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A Performance Comparison of PSO based MPPT Algorithms for Various Partial Shading Conditions

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Abstract

Background/Objectives: PV array being shaded partially by buildings, trees or passing clouds is common. This makes the P-V curve of the PV system complex with more than one peak. MPPT algorithm capable of consistently detecting the global peak within a short duration of time is essential. **Methods/Statistical Analysis:** Lately Particle Swarm Optimization (PSO) algorithm has been used for Maximum Power Point (MPP) tracking due to its ability to locate the MPP irrespective of its location in the P-V curve. This paper evaluates and compares the performance of the basic PSO algorithm and the modified PSO algorithms for ten different shading patterns. **Findings:** The basic PSO algorithm is compared with three modified PSO algorithms - PSO algorithm with random numbers eliminated, PSO algorithm with linearly varying constants and PSO algorithm with fixed maximum iterations. The basic PSO algorithm gives good results but random numbers in the algorithm tends to make the convergence time random for the same shading pattern and makes hardware implementation difficult. The PSO algorithm with random numbers eliminated overcomes this disadvantage and is found to give good results. But the convergence time is a little higher and varies with shading pattern. The PSO algorithm with fixed maximum iterations gives good performance with shorter and fixed convergence time. **Application/Improvements:** PSO algorithm with fixed maximum iterations thus improves the responsiveness of the algorithm to rapidly changing patterns of shading.

Keywords: Maximum Power Point Tracking, Partial Shading, Particle Swarm Optimization, PV Array

1. Introduction

There has been a paradigm shift in the area of photovoltaic (PV) power generation due to the increasing demand and the various advantages it offers. PV systems consist of many PV panels connected as an array. The P-V characteristics of a PV cell has a unique maximum power point (MPP) which changes with changing environmental conditions. Hence a maximum power point tracking (MPPT) algorithm is employed to track the MPP. The Perturb and Observe and incremental conductance algorithms perform well under uniform irradiance[1–3]. When the PV array gets partially shaded there are multiple peaks in its P-V characteristics. In such conditions the MPPT algorithm should have the ability to set the operating point at the MPP. Several algorithms for maximum power tracking under partial shading have been reported in the literature[4–8].

Recently many metaheuristic algorithms with global search ability have come to light[9,10]. These algorithms emulate the best features in nature. Particle swarm optimization (PSO) algorithm, which imitates the behavior of swarms, has been used in diverse fields[11–15]. Recently it has been shown to give promising results in MPPT under partial shading[16–19]. The parameter setting method in PSO algorithm is modified[20] taking the hardware limitation into account. A deterministic PSO algorithm which eliminating the random numbers has been proposed[21]. An improved PSO algorithm to reduce the steady state oscillations is proposed[22]. The basic

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PSO algorithm is modified[23] by addition repulsive force between the agents and an adaptive PSO algorithm is also proposed[24].

In this paper the performance of the PSO algorithm is evaluated and compared for different variations. The first variation considered is linearly varying constants in the algorithm instead of fixed constants. The second variation is elimination of random constants and making the algorithm a deterministic one. The third variation is modifying the convergence criterion of the algorithm as maximum iterations. Simulation is done in MATLAB to compare the performance of the algorithms for various shading patterns.

2. Modelling of PV Array under Partial Shading

It is necessary to model a partially shaded PV array to understand its P-V characteristics. Figure 1 shows the single diode model of a PV cell.

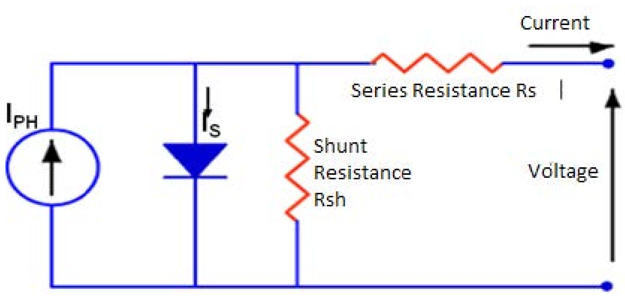

Figure 1. Equivalent circuit of a solar cell.

The PV cell current I is given as[25,26]

$$I = I_{PH} - I_S\left[e^{\left(\frac{q(V+IR_s)}{kT_C A}\right)} - 1\right] - \frac{(V + IR_S)}{R_{SH}} \tag{1}$$

where, I_{PH} is the light generated current, I_S is the dark saturation current, R_{SH} and R_s are the shunt and series resistance respectively, q is the electron charge, T_c is the temperature of the PV cell, A is the ideal factor and k is the Boltzmann's constant. The light generated current I_{PH} is defined as

$$I_{PH} = \left(I_{SC} + K_I(T_C - T_{Ref})\right)\lambda$$

where, λ is the solar irradiation, I_{SC} is the short circuit current of the cell, T_{Ref} is the reference temperature and K_I is the temperature coefficient of short circuit current.

