Novel Hybrid GWO–IC based MPPT Technique for PV System under Partial Shading Conditions

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Abstract

This study presents the possible solution to the problem of extraction of maximum power from PV systems under non-uniform irradiance such as partial shading condition (PSC). The grey wolf optimization (GWO) and Incremental Conductance (IC) MPPT methods are integrated to design a hybrid MPPT approach so as to extract maximum possible power from PV modules under partial shading conditions. In this technique, GWO operates in the early stages to track the MPP, while IC operates in the latter stages for higher tracking efficiency and faster convergence to the global peak. The proposed hybrid-MPPT technique is simulated for a 1 kWp PV system using MATLAB/SIMULINK tool. The designed model is studied for two different configurations i.e. 4S and 2S2P topologies under different shading patterns to verify its effectiveness under rapidly varying irradiance. The simulated results clearly indicate that the proposed hybrid MPPT exhibits higher tracking efficiency (>99%), faster convergence to the global peak with minimal time (<0.1s), negligible oscillations around MPP and thereby enables it to extract the maximum possible power from the PV system as compared to P&O, IC, and GWO based MPPT methods.

Keywords: Hybrid MPPT, Grey Wolf Optimization (GWO), Incremental Conductance, Partial Shading Conditions.

1. Introduction

Solar photovoltaic (PV) systems have drawn great attention and become a significant energy source in various applications because of its impressive advantages such as environmental friendliness, inexhaustible resources, free to harvest, cost competitiveness, and minimal maintenance. The photovoltaic systems are considered clean and sustainable energy sources. The PV system performance depends on solar radiation, ambient temperature, soiling, and shading, etc. Some other factors like the design and installation of the systems i.e. tilt, orientation, and string configurations also affect the energy production of the photovoltaic system. Therefore, to extract maximum power from a PV module or array, various maximum power tracking (MPPT) systems have been developed to optimize its operating voltage by switching the dc-dc boost converter. These MPPT approaches enable the PV system in transferring the maximum possible power generated to the load or grid by regulating the converter's duty ratio according to the changes in weather conditions. Under uniform solar irradiance, the MPP can easily be tracked by using the conventional MPPT algorithms as these methods are based on a simple peak detection of the P-V characteristic curve. However, these conventional techniques fail to detect MPP under partial shading conditions (PSCs) with rapid changes in solar insolation. In the event of non-uniform solar insolation or during PSCs, triggering of the bypass diodes to disintegrate the shaded modules from the array, generates numerous peaks i.e., various local peaks (LP) and one global peak (GP). These create a serious challenge to the conventional MPPTs in order to differentiate between these local and global maxima.

Saravanan and Babu, (2016) presented a detailed review on various real-time MPPTs based on Perturbation and Observation techniques (such as fixed step P&O, variable step size P&O, multivariable P&O, PSO based P&O, hybrid P&O MPPT); Incremental Conductance technique (such as modified IC, variable step IC, improved variable step IC, power increment based IC, modified adaptive IC); Intelligent MPPT techniques (such as FLC, Neural Network, ANFIS, FL-GA); and Partial Shading based MPPT techniques (such as Improved PSO, Deterministic PSO, Dormant PSO). These methods mainly vary in terms of complexity in the algorithm, speed of convergence, oscillations near the MPP, required electronic components for its integration, and cost. In order to overcome these tracking problems being associated with the conventional MPPTs, several advanced computing

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and meta-heuristic techniques have been introduced such as Whale Optimization (WO) (Premkumar and Sowmya, 2019), Grey Wolf Optimization (GWO) (Mirjalili et al., 2014), Flower Pollination (Shang et al., 2018), Cuckoo Search (Peng et al., 2018), Jaya algorithm (Huang et al., 2018), Fireflies (Sundareswaran et al., 2014), Artificial Neural Network (ANN) (Rizzao and Scelba, 2015), Artificial Bee Colony (ABC) (Benyoucefa et al., 2015), Particle Swarm Optimization (PSO) (Liu et al., 2012), and so on. These methods are primarily based on search and optimization approach and can detect the global peak correctly and as a result, the performance of the PV system improves. The major drawbacks associated with these techniques are slow tracking speed and higher complexity than the conventional algorithms. However, these methods are effective in accurately determining the MPP.

