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COMPARISON BETWEEN PSO AND DE ALGORITHMS BASED ON MPPT IN SOLAR PV SYSTEMS

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ABSTRACT: This paper proposes a comparison between two algorithms used for tracking the maximum power point in a Solar PV system. MPP is achieved in renewable energy systems such as solar energy system. Various algorithms are used to achieve MPP. In this paper, the particle swarm optimization and differential evolution algorithm are used to achieve the maximum power from the solar energy system. The particle swarm optimization algorithm uses the particles best position and velocity for achieving the maximum power point. The differential evolution algorithm uses the iterative technique to optimize the solution that is to be obtained. These two optimization algorithms are compared in this paper and conclusions are drawn in terms of speed of convergence, response, etc., to track maximum power from the solar PV system.

KEYWORDS - Differential Evolution (DE), Maximum Power Point Tracking (MPPT), Maximum Power Point (MPP), Particle Swarm Optimization (PSO)

I. INTRODUCTION

A growing world energy demand and soaring prices of fossil fuels combined with concern about environmental issues have generated enormous interest in the utilization of renewable energy sources. The photovoltaic (PV) power generation has seen a rapid growth in the last few years leading to extensive use of solar energy; a PV system has the advantages of low maintenance cost, absence of moving or rotating parts and freedom from environmental pollution.

The efficiency of a PV plant is affected mainly by three factors: the efficiency of the PV panel, the efficiency of the inverter and that of the maximum power point tracking (MPPT) algorithm. Improving the efficiency of the PV panel and that of inverter are not easy as it depends on the technology available, it may require better components which can increase drastically the cost of the installation. Instead, improving the tracking of the maximum power point (MPP) with new control algorithms is easier, not expensive and can be done even in plants which are already in use by updating their control algorithms, which would lead to an immediate increase in PV power generation.

MPPT algorithms are necessary because PV arrays have a nonlinear voltage-current characteristic with a unique point where the power produced at PV array is maximum. This point depends on the temperature of the panels and on the irradiance conditions. Both conditions change during the day and are also different depending on the season of the year. Furthermore, irradiation can change which is due to changing atmospheric conditions such as clouds this condition is called Partial shaded conditions [1]. It is very important to track the MPP accurately under all possible conditions so that the maximum available power is always obtained.

In the case of a shaded PV system, the PV curve possesses multiple peaks and convergence to global MPP is mandatory for extracting maximum power from the PV system. The optimization algorithm selected for MPPT should ideally possess the properties of simple computational steps, faster convergence, and guaranteed convergence to GMPP together with the feasibility of implementation in a low-cost digital controller.

This paper consist the brief concept of PV characteristics and Mathematical modeling of single PV cell. The next section provides an overview of the characteristic of partial shaded conditions. The MPPT techniques PSO and DE algorithms are discussed. Finally, comparison and discussion on the characteristics of MPPT techniques are clarified and the results are concluded.

II. MATHEMATICAL MODELING OF SINGLE PV CELL AND PV CHARACTERISTICS

1. Mathematical modeling of PV cell

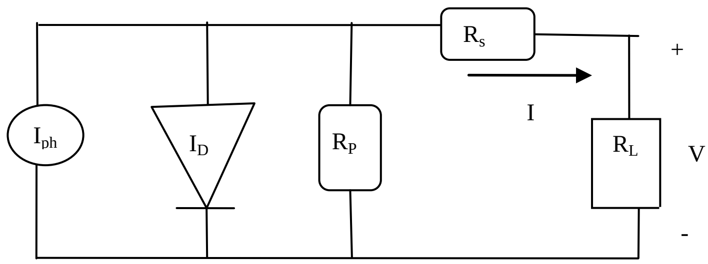


Fig.1. a single diode model of PV cell

An ideal PV cell is modeled by a current source in parallel with a diode. However, no solar cells are ideal and thereby shunt and series resistances are added to the model as shown in the Fig. 1 [2]. R_s are the intrinsic series resistance whose value is very small. R_p is the equivalent shunt resistance which has a very high value.

