IEEE Trans Ind Electron 2011;58:2435–43.
[2] Gu Y, Li W, He X. Frequency Coordinating virtual impedance for autonomous power management of DC microgrid; 2015.
[3] Gu Y, Xiang X, Li W, He X. Mode-adaptive decentralized control for renewable DC microgrid with enhanced reliability and flexibility. IEEE Trans Power Electron 2014;29:5072–80.
[4] Manganiello P, Ricco M, Petrone G, Monmasson E, Spagnuolo G. Optimization of Perturbative PV MPPT Methods Through On Line System Identification; 2014.
[5] Romero-Cadaval E, Spagnuolo G, Garcia Franquelo L, Ramos-Paja C-A, Suntio T, Xiao W-M. Grid-connected photovoltaic generation plants: components and operation. Ind Electron Mag IEEE 2013;7:6–20.
[6] Sreeraj E, Chatterjee K, Bandyopadhyay S. One-cycle-controlled single-stage single-phase voltage-sensorless grid-connected PV system. IEEE Trans Ind Electron 2013;60:1216–24.

[7] Bialasiewicz JT. Renewable energy systems with photovoltaic power generators: operation and modeling. IEEE Trans Ind Electron 2008;55:2752–8.
[8] Nianchun W, MeiYue W, GuoSHeng S. Study on characteristics of photovoltaic cells based on MATLAB simulation. In: Proceedings of the Asia-Pacific power and energy engineering conference (APPEEC); 2011. p. 1–4.
[9] Subudhi B, Pradhan R. A comparative study on maximum power point tracking techniques for photovoltaic power systems. IEEE Trans Sustain Energy 2013;4:89–98.
[10] Bhatnagar P, Nema R. Maximum power point tracking control techniques: State-of-the-art in photovoltaic applications. Renew Sustain Energy Rev 2013;23:224–41.
[11] Xiao W, Elnosh A, Khadkikar V, Zeineldin H. Overview of maximum power point tracking technologies for photovoltaic power systems. In: IECON 2011-37th annual conference on IEEE industrial electronics society; 2011. p. 3900–5.
[12] Verma D, Nema S, Shandilya A, Dash SK. Maximum power point tracking (MPPT) techniques: Recapitulation in solar photovoltaic systems. Renew Sustain Energy Rev 2016;54:1018–34.
[13] Tajuddin M, Arif M, Ayob S, Salam Z. Perturbative methods for maximum power point tracking (MPPT) of photovoltaic (PV) systems: a review. Int J Energy Res 2015;39:1153–78.
[14] Eshram T, Chapman PL. Comparison of photovoltaic array maximum power point techniques. IEEE Trans Energy Convers 2007;22:439–49.
[15] Reisi AR, Moradi MH, Jamasb S. Classification and comparison of maximum power point tracking techniques for photovoltaic system: a review. Renew Sustain Energy Rev 2013;19:433–43.
[16] Salas V, Olias E, Barrado A, Lazaro A. Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems. Sol Energy Mater Sol Cells 2006;90:1555–78.
[17] Faranda R, Leva S, Maugeri V. MPPT techniques for PV systems: energetic and cost comparison. In: Proceedings of the IEEE Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century; 2008. p. 1–6.
[18] Nasr A, Ali A, Saied M, Mostafa M, Abdel-Moneim T. A survey of maximum ppt technique of PV systems. In: Proceedings of the IEEE energy tech; 2012.
[19] Hohm D, Ropp ME. Comparative study of maximum power point tracking algorithms. Prog Photovolt: Res Appl 2003;11:47–62.
[20] Kazmi SMR, Goto H, Guo H-J, Ichinokura O. Review and critical analysis of the research papers published till date on maximum power point tracking in wind energy conversion system. IEEE Energy Conversion Congress and Exposition (ECCE) 2010:4075–82.
[21] 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.
[22] Jain S, Agarwal V. Comparison of the performance of maximum power point tracking schemes applied to single-stage grid-connected photovoltaic systems. IET Electric Power Applications 2007;1:753–62.
[23] Salam Z, Ahmed J, Merugu BS. The application of soft computing methods for MPPT of PV system: a technological and status review. Appl Energy 2013;107:135–48.
[24] Kumar D, Chatterjee K. A review of conventional and advanced MPPT algorithms for wind energy systems. Renew Sustain Energy Rev 2016;55:957–70.
[25] Rezk H, Eltamaly AM. A comprehensive comparison of different MPPT techniques for photovoltaic systems. Sol Energy 2015;112:1–11.
[26] Rauschenbach H. Solar cells array design handbook: the principles and technology of photovoltaic energy conversion. Van Nostrand Reinhold; 1980.
[27] Villalva MG, Gazoli JR. Comprehensive approach to modeling and simulation of photovoltaic arrays. IEEE Trans Power Electron 2009;24:1198–208.
[28] Kreyszig E. Advanced engineering mathematics. John Wiley & Sons; 2010.
[29] Asaithambi N. Numerical analysis: theory and practice. Harcourt College Pub; 1995.
[30] Chun S, Kwasinski A. Analysis of classical root-finding methods applied to digital maximum power point tracking for sustainable photovoltaic energy generation. IEEE Trans Power Electron 2011;26:3730–43.
[31] Merhej P. Solar cells modellization and power management in photovoltaic generation systems. UniversitáDegli Studi Di Pavia, FacoltáDi Ingegneria; 2009.
[32] Recktenwald GW. Numerical methods with MATLAB: implementations and applications. NJ: Prentice Hall Upper Saddle River; 2000.
[33] Zazo H, Leyva R, del Castillo E. MPPT based on newton-like extremum seeking control. In: IEEE International Symposium on Industrial Electronics (ISIE); 2012. p. 1040–5.
[34] Ghaffari A, Krstić M, Nešić D. Multivariable newton-based extremum seeking. Automatica 2012;48:1759–67.
[35] Li H, Peng J, Liu W, Huang Z, Lin K-C. A Newton-based extremum seeking MPPT method for photovoltaic systems with stochastic perturbations. Int J Photoenergy 2014;2014.
[36] Moura SJ, Chang YA. Lyapunov-based switched extremum seeking for photovoltaic power maximization. Control Eng Pract 2013;21:971–80.
