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Improved Grey Wolf assists MPPT Approach for Solar Photovoltaic System under Partially Shaded and Gradually Atmospheric Changing Condition

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Abstract – *Solar energy seems to be most sustainable way which can conserve the environment from negative impacts caused by electrical power generation from fossil fuels. For achieving the utmost power in output, photovoltaic (PV) array should operate on its optimal power point. When PV arrays are subjected to a partial shading state, several local peaks are experienced by power-voltage performance curve of PV system which significantly trims down the efficiency of complete system. So it becomes vital to locate the global peak of PV system for harvesting the upper limit power for better performance. This paper presents an improved grey wolf optimization (IGWO) technique which employs the concepts of parallel grey wolf optimization and opposition-based learning to trace the GMPP under partial shading situation and also figure out the performance for gradually varying with irradiance and temperature for PV system. This IGWO-based MPPT scheme has been implemented in MATLAB simulation environment. The outcome of the simulation is verified by the past-proposed MPPT techniques namely perturb and observe (P&O) and particle swarm optimization (PSO). It has been found from the simulation results that the performance of the suggested IGWO based MPPT design is advanced than the P&O and PSO techniques in terms of tracking speed, steady-state oscillation under partial shading conditions (PSCs) and accuracy.*

Keywords – *maximum power point tracking, opposition-based learning, parallel grey wolf optimizer, partial shading conditions (PSCs), photovoltaic (PV).*

1. INTRODUCTION

At present due to globalization and industrialization, the non-renewable energies are not sufficient to meet up with the need for an upcoming energy requirement. To comply with these needs it is essential to think for alternative of non-renewable energies because without energy no sectors in the world can run in its accurate manner. Generating electrical power from fossil fuels is unfriendly and the outcome of the emissions from the combustion of fossil fuel causes severe environmental issues like ozone layer depletion, global warming, acid rain, air pollution are few of them. To mitigate such issues an alternative viable option is to use Renewable energy resources (RESs) based electricity generation. Considering the benefits of the use of PV system such as it produces no toxic emission to the environment, noiseless operation and ample availability of solar radiation may serve as a promising option for rural electrification where grid extension is not a viable option due to economic issues or it may also be used in various agricultural applications such as PV-based water pumping system. The PV cell absorbs the photons of the sunlight and converts it into direct current by the photovoltaic effect.

The efficiency comes out from a typical PV cell is 12%-18% but the test cells are built-up in a way that is able to give efficiency up to 30% [1]. For this downside of low conversion efficiency of the solar photovoltaic system, an efficient maximum power point tracking (MPPT) skill is needed to accomplish the criterion of tracking the maximum power available in a complete unit. Photovoltaic modules are greatly affected by environmental conditions (solar irradiance, cell temperature, nature of load used, partial shading). There is only one maximum peak in output power under uniform solar irradiance and several local peaks under partial shading conditions. There is a significant power loss due to these multiple peaks and for that reason, photovoltaic systems should be manufactured in such a manner that could extract maximum power at any natural circumstances. Several MPPT algorithms have been highlighted in literature for maximizing the power output such as artificial neural network [2]-[3], fuzzy controller [4], perturb and observe (P&O) [5], hill climbing (HC) technique [6]. Fuzzy logic and ANN successfully track the MPP but both of them require bulky memory as data has to be trained prior to implementation. In the perturb and observe method, the power output changes by perturbing the PV array voltage and hill climbing method is based on perturbing the duty ratio of a power converter in order to accomplish the maximum power peak. P&O and Hill climbing arrangements are advantageous for their easiness in implementation and cost-effectiveness. But both the methods are diverging from the MPP under challenging atmospheric conditions. To eliminate this problem, the author in [7] introduced a variable perturbation algorithm (VPA) that lessens the perturbation size and permits to achieve maximum power without oscillation. A modified adaptive hill climbing technique under non-uniform irradiance was projected in [8]. This algorithm uses an automatic tuning

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parameter for tracking MPP with 17.5% faster-tracking speed. In [9], ant colony optimization has been used for searching a global peak where the P&O technique assists for find out the local peak and together aimed for formulating GMPP with least tracking speed. The authors also here looked after the static and dynamic response of various shading patterns of a PV system. Another popular technique is incremental conductance (IC) method where maximized power is introduced by considering the array conductance (I/V) to the incremental conductance (ΔI/ΔV) and MPP voltage is obtained when I/V is equal to ΔI/ΔV [10]. But this method required more computational time and oscillates near MPP. S. Motahhir et.al in [11] modified the classical IC method where steady-state oscillation is removed under a sudden change in irradiance. Another efficient algorithm named particle swarm optimization (PSO) method can track maximum power point in irregular environment efficiently but for high dimensional search space, it required much time for searching GMPP and there is a possibility to fall in local optimum with significant power loss [12]. The authors in [13] proposed an improved PSO methodology where duty cycles have been used to detect P_{best} and G_{best} under irregular insolation and partial shading condition. But oscillations are partially removed in this paper. K. Ishaque and Z. Salam in [14] simplified the MPP design by eliminating the random number from the velocity equation of classical PSO, hence convergence towards the GMPP more rapidly under partial shading condition. H. Patel and V. Agarwal in [15] have worked on a comprehensive study on PV performance for getting global power peak under a partially shaded condition in association with a dc-dc converter which uses a feed-forward control strategy to step-up the tracking speed but this scheme is not fit for a portable PV system.

Currently, various nature-inspired soft computing approaches have been adopted by the research workers to supervise the PV system under different natural calamities such as Artificial Bee Colony (ABC) [16], Flower Pollination Algorithm [17], Grey Wolf Optimization (GWO) [18], and Dragonfly Optimization [19]. A hybridization arrangement of GWO and P&O method was examined to reach the GMPPT under PSCs but the performance result was not satisfactory [20]. However, all the above proposals required a sophisticated processor which in terms to increase the price of the system.

After the research articles survey, it has been found that IGWO which uses parallel grey wolf optimization and opposition-based learning has not been yet synthesized for tracking the global maximum power point under partial shading condition on PV array. The IGWO technique has came into interest for its robustness, easiness in implementation, faster convergence speed towards GMPPT as compare to other meta-heuristic methodology.

2. MATHEMATICAL MODEL OF PHOTOVOLTAIC CELL

Figure 1 represents the equivalent circuitry of single diode solar cell which comprises a diode (D), one current source (I_{ph}), a series resistance (R_S) in ohms (Ω) which describes each cell resistance keeping as possible as low and a parallel resistance (R_P) in ohms (Ω) desirable as possible as high.

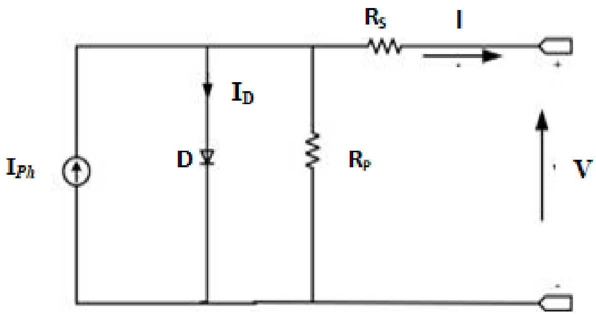


Fig. 1. Equivalent module of a solar cell with single diode.