Applying Kirchhoff's law to the node where I_{ph}, diode, R_p and R_s meet, we get

$$I_{ph} = I_D + I_{RP} + I \tag{1}$$

We get the following equation for the photovoltaic current

$$I = I_{ph} - I_D - I_{Rp} \tag{2}$$

Where, $I_D = I_o\left[\exp\left(\frac{V}{AV_T}\right) - 1\right]$

$$I = I_{ph} - I_o\left[\exp\left(\frac{V}{AVT}\right) - 1\right] - \left[\frac{V + IRs}{Rp}\right] \tag{3}$$

Where,

- I_{ph} is the Isolation current
- I is the Cell current
- Io is the Reverse saturation current
- V is the Cell voltage
- R_s is the Series resistance
- R_p is the Parallel resistance
- V_T is the Thermal voltage
- K is the Boltzmann constant
- T is the cell temperature in Kelvin
- q is the Charge of an electron
- A is the p-n junction ideality factor

Usually the value of R_{sh} is very large and that of Rs is very small, hence they may be neglected to simplify the analysis. PV cells are grouped in larger units called PV modules which are further interconnected in series-parallel configuration to form PV arrays or PV generators. The PV mathematical model used to simplify our PV array is represented by the equation (4) [3]:

$$I = n_p I_{ph} - n_p I_o\left[\exp\left(\frac{q}{KTA} \times \frac{V}{n_s}\right) - 1\right] \tag{4}$$

Where,

I is the PV array output current
V is the PV array output voltage
n_s is the number of cells connected in series
n_p is the number of cells connected in parallel
I_o is the cell reverse saturation current

The factor '*A*' in equation (4) determines the cell deviation from the ideal p-n junction characteristics and it ranges between 1-5. The cell reverse saturation current Io varies with temperature according to the following equation:

$$I_O = I_{rr}\left[\frac{T}{T_r}\right]^3 \exp\left(\frac{qE_G}{KA}\left[\frac{1}{T_r}-\frac{1}{T}\right]\right) \tag{5}$$

Where,
T_r is the cell reference temperature
I_{rr} is the cell reverse saturation current at temperature T_r
E_G is the band gap of the semiconductor used in the cell

The temperature dependence of the energy gap of the semi conductor is given by:

$$E_G = E_G(0) - \frac{\alpha T^2}{T+\beta} \tag{6}$$

The photo current I_{ph} depends on the solar radiation and cell temperature as follows:

$$I_{ph} = \left[I_{scr} + K_i(T - T_r)\right]\left(\frac{S}{100}\right) \tag{7}$$

Where,
I_{scr} is the cell short-circuit current at reference
K_i is the short circuit current temperature coefficient
S is the solar radiation in mW/cm2

The PV power can be calculated using equation (4) as follows:

$$P = VI$$

$$P = n_p I_{ph} V\left[\left(\frac{q}{KTA} \times \frac{V}{n_S}\right) - 1\right] \tag{8}$$

2. PV array characteristics

General V-I characteristics of a PV array are non-linear, so it is difficult to track the MPPT. Fig.2 and Fig.3 shows the P-V and I-V characteristics under fixed irradiation and temperature conditions [4].