[37] Nesic D, Tan Y, Moase WH, Manzie C. A unifying approach to extremum seeking: adaptive schemes based on estimation of derivatives. In: Proceedings of the 49th IEEE conference on decision and control (CDC); 2010. p. 4625–30.
[38] Brahmi H, Dhifaoui R. Dynamic characteristics and improved MPPT control of PV generator. Front Energy 2013;7:342–50.
[39] Hosseini SH, Farakhor A, Khadem Haghighian S. Novel algorithm of MPPT for PV array based on variable step Newton-Raphson method through model predic tive control. In: Proceedings of the 13th international conference on control, automation and systems (ICCAS); 2013. p. 1577–82.
[40] Petrone G, Spagnuolo G, Vitelli M. Analytical model of mismatched photovoltaic fields by means of Lambert W-function. Sol Energy Mater Sol Cells 2007;91:1652–7.
[41] Picault D, Raison B, Bacha S, De La Casa J, Aguilera J. Forecasting photovoltaic array power production subject to mismatch losses. Sol Energy 2010;84:1301–9.
[42] Uoya M, Koizumi H. A calculation method of photovoltaic array's operating point for MPPT evaluation based on one-dimensional Newton-Raphson method; 2015.
[43] Xiao W, Dunford WG, Palmer PR, Capel A. Application of centered differentiation and steepest descent to maximum power point tracking. IEEE Trans Ind Electron 2007;54:2539–49.
[44] Xiao W, Lind MG, Dunford WG, Capel A. Real-time identification of optimal operating points in photovoltaic power systems. IEEE Trans Ind Electron 2006;53:1017–26.
[45] Gonzalez Montoya D, Ramos-Paja CA, Giral R. Improved design of sliding-mode controllers based on the requirements of MPPT techniques. IEEE Trans Power Electron 2016;31:235–47.
[46] Pradhan R, Subudhi B. Design and real-time implementation of a new auto-tuned adaptive MPPT control for a photovoltaic system. Int J Electr Power Energy Syst 2015;64:792–803.
[47] Hasan M, Parida S. An overview of solar photovoltaic panel modeling based on analytical and experimental viewpoint. Renew Sustain Energy Rev 2016;60:75–83.
[48] Ma J, Man K, Zhang N, Guan S, Wong P, Lim E, et al. Improving power-conversion efficiency via a hybrid MPPT approach for photovoltaic systems. Elektronika ir Elektrotechnika 2013;19:57–60.
[49] Hosseini SH, Farakhor A, Haghighian SK. Novel algorithm of maximum power point tracking (MPPT) for variable speed PMSG wind generation systems through model predictive control. In: Proceedings of the 8th international conference on electrical and electronics engineering (ELECO); 2013. p. 243–247.
[50] Mahmodian M, Rahmani R, Taslimi E, Mekhilef S. Step by step analyzing, modeling and simulation of single and double array PV system in different environmental variability. Proc Int Conf Future Environ Energy 2012:37–42.
[51] Wang P, Zhu H, Shen W, Choo FH, Loh PC, Tan KK. A novel approach of maximizing energy harvesting in photovoltaic systems based on bisection search theorem. In: Proceedings of the twenty-fifth annual IEEE applied power electronics conference and exposition (APEC); 2010. p. 2143–8.
[52] Prianandа CW, Haikal MA. Maximum power point tracking photovoltaic using root finding modified bisection algorithm. In: Proceedings of the 1st international conference on information technology, computer and electrical engineering (ICITACEE); 2014. p. 394–9.
[53] Ma J, Man KL, Ting T, Zhang N, Lei C-U, Wong N. Low-cost global mppt scheme for photovoltaic systems under partially shaded conditions. In: Proceedings of the IEEE international symposium on circuits and systems (ISCAS); 2013. p. 245–8.
[54] Zhang Q, Hu C, Chen L, Amirahmadi A, Kutkut N, Shen ZJ, et al. A center point iteration MPPT method with application on the frequency-modulated LLC microinverter. IEEE Trans Power Electron 2014;29:1262–74.
[55] Chen L, Amirahmadi A, Zhang Q, Kutkut N, Batarseh I. Design and implementation of three-phase two-stage grid-connected module integrated converter. IEEE Trans Power Electron 2014;29:3881–92.
[56] Yang WY, Cao W, Chung T-S, Morris J. Applied numerical methods using MATLAB. John Wiley & Sons; 2005.
[57] Young T, Mohlenkamp MJ. Introduction to numerical methods and Matlab Programming for Engineers. OH: Ohio University Department of Mathematics; 2009.
[58] Dowell M, Jarratt P. A modified regula falsi method for computing the root of an equation. BIT Numer Math 1971;11:168–74.
[59] Chun S, Kwasinski A. Modified Regula Falsi optimization method approach to digital maximum power point tracking for photovoltaic application. In: Proceedings of the twenty-sixth annual IEEE applied power electronics conference and exposition (APEC); 2011. p. 280–6.
[60] Pei-chun Q, Bao-ming G, Da-qiang B. An improved MPPT method for photovoltaic power generation system. In: Proceedings of the 2nd IEEE international symposium on power electronics for distributed generation systems (PEDG); 2010. p. 144–7.
[61] Wang M, Qin H, Zhou J, Hu G. The design of photovoltaic maximum power automatic tracking and controlling system. In: Proceedings of the international conference on image analysis and signal processing; 2012.
[62] Hu J, Zhang J, Wu H. A novel MPPT control algorithm based on numerical calculation for PV generation systems. In: IEEE 6th international power electronics and motion control conference IPEMC'09; 2009. p. 2103–7.
[63] Xin H, Liu Y, Wang Z, Gan D, Yang T. A new frequency regulation strategy for photovoltaic systems without energy storage. IEEE Trans Sustain Energy 2013;4:985–93.
[64] Pai F-S, Chao R-M, Ko SH, Lee T-S. Performance evaluation of parabolic prediction to maximum power point tracking for PV array. Sustain Energy IEEE Trans Sustain Energy 2011;2:60–8.
[65] Liu Y, Chen L, Chen L, Xin H, Gan D. A newton quadratic interpolation based control strategy for photovoltaic system; 2012.
[66] Jing H, Jiancheng Z. Research on MPPT control algorithm based on numerical method for PV generation systems. Electric Power Sci Eng 2009;7:002.