Yilmaz et al. (2019) has adopted an improved FLC MPPT based on two blocks (i) calculation block to calculate the operating voltage point of MPP and (ii) FLC block for adjusting the duty ratios of PWM waveform that switches the dc-dc boost converter according to changes in environmental conditions. The study compared the performance with the conventional MPPTs such as FLC, P&O and IC techniques and has claimed that the efficiency of the proposed method is found between 99.5% - 99.9% and the duration in reaching GP is measured to be 0.021 sec. Premkumar et al. (2019) has presented a bio-inspired Whale Optimization (WO) MPPT method that tackles rapid environmental changes specially PSCs. The study concluded that the proposed algorithm, under partial shading conditions resulted in tracking efficiency of more than 95% and the convergence time is less than 0.15 sec. Shang et al. (2018) has proposed a unique MPPT method using Flower Pollination (FP) algorithm, developed by Yang et al. (2013), that reduces the start-up time and steady-state power oscillation by implementing an effective iterative termination strategy once the GP is tracked and exhibits better system response speed and higher tracking efficiency under rapid changes in irradiance and PSCs compared with the traditional P&O and PSO MPPT methods.

Another advanced soft computing technique called Grey Wolf Optimization (GWO), first developed by Mirjalili et al. (2014), was inspired by the hunting techniques of grey wolves for attacking prey. Mohanty et al. (2016) has implemented this approach for designing a robust MPPT technique to deal with the rapid environmental changes in solar irradiance and PSCs. This study has compared the proposed GWO technique with the conventional P&O and an Improved Particle Swarm Optimization (IPSO) technique and has observed that the algorithm performs better in terms of tracking speed, accuracy, convergence rate, and steady-state oscillations. However, this GWO method exhibits computational complexity. Later to overcome this, a new hybrid MPPT algorithm is proposed that uses both GWO and P&O technique where GWO operates during the initial stages for tracking of the MPP and P&O algorithm during the final stages so as to achieve faster convergence towards the GP compared to the former one (Mohanty et al. 2017). Jiang et al. (2015) have proposed a hybrid-ANN method where ANN is merged with P&O to achieve GP at a better convergence rate. The ANN tracks the GP during the initial stage, and finally, P&O locates the MPP under PSC. Several other hybrid MPPTs are also introduced such as hybrid-WO (Premkumar and Sumithira, 2018), hybrid-PSO (Farh et al., 2018), Hybrid-Jaya (Huang et al., 2019), etc. to improve the convergence speed in reaching MPP.

This study proposes a novel hybrid GWO-IC MPPT algorithm that has greater significance than other techniques due to its explorative and exploitative capability, as well as its ability to avoid local peaks. The proposed algorithm's search time is lower without sacrificing its accuracy by lowering the number of search agents. As a result, the convergence time is also getting considerably reduced due to the lower number of search agents. Furthermore, the algorithm quickly tracks and reaches the MPP, with minimal power oscillation in the steady-state. The rest of this paper is structured as follows. Section 2 describes the modeling of the PV module and its characteristics under PSCs. Section 3 presents the overview of the proposed algorithm and its role in designing for the MPPT application. Section 4 presents the simulation results and discussions. Lastly, the paper is concluded in Section 5.

2. PV Characteristics under PSCs

2.1 Mathematical modeling of PV module

Fig. 1 depicts the equivalent circuit of a typical solar cell, which includes a light-driven current source, a shunt resistance, a series resistance, and a diode. Using the equivalent circuit, the characteristic equation that links to output voltage and current is presented in equation 1 (Ahmed and Salam, 2015).

$$I = I_{PV} - I_o[exp(\frac{V+IR_S}{V_T}) - 1] - (\frac{V+IR_S}{R_P}) \qquad \text{(eq. 1)}$$

Where, I_{PV} indicates PV current (in A), R_s indicates series resistance (in Ω), I_0 represents reverse saturation current (in A), R_{sh} is shunt resistance (in Ω), V is output voltage (in V) and V_T indicates thermal voltage of the PV module and is given by:

$$V_T = \frac{nkT}{q} \qquad \text{(eq. 2)}$$

Where, q indicates electronic charge (1.6×10^{-19} C), n indicates diode factor, T indicates module temperature (K), and k indicates Boltzmann Constant (1.38×10^{-23} J/K). The current generated from the PV module can be expressed as:

$$I_{PV} = \frac{G}{G_{STC}}(I_{PV,STC} + K_t.\Delta T) \qquad \text{(eq. 3)}$$

Where $I_{PV,\,STC}$ indicates the PV module current at Standard Test Condition (STC), G_{STC} indicates solar irradiation under STC, G indicates irradiation falling on surface of PV module, and K_t indicates temperature coefficient of PV current.

