# Improved Invasive Weed Optimization Algorithm for Global Maximum Power Point Tracking of PV Array Under Partial Shading Conditions

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# ABSTRACT

Photovoltaic (PV) array under partial shading conditions (PSCs) has several maximum power points (MPPs) on the power-voltage curve of the PV array. These points have a unique global peak (GP) and the others are local peaks (LPs). This paper aims to study an improved version of a heuristic optimization technique namely, invasive weed optimization (IWO), to track the global maximum power point (GMPP) of a PV array which is an important issue. The proposed improved IWO (IIWO) algorithm modifies IWO to speed up the convergence and make the system more efficient and to study the effect of changing input parameters of IIWO on its performance. An overall statistical evaluation of IIWO with standard IWO and particle swarm optimization (PSO) is executed under different shading conditions. The simulation results show that IIWO has faster and better convergence as it can reach the GMPP in less time compared with other techniques.

## **KEYWORDS**

Global Maximum Power Point Tracking, Improved Invasive Weed, Modern Optimization, Partial Shading, PV Systems

## **1. INTRODUCTION**

Photovoltaic systems are a superior technology for generating electricity for electric utility applications, in particular for autonomous applications. The main advancement is to improve the operation of the PV system by utilizing new techniques to extract the maximum power available from the PV array (Gosumbonggot & Fujita, 2019a). The idea of the maximum power point tracker (MPPT) is to track the maximum power available in the PV systems by controlling its terminal voltage. The power voltage characteristic curve of a uniformly distributed irradiance PV array has only one peak which can be tracked easily using conventional MPPT techniques, such as incremental conductance (IC),

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perturb and observe (P&O), hill climbing constant voltage techniques, etc. (Dhimish, 2019; Kihal et al., 2018; Loukriz et al., 2019; Pati & Sahoo, 2019; Ramli & Salam, 2019).

The PV array under partial shading condition (PSC) occurs when the PV modules connected in series and parallel receive different radiations due to varied reasons such as trees, clouds, dust or buildings. Partial Shading Conditions decrease the generated power extremely as the shaded modules where the P-V curve will have a unique global peak and multiple local peaks (Abdel-rahman et al., 2018; Ahmad et al., 2019; Bahrami et al., 2018; El-Helw et al., 2017; Gosumbonggot & Fujita, 2019b; Hosseini et al., 2019; Krishna & Moger, 2019; Necaibia et al., 2019).

The conventional MPPT techniques cannot track the global peak, and due to this reason, these techniques will not be researched anymore in this field. Meta-heuristic optimization techniques are able to track the global peak in case of Partial Shading Conditions. In MPPT many meta-heuristic optimization techniques have been used, such as Genetic algorithm (GA) (Alshafeey & Csaba, 2019; Khan et al., 2018; Venkateswari & Sreejith, 2019), Particle Swarm Optimization (PSO) (Alshareef et al., 2019; Džakula et al., 2019; Eltamaly et al., 2019; Ibrahim, 2019; Ma et al., 2019; Naga Durga et al., 2019; Tatsuhiko Mitsuya & Alvarenga de Moura Meneses, 2019; Trivedi et al., 2019; Valladolid et al., 2019; Veerapen et al., 2019), Differential Evolution (DE) (Narayanam et al., 2019; Somashree Pathy et al., 2019; Zijing et al., 2018), Ant Colony Optimization (ACO) (Priyadarshi et al., 2019), Harmony Search Algorithm (HSA) (Aarich et al., 2016; Othman, 2017), Artificial Fish Swarm Algorithm (AFSA) (Mao et al., 2016), Artificial Bee Colony (ABC) (Narayanam et al., 2019), Shuffled Frog Leaping Algorithm (SFLA) (Kaveh et al., 2019), The Cat Optimization Algorithm (COA) (Belhachat & Larbes, 2019), Moth Flame Optimization (MFO) (Belhachat & Larbes, 2019), Firefly Algorithm (FA) (Kasdirin, 2017; Panda et al., 2018), Flower Pollination Algorithm (FPA) (Subha & Himavathi, 2017) and Bacteria Foraging Optimization Algorithm (BFOA) (Sharma & Kumar, 2018).