[67] Qiu P-C, Ge B-M, Bi D-Q. MPPT control for PV power generation system based on P&O algorithms and quadratic interpolation. Power Syst Prot Control 2011;39:62–7.
[68] Kumar G, Panchal AK. Geometrical prediction of maximum power point for photovoltaics. Appl Energy 2014;119:237–45.
[69] Thongam J, Bouchard P, Beguenane R, Okou A, Merabet A. Control of variable speed wind energy conversion system using a wind speed sensorless optimum speed MPPT control method. In: Proceedings of the 37th annual conference on IEEE industrial electronics society IECON; 2011. p. 855–60.
[70] Thongam J, Tarbouchi M, Beguenane R, Okou A, Merabet A, Bouchard P. An optimum speed MPPT controller for variable speed PMSG wind energy conversion systems. In: Proceedings of the 38th Annual Conference on IEEE Industrial Electronics Society IECON; 2012. p. 4293–7.
[71] Thongam J, Bouchard P, Beguenane R, Fofana I. Neural network based wind speed sensorless MPPT controller for variable speed wind energy conversion systems. In: Proceedings of the IEEE electric power and energy conference (EPEC); 2010. p. 1–6.
[72] Arayashiki T, Koizumi H. A simulation method for maximum power point tracking against stepped *I–V* characteristics. In: Proceedings of the international conference on sustainable energy technologies ICSET; 2008. p. 611–5.
[73] Phang J, Chan D, Phillips J. Accurate analytical method for the extraction of solar cell model parameters. Electron Lett 1984;20:406–8.
[74] Kawamura H, Koizumi H. Development of photovoltaic arrays model for maximum power point tracking simulation. In: Proceedings of the IEEE International conference on sustainable energy technologies (ICSET); 2010. p. 1–6.
[75] Lad R, Wohlgemuth J, TamizhMani G. Outdoor energy ratings and spectral effects of photovoltaic modules. In: Proceedings of the 35th IEEE Photovoltaic Specialists Conference (PVSC); 2010. p. 002827–32.
[76] Fermia N, Granozio D, Petrone G, Vitelli M. Predictive & adaptive MPPT perturb and observe method. IEEE Trans Aerosp Electron Syst 2007;43:934–50.
[77] Mamarelis E, Petrone G, Spagnuolo G. A two-steps algorithm improving the P&O steady state MPPT efficiency. Applied Energy 2014;113:414–21.
[78] Salas V, Olías E, Alonso-Abellá M, Chenlo F. Analysis of the maximum power point tracking in the photovoltaic grid inverters lower than 5 kW. In: Proceedings of ISES World Congress vol. I–V; 2009. p. 1376–80.
[79] Koka K, TamizhMani G. Automatic performance matrix generation as per IEC 61853–1 standard using only monitored outdoor MPPT data. In: Proceedings of the 37th IEEE photovoltaic specialists conference (PVSC); 2011. p. 003174–8.
[80] Kim J, Kwasinski A. Maximum power point tracking for multiple photovoltaic modules using root-finding methods. In: Proceedings of the IEEE energy conversion congress and exposition (ECCE); 2014. p. 9–16.
[81] Brent RP. Algorithms for minimization without derivatives: Courier Corporation; 2013.
[82] Press W, Teukolsky S, Vetterling W. Numerical Recipes in FORTRAN Flannery BP. Cambridge University Press; 1992.
[83] Yang X-S. Firefly algorithms for multimodal optimization. Stochastic algorithms: foundations and applications. Springer; 2009. p. 169–78.
[84] Yang X-S. Nature-inspired metaheuristic algorithms. Luniver press; 2010.
[85] 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.
[86] Kofinas P, Dounis AI, Papadakis G, Assimakopoulos M. An Intelligent MPPT controller based on direct neural control for partially shaded PV system. Energy Build 2015;90:51–64.
[87] Pai F-S, Chao R-M. A new algorithm to photovoltaic power point tracking problems with quadratic maximization. IEEE Trans Energy Convers 2010;1:262–4.
[88] Wang P, Li D, Wu X, Lü J, Yu X. Ultimate bound estimation of a class of high dimensional quadratic autonomous dynamical systems. Int J Bifurcation and Chaos 2011;21:2679–94.
[89] Piccirillo V, Balthazar JM, Pontes Jr B, Felix J. Chaos control of a nonlinear oscillator with shape memory alloy using an optimal linear control: Part II: Nonideal energy source. Nonlinear Dyn 2009;56:243–53.
[90] 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.
[91] Zhou L, Chen Y, Liu Q, Wu J. Maximum power point tracking (MPPT) control of a photovoltaic system based on dual carrier chaotic search. J Control Theory and Appl 2012;10:244–50.
[92] Wang L, Wei X, Zhu T, Zhang J. Two-stage chaos optimization search application in maximum power point tracking of PV array. Math Problems Eng 2014;2014.
[93] Dorigo M, Maniezzo V, Colorni A. Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern Part B: Cybern 1996;26:29–41.
[94] Adly M, Besheer A. A meta-heuristics search algorithm as a solution for energy transfer maximization in stand-alone photovoltaic systems. Int J Electr Power Energy Syst 2013;51:243–54.
[95] Adly M, Besheer AH. An optimized fuzzy maximum power point tracker for stand alone photovoltaic systems: ant colony approach. In: Proceedings of the 7th IEEE Conference on Industrial Electronics and Applications (ICIEA); 2012. p. 113–9.
[96] 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.
[97] Besheer AH, Adly M. Ant colony system based PI maximum power point tracking for stand alone photovoltaic system. In: IEEE International Conference onIndustrial Technology (ICIT); 2012. p. 693–698.
[98] L. Zhang Y. Bai A. Al-Amoudi. GA-RBF neural network based maximum power point tracking for grid-connected photovoltaic systems 2002.
[99] Ramaprabha R, Gothandaraman V, Kanimozhi K R. Divya B. Mathur. Maximum power point tracking using GA-optimized artificial neural network for Solar PV system. In: Proceedings 1st international conference onelectrical energy systems (ICEES); 2011. p. 264–8.
[100] Messai A, Mellit A, Guessoum A, Kalogirou S. Maximum power point tracking using a GA optimized fuzzy logic controller and its FPGA implementation. Sol Energy 2011;85:265–77.