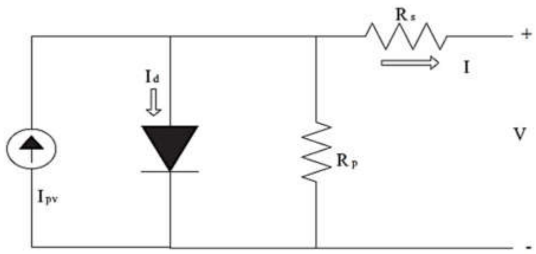


Fig. 1: Equivalent circuit of a typical solar cell

The parameters of a PV module or manufacturer ratings are based on STC which include the temperature of 25°C, irradiation of 1000 W/m^2, and air mass of 1.5. Fig. 2 presents the typical solar cell characteristics profile under STC. For maximum power extraction or optimum production from PV systems, its installation depends on site such as longitude and latitude of the location, orientation factors such as tilt angle and altitude etc. It also depends on various environmental factors such as humidity, ambient temperature, dust, etc. and the module technology such as poly-crystalline, mono-crystalline, amorphous, thin film etc.

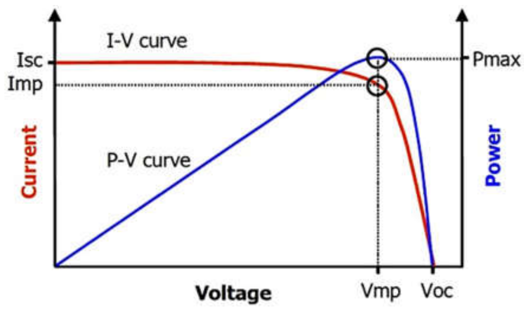
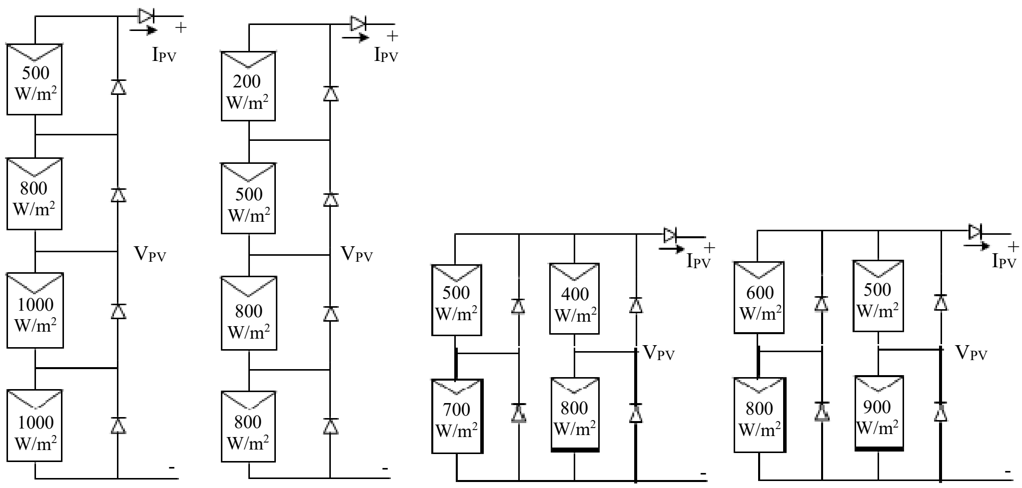