IWO technique is previously applied for many applications of power system and proved its superiority (Shao et al., 2019; Yue & Zhang, 2019). Where it has many merits such as: it shows efficient exploration, exploitation, and diversity. It takes an exceptional place for solving continuous optimization problems. Its robustness, adaptation and randomness which make it more effective for global search. It has a simple structure containing few parameters to adjust and is easy to implement.

In a previous study, IWO is proved its superiority over eight compared optimization techniques (Zaher & Mohamed, 2020). In this paper, the PV array efficiency is improved using IWO technique for extracting the maximum power under PSCs. The IWO technique is improved by modifying the termination condition of the weed population to be faster and more efficient. The effect of changing the algorithm parameters of IIWO on its performance have been investigated.

An overall statistical evaluation of IIWO, with standard IWO and (PSO) is executed under different shading conditions. Seven statistical metrics are used for the evaluation like metrics including mean absolute error, geometric mean, arithmetic mean, the root mean square error, standard deviation, efficiency, and iteration saving percentage. For the comparison, several different irradiance models are considered. Furthermore, every technique has been tested for 40 runs to verify the performance of each one.

The rest of the paper is organized as follows; Section 2 gives a brief summary about system description under Partial Shading Conditions. Section 3 explains modeling of PV array under Partial Shading Conditions. Section 4 explains the standard IWO, the proposed IIWO and PSO based global MPPT, while the Fifth Section introduces Comparative study between the proposed technique and the comparative techniques. Simulation results and discussion are presented in Section 6 and finally the conclusion is illustrated in Section 7.

## 1.1 Modeling of PV Array Under Partial Shading

A PV array consisting of four modules connected in series in different cases is shown in Figure 1. Figure 1(a) shows unshaded PV array on the other side Figure 1(b, c, d) shows a partially shaded PV array in different scenarios. The equivalent circuit of PV array is shown in Figure 2.

#### Figure 1. (a) Unshaded PV array, (b, c, d) Shaded PV array



Figure 2. Equivalent circuit of PV array



The optimal value from the PV array under partial shading will be reached by maximizing the expected power from the PV system by using the following objective function (Belhachat & Larbes, 2019):

Maximize: 
$$P_{pv,array} = I_{pv,array} * V_{pv,array}$$
 (1)

where:

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$$\begin{split} I_{pv,array} &= I_{ph,array} - I_{o,array} * \left[ \exp \left( \frac{q * \left( V_{pv,array} + I_{pv,array} * R_{s,array} \right)}{N_s * A * K * T} \right) - 1 \right] \\ &- \frac{V_{pv,array} + R_s * I_{pv,array}}{R_{sh,array}} \end{split}$$
(2)

$$I_{ph,array} = \left(I_{sc}\left(T\right)_{array} + K_{i}*\left(T_{ak} - T_{rk}\right)\right)*\frac{G}{G_{STC}}$$
(3)

$$\begin{split} I_{o,array} &= \left[ I_{sc} \left( T \right) - \frac{V_{oc} \left( T \right)_{array} - I_{sc} \left( T \right)_{array} * R_{s,array}}{R_{sh,array}} \right] \\ &* \exp \left( - \frac{V_{oc} \left( T \right)_{array}}{A * N_s * V_t} \right) \end{split}$$
(4)

where the parameters:

$$I_{\it ph,array}, I_{\it o,array}, V_{\it PV,array}, R_{\it s,array}, ~and~R_{\it sh,array}$$

may be expressed as:

$$\begin{split} I_{ph,array} &= I_{ph} * N_{par}, \ and \ I_{o.array} = I_{o} * N_{par}, \\ V_{oc,array}(T) &= V_{oc}(T) * N_{scr}, \\ V_{oc}(T,G) &= V_{oc} + k_{v} \left(T - T_{stc}\right) + N_{s} A(T) V_{t} \ln\left(\frac{G}{G_{stc}}\right) \\ I_{sc}(T) &= I_{sc} + K_{i} * \left(T_{ak} - T_{rk}\right), \\ R_{s,array} &= R_{s} * \left(N_{ser} / N_{par}\right), \ and \ R_{sh,array} = R_{sh} * \left(N_{ser} / N_{par}\right) \\ \end{split}$$

where, N<sub>ser</sub>, N<sub>par</sub>, and N<sub>s</sub> are number of series modules, parallel modules, and number of cells in one module respectively. A; Ideality factor of diode, T,  $T_{stc}$  the temperature of the PV array under normal operation and at standard test condition. G,  $G_{stc}$ : irradiance level under normal operation and at standard test condition, W/m<sup>2</sup>. K: Boltzmann's constant, 1.3805\*10<sup>-23</sup>J/K. q: Electron charge, 1.6\*10<sup>-19</sup>c.