[101] Nayanar V, Kumaresan N, Ammasaiounden N. A Single-sensor-based MPPT Controller For Wind-driven Induction Generators Supplying DC microgrid. IEEE Trans Power Electron 2016;31:1161–72.
[102] Taheri H, Salam Z, Ishaque K. A novel maximum power point tracking control of photovoltaic system under partial and rapidly fluctuating shadow conditions using differential evolution. In: Proceedings of the IEEE Symposium onIndustrial Electronics Applications (ISIEA); 2010. p. 82–87.
[103] 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.
[104] da Costa WT, Fardin JF, Simonetti DS, L. d V. Neto. Identification of photovoltaic model parameters by differential evolution. In: Proceedings of the IEEE international conference on industrial technology (ICIT); 2010. p. 931–6.
[105] Miyatake M, Toriumi F, Fujii N, Ko H. Maximum power point tracking of multiple photovoltaic arrays: a PSO approach. In: Proceedings of the IEEE transactions on aerospace and electronic systems 47; 2011. p. 367–80.
[106] Abdullah M, Yatim A, Tan CW, Samosir A. Particle swarm optimization-based maximum power point tracking algorithm for wind energy conversion system. In: Proceedings of the IEEE international conference on power and energy (PECon); 2012. p. 65–70.
[107] Abdulkadir M, Yatim A, Yusuf S. An improved PSO-based MPPT control strategy for photovoltaic systems. Int J Photoenergy 2014;2014.
[108] Chowdhury SR, Saha H. Maximum power point tracking of partially shaded solar photovoltaic arrays. Sol Energy Mater Sol Cells 2010;94:1441–7.
[109] Kondo Y, Phimmasone V, Ono Y, Miyatake M. Verification of efficacy of PSO-based MPPT for photovoltaics. In: Proceedings of the international conference on electrical machines and systems (ICEMS); 2010. p. 593–6.
[110] Ishaque K, Salam Z, Amjad M, Mekhilef S. An improved particle swarm optimization (PSO)–based MPPT for PV with reduced steady-state oscillation. In: Proceedings of the IEEE transactions on power electronics vol. 27; 2012. p. 3627–38.
[111] Sandrolini L, Artioli M, Reggiani U. Numerical method for the extraction of photovoltaic module double-diode model parameters through cluster analysis. Appl Energy 2010;87:442–51.
[112] Ishaque K, Salam Z, Shamsudin A, Amjad M. A direct control based maximum power point tracking method for photovoltaic system under partial shading conditions using particle swarm optimization algorithm. Appl Energy 2012;99:414–22.
[113] Kuo J-L, Chao K-L, Lee L-S. Dual mechatronic MPPT controllers with PN and OPSO control algorithms for the rotatable solar panel in PHEV system. In: Proceedings of the IEEE transactions on industrial electronics vol. 57; 2010. p. 678–89.
[114] Soon JJ, Low K-S. Photovoltaic model identification using particle swarm optimization with inverse barrier constraint. IEEE Trans Power Electron 2012;27:3975–83.
[115] Fu Q, Tong N. A complex-method-based PSO algorithm for the maximum power point tracking in photovoltaic system. In: Proceedings of the second international conference oninformation technology and computer science (ITCS); 2010. p. 134–7.
[116] Renaudineau H, Donatantonio F, Fontchastagner J, Petrone G, Spagnuolo G, Martin J-P, et al. A PSO-based global MPPT technique for distributed PV power generation. IEEE Trans Ind Electron 2015;62:1047–58.
[117] Hasanien HM. Shuffled frog leaping algorithm for photovoltaic model identification. IEEE Trans Sustain Energy 2015;6:509–15.
[118] Eusuff M, Lansey K, Pasha F. Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization. Eng Optim 2006;38:129–54.
[119] Keyrouz F, Georges S. Efficient multidimensional maximum power point tracking using bayesian fusion. In: Proceedings of the 2nd international conference on electric power and energy conversion systems (EPECS); 2011. p. 1–5.
[120] Tereshko V, Loengarov A. Collective decision making in honey-bee foraging dynamics. Comput Inf Syst 2005;9:1.
[121] soufyane Benyoucef A, 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.
[122] Mirjalili S, Mirjalili SM, Lewis A. Grey wolf optimizer. Adv Eng Softw 2014;69:46–61.
[123] Mohanty S, Subudhi B, Ray PK. A new MPPT design using grey wolf optimization technique for photovoltaic system under partial shading conditions. IEEE Trans Sustain Energy 2016;7:181–8.
[124] Yang X-S, Deb S. Cuckoo search via Lévy flights. In: World congress on nature & biologically inspired computing NaBIC; 2009. p. 210–4.
[125] TEUSCHL Y, TABORSKY B, TABORSKY M. How do cuckoos find their hosts? The role of habitat imprinting Anim Behav 1998;56:1425–33.

[126] 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.
[127] Berrazouane S, Mohammedi K. Parameter optimization via cuckoo optimization algorithm of fuzzy controller for energy management of a hybrid power system. Energy Convers Manag 2014;78:652–60.
[128] Sofiane B, Kamal M, Said A. Design and optimal energy management strategy for stand-alone PV-battery-Diesel systems using cuckoo search algorithm. In: Proceedings of the 3rd international conference on systems and control (ICSC); 2013. p. 230–5.
[129] Ahmed J, Salam Z. A soft computing MPPT for PV system based on Cuckoo Search algorithm. In: Proceedings of the fourth international conference on power engineering, energy and electrical drives (POWERENG); 2013. p. 558–562.
[130] Habibi M, Yazdizadeh A. New MPPT controller design for pv arrays using neural networks (Zanjan City case study). Advances in Neural Networks–ISNN 2009. Springer; 2009. p. 1050–8.
[131] Z. Yong L. Hong L. Liqun G. XiaoFeng. The MPPT Control Method by Using BP Neural Networks in PV Generating System. In: Proceedings of the international conference onindustrial control and electronics engineering (ICICEE); 2012. p. 1639–42.
[132] Sedaghati F, Nahavandi A, Badamchizadeh MA, Ghaemi S, Abedinpour Fallah M. PV maximum power-point tracking by using artificial neural network. Math Prob Eng 2012;2012.
[133] Lin W-M, Hong C-M, Chen C-H. Neural-network-based MPPT control of a stand-alone hybrid power generation system. IEEE Trans Power Electron 2011;26:3571–81.
