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A new global maximum power point tracking technique for solar photovoltaic (PV) system under partial shading conditions (PSC)

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A B S T R A C T

Over a period of years, Maximum Power Point Tracking has become a mandatory requirement for Solar Photo Voltaic (PV) systems. Being dependent to environmental changes, the PV power constantly fluctuates due to change in irradiation. Under such conditions, large PV array connected in interconnection will experience non-uniform irradiation thus results multiple peaks in P-V characteristics. Although many conventional and soft computing techniques have been proposed in literature, the ability to identify global peak under strong shading conditions is not guaranteed. Particularly, local peak in close agreement to global peak makes most of the algorithms to get trapped in local peaks. This condition often occurs due to insufficient randomness in algorithm hence, a new Flower Pollination Algorithm (FPA) is investigated in this research. Proposed method has dual mode search ability which creates required randomness in every iteration is the key reason to suit FPA for MPPT. Simulation and experimental results verified with different patterns portray FPA excellence under all irradiated conditions. Further performance of FPA is verified with Particle swarm Optimization method and conventional P&O method.

1. Introduction

Owing to numerous advantages such as Environmental friendly, absence of moving parts, less maintenance, zero noise and abundant availability, power generation via PhotoVoltaic (PV) panels nowadays has become an unavoidable source of power generation [1,2]. However, low panel efficiency dependent to climatic changes still prevail as a drawback with solar PV panels. Therefore to convert the available useful power, PV systems employ Maximum Power Point Tracking (MPPT) techniques [2,3].

Generally PV array is formed by connecting panels in series-parallel, bridged link and total cross ties however, PV array under Partial Shading Condition (PSC) experience uneven distribution of irradiation that create multiple peaks in P-V curve [3]. Under such conditions identifying global peak with highest power output is a challenging task hence, MPPT controller is incorporated. Various methodologies have been put forward in literature to track maximum power and these techniques can be categorized into (i) conventional techniques [4–6] (ii) Evolutionary/swarm Algorithm (EA) and bio inspired techniques [2,3]. Conventional algorithms suffer due to fixed step size moreover its inherent oscillating nature results in low average power values and deviates the operating point away from Maximum Power Point [2]. To overcome the inability of conventional methods adaptive and modified conventional techniques were proposed. These algorithms show good performance under constant change in environmental conditions [4]. Further, it is noteworthy to mention that conventional methods miserably fail when non-homogeneous insolation occur.

Failure of conventional methods compelled PV researchers to use evolutionary/Swarm intelligence algorithms like Genetic Algorithm (GA) [7], Artificial Neural Network (ANN) [8] and Fuzzy Logic Control (FLC) [9,10] method. These methods are known for their ability to solve non linear objective functions and suit to reach global peak under PSC. However, GA method follows complex computations via crossover, selection and mutation while ANN method performs training of neurons. FLC method requires the knowledge base to create rules for tracking. Thus large memory size, complex computation and prior knowledge for training limit its usage [3]. Moreover both conventional and EA MPPT implementation do not provide convergence to global peak point at all the times. Hence, these methods are blended with conventional

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and soft computing methods to arrive at global MPP [2]. These hybrid approaches often show improved performance; but use of two method and individual methods drawbacks still persist [3].

Recently the swarm optimized methods are successfully employed. On applying these methods to non-linear objectives, quick response with faster convergence is obtained. Some of swarm evolutionary algorithms that successfully addressed the problem of reaching global peak are Particle Swarm Optimization (PSO) [11–13], Modified PSO (MPSO) [14], Deterministic PSO (DPSO) and Improved PSO (IPSO) methods [2] under partial shading condition. However, these methods require periodic tuning and proper initialization to find the optimal duty cycle. Further, improper parameter tuning results with large velocities in particle updation that attribute reduced randomness/diversity in particles [2]. Hence as an alternative to PSO methods, bio-inspired methods following the biological behavior of birds, ants and bees are applied in MPP tracking [15–18]. Methods like Ant Colony optimization [2], Cuckoo Search [15], Firefly Algorithms [16], Artificial Bee colony methods [17] and Grey Wolf Optimization [2] are attempted in literature to track MPP. These methods have the benefit of (i) System independency (ii) ability to differentiate local and global peaks and (iii) Fewer implementation steps. Although bio-inspired methods are supreme to PSO method and yield far better results in MPPT province, absence of exploration/randomness after reaching MPP region is seen as a setback for these methods. Alike hybrid methods, several attempts on fusing conventional methods with swarm/bio inspired methods can be perceived in literature as follows (i) PSO blended with P&O [13] (ii) Differential Evolution (DE) blended with PSO to form DEPSO method [18] and (iii) Ant colony optimization blended to P&O [2]. Although these methods have convinced with good deal of results with necessary randomness around MPP, dual stage process involved increases the complexity in implementation and further complicates the procedure followed for tracking [2].

Thus from the literature it is found that there is always a requirement for a simple, accurate tracking method. Hence in this paper, a new Flower Pollination Algorithm (FPA) is introduced for MPP tracking. FPA method follows only two simple steps (Cross pollination and Local pollination) in single stage to update the control variable/duty cycle. Further features like two modes of search; inherent simplicity and robustness are value added merits of FPA method. Furthermore, the most required randomness in control variable is created in all the stages of computation via local and global search. Recognizing its immense potential and added advantages, FPA algorithm is used in many applications such as (i) Multilevel Image thresholding [23], (ii) Economic dispatch problem [24] (iv) Radial distribution systems [25]. In this work, performance of FPA based MPPT is validated with four different case studies and the test results are compared with conventional PSO and P&O methods. Remaining sections are organized as follows.

Section 2 validates the modeling of Solar PV. In Section 3 the control structure with the effect of PSC is explained. Section 4 comprises the proposed FPA on application to MPPT. Sections 5&6 analyses the simulation and hardware results obtained via FPA. In addition an economy analysis is exclusively performed to validate the truthfulness in the proposed algorithm. Finally conclusions are arrived and presented at the last.

2. Modeling of solar PV

Solar PV modeling is one of the important research areas where accuracy of PV characteristics is given significant importance [19–21]. Two types of modeling followed in literature are (i) single diode modeling and (ii) Double diode modeling. Double diode is more accurate but it requires more parameters to model an accurate solar PV hence, the authors used single diode model for simplicity. The schematic of single diode model is shown in Fig. 1.

The single diode requires five parameters to model a solar PV, they are (I_{PVn},I_D,R_S,R_P&a). The output equation of solar PV using KCL is given by,

$$I = I_{PVn} - I_D - \frac{V + I_{PV}Rs}{Rp} \tag{1}$$

where 'I_D' is the diode current equation in which 'I_O' is the reverse saturation current and 'R_S,R_P' are the series and parallel resistances.

$$I_D = I_O\left(e^{V_D/aV_T} - 1\right) \tag{2}$$

where 'a' is the diode ideality factor and 'V_T' is the thermal voltage at any temperature is given by $V_T = \frac{N_S KT}{q}$ where 'N_S' is the number of cells connected in series, 'K' is the Boltzmann constant 1.3805×10^{-23}, 'T' temperature at STC (Standard Test Conditions) and 'q' is the charge of the electron 1.9×10^{-19} C. From the above equations, a PV module current equation can be given as,

$$I = N_{pp}\left\{I_{PV} - I_O\left[\exp\left(\frac{V + I_{PV}R_S}{V_t N_{ss}}\right) - 1\right]\right\} - \left(\frac{V + I_{PV}R_S}{R_P}\right) \tag{3}$$

where'N_{SS}' and'N_{PP}' are the number of cells connected in series and parallel.

3. PV and its characteristics

To explain the occurrence of partial shading, 4 PV modules connected in series are exposed to two types of shading (i) Uniform shading & (ii) non-uniform partial shading. Partial shading is the phenomenon of uneven disclosure of irradiation over a PV string caused due to pole shadows, building shadows and bird droppings [13,14,16]. Schematic of PV string with 4 modules in the string with partial shading and uniform irradiation is shown in Fig. 2. As a consequence of non-uniform irradiation, hot spots are created in panel receiving lower irradiation and thus PV array output power is reduced. Hence, a bypass diode is connected in parallel to protect panel from hotspot. This arrangement helps PV panel getting damaged and eliminates thermal stress occurring on PV modules [17]. Occurrence of partial shading creates steps in I-V curve and multiple peaks in P-V curves as shown in Fig. 3. Thus the above discussion leads to a conclusion that to track global maximum power point under partial shading condition, MPPT methods are mandatory [2]. Hence, in this paper FPA based MPPT controller is designed and tested with various dynamic irradiated conditions to ensure global maximum is achieved at all the time.

4. Flower pollination algorithm and its implementation

4.1. Flower pollination algorithm

Flower Pollination Algorithm was first proposed by xie yang in 2012 [22]. Generally, pollination is the phenomena that refer to

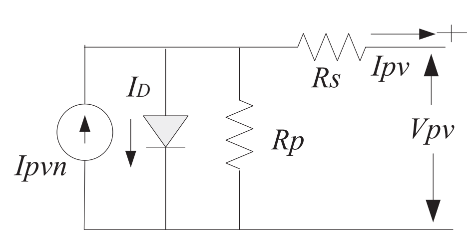

Fig. 1. Single diode model of solar PV.