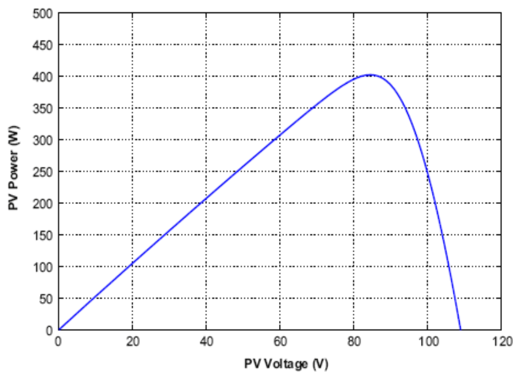


Fig.2. P-V characteristics of a typical PV array

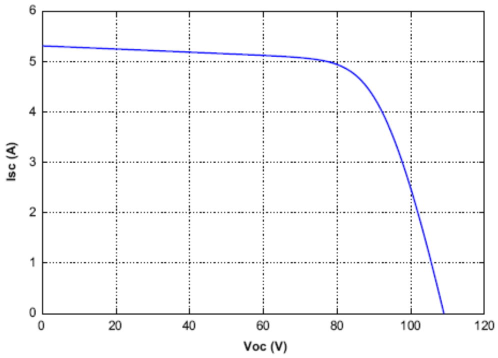


Fig.3. I-V characteristics of a typical PV array

3. Temperature and irradiance effects

Two main factors that have to be taken into consideration are the irradiation and the temperature. They robustly affect the characteristics of PV modules. As a result, the MPP varies during the day and that is the main reason why the MPP must regularly be tracked and ensure that the maximum available power is obtained from the panel. The effect of the irradiance on the power-voltage (P-V) characteristics is depicted in the Fig. 4, where the curve is shown, i.e. the voltage and current are normalized using the V_{OC} and the I_{SC} respectively, in order to better demonstrate the effects of the irradiance on P-V curves. As was previously mentioned, the photo-generated current is directly proportional to the irradiance level, so an increment in the irradiation leads to a higher photo-generated current [4]-[5]. Moreover, the short circuit current is directly proportional to the photo generated current therefore, it is directly proportional to the irradiance. When the operating point is not the short circuit, in which no power is generated, the generated current is also the main factor in the PV current, as is expressed by equation (1) and (2). For this reason the voltage-current characteristic varies with the irradiation. In contrast, the effect on the open circuit voltage is quite small, as the dependence of the light generated current is logarithmic, as is shown in equation (4) which shows that the change in the current is greater than in the voltage [6].

4. Effect of Partial Shading

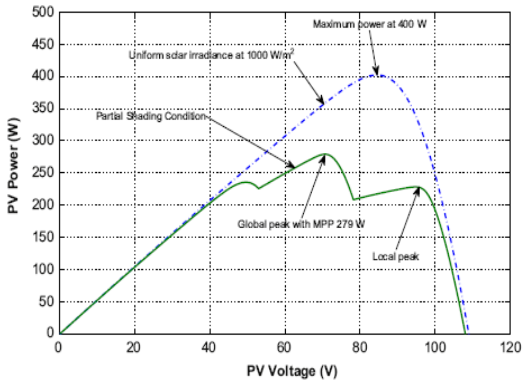


Fig. 4. A comparison of PV characteristics between the uniform solar irradiance and Partial shaded conditions

Fig. 4 illustrates typical current–voltage and power–voltage curves for a homogeneous PV array under uniform insolation of all the PV modules. Conventional MPPT techniques find the voltage V_{mpp} and current I_{mpp} at which the PV array operates at the MPP. However, these techniques may malfunction for non uniform insolation of the PV array [7]. Various factors such as aging, dust, and partial shading result in mismatching and, hence, non uniform operation conditions present. Partial shading is a frequent phenomenon that occurs when some cells within a module or array are shaded by say buildings, birds, passing clouds, or some other object, since the short-circuit current of a PV cell is proportional to the insolation level, the result of partial shading effect is a reduction of the photocurrent for the shaded PV cells while the unshaded cells continue to operate at a higher photocurrent. Since the string current must be equal through all the series-connected cells, the result is that the shaded cells operate in the reverse bias region to conduct the larger current of the unshaded cells [7]–[8]. The string current flows through all the series-connected cells including shaded and unshaded. The bias voltage V_{bias}

is the reverse voltage at which the shaded cells must operate to support the common string current. The shaded cells consume power due to the reverse voltage polarity. Therefore, the maximum extractable power from the shaded PV array decreases. The high bias voltage may also lead to an avalanche break down. This, in turn, may cause the thermal breakdown of the cell, creating a so-called hot spot [9]. If untreated, excessive heating can result in cell burn out and create an open circuit in the shaded string. This hot spot can be avoided by using the bypass diodes. These diodes are connected parallel to the cells to limit the reverse voltage and, hence, the power loss in the shaded cells. If the reverse voltage across the shaded cell increases, the bypass diode restricts the reverse voltage to less than the breakdown voltage of the PV cells as shown in below Fig.5.

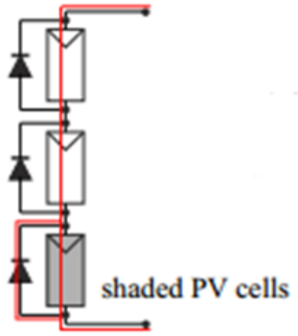


Fig. 5. Position of bypass diode

Since the bypass diodes provide an alternate current path, cells of a module no longer carry the same current when partially shaded. Therefore, the power–voltage curve develops multiple maxima called as Global peak, shown in Fig. 4 and the remaining peaks are Local peaks.