Fig. 2: Characteristic curve of a PV cell at STC

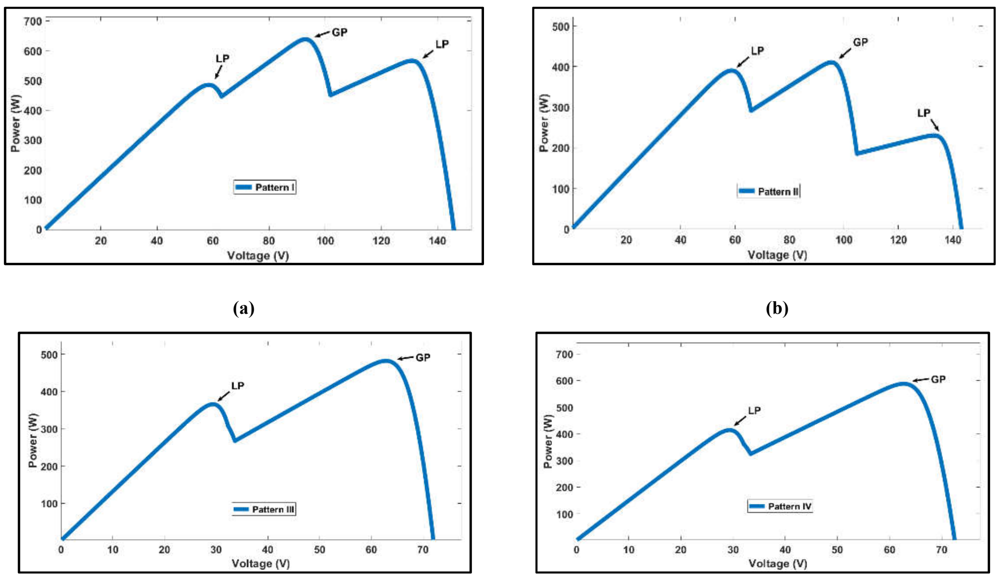
2.2 Description of PV system

A PV system consists of a number of PV modules connected in series and parallel combinations. When a PV module subjected to PSCs, the shaded PV cell functions as a resistive load and causes local overheating or hotspots by dissipating a high amount of power from the energy generated by the unshaded cells. This overheating may lead to permanent damage of the cell, and even cracking of protective glass. In order to protect these modules from shading effects, PV systems are nowadays installed with a power diode, called the bypass diode to bypass the shaded cells or modules. The inclusion of these bypass diodes across a PV module results in numerous local peaks in P-V and multiple steps in its I-V characteristics. Therefore, it is necessary to investigate the characteristics of the systems for both uniform and non-uniform solar insolation levels.



(a) (b) (c) (d)

Fig. 3: PV array configurations: (a)-(b) 4S topology (c)-(d) 2S2P topology



(c) (d)

Fig. 4: Shading patterns (a)-(b) 4S configuration (c)-(d) 2S2P configuration

The designed model is studied for two different configurations i.e. 4S and 2S2P topologies under different shading patterns. Fig 3a-b shows the 4S configuration where four modules are connected in series. Fig 3c-d presents the 2S2P configuration where four PV modules are connected separately in two parallel configurations, each consists of two serially connected PV modules. Fig 4a-b presents the P-V curves for 4S configuration with clearly labeled GP and LP locations under two different shading patterns, i.e., Pattern I and Pattern II respectively. Similarly, the P-V curves for 2S2P configuration at two different shading patterns, i.e., Pattern III and Pattern IV are respectively shown in Fig 4c-d.

3. Overview of Proposed MPPT Method

3.1 Grey Wolf Optimization and its role in designing of MPPT

The GWO algorithm adopted by Mirjalili et al. (2014) has received immense acceptance in determining efficient global optimum solutions compared to other meta-heuristic approaches. The GWO approach mimics the natural leadership hierarchy and the hunting strategy of grey wolves while attacking prey. Grey wolves are categorized into four types: alpha (α), beta (β), delta (δ), and omega (ω). They are regarded as the top of the food chain, and like to stay in packs with a strict social dominating hierarchy, as seen in Fig 5. In order to design the GWO technique, the social hierarchy of the wolves is mathematically modelled by assuming alpha (α) to be the fittest candidate. While, beta (β) and delta (δ) is regarded as the second and third best solutions, respectively and omega (ω) are regarded as the remaining candidate solutions. Fig 6 presents the three primary steps of the GWO algorithm for executing the optimization process are: (a) chasing and tracking prey, (b) encircling and harassing the prey unless it stops changes direction, and (c) attacking the targeted prey.

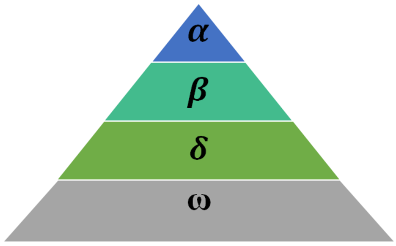


Fig. 5: Hierarchy of grey wolf (dominance decreases from top down)

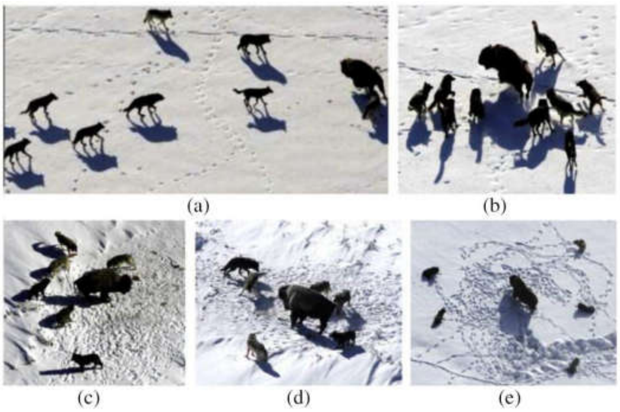


Fig. 6: Hunting behavior of grey wolves: (A) chasing and tracking prey (B-D) harassing and encircling (E) attacking the prey