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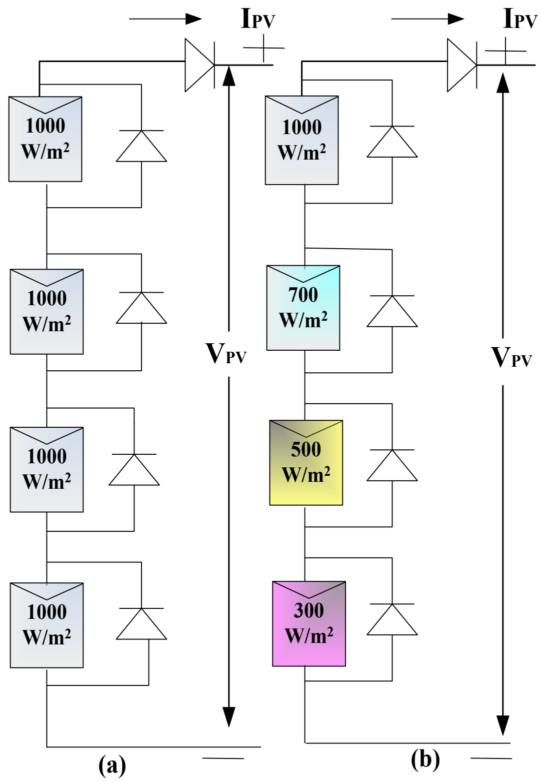


Fig. 2. PV patterns for (i) uniform irradiation and (ii) Partial Shaded condition.

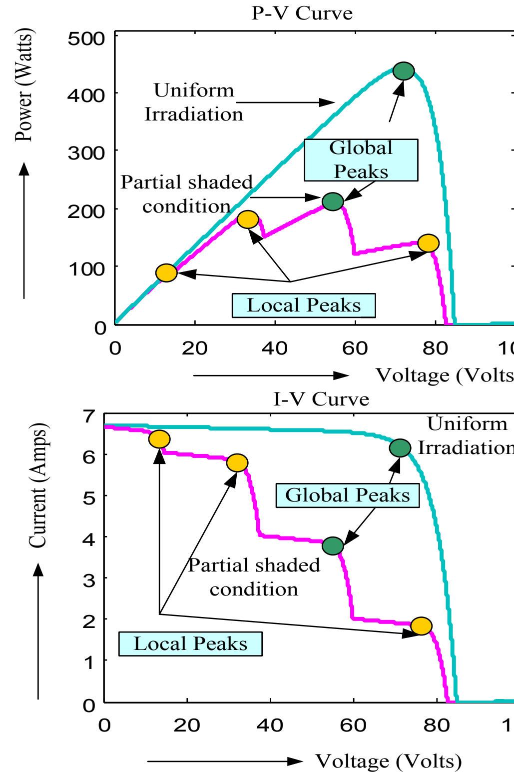


Fig. 3. I-V and P-V curve for uniform and partial shaded condition.

transfer of pollens from one species to the other. Pollination process will emerge out with new species in flower where it depends on the flowers involving in pollination process. Further FPA follows two pollination process (a) Local pollination- The transfer of pollens between same species (i.e), pollens of same plants will fertilize with species of its own, where the pollinator is wind. (b) Cross pollination refers to transfer of pollens between two different species of flowers, where the pollinators are bees, bats and birds. Since the pollens in cross pollination process are transferred to a long distance, it is associated with levy flight. Further, it is essential to give a note that, among the total pollination process, 90% of it is cross pollination and 10% is self pollination [22–25]. The switch between local and global pollination is decided by probability switch '*P*'. To implement FPA, the following design rules are to be followed:

Rule 1: Biotic and cross-pollination is characterized under global pollination process where a Levy flight is used to transfer pollens. The characterized equation for global pollination is given as follows

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)\ gbest - x_i^t) \tag{4}$$

where '$L(\lambda)$' is the levy distribution that is responsible to transfer pollens to different species of flowers. Further, it also helps to improve the strength of the pollination, 'γ' is the scaling factor that is controls the step size [22,24].

$$L(\lambda) = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\,\frac{1}{S^{1+\lambda}}(S>>S_0>0) \tag{5}$$

where '$\Gamma(\lambda)$' the standard gamma function and the levy distribution is applicable for large step size which is greater than zero $(S>>S^0>0)$. In this work, FPA implemented for MPPT have used '$\lambda = 1.5$' to ensure optimal performance.

Rule 2: Abiotic and self-pollination characterized under local pollination process [22–25]. The characteristic equation for local pollination is given as follows

$$x_i^{t+1} = x_i^t + \varepsilon\left(x_k^t - x_j^t\right) \tag{6}$$

where 'x_k^t' and 'x_j^t' are pollens of same species. The term 'ε' (epsilon) represents the local search in uniform distribution $\varepsilon\in[0, 1]$.

Rule 3: Pollinators have the trait to develop flower constancy through which reproduction probability of the new species will improve the similarity of flowers involved in pollination.

Rule 4: The control between local and global pollination is restricted by probability switch $P\in[0,1]$ and is found to be optimal at 0.8 in most of the cases.

Since the FPA method has two stages in computation of control variable, (i.e) Global and local pollination, it is very much suited for optimization of nonlinear problems because, application of MPPT in solar requires exploration followed by exploitation to get the benefit of achieving higher efficiency. Till date, no algorithm has the feature of dual search in single stage process. Instead, the process can be carried out by fusing two algorithms [18]. In such cases, since two methods are being used; tuning of parameters and implementation complexity of the method is increased.

4.2. FPA implemented for MPPT

Application of FPA method MPPT application devised in steps as follows. Considering the objective function *f*(*X*) as output power maximization, the duty cycle X_1,X_2,X_3…*Xn* are effectively altered to obtain maximum power point via self and cross pollination.

1. *Initialization of Parameters:* Set maximum iteration number as ($N = 25$), initial population of 5 pollens/duty cycle; define the limits for duty cycle asX_{min}&X_{max} and probability switch as 0.8.

2. *Identification of best particles:* For the PV configuration, validate the duty cycles and extract the exact duty cycle capturing maximum power ***(Pbest)*** from the initial pool of duty cycles. In forth coming iterations, ***(Pbest)*** is updated to attain ***(Gbest)*** where it is the best power in sum of all the iteration.
3. *Updation of pollens via Global and Local Pollination*: Based on probability switch, perform Global & local pollination to arrive new set of pollens/duty cycle for next iteration. Updation for duty cycle utilizes following equations to attain their position. (i) For global pollination: $x_i^{t+1} = x_i^t + \gamma L(\lambda)(gbest - x_i^t)$ (ii) For Local pollination: $x_i^{t+1} = x_i^t + \varepsilon(x_k^t - x_j^t)$.
4. *Convergence towards global Maximum:* Continue step 2 and 3 continuously to update the next set of pollens via local and global search until the power convergence is obtained.
5. *Termination Criterion:* Stop the process if $P^{opt} = P^{max}$ is achieved.
6. *Re- initialization for Irradiation Change:* PV characteristics vary according to the environmental changes. Under such conditions, MPP will shift to another location depending on the shade. Hence, the pollens should be re-initialized to search for new MPP. This can be detected by recording the threshold change in voltage and current values between iterations. To find the optimal threshold limits numerous experimentations based on trial and error method for different PV configuration is attempted. Based on comparison it is found that optimal voltage and current limit to detect irradiation change are 0.2 and 0.1 respectively. It is noteworthy to mention that these values are found effective even at lower irradiation as well [19,20,22]. Further, the same values reflected in literature ensure the judicial experimentation of FPA method. The current and voltage equations used in detecting PSC are given below.

$$\frac{V_{PV}(k) - V_{PV}(k-1)}{V_{PV}(k)} \geq 0.2 \tag{7}$$

$$\frac{I_{PV}(k) - I_{PV}(k-1)}{I_{PV}(k)} \geq 0.1 \tag{8}$$

where 'V_{PV}' is the PV voltage, '$I_{PV}(k)$' is the PV current and 'k' corresponds to the iteration. The flowchart for implementation of FPA-MPPT is shown in Fig. 4.

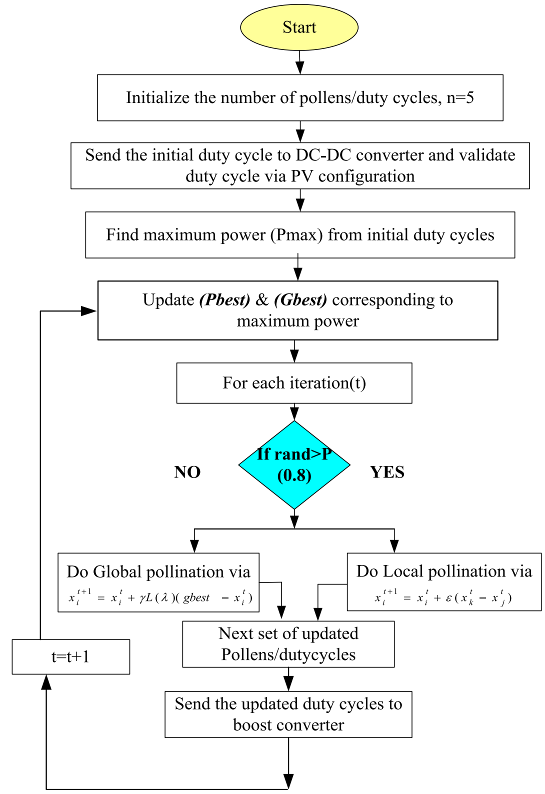


Fig. 4. Flowchart for FPA implemented MPPT.

5. Simulation results

To inspect the FPA's suitability for MPPT application, two PV arrangements of 6S & 4S-2P configuration shown in Fig. 5 with four different P-V patterns are analyzed. Corresponding P-V characteristics for four different PV patterns are shown in Fig. 6. Further, to experiment the suitability of FPA method under partial shaded conditions, the system is exclusively tested with tough and fragile shaded conditions with six peak and four peak occurrences. Moreover, a case study under irradiation change is performed to experiment the ruggedness of the designed algorithm. The algorithm is coded and developed in MATLAB platform with the system of 500 GB Memory, 4 GB RAM & Intel I7 Processor.

For performance estimation, the FPA method results are compared and verified with proven PSO and timeworn P&O methods. All the algorithms (FPA, PSO, and P&O) considered in our study is carefully coded and their parameters are tuned to exhibit similar performance. In literature it is seen that less number of duty cycle initialization sometimes make the algorithm to converge at local peak, hence plentiful number of experimentation is performed and the number of pollen/duty cycle initialization is fixed at 5 to improve convergence rate. It is noteworthy to mention that both PSO and FPA method follow a similar initialization of duty with five particles to encourage uniformity. The control scheme for the proposed system with a DC-DC boost converter is shown in Fig. 7. The sampling time for each duty cycle is set to 0.03 s.