The net output current equation for a single diode PV cell is written as follows:

$$I = I_{ph} - I_S(e^{\frac{q(V+IR_S)}{AkT}} - 1) - \frac{V + IR_S}{R_P} \quad (1)$$

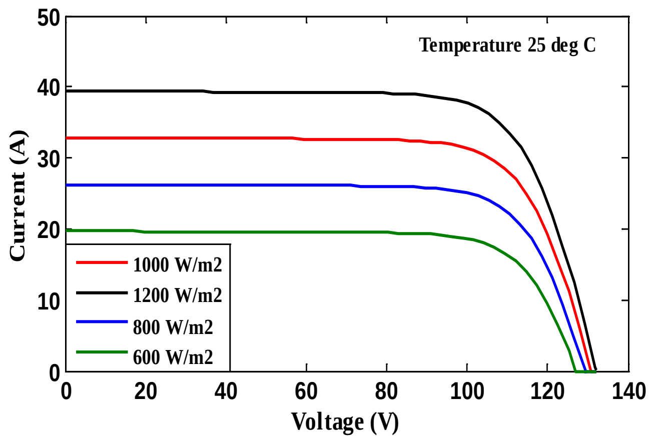
Where V represents the outcome voltage of PV cell in volt, I is the generated outcome current, I_{Ph} is the photocurrent, I_s denotes diode reverse saturation current, A denotes p-n junction ideality factor of diode (dimensionless), q represents electron charge which is equal to 1.6x 10^{-19} C, k is the Boltzmann's constant (1.380x 10^{-23} J/K) and T denotes junction temperature in Kelvin (K), For this study, the electrical specifications given in Table 1 are considered.

Table 1. Parameters of the simulated PV module.

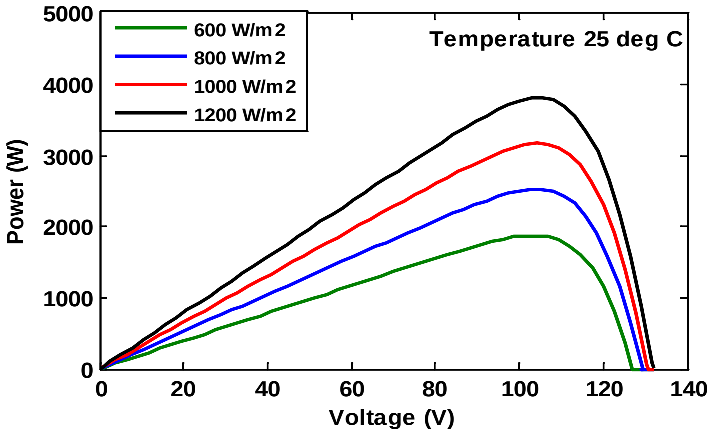
Parameters	Specification
Maximum Power	200W
Maximum Voltage	26.3V
Open Circuit Voltage	32.8V
Maximum Current	7.61 A
Short Circuit Current	8.21A
Temperature	25^0C
Configuration	4S, 2S2P

2.1 The PV Module Performance

The current-voltage and power-voltage characteristics of a PV system fiercely depend on solar radiation, ambient temperature, internal parameters, and connected load. If the ambient conditions change then the P-V and I-V characteristics should also change. Figure 2(a)-2(b) represents the influence of insolation of the PV module. Here the insolation level varying between 600 W/m^2 to 1200 W/m^2 (the temperature at 25^0C).



(a)

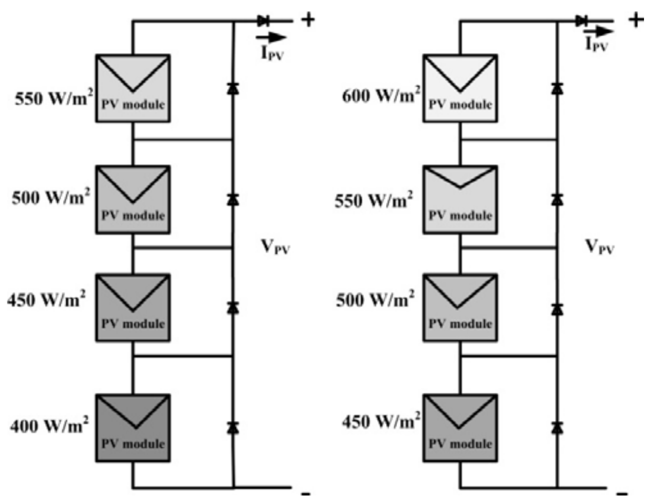


(b)

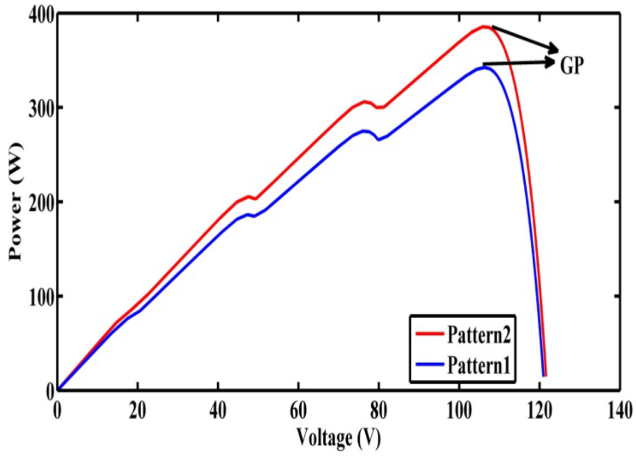
Fig. 2. (a) Typical $I-V$ curve at different irradiance, (b) Typical $P-V$ curve at different irradiance.

2.2 System Description

In a photovoltaic array, multiple PV modules are electrically assembled to each other in various combinations (series, parallel or series-parallel) for getting higher voltage and electrical current. Sometimes PV modules are being partially shaded with overhead objects such as trees, poles, buildings, clouds, etc. and then due to this several peaks are observed in the P-V characteristics curve. In this study, two different PV array configurations are considered namely 4S configuration where four modules are connected in series and 2S2P configuration where two series modules are connected with another two series module by two parallel paths shown in Figure 3(a)-3(b) and Figure 4(a)-4(b) with their respective shading patterns. The PV curve with distinct GP locations for 4S and 2S2P configuration with two dissimilar shading patterns are exposed in Figure 3(c) and Figure 4(c), respectively.

