MPPT OF PV SYSTEMS UNDER PARTIAL SHADED CONDITIONS BY USING DIFFERENTIAL EVOLUTION AND PSO

[1]Atthipatla Uday Kumar, [2]Devadi Jagadeesh
[1]PG Student, [2]Asst. Prof
[1,2]Electrical and Electronics Engineering,
[1]Sree Vidyanikethan Engineering College, A.Rangampeta, Tirupati

Abstract: - With the increasing demand of energy, renewable energy sources such as wind, solar are getting more attention as compared to conventional energy sources because of fuel cost, global warming, depletion of fossil fuels and lesser noise. Among different renewable energy sources, the photovoltaic generation is the most attractive research during the past decades. The major issue involved in solar PV system is low conversion efficiency; further the efficiency reduces under partial shaded conditions (PSC). Thus there is need of control algorithms which can extract the maximum power from this system irrespective of the environmental conditions such as temperature and irradiations. Numerous control algorithms have been proposed in recent years like PSO, Firefly and Differential evaluation. The performance of PSO and DE algorithms in terms of tracking speed, initial oscillations and tracking efficiency is validated through simulation studies and hardware implementation.

Keywords: **- Maximum Power Point (MPP), Photo Voltaic (PV), Particle Swarm Optimization (PSO), Partial Shaded Conditions (PSC) and Differential Evolution (DE).**

1. INTRODUCTION

The ever-increasing demand for low-cost energy and growing concern about environmental issues has generated enormous interest in the utilization of nonconventional energy sources such as the solar, wind etc., energies. The freely and abundantly available solar energy can be easily converted into electrical energy using photovoltaic (PV) cells. A PV source has many advantages viz., low maintenance cost, absence of moving/rotating parts, pollution-free energy conversion process etc. However, the major drawback of the PV source is its ineffectiveness during the nights, low insolation periods, or during partially shaded conditions etc., [1], [2]. India is one of the largest and fastest growing countries in the world with an expansive population of above 1.1 billion people [3]. There is a very high demand for energy, which is currently satisfied mainly by coal, foreign oil and petroleum, which apart from being a non-renewable energy sources. This is not a permanent solution to the energy crisis since power production through fossil fuels would affect the environment and may result in depletion of fossil fuels. India is blessed with an abundance of sunlight, water and biomass. Vigorous efforts during the past two decades are now bearing fruits as people in all walks of life have become more aware of the benefits of renewable energy, especially decentralized energy where required in villages and in urban or semi urban centers.

2. MODELLING OF MPPT SYSTEMS

PV system converts sunlight to electricity using the basic device of this system, which is the PV cell. On the other hand, because of the high investment cost on PV modules, optimal use of the available solar energy has to be ensured. This necessitates a precise and reliable simulation of the designed PV systems prior to installation. The most important component that affects the accuracy of simulation is the PV cell modelling [1].

2.1 Mathematical modelling of PV cell :

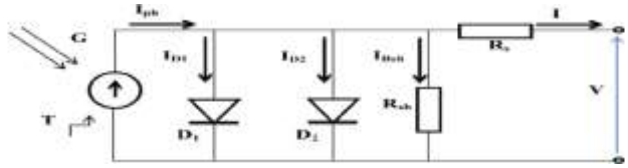


Fig. 2.1 Equivalent circuit of a Double Diode model

In this model, the solar cell is modelled as a current source connected in parallel with a rectifying diode. However, in practice the current source is also shunted by another diode that models the space charge recombination current and a shunt leakage resistor to account for the partial short circuit current path near the cell's edges due to the semiconductor impurities and non-idealities [10]. In addition, the solar cell metal contacts and the semiconductor material bulk resistance are represented by a resistor connected in series with the cell shunt elements. In this double-diode model, the cell terminal current is calculated as follows:

$$I = I_{ph} - I_{D1} - I_{D2} - I_{sh} \tag{2.1}$$

$I =$ Terminal current

$I_{ph} =$ The cell-generated photocurrent

$I_{D1}, I_{D2} =$ First and second diode currents

$I_{sh} =$ Shunt resistor current

The two diodes currents are expressed by Shockley equation as illustrated respectively in equations (2.2) and (2.3), While the leakage resistor current I_{sh} is formulated as shown in equation (2.4).

