

## Effects of PSO Algorithm Parameters on the MPPT System Under Partial Shading Condition

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### ARTICLE INFO

#### Article history:

Received 12 December 2022

Accepted 15 March 2023

#### Keywords:

MPPT

Photovoltaic

PV

PSO parameters

partial shading

solar energy

### ABSTRACT

Maximum Power Point Tracking (MPPT) systems enable photovoltaic (PV) panels to work at their Maximum PowerPoint (MPP). To do this, several algorithms have been developed, including conventional, intelligent, and meta-heuristic. Once a partial shading condition (PSC) occurs, more than one peak emerges in the power-voltage curve of photovoltaic arrays. Under PSCs, conventional algorithms get stuck at the local maximum point and fail to reach the global maximum point. Being an alternative method, Particle Swarm Optimization (PSO) algorithm has been frequently employed for MPPT systems under PSCs. This algorithm has some parameters that affect its performance to reach the global MPP of the PV panel. Therefore, with well-tuned parameters, the effectiveness of the PSO will increase for the different PSCs. In this study, the effects of the cognitive learning and social learning parameters of the PSO algorithm are investigated under different PSCs. To achieve this, an MPPT system, including a boost-type DC-DC converter, is created in MATLAB®/Simulink®. Simulation studies show that the PSO algorithm fails to track global MPP with constant cognitive and social learning parameters under changing partial shading conditions. Furthermore, the results show that these two parameters affect the time to reach the MPP of the PSO algorithm.



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## 1. INTRODUCTION

Being the most widely used energy resource, fossil fuels are rapidly depleted, and it takes a very long time to form them. With the increase in the world population and energy demand, the harmful effects of fossil fuels lead to environmental concerns. For these reasons, renewable energy sources, which are clean and inexhaustible sources that do not pollute the environment, have emerged as an alternative to traditional energy sources in energy production [1]. Recently, renewable energy sources have become vital in meeting the world's energy needs due to the reduction of their costs and easy connection to countries' grids [2]. Among the renewable energy sources, such as wind, hydroelectric and solar energy, the latter is the most used one, as its installation cost is low and configured. Besides the heating system, solar energy is also used to generate electrical power via Photovoltaic (PV) panels. The energy conversion efficiencies of PV modules are around 6-20%, and their power outputs vary depending on environmental impacts such as ambient temperature and irradiation, which can seriously affect PV efficiency [3].

For these reasons, it is essential to keep the efficiency of photovoltaic systems high under all weather conditions. Therefore, obtaining the maximum power from photovoltaic panels is one of the most discussed tasks. When it is done, the nonlinear characteristics of PV panels, variable irradiation levels, and temperature make it difficult to extract maximum power from PV panels. Maximum Power Point Tracking (MPPT) systems ensure power is generated at the maximum level from the PV module [4].

Any situation that prevents the irradiation of the PV panel is defined as partial shading, which emerges in many different situations, such as moving clouds, bird droppings, and surrounding buildings. In partial shading conditions, the productivity and life of the panels are reduced. Additionally, it causes a derivation of the P-V and I-V characteristics of the PV panel. During partial shading, the P-V characteristic of the PV array can have more than one peak in the P-V curve. The maximum power value on the P-V curve is called the global maximum, while the other peaks on the curve are called local maximum points. These peaks vary with irradiation and temperature levels of the PV system. Having more than one peak in the characteristic curve is a major issue for MPPT algorithms.

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Many MPPT algorithms have been developed and applied in the literature to operate PV systems efficiently at the Maximum Power Point (MPP) [5]. Conventional algorithms such as perturbation and observe (P&O) and incremental conductance (INC) methods are simple to implement at low cost and perform well under normal irradiation conditions, which makes them very popular. However, these algorithms can get stuck at the local maximum point instead of reaching the global maximum under partial shading. Artificial intelligence-based and metaheuristic algorithms can be replaced with conventional algorithms to solve multiple MPPs of PV curves. These algorithms are more complex when compared with conventional algorithms. However, their flexible and reliable structure makes them more suitable for partial shading conditions.

Fuzzy logic (FL) controllers and artificial neural network (ANN) are used mostly in MPPT systems as artificial intelligence algorithms. These algorithms successfully track the global maximum point in partial shading conditions; however, they also have some disadvantages, which require comprehensive data sets and calculations. Metaheuristic algorithms have been developed as an alternative to these systems. These algorithms can find the global maximum under partial shading conditions because they inherently have some parameters that allow them to keep searching for the global point of power. For this reason, it achieves better results compared to conventional algorithms.