Tuning parameters is one of the important factors that influence the convergence of any optimization algorithm. Higher number of parameters induced increase the computational burden and demands a high end controller. Parameter tuning in PSO involves 6 variables namely velocity limits-(C_1,C_{1min},C_2&C_{2min}) and inertia weights (W_{min}&W_{max}), FPA involves only two parameters (i) Probability switch (P) and (ii) Scaling factor (γ), and conventional P&O also involves two parameters change in duty (ΔD) and initial duty (D). The details of value initialized for FPA, PSO and P&O are presented in Table 1.

5.1. Simulation result for 4S-2P- pattern (a) and (b)

To show the severity of partial shading conditions two different shades having three peaks and four peaks in P-V curve is considered in 4S-2P configuration. For pattern (a) having three peaks, the global peak is located at 212.2 W, where the other two local peaks are at 181.5 W and 142.3 W. Having the unique ability to differentiate local and global peak, the FPA method converges to global peak within 0.523 s at an attractive efficiency of 99.7%. Since the power difference between local and global peaks are not very high, Pattern (a) is less complex and resembles weak shading; hence PSO achieves its convergence at 1.6 s. Similarly the conventional P&O has also located Global Maximum Power Point (GMPP) since the initialization of duty is made nearer from GMPP. However, the traditional three point behaviors have increased steady state oscillations.

In Pattern (b), the P-V characteristics for given shade introduces 4 peaks where GMPP is located at 212.9 W and Local Maximum

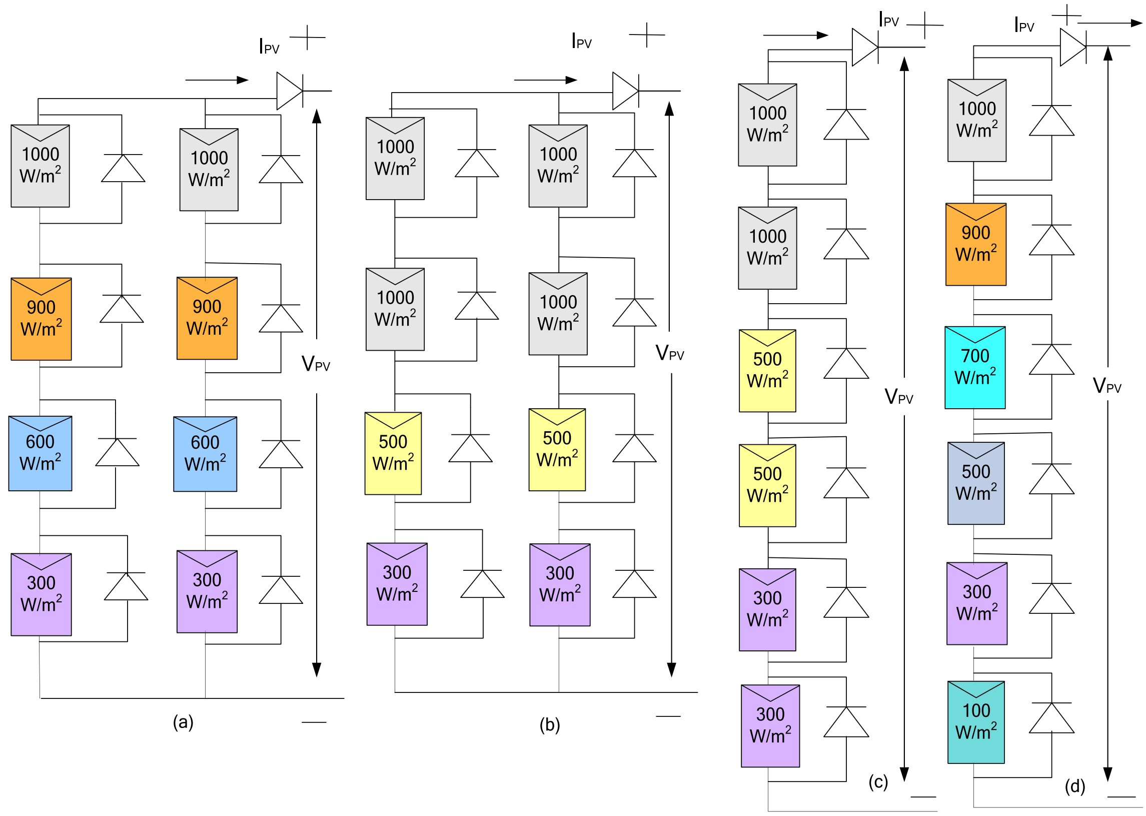


Fig. 5. Tested PV patterns.

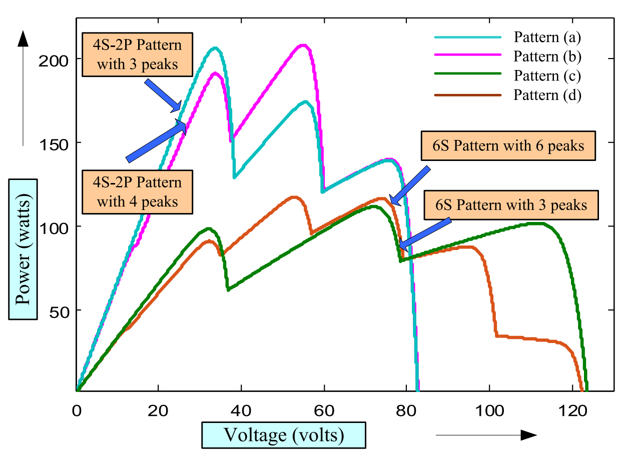


Fig. 6. P-V curves for different shading patterns.

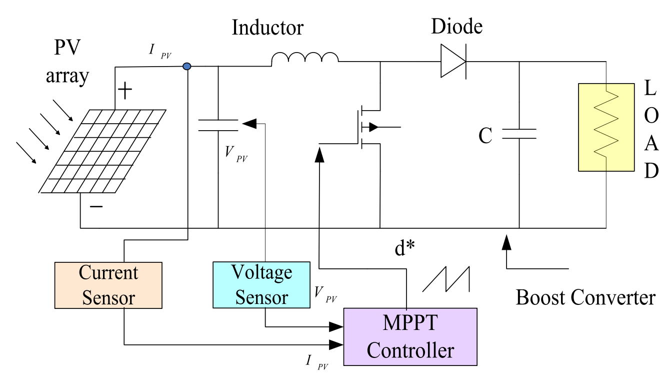


Fig. 7. Control scheme for MPPT implementation.

Table 1
Parameters of PSO, P&O and FPA.

PSO	P&O	FPA
C2 = 1.8	D = 0.75	P = 0.8
C2min = 1	ΔD = 0.005	γ = 1.5
Wmax = 0.3	–	–
Wmin = 1	–	–
C1 = 1.4	–	–
C1min = 1	–	–

Power Points (LMPP) are located at 86.68 W, 196.7 W & 139.5 W respectively. Generally irradiation change on a cloudy day will induce similar type of shading with more peaks. Though multiple peaks are present, the FPA has founded GMPP faster within 0.6 s and PSO has also climbed to GMPP at 1.6 s respectively. Though the pattern has stronger shading, power-voltage characteristics curve pattern resembles simpler structure because only three strong peaks are present. Among which, GMPP is far away when compared to local peaks. Thus, PSO has identified GMPP to illustrate its ability under PSC. However, the conventional P&O got trapped in one of the local peaks at 196.6 Watts. It is noteworthy to mention that P&O being initialized at 0.8 duty, it bypassed one of the local peaks at 86.68 W since, the peak at 86.6 W is created by weak shade. However, the P&O method produces high steady state oscillations around MPP. The simulated power voltage and current curves for pattern (a) and (b) are shown in Figs. 8 and 9.

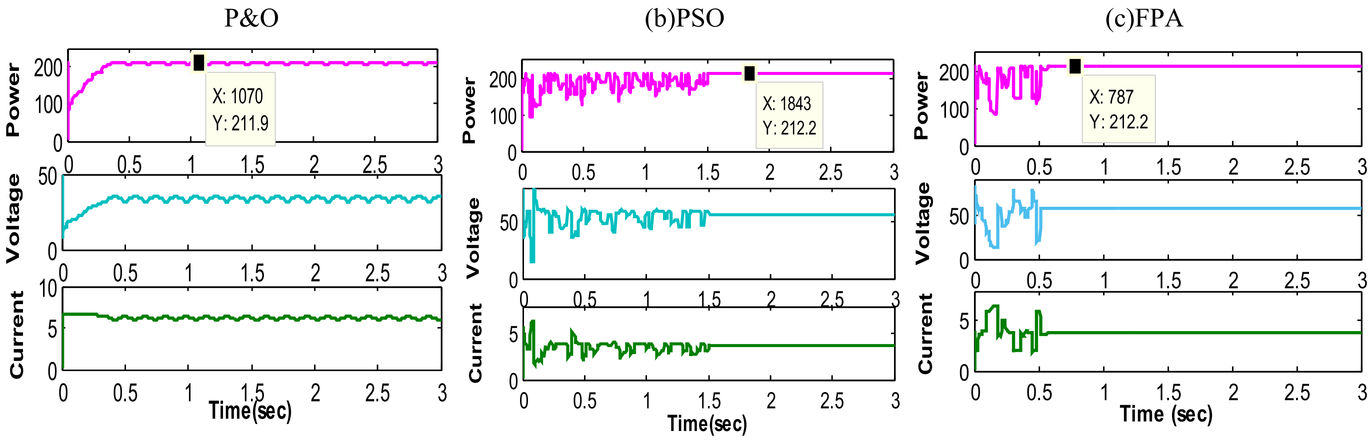


Fig. 8. Simulated Power, Voltage and Current curves of P&O, PSO and FPA for 4S-2P - Pattern (a).