$$I_{D1} = I_{s1}\left[\exp\left(\frac{q(V_L + IR_s)}{n_1 KT}\right) - 1\right] \tag{2.2}$$

$$I_{D2} = I_{s2}\left[\exp\left(\frac{q(V_L + IR_s)}{n_2 KT}\right) - 1\right] \tag{2.3}$$

$$I_{sh} = \frac{V_L + IR_s}{R_{sh}} \tag{2.4}$$

n_1 and n_2 are the diffusion and recombination diode ideality factors; k is Boltzmann's constant; q is the electronic charge and T is the cell absolute temperature in Kelvin. Substituting equations (2.2), (2.3) and (2.4) into equation (2.1), the cell terminal current is now rewritten as shown in equation (2.5).

$$I = I_{s1}\left[\exp\left(\frac{q(V_L + IR_s)}{n_1 KT}\right) - 1\right] - I_{s2}\left[\exp\left(\frac{q(V_L + IR_s)}{n_2 KT}\right) - 1\right] - \left[\frac{(V_L + IR_s)}{R_{sh}}\right] \tag{2.5}$$

The dependency of the saturation current and the photo- generated current in a PV cell on temperature and insolation is shown by the following conditions.

(i) Saturation current of a solar cell varies with the cubic function of temperature,

$$I_s = I_{rs}(T/T_r)^3 e^{\left[\frac{q \times E_{bg}}{nK}[1/T_r - 1/T]\right]} \tag{2.6}$$

Where, $I_{rs} =$ reverse saturation current

$T_r =$ Ambient temperature

$E_{bg} =$ Energy band gap = 1.1eV

(ii) Reverse saturation current at a reference temperature T, can be given by the equation,

$$I_{rs} = I_{sc} / e^{(q \times V_{oc} / nKT)} - 1 \tag{2.7}$$

$I_{sc} =$ Short-circuit current

$V_{oc} =$ Open-circuit voltage

The saturation current depends on current density and effective area of cell.

(iii) Photo generated current shows a linear relationship with insolation and depends on temperature,

$$I_{ph} = \{I_{sc} + K_i (T - T_r)\} \frac{H_T}{1000} \tag{2.8}$$

Where, K_i is the temperature coefficient of cell's short circuit current and H_T is the insolation on the solar cell. Assuming 12hours of sun in a day, the solar insolation for a day can be,

$$H_T = 7596 \ watts/m^2 \ \ in \ \ a \ \ day$$

The photo current generated by incident solar radiation varies with change in temperature and solar radiation.

By determining the above parameters, modeling of solar PV arrays can be achieved.

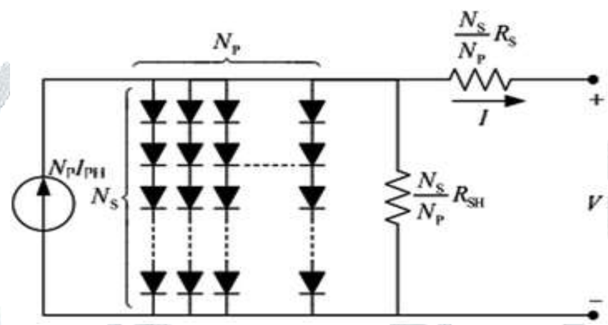


Fig. 2.2 Equivalent circuit model of PV array

Table 1.1 Transformed parameters for series and parallel connected modules

Parameters of SPV cell	Parameters of series arrays of N_s cells	Parameters of parallel arrays of N_p cells
I_{ph}	I_{ph}	$N_p I_{ph}$
I_{rs}	I_{rs}	$N_p I_{rs}$
V_t	$N\ V_t$	V_t
R	$N_s R_s$	R_s / N_p
R_{sh}	$N_s R_{sh}$	R_{sh} / N_p

The output current for series–parallel configuration for double diode model can be written as,

$$I = N_p \left\{ \begin{array}{l} I_{ph} - I_{s1}\left[\exp\left(\dfrac{V + IR_s\left(\dfrac{N_s}{N_p}\right)}{V_{T1}N_s}\right) - 1\right] \\ - I_{s2}\left[\exp\left(\dfrac{V + IR_s\left(\dfrac{N_s}{N_p}\right)}{V_{T2}N_s}\right) - 1\right] - \left[\dfrac{V + IR_s\left(\dfrac{N_s}{N_p}\right)}{R_p\left(\dfrac{N_s}{N_p}\right)}\right] \end{array} \right\} \tag{2.9}$$