III. MPPT TRACKING AND ALGORITHMS USED

1. Maximum Power Point Tracking

Maximum Power Point tracking is a technique that is used to get maximum possible power from one or more photo-voltaic (PV) devices. Solar cells have a complex relationship between solar irradiation, temperature and total resistance that produces non-linear output efficiency which can be analyzed based on I-V curve. It is MPPT system to sample the output of the cells and apply the proper resistance load to obtain maximum power for any given environmental conditions. MPP (Maximum power point) is the product of the MPP voltage (V_{mpp}) and MPP current (I_{mpp}). MPPT devices are typically used in electric power system that provides voltage or current conversion, filtering, and regulation for various loads such as power grids, batteries, or motors. Maximum Power Point Tracking frequently referred to as MPPT is an electronic system. MPPT is an essential part of PV system. It operates in a manner such that it optimizes the power generated by the photovoltaic panel. It functions as an optimal electric load for a PV cell, and converts the power to a voltage or current level which is more suitable to whatever load the system is designed to drive [10]. It consists of a DC-DC converter which limits power loss by matching the photovoltaic panel and the load impedances by varying the duty cycle of the switch used in the converter circuit. MPPT scheme can be performed as shown in Fig. 6.

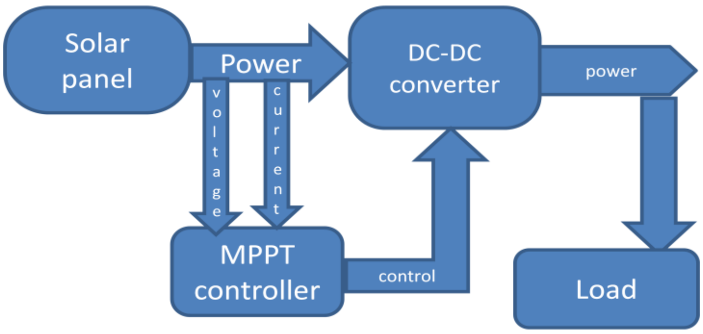


Fig. 6. MPPT scheme

2. MPPT Algorithm

MPPT utilize some type of control circuit or logic to search for the MPP and thus allow the converter circuit to extract maximum power available from a PV. There are various controlling algorithms which are used as tracking algorithms.

3. Types of MPPT Algorithm

They are mainly grouped as indirect method and direct method of tracking. The indirect methods have a particular feature that the MPP is estimated from the measures of PV Voltage, Current, the irradiance and temperatures, by mathematical expressions of numerical approximations [11], [12]. Therefore, the estimations are carried out for a specific PV panel and they do not obtain the maximum power for varying irradiance or temperature. The various methods are grouped as:

a. **Conventional techniques**
    a. Short circuit current
    b. Perturb and observe
    c. Open circuit voltage

b. **Biologically inspired**
    a. Ant colony algorithm
    b. Genetic algorithm
    c. Particle swarm optimization
    d. Firefly

c. **Evolutionary algorithms**
    a. Differential evolution (DE)

4. Particle Swarm Optimization

In general Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a solution with regard to a given measure of quality[13]. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm [14], [15]. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

4.1. Algorithm

Step-1: Choose the number of particles.
Evaluate the objective function.

$$P=V*I$$

Step-2: Find the personal best for each particle.

$$P_{best}$$

Step-3: Find the global best.

$$G_{best}$$

Step-4: Find the velocities of particle

$$v_{ij}^{t+1}=v_{ij}^{t}+c_1r_1[P^t_{best,ij}-X_{ij}]+c_2r_2[G^t_{best,ij}-X_{ij}]$$

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.
$r_1$and r_2 are random numbers from uniform distribution U(0, 1) at time t.

Step-5: Find the new positions of the particles

$$X_i^{t+1}=X_i^{t}+v_i^{t+1}$$

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.

5. Differential Evolution

Differential evolution (DE) is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. DE does not guarantee an optimal solution that ever found. DE is used for multidimensional real-valued functions but does not use the gradient of the problem being optimized, which means DE does not require for the optimization problem to be differentiable as is required by classic optimization methods such as gradient descent and quasi-Newton methods. DE can therefore also be used on optimization problems that are not even continuous, are noisy, change over time, etc. DE optimizes a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimization problem at hand. In this way the optimization problem is treated as a black box that merely provides a measure of quality given a solution and the gradient is, therefore, not needed. A basic variant of the DE algorithm works by having a population for solutions (called agents). These agents are moved around in the search-space by using simple mathematical formulae to combine the positions of existing agents from the population [16]. If the new position of an agent is an improvement it is accepted and forms part of the population, otherwise the new position is simply discarded. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

5.1. Algorithm

Step 1: Initialize the **population**

(R1, R2, R3, R4)

Here, R1 is target.