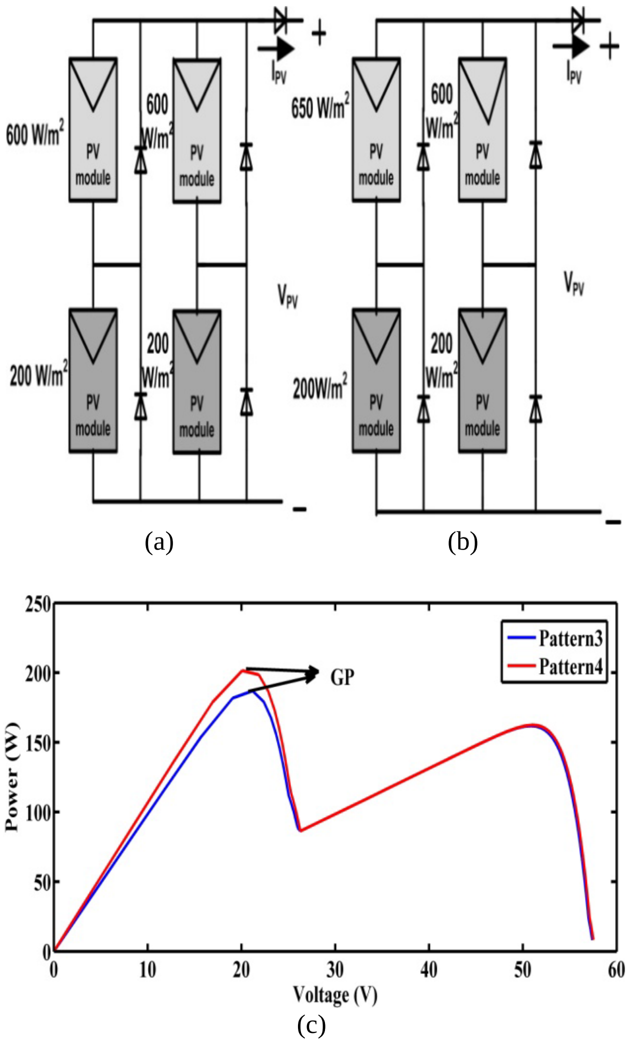


(a) (b)



(c)

Fig. 3. 4S arrangement under different shading patterns (a) Pattern 1, (b) Pattern 2, (c) P-V curve under PSCs.



(c)

Fig. 4. 2S2P arrangement under different shading patterns (a) Pattern 3, (b) Pattern 4, (c) P-V curve under PSCs.

3. BLOCK DIAGRAM OF THE SUGGESTED SYSTEM

The following system subsists of a PV array in which a DC-DC SEPIC converter is employed to drive the load. Voltage and current sensors are interfaced in-between PV array and the DC-DC SEPIC converter. The pulse width modulation (PWM) signal to the DC-DC converter is given through a microcontroller (MPP Tracker) in which the suggested IGWO algorithm is implemented. The microcontroller tracks the maximum power with the help of IGWO algorithm which is attached to the output of the solar PV array. The block diagram is shown in Figure 5 below.

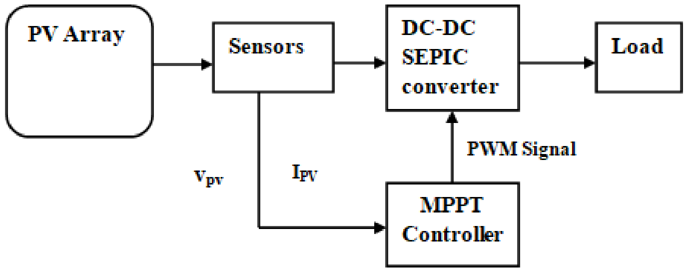


Fig. 5. Block diagram of the proposed MPPT method.

4. OVERVIEW OF GREY WOLF OPTIMIZATION

The Grey wolf optimization is a meta-heuristic algorithm inspired by the grey wolves' behavior while they are hunting [21]. They mostly favor to live in a group and considered as an alpha predator. The social hierarchy of the grey wolves is shown in Figure 6. The alphas (α), are called the most dominant wolves takes all the necessary decisions about the group. The β (beta) and δ (delta) are the adjuvant wolves that help the leader (α) to accomplish a decision. The lowest grading grey wolves are omega (ω) which always has to submit all other dominant wolves. Chasing, surrounding the prey and attacking the prey- are the three steps in hunting process.

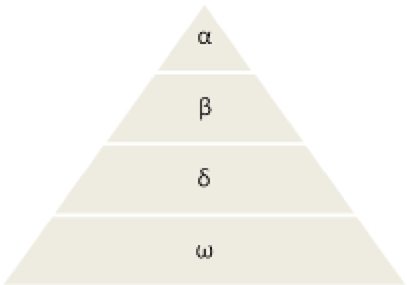


Fig. 6. Social hierarchy of grey wolves.

For mathematical modelling, in the Grey Wolf optimization technique, the leader (α) is acknowledged as the fittest solution. Consequently, the second and third fittest solution is β and δ. The remaining applicant solutions are taken under omega (ω). As said above, the prey is surrounded by wolves during the hunting process and the encircling performance can be represented by the proposed Equations (2)-(5).

$$\vec{g} = |\,\vec{e}.\vec{x}_p\,(t) - \vec{x}(t)| \qquad (2)$$

$$\vec{x}(t+1) = \vec{x}_p\,(t) - \vec{a}.\vec{g} \qquad (3)$$

$$\vec{a} = 2\,\vec{c}.\vec{r}_1 - \vec{c} \qquad (4)$$

$$\vec{e} = 2.\vec{r}_2 \qquad (5)$$

Where t signifies current iteration, $\vec{a}$ and $\vec{e}$ are coefficients of vectors, $\vec{x}_p$ indicates the position vector of the prey and $\vec{x}$ denotes the position vector of the grey wolf, random numbers between [0, 1] are represented by r_1 and r_2, elements of c are linearly reduced from 2 to 0 throughout the iteration.

The hunting process of grey wolves is directed by alpha (α) and beta (β), and delta (δ) took part in this process occasionally. The alpha (α), beta (β) and delta (δ) are the most excellent search agents and familiar about the potential position of prey. The omega (ω) updates their locations according to the position of three best search agents. The hunting procedure is finished by attacking the prey until it stops moving and with the help of following Equations (6)-(12) the whole iteration is done.

$$\vec{g}_{alpha} = |\,\vec{e}_1.\vec{x}_{alpha} - \vec{x}\,| \qquad (6)$$

$$\vec{g}_{beta} = |\,\vec{e}_2.\vec{x}_{beta} - \vec{x}\,| \qquad (7)$$

$$\vec{g}_{delta} = |\,\vec{e}_3.\vec{x}_{delta} - \vec{x}\,| \qquad (8)$$

$$\vec{x}_1 = \vec{x}_{alpha} - \vec{a}_1|\,\vec{g}_{alpha}| \qquad (9)$$

$$\vec{x}_2 = \vec{x}_{beta} - \vec{a}_2|\,\vec{g}_{beta}| \qquad (10)$$

$$\vec{x}_3 = \vec{x}_{delta} - \vec{a}_3|\,\vec{g}_{delta}| \qquad (11)$$

$$\vec{x}(t+1) = \vec{x}_1 + \vec{x}_2 + \vec{x}_3 \,/\, 3 \qquad (12)$$

4.1 Improved Grey Wolf Optimization (IGWO)

There are two methods that are used for improving the performance of GWO proposed by Nasrabadi et al [22].

4.1.1 Opposition based learning (OBL)

Let p = (y_1, y_2,……….,y_n) be a point in n-dimensional space, where $y_i \in [\,a_i\,,\,b_i\,]$, $\forall_i \in \{1, 2,\ldots, n\}$. The opposite point $\breve{p}$ = ($\breve{y}_1$, $\breve{y}_2$…., $\breve{y}_n$) is described by its coordinates [23].

$$y = a_i + b_i - y_i \qquad (13)$$

This technique can be performed as a lateral idea with the main algorithm as the use of this method can lead the dimensions of one member to become opposite with respect to the source shown in Figure 7. Hence this result in a combination of the population to have more diversity and also increases the probability in the search space to reach the optimum point.