During the hunt, these wolves encircles the prey and the following set of equations can be used to model their encircling behavior:

$$\vec{E} = |\vec{C}.\vec{X_p}(t) - \vec{X}(t)| \quad \text{(eq. 4)}$$

$$\vec{X}(t+1) = \vec{X_p}(t) - \vec{A}.\vec{E} \quad \text{(eq. 5)}$$

Where t is the current value of iteration, $\vec{A}$, $\vec{C}$ and $\vec{E}$ are coefficient vectors, $\vec{X_p}$ denotes the position vector of prey, and $\vec{X}$ denotes the wolf's position vector. The $\vec{A}$ and $\vec{C}$ vectors are computed in the following manner:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \quad \text{(eq. 6)}$$

$$\vec{C} = 2.\vec{r_2} \quad \text{(eq. 7)}$$

Where $\vec{a}$ component is linearly declined from 2 to 0 during the iteration process and r_1, r_2 are the random vectors in the range of [0,1]. The alpha usually guides the pack for hunting the prey. Therefore, alpha is referred to as the best candidate option, whereas beta and delta gather information about probable prey locations. As a result, the first three best solutions retrieved are then saved and assessed, and the omegas or other search agents are commanded to update their current positions in accordance with the best search agent's position. These grey wolves complete the hunting process by chasing, harassing and lastly attacking the targeted prey when it stops escaping. For designing an MPPT method based on this GWO technique, we redefined the duty ratio (d) as the current position of the grey wolf. Thus, equation (5) is updated as:

$$D_i(k+1) = D_i(k) - A.E \qquad \text{(eq. 8)}$$

3.2 Incremental Conductance (IC) MPPT

The Incremental Conductance approach helps to track the peak point by correlating the instantaneous conductance (I/V) value of the module or array with its incremental conductance ($\Delta I/\Delta V$) value on a continuous basis. As we know, the slope of P-V characteristic is zero at MPP, negative when operating point is at the right side of MPP, and positive when it is on the left side of MPP (Saravanan and Babu, 2016), i.e.,

$$\left.\begin{array}{ll} \frac{dP}{dV} = 0, & \text{at MPP} \\ \frac{dP}{dV} > 0, & \text{left of MPP} \\ \frac{dP}{dV} < 0, & \text{right of MPP} \end{array}\right\} \qquad \text{(eq. 9)}$$

Now, the above Eq. (9) can be represented as:

$$\frac{dP}{dV} = \frac{d(I.V)}{dV} = I + V\frac{dI}{dV} = I + V\frac{\Delta I}{\Delta V} \qquad \text{(eq. 10)}$$

Comparing both these equations (9) and (10), Eq. (9) can be rewritten as,

$$\left.\begin{array}{ll} \frac{\Delta I}{\Delta V} = -\frac{I}{V}, & \text{at MPP} \\ \frac{\Delta I}{\Delta V} > -\frac{I}{V}, & \text{left of MP} \\ \frac{\Delta I}{\Delta V} < -\frac{I}{V}, & \text{right of MPP} \end{array}\right\} \qquad \text{(eq. 11)}$$

The objective of the IC algorithm is to find and select a suitable perturbation value so that incremental conductance becomes equals to the instantaneous conductance value and the PV system constantly maintains at peak operating point.

3.3 Proposed Hybrid MPPT technique

In this study the advantages of both grey wolf optimization (GWO) and incremental conductance (IC) MPPT are integrated to design a new hybrid MPPT approach so as to extract maximum possible power from an array or modules under partial shading conditions. The proposed technique, based on search and optimization approach, is intended to detect the global peak correctly and as a result, the overall performance of the PV system is improved under any environmental changes within the shortest time possible, with higher tracking speed and lower oscillations around the MPP. This method forces the GWO to operate during the initial stages for tracking the GP and the IC to operate during the final stages to locate the peak operating point by regulating the duty ratio of the converter to achieve high tracking efficiency and faster convergence rate. In this method, the duty cycle of the boost converter indicates the current position of a grey wolf. When these wolves find the GP i.e., when they reach close to each other, the IC method activates at the position of the best candidate search agent (wolf) in the GWO process. The flow-chart of the proposed Hybrid GWO-IC MPPT technique is presented in Fig 7.