Step 2: Mutation

Fix a target vector, say for example, R1 and then randomly select three other vectors (individuals) say for example R2, R3, R4 and performs mutation. Mutation is done as follows,

Mutant Vector = R2 + F (R3-R4)

Where, F=Scaling Factor (0, 1)

Step 3: Crossover

Crossover can be done between Target and Mutant. Now that we have a target vector and a mutant vector MV formed from R2, R3 & R4, we need to do a crossover. Consider R1 and MV as two parents and we need a child from these two parents. Crossover is done to determine how much information is to be taken from both the parents. It is controlled by Crossover rate (CR). Every gene/chromosome of the child is determined as follows:

A random number between 0 & 1 is generated, if it is greater than CR, then inherit gene from Target (R1) else from mutant (MV).

Step 4: Selection

Now we have a child and target. Compare the objective function of both, see which is smaller (minimization problem). Select that individual out of the two for the next generation. If the child is better, replace the target (R1) with child.

This procedure will be continued either till the number of generations desired has reached or till we get our desired value.

IV. RESULTS AND DISCUSSIONS

In order to evaluate the performance of PSO method MATLAB coding is done. Mathematical modeling of a single diode model of solar cell is developed and those equations are used in coding. The performance is evaluated for 6S (6-series panels) configurations under partial shaded conditions as shown in Fig.7.

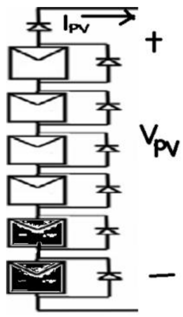


Fig. 7. 1P6S configuration

The MPPT curves for 6S configuration shown in Fig. 7 employing PSO and DE detail in Fig. 8.

1. P-V curve of solar array

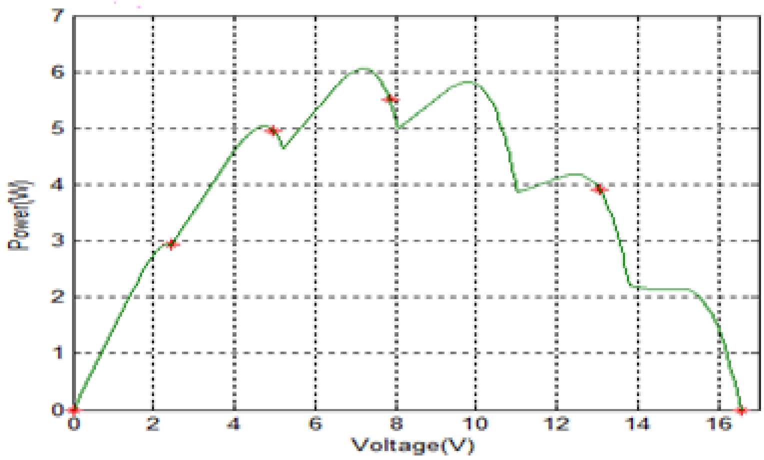


Fig. 8. P-V characteristics of 6S configuration

The P-V characteristics of 6-series configuration under partial shaded conditions are shown in Fig. 8. The red star (*) marks indicate the population in DE algorithm and particles in PSO before tracking the maximum power point.

The multiple peaks in the P-V curve shown in Fig. 8 are due to partial shaded conditions and variations in temperature.

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

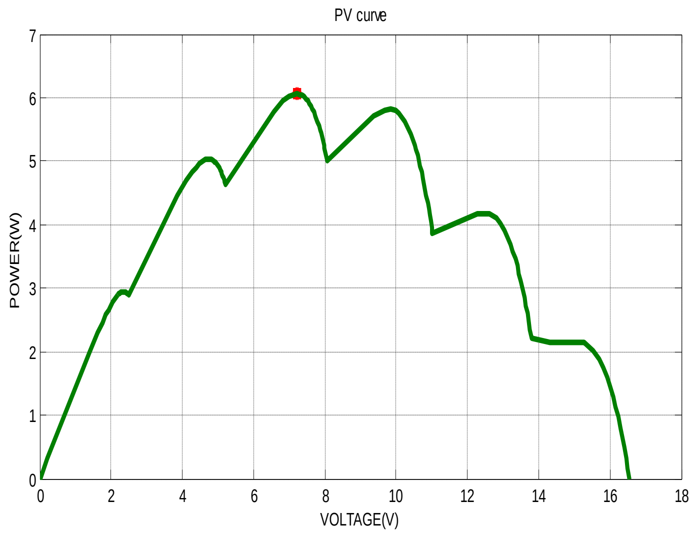
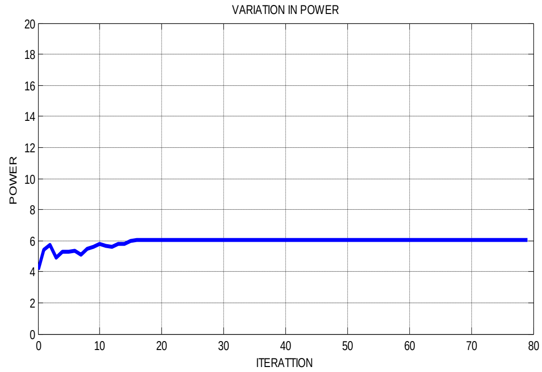