[134] Elobaid L, Abdelsalam A, Zakzouk E. Artificial neural network based maximum power point tracking technique for PV systems. In: Proceedings of the 38th annual conference on IEEE industrial electronics society IECON, 2012, pp. 937–42.
[135] Veerachary M, Senjyu T, Uezato K. Neural-network-based maximum-power-point tracking of coupled-inductor interleaved-boost-converter-supplied PV system using fuzzy controller. Ind Electron IEEE Trans Ind Electron 2003;50:749–58.
[136] Pucci M, Cirrincione M. Neural MPPT control of wind generators with induction machines without speed sensors. IEEE Trans Ind Electron 2011;58:37–47.
[137] Sahnoun MA, Ugalde HMR, Carmona J-C, Gomand J. Maximum power point tracking using p&o control optimized by a neural network approach: a good compromise between accuracy and complexity. Energy Procedia 2013;42:650–9.
[138] Singh MD, Shine V, Janamala V. Application of artificial neural networks in optimizing MPPT control for standalone solar PV system. In: Proceedings of the international conference on contemporary computing and informatics (IC3I); 2014. p. 162–6.
[139] Chao K-H, Li C-J, Wang M-H. A maximum power point tracking method based on extension neural network for PV systems. Advances in Neural Networks–ISNN 2009. Springer; 2009. p. 745–55.
[140] El-Saadany E, Salama M. Maximum power point tracking for photovoltaic systems using fuzzy logic and artificial neural networks. In: Proceedings of the IEEE power and energy society general meeting; 2011. p. 1–9.
[141] Yang YR. A neural network controller for maximum power point tracking with 8-bit microcontroller. In: Proceedings of the 6th IEEE conference on industrial electronics and applications (ICIEA); 2011. p. 919–24.
[142] Dkhichi F, Oukarfi B, El Kouari Y, Ouoba D, Fakkar A. Neural network based integration of MPPT and diagnosis of degradation for photovoltaic module. Opt Quantum Electron 2016;48:1–12.
[143] Rizzo SA, Scelba G. ANN based MPPT method for rapidly variable shading conditions. Appl Energy 2015;145:124–32.
[144] Chine W, Mellit A, Lughi V, Malek A, Sulligoi G, Pavan AM. A novel fault diagnosis technique for photovoltaic systems based on artificial neural networks. Renew Energy 2016;90:501–12.
[145] 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: 30th annual conference of IEEE on industrial electronics society IECON; 2004. p. 2673–8.
[146] Mamdani EH, Assilian S. An experiment in linguistic synthesis with a fuzzy logic controller. Int J Man-machine Stud 1975;7:1–13.
[147] Won C-Y, Kim D-H, Kim S-C, Kim W-S, Kim H-S. A new maximum power point tracker of photovoltaic arrays using fuzzy controller PESC'94 Record., 25th Annual IEEE Power Electronics Specialists Conference; 1994. p. 396–403.
[148] El Khateb A, Rahim NA, Selvaraj J, Uddin MN. Fuzzy logic controller based SEPIC converter of maximum power point tracking. In: Proceedings of the IEEE industry applications society annual meeting (IAS); 2012. p. 1–9.
[149] Mohamed A, Shareef H. Hopfield neural network optimized fuzzy logic controller for maximum power point tracking in a photovoltaic system. Int J Photoenergy 2011;2012.
[150] Ruddin S, Karatepe E, Hiyama T. Artificial neural network-polar coordinated fuzzy controller based maximum power point tracking control under partially shaded conditions. IET Renew Power Gen 2009;3:239–53.
[151] Purnama I, Lo Y-K, Chiu H-J. A fuzzy control maximum power point tracking photovoltaic system 2011 IEEE international conference onfuzzy systems (FUZZ); 2011. p. 2432–9.
[152] 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.
[153] Kottas TL, Boutalis YS, Karlis AD. New maximum power point tracker for PV arrays using fuzzy controller in close cooperation with fuzzy cognitive networks. IEEE Trans Energy Convers 2006;21:793–803.
[154] Chiu C-S. TS fuzzy maximum power point tracking control of solar power generation systems. IEEE Trans Energy Convers 2010;25:1123–32.
[155] Arulmurugan R, Suthanthira Vanitha N. Intelligent fuzzy MPPT controller using analysis of DC to DC novel buck converter for photovoltaic energy system applications. In: Proceedings of the international conference on pattern recognition, informatics and mobile engineering (PRIME); 2013. p. 225–31.
[156] Boukenoui R, Salhi H, Bradai R, Mellit A. A new intelligent MPPT method for stand-alone photovoltaic systems operating under fast transient variations of shading patterns. Sol Energy 2016;124:124–42.
[157] 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.
[158] Xiao W, Dunford WG. A modified adaptive hill climbing MPPT method for photovoltaic power systems.In: Proceedings of the IEEE 35th annual power electronics specialists conference PESC; 2004. p. 1957–63.
[159] Al-Atrash H, Batarseh I, Rustom K. Statistical modeling of DSP-based hill-climbing MPPT algorithms in noisy environments. In: Proceedings of the twentieth annual IEEE applied power electronics conference and exposition APEC; 2005. p. 1773–7.
[160] Peftitsis D, Adamidis G, Balouktsis A. A new MPPT method for Photovoltaic generation systems based on Hill Climbing algorithm. In: Proceedings of the 18th international conference on electrical machines ICEM; 2008. p. 1–5.
[161] 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.
[162] Wasynezuk O. Dynamic behavior of a class of photovoltaic power systems. IEEE Trans Power Apparatus Syst 1983:3031–7.
[163] Hussein K, Muta I, Hoshino T, Osakada M. Maximum photovoltaic power tracking: an algorithm for rapidly changing atmospheric conditions. IEE Proc – Gen Transm Distrib 1995;142:59–64.
[164] Kjaer SB. Evaluation of the “hill climbing” and the “incremental conductance” maximum power point trackers for photovoltaic power systems. IEEE Trans Energy Convers 2012;27:922–9.
[165] Lee K, Fujii Y, Sumiya T, Ikawa E. Development of a 250 kW PV PCS and adaptive MPPT method. In: Proceedings of the international power electronics conference (IPEC); 2010. p. 2598–602.