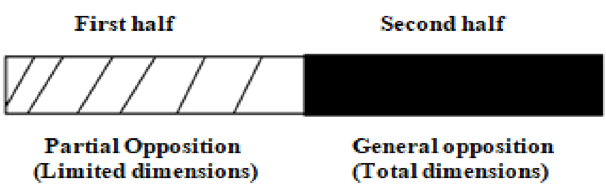


Fig. 7. Dividing the population.

The population is divided into two forms and OBL is applied in each of them separately. In the beginning, the wolves are sorted in accordance with their fitness function and in the next phase the population is divided into two equal halves as shown in Figure 7. The wolves in the first half get partially opposite position with respect to their ranks corresponding to the value of their fitness. The dimension is selected randomly. The wolves which have a better position with respect to others would get less change and the wolves which have worse position will have more change.

4.1.2 Parallel grey wolf optimizer

At first, the wolves are divided into two or several sub-groups. Afterwards, each of those sub-groups is implemented independently based on the main algorithm structure and each time of iteration, they share their results shown in Figure 8. In addition in each run, the worst wolves of other sub-group are replaced by the best wolves of each sub-group.

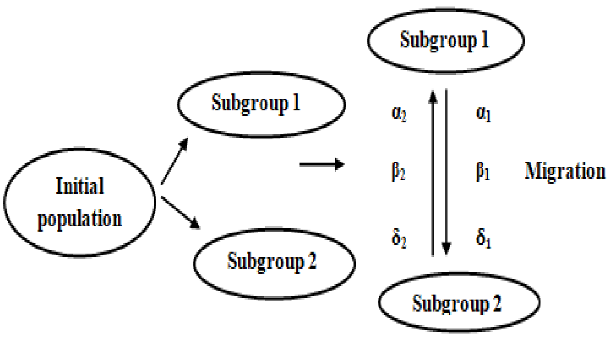


Fig. 8. Migration between subgroups in the algorithm.

5. APPLICATION OF IGWO FOR MPP TRACKING

The aim is to pull out the maximum power by using the suggested algorithm from the PV system and the optimization problem [20] is composed as follows:

Maximize: P(d)

$$P(d) = \frac{1}{(1-d)^2}\frac{V_{in}^2}{R_L} \tag{14}$$

$$\text{Subjected: } d_{min} \le d \le d_{max} \tag{15}$$

Where, P(d) = PV outcome power
R_L= load resistance
V_{in}= 0-130V (input voltage of converter)
d = duty ratio of the converter
d_{min} = 0.1 (lower limit of the duty ratio)
d_{max} = 0.9 (upper limit of the duty ratio)

The algorithm is implemented in the digital microcontroller which senses V_{pv} and I_{pv} and calculates the output power. In the proposed design parallel grey wolf is merged with opposition-based learning which triggers the duty cycle of the converter. By varying the duty cycle of the DC/DC converter, the maximum power of PV panel will be delivered to the load. The algorithm is implemented in the microcontroller according to the flowchart shown in Figure 9. During the initial startup phase, V_{pv} and I_{pv} are sensed for a randomly generated initial solution after which the algorithm tests output power at different duty cycles. After a few iterations, IGWO manages to track MPP even if multiple peaks are present. Near MPP (maximum power point), the co-related coefficients nearly become zero. The algorithm then output a constant duty cycle which reduces power loss from the steady-state oscillation which can be seen in the P&O algorithm, until a significant change in output power is detected (due to partial shading). The Matlab/Simulink configuration is shown in Figure 10 which represents the whole PV panel. The variables chosen for PSO technique for all the conditions here are $c_{1,min}$ = 1, $c_{1,max}$ = 2, $c_{2,min}$ = 1, $c_{2,max}$ = 2, w_{min} = 0.1, w_{max} = 1, and number of particles = 10 for the whole MPPT technique.

6. SIMULATION RESULTS

6.1 MPP Tracking by IGWO under Partial Shading Condition

The power, voltage and current curve with partial shading conditions for the 4S configuration and 2S2P configuration working with IGWO, PSO, and P&O are shown in Figure 11 and Figure 12. For simulation analysis, pattern 1 is continued for the first 0.75s and then pattern 2 performs for the next 0.25s for 4S configuration. Similarly, pattern 3 for 2S2P configuration performs for the first 0.7s and pattern 4 is available for the next 0.3s. In pattern 1 and pattern 2, global peak achieves for IGWO at 342.47W whereas PSO attains a global point of 341.5W and 384.6W respectively. Simulation is repeated for pattern 3 and pattern 4 where IGWO finds the GP at 195.62W and 208.66W whereas PSO takes GP at 190.54W and 207.65W respectively. But for pattern 1 and pattern 2, P&O possesses a local peak with oscillation and tracks a global peak of 205W for pattern 4. The comparison table for MPPT under partial shading condition is based on IGWO, PSO and P&O with 4S and 2S2P configuration are shown in Table 2 and Table 3.

