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Modified grey wolf optimization for global maximum power point tracking under partial shading conditions in photovoltaic system

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Summary

In the study of photovoltaic (PV) system, power-voltage (P-V) curves exposed to view several peaks under partial shaded condition (PSC), which brings about muddled and most extreme maximum power point tracking (MPPT) process. Under uniform weather conditions, regular MPPT algorithms such as perturb and observe (P&O), hill climbing (HC), and incremental conductance (INC) work in an effective manner. However, these conventional methods are unable to track global peak successfully under PSC. In this context, the evolutionary algorithms such as grey wolf optimization (GWO) perform better than conventional algorithms. However, the conventional GWO is not sufficient for exploration point of view to locate global best particles; and moreover, GWO deteriorates the convergence process. To overcome these drawbacks, a modified GWO (MGWO) is proposed in this paper to track global best particle, which improves the convergence process under static condition and as well as re-initialization of parameters under dynamic conditions. The proposed method is verified using simulations as well as using experimental results. The obtained results demonstrate superiority compared to conventional GWO and HC methods under partial shaded patterns of PV array.

KEYWORDS

maximum power point tracking, partial shading, particle swarm optimization, photovoltaic system

1 | INTRODUCTION

Due to growing environmental concerns, there has been a paradigm shift in power generation technologies, that is, from conventional generation to renewable sources. Photovoltaic (PV) system has some advantages like less maintenance, require less time to install, flexible to place on buildings, while capital cost turn down due to the rapidly growing PV development compared to other renewable sources.[1] For power conversion, many converter topologies have been performed to PV applications, such as boost and SEPIC converter that are mainly in power sector as well as in rural electrification and industrial applications, power location for charging of vehicle and for the purpose of battery charging.[2] Power generation from a PV varies based on temperature and irradiance; power-voltage (P-V) characteristics with one peak is called maximum power point tracking (MPPT). There are many conventional algorithms available for MPPT which such as hill climbing (HC), perturb and observe (P&O), and incremental conductance (IC).

PV arrays comprise a many modules; each one constitutes a number of series–parallel connections of cells.[3] Each module of PV pattern receives non-uniform solar irradiance due to weather conditions, shading from trees, utility poles and tall buildings. During PSC, PV modules that are subjected to uneven irradiance consume more power, thereby creating hotspots. The hotspots are avoided by placing bypass diode at terminals of the PV module. Under PSC, the current through the parallel connected PV modules and the voltage across the series connected PV modules are different. This phenomenon results in achieving various peaks on P-V characteristic. Among the peaks, uppermost peak is noticed as Global Maximum Power Point (GMPP) and rest of the peaks are named as Local Maximum Mower Points (LMPP). These peaks location vary based on change of weather conditions. Traditional MPPT techniques are unable to trace GMPP under shaded condition of PV pattern; they are best suited to locate one peak curve. This difficulty can be reduced by optimization algorithm under PSC. Traditional methods such as P&O,[4] HC,[5] and IC[6] are best methods for MPPT of one peak curves and also its upgraded for to improve dynamic response in other studies.[7–11] The main problems of these methods are power loss during initial tracking and steady-state condition, and inability to capture MPPT when there is sudden change of shading occur lack of unsuitable step size. Nguyen and Low,[12] Patel and Agarwal,[13] Alireza et al[14] have proposed various MPPT algorithms for tracking of global peak (GP), but the initialization conditions are dependency on PV voltage. Moreover, even though the GP power is found, Jubaer and Zainal[15] report that voltage dependent solution is not always true, especially in more series connected PV modules. These algorithms may find a location of local power rather than global power on the P-V characteristics. Optimization techniques under shading such as particle swarm optimization (PSO)[16] were executed with three parameters vary based on iteration number, which gives higher efficiency by taking 30 iterations to track GP. Deterministic PSO[17] tackles the limitation to velocity, eliminates random number, improves tracking performance of PSO, but according to Lipschitz optimization (LIPO),[18] the significance of random numbers is to advice the algorithms jump from local MPP to search for GMPP and modified PSO[19] fixed the values of velocity of PSO (i.e., w, C_1, and C_2), PSO based on velocity[20] discarding the weight factor variation according to iteration number of PSO, deterministic behavior; adapting and regulating acceleration factors through present particle. Further MPPT methods, such as adaptive differential evolution (ADE) was tested with five statistical metrics at various shading conditions,[21] a novel deep recurrent neural network presented for tracking of dynamic global maximum peak under time-variant partial shading[22] and Artificial Bee Colony (ABC)[23] are also improves over PSO. Grey wolf optimization (GWO)[24] had better tracking performance over PSO and P&O. However, it has lack of exploration which results a delay in convergence criteria. The hybrid of GWO-P&O[25] improves performance compared to hybrid PSO-P&O and GWO without taking into account re-initialization under dynamic case. GWO-FLC[26] proposed a different re-initialization under PSC with minimum of initial grey wolves as five. The enhanced GWO[27] is implemented in the absence of solutions delta (δ), omega (ω), and position updated based on first wolf (α) and second wolf (β) best solutions. Recent methods to speed up tracking includes the accuracy of ANN-PSO[28] can generate up to 97% of the actual maximum power for any environmental variations and large fluctuations of irradiation and temperature. PSO can generate up to 94% while ANN can generate up to 96%; overall distribution of PSO[29] is to find GMPP accurately and rapidly but having five initial duties thereby more burden and complexity. Adaptive radial movement optimization (ARMO)[30] tracks location(s) of global power at faster rate by considering independent initial duties, and these are greater than five with three adaptive parameters. Hybrid-enhanced leader PSO-P&O[31] was implemented for fast tracking with more initial values along with regulating parameter though this paper had not mentioned the efficiency. The aim of work[32] is to determine GP at a fast rate. In order to mitigate main unnecessary sweeping of the PV output power curve, there are three methods are proposed named as large and small duty step (LSDS), large and mutable duty step (LMDS), and fast and intelligent global maximum power point tracking (GMPPT) (FI-GMPPT). These methods have been realized by modifying the conventional IC method to improve its working under PSCs. A new optimizing algorithm was implemented to improve accuracy and convergence time but requires pre-calculated voltages for implementation of the ANN[33] method. High speed (HS)[34] is fast tracking to GP compared with duty sweep and PSO methods, but it uses PI controller to track global, and its tracking time depends on inductance of converter, magnitude of PV voltage, and magnitude of current at previous operating point, but this HS tracking method is not suitable for all topologies of converter.

This paper proposes modified grey wolf optimization (MGWO) for global best particles. This method tracks GMPP with fewer number of iterations, leading to reduction of oscillations around GP and less tracking time under shaded PV patterns and re-initializing the parameters under change of shaded conditions of PV array. The proposed method is verified using simulations as well as using experimental results.

2 | DESIGN OF PV SYSTEM

The PV system is modeled and simulated using MATLAB/SIMULINK based on a single-diode PV cell and shown its equivalent circuit in Figure 1.[35] The equations associated with the PV system are explained below, and the PV module ratings are presented in Table 1.

The output current I_L is represented by

$$I_L = I_{PH} - I_D - \frac{V_L + I_L R_S}{R_{sh}} \tag{1}$$

The PV module current is given by

$$I_m = N_P I_{PH} - N_P I_D - \frac{V_m + I_m R_{s\bar{m}}}{R_{sh\bar{m}}} \tag{2}$$

The current flow through the Shockley diode I_D is

$$I_D = I_{sat}\left[e^{\frac{q(V_L + I_L R_S)}{akTN_s}} - 1\right] \tag{3}$$

$$I_{sat} = I_{sat\_n}\left(\frac{T_n}{T}\right)^3 exp\left[\frac{qE_g}{ak}\left(\frac{1}{T_n} - \frac{1}{T}\right)\right] \tag{4}$$

$$I_{sat\_n} = \frac{I_{sc\_n}}{exp(V_{oc\_n}/AV_{t\_n}) - 1} \tag{5}$$

Incoming solar irradiance which is in terms of current I_{PH} is focused on the PV cell. This I_{PH} is a function of irradiance and temperature, and is shown as

$$I_{PH} = (I_{PH_n} + K_i \Delta T)\frac{G}{G_n} \tag{6}$$

where

$$\Delta T = T - T_n$$

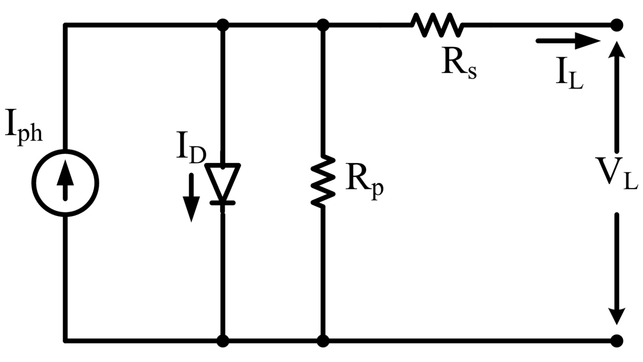

FIGURE 1 Equivalent model of PV

TABLE 1 Photovoltaic (PV) module specifications

P_{max}	V_{OC}	I_{SC}	V_{max}	I_{max}
60 W	21 V	3.8 A	17.1 V	3.5 A

The performance of MGWO algorithm can be proven with two PV arrays under PSC. The two PV arrays are designed by three PV modules are in series (3S), four PV modules are in series, and with two such combinations in parallel (4S2P) according to Figure 2 and related P-V curves with shading conditions are shown in Figure 3, where the irradiance considered to shading cases (patterns) is shown in Table 2.