In the literature, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Cuckoo Optimization Algorithm (COA), Firefly Algorithm (FA), and Grey Wolf Optimizer (GWO) algorithms can be found for the MPPT system. The most widely used metaheuristic algorithm to extract optimal power from the PV source is PSO. This algorithm has a simpler structure than other metaheuristic algorithms and does not require a mathematical model. Moreover, it has high adaptability characteristics and fewer parameters that need to be adjusted. These parameters are quite important, as they directly affect the correct functioning of the algorithm. Therefore, the parameter tuning of the PSO algorithms plays an important role in achieving high efficiency in MPPT systems.

In this study, a comparison of different PSO parameters is made under partial shading conditions. The remainder of this paper is organized in the following manner. In section 2, the PSO algorithm used in the research is explained. In section 3, simulation design and shading conditions are described. In section 4, the comparison of different irradiation and PSO parameters is simulated, and the results are explained. Finally, section 5 explains which PSO parameter is better under which shading condition and recapitulates the research findings.

## 2. PSO for MPPT System

The PSO technique was proposed by Eberhart and Kennedy in 1995, inspired by the behavior of birds, fish, and various flocking animals. Being a metaheuristic approach based on swarm behaviors, the PSO algorithm consists of many particles [6]. These particles continue to search according to the velocity and position vector to reach the best position by transferring their experiences [7-8]. The position and velocity of each particle are updated with the formula given in Equations 1 and 2, respectively, at the end of each iteration of the PSO algorithm.

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (1)$$

$$v_i(k+1) = wv_i(k) + c_1r_1[P_{best} - x_i(k)] + c_2r_2[G_{best} - x_i(k)] \quad (2)$$

where  $k$  is the number of repetitions,  $w$  is the inertia weight,  $i$  is the particle number,  $x_i$  is the best position,  $v_i$  is the velocity,  $P_{best}$  and  $G_{best}$  are the best local and global points and  $c_1$ ,  $c_2$  are the learning coefficients. The  $r_1$  and  $r_2$  values are randomly chosen values between 0 and 1.

As shown in Figure 1, the movement of the particles is affected by the influence of the swarm and the particle memory. Therefore, the number of iterations for the particles to find the best solution varies depending on the problem. Increasing the number of iterations leads to success in finding the best solution; however, it also causes an increase in the calculation time. Moreover, there are some cases where it can fail to solve by increasing the number of iterations, where the PSO parameters have major significance. The effect of the parameters of the PSO algorithm is not only on the success but also on the performance of the algorithm.

The inertia weight ( $w$ ) parameter is used to provide a balance between the global maximum search and the local maximum search. On the other hand, cognitive learning ( $c_1$ ) and social learning ( $c_2$ ) parameters direct the searching direction of the particles. Parameter  $c_1$  directs the particles to move towards the  $P_{best}$  value, and parameter  $c_2$  directs them to the global maximum  $G_{best}$  value [9]. With the higher value of the cognitive and social learning parameters, the searching area of the particle is narrowed, which causes a fast convergence time. Table 1 shows these parameter values used in the literature.

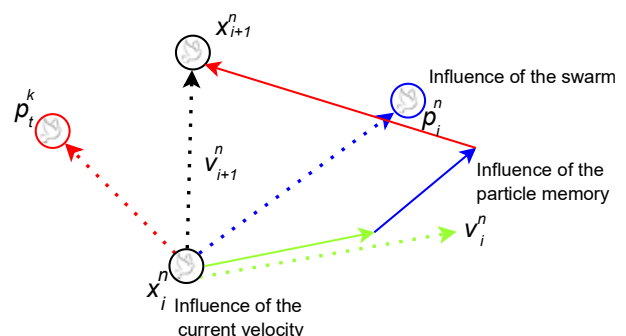


Figure 1. Particle movement in the PSO algorithm

**Table 1.** PSO parameters used in the literature

ref	PSO-Parameters					
	$c_1$		$c_2$		$w$	
	max	min	max	min	max	min
[10]	2	1	2	1	1	0.1
[11]	1.2	1	1.6	1	0.9	0.1
[12]	4	1	4	1	0.8	0.2
[13]	2	1	2	1	1	0.1
[14]	1.5		1.5		0.4	
[15]	1		2		1	
[16]	0.6		0.8		0.5	
[17]	0.012		0.012		0.5	