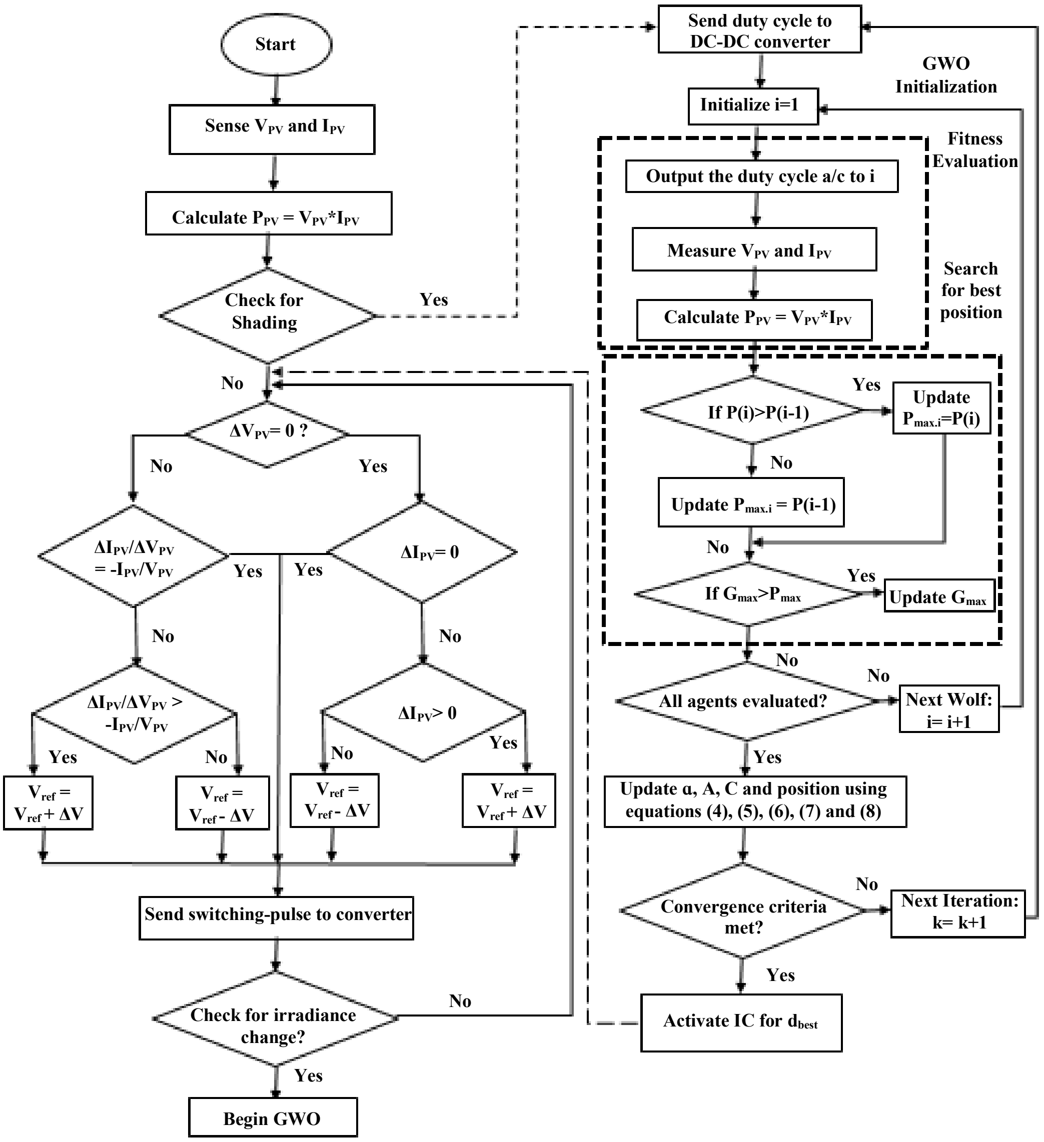


Fig. 7: Flowchart of the proposed Hybrid-MPPT technique

4. Results and discussion

The block diagram of the PV system incorporated with the proposed hybrid-MPPT technique is depicted in Fig 8. The proposed technique is simulated for a 1 kWp PV system for 4S and 2S2P topologies to verify its effectiveness under rapidly varying PSCs using MATLAB/Simulink tool. The PV module chosen in this study is Tata Power Solar System TP250MBZ and its parameters under STC is presented in Table 1. The main components used in simulation are C_{in} = 10μF, C = 470μF, L = 1.2mH, f = 20 kHz, and R_L = 53Ω for designing the boost converter (DC-DC). The GWO-IC MPPT is compared with conventional P&O, IC and GWO based MPPT methods for evaluation of its performance.