2.2 Partial Shaded Conditions

In large PV systems, partial shaded conditions (PSC) occur wherein PV modules receive different solar insolation due to shadow of buildings, moving clouds, and other neighbouring objects [1]. The presence of non-uniform irradiation produces the hotspot problem, and the effect of a potential difference between the PV strings. In addition, the blocking diode is connected in series with each string; to protect the modules from the effect of the potential difference between the series connected PV strings. Because of these diodes in the PV array, multiple peaks will be exhibited in the PV characteristic curve under partial shading conditions. The output power of the PV array decreases largely due to PSC and the quantum of power lost depend on system configuration, shading pattern and the bypass diodes incorporated in the PV modules [2]. The immediate effect of PSC is that the resulting PV characteristic curve becomes complex with multiple peaks as depicted in **Fig. 2.3**.

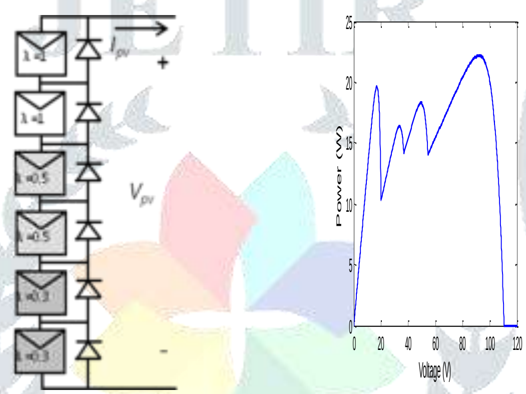


Fig. 2.3 P-V curve under partial shaded condition [1]

3. MAXIMUM POWER POINT TRACKING

3.1 MPPT scheme

Tracking of the maximum power point (MPP) of a photovoltaic (PV) array is usually an essential task in PV systems. In general, PV generation systems have two major problems; the conversion efficiency of electric power generation is low (in general less than 17%, especially under low irradiation conditions), and the amount of electric power generated by solar arrays changes continuously with weather conditions [3]. Moreover, the solar cell (current – voltage) characteristic is nonlinear and varies with irradiation and temperature. There is a unique point on the I-V or (power – voltage) curve of the solar array called MPP, at which the entire PV system (array, converter, etc…) operates with maximum efficiency and produces its maximum output power [1]-[3].

Maximum power point tracking (MPPT) techniques are used in photovoltaic (PV) systems to maximize the PV array output power by tracking continuously the maximum power point (MPP) which depends on panel temperature and on irradiance conditions [11]. This was explained in the previous chapters.
The combination of a suitable dc to dc converter and an accurate tracking algorithm would give an effective MPPT with the following desired features.

- Low price.
- Easy to implement.
- For dynamic analysis, tracking response must be rapid.
- For steady-state analysis, Correctness and no oscillation around the MPP are needed.
- For wide-ranging solar radiation and temperature, the MPPT must be capable to track the MPP.

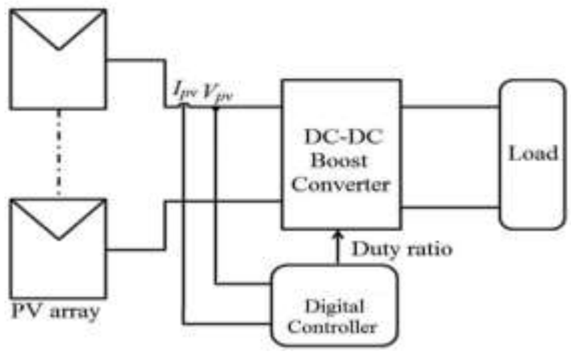


Fig. 3.1 Block diagram of MPPT scheme [1]

3.2.2 Failures of Conventional MPPT Techniques

The competences of conventional MPPT techniques (i.e., P&O, Incremental Conductance and short circuit current method etc.,) have been known as over 99% under unvarying solar irradiance condition.

However, the usefulness of conventional MPPT techniques might be lessened under PSC due to the multiple local maxima [1], [13].

Fig. 3.2 shows the cause that the tracking disappointment of conventional MPPTs under PSC. In **Fig. 3.2**, the operating point of PV array is on the "point A" before PSC is occurred. After PSC is occurred, the operating point is moved to "point B". In this case, the real MPP is to be found on "point C". Nevertheless, because of the conventional methods changes the operating point due to predetermined voltage reference step (△V), the operating point is oscillated on vicinity of "point B". At the same time, the difference in power capacity between P_C and P_B is lost due to this MPPT failure. To prevent this power loss, MPPT methods have to move the operating point to "point C".