The individual panels in the array are modeled using the above equations. To model a PV array with partial shading, a 5x5 array with a shading pattern shown in Figure 2 is considered. The irradiation level in the unshaded cells is taken as 1 kW/m^2 and that in shaded cells is taken as 0.5 kW/m^2. The array is divided into groups and subgroups based on the number of strings with the same shading pattern and the number of irradiation levels in that group respectively. For the pattern in Figure 2, there are three groups and two subgroups in each group[27].

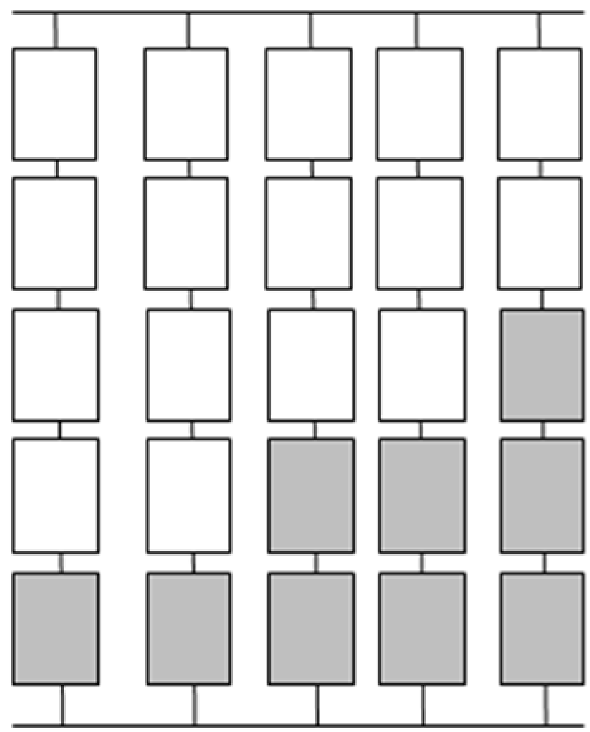

Figure 2. A partially shaded 5x5 array.

Figure 3 shows the characteristics of each group and the final characteristics for the shading pattern in Figure 2.

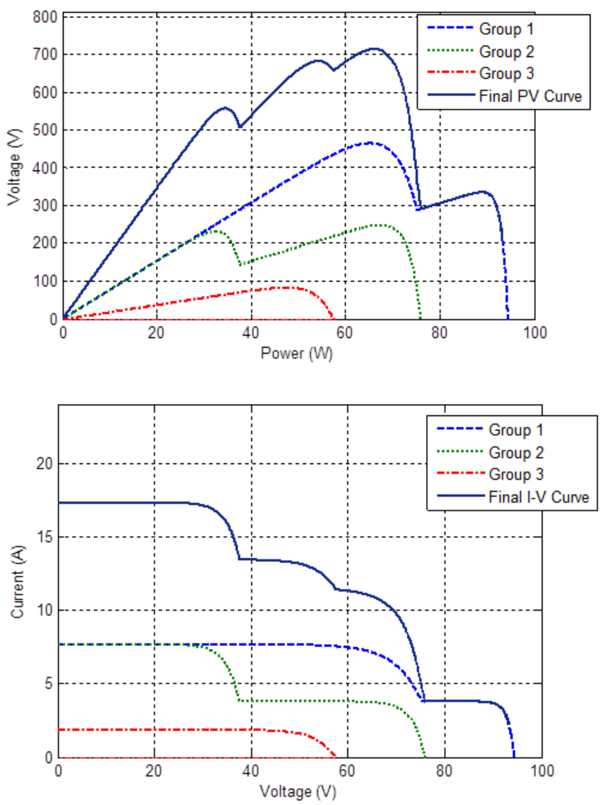

Figure 3. P-V and I-V characteristics of the partially shaded 5x5 array.

3. Basic PSO Algorithm

Particle Swarm Optimization (PSO) is modeled based on swarm behavior. Each particle in the algorithm is attracted toward the global best position G_{best} and the personal best position P_{best}, while at the same time it has a tendency to move randomly.