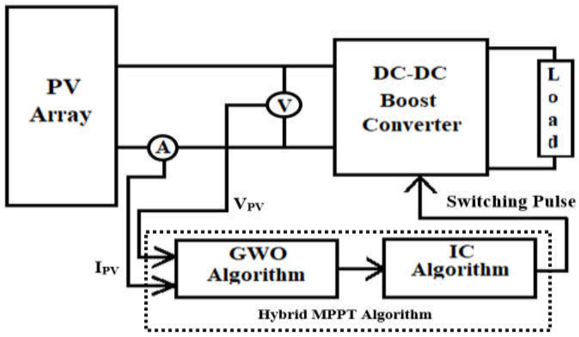
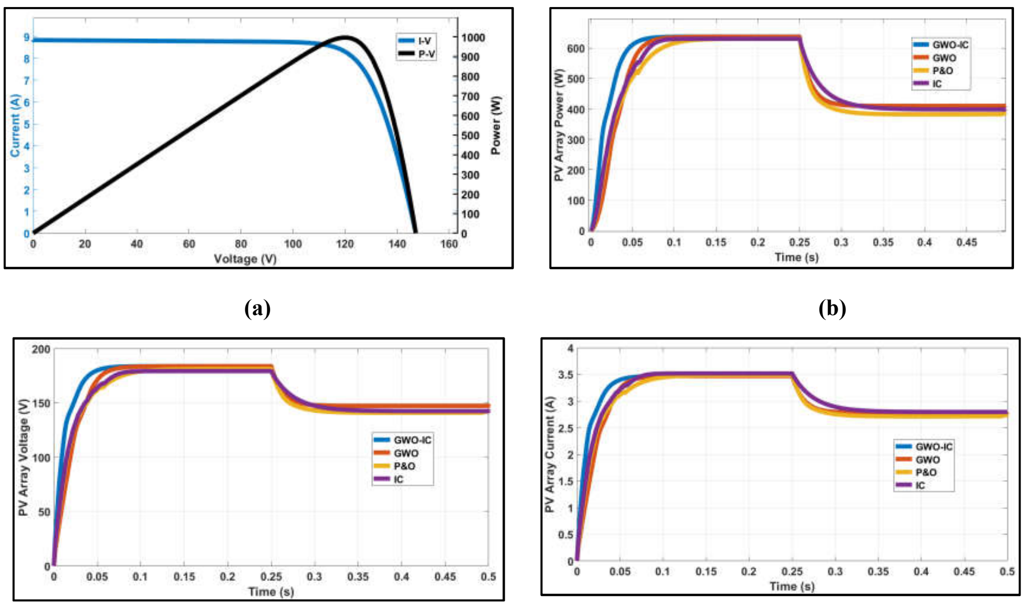


Fig. 8: Block Diagram of Proposed Hybrid-MPPT Algorithm

Tab 1: Datasheet of the simulated PV module

Parameters	Value
Maximum power (W)	249
Open circuit voltage (V)	36.8
Short circuit current (A)	8.83
MPP voltage (V)	30
MPP current (A)	8.3
Temperature co-efficient of open circuit voltage (% /°C)	- 0.33
Temperature co-efficient of short circuit current (% /°C)	0.0638



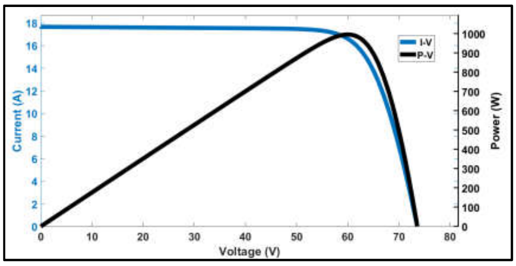
(a) **(b)**

(c) **(d)**

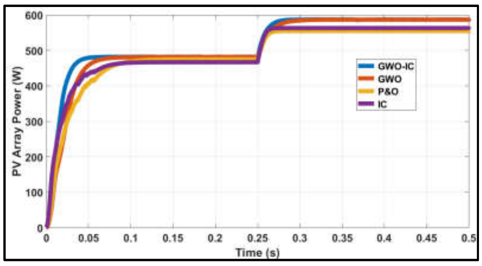
Fig. 9: Simulated waveforms for 4S configuration (a) STC (b)-(d) Tracking curves under PSCs

Fig 9 and 10 presents the simulated tracking waveforms of power, voltage, and current for both 4S and 2S2P configuration under PSCs considering GWO-IC, GWO, P&O, and IC methods. During the simulation of 4S configuration, shading pattern I turn up for first 0.25s and shading pattern II appears for next 0.25s. The proposed GWO-IC MPPT tracks the GP of 637.91W at 0.078s, while GWO finds the peak of 637.10W at 0.110s, IC detects the peak of 630.32W at 0.118s, and the P&O method converges to peak of 631.22W at 0.148s under shading