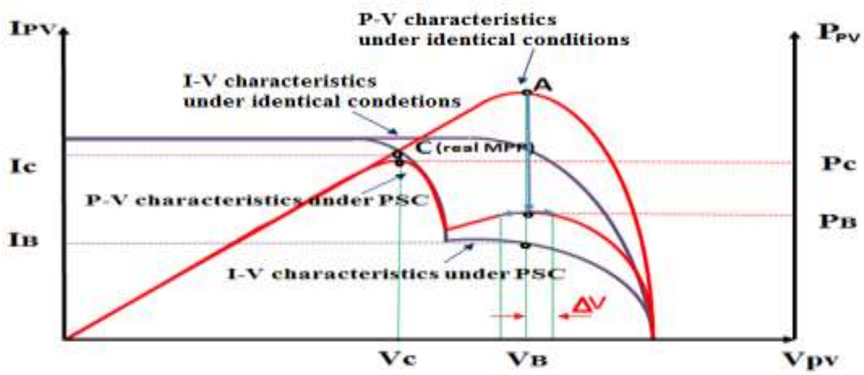


Fig. 3.2 P-V and I-V curves with MPP's [10]

Actually, some researchers have worked on real MPP tracking under PSC. As mentioned above, these methods have some drawbacks with complexity of method, tracking failure according to the real MPP position, and difficulties on the application to the installed power conditioning system [14].

The drawbacks of the conventional methods can be overcome with biologically inspired algorithms like PSO and FA etc.,

4. ALGORITHMS USED

4.1 Differential Evolution Algorithm

It is an Evolutionary Algorithm introduced by Rainer Storn and Kenneth Price in 1995. It is stochastic, real valued and population based optimization algorithm. Therefore DE is used to find exact or approximate solutions to these problems. The various steps involved in DE optimization algorithm are listed below [21].

Initialization: The initial population of solutions are generated randomly with constraints of each parameter are known.

$$X_k = a + (b - a) * rand(N, D) \tag{4.1}$$

Where, X_k is the initial random solutions, a is lower bound of the parameter, and b is the upper bound of the parameter, $rand(N,D)$ randomly generates population of size NXD, D is the dimension of the vector or the number of variables and N is the population size or number of solutions.

Then the fitness of the initial population is evaluated.

Mutation: It expands the search space. It adds difference vector to base vector in order to explore search space.

$$V_k = F\left(X_{3,k} - X_{2,k}\right) + X_{1,k} \tag{4.2}$$

Where V_k is the donor vector, $X_{1,k}$, $X_{2,k}$, $X_{3,k}$ are randomly chosen vectors and F is the mutation constant.

Crossover: To increase the diversity of the mutated vector, crossover is done. The trial vector U_k is developed from the crossover of the target vector, X_k and the donor vector V_k.

$$U_k = \begin{cases} V_k & if\ rand_j \le CR\ or\ j = I_{rand} \\ X_k & if\ rand_j > CR\ or\ j \ne I_{rand} \end{cases} \tag{4.3}$$

Where, CR is crossover rate, $rand_j$ is random value from [0, 1], I_{rand} = random integer from [1, 2. . . D]. I_{rand} ensures that $V_{k+1} = X_k$.

Selection: It mimics survival of the fittest. The fitness of target vector $f(X_k)$ is compared with fitness of trial vector $f(U_k)$ and the one with the better fitness value, the corresponding vector is admitted to the next generation.

$$X_{k+1} = \begin{cases} U_k & if\ \ f(U_k) < f(X_k) \\ & else \end{cases} \tag{4.4}$$

Where, X_{k+1} is next generation vector, $f(X_k)$ fitness value of target vector, $f(U_k)$ is fitness of trial vector.

The typical DE flowchart is shown in **Fig. 4.1.**

4.1.1 Steps involved in DE:

Step-1: Choose the number of particles
Scaling Factor F= 0.7;
Crossover CR = 0.8;
PV array output current [I]
Evaluate the objective function values from equations (2.7), (2.8) and (2.9).
P=V*I

Step 2: Get the value of V_{pv} and I_{pv} from the PV panel output. Step 3: Calculate the power values of all the voltages. Step 4: Select the individual (Voltage) with maximum power as the target vector X_k . Step 5: Select three more individuals namely $X_{1,k}, X_{2,k}$ and $X_{3,k}$ by random, such that $X_{1,k} \ne X_{2,k} \ne X_{3,k} \ne X_k$.