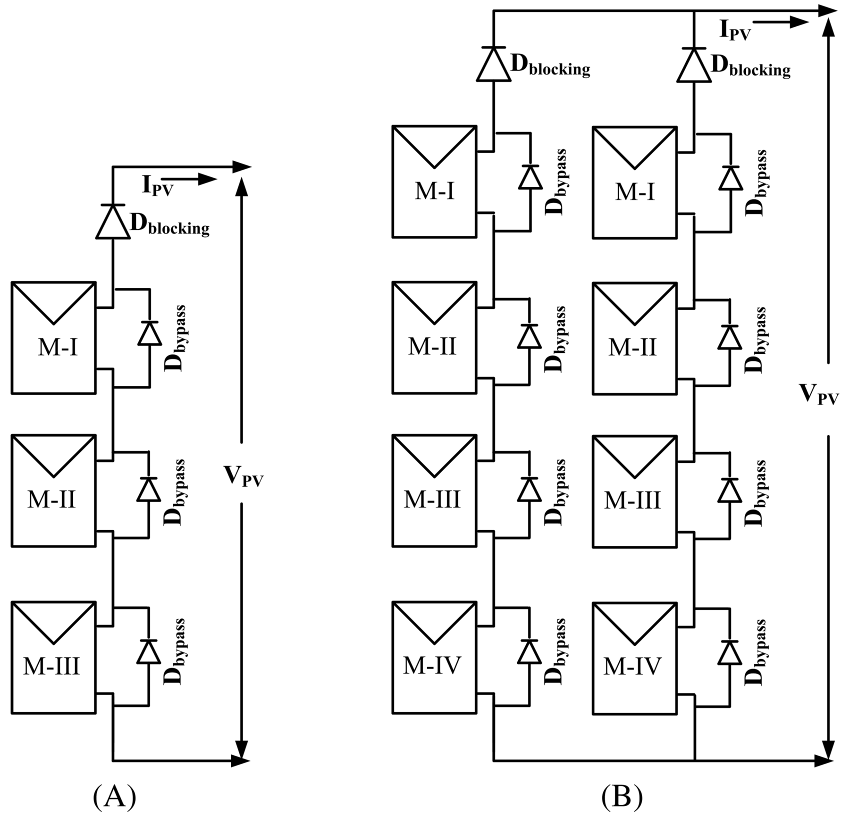

FIGURE 2 PV array configurations (A) 3S and (B) 4S2P

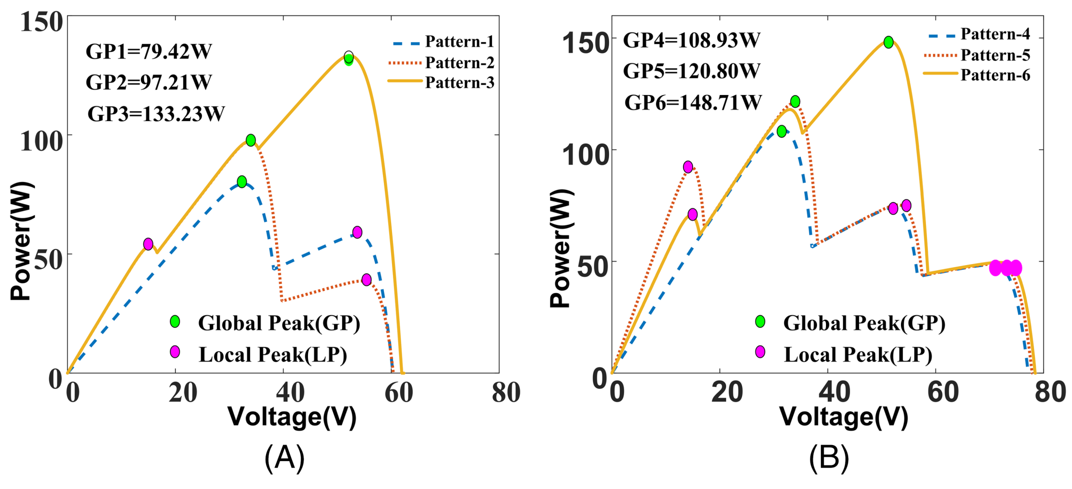

FIGURE 3 PV array characteristics (A) 3S and (B) 4S2P [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Irradiance (W/m^2) of module in photovoltaic (PV) arrays

Module (M)	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
M-I	700	1,000	1,000	500	900	700
M-II	700	800	800	500	500	500
M-III	300	200	700	200	200	400
M-IV	—	—	—	100	100	100

3 | TRACKING METHODS FOR GMPP

3.1 | HC algorithm for GMPPT

The best MPPT technique is HC due to its directness and less cost. The duty cycle[4] to converter is directly provided by the algorithm. By providing duty to the converter, maximum power can be measured. The traditional methods presented in the literature are described in previous studies.[4–11,13] The duty cycle $d(k)$ of HC is varied by the size of perturbation θ. The perturbation size plays important role for maximum power and the equations are given as follows:

$$d_{new} = d_{old} + \theta \ \ if \ \ P > P_{old} \tag{7}$$

$$d_{new} = d_{old} - \theta \ if \ P < P_{old} \tag{8}$$

The benefit of HC algorithm is that no additional controllers (such as P or PI) are required for generation of pulses to control the duty of converter.

3.2 | Application of GWO algorithm to GMPPT

The GWO is an advanced algorithm motivated by behavior of grey wolves and introduced by Mirjalili et al.[36] It mimics the nature of social leadership and hunting behavior of grey wolves. In GWO algorithm, the optimum solution (leader wolf) is denoted by alpha (α). The second and third best solutions (wolves) are represented as beta (β) and delta (δ), respectively. The other solutions (wolves) within the population are represented as omega (ω). Mathematically, the encircling mechanism of grey wolves is given by the below equation:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \tag{9}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{10}$$

where $\vec{X}$ is the position of a grey wolf vector, t is the current iteration, $\vec{X}_p$ specify the position of the prey vector, and A and C are coefficient vectors

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{11}$$

$$\vec{C} = 2 \cdot \vec{r}_2, \tag{12}$$

where r_1 and r_2 are random vectors in [0,1], respectively, and $\vec{a}$ is linearly reduced from 2 to 0 according to Equation 13

$$\vec{a}(t) = 2 - \frac{2t}{MaxIter} \tag{13}$$

MaxIter denotes the number of maximum iterations. The positions updated according to the positions of α, β, and δ in the following equations:

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right| \tag{14}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right| \tag{15}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \left| \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} \right| \tag{16}$$

$$\vec{X}_{GWO}(t+1) = \frac{\vec{X}_1(t) + \vec{X}_2(t) + \vec{X}_3(t)}{3} \tag{17}$$

The schematic diagram of Figure 4 shows the proposed algorithm to application of PV system. The grey wolves are duty ratios to converter, the controller implements by sensing V_{pv} and I_{pv}. To update the position of GWO based on MPPT, duty cycle (D) denoted as grey wolf. Therefore, Equation 10 changed as below:

$$D_i(k+1) = D_i(k) - A \cdot D \tag{18}$$

The fitness function of GWO is denoted as power

$$P\left(d_i^k\right) > P\left(d_i^{k-1}\right) \tag{19}$$

where P is power and d is duty cycle and i and k denotes present grey wolf and maximum number of iterations, respectively.