)

- $R_{s}, R_{sh}$ : Panel series resistance and parallel (shunt) resistance.
- $V_{oc}$ : Open circuit voltage. •
- $T_{ak}^{oc}$ ,  $T_{rk}^{i}$ : Actual and Relative temperature in Kelvin.  $K_{r}^{i}$ : Temperature coefficient of  $V_{oc}$ .  $K_{i}^{i}$ : Temperature coefficient of  $I_{sc}^{i}$ . •
- •
- •

- *I*<sub>s</sub>: Short circuit current.
- $V_{i}^{*}$ : The junction thermal voltage,  $(K^{*}T_{a})/q$ .

Under PSC, the P–V characteristic contains one global peak and many Local peaks as shown in Figure 3.

Figure 3 shows that the position and the value of the global peak change according to the PSC change and it may occur at the beginning, at the middle, or at the end. Therefore, this paper focused on the meta-heuristic GMPPT techniques to track the dynamic global peak under variant PSC. The input variables of the GMPPT are the PV output voltage and current while the output is the global PV power (Paula dos Santos et al., 2019)-(Mastromauro et al., 2012).

# 2. META-HEURISTIC TECHNIQUES USED AS GMPPT

## 2.1 Modeling of Standard IWO Technique

Invasive Weed Optimization technique was inspired by Mehrabian and Lucas (2006) for solving optimization problems, (Sridhar et al., 2019)-(Pradhan et al., 2020). The technique imitates distribution process and the ecological colonization of weeds. Weeds are adaptive to environmental changes and robust. As the algorithm is derivative free, it has high convergence. IWO is summarized by the following steps (Sridhar et al., 2019):

- 1. **Primary population initialization:** Define maximum (S<sub>max</sub>) and minimum (S<sub>min</sub>) number of seeds in the colony and distributed randomly the finite number (N) of seeds in the solution space.
- 2. Reproduction and ranking: Each distributed seed grows to a flowering weed plant and holds a fitness indicating its strength to survive in the competition. The plants are classified according to their fitness, i.e. Plants are ranked and allowed to produce new seeds depending on their fitness and lowest (F<sub>lowest</sub>) fitness and highest (F<sub>lighest</sub>) fitness of the colony. In each iteration, the number of seeds produced by a plant varies linearly concerning the fitness of the respective plant which is given by the expression (Zaher & Mohamed, 2020):

Number of seeds = 
$$\frac{f - f_{lowest}}{f_{highest} - f_{lowest}} \left( s_{\max} - s_{\min} \right) + s_{\min}$$
(5)



#### Figure 3. P–V curves under No PSC and different PSC cases

where f is the fitness of the current weed.  $f_{lowest}$  and  $f_{highest}$  respectively represent the lowest fitness and the highest of the current population.  $s_{min}$  and  $s_{max}$  respectively represent the least and the maximum value of a weed.

3. **Spectral Spread:** The seeds produced from reproduction stage are randomly spread in the search space with a mean at parent plant position and standard deviation (SD). The standard deviation (SD),  $\sigma$ , is usually defined iteration wise and expressed by (Sridhar et al., 2019):

$$\sigma_{t} = \left(\frac{t_{M} - t}{T}\right)^{n} \times \left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{final}$$
(6)

where  $\sigma_t$  is the standard deviation at the current iteration t, and  $t_M$  is the maximum number of iterations, and n is a nonlinear modulation index having the value in the range of 2 to 3. The standard deviation  $\sigma$  of random function goes on reducing from previously defined initial value  $\sigma_{init}$  to final value  $\sigma_{final}$  with the increase of number of iterations.

- 4. **Competitive exception:** If the numbers of weeds exceed the maximum numbers of weeds in the colony (P<sub>max</sub>), the weed with worst fitness is removed from the colony so that a constant number of herbs are rested in the colony.
- 5. **Termination condition:** This process continues until the maximum number of iterations is reached.