Let x_i^t and v_i^t be the current position and velocity vector respectively for particle i. The next velocity vector v_i^{t+1} is determined by the following formula

$$v_i^{t+1} = \theta v_i^t + \alpha\epsilon_1(G_{best} - x_i^t) + \beta\epsilon_2(P_{best} - x_i^t) \tag{3}$$

where, ϵ_1 and ϵ_2 are two random constants between 0 and 1, α and β are the learning parameters or acceleration constants and θ is the inertia constant. The next position of the particles is then determined as

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{4}$$

For tracking the MPP the initial position of n particles is defined as

$$x_i^t = [V_1^t, V_2^t, V_3^t \dots . V_n^t] \tag{5}$$

where, V_i is the operating voltage of the PV array. The steps for the implementation of PSO algorithm is as follows.

- The initial particle positions and the algorithm parameters are initialized.
- For each particle position V_i, the power is measured. The global best and personal best positions are identified.
- The next position of the particle is calculated using equations (3) and (4).
- Steps 2 and 3 are repeated for new particle positions till convergence.

4. Variations in PSO Parameters

The various parameters in the PSO algorithm are the acceleration constants α and β, the inertia constant θ, the random constants ϵ_1 and ϵ_2, the convergence criterion. The various modifications to the PSO algorithm considered for evaluating its performance are as follows.

4.1 Linearly varying Parameters θ, α and β

In equation (3), the term θv_i^t ensures the controlled movement of the particle. The value of θ needs to be initialized to a higher value to stabilize the motion of particles. During further iterations the value of θ is reduced to bring down the influence of v_i^t and to ensure faster convergence. Hence θ is defined as a linearly decreasing function whose value continuously decreases as iteration number increases.

$$\theta(j) = \theta_{max} - \frac{j}{j_{max}(\theta_{max} - \theta_{min})} \tag{6}$$

where, j and j_{max} are the current and maximum iteration numbers respectively. θ_{max} and θ_{min} are the upper and lower limits of θ.

Similarly, the value α and β has a profound influence on the direction of particle movement. Higher value of α will cause the particles to move towards the global best whereas higher value of β will increase the particle movement towards their personal best. Hence to enable faster convergence, α is defined as linearly increasing function and β is defined as linearly decreasing function as given below.

$$\alpha(j) = \alpha_{min} + \frac{j}{j_{max}(\alpha_{max} - \alpha_{min})} \tag{7}$$

$$\beta(j) = \beta_{max} - \frac{j}{j_{max}(\beta_{max} - \beta_{min})} \tag{8}$$

where, α_{max} and α_{min} are the upper and lower limits of α and β_{max} and β_{min} are the upper and lower limits of β

4.2 Elimination of Random Constants ϵ_1 and ϵ_2

The basic PSO algorithm as in equation 3 has two random constants ϵ_1 and ϵ_2 which gives the algorithm a random behavior. Hence the number of iterations the algorithm takes to converge to a final solution is not consistent. Also it poses a limitation in hardware implementation. Hence equation 3 is modified by eliminating the random numbers and adding a constraint to the velocity as given below.

$$v_i^{t+1} = \theta v_i^t + \alpha\left(G_{best} - x_i^t\right) + \beta\left(P_{best} - x_i^t\right) \quad (9)$$

$$0 \le v_i^{t+1} \le v_{max}$$

4.3 Convergence Criterion as Maximum Iterations

The basic PSO algorithm is said to converge when the velocity of all the particles are within a threshold value. $v_i^{t+1} < v_{threshold}$ for all values of i.

The algorithm takes a longer time to converge as the particles oscillate around the global best. The tracking time can be reduced by fixing the maximum iteration j_{max} as the condition for convergence.

The performance of the algorithm with the above three modifications is discussed in the next section.

5. Results and Discussion

A 3x3 PV array is simulated to evaluate and compare the modified PSO algorithms and the basic PSO algorithm. The model described in section 2 has been used to generate the P-V characteristics for ten different shading patterns is shown in Figure 4. Patterns 1, 2 and 3 have two peaks in the P-V characteristics. The global peak in pattern 1 is on the right half of the P-V characteristics and that in pattern 2 is on the left half. Pattern 3 has two peaks with the power at the two peaks close to each other. Patterns 4, 5 and 6 and patterns 7, 8, 9, 10 have got three and four peaks respectively in the P-V characteristics with the global peak positioned at different places.