3.3 | GMPPT through proposed MGWO algorithm

The conventional GWO is a population-based optimization algorithm motivated by hunting strategy of grey wolves to optimize the global optimum solution. GWO is simple and applicable for MPPT, but GWO does not maintain enough exploration process in the search space with current position update Equation 17, and linear tuning of control parameter ($\vec{a}$), due to which slow convergence occurs in Mohanty et al.[24] So that, the GWO maintains imbalance between the exploitation and exploration process. To enhance exploration process of GWO, this paper proposes the MGWO algorithm for better convergence over to existing GWO. The update-position Equation 17 of GWO is modified by the inspiration of PSO in proposed MGWO algorithm for better exploration process.[37] In proposed method, each particle (wolf) is updated using modified updated-position Equation 20. According to the modified updated-equation of the proposed MGWO algorithm, the new updated-position equation maintains proper search process to improve the exploration process. Therefore, the exploration and exploitation process is well in the proposed MGWO algorithm, which makes better convergence compare to GWO algorithm in terms of less tracking time and minimum number of iterations are required to reach GP power under partial shaded conditions of PV array.

$$\vec{X}_{MGWO}(t+1) = b_1 \times \vec{X}_{GWO}(t+1) + b_2 \times \left(\vec{X}' - \vec{X}\right) \tag{20}$$

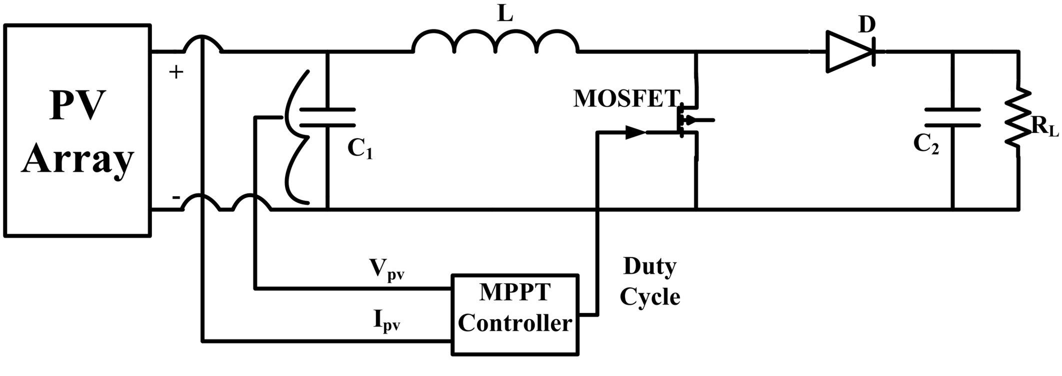

FIGURE 4 PV array to boost converter

$\vec{X}'$ is the particle selected from the wolves randomly but different to $\vec{X}$ and $b_1 \in (0, 1)$ and $b_2 \in (0, 1)$ are constant coefficients used to regulate the exploration and exploitation capabilities of Equation 20, respectively; several simulations are conducted by varying the parameters b_1 and b_2, and optimal solutions are at as $b_1 = 0.9$ and $b_2 = 0.1$ according to Wen et al.[37] Population-based optimization techniques have to deal with both exploration and exploitation capabilities in a search operation, where exploration addresses the ability to explore unknown regions of the design (search) space to realize the global optima, while exploitation addresses the ability to relate the knowledge of the existing particles in order to obtain better particles.

In the conventional GWO algorithm, $\vec{a}$ reduces linear fashion from 2 to 0 with Equation 13. But the linear changes in $\vec{a}$ would not reflect proper search process. Better performance can be obtained if $\vec{a}$ decreases as nonlinearly instead of linear Equation 13.[38] Based on the above information, the modified control parameter ($\vec{a}$) is shown in Equation 21 in order to trade-off the exploration and exploitation capabilities, and the specific control parameter ($\vec{a}$) has to be tuned nonlinearly for proper search process. Here, the control parameter ($\vec{a}$) is modified in Equation 21 and decreased from 2 to 0, which makes crucial contribution in the proposed algorithm to balance the exploration and exploitation in design process. A suitably large value of $\vec{a}$ helps exploration; however, a relatively small value of $\vec{a}$ helps exploitation process.

$$\vec{a}(t) = a_{initial} - \left(a_{initial} - a_{final}\right) \times \left(\frac{Max\_iter - t}{Max\_iter}\right)^{\mu} \tag{21}$$

where t is present iteration number, Max_iter specify the maximum iterations, μ denotes modulation index, in (0, 2) and assumed as 2 for better solution, and $a_{initial}$ and a_{final} are initial and final value of control parameter, respectively.[37]

3.4 | Steps to implement the proposed MGWO algorithm

Step 1: Initialize the wolves between 0.1 and 0.9 of the duty cycle.
Step 2: Measure the power P_{pv} from output of PV array at each location of wolf (duty) by sensing V_{pv} and I_{pv} and corresponding duty cycle to boost converter

$$P_{pv} = V_{pv} \times I_{pv}$$

Step 3: Updated-positions of wolves as duty of converter according to Equation 20.
Step 4: Update A, C, and $\vec{a}$ according to Equations 11, 12, and 21.
Step 5: Repeat steps 2 and 4 till to reach GP of P-V curve.
Step 6: If any new shaded PV array is presents then re-initialize the parameters of proposed MGWO algorithm.

The change of PV pattern is recognized by proposed algorithm with the following power equation:

$$\frac{|P_{n+1} - P_n|}{P_n} \geq \delta \tag{22}$$

Term P_n, P_{n+1} are current and next power outputs, δ is 2%.[39]

4 | SIMULATION RESULTS

The scheme of converter to PV application is shown in Figure 4. The results were carried out using the proposed method for GMPPT in simulation for six feasible shaded conditions of PV array. In these shaded conditions, 3S configuration of PV array for three patterns and the remaining three patterns were formed by 4S2P configurations of PV array. In these, one is on leftmost peak, one in center peak, and another on rightmost peak of 3S configuration. GP point of 4S2P configuration has first, second, and third peaks from left side of the P-V curve. Initial wolves of the proposed and GWO labelled as duty to converter were three $x_1 = 0.2$, $x_2 = 0.3$, and $x_3 = 0.7$. The designed values of algorithm and converter[39] are presented in Table 3.

The implementation of PV array with boost converter of the proposed algorithm in SIMULINK is modeled as per Figure 6. The PV modules connected in series/parallel with bypass and blocking diodes to form PV array. Implementation of proposed technique in MATLAB/SIMULINK using s-function is as per flowchart (Figure 5). The proposed algorithm provides duty to switch of boost converter by taking voltage and current signals from output of PV array. To prove the performance of the proposed MGWO algorithm, it was compared with conventional GWO and HC algorithms. The results were verified with six different shaded conditions of PV array.

TABLE 3 Details of algorithm and converter

Particulars	Parameters
Proposed	$\mu = 2, b_1 = 0.9$ and $b_2 = 0.1$ Population size = 3
GWO	Population size = 3
HC	$\theta = 0.05$
Boost converter	$L = 1.928$ mH, $C_1 = C_2 = 100$ µF, $F_s = 10$ kHz, Diode – *MUR*860, *IRFP*460 – *N CHANNEL MOSFET*, $V_{DDS} = 500$ V, $I_D = 20$ A 100 Ω 10 A Variable Rheostat load
Sampling period (T_s)	For simulation $T_s = 50$ ms, For experimental $T_s = 100$ ms.