[166] Kuo Y-C, Liang T-J, Chen J-F. Novel maximum-power-point-tracking controller for photovoltaic energy conversion system. IEEE Trans Ind Electron 2001;48:594–601.
[167] Chen K, Tian S, Cheng Y, L. Bai. An improved MPPT controller for photovoltaic system under partial shading condition 2014.
[168] D'Souza NS, Lopes LA, Liu X. Peak current control based maximum power point trackers for faster transient responses 2006. '06. Canadian Conference on Electrical and Computer Engineering CCECE; 2006. p. 659–63.
[169] Femia N, Petrone G, Spagnuolo G, Vitelli M. Optimization of perturb and observe maximum power point tracking method. IEEE Trans Power Electron 2005;20:963–73.
[170] Femia N, Petrone G, Spagnuolo G, Vitelli M. Optimizing sampling rate of P&O MPPT technique. In: Proceedings of the IEEE 35th annual power electronics specialists conference PESC; 2004. p. 1945–9.
[171] Jiang Y, Qahouq JA, Haskew TA. Adaptive step size with adaptive-perturbation-frequency digital MPPT controller for a single-sensor photovoltaic solar system. IEEE Trans Power Electron 2013;28:3195–205.
[172] Khaehintung N, Wiangtong T, Sirisuk P. FPGA implementation of MPPT using variable step-size P&O algorithm for PV applications. In: Proceedings of the international symposium on communications and information technologies ISCIT; 2006. p. 212–5.
[173] Mummadi V. Maximum Power point tracking algorithm for non-linear DC Sources. In: Proceedings of the IEEE Region 10 and the third international conference on industrial and information systems ICIIS; 2008. p. 1–6.
[174] Youssef E, Stephane P, Bruno E, Corinne A. New P&O MPPT algorithm for FPGA implementation. In: Proceedings of the 36th annual conference on IEEE industrial electronics society IECON; 2010. p. 2868–73.
[175] Pandey A, Dasgupta N, Mukerjee AK. Design issues in implementing MPPT for improved tracking and dynamic performance. In: IECON 2006-32nd Annual Conference onIEEE Industrial Electronics 2006 4387 4391.
[176] Femia N, Petrone G, Spagnuolo G, Vitelli M. Perturb and observe MPPT technique robustness improved. In: Proceedings of the IEEE international symposium on industrial electronics; 2004. p. 845–50.
[177] Tan CW, Green TC, Hernandez-Aramburo CA. An improved maximum power point tracking algorithm with current-mode control for photovoltaic applications. In: Proceedings of the international conference on power electronics and drives systems PEDS; 2005. p. 489–94.
[178] Sera D, Teodorescu R, Hantschel J, Knoll M. Optimized maximum power point tracker for fast changing environmental conditions. In: Proceedings of the IEEE international symposium on industrial electronics ISIE; 2008. p. 2401–7.
[179] Zhang F, Thanapalan K, Maddy J, Guwy A. Development of a novel hybrid maximum power point tracking methodology for photovoltaic systems. In: Proceedings of the 18th international conference on automation and computing (ICAC); 2012. p. 1–6.

[180] Sera D, Kerekes T, Teodorescu R, Blaabjerg F. Improved MPPT algorithms for rapidly changing environmental conditions 2006. EPE-PEMC 2006. In: Proceedings 12th international power electronics and motion control conference; 2006. p. 1614–9.
[181] Mastromauro RA, Liserre M, Dell'Aquila A. Control issues in single-stage photovoltaic systems: MPPT, current and voltage control. IEEE Trans Ind Inf 2012;8:241–54.
[182] Hsiao Y-T, Chen C-H. Maximum power tracking for photovoltaic power system. In: Proceedings of the 37th IAS annual meeting conference record of the industry applications conference; 2002. p. 1035–40.
[183] Liu C, Wu B, Cheung R. Advanced algorithm for MPPT control of photovoltaic systems. Can Sol Build Conf Montreal 2004:20–4.
[184] Killi M, Samanta S. Modified perturb and observe MPPT algorithm for drift avoidance in photovoltaic systems. IEEE Trans Ind Electron 2015;62:5549–59.
[185] Duan Q, Leng J, Duan P, Hu B, Mao M. An improved variable step PO and global scanning MPPT method for PV systems under partial shading condition. In: Proceedings of the 7th international conference onintelligent human-machine systems and cybernetics (IHMSC); 2015. p. 382–6.
[186] Elgendy MA, Zahawi B, Atkinson DJ. Assessment of the incremental conductance maximum power point tracking algorithm. IEEE Trans Sustain Energy 2013;4:108–17.
[187] Hsieh G-C, Hsieh H-I, Tsai C-Y, Wang C-H. Photovoltaic power-increment-aided incremental-conductance MPPT with two-phased tracking. IEEE Trans Power Electron 2013;28:2895–911.
[188] Lee JH, Bae H, Cho BH. Advanced incremental conductance MPPT algorithm with a variable step size. In: Proceedings of the 12th international power electronics and motion control conference; 2006. p. 603–7 EPE-PEMC.
[189] Li J, Wang H. A novel stand-alone PV generation system based on variable step size INC MPPT and SVPWM control. In: Proceedings of IEEE 6th international power electronics and motion control conference IPEMC; 2009. p. 2155–60.
[190] Liu B, Duan S, Liu F, Xu P. Analysis and improvement of maximum power point tracking algorithm based on incremental conductance method for photovoltaic array. In: Proceedings of the 7th international conference on power electronics and drive systems PEDS; 2007. p. 637–41.
[191] Liu F, Duan S, Liu F, Liu B, Kang Y. A variable step size INC MPPT method for PV systems. IEEE Trans Ind Electron 2008;55:2622–8.
[192] Mei Q, Shan M, Liu L, Guerrero JM. A novel improved variable step-size incremental-resistance MPPT method for PV systems. IEEE Trans Ind Electron 2011;58:2427–34.
[193] Mirbagheri SZ, Mekhilef S, Mirhassani SM. MPPT with Inc. Cond method using conventional interleaved boost converter. Energy Procedia 2013;42:24–32.
[194] Rahman NA, Omar A, Saat EM. A modification of variable step size INC MPPT in PV system. In: Proceedings of the IEEE 7th international power engineering and optimization conference (PEOCO); 2013. p. 340–345.