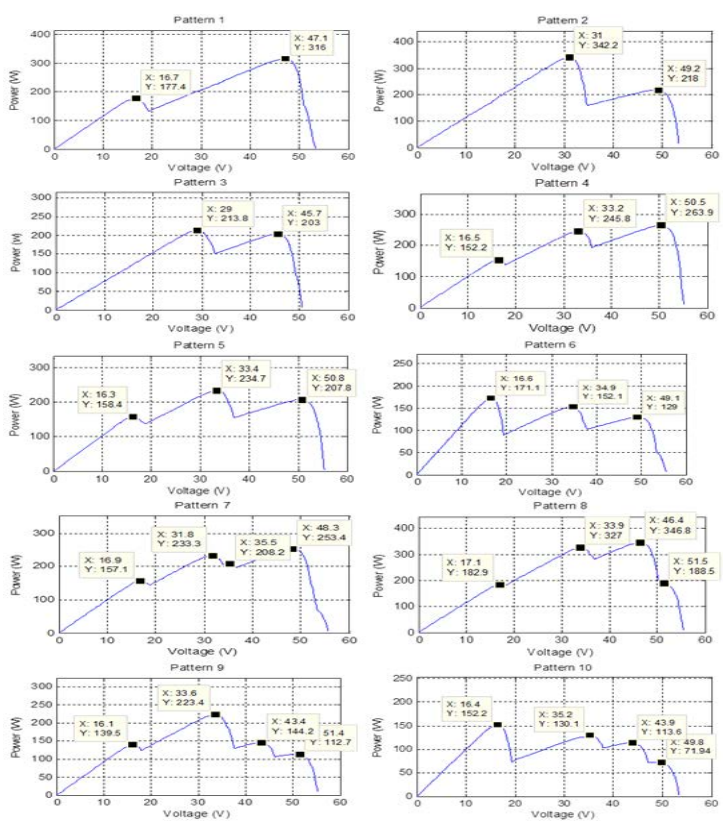

Figure 4. P-V characteristics for a 3x3 array for ten shading patterns.

The values assigned for parameters in basic PSO algorithm, the PSO algorithm with linearly varying constants, PSO algorithm with random numbers eliminated and PSO algorithm with fixed maximum iterations is given in Table 1.

Table 2 shows a comparison between the performances of the four algorithms for the ten shading patterns in Figure 4. The MPP as obtained from the model is also given in the table. For each algorithm the table gives the panel voltage and power for that shading pattern. Figure 5. shows the panel power for the four algorithms. At t=0s shading pattern 1 is applied to the array and at t=4.5s shading pattern 2 is applied. The performance of the four algorithms is discussed.

5.1 Basic PSO algorithm

As seen from Figure 5(a), the algorithm takes around 2.5s to track the MPP for shading pattern 1. As observed from Table 2, it takes 11 to 27 iterations for the algorithm to converge. Also the convergence time and the number of iterations changes for every independent run for the same shading pattern due to the random constants in the algorithm.

5.2 Linearly varying Parameters θ, α and β

With this algorithm the MPP is tracked but requires variation in the parameters listed in Table 1 for different shading patterns. Also as observed from Table 2 the number of iterations that it takes to converge is higher than that of the other algorithm for most of the patterns. As seen from Figure 5(b) it takes around 3.4s to detect the global peak for shading pattern 1 and the oscillations is more.

5.3 Elimination of Random Constants ϵ_1 and ϵ_2

The number of iterations taken with this algorithm varies

Table 1. Parameters for different PSO algorithms

Parameters	Basic PSO		PSO with Linearly Varying Parameters		PSO with Random Numbers Eliminated		PSO with Fixed Maximum Iterations	
1	n	3	n	3	n	3	n	3
2	α	2	α_{min}	1	α	0.9	α	0.9
3	β	1	α_{max}	2.5	β	0.4	β	0.4
4	θ	0.4	β_{min}	0.5	θ	0.4	θ	0.4
5			β_{max}	2.5	v_{max}	4	v_{max}	4
6			θ_{min}	0.1			j_{max}	12
7			θ_{max}	0.9				
			j_{max}	30				