### 3. The Designed System

To test the effects of cognitive learning and social learning parameters on the PV-MPPT system under partial shading conditions, the designed PV system consists of a PV array, a DC-DC boost converter, resistive load, and a PSO algorithm, is created in the MATLAB<sup>®</sup>/Simulink<sup>®</sup>. The block diagram of the system is given in Figure 2. As seen in Figure 2, to simulate three different partial shading conditions, the irradiance of the PV array is changed. At the output of the PV array, a boost-type DC-DC converter is connected to supply a stable voltage to the resistive load under all partial shading cases. To attain the maximum power of the PV array, the voltage and current of the array are measured and used in the PSO algorithm. The calculated duty ratio ( $d$ ) by the algorithm is used to generate the gate signal of the MOSFET in the converter. The parameters of the employed converter can be found in Table 2.

**Table 2.** The parameters of the DC-DC converter

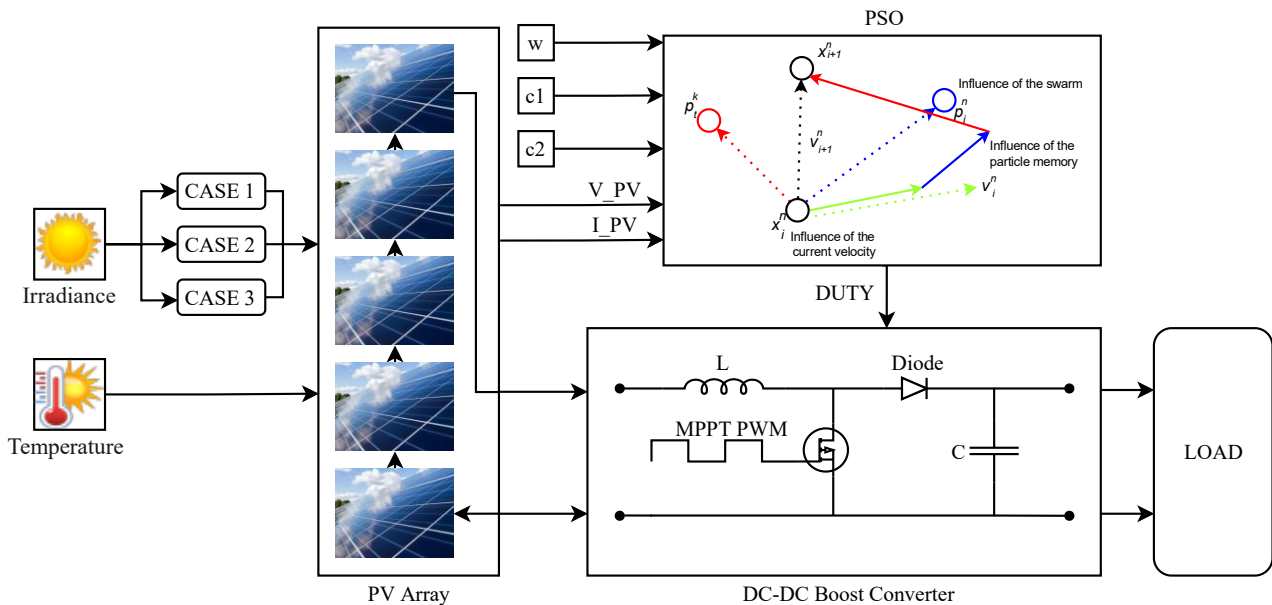
Parameters	Values
Frequency ( $f$ )	5 kHz
Capacitance ( $C$ )	450 $\mu F$
Inductance ( $L$ )	8.8 mH
Resistance ( $R$ )	50 $\Omega$

### 4. Simulation Study

In simulation studies, the PV array is created with 5 Kyocera Solar KD215GX-LFBS panels connected in series. The parameters of the PV panels are given in Table 3. The partial shading condition is simulated with three different cases. In the first case (Case-1), the irradiance of each panel is set to 1000 W/m<sup>2</sup>. In Case-2, three panels have 800 W/m<sup>2</sup> and the others have 300 W/m<sup>2</sup> irradiances. In Case-3, two panels have 800 W/m<sup>2</sup>, the other two have 600 W/m<sup>2</sup>, and the last one has a 300 W/m<sup>2</sup> irradiance level. All cases can be seen in Figure 3. Being a different irradiance level, all cases have different Power-Voltage characteristics, as in Figure 4. It is shown in Figure 4, in Case-2 and Case-3, the characteristics of the PV array have a global MPP and a local MPP. The global and local maximum values for each case are shown in Table 4.