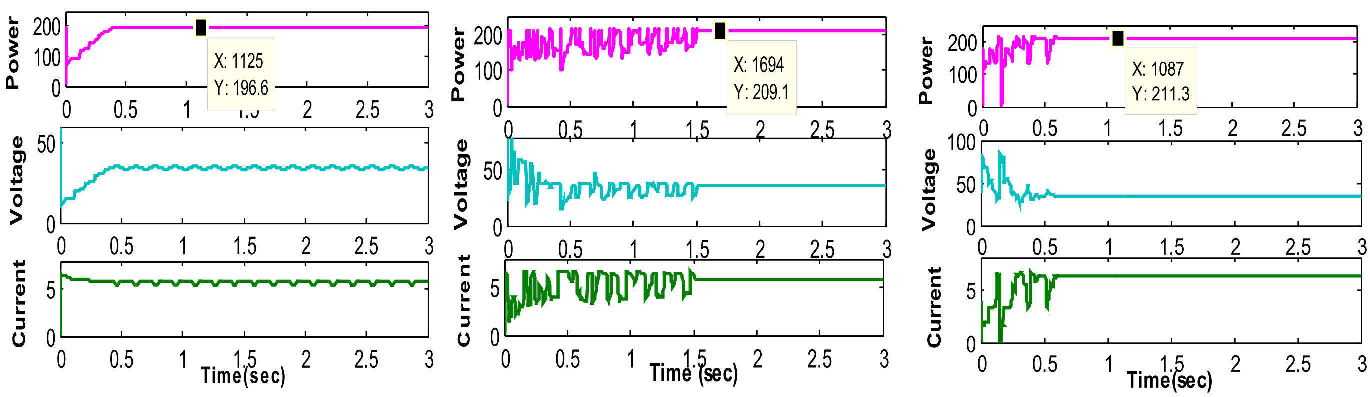


Fig. 9. Simulated Power, Voltage and Current curves of P&O, PSO and FPA for 4S-2P-Pattern (b).

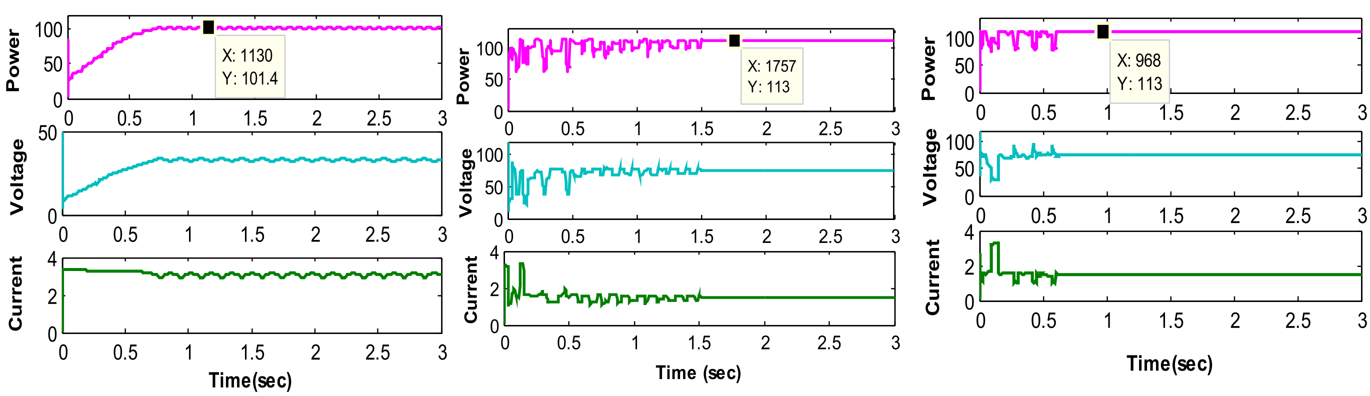


Fig. 10. Simulated Power, Voltage and Current curves of P&O, PSO and FPA for 6S-Pattern (c).

5.2. Simulation results for 6S-Pattern (c) and (d)

To evaluate the performance of the algorithm a PV string with 6S configuration having two different conditions is applied. Pattern (c) produce three peaks with global peak situated at 113 W and other local peaks are situated at 101.3 W and 105.6 W. Although, the peak power value is closer but the distance between the peaks is far. (i.e), the voltage and current value at both the peaks are different. Starting with random initial values both the methods FPA and PSO converge to GMPP. While P&O method is trapped in local peak of 101.3 W. Though the PSO method settled at GMPP, the convergence rate is slower and produce transients with larger amplitude.

Strong shade with six peaks is introduced in pattern (d) to test the robustness of the algorithm. Very close local peaks with a similar resemblance of global peak is created to experiment FPA's suitability. FPA method reaches the global peak of 118.5 W in this case. Since the unique randomness created in algorithm made the FPA to deliver optimal performance notably under strong shading conditions. Witnessing the GMPP at earlier stages of iteration made it to converge faster within 0.6 s. Having exposed to extremely strong shade pattern PSO fails to locate GMPP in this case and settles to one of the closest local peak situated at 116.7 W. As

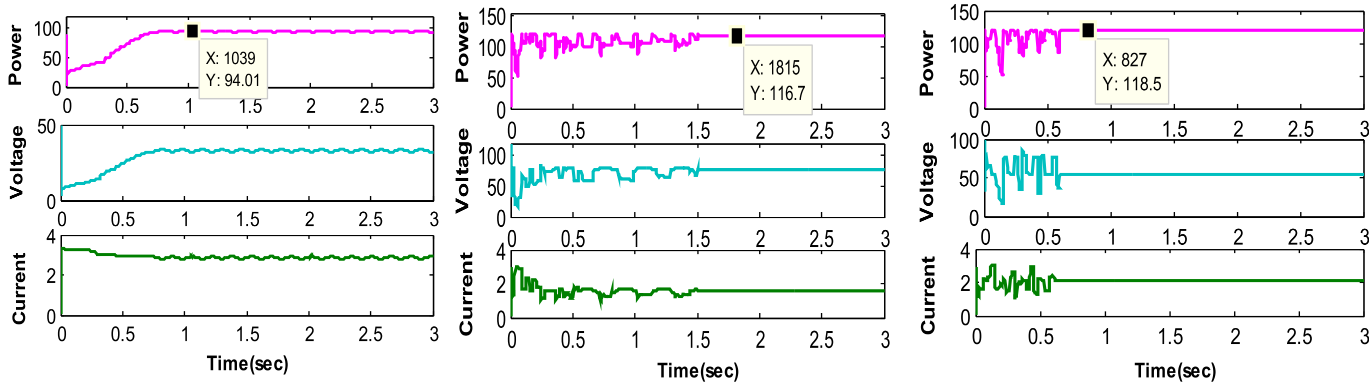


Fig. 11. Simulated Power, Voltage and Current curves of P&O, PSO and FPA for 6S-Pattern (d).

expected P&O has settled to local peak at 94.01 W. The simulated power voltage and current curves for pattern (c) and (d) is shown in Figs. 10&11. Based on the different pattern the performances of the methods are studied in simulation. With the help of simulation results, certain performance indexes are arrived for P&O, PSO and FPA method and are presented in Table 2.

From the table, FPA method show good convergence with lesser time to reach GMPP in all the cases. However premature convergence due to reduced randomness attribute to poor performance of PSO method. On the other hand due to fixed step size the P&O method takes larger time to settle at local peak.

5.3. Simulation study under change in irradiation conditions

PV array under constant irradiation change will be less complex and its operating point will not undergo enormous change under normal operating conditions. However, in real time conditions, the PV located on tropical regions will experience dynamic shaded conditions where the operating point on PV is shifted much often to ensure panel operating at maximum power. To experiment such conditions, two different patterns (1) and (2) is considered and is shown in Fig. 12. Both patterns follow 4S-2P configuration having PSC with 4 peaks and 3 peaks in pattern (1) and pattern (2)

Table 2
Performance assessment on P&O, PSO and FPA based for simulation studies.

S. No	PV configuration	Pattern number	Method	Power from MPP curve (watts)	Voltage at MPP (Volts)	Current at MPP (Amps)	Power at MPP (Watts)	Efficiency (%)	Tracking speed (sec)
1	4S-2P	Pattern (a)	FPA	212.28	33.5	6.308	212.26	99.71	0.523
			PSO		35.9	5.826	212.20	99.67	1.7
			P&O		35.24	6.422	209.4	98.82	0.35
		Pattern (b)	FPA	212.9	56.79	3.737	211.36	99.10	0.6
			PSO		56.79	3.721	209.12	98.58	1.6
			P&O		35.78	5.49	196.6	92.25	0.35
2	6S	Pattern (c)	FPA	113.2	74.66	1.514	113.1	99.82	0.47
			PSO		74.66	1.512	113	99.72	1.52
			P&O		34.12	3.177	101.4	89.57	0.75
		Pattern (d)	FPA	118.73	55.27	2.143	118.5	99.80	0.52
			PSO		76.7	1.521	116.7	98.29	1.68
			P&O		33.04	2.904	94.01	79.17	0.7

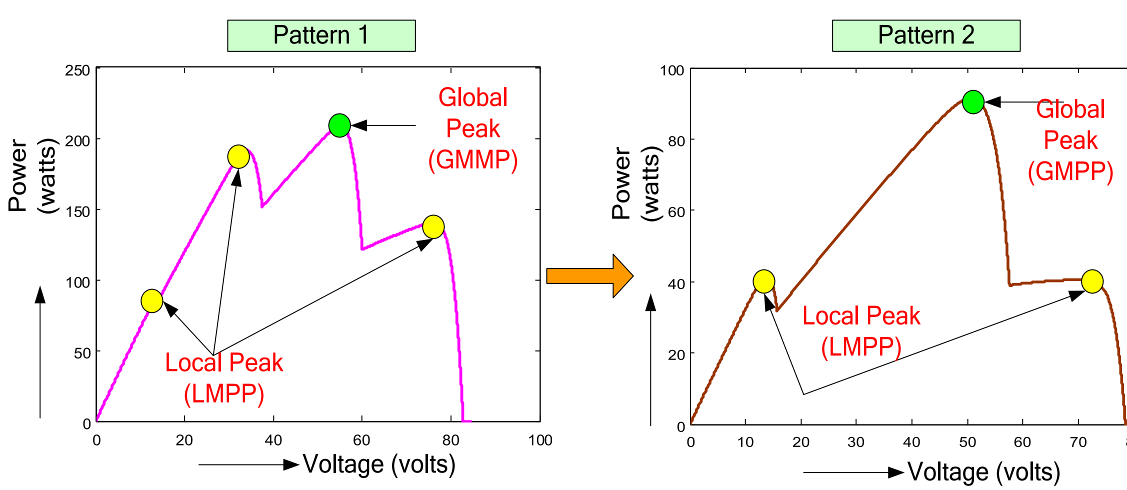


Fig. 12. 4s-2P patterns considered for irradiation change.