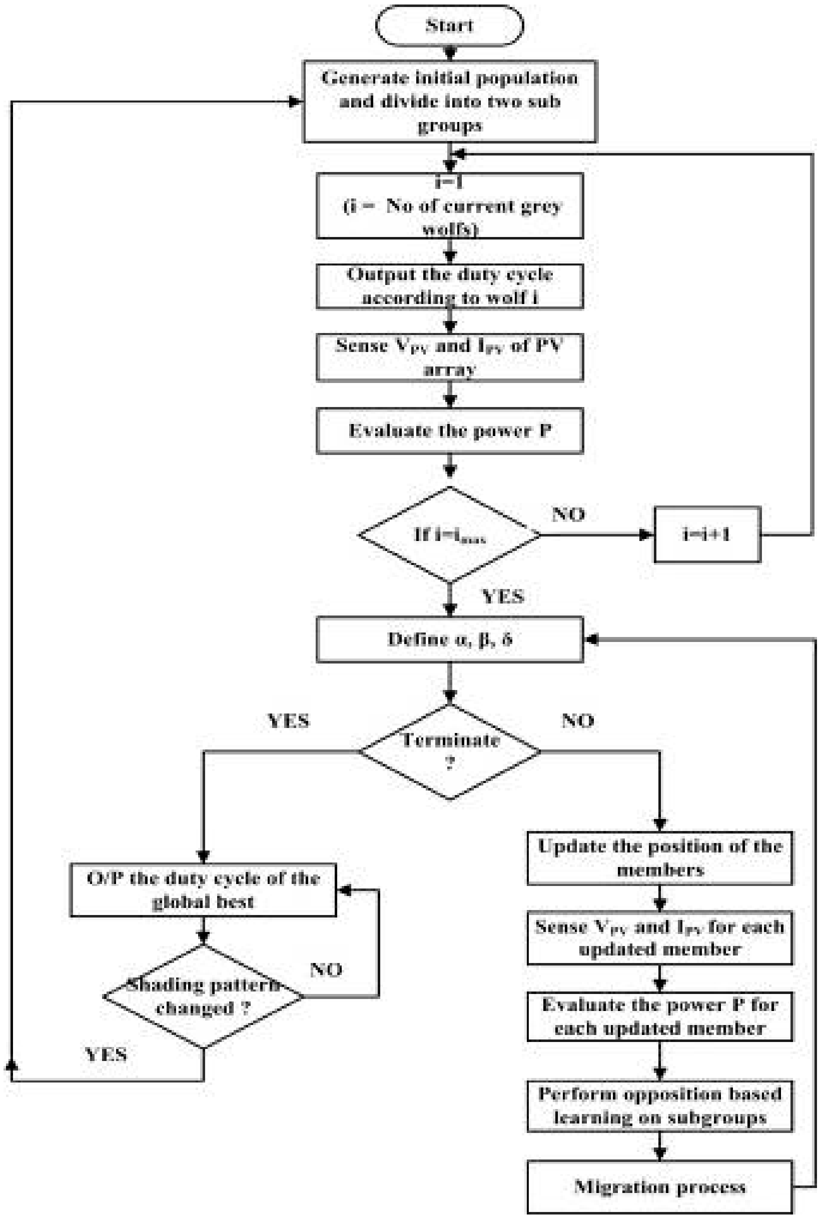


Fig. 9. Flowchart of the proposed algorithm.

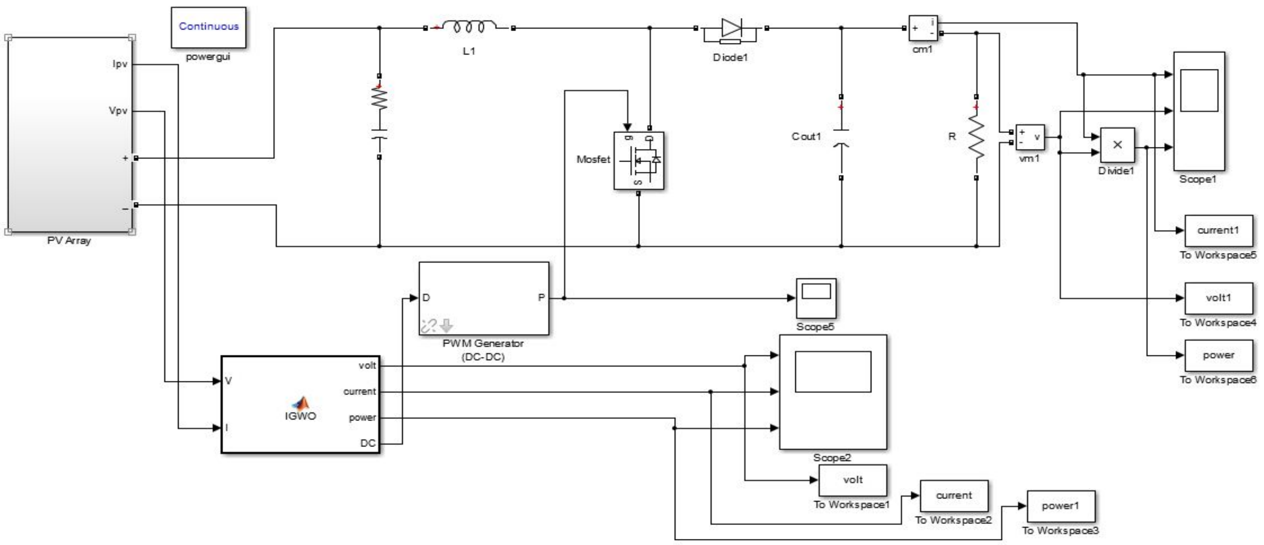


Fig. 10. The proposed model of PV system.

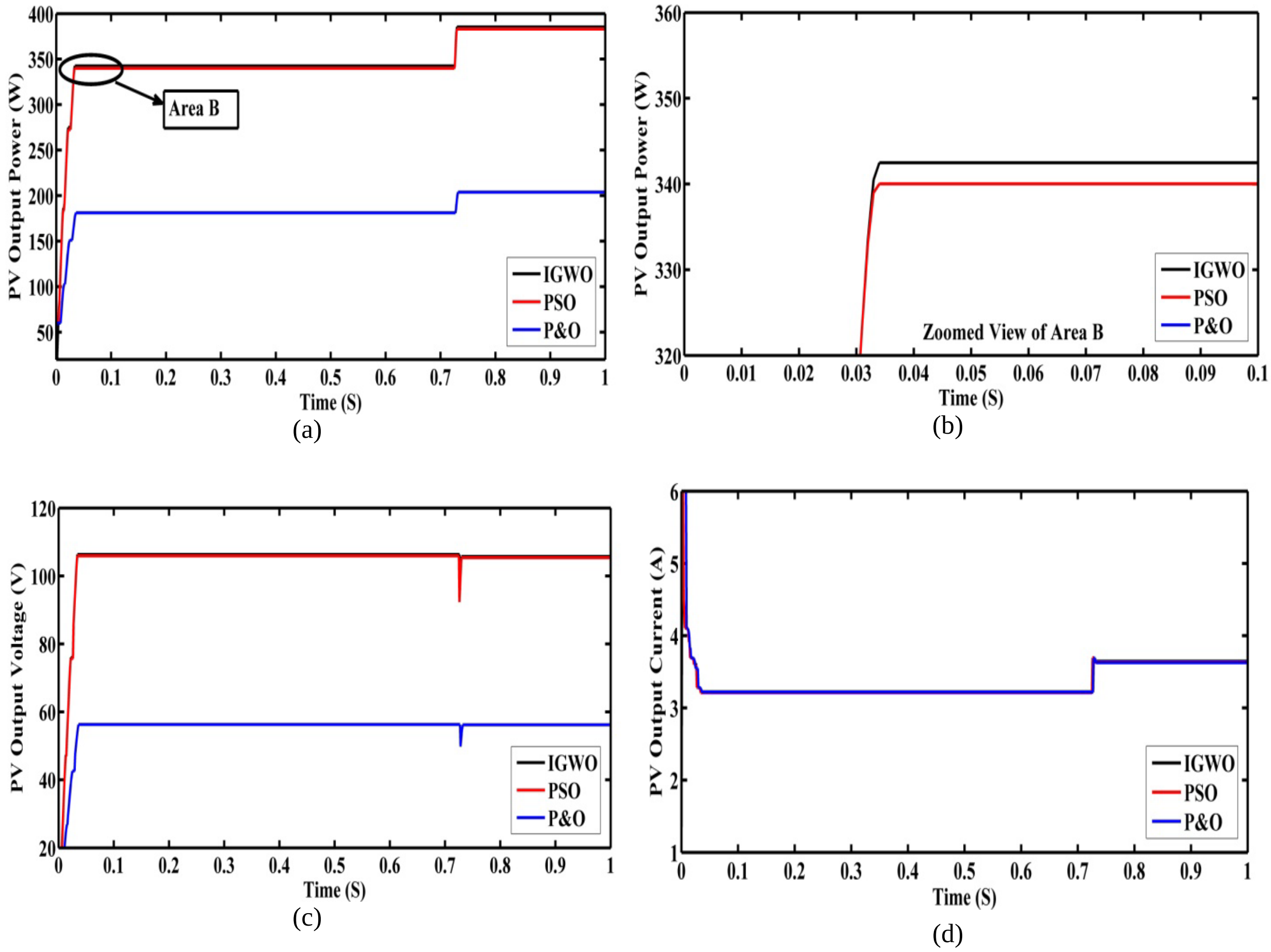


Fig. 11. Tracking curves of 4S arrangement (a) PV output power of IGWO with other methods like PSO, P&O based MPPT, (b) Zoomed view of Area '*B*', (c) PV output voltage (d) PV output current.