Step 6: Create the trial vector

$$V_k = F\left(X_{3,k} - X_{2,k}\right) + X_{1,k}$$

Step 7: Create a constant randomly whose value lies between 0 and 1, CR = rand (0, 1);
Step 8: Compare the values of random vector with crossover constant.

$$U_k = \begin{cases} V_k & if\ rand_j \le CR\ or\ j = I_{rand} \\ X_k & if\ rand_j > CR\ or\ j \ne I_{rand} \end{cases}$$

Step 9: Calculate the power of the resultant vector.
Step 10: If the power of the resultant vector is greater than the power of the target vector, then the resultant vector is selected for the next iteration. Else the target vector is selected for the next generation.
Step 11: Repeat the steps 5 to 10 for the remaining particles.
Step 12: Repeat the steps 3 to 11 till the end criteria that is maximum iteration.
Step 13: Obtain the output voltage corresponding to the maximum power.

4.2 Particle Swarm Optimization Algorithm

The PSO algorithm was first introduced by Dr. Kennedy and Dr. Eberhart in 1995 and its basic idea was originally inspired by simulation of social behaviour of animals such as bird flocking, fish schooling and so on. In this method each individual particle has a current position in search space, 'xi' where i ε [1,2,…,n] and n>1, a current velocity, vi, and a personal best position in search space, Pbest,i. In addition, the position yielding the lowest value amongst all the personal best Pbest,i is known as global best which is denoted by Gbest.
Considering minimization problems, then the personal best position Pbest,i at the next time step, t+1, where t ε [0,1,….,N], is calculated as

$$P_{best,i}^{t+1} = \begin{cases} P_{best,i}^{t} & if \ f(x_i^{t+1}) > P_{best,i}^{t} \\ x_i^t & if \ f(x_i^{t+1}) \leq P_{best,i}^{t} \end{cases}$$
(4.5)

For maximization problem, $P_{best,i}$ is vice versa.

The global best position G_{best} at time step'‘t’ is calculated as

$$G_{best} = min\{P_{best,i}^t\},$$ where ‘i’ ε [1,2,……, n] and n>1
(4.6)

For maximization problem $G_{best} = max\{P_{best,i}^t\}$

Therefore, the personal best $P_{best,i}$ is the best position of the individual particle ‘i’. On the other hand, the global best position G_{best} is the best position identified by any of the particle in the entire swarm.

The velocity of particle ‘i’ is calculated by

$$v_{ij}^{t+1} = v_{ij}^t + c_1 r_{1j}^t \left[P_{best,i}^t - x_{ij}^t\right] + c_2 r_{2j}^t \left[G_{best} - x_{ij}^t\right]$$

(4.7)

Where,

v_{ij}^t is the velocity vector of particle ‘i’ in dimension ‘j’ at time t

x_{ij}^t is the position vector of particle ‘i’ in dimension ‘j’ at time t

c_1 and c_2 are positive acceleration constants which are used to level the contribution of the cognitive and social components respectively

r_{1j}^t and r_{2j}^t are random numbers from uniform distribution U(0, 1) at time t.

4.2.1 Steps involved in PSO:

Step-1: Choose the number of particles

PV array output current [I]

Evaluate the objective function values from equations (2.7), (2.8) and (2.9).

P=V*I

Step-2: Find the personal best for each particle

$$P_{best}^t$$

Step-3: Find the global best

$$G_{best}^t$$

Step- 4: Find the velocities of the particles

$$v^{t+1} = v^t + C_1 r_1 \left(P_{best}^t - I\right) + C_2 r_2 \left(G_{best}^t - I\right)$$

Step -5: Find the new values (or) positions of particles

$$I^{t+1} = I^t + v^{t+1}$$

Step -6: Find the objective function values by using new particle positions

Step -7: Check whether all the particles converge to similar values or not, if satisfied stop the iteration, otherwise go to step 2.

The algorithm is pictorially shown in **Fig. 4.2**.

5. RESULTS AND DISCUSSION

In order to evaluate the performance of PSO, DE methods MATLAB coding is done. Mathematical modelling of a double diode model of solar cell is developed and those equations are used in coding. The performance is evaluated for 6S (6-series panels) configuration shown in **Fig. 5.1** under partial shaded conditions.