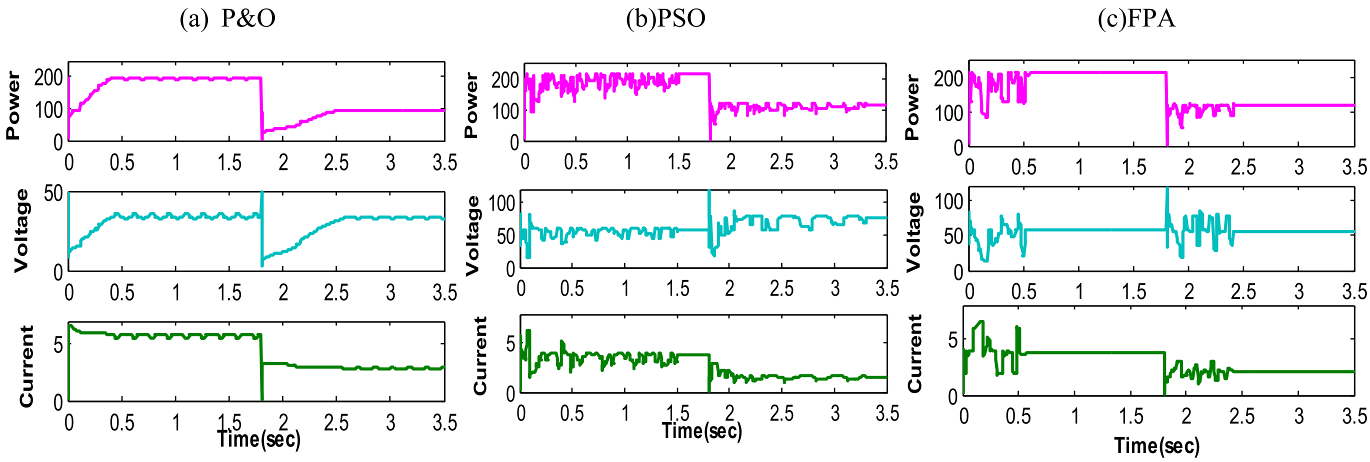


Fig. 13. Power, Voltage and Current convergence for P&O, PSO and FPA.

respectively. With each patterns run for 5 s, FPA method settles to global peak at less than 0.65 s whereas PSO method took large number of iterations to converge. The simulated power, voltage and current characteristics for P&O, PSO and FPA under irradiation change/partial shading are shown in Fig. 13. To understand the phenomenon occurs in the convergence delay, a specific duty cycle convergence is explained.

To illustrate faster convergence that occurs with FPA, an exclusive analysis with duty cycle convergence is illustrated in Fig. 14. From the figure it is seen that FPA is very quick in achieving its convergence. Also once FPA finds its global position, the duty cycle at GMPP suddenly pushing the other duty cycles to global vicinity is clearly seen in figure. It is worth to notify that the randomness created by FPA in global and local search is the key tool for its success. In case of PSO uncertain oscillations are observed at initial stages of computation. Further, large velocity updation making the particles to drag the convergence is noticed in PSO. Thus, the insufficient randomness in PSO makes it to loose diversity in particles and converge to local peaks under strong shading conditions.

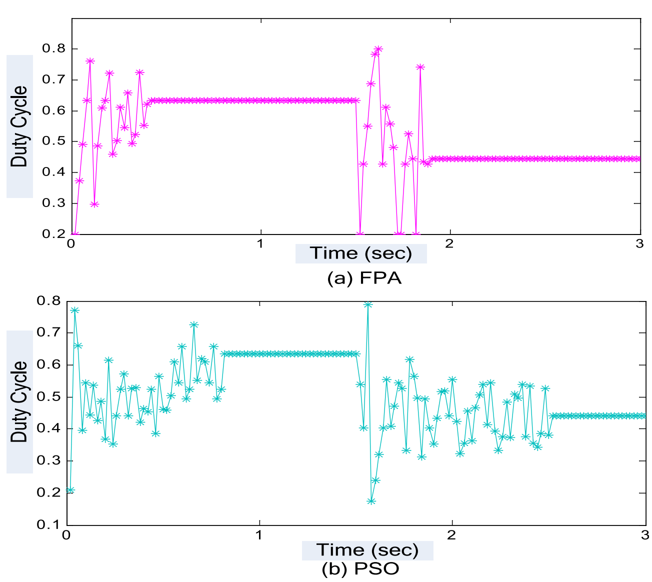


Fig. 14. Duty cycle convergence for FPA and PSO.

6. Experimental validation

To authenticate the simulated results, a prototype model of MPPT system comprising a PV source, DC-DC boost converter is constructed in laboratory. In this research, a dedicated PV simulator (CHROMA 62050H) is used as PV source where shell SM55 panel is utilized for testing the algorithm. MPPT algorithm are coded and executed in Arduino Uno controller. This controller can support up to 10 KHz frequency with two timer circuit arrangement. The design values of DC-DC boost converter and panel specifications are given in Table 3. As executed in simulation study, an experiment with the hardware setup is also performed for all the four different cases. The boost converter is operated in Continuous conduction mode with reduced ripple level ensure safer operation of the hardware model. Hardware prototype developed in the laboratory is shown in Fig. 15. The unit comprises of LEM voltage sensor for voltage and current measurement and DC-DC converter for PV interface. By sensing the current and voltage values the duty cycle pulses are generated using Arduino uno controller with the help of MPPT algorithm. To isolate the control signal TLP350 isolator is used. To maintain uniformity in measurements alike simulation; similar duty cycle initialization is followed for PSO and FPA in hardware. The sampling period for duty cycle is taken as 300 msec. Further, four different PV evaluations under PSC via 4S-2P and 6S configuration are experimented and their results are discussed.

6.1. Hardware result for 4S-2P- pattern (a) and (b)

Similar to simulation; FPA results are verified via hardware prototype under similar operating condition for the following patterns (a), (b), (c) and (d). Experimental results for pattern (a) and (b) with FPA, PSO and P&O methods are shown in Fig. 16 and Fig. 17.

Table 3
Boost converter and PV panel specifications.

S.No	Parameter	Value
1	Switching frequency	10 KHz
2	Inductor	0.5 mH
3	Capacitor	450 V,100 μF
4	Load resistance	10 A,100 Ω
Shell SM55 panel details		
1	Voltage at MPP	16.5 V
2	Power at MPP	55 W
3	Short circuit current	3.382 A
4	Open circuit voltage	20.5 V

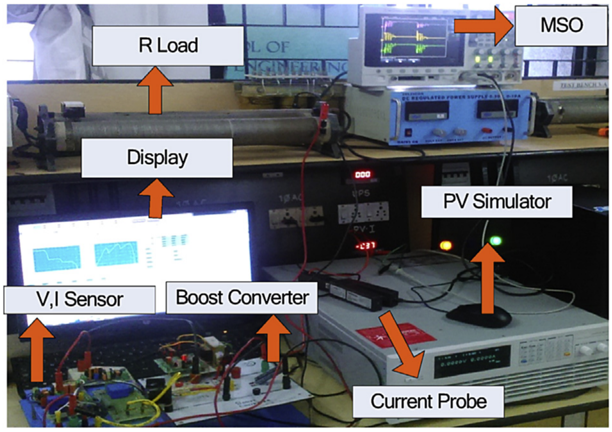
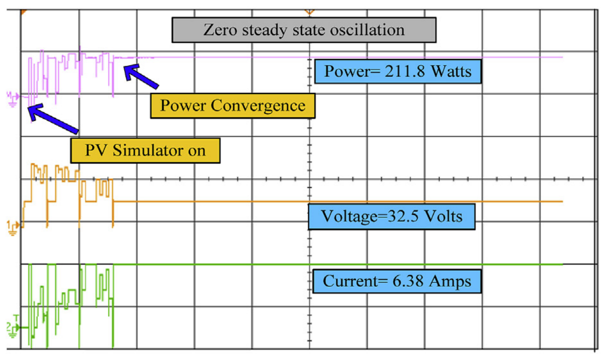
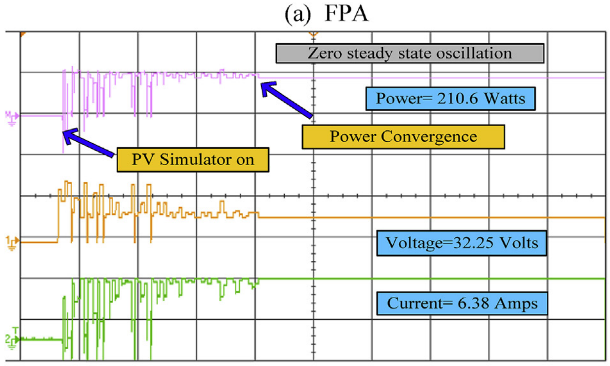


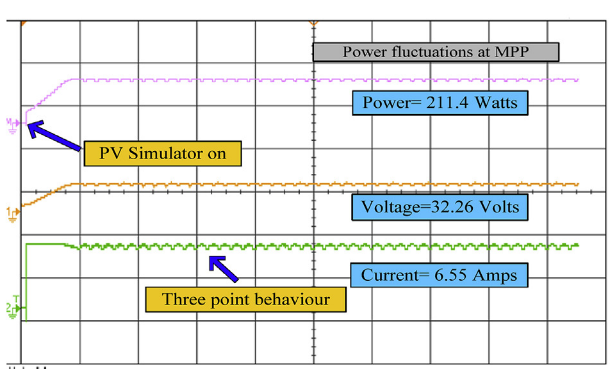
Fig. 15. Hardware model for proposed MPPT scheme.