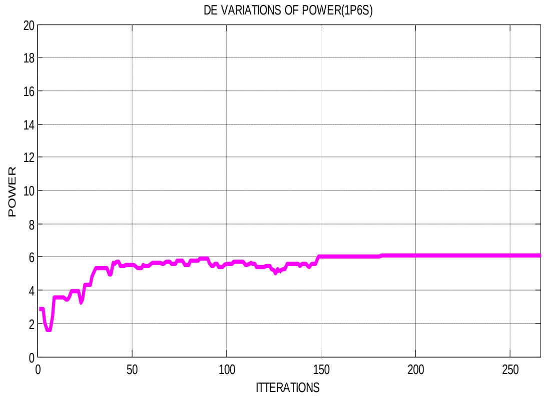
Fig. 9. 1P6S Configuration MPP tracking using PSO and DE

The particles positioned randomly over the P-V curve in Fig. 8 are converged to a single MPP as shown in Fig. 9. In PSO and DE all particles are converted to a global MPP (GMPP).

2. Variations in Output Power (1P6S)



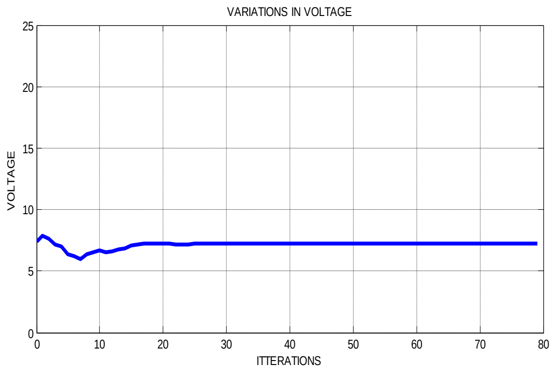
PSO variations



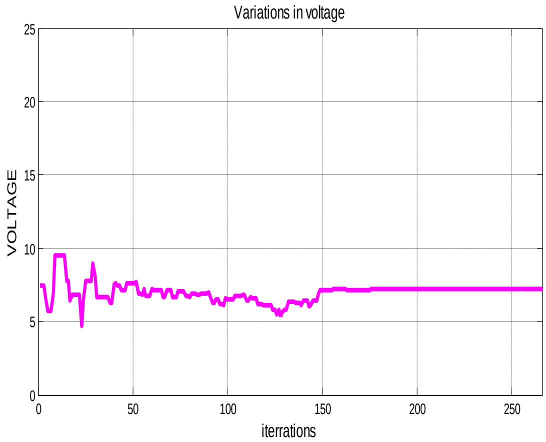
DE Variations

Fig. 10. Power variations at the time of MPPT

3. Variations in Voltage (1P6S)



PSO Variations



DE Variations

Fig. 11.Voltage variations at the time of MPPT

From Fig. 10 and Fig. 11 the voltage and power, oscillations before GMPP tracking are very low in PSO algorithm compared to DE.

Comparison between PSO and DE while tracking MPPT and the number of iterations at which its convergence are shown in Table 1. Comparison between PSO and Firefly with respect to different parameters like speed of convergence, accuracy, etc., is shown in Table 2.

Table 1: Comparison of PSO and DE while tracking MPPT

Method	Iterations	MPPT
Particle swarm optimization	30	6.0536
Differential Evolutionary	75	6.0536

Table 2: Comparison of PSO and DE based on characteristics

Parameter	PSO	DE
Tracking Speed	Fast	Medium
Tracking Accuracy	Accurate	Accurate
Dynamic response	Good	Oscillatory
Power Oscillations	medium	high

V. CONCLUSION

MPPT algorithms track the maximum power point even under partially shaded conditions. The accurate MPPT tracking algorithms like Particle Swarm and differential evolution algorithms are analyzed and comparative study can be performed. From this comparative study PSO is found better than DE. DE takes more time to converge.

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