**Table 3.** The parameters of the DC-DC converter

Parameters	Values
Open-circuit voltage, $V_{oc}$	33.2 V
Short circuit current, $I_{sc}$	8.78 A
The voltage at Pmax, $V_{MPP}$	26.6 V
Current at Pmax, $I_{MPP}$	8.09 A
Maximum Power, $P_{MPP}$	215.2 W



**Figure 2.** Simulation circuit diagram of the designed system

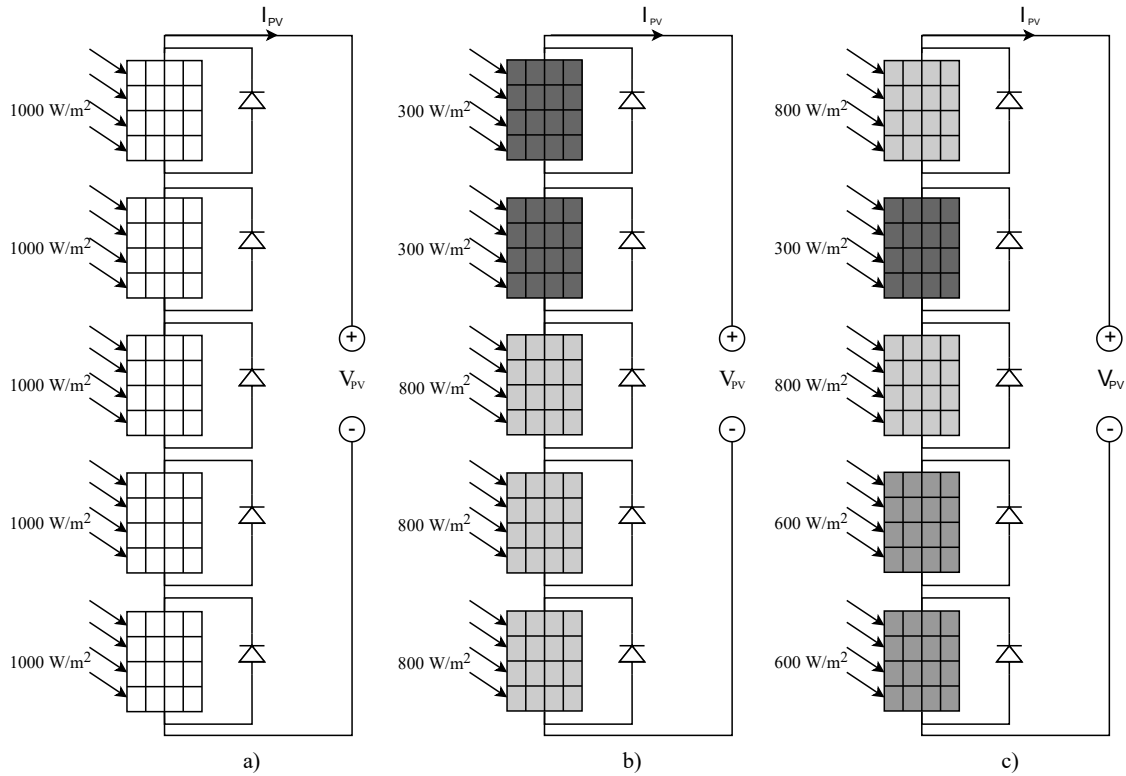


Figure 3. The tested PV array cases a) Case-1 b) Case-2 c) Case-3

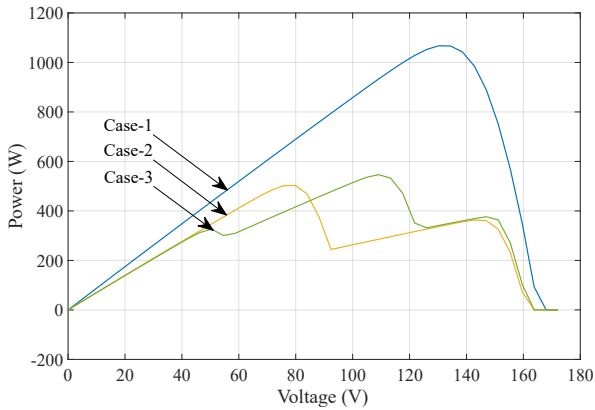


Figure 4. Power-Voltage characteristics of the PV array for the cases

Table 4. Global and local MPP value of each case

	Global Max.	Local Max-1	Local Max-2
Case-1	1067.15 W	N/A	N/A
Case-2	503.26 W	363.214 W	N/A
Case-3	546.577 W	376.544 W	326.683 W

5. Simulation Results

To evaluate the effects of the parameters  $c_1$  and  $c_2$  of the algorithm on system performance, the values of these parameters are changed to 1, 1.5 and 2 under a constant inertia weight. With the changing of the  $c_1$  and  $c_2$  parameters, the output of the PSO algorithm (duty) varied in all cases to keep the system at the maximum power point. In Case-1, where all panels have 1000 W/m<sup>2</sup> irradiances, changing the PSO parameters almost has no impact on the final value of the duty ratio; however, in

Case-2 and Case-3, the parameter change has a major impact on the duty ratio. Therefore, this parameter change for Case-2 and Case-3 was evaluated according to the PV array and the settling time of the duty ratio. In Table 5, the results of the PV system output power, duty ratio and the settling time of the duty are given for the changing cognitive learning and social learning parameters of the PSO algorithm. As seen in the table, although condition  $c_2=1$  made the system fails to find the global or local maximum point, the increase in the parameter  $c_2$  made it easier to find the global MPP of the system for Case-2 and Case-3. Also, it is shown from the output power graph that the output power is highly oscillating in Case-2 when the value of the  $c_2$  parameter is low. As for the settling time, it is highly sensitive to both parameters  $c_1$  and  $c_2$  for all cases.

6. Conclusion