(a) FPA



(b) PSO



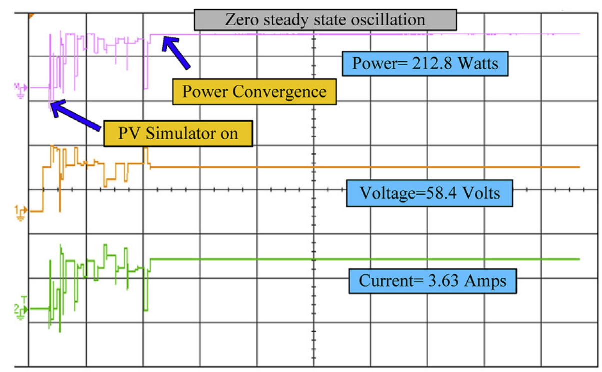
(C) P&O

Fig. 16. Hardware realization for FPA, PSO and P&O for Pattern (a).

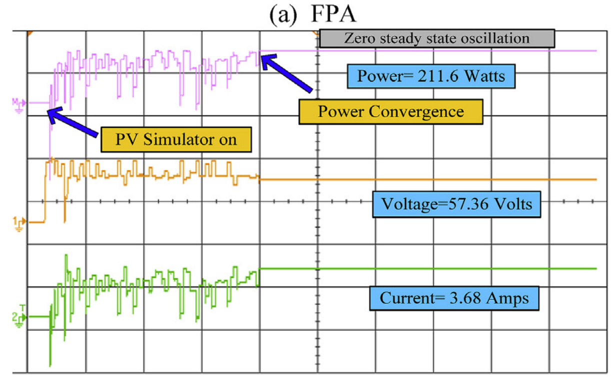
PV simulator is coded with shell SM55 data to match the characteristics with original panel. Compared to PSO and P&O methods; FPA is the fastest method to converge in shortest time for both the patterns. Further in both the cases FPA has reached GMPP comprehensively with fewer transients at the duty of 0.80 and 0.67. In case of PSO method, its ability to converge at GMPP is clearly visible but the time taken to converge and oscillations are high. Though P&O method converged to GMPP for pattern (a), it is trapped to one of the local peaks for pattern (b). Moreover, the traditional three point behavior is clearly seen in both the waveforms.

6.2. Hardware result for 6S pattern (c) and (d)

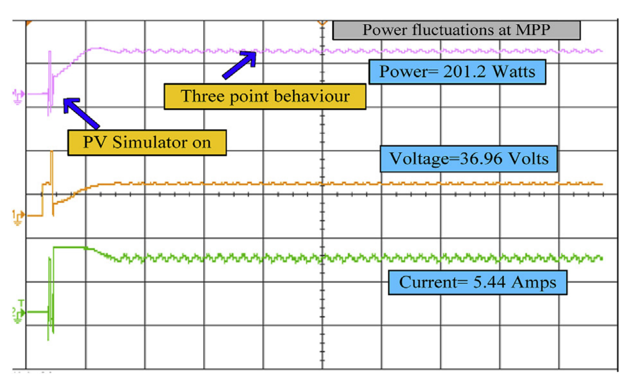
To experiment the proposed method with single string PV array,



(a) FPA



(b) PSO



(C) P&O

Fig. 17. Hardware realization for FPA, PSO and P&O for Pattern (b).

6 PV panels in a string with two different shading; pattern (c) and (d) is performed in hardware model. FPA is dominant in reaching global peak within 4 iterations. Optimal duty ratio for which the MPP located is found to be 0.42 and 0.41 respectively. Even though PSO has converged to global peak in pattern (c), it reflects its convergence similar to simulation in pattern (d). As multiple peaks present with both the PV patterns in 6S string, the P&O method is trapped to local peak in either of the cases. The realization of hardware results for pattern (c) and (d) is shown in Figs. 18&19.

To visualize the real time irradiation change and to test the accuracy of proposed method in partial shaded conditions, experimentation for detecting partial shading from pattern (1) to (2) as shown in Fig. 12 is performed. Each pattern is made to run for 50 s and once partial shading is sensed, the duty cycle is reinitialized to search for new MPP. Having an utmost uniqueness in various shading patterns as discussed above, FPA has yet another time stood out to outperform PSO and P&O method and maintain its credibility of achieving global peak all the time. The convergence characteristics of power, voltage, and current for change in irradiation/Partial shading conditions are shown in Fig. 20.

7. Comparative study

In order to authenticate the suitability of FPA algorithm a fair comparison with existing MPPT methods considering various performance parameters is carried out. Further, a reasonable study on influence of parameters on optimal performance of the algorithm is also elaborated under common arena. Various criteria considered for the study is detailed in Table 4 along with other MPPT methods.

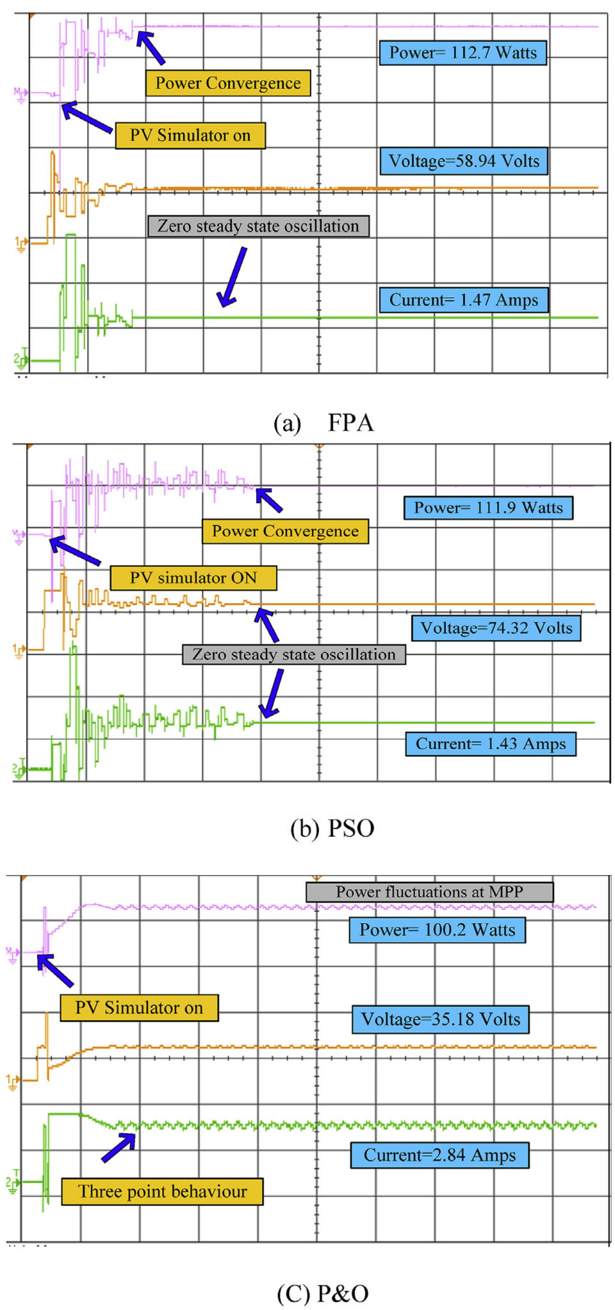


Fig. 18. Hardware realization for FPA, PSO and P&O for Pattern (c).

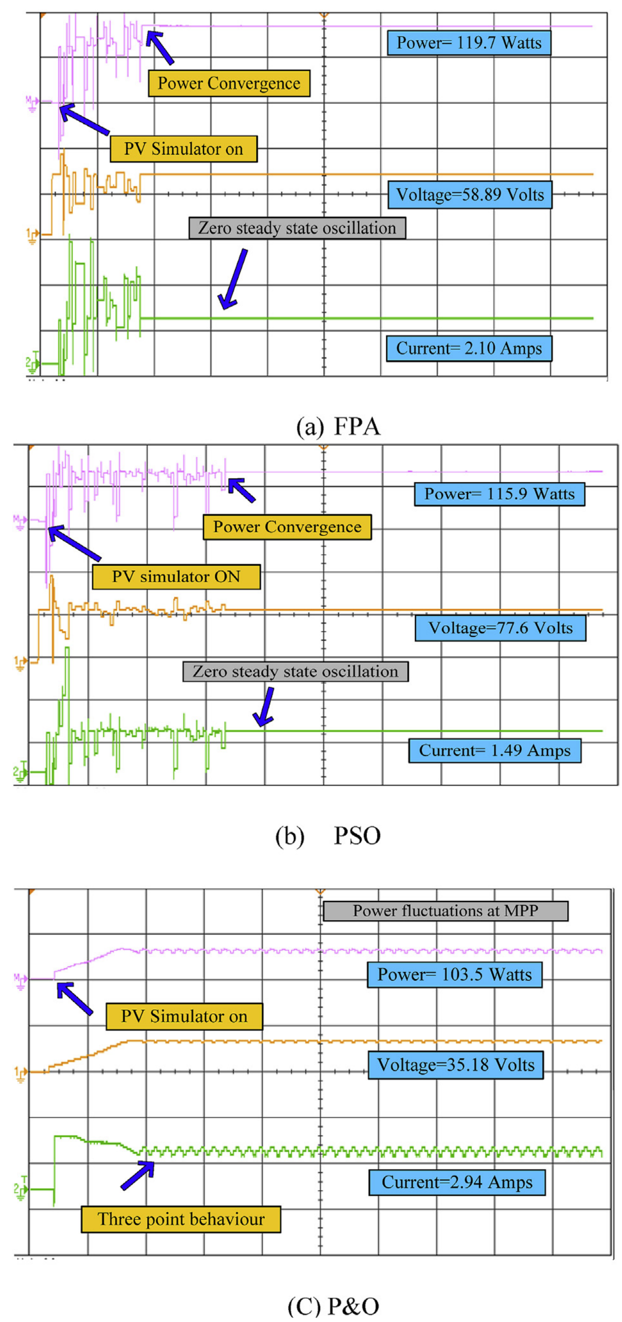


Fig. 19. Hardware realization for FPA, PSO and P&O for Pattern (d).