5.1 P-V curve of solar array

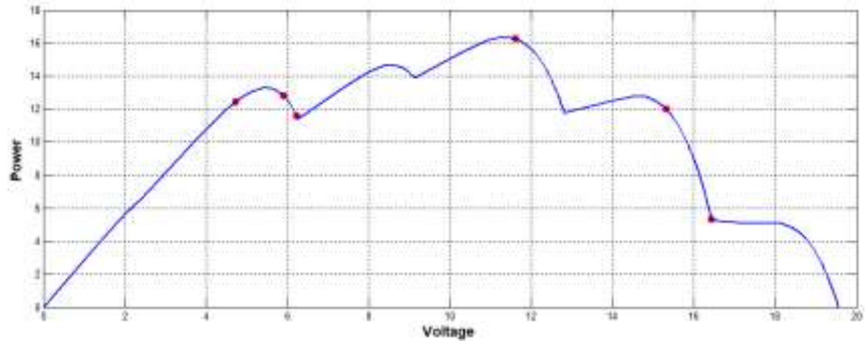


Fig.5.1 P-V characteristics of 6S configuration

The P-V characteristics of 6-series configuration under partial shaded conditions are shown in **Fig. 5.2**. The red star (*) marks indicate initial particle positions in PSO and DE before tracking the maximum power point.

The multiple peaks in P-V curve shown in **Fig. 5.2** are due to partial shaded conditions and variations in temperature.

- Change in irradiation causes variations in current
- Change in temperature causes variations in voltage

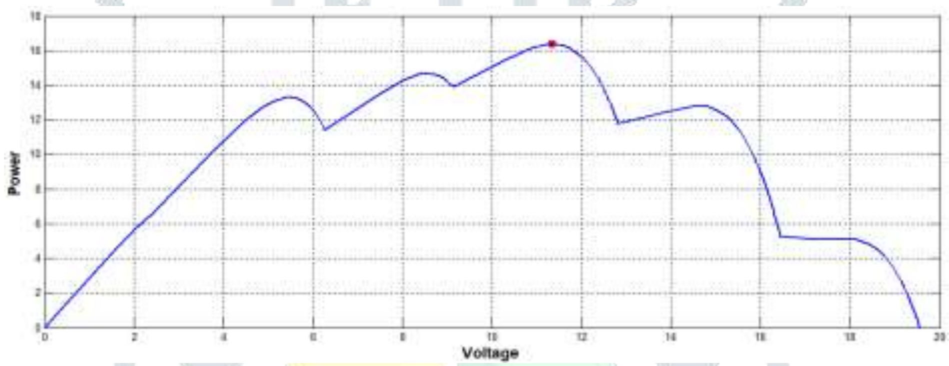


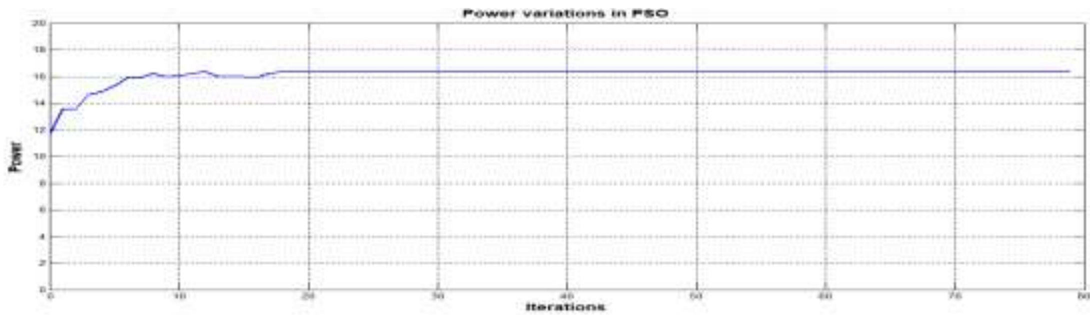
Fig.5.2 P-V characteristics after MPP tracking for both PSO and DE

The particles positioned randomly over the P-V curve in **Fig. 5.2** are converged to a single MPP a shown in **Fig. 5.3.** In DE and PSO all particles are converged to a global MPP (GMPP).