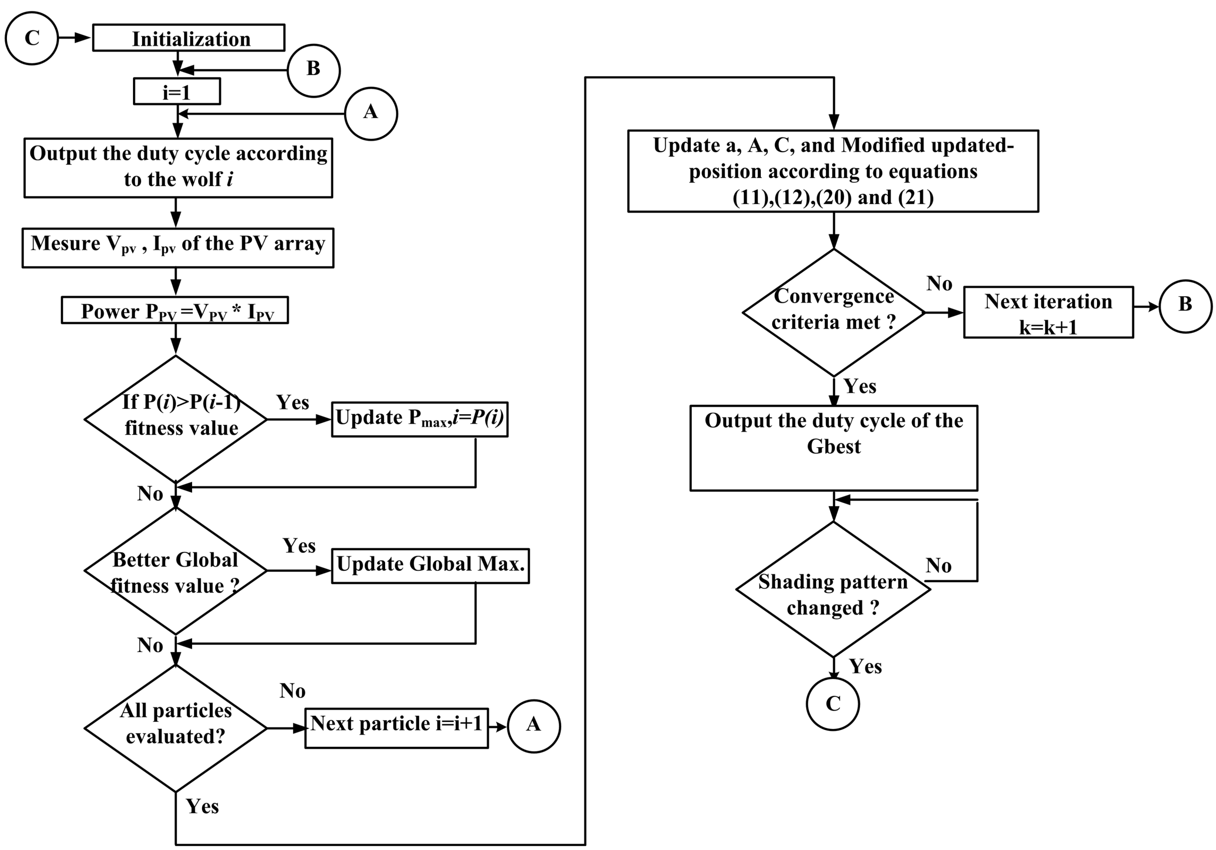

FIGURE 5 Flowchart of the proposed MGWO algorithm

4.1 | Simulation performance of 3S PV array

Pattern-1: In this pattern, the PV array consists of three PV modules, and these are placed in series to form 3S configuration. The irradiances are 700, 700, and 300 W/m^2. Due to two different irradiances in pattern-1, there will be two peaks in P-V characteristics of PV array in Figure 3A. The first peak from left side is GP, and the second peak is local peak (LP). The global point is left most peak, and its corresponding power is 79.42 W. By considering pattern-1 as PV source and connecting this as a source to boost converter (shown Figure 6), the converter switch (MOSFET) can be operated by taking the signal from MPPT algorithm. The proposed MGWO algorithm can be operated by sensing voltage and current from the output of PV array. The power observed by HC algorithm is 76.91 W with tracking time of 0.1 s, but there are oscillations at steady state. The tracking power obtained by GWO is 79.05 W with a time of 1.50 s to reach global power along with 10 cycles; in GWO, steady-state oscillations are reduced, but they take more time to reach GP power because they do not have enough exploration search process in GWO. The GP power obtained by the proposed algorithm is 79.05 W with a 0.96 s in six iterations, the corresponding simulation results are shown in Figure 7A. From the results, it was realized that the proposed MGWO technique is superior to GWO and HC algorithm in terms of steady-state oscillations, tracking time, and iterations. GWO algorithm does not have enough exploration due to which there is convergence delay. In this proposed MGWO algorithm, with the help of modified updated-position and non-linear variation of control parameter improves the exploration and exploitation process for global best particle to reach global power, so the time consumed by the proposed MGWO algorithm is less.

Patttern-2 and Pattern-3: Global power is the center peak in pattern-2 and rightmost peak in pattern-3, and its corresponding irradiances (W/m^2) are shown in Table 2; GP powers and P-V characteristics are shown in Figure 3A. The power extracted by HC algorithm in pattern-2 is 94.18 W with a tracking time of 0.1 s but oscillations at steady

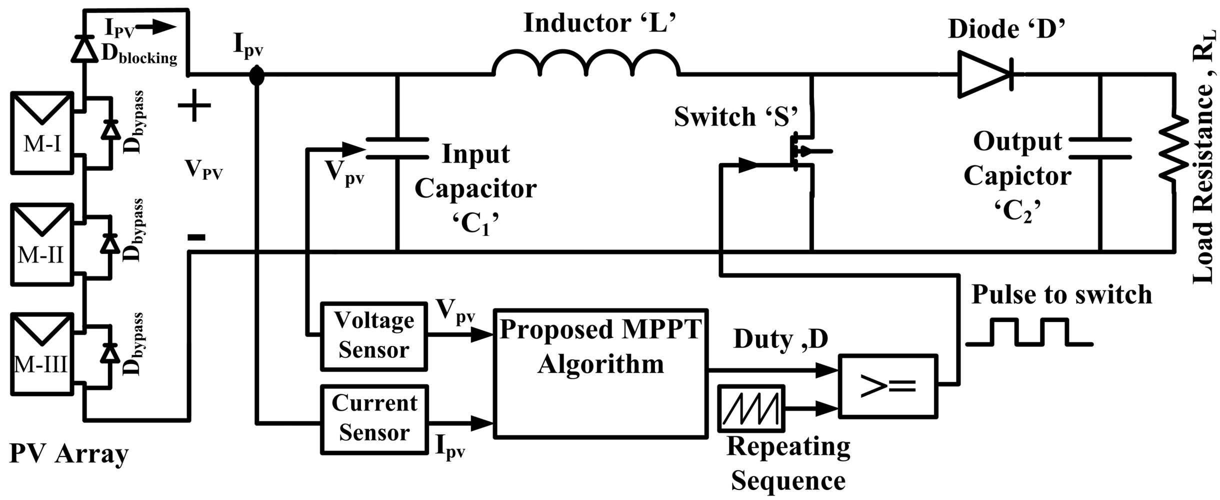

FIGURE 6 Schematic diagram of PV array to boost converter with a proposed MPPT algorithm

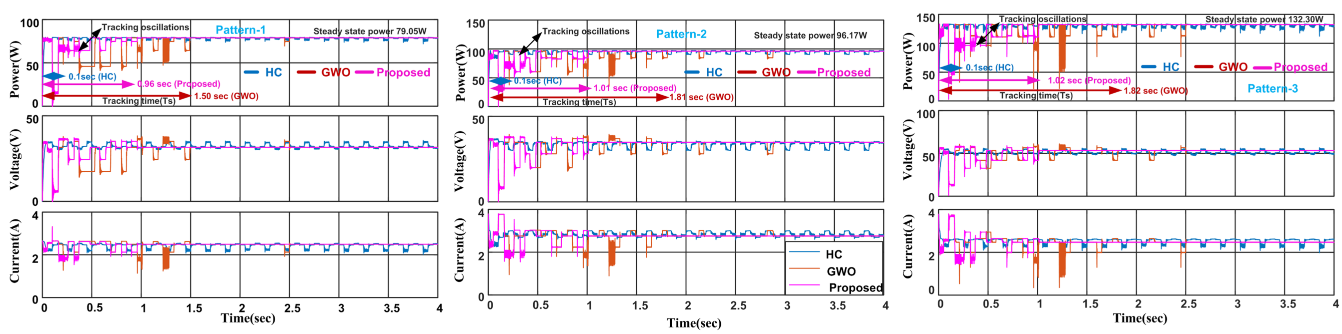

FIGURE 7 Simulation results of 3S PV configuration (A) pattern-1, (B) pattern-2, and (C) pattern-3 [Colour figure can be viewed at wileyonlinelibrary.com]

state. The power achieved by GWO and the proposed algorithm is 96.17 W, but the proposed algorithm reaches GP with 1.01 s and 7 iterations, whereas GWO takes 1.81 s with 12 iterations. The power obtained by HC algorithm of pattern-3 is 126.34 W with 0.1 s, while GWO takes 12 iterations to catch highest peak power 132.30 W with 1.82 s, and the proposed MGWO algorithm reaches highest peak power of 132.30 W in 7 iterations within 1.02 s. The advantages of these patterns are similar to pattern-1, and the simulation results are in Figure 7B,C, and the corresponding comparisons are presented in Table 4.