Figure 4 shows the searching mechanism flowchart that is done by standard IWO for the purpose of MPPT tracking (Zaher & Mohamed, 2020).

# 2.2 Modeling Improved IWO Technique

In any classical optimization problem, the optimization technique is expected not only to find the optimal solution but also find it as fast as possible. In traditional IWO, the termination condition is achieved when the maximum number of iterations is reached. In IIWO, the termination condition is improved by the following condition:

$$t < T \tag{7}$$

$$\sum F_i \sim = length(F_i) \tag{8}$$

where  $F_i$  is fitness of the current weed and as mentioned before, t is the current iteration, and T is the maximum number of iterations. If the current iteration less than the maximum number of iterations and the fitness summation of the reproduced weeds is not equal the length of the fitness vector, convergence is judged as satisfied. Figure 5 shows the searching mechanism flowchart that is done by IIWO for the purpose of MPPT tracking.

# 2.3 Modeling of PSO Technique

Particle Swarm Optimization developed by Kennedy & Eberhart (1995), (Eltamaly et al., 2019). PSO technique is taken from the behavior of bird flock or from fish school. It uses some of particles, which frame a swarm travelling alongside the search space in order to find the best solution. PSO

#### Figure 4. Standard IWO algorithm



technique explores a specific area named solution space, each position in this area has potential degree for solving of problems. At first stage, several particles are randomly spread in the search area and the initial locations for every particle are saved as the best position of it ( $P_{best}$ ). The best positions between all of particles are saved as the global best ( $G_{best}$ ). At next stage, a velocity vector is updated for all particles and then the objective functions are calculated and compared with ( $P_{best}$ ) and ( $G_{best}$ ) to be updated. This process is repeated until reaching the  $G_{best}$ .

The following two equations can be used to distinguish the PSO technique (Ibrahim, 2019):

$$v_i^{k+1} = wv_i^k + c_1 r_1 [P_{best} - x_i^k] + c_2 r_2 [G_{best} - x_i^k]$$
(9)

#### Figure 5. IIWO algorithm



$$x_i^{k+1} = x_i^k + v_i^{k+1} (10)$$

where  $x_i^k$  is the position of the particle i, and  $v_i^k$  represents its velocity. The iteration number is denoted by k, and w is the inertia weight.  $r_1$  and  $r_2$  are random values having the value in the range of 0 to 1., and the cognitive and social coefficients are described by  $c_1$  and  $c_2$ , respectively.  $P_{best}$  is used to store the best experience by the particle itself, and the best position of all particles is kept in  $G_{best}$ . Figure 6 shows the searching mechanism flowchart that is done by PSO for the purpose of MPPT tracking.

#### Figure 6. PSO flowchart



### **3. COMPARATIVE STUDY**

The overall comparison through a comprehensive statistical analysis between IWO and other techniques like PSO, DE, HSA, Bat, SCA, WDO, CS and GA under different scenarios of shading condition indicates the superiority of IWO over these techniques (Zaher & Mohamed, 2020). In this paper, the improved IWO technique for MPPT of PV array under Partial Shading Conditions will be suggested to improve the convergence to make the system faster and more efficient. Hence, the proposed technique is compared with traditional IWO and PSO technique which is evolutionary algorithm. The effect of changing input parameters of IIWO on its performance have been investigated.

MATLAB R2018b program is used in coding the proposed and comparative techniques. The computer specifications are Processor: Intel ® Core <sup>TM</sup> i5 -5200U CPU @ 2.20 GHZ and Installed Memory (RAM): 8.00 GB.

The validation of the proposed IIWO technique was carried out by using CENTSYS 250W solar module. The specifications of this module are given in Table 1. A comparative study was performed with others efficient techniques such as conventional IWO and PSO under different Partial Shading Conditions.