5.2 Output power and voltage variations of DE

Fig. 5.3 Power and Voltage variations at the time of MPP tracking

5.3 Output power and voltage variations of PSO



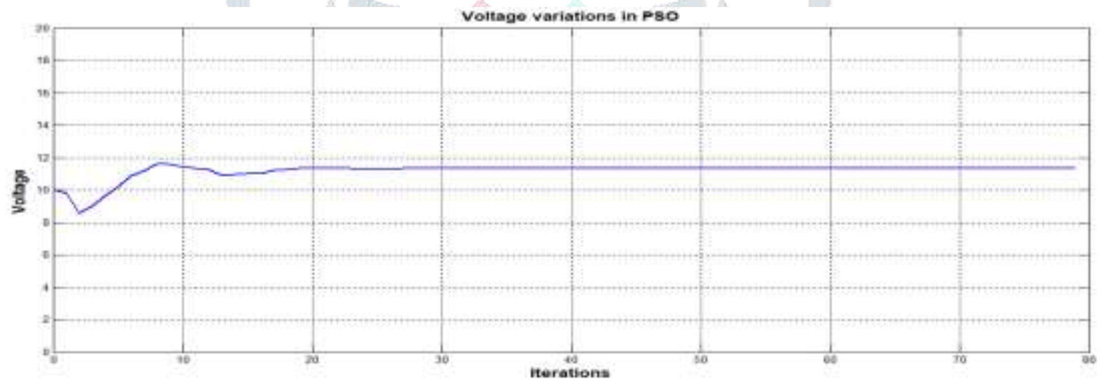


Fig. 5.4 Power and voltage variations at the time of MPP tracking

From **Fig. 5.3** and **5.4** the voltage and power, oscillations before GMPP tracking are very low in PSO compared to Differential Evolution. In PSO the oscillations are nullified in 35th iteration approximately and in DE around 164th iteration

5.4 Interpretation of results

Table 5.1: Particles position with respect to iterations in DE

Iterations	P1	P2	P3	P4	P5	P6
1	0	10.2262	17.4115	13.0693	14.2240	0
5	0	10.2262	0	14.4177	12.8441	0
10	10.2262	5.6736	15.5584	13.9206	12.7236	6.4818
20	12.3538	15.6324	15.5584	13.9206	12.7236	16.3204
30	15.6039	15.6324	15.5584	13.9206	15.3491	16.3204

50	15.6039	17.4021	15.4919	17.5247	12.4903	15.5487
75	17.4104	12.9679	15.9633	13.7048	17.1528	13.7067
100	17.4104	15.6060	17.5228	17.4948	14.8777	15.6349
125	17.5238	17.2490	14.8749	17.4612	17.2530	14.9309
150	17.5238	17.5256	17.5256	17.5255	17.5248	17.3707
163	17.5256	17.5256	17.5256	**17.5255**	17.5256	17.5256
164	**17.5256**	**17.5256**	**17.5256**	**17.5256**	**17.5256**	**17.5256**

Table 5.2: Particles position with respect to iterations in PSO

Iterations	P1	P2	P3	P4	P5	P6
1	5.3191	12.0229	16.2507	11.5903	12.8130	12.4454
5	12.4769	16.2499	16.2507	16.1490	14.0258	13.9592
10	14.1591	16.3558	16.2507	16.3552	16.2878	16.2929
15	16.3488	16.3488	16.3372	16.3509	16.3562	16.3562
20	16.2986	16.3548	16.3571	16.3553	16.3564	16.3570
25	16.2986	16.3572	16.3572	16.3572	16.3571	16.3568
30	**16.3502**	16.3572	16.3572	16.3572	16.3572	16.3572
35	**16.3567**	**16.3572**	**16.3572**	**16.3572**	**16.3572**	**16.3572**

From **Tables 5.1 & 5.2** the particles at different locations on the P-V curve and in final iteration all the particles converge to a same point, but the number of iterations used to converge is less in particle swarm optimization compared to Differential Evolution.

Comparison between PSO and DE with respect to different parameters like speed of convergence, accuracy, complexity etc, is shown in **Table 5.3**.

Table 5.3: Qualitative comparison between the methods

Type	PSO	Differential Evolution
Tracking Speed	Fast	Medium
Tracking Accuracy	Accurate	Accurate
Implementation complexity	Medium	Medium
Dynamic response	Good	Oscillatory
Periodic tuning	Not Required	Not Required
Power Oscillations	Zero	Medium

6. CONCLUSION

MPPT algorithms track the maximum power point even under partially shaded conditions. The accurate MPPT tracking algorithms like Particle Swarm Optimization and Differential Evolution algorithms is analyzed and comparative study is also done.

From this comparative study PSO has high tracking speed than DE

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