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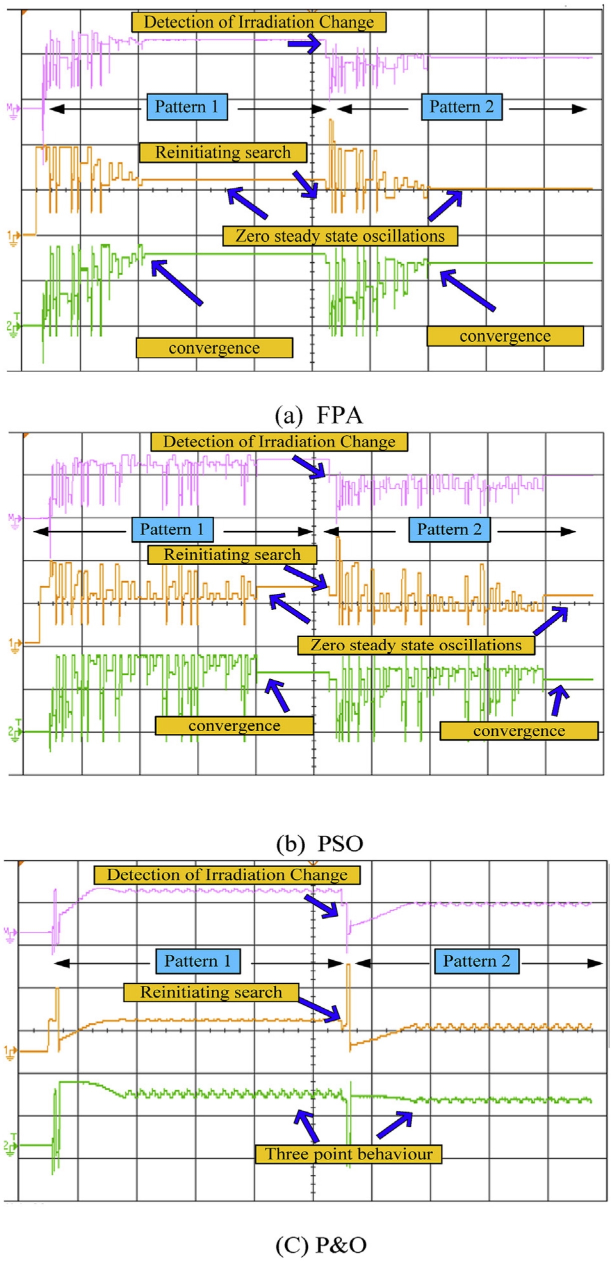

Fig. 20. Hardware realization for FPA, PSO and P&O for change in irradiation condition.

Witnessing the competence in FPA, a fair comparison with existing literature works is mandatory to substantiate the research carried in this work. Hence the authors have compiled a fair comparison with the following algorithms (i) PSO (ii) FA and (iii) Cuckoo (iv) ABC (v) DEPSO and (vi) FPA.

Complexity of algorithm is one among the parameters that influences the ease of coding. FPA and FA methods are simpler in structure and have fewer steps in implementation while the PSO and cuckoo search methods have moderate complexity since position and particle updation of control variables involves additional steps compared to FPA. In case of hybrid DEPSO method the complexity following two methods increases the computational burden.

Following to fixed step size, the conventional methods produce higher steady state oscillations around MPP. As an alternative to conventional methods swarm intelligence algorithms like PSO, FPA, cuckoo, ABC methods having zero steady state oscillation is proposed. However the hybrid methods involving P&O still introduce power frequency oscillations around MPP.

One of the major advantages lie with FPA method over other algorithms is its exploration via global pollination along with exploitation through local pollination. While global mode searches for the region of MPP, the local search explores the MPP area to keep alive the tracking process. One among the recent research to create randomness in duty cycle is via DEPSO method attempted in improving the tracking performance. But fusing two algorithms increases coding complexity. As clearly notified in literature, parameter tuning is also major factor that influence the convergence rate. FPA use only two parameter for tuning ('γ'-scaling factor), whereas PSO, ABC, FA, Cuckoo and DEPSO methods use more number of parameters than FPA thus it increases the computational burden.

Irrespective of these parameters, procedural complexity plays a major role while implementing the algorithm. In case of artificial intelligence methods like Fuzzy and ANN a prior experience is expected to code the algorithm and moreover, its memory requirement needs high end controller for the system. In recently proposed PSO and DEPSO methods involve initialization conflicts may occur whereas, FPA method is credited with simpler structure involving very less computations. Thus, the discussion concludes that, in all the parameters discussed above FPA is emerged as suitable alternatives for conventional and soft computing methods in the entire category. From the above discussion, the FPA has notable merits as follows (i) Robust and Reliable (ii) Simpler in structure and easy to code and compile. (iii) Effective to differentiate local and global peaks under partial shaded conditions. (iv) Quick convergence with zero steady state oscillations.

Table 4
Comparison of parameters of different algorithms.

S.No	Parameter	PSO	FA	Cuckoo	ABC	DEPSO	FPA
1	Steady state oscillation	zero	zero	zero	zero	zero	zero
2	Tracking speed	Moderate	Fast	Fast	Fast	Fast	Fast
3	Complexity	Moderate	Less	Moderate	high	High	Less
4	Procedural complexity	Moderate	Less	Less	Moderate	Large	Less
5	Memory requirement	Less	Less	Less	Less	High	Less
6	Computational complexity	Moderate	Less	Moderate	Moderate	High	Less
7	Performance under PSC	Moderate	High	High	Moderate	High	High
8	Exploration process	✓	✓	✓	✓	✓	✓
9	Exploitation process	–	–	–	–	✓	✓
10	Execution time	Moderate	Fast	Moderate	Moderate	Fast	Fast
11	Total No of parameters used	6	2	4	4	10	2
12	Efficiency	Moderate	High	High	Moderate	High	High

Table 5
Irradiation profile for different patterns.

S. no	Pattern no	Irradiation profile data
1	Pattern 1	G1 = 0.1,G2 = 0.1,G3 = 0.3,G4 = 0.3,G5 = 0.9,G6 = 0.9,G7 = 0.5,G8 = 0.5
2	Pattern 2	G1 = 0.5,G2 = 0.5,G3 = 0.8,G4 = 0.8,G5 = 0.3,G6 = 0.3,G7 = 1,G8 = 1
3	Pattern 3	G1 = 0.9,G2 = 0.6,G3 = 0.8,G4 = 0.5,G5 = 0.5,G6 = 0.7,G7 = 0.3,G8 = 0.1
4	Pattern 4	G1 = 1,G2 = 0.5,G3 = 0.9,G4 = 0.3,G5 = 0.8,G6 = 0.5,G7 = 0.9,G8 = 0.6
5	Pattern 5	G1 = 1,G2 = 0.5,G3 = 0.9,G4 = 0.3,G5 = 0.8,G6 = 0.5,G7 = 0.9,G8 = 0.6
6	Pattern 6	G1 = 1,G2 = 1,G3 = 0.8,G4 = 0.1,G5 = 0.9,G6 = 0.6,G7 = 0.8,G8 = 0.7
7	Pattern 7	G1 = 0.6,G2 = 0.5,G3 = 0.8,G4 = 0.1,G5 = 0.9,G6 = 0.6,G7 = 0.8,G8 = 0.7

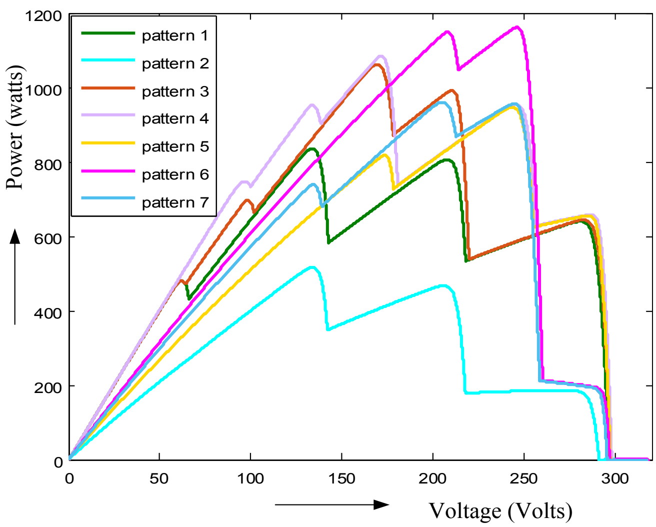

Fig. 21. PV pattern considered for economy analysis.

8. Energy saving and income generation

Tracking Maximum Power Point is a key tool to extract available maximum energy however, energy saving and income generated via tracking will decide the viability of the method before selection. Hence, the authors performed a performance analysis for the proposed algorithm on a real time conditions with 2.1 KW PV systems located at Technology Towers building of VIT University. With eight 250 W PV panel connected in a string, maximum deliverable output by the system is estimated as 2.1 KW. Since the system with shaded conditions are more complex and challenging in tracking, different PV pattern that occurs often in a day due to cloud passage and building shadows are considered for energy saving evaluation. It is noteworthy to mention that, tracking speed and efficiency are the key parameters that influence the amount of energy saved and income generated. To validate the evaluation on energy savings PSO and P&O algorithms are also executed in real time conditions and the results are compared.