Table 1. PV module specifications

Туре	CENTSYS 250W solar panel				
Maximum power, P <sub>max</sub>	250 W				
Open circuit voltage, V <sub>oc</sub>	37.8 V				
Voltage at maximum power point	31.5 V				
Short circuit current, <i>I</i> <sub>sc</sub>	8.7 A				
Current at maximum power point	7.94 A				
Short circuit current temperature coefficient, $K_i$	0.06 A/°C				
Open circuit voltage temperature coefficient, $K_{v}$	-0.34 V/°C				
Reference temperature, $T_{ref}$	25 °C				

It observed from the prior studies that most researches had considered just a single radiation model or few models of PSC to check the strength of the optimization technique for tracking the global MPP without an extensive statistical analysis (i.e. only one trial for each technique). This in turns encouraged the authors to put in a global arbitrage via an extensive statistical analysis of different global MPPT techniques based on modern optimization algorithms. In this study, every technique is verified for 40 trial (runs) in order to evaluate and validate the performance of each one.

The worthy seven statistical metrics for this evaluation are; Geometric mean error (GM): which is an important parameter in our comparison and considered the best average for the construction of index numbers as it is suitable for measuring the relative changes and it gives more weights to the small values and less weights to the large values (Mehmet et al., 2019). The others statistical metrics are: the arithmetic mean (AM), the root mean square error (RMSE), the mean absolute error (MAE), standard deviation (SD), efficiency, and iteration saving percentage (Li et al., 2020; Mehmet et al., 2019):

$$\begin{split} GM &= \sqrt[n_r]{\prod_{i=1}^{n_r} P_{pve,i}} \\ MAE &= \frac{\sum\limits_{i=1}^{n_r} \left| P_{pve,i} - P_{pvt} \right|}{n_r} \\ AM &= \frac{\sum\limits_{i=1}^{n_r} P_{pve,i}}{n_r} \\ SD &= \sqrt{\frac{\sum\limits_{i=1}^{n_r} \left| AM - P_{pve,i} \right|^2}{n_r}} \\ RMSE &= \sqrt{\frac{\sum\limits_{i=1}^{n_r} \left| P_{pve,i} - P_{pvt} \right|^2}{n_r}} \end{split}$$

$$Efficiency = \frac{GM}{P_{pvt}} * 100$$

 $\textit{Iteration Saving percentage} = \frac{\textit{iter}_{\text{max}} - \textit{iter}_{\text{end}}}{\textit{iter}_{\text{max}}} * 100$ 

where:

- $P_{pve,i}$ : Current value of obtained PV power by optimizer for each run.
- $P_{pve,i}$ : Average obtained PV power by optimizer.
- $P_{pvt}$ : Theoretical global PV power.
- *n*: Represents the number of the model runs.

In this study, there are two partial shading scenarios: the 1<sup>st</sup> the solar irradiance level of the five PV modules is 1000, 300, 600, 200, 400 W/m<sup>2</sup> and the 2<sup>nd</sup> the solar irradiance level of the six PV modules is 400, 500, 600, 700, 800, 950 as shown in Figure 7. In this study, the effect of changing of input parameters of IWO technique: the modulation index (n) and initial value of standard deviation ( $\sigma_{init}$ ) are concerned.

The considered PV system in the two cases study is shown in Figure 8. It contains PV module, boost converter and resistive load. The values of Boost converter components used for the simulations are 1mH,  $47\mu$ F and  $47\mu$ F for the input inductance, input capacitor and output capacitor respectively. The switching frequency of the boost converters is 10 kHz. The resistive load equal 20 $\Omega$ .

Each technique in the system is executed individually to output the duty cycle which is converted to pulses by the pulse width modulation block. The boost converter deals with the pulses to feed the resistive load.

## 4. SIMULATION RESULTS AND DISCUSSION

To estimate and analyze the performance of the presented algorithms, the algorithms parameters are set to be; population size = 15, maximum number of iterations=80, and no. of executions for each algorithm (40 trials, i.e. 40 run). Figure9 show the effect of changing iter<sub>max</sub> on PSO and IIWO with the detailed performance of each technique for the different scenarios. Figure 10 show the iteration saving percentage of IIWO and PSO to reach to GMPP for the different scenarios. Figure 11 and Figure 12 show the effect of changing the input parameters of the IIWO technique: the modulation





Figure 7. The P-V curves of the studied PV array with different shading scenarios

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Figure 8. Schematic diagram for PV system



index (n) and initial value of standard deviation ( $\sigma_{init}$ ) by 4 times of the fixed value and ¼ of the fixed value. Figure 13 shows the convergence curves for the two scenarios. Table 2 and Table 3 show the detailed performance of IIWO after increasing the value n &  $\sigma_{init}$  by four times. Table 4 shows the statistical measured performance evaluation for each technique and average number of iter<sub>end</sub> to GMPP for each technique under the studied shadow scenarios for iter<sub>max</sub>=80.