Dynamics of pattern-1 and pattern-2: In order to verify the dynamic operation of proposed algorithm, pattern-1 and pattern-2 were considered. First, pattern-1 is assumed as source to boost converter, and it tracks highest peak power with minimum number of iterations using the proposed algorithm; after 4 s, pattern-2 acts as source and the proposed algorithm re-initializes the parameter by considering power Equation 22 where again it tracks new GP power of pattern-2 with less tracking time and fewer cycles. Hence, the proposed algorithm works well even in dynamic cases also and compared with GWO and HC algorithms, and its corresponding simulations results are shown in Figure 8.

4.2 | Simulation performance of 4S2P PV array

Here, the complexity of PV system pattern is increased compared to previous patterns; here, four series PV modules and two such parallel paths are called 4S2P configuration. Based on these configurations, three patterns are formed, in which the first, second, and third peak from the left side of characteristics of PV array are shown in Figure 3B along with GP powers. The individual PV module irradiances (W/m^2) of each 4S2P pattern are presented in Table 2. In pattern-4, due to three dissimilar irradiances, there would be three peaks with the first peak being GP. The power absorbed by HC algorithm is 105.70 W with a tracking time 0.1 s, but there are oscillations at steady-state position; the GWO algorithm reaches GP power of 108.09 W with a taking time of 1.81 s along with 12 cycles; and the proposed algorithm attains global peak power of 108.09 W with fewer iterations (seven) and tracking time (1.01 s). The advantages of pattern-5 and pattern-6 are that of same as above patterns even if complexity of the system increases, and simulation results are shown in Figure 9; corresponding values are presented in Table 4.

TABLE 4 Simulation performance analysis of 3S and 4S2P PV array configurations

Method	Rated power (W)	Power from PV (W)	Voltage from PV (V)	Current from PV (A)	Tracking time (s)	Iterations	Tracking efficiency (%)
Proposed	79.42	79.05	31.62	2.50	0.96	06	99.53
GWO	Pattern-1	79.05	31.62	2.50	1.50	10	99.53
HC		76.91	32.18	2.39	0.10	—	96.83
Proposed	97.21	96.17	34.84	2.76	1.01	07	98.93
GWO	Pattern-2	96.17	34.84	2.76	1.81	12	98.93
HC		94.18	33.28	2.83	0.10	—	96.88
Proposed	133.23	132.30	53.56	2.47	1.02	07	99.30
GWO	Pattern-3	132.30	53.56	2.47	1.82	12	99.30
HC		126.34	51.15	2.47	0.10	—	94.82
Proposed	108.93	108.09	32.56	3.32	1.01	07	99.22
GWO	Pattern-4	108.09	32.56	3.32	1.81	12	99.22
HC		105.70	31.75	3.32	0.10	—	97.03
Proposed	120.80	119.75	34.61	3.46	1.01	07	99.13
GWO	Pattern-5	119.75	34.61	3.46	1.82	12	99.13
HC		114.90	33.20	3.46	0.10	-	95.11
Proposed	148.71	148.60	51.60	2.86	1.02	07	99.92
GWO	Pattern-6	148.60	51.60	2.86	1.33	09	99.92
HC		140.70	52.69	2.67	0.10	—	94.61

Abbreviations: GWO, grey wolf optimization; HC, hill climbing; PV, photovoltaic.

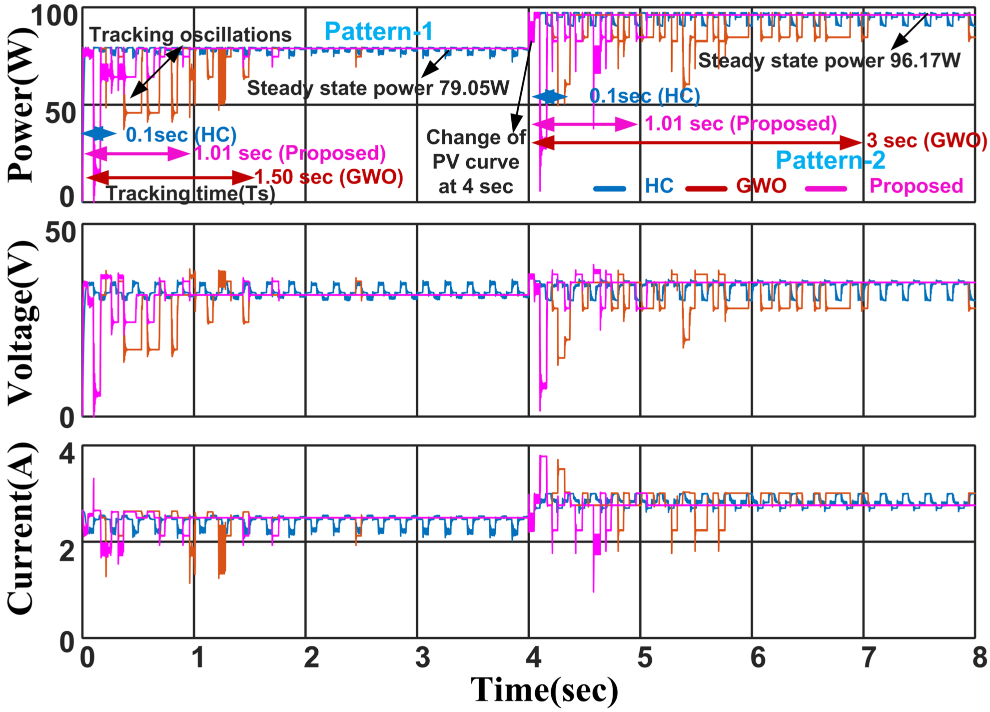

FIGURE 8 Simulation results of HC, GWO, and proposed MGWO algorithm during dynamic condition of pattern-1 and pattern-2 [Colour figure can be viewed at wileyonlinelibrary.com]

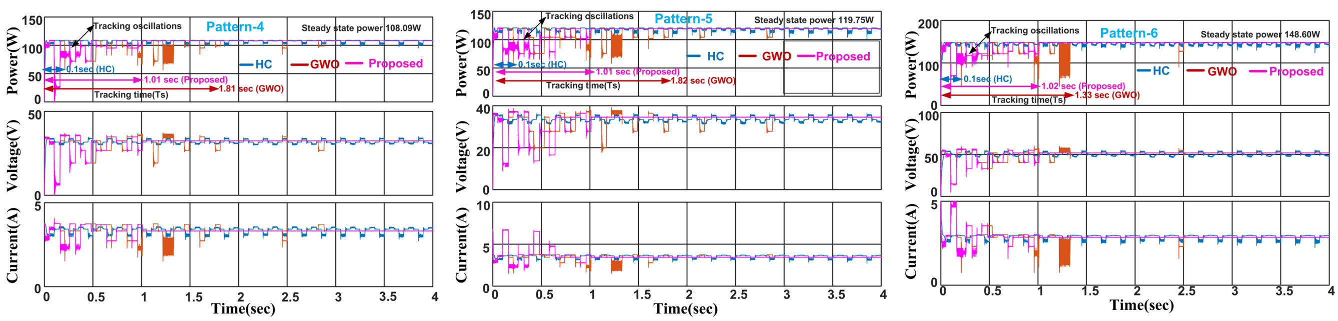

FIGURE 9 Simulation results of 4S2P PV configuration (A) pattern-4, (B) pattern-5, and (C) pattern-6 [Colour figure can be viewed at wileyonlinelibrary.com]

The simulation performance of HC, GWO, and proposed MGWO algorithms were tested under six shading patterns of PV array; corresponding results are shown in Figures 7 and 9 and also presented its performance in Table 4. From the simulation results, HC algorithm displays oscillations around steady-state point, and there is a loss of power during transient period due to step size. GWO algorithm does not have enough exploration with updated position and linear variation of control parameter ($\vec{a}$) of GWO algorithn due to which there is convergence delay, taking more number of iterations to reach global power and also observed from Table 4. In this proposed algorithm, due to modified updated-position, Equation 20 and the modified control parameter updated Equation 21 maintain better exploration and exploitation process for global best particle to reach global power, so the time consumed by the proposed algorithm is less and takes fewer number of iterations compared to GWO. From these results, it was realized that the proposed MGWO technique is superior to GWO and HC algorithm in terms of steady-state oscillations, tracking time, and number of iterations to reach GMPP.