Over a month the irradiation profile in vellore is kept under observation to estimate the effective sun hours and it is found that, the tropical regions in vellore have feasible sunlight for solar power generation between 10 a.m and 5 p.m. Further, for analysis seven different patterns occurring in a day at random intervals is considered and their irradiation profile data is tabulated in Table 5. To verify the performance of algorithm under multiple peak occurrences, P-V curves for all the PV patterns considered under study are simulated using MATLAB and plotted in Fig. 21.

With each PV pattern running for an hour, the convergence to global peak for PSO, P&O and FPA is closely watched. Power, Voltage and current at MPP are monitored and tabulated for verification. Irrespective of multiple peak occurrences, it is observed that FPA in all the cases has climbed to global peak and assures it supreme robustness over all climatic changes. Whereas PSO and P&O have delivered less power output when compared to FPA. Notably, for pattern 3 and 4 the PSO method has produced less power since PSO have got trapped in local peaks. In case of P&O

Table 6
Performance assessment on energy savings for FPA, PSO and P&O methods.

Pattern no	Type of method	Maximum attainable Power	Tracking speed	Power obtained	GMPP/ LMPP	Efficiency	Units generated	Income generated at Rs. 12/ unit	Capacity utilization factor
Pattern 1	FPA	1160	0.75	1159.6	GMPP	99.97	1.16	13.92	0.56
	PSO		1.63	1158.7	GMPP	99.89	1.16	13.90	0.56
	P&O		0.8	1148.3	LMPP	98.99	1.15	13.78	0.55
Pattern 2	FPA	946.2	0.96	946.15	GMPP	99.99	0.95	11.35	0.45
	PSO		1.83	945.38	GMPP	99.91	0.95	11.34	0.45
	P&O		0.35	814.82	LMPP	86.11	0.81	9.78	0.39
Pattern 3	FPA	1085	0.63	1084.3	GMPP	99.94	1.08	13.01	0.52
	PSO		1.58	950.82	LMPP	87.63	0.95	11.41	0.46
	P&O		0.53	747.29	LMPP	68.87	0.75	8.97	0.36
Pattern 4	FPA	1062	1.09	1061.15	GMPP	99.92	1.06	12.73	0.51
	PSO		1.96	991.5	LMPP	93.36	0.99	11.90	0.48
	P&O		0.63	694.8	LMPP	65.42	0.69	8.34	0.33
Pattern 5	FPA	835.1	0.45	834.52	GMPP	99.93	0.83	10.01	0.40
	PSO		2.52	832.96	GMPP	99.74	0.83	10.00	0.40
	P&O		1.05	477.86	LMPP	57.22	0.48	5.73	0.23
Pattern 6	FPA	516.4	1.1	516.32	GMPP	99.98	0.52	6.20	0.25
	PSO		0.49	515.93	GMPP	99.91	0.52	6.19	0.25
	P&O		1.62	513.81	GMPP	99.50	0.51	6.17	0.25
Pattern 7	FPA	958.7	0.65	958.52	GMPP	99.98	0.96	11.50	0.46
	PSO		2.14	957.3	GMPP	99.85	0.96	11.49	0.46
	P&O		0.82	737.68	LMPP	76.95	0.74	8.85	0.35

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Table 7
Evaluation on income generation.

Hours	Duration	Units generated			Income generated		
		FPA	PSO	P&O	FPA	PSO	P&O
Hour 1	10 a.m-11 a.m	1.1596	1.1587	1.1483	13.9152	13.9044	13.7796
Hour 2	11 a.m-12 noon	0.94615	0.94538	0.81482	11.3538	11.34456	9.77784
Hour 3	12 noon-1 p.m	1.0843	0.95082	0.95082	13.0116	11.40984	11.40984
Hour 4	1 p.m-2 PM	1.06115	0.9915	0.9915	12.7338	11.898	11.898
Hour 5	2 p.m-3 p.m	0.83452	0.83296	0.83296	10.01424	9.99552	9.99552
Hour 6	3 p.m-4 p.m	0.51632	0.51593	0.51593	6.19584	6.19116	6.19116
Hour 7	4 p.m-5 p.m	0.95852	0.9573	0.73768	11.50224	11.4876	8.85216
Number of units and income generated per day		6.56056	6.35259	5.99201	78.72672	76.23108	71.90412
Number of units and income generated for a year		2394.604	2318.695	2187.08365	28735.25	27824.34	26245

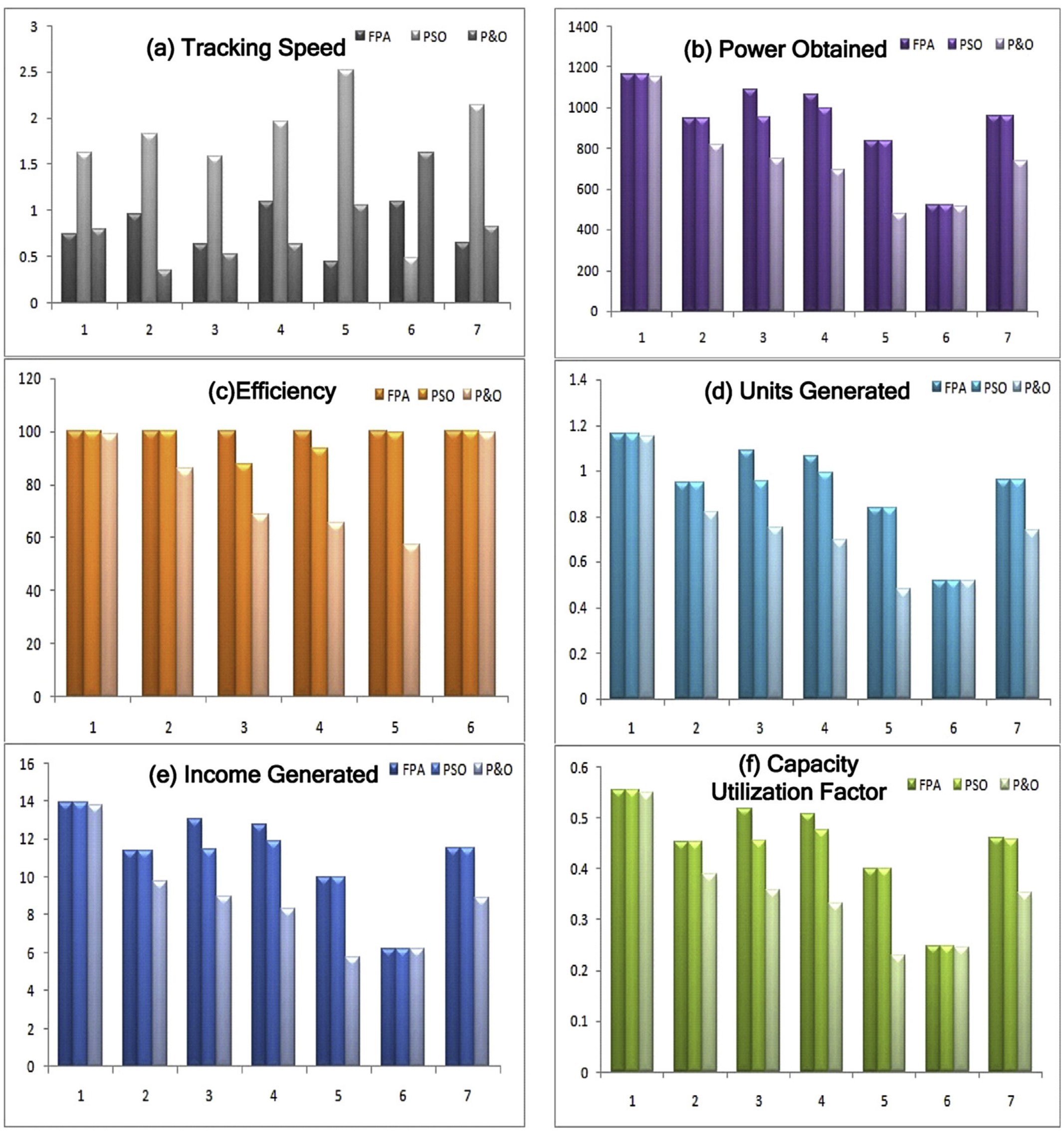

Fig. 22. Quantified analysis on FPA, PSO and P&O.

method, except pattern 6, in all other cases it is trapped under local peaks. Hence, the algorithm performance studied with different patterns are quantitatively compared and compiled in Table 6.

Based on the critical analysis performed with 7 different patterns, a summary on amount of revenue generation, cumulative energy generation for ESH for a day is estimated and included in Table 7. To show the importance of income generation relying on energy saving, units generated via all the methods is scaled for a year in which, FPA yet again proved its quality as promising alternative in MPPT implementation. From both simulation and hardware analysis performed earlier section and in energy saving, it is observed that dual search process in FPA with reduced complexity is the key success for its suitability for tracking. Further various results obtained in this section are clearly quantified in bar chart as presented in Fig. 22. From the figure, it is seen that except tracking speed, FPA has excelled to stand tall in all the other criteria considered for energy evaluation. Since P&O have a short coming of trapping under local power peaks, it attains faster convergence superior to FPA. However, the power generated via P&O is always less when compared to FPA. Thus the discussion clarifies that FPA has emerged to be a finest alternatives to conventional and swarm optimization methods.

9. Conclusion

In this article a new Flower pollination algorithm is proposed for solar PV Maximum Power Point Tracking. Application of FPA to PV tracking has successfully identified global peak irrespective of critical shade conditions. Randomness created in local and global pollination is the novel quality in FPA which posses quick convergence at strong shaded conditions. Further, simple structure and less steps implementation are the key merits to construct a dynamic MPPT system. Various PV patterns tested under all irradiated conditions illustrate the FPA superiority in all the cases and confirm the proposed FPA method is one of the effective replacements for conventional and Evolutionary methods. Finally an exclusive analysis on income generation demonstrated in real time conditions also strongly suggest that the FPA MPPT can harvest more energy and helps in generating higher income leading to quick payback period.

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