Figure 9 shows that by increasing the value of iter $_{max}$ , the results of PSO and IIWO is improved and IIWO is characterized by accurate results in less number of iterations compared by other comparative



Figure 9. Effect of iter<sub>max</sub> change on the performance for 1<sup>st</sup> and 2<sup>nd</sup> shading scenarios

techniques. Figure 10 shows that the iteration saving percentage of IIWO to reach to GMPP is bigger than that of PSO which indicating the superiority of IIWO technique.

Figure 11 and Figure 12 show that the increase of n &  $\sigma_{init}$  by four times has a great effect on the results. IIWO after increasing the value n &  $\sigma_{init}$  by four times gives more accurate results as shown in Table 2 and Table 3. Figure 13 shows that the convergence curves for the 1<sup>st</sup> and 2<sup>nd</sup> scenarios in which IIWO\_UPC reach to GMPP faster than the comparative techniques.

Table 4 shows that, IIWO\_UPC has higher success rate of (99.99%) as IWO but, IIWO\_UPC is characterized by reaching to the global peak in less number of iter<sub>end</sub>. It is obvious from the results that IIWO has high GM compared to PSO. IIWO\_UPC has better results for MAE, RMSE and SD compared to PSO. IIWO\_UPC has the lowest time of convergence compared to the other comparative techniques.

#### Figure 10. Iteration saving percentage to reach to GMPP for 1st and 2nd shading scenarios







Figure 12. Effect of IIWO parameters on the performance for 2<sup>nd</sup> shading scenario





First Scenario											
IIWO_UPC											
Runs         Power         Iter <sub>end</sub> Runs         Power         Iter <sub>end</sub> Runs         Power         Iter <sub>end</sub> Runs         Power         Iter										Iter <sub>end</sub>	
1	321.7	3	11	321.7	5	21	321.7	3	31	321.7	3
2	321.7	3	12	321.7	3	22	321.7	3	32	321.7	3
3	321.7	3	13	321.7	3	23	321.7	3	33	321.7	3
4	321.7	3	14	321.7	3	24	321.7	3	34	321.7	3
5	321.7	3	15	321.7	3	25	321.7	3	35	321.7	3
6	321.7	3	16	321.7	3	26	321.7	3	36	321.7	3
7	321.7	3	17	321.7	3	27	321.7	3	37	321.7	3
8	321.7	3	18	321.7	4	28	321.7	3	38	321.7	3
9	321.7	3	19	321.7	4	29	321.7	3	39	321.7	3
10	321.7	3	20	321.7	3	30	321.7	3	40	321.7	3

#### Table 2. The performance of IIWO\_UPC for 1st shading scenario

#### Table 3. The performance of IIWO\_UPC for 2<sup>nd</sup> shading scenario

Second Scenario											
IIWO_UPC											
Runs	Power	Iter <sub>end</sub>	Runs	Power	Iter <sub>end</sub>	Runs	Power	Iter <sub>end</sub>	Runs	Power	Iter <sub>end</sub>
1	664.8	4	11	664.8	3	21	664.8	3	31	664.8	5
2	664.8	3	12	664.8	7	22	664.8	3	32	664.8	7
3	664.8	4	13	664.8	4	23	664.8	4	33	664.8	4
4	664.8	4	14	664.8	3	24	664.8	4	34	664.8	3
5	664.8	12	15	664.8	3	25	664.8	4	35	664.8	6
6	664.8	3	16	664.8	5	26	664.8	4	36	664.8	3
7	664.8	3	17	664.8	5	27	664.8	12	37	664.8	3
8	664.8	5	18	664.8	7	28	664.8	3	38	664.8	6
9	664.8	3	19	664.8	4	29	664.8	3	39	664.8	3
10	664.8	5	20	664.8	7	30	664.8	4	40	664.8	5