5 | EXPERIMENTAL RESULTS

An experimental setup is shown in Figure 10 comprising programmable PV simulator (Magna power electronics XR600-9.9/415 + PPPE+HS), boost converter, voltage sensor (LV25-p), current sensor (LA55-p), and D-space 1104 controller which is interfaced with MATLAB. The P-V curves are taken from PV simulator for different PV array patterns. The proposed algorithm was verified by D-space 1104 controller by sensing voltage and current from output of PV simulator with the help of sensors. The output of proposed algorithm duty is given to switch of boost converter, and the converter details are mentioned same as simulations values, which are shown in Table 3. The verification of GMPP using the proposed algorithm with two PV array configurations at various peaks on P-V curve under different shaded patterns of PV array. The corresponding irradiances (W/m^2) are represented in Table 2, and the P-V curves are in Figure 3.

5.1 | Experimental performance of 3S PV array

The superiority of the MGWO algorithm over HC and GWO is that the fewer cycles are needed to track highest peak of P-V curve and oscillations around GP and the convergence time is also minimum as was noticed in Section 4 results. The proposed MGWO algorithm was developed in experimental to compare with Section 4 results, and the operating point GMPP on P-V characteristics was also observed to justify the efficiency. Table 5 shows the results of experimental analysis of two PV array configurations.

The experimental results of the proposed MGWO, GWO, and HC algorithms of pattern-1 are shown in Figure 11 along with an operating point on P-V characteristic which is inscribed in each figure at the right-hand corner. The power obtained by HC algorithm of pattern-1 is 75 W with a time of 1.12 s; the GWO algorithm tracks global power of 78.12 W with a time of 3 s and takes 10 iterations; and the proposed method observed 78.72 W of GP power within five iterations with a time of 1.5 s. In hardware implementation also, the steady-state oscillations were observed in HC, whereas GWO takes more time and iterations to achieve GMPP, so that the proposed MGWO method overcomes problems associated with HC and GWO algorithms; the performance results are shown in Figure 11. In order to know the performance of the proposed algorithm, it is verified with two more shaded patterns of 3S configuration with middle and rightmost peak as GP in each P-V characteristic. The advantages of the proposed algorithms with pattern-2 and pattern-3 as PV source also have minimum tracking time and fewer cycles compared to HC and GWO methods; the related results are presented in Figures 12 and 13, and the corresponding observations are presented in Table 5.

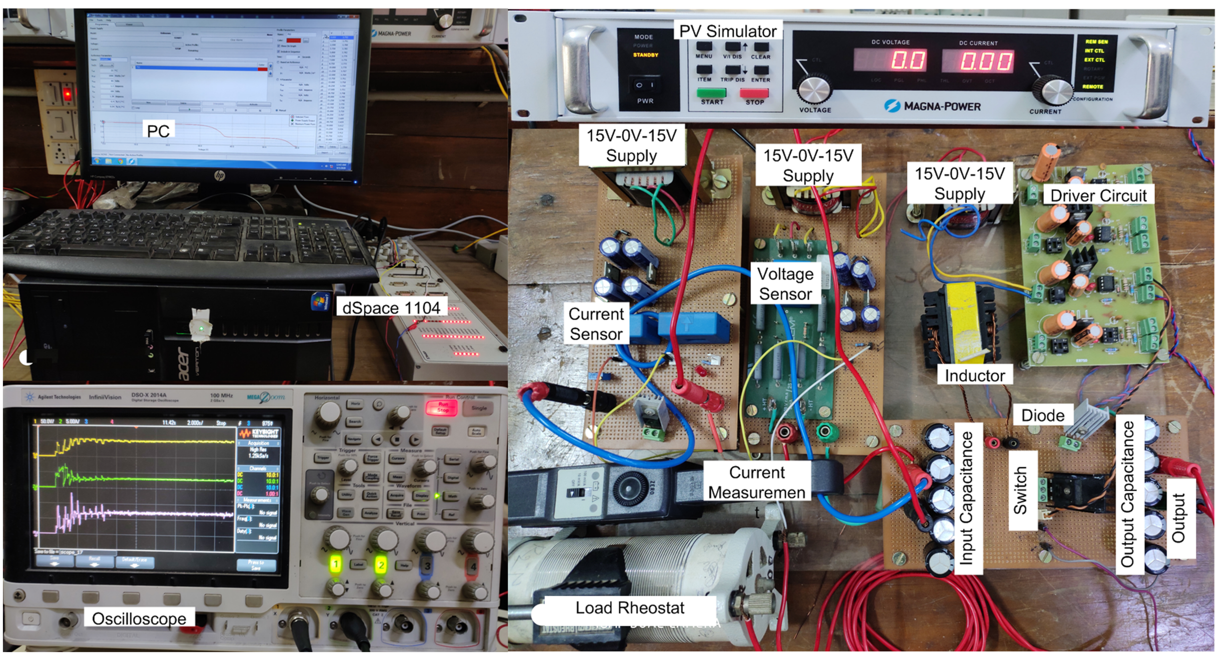

FIGURE 10 Experimental setup [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Experimental performance results of 3S and 4S2P PV array configurations

Method	Rated power (W)	Power from PV (W)	Voltage from PV (V)	Current from PV (A)	Tracking time (s)	Iterations	Tracking efficiency (%)
Proposed	79.42	78.72	33.50	2.35	1.50	05	99.11
GWO	Pattern-1	78.12	31.00	2.52	3.00	10	98.36
HC		75.00	30.00	2.50	1.12	—	94.43
Proposed	97.21	97.00	33.45	2.90	1.50	05	99.78
GWO	Pattern-2	94.47	33.50	2.82	3.50	12	97.18
HC		90.02	32.15	2.80	1.00	—	92.60
Proposed	133.23	132.60	51.00	2.60	1.80	06	99.52
GWO	Pattern-3	132.30	49.00	2.70	3.25	11	99.30
HC		126.10	48.50	2.60	1.50	—	94.64
Proposed	108.93	108.67	31.50	3.45	2.12	07	99.76
GWO	Pattern-4	108.00	30.00	3.60	3.37	11	99.14
HC		104.40	29.00	3.60	1.25	—	95.84
Proposed	120.80	120.45	33.00	3.65	2.00	07	99.71
GWO	Pattern-5	119.70	31.50	3.80	3.80	12	99.08
HC		115.20	32.00	3.60	0.25	—	95.36
Proposed	148.71	147.50	50.00	2.95	1.75	06	99.18
GWO	Pattern-6	146.30	50.45	2.90	2.90	08	98.37
HC		126.00	45.00	2.80	0.50	—	84.72

Abbreviations: GWO, grey wolf optimization; HC, hill climbing; PV, photovoltaic.

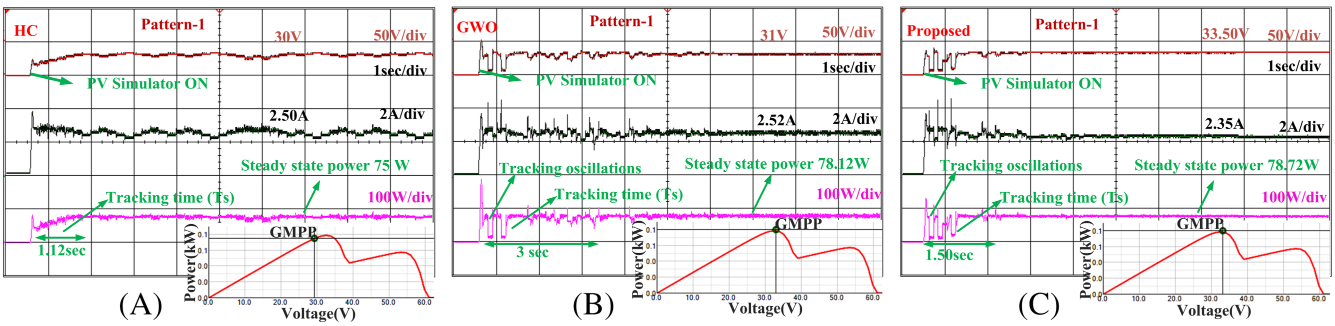

FIGURE 11 Experimental results of shading pattern-1 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

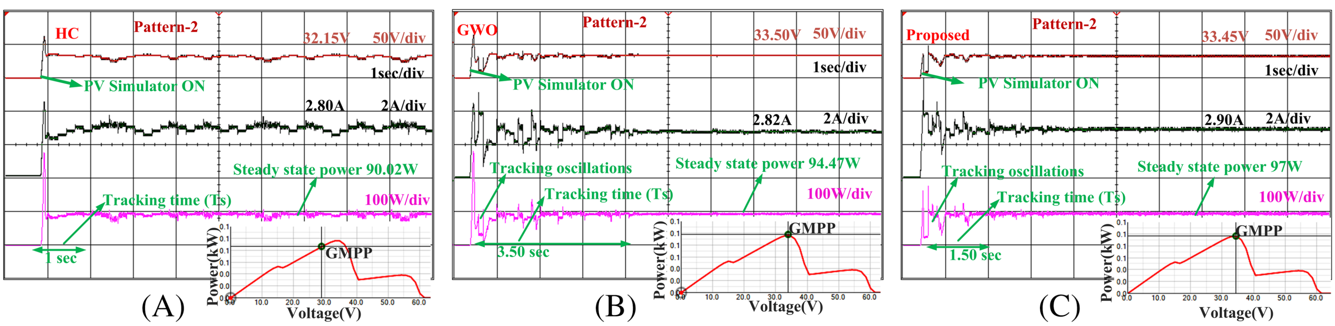

FIGURE 12 Experimental results of shading pattern-2 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