This study presents a comparison of different PSO parameters effects under different partial shading conditions. With the three different partial shading cases, the cognitive and social learning parameters of the PSO algorithm are changed. The simulation results are evaluated according to the duty ratio found by the algorithm, the power output power, and the settling time. The result is that the cognitive and social learning parameters of the PSO algorithm should be tuned to get maximum power from the photovoltaic array and have high accuracy and performance of the MPPT system.

**Table 5.** Simulation result with duty ratio values, output power of the system and settling time @  $w = 0.1$ 

Duty Ratio										
		$c_1 = 1$			$c_1 = 1.5$			$c_1 = 2$		
		Case-1	Case-2	Case-3	Case-1	Case-2	Case-3	Case-1	Case-2	Case-3
$c_2$	1	0.412	0.386	0.376	0.411	0.389	0.376	0.417	0.433	0.296
	1.5	0.417	0.478	0.306	0.407	0.478	0.322	0.409	0.501	0.315
	2	0.417	0.501	0.289	0.414	0.501	0.305	0.407	0.487	0.334
Output Power (W)										
$c_2$	1	1.068.10	419.89	494.36	1067.30	421.32	491.14	1067.40	463.87	541.57
	1.5	1.067.20	505.13	544.95	1065.10	505.21	545.78	1063.50	505.15	546.62
	2	1.068.50	505.56	536.51	1068.30	505.61	544.83	1066.60	504.14	546.37
Settling Time (s)										
$c_2$	1	0.72	0.58	0.56	0.69	1.29	0.54	0.93	1.62	1.26
	1.5	0.42	0.54	0.82	1.35	0.63	1.05	17.48	2.01	1.11
	2	0.96	14.75	1.05	1.38	0.50	14.47	19.76	19.59	7.50

## 7. Conclusion

This study presents a comparison of different PSO parameters effects under different partial shading conditions. With the three different partial shading cases, the cognitive and social learning parameters of the PSO algorithm are changed. The simulation results are evaluated according to the duty ratio found by the algorithm, the power output power, and the settling time. The result is that the cognitive and social learning parameters of the PSO algorithm should be tuned to get maximum power from the photovoltaic array and have high accuracy and performance of the MPPT system.

## Author's Note

Abstract version of this paper was presented at 6th International Conference on Engineering Technologies (ICENTE'22), 17-19 November 2022, Konya, Turkey.

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