[195] Shadmand MB, Mosa M, Balog RS, Rub HA. An improved MPPT technique for high gain DC–DC converter using model predictive control for photovoltaic applications. In: Proceedings of the twenty-ninth annual IEEE applied power electronics conference and exposition (APEC); 2014. p. 2993–9.
[196] Siwakoti YP, Chhetri BB, Adhikary B, Bista D. Microcontroller based intelligent DC/DC converter to track Maximum Power Point for solar photovoltaic module. In: Proceedings of the IEEE Conference on innovative technologies for an efficient and reliable electricity supply; 2010. p. 94–101.
[197] Zainudin HN, Mekhilef S. Comparison study of maximum power point tracker techniques for PV systems; 2010.
[198] Zakzouk NE, Elsaharty MA, Abdelsalam AK, Helal AA, Williams BW. Improved performance low-cost incremental conductance PV MPPT technique. IET Renew Power Gen 2016.
[199] Boztepe M, Guinjoan F, Velasco-Quesada G, Silvestre S, Chouder A, Karatepe E. Global MPPT scheme for photovoltaic string inverters based on restricted voltage window search algorithm. Ind Electron IEEE Trans 2014;61:3302–12.
[200] Koutroulis E, Blaabjerg F. A new technique for tracking the global maximum power point of PV arrays operating under partial-shading conditions. Photovolt IEEE J 2012;2:184–90.
[201] Tey KS, Mekhilef S. Modified incremental conductance algorithm for photovoltaic system under partial shading conditions and load variation. Ind Electron IEEE Trans 2014;61:5384–92.
[202] Wang Y, Li Y, Ruan X. High-accuracy and fast-speed MPPT methods for PV string under partially shaded conditions. Ind Electron, IEEE Trans 2016;63:235–45.
[203] De Brito MA, Sampaio LP, Junior LG, Canesin C. Evaluation of MPPT techniques for photovoltaic applications. In: Proceedings of the IEEE international symposium on industrial electronics (ISIE); 2011. p. 1039–44.
[204] Jain S, Agarwal V. A new algorithm for rapid tracking of approximate maximum power point in photovoltaic systems. Power Electron Lett IEEE 2004;2:16–9.
[205] M. Bodur M. Ermiş. Maximum power point tracking for low power photovoltaic solar panels. In: Proceedings of the 7th mediterranean electrotechnical conference; 1994. p. 758–61.
[206] Pan C-T, Chen J-Y, Chu C-P, Huang Y-S. A fast maximum power point tracker for photovoltaic power systems. '99 Proceedings. the 25th Annual Conference of the IEEEIndustrial Electronics Society IECON; 1999. p. 390–3.
[207] Chu C-C, Chen C-L. Robust maximum power point tracking method for photovoltaic cells: a sliding mode control approach. Sol Energy 2009;83:1370–8.
[208] Aghatehrani R, Kavasseri R. Sensitivity-analysis-based sliding mode control for voltage regulation in microgrids. Sustain Energy IEEE Trans 2013;4:50–7.
[209] Kim I-S, Kim M-B, Youn M-J. New maximum power point tracker using sliding-mode observer for estimation of solar array current in the grid-connected photovoltaic system. Ind Electron IEEE Trans 2006;53:1027–35.
[210] Zhang M, Wu J, Zhao H. The application of slide technology in PV maximum power point tracking system. In: Proceedings of the fifth world congress on intelligent control and automation WCICA 2004 5591 5594.
[211] Costabeber A, Carraro M, Zigliotto M. Convergence analysis and tuning of a sliding-mode ripple-correlation MPPT. Energy Convers IEEE Trans 2015;30:696–706.
[212] Pradhan R, Subudhi B. Double integral sliding mode MPPT control of a photovoltaic system. Control Syst Technol IEEE Trans 2016;24:285–92.
[213] Yan S, Tan S-C, Hui S. Sliding mode control for improving the performance of PV inverter with MPPT—A comparison between SM and PI control. In: Proceedings of the 17th European conference onpower electronics and applications (EPE'15 ECCE-Europe); 2015. p. 1–10.
[214] Khatib TT, Mohamed A, Amin N, Sopian K. An efficient maximum power point tracking controller for photovoltaic systems using new boost converter design and improved control algorithm. WSEAS Trans Power Syst 2010;5:53–63.
[215] Chen Y, Smedley K, Vacher F, Brouwer J. A new maximum power point tracking controller for photovoltaic power generation. In: Proceedings of the eighteenth annual IEEE applied power electronics conference and exposition APEC'03; 2003. p. 58–62.
[216] Jiang J, Huang T, Hsiao Y, Chen C. Maximum power tracking for photovoltaic power systems. Tamkang J Sci Eng 2005;8:147.
[217] Ibrahim H-S, Houssiny FF, El-Din HZ, El-Shibini MA. Microcomputer controlled buck regulator for maximum power point tracker for DC pumping system operates from photovoltaic system. In: IEEE InternationalFuzzy Systems Conference Proceedings FUZZ-IEEE; 1999. p. 406–11.
[218] Hiyama T, Kitabayashi K. Neural network based estimation of maximum power generation from PV module using environmental information. Energy Convers IEEE Trans 1997;12:241–7.
[219] Duru HT. A maximum power tracking algorithm based on I mpp= f (P max) function for matching passive and active loads to a photovoltaic generator. Solar Energy 2006;80:812–22.
[220] Lei M, Yaojie S, Yandan L, Zhifeng B, Liqin T, Jieqiong S. A high performance MPPT control method. In: Proceedings of the international conference on materials for renewable energy environment (ICMREE); 2011. p. 195–9.
[221] Chao K-H, Ho S-H, Wang M-H. Modeling and fault diagnosis of a photovoltaic system. Electr Power Syst Res 2008;78:97–105.
[222] El-Shibini M, Rakha H. Maximum power point tracking technique. In: Proceedings of the electrotechnical conference on integrating research, industry and education in energy and communication engineering MELECON. Mediterranean; 1989. p. 21–24.
[223] Park M, Yu I-K. A study on the optimal voltage for MPPT obtained by surface temperature of solar cell. In: Proceedings of the 30th annual conference of IEEE industrial electronics society IECON; 2004. p. 2040–5.