Table 2. Comparison of panel voltage and power with different PSO algorithms

Shading Pattern No.		1	2	3	4	5	6	7	8	9	10
As obtained from the model	MPP Voltage (V)	47.1	31	29	50.5	33.4	16.6	48.3	46.4	33.6	16.4
	MPP Power (W)	316	342.2	213.8	263.9	234.7	171.1	253.4	346.8	223.4	152.2
Using Basic PSO algorithm	Panel Voltage (V)	46.83	31.25	29.33	50.56	33.13	15.34	49	46.17	33.67	15.91
	Power Extracted (W)	315.6	339.8	213.1	263.8	234	167.2	252.7	346	223.2	150.5
	Iterations	18	11	23	27	17	19	18	15	15	27
Using PSO algorithm with Linearly Varying Parameters	Panel Voltage (V)	47.11	30.63	29.44	50.5	33.26	16.22	48.82	46.57	33.67	16.25
	Power Extracted (W)	315.8	340.5	213	263.8	234.2	169.1	253.1	346.5	223.2	150.4
	Iterations	27	20	26	25	26	24	23	27	27	19
Using PSO algorithm with Random Numbers Eliminated	Panel Voltage (V)	47.05	30.12	29.21	50.61	34.13	17.28	48.66	46.73	34.16	16.23
	Power Extracted (W)	315.9	338.6	213.1	263.8	232.9	167.5	253.3	346.3	222.4	150.4
	Iterations	24	22	23	24	25	17	20	27	22	28
Using PSO algorithm with Fixed Maximum Iteration	Panel Voltage (V)	47.05	31.15	28.65	50.34	33.24	16.2	48.66	46.6	33.6	16.39
	Power Extracted (W)	315.9	339.7	212.7	263.8	234.2	169	253.3	346.9	223.2	150.1

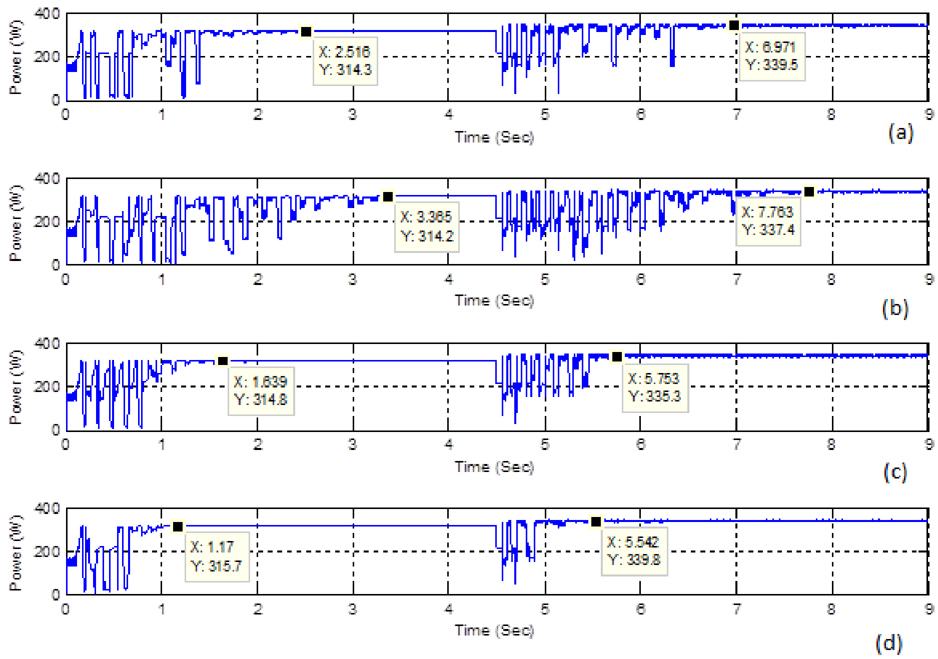

Figure 5. Power extracted from 3x3 PV array with (a) basic PSO algorithm (b) PSO algorithm with linearly varying parameters (c) PSO algorithm with random constants eliminated and (d) PSO algorithm with fixed maximum iterations.

from 17 to 28 for different patterns. The particles usually take a larger time to converge at the MPP as they tend to oscillate around the MPP. As seen from Figure 5 (c), this algorithm takes around 1.6s to track the MPP.

5.4 Convergence Criterion as Maximum Number of Iterations

In this case the maximum iterations was fixed to 12 and as seen from Table 2, the algorithm gives good results for all shading patterns. As seen from Figure 5(d), the MPP is tracked faster as at least one of the particles comes very near to MPP before maximum iterations are reached and the other particles are in the close vicinity. The advantage of this algorithm is the time it takes to converge is shorter and is fixed and hence is capable of detecting fast changes in shading pattern. Same trend can be observed in Figure 5(a)-(d) for shading pattern 2 also.

6. Conclusion

A 3x3 PV array and a boost converter has been modeled and simulated in MATLAB Simulink. The performance of the basic PSO algorithm and its variations have been evaluated and compared for ten different shading patterns. The basic PSO algorithm gives good results but random numbers in the algorithm tends to make the convergence time random for the same shading pattern and makes hardware implementation difficult. The PSO algorithm with random numbers eliminated overcomes this disadvantage and is found to give good results. But the convergence time is a little higher and varies with shading pattern. The PSO algorithm with fixed maximum iterations gives good performance with shorter and fixed convergence time thus improving the responsiveness of the algorithm to rapidly changing shading patterns.

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