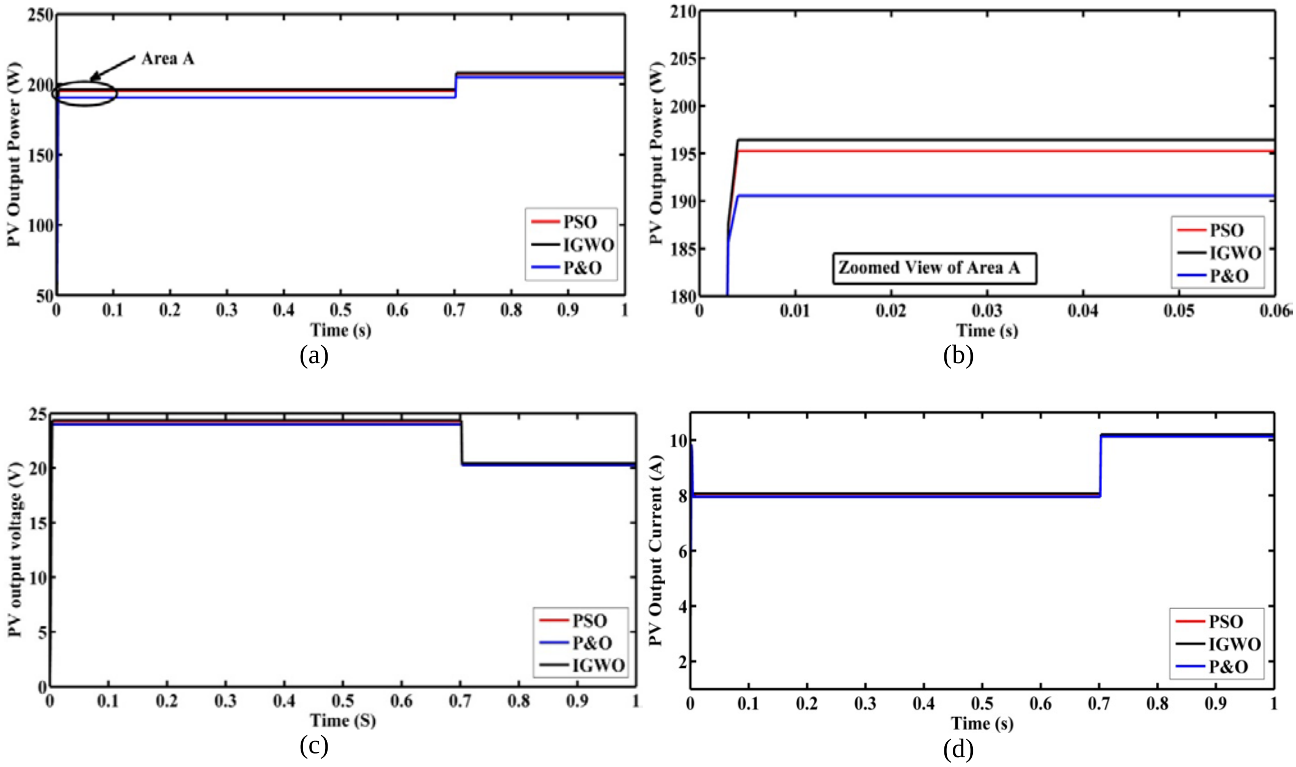
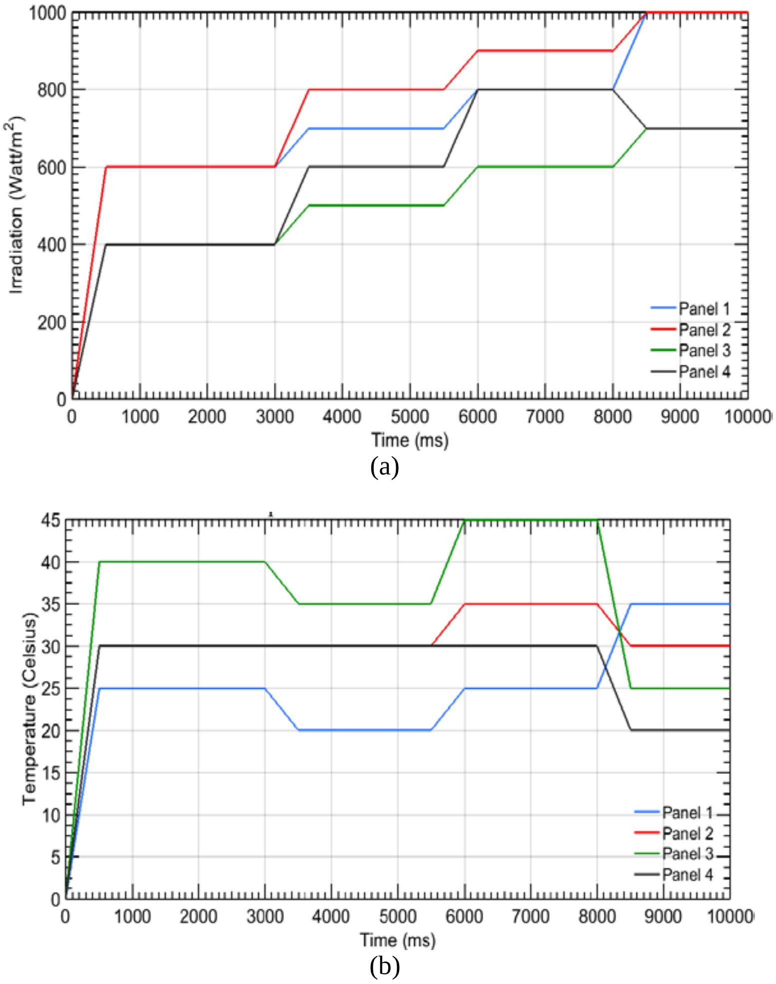


Fig. 12. Tracking curves of 2S2P arrangement (a) PV output power of IGWO with other methods like P&O, PSO based MPPT, (b) Zoomed view of Area '*A*', (c) PV output voltage, (d) PV output current.

6.2 MPP Tracking under Gradually varying with Irradiation and Temperature

This section of the simulation is designed to check out the efficacy of the suggested algorithm for gradual changes in the environment. In this type of environment the irradiation and temperature increases or decreases gradually. Here the system initiates the tracking algorithm in response to even a little change in the output power to continuously track the MPP. A simulation was performed on two different configurations based on MATLAB, 4S and 2S2P where the irradiation and temperature of the panels are varied continuously from an initial value to a final value in form of a ramp. In the 4S configuration, all the panels (1-4) are in series whereas in 2S2P configuration panel 1 and panel 2 form one series combination, panel 3 and panel 4 forms another series combination and these two combinations are connected parallel to form 2S2P configuration. The manner in which the irradiation and temperature of these panels are changed during the simulation are shown in Figure 13(a)-13(b) and the MPP tracking under gradually varying with irradiation and temperature are illustrated in Figure 14(a) and Figure 14(b) for the 2S2p module and 4S module respectively. For an unbiased comparison, both the algorithms (IGWO and PSO) were given equal computation allowance by limiting the number of particles and a number of iterations to a fixed value.