[224] Coelho RF, Concer FM, Martins DC. A MPPT approach based on temperature measurements applied in PV systems. In: Proceedings of the 9th IEEE/IAS international conference on industry applications (INDUSCON); 2010. p. 1–6.
[225] Arias J, Linera F, Martin-Ramos J, Pernia AM, Cambronero J. A modular PV regulator based on microcontroller with maximum power point tracking. In: Proceedings of the 39th IAS Annual Meeting Conference Record of the IEEE, Industry Applications Conference; 2004. p. 1178–84.
[226] Shmilovitz D. On the control of photovoltaic maximum power point tracker via output parameters. Electr Power Appl IEE Proc 2005:239–48.
[227] Mutoh N, Ohno M, Inoue T. A method for MPPT control while searching for parameters corresponding to weather conditions for PV generation systems. Ind Electron IEEE Trans 2006;53:1055–65.
[228] Krein PT. Ripple correlation control, with some applications. '99. Proceedings of the 1999 IEEE international symposium on circuits and systems ISCAS;1999. p. 283–6.
[229] Midya P, Krein PT, Turnbull RJ, Reppa R, Kimball J. Dynamic maximum power point tracker for photovoltaic applications.In: Proceedings of the 27th annual IEEE power electronics specialists conference; 1996. p. 1710–6.
[230] Logue D, Krein P. Observer-based techniques in ripple correlation control applied to power electronic systems. 2001. In: Proceedings of the IEEE 32nd annual power electronics specialists conference PESC; 2001. p. 2014–8.
[231] Kimball JW, Krein PT. Discrete-time ripple correlation control for maximum power point tracking. Power Electron IEEE Trans 2008;23:2353–62.
[232] Esram T, Kimball JW, Krein PT, Chapman PL, Midya P. Dynamic maximum power point tracking of photovoltaic arrays using ripple correlation control. Power Electron IEEE Trans 2006;21:1282–91.
[233] Casadei D, Grandi G, Rossi C. Single-phase single-stage photovoltaic generation system based on a ripple correlation control maximum power point tracking. Energy Convers IEEE Trans 2006;21:562–8.
[234] Giustiniani A, Petrone G, Spagnuolo G, Vitelli M. Low-frequency current oscillations and maximum power point tracking in grid-connected fuel-cell-based systems. Ind Electron IEEE Trans 2010;57:2042–53.
[235] Tse K, Ho M, Chung HS, Hui SR. A novel maximum power point tracker for PV panels using switching frequency modulation. IEEE Trans Power Electron 2002;17:980–9.
[236] Chung HS-H, Tse K, Hui SR, Mok C, Ho M. A novel maximum power point tracking technique for solar panels using a SEPIC or Cuk converter. IEEE Trans Power Electron 2003;18:717–24.

[237] Ho BM, Chung HS, Lo W. Use of system oscillation to locate the MPP of PV panels. Power Electron Lett IEEE 2004;2:1–5.
[238] Matsui M, Kitano T, Xu D-H, Yang Z-Q. A new maximum photovoltaic power tracking control scheme based on power equilibrium at DC link. Industry Applications Conference. Thirty-Fourth IAS Annual Meeting. Conference Record of the 1999 IEEE; 1999. p. 804–9.
[239] Kitano T, Matsui M, Xu D-H. Power sensor-less MPPT control scheme utilizing power balance at DC link-system design to ensure stability and response 2001. IECON'01. In: Proceedings of the 27th annual conference of the IEEE industrial electronics society; 2001. p. 1309–4.
[240] Solodovnik EV, Liu S, Dougal RA. Power controller design for maximum power tracking in solar installations. IEEE Trans Power Electron 2004;19:1295–304.
[241] Subudhi B, Pradhan R. Characteristics evaluation and parameter extraction of a solar array based on experimental analysis. In: Proceedings of the IEEE ninth international conference on power electronics and drive systems (PEDS); 2011. p. 340–4.
[242] Masoum MA, Dehbonei H, Fuchs EF. Theoretical and experimental analyses of photovoltaic systems with voltageand current-based maximum power-point tracking. IEEE Trans Energy Convers 2002;17:514–22.
[243] López-Lapeña O, Penella MT, Gasulla M. A new MPPT method for low-power solar energy harvesting. IEEE Trans Ind Electron 2010;57:3129–38.
[244] De Carvalho P, Pontes R, Oliveira D, Riffel D, de Oliveira R, Mesquita S. Control method of a photovoltaic powered reverse osmosis plant without batteries based on maximum power point tracking. In: IEEE/PES transmission and distribution conference and exposition: Latin America; 2004. 137–42.
[245] Egiziano L, Femia N, Granozio D, Petrone G, Spagnuolo G, Vitelli M. Photovoltaic inverters with Perturb & Observe MPPT technique and one-cycle control. In: Proceedings of the IEEE international symposium on circuits and systems (ISCAS) 4; 2006. 3721.
[246] Femia N, Fortunato M, Petrone G, Spagnuolo G, Vitelli M. Dynamic model of a grid-connected photovoltaic inverter with one cycle control. In: Proceedings of the 35th annual conference of IEEE industrial electronics (IECON'09); 2009. p. 4561–5.
[247] Chatterjee K, Ghodke D, Chandra A, Al-Haddad K. Simple controller for STATCOM-based var generators. IET Power Electron 2009;2:192–202.
[248] Smedley KM, Zhou L, Qiao C. Unified constant-frequency integration control of active power filters-steady-state and dynamics. IEEE Trans Power Electron 2001;16:428–36.
[249] Qiao C, Smedley KM. Unified constant-frequency integration control of three-phase standard bridge boost rectifiers with power-factor correction. IEEE Trans Ind Electron 2003;50:100–7.
[250] Fortunato M, Giustiniani A, Petrone G, Spagnuolo G, Vitelli M. Maximum power point tracking in a one-cycle-controlled single-stage photovoltaic inverter. IEEE Trans Ind Electron 2008;55:2684–93.
[251] Femia N, Granozio D, Petrone G, Spagnuolo G, Vitelli M. Optimized one-cycle control in photovoltaic grid connected applications. IEEE Trans Aerosp Electron Syst 2006;42:954–72.
[252] Chen Y, Smedley KM. A cost-effective single-stage inverter with maximum power point tracking. IEEE Trans Power Electron 2004;19:1289–94.