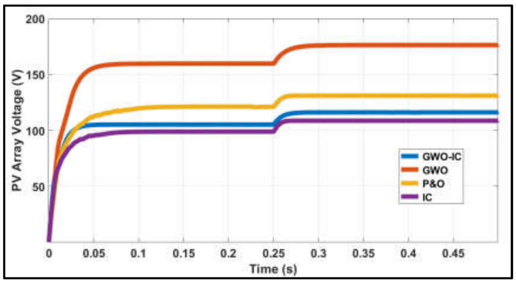
Pattern-I. At time 0.25s, shading Pattern-I gets replaced by pattern-II and the MPPT algorithms restarts to track the peak operating point. Under shading pattern-II, GWO-IC locates the GP of 409.99W at 0.052s, GWO tracks the peak of 409.33W at 0.053s, while IC and P&O fails to detect GP and tracks the LP of 398.87W and 388.63W respectively at convergence time of 0.098s and 0.089s. The tracking waveforms under PSCs and STC for 4S configuration are shown in Fig 9. Similarly, for 2S2P configuration shading pattern III and IV appears for each 0.25s intervals. The assigned values of irradiance for different shading patterns are indicated in Fig 3. Under shading pattern-III, GWO-IC MPPT tracks the GP of 482.34W at 0.056s, GWO detects the peak of 480.69W at 0.094s, IC reaches the peak of 466.91W at 0.109s, and the P&O locates the peak of 474.37W at 0.156s. While, under shading pattern-IV, GWO-IC locates the GP of 587.73W at 0.043s, GWO tracks the peak of 585.91W at 0.073s, IC detects the peak of 562.56W at 0.044s, and the P&O converges to peak of 554.41W at 0.046s. The tracking waveforms under PSCs and STC for 2S2P configuration are shown in Fig 10.



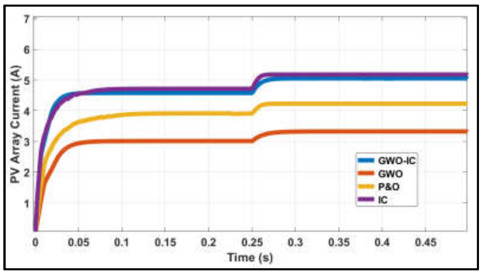
(a)



(b)



(c)



(d)

Fig. 10: Simulated waveforms for 2S2P configuration (a) STC (b)-(d) Tracking curves under PSCs

Tab. 2: Performance comparison of the proposed hybrid MPPT method for 4S configuration

Shading pattern and Maximum power (W)	MPPT technique	PV power (W)	Convergence time (s)	Tracking efficiency (%)
Pattern I (637.96 W)	GWO-IC	637.91	0.078	99.99
	GWO	637.10	0.110	99.86
	IC	630.32	0.118	98.80
	P&O	631.22	0.148	98.94
Pattern II (410.18 W)	GWO-IC	409.99	0.052	99.95
	GWO	409.33	0.053	99.79
	IC	398.87	0.098	97.24
	P&O	388.63	0.089	94.74

Table 2 and 3 summarizes the simulated results displayed in Fig 9 and 10 respectively. It is found from these Tables that the proposed hybrid GWO-IC MPPT exhibits higher tracking efficiency (>99%), faster tracking speed

(<0.1s), and negligible oscillations around MPP. Thus, it is clear that the GWO-IC deals with PSCs efficiently and outperforms the other MPPTs namely, P&O, IC and GWO methods. Table 4 presents the comparison between different MPPT methods with respect to convergence speed, tracking accuracy, implementation complexity, power oscillations and dynamic response. It is observed from Table 4 that the proposed method performance is much better compared to all other methods.

Tab. 3: Performance comparison of the proposed hybrid MPPT method for 2S2P configuration

Shading pattern and Maximum power (W)	MPPT technique	PV power (W)	Convergence time (s)	Tracking efficiency (%)
Pattern III (482.34 W)	GWO-IC	482.34	0.056	100
	GWO	480.69	0.094	99.65
	IC	466.91	0.109	96.80
	P&O	474.37	0.156	98.34
Pattern IV (587.79 W)	GWO-IC	587.73	0.043	99.99
	GWO	585.91	0.073	99.68
	IC	562.56	0.044	95.71
	P&O	554.41	0.046	94.32

Tab. 4: Comparison of hybrid GWO-IC MPPT with other MPPT algorithms

MPPT technique	Convergence speed	Tracking accuracy	Implementation complexity	Power oscillations	Dynamic response
P&O	Slow	Low	Simple	High	Poor
INC	Fast	Accurate	Complex	Less	Good
OCV	Slow	Low	Simple	High	Poor
SCC	Slow	Low	Simple	High	Poor
GWO	Fast	Highly accurate	Medium	Zero	Very good
GWO-IC	Very fast	Highly accurate	Medium	Zero	Very good

5. Conclusions

A hybrid GWO-IC MPPT based on grey wolf optimization and incremental conductance is proposed that can effectively track the MPP under any environmental conditions. The detailed performance comparison of GWO-IC method with the traditional MPPTs such as P&O, IC and Grey Wolf Optimization MPPT method is carried out. The comparison is done with reference to tracking efficiency, faster convergence to GP, and low oscillations around MPP for different configurations and at rapidly changing partial shading conditions. The results obtained from the simulation clearly indicate that the proposed hybrid MPPT exhibits higher tracking efficiency (>99%), faster convergence to the global peak with minimal time (<0.1s), negligible oscillations around MPP as compared to P&O, IC and GWO based MPPT technique.

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