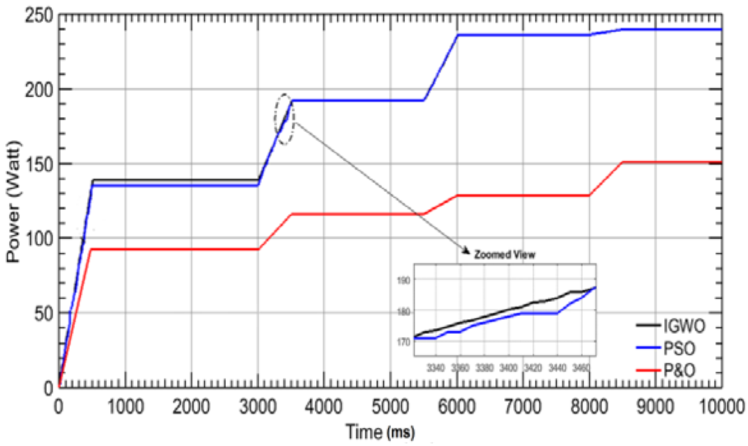
(b)

Fig. 13. (a) Irradiation profile, (b) Temperature profile.

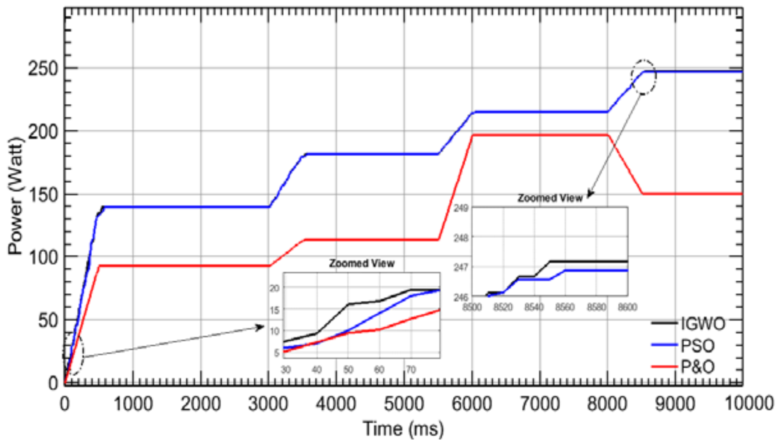
The tracking efficiency of IGWO as compared to PSO is better in most of the cases which can be clearly seen from the inset images of Figure 14(a) and Figure 14(b). In the zoomed inset images of Figure 14(a), it is noted that throughout the changes in temperature and irradiation, the IGWO performs better in tracking MPP almost all the time compared to PSO and P&O. From Figure 14(b), it can be asserted that IGWO tracks better MPP from the initial startup of the simulation until it reaches t=3s. Then IGWO and PSO both converge to the same value but P&O converges to a local maximum. The irradiation and temperature remain constant until t=5.5s. The MPP tracking algorithm triggers again at t=5.5s and both IGWO and PSO manage to track almost the same MPP during the gradual changes in irradiation and temperature till t=8s. During this rally, IGWO performs better than PSO and P&O under gradually varying with irradiation and temperature and at the end, it manages to track better MPP at a faster rate shown in Table 4. The simulation was done with a sampling rate of 0.1ms.

6.3 MPP Tracking under Rapid Change in Irradiance and Temperature

Rapid change in irradiance and temperature occur basically in tropical areas (that part of the earth closer to the equator) where the sun is rapidly covered by a dark cloud. This realistic change is simulated using step change in irradiation and temperature which is shown in Figure 15(a)-15(b). It can be seen that even during rapid changes in irradiation and temperature, IGWO converges faster towards MPP than that of PSO and P&O. This is because the IGWO uses both exploration and exploitation simultaneously resulting in faster tracking during abrupt changes. Figure 16(a) and Figure 16(b) shows the performance of IGWO, PSO, and P&O for tracking the maximum power point both for 4S and 2S2P configuration under abrupt weather condition and the results are shown in Table 4. Sampling rate is taken 0.1ms as before.

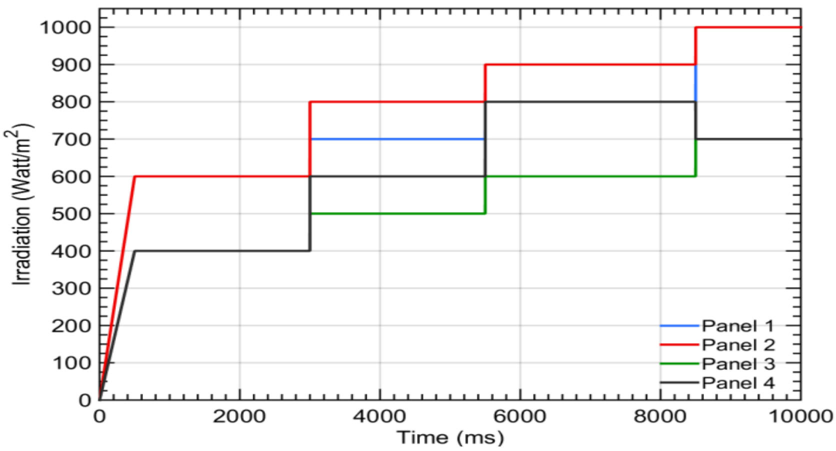


(a)

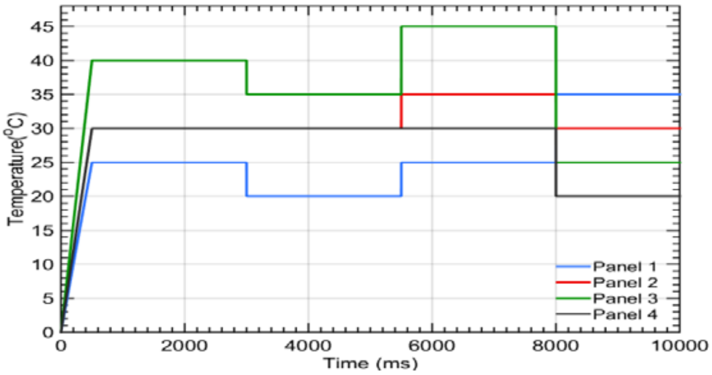


(b)

Fig. 14. Response of IGWO, PSO and P&O techniques during gradual change in environment: (a) 2S2P module, (b) 4S module.