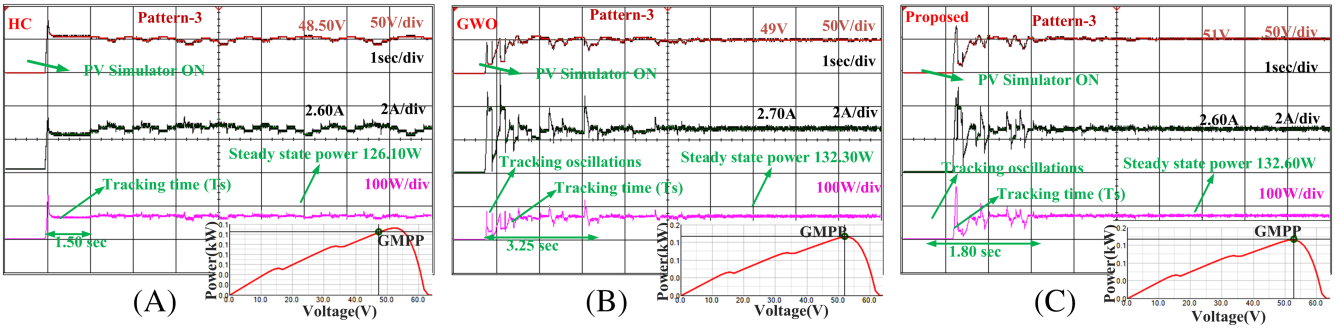

FIGURE 13 Experimental results of shading pattern-3 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

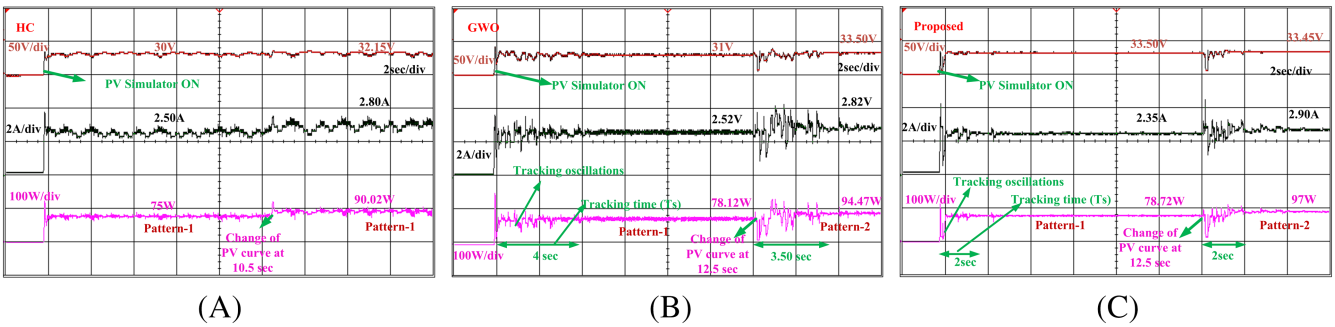

FIGURE 14 Experimental results changing from shading pattern-1 to shading pattern-2 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

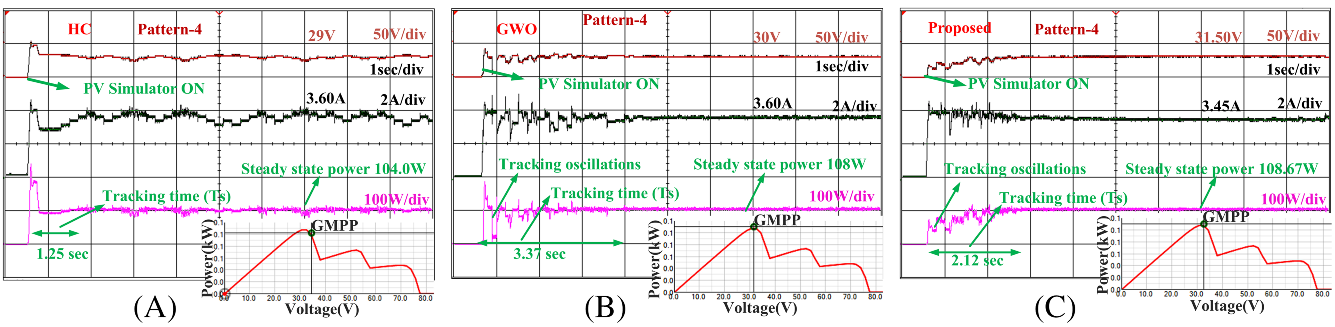

FIGURE 15 Experimental results of shading pattern-4 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

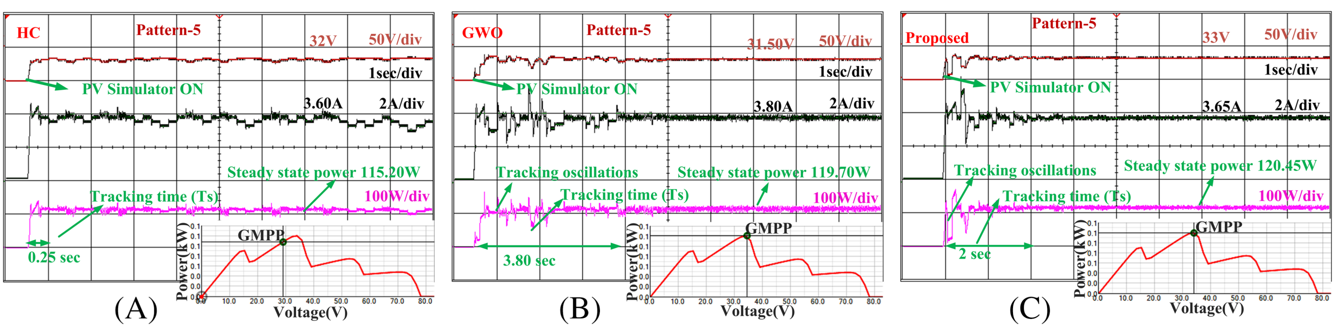

FIGURE 16 Experimental results of shading pattern-5 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

Dynamics of pattern-1 and pattern-2: To test the proposed MGWO algorithm with a sudden change of one shading pattern to another shading pattern at a particular period is also observed in Figure 14. The proposed MGWO algorithm tracks global power (78.71 W) with minimum tracking time of 2 s when pattern-1 is acting as PV source under PSC, then maintains constant power as global power and at 12.5 s PV source changes to pattern-2; the algorithm has to re-initialize the parameters of proposed MGWO algorithm and track new global power according to pattern-2 with fewer iterations and less tracking time; this dynamic case was also compared with GWO and HC algorithms as shown in Figure 14.