## 5. CONCLUSION

This paper addressed the feasibility of application of the IWO algorithm for global maximum power point tracking of PV array under partial shading conditions. The slow convergence characteristic of standard IWO has been improved by modifying the convergence condition, resulting in IIWO in which reaching to the global peak in less number of iterations. However, to achieve success goal in problems relies too much on its initial parameters and these parameters should be wisely selected based on the problem to be solved. This is in turn encourage us to





study the performance after changing the input parameters and we found that it is a must to optimize the input parameters for better results. The simulation results show that the IIWO has a faster and better convergence rate indeed compared to IWO and as a result, better optimal results are found. The results of IWO and IIWO is compared to PSO. Also, in this paper studying the effect of changing the input parameters of IIWO: modulation index (n) and the initial value of step length ( $\sigma_{initial}$ ) is concerned. It is noticed that the IIWO with changing input parameters is superior to IWO, IIWO and PSO.

Algorithm		PSO	IWO		IIWO		IIWO_UPC	
GM								
1 <sup>st</sup> Scenario	321.34			321.7	321.42		321.7	
2 <sup>nd</sup> Scenario	664.63			664.8	664.78	664.8		
AM								
1 <sup>st</sup> Scenario	321.11			321.7	321.42		321.7	
2 <sup>nd</sup> Scenario	664.63			664.8	664.78	664.8		
RMSE								
1 <sup>st</sup> Scenario	1.05			6.65*10-7	1.56	8.8*10-8		
2 <sup>nd</sup> Scenario	0.36			7.73*10-6	0.04	3.58*10 <sup>-8</sup>		
Average	0.705			4.2*10-6	0.8		6.19*10 <sup>-8</sup>	
MAE								
1 <sup>st</sup> Scenario	0.29			2.05*10-7	0.22	0.22		
2 <sup>nd</sup> Scenario	0.13			1.09*10-6	0.01	1.09*10-6		
Average	0.21			6.48*10-7	0.12		3.24*10-7	
SD								
1st Scenario	1.0042			2.54*10-13	1.54		2.54*10-13	
2 <sup>nd</sup> Scenario	0.33			7.63*10-6	0.04		7.63*10-6	
Average	0.67			3.82*10-6	0.79		3.82*10-6	
Efficiency								
1 <sup>st</sup> Scenario	99.82%			99.99%	99.91%		99.99%	
2 <sup>nd</sup> Scenario	99.97%			99.99%	99.99%		99.99%	
Average	99.9%			99.99%	99.95%	99.99%		
Average Number of iter <sub>end</sub> to GMPP								
1 <sup>st</sup> scenario	66			80	5		3	
2 <sup>nd</sup> scenario	63			80	8	5		
Average iteration saving percentage (%)								
1 <sup>st</sup> scenario	1 <sup>st</sup> scenario 16.9			0	93.7		96.1	
2 <sup>nd</sup> scenario	21.25			0	89.5		94.3	
Time of Conv	ergence (s)							
1 <sup>st</sup> scenario		0.0099	0.4056			0.0077	0.0044	
2 <sup>nd</sup> scenario		0.0512	0.5384			0.0375	0.0102	

Table 4. Evaluation of statistical performance of different global MPPT for iter\_max=80

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## **APPENDIX**

#### Table 5. Nomenclature

ABC	Artificial Bee Colony	IWO	Invasive Weed Optimization
AFSA	Artificial Fish Swarm Algorithm	MAE	Mean Absolute Error
AM	Arithmetic Mean	MFO	Moth Flame Optimization
BFOA	Bacteria Foraging Optimization Algorithm	MPPs	Maximum Power Points
СОА	Cat Optimization Algorithm	MPPT	Maximum Power Point Tracking
DE	Differential Evolution	P&O	Perturb & Observe
FPA	Flower Pollination Algorithm	PSO	Particle Swarm Algorithm
GA	Genetic Algorithm	PV	Photovoltaic
GM	Geometric Mean	RMSE	Root Mean Square Error
GMPP	Global Maximum Power Point	SD	Standard Deviation
GMPPT	Global Maximum Power Point Tracking	SFLA	Shuffled Frog Leaping Algorithm
HAS	Harmony Search Algorithm		
IC	Incremental Conductance		
ПЖО	Improved Invasive Weed Optimization	]	
IIWO_UPC	IIWO under parameters change	]	

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