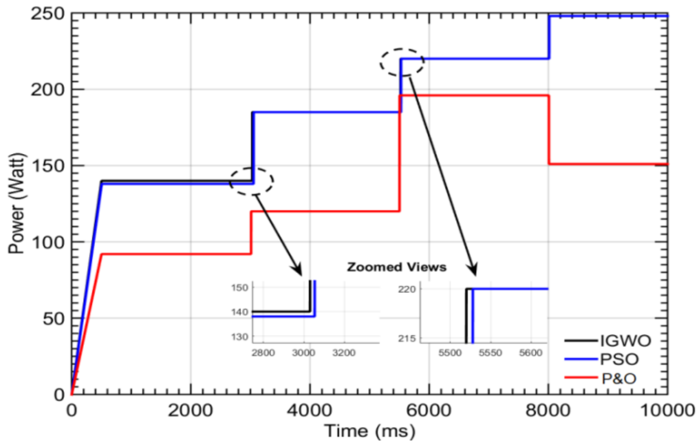


(a)

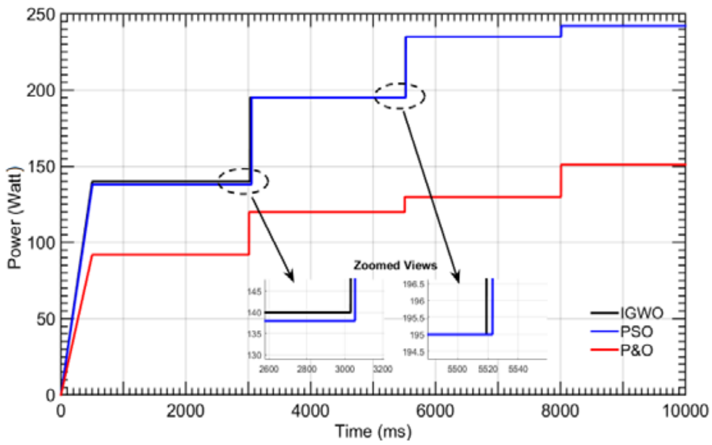


(b)

Fig. 15. (a) Irradiation profile, (b) Temperature profile.



(a)



(b)

Fig. 16. Response of IGWO, PSO and P&O techniques during an abrupt change in environment: (a) 4S module, (b) 2S2P module.

6.4 Accuracy

Here to analyze the accuracy of IGWO, PSO, and P&O, a simulation was prepared to test these algorithms on 1000 different partial shading scenarios by changing the irradiation and temperature. In all the cases, efficiency was calculated by using the Equation (16). Histograms are drawn to visualize the worst case, average case and best-case scenarios which are shown in Figure 17. The accuracy of P&O technique ranges from mid 20% to 90% with a mean accuracy of around 55%, while in the case of PSO, the accuracy clutters around 99% with a mean accuracy of 98.8%. IGWO outperforms the other two with a mean accuracy of 99.4%. The tracking efficiency is calculated by taking ratio of the tracked output power to the available maximum power at the input of the PV system. The qualitative performance of IGWO with other renowned techniques is described in Table 5.

$$\eta = \frac{Tracked\ output\ power}{Maximum\ power\ available\ to\ the\ input} x100\% \qquad (16)$$

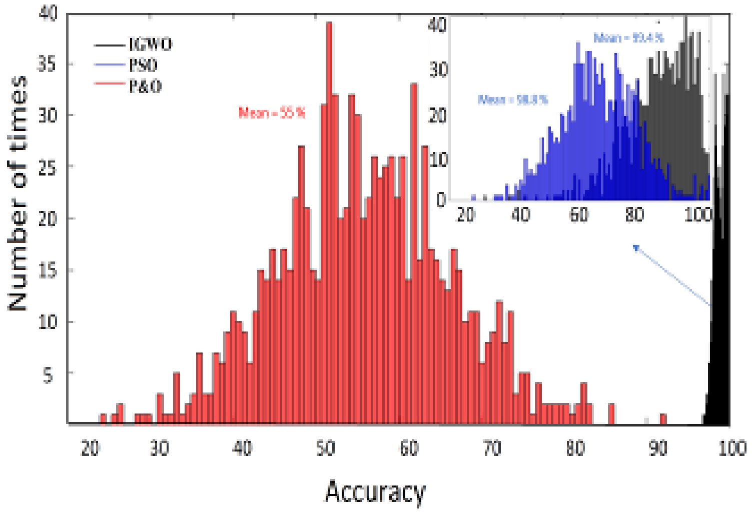


Fig. 17. Histogram of the accuracy of IGWO, PSO, and P&O when subjected to 1000 simulated partial shading cases.

Table 2. Performance comparison of the IGWO based MPPT method for 4S arrangement.

Shading pattern	Maximum power from PV curve (W)	Tracking technique	Maximum Power (W)	Maximum Voltage (V)	Maximum current (A)	Tracking efficiency (%)
1	342.5	P&O	181.08	56.29	3.21	52.87
		PSO	341.50	106.38	3.21	99.70
		IGWO	342.47	106.30	3.22	99.96
2	385.55	P&O	203.73	56.19	3.62	52.84
		PSO	383.07	105.38	3.63	99.75
		IGWO	385.37	105.71	3.64	99.95

Table 3. Performance comparison of the IGWO based MPPT method for 2S2P arrangement.

Shading pattern	Maximum power from PV curve (W)	Tracking technique	Maximum power (W)	Maximum Voltage (V)	Maximum current (A)	Tracking efficiency (%)
3	196.5	P&O	190.54	24.05	7.97	96.96
		PSO	195.53	24.32	8.04	99.56
		IGWO	196.42	24.39	8.06	99.94
4	208.1	P&O	205	20.25	10.12	98.51
		PSO	207	20.37	10.18	99.78
		IGWO	208.06	20.39	10.19	99.95

Table 4. Performance comparison of the IGWO based MPPT method for 2S2P and 4S arrangement under a gradual and rapid change in environment.

An environmental condition during MPP tracking	Tracking Techniques	Tracking Efficiency (%) for 2S2P Module	Tracking Efficiency (%) for 4S Module
MPP tracking under gradually varying with irradiation and temperature	IGWO	99.31	100
	PSO	98.05	100
	P&O	61.59	65.79
MPP tracking under a rapid change in irradiation and temperature	IGWO	99.67	100
	PSO	99.67	99.87
	P&O	55.27	61.46

Table 5. Qualitative comparison of IGWO technique between different fast converting methods.

Type	P&O	Standard PSO	[24]	[25]	[26]	Proposed algorithm
Tracking speed	Slow	Medium	Fast	Fast	Fast	Very fast
Tracking accuracy	Low	Accurate	Highly accurate	Highly accurate	Highly accurate	Highly accurate
Implementation complexity	Low	Medium	Medium	Medium	Medium	Medium
Dynamic response	Poor	Good	Good	Good	Good	Accurate and Good
Execution time	Very Fast	Fast	Fast	Fast	Fast	Fast
Steady state oscillations	Large	Zero	Zero	Less	Less	Zero
Periodic tuning	Not required	Not required	Not required	Required	Not required	Not required
Conditions for Convergence / limitations	May trap to local peak	Always guaranteed for global peak	Always guaranteed for global peak	Always guaranteed for global peak	Always guaranteed for global peak	Always guaranteed for global peak
Power efficiency	High at uniform insolation and low at non-uniform insolation	High	High	High	High	High

7. CONCLUSION

The IGWO based MPPT algorithm was implemented and a comparative study is done with the existing particle swarm optimization (PSO) and perturb and observe (P&O) MPPT approaches for verifying the reliability and effectiveness of the suggested technique. From the simulation outcomes, it is concluded that the proposed IGWO based MPPT algorithm is capable of tracking the global peak under partial shading situation. It is found that under partial shading situations and varying with solar radiation and temperature, the tracking efficiency of IGWO based MPPT shows better results than that of PSO and P&O MPPT methods.

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