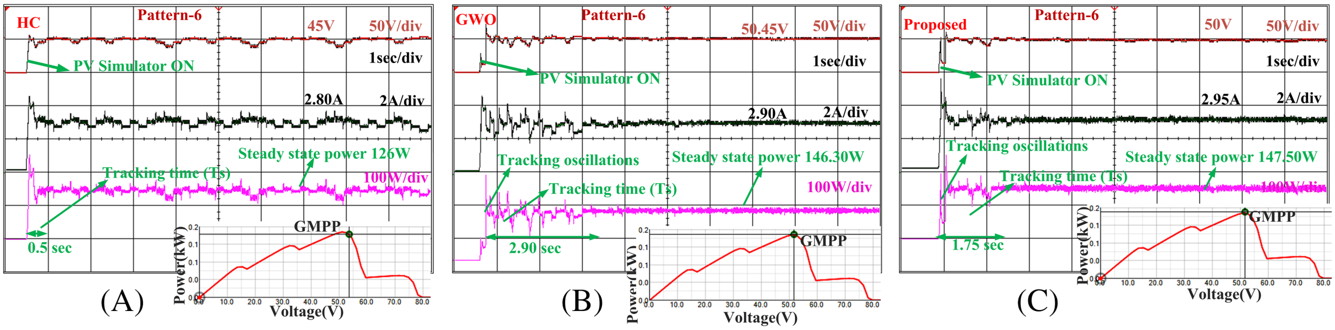

FIGURE 17 Experimental results of shading pattern-6 (A) HC, (B) GWO, and (C) proposed MGWO algorithm [Colour figure can be viewed at wileyonlinelibrary.com]

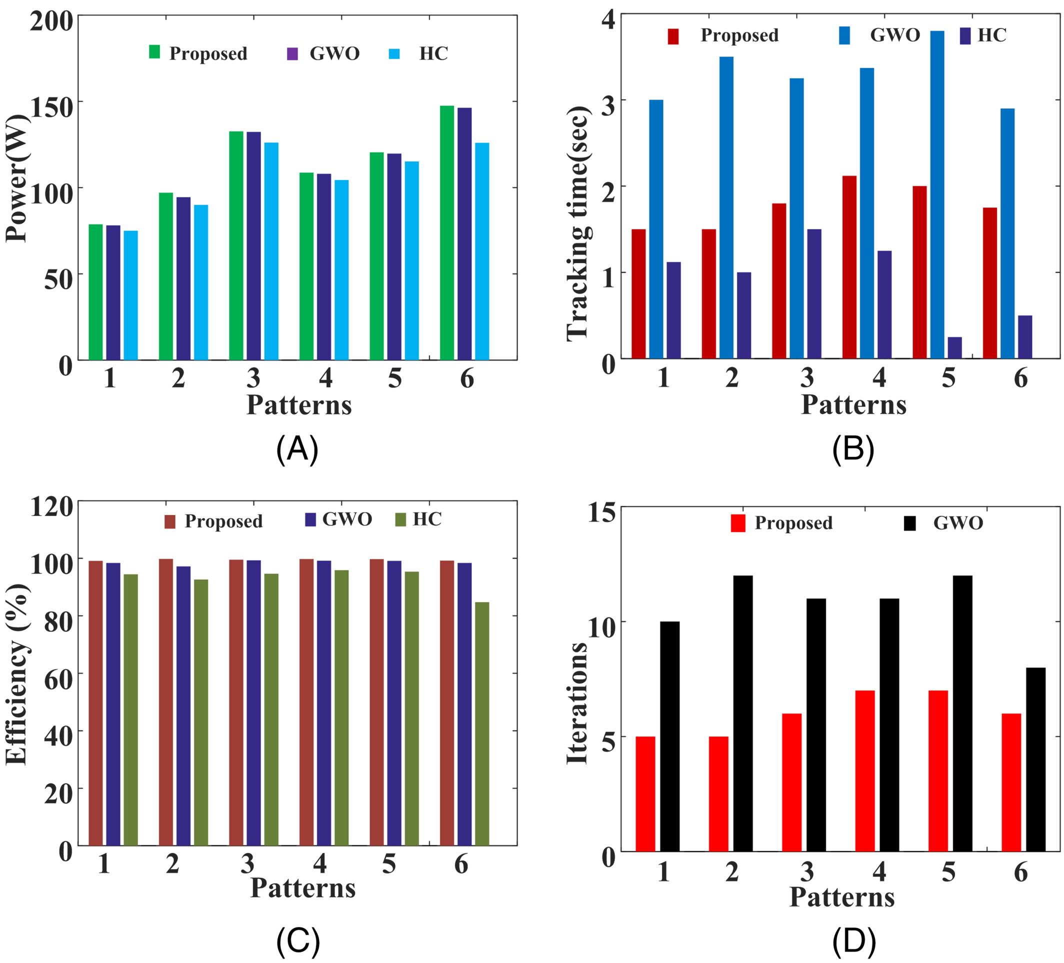

FIGURE 18 Experimental comparison of proposed MGWO, GWO, and HC algorithms of (A) power, (B) tracking time, (C) efficiency, and (D) iterations with respect each shading pattern [Colour figure can be viewed at wileyonlinelibrary.com]

5.2 | Experimental performance of 4S2P PV array

In this configuration, the complexity of PV source is increased compared to 3S PV array configuration and also multiple peaks present in P-V characteristics. Based on 4S2P PV array, three shaded patterns are considered, and the power observed by HC algorithm of pattern-4 is 104.40 W with a time of 1.25 s; the GP power observed by GWO algorithm is 108 W with a time of 3.37 s along with 11 iterations, whereas the proposed MGWO algorithm converges to GP power 108.67 W with seven iterations along with minimum tracking period of 2.12 s. In this case also, the proposed MGWO algorithm outperforms GWO and HC, and corresponding results of pattern-4 are shown in Figure 15. Similarly, pattern-5 and pattern-6 are performed to know the effectiveness of the proposed algorithm for different shading conditions; these also overcome problems faced by conventional HC and GWO algorithms, and the corresponding results are in Figures 16 and 17, and the observations are presented in Table 5.

6 | COMPARATIVE STUDY

The proposed algorithm finds GMPP with fewer iterations, less tracking period, and minimum oscillations around GP compared conventional GWO and HC. The conventional GWO[24] algorithm have delay in convergence process due to poor exploration process; also, it is not performed with re-initialization of parameters under dynamic case, whereas in the proposed MGWO, algorithm implemented with modified updated-position along with $\vec{a}$ is used for better convergence process and also performed with re-initialization of parameters under dynamic conditions. The change of step size is difficult under dynamic coditions in HC algorithm. The comparison of power, tracking time, efficiency, and iterations of three algorithms with respect to the number of patterns is shown in Figure 18. The PSO[16] implemented for GMPP with three tuning parameter and five initial particles takes more number of iterations. ARMO[30] algorithm reaches GP with low tracking period but is implemented with three tuning parameter, and initial particles are greater than five. Hybrid GWO-P&O[25] tracks global power fast but not re-initialized the parameter during change of PV shaded patterns. MPV-PSO[20] tracks fast with the removal of tuning of weight factor, while cognitive factors are in tune with

TABLE 6 Comparison of the proposed modified grey wolf optimization (MGWO) method with other global maximum power point tracking (GMPPT) algorithms

Parameters/method	Tracking time	Iterations	Tuning parameters	Initial duties	Population size	Re-initialization	Sensors required	Cost factor
PSO[16]	Moderate	More	3	Independent	5	Considered	Voltage, current	Moderate
ARMO[30]	Less	Less	3	Independent	Greater than 5	Considered	Voltage, current	Moderate
GWO[24]	Moderate	Moderate	1	Independent	3	Not considered	Voltage, current	Moderate
GWO–P&O[25]	Less	Less	1	Independent	3	Not considered	Voltage, current	Moderate
MPV-PSO[20]	Less	Less	2	Dependent	3	Considered	Voltage, current	Moderate
GWO-FLC[26]	Less	Less	1	Independent	Greater than 5	Considered	Voltage, current	Moderate
OD-PSO[29]	Moderate	Moderate	—	Independent	5	Considered	Voltage, current	Moderate
HS[34]	Less	—	—	Dependent	—	Considered	Voltage, current	Moderate
Proposed	Less	Less	1	Independent	3	Considered	Voltage, current	Moderate

Abbreviations: ARMO, adaptive radial movement optimization; GWO, grey wolf optimization; HC, hill climbing; HS, high speed; P&O, perturb and observe; PSO, particle swarm optimization.

current particle, and initial particles are dependent. Hybrid GWO-FLC[26] is implemented with higher power ratings with different re-initialization methods by considering an average of 5 to 10 grey wolves as a population. Due to higher number of initial particle, the burden on the system is increased. The proposed MGWO algorithm was compared with existing MPPT algorithm, which are presented in Table 6, and the experimental performance of the proposed algorithm is presented in Table 5.

7 | CONCLUSIONS

This paper proposed a novel GMPP tracking algorithm for shaded conditions of PV array. The proposed algorithm enhances existing GWO algorithm by using modified updated-position and control parameter ($\vec{a}$), to enhance fast convergence. The proposed algorithm (MGWO) tracks the GP power under shaded condition of PV array with reduced number of iterations and less tracking period. The steady-state oscillations also reduced around GP point successfully with only one tuning control parameter; initial duties are not dependent on PV system. To highlight the proposed method, a detailed comparison with conventional GWO and HC algorithms is presented. The proposed method demonstrated better performance than conventional GWO and HC methods and can track GP with any shading condition of PV pattern, and as moreover, outperformed even in dynamic shaded conditions and offered high efficiency.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available within the article and also in appropriate references.

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