Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 00000000.DOI

A novel hybrid MPPT algorithm based on Grey wolf optimization and differential evolution for photo voltaic system under partial shading conditions

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This paragraph of the first footnote will contain support information, including sponsor and financial support acknowledgment. For example, "This work was supported in part by the U.S. Department of Commerce under Grant BS123456."

ABSTRACT Maximum power point tracking (MPPT) methods have been widely researched in order to extract maximum power from the output of a PV array in a solar renewable energy system, but conventional MPPT methods are unable to track global maximum power point (GMPP) under partial shading conditions (PSC's). During PSC's, multiple peaks are generated in the PV characteristic of the PV system. To solve this issue, a new and improved hybrid MPPT method is proposed by combining two evolutionary algorithms, Grey wolf optimization (GWO) with an improved and new convergence factor and Differential evolution (DE) with a dynamic scaling factor using a crossover operator. The proposed algorithm can find GMPP at a high speed, and because it is simple in structure, it can be easily implemented without putting too much strain on the microcontroller. To assess the proposed method's performance, it was first compared to conventional GWO and DE-based MPPT techniques, and the simulation results were compared to determine the efficacy of the proposed MPPT method under various PSCs. Next, a standalone PV battery system with a flyback converter was designed and simulated using MATLAB SIMULINK, and the proposed technique was implemented in the MPPT controller of aforementioned system. The simulation results show that this system meets the load demand, operates at GMPP under varying irradiance, and keeps a constant voltage across the load.

INDEX TERMS Partial shading conditions, Grey wolf optimization, Differential evolution, PV system, Local maximum power point (LMPP), Flyback converter, Global maximum power point (GMPP), Maximum power point tracking (MPPT).

I. INTRODUCTION

THE energy sources are insufficient to satisfy the increasingly rising demand as energy demand grows day by day. On the other hand the conventional energy sources has a negative impact on the environment. In light of this, several renewable energy sources, such as solar energy, tidal energy, wind energy, geothermal energy etc have been described in literature[1]. Solar energy is considered to be the most successful and promising form of renewable energy source among all of these renewable energy sources. Solar energy has many advantages, including low maintenance costs, zero emissions, zero input costs, and the ability to operate as a standalone system with output ranging from microwatts to megawatts[2][3]. Solar energy has a wide variety of applications, ranging from water pumps, reverse osmosis, solar home systems, electric car charging[4], communication satellites, space vehicles, power plants, solar powered UAV[5] and among others[6][7]. However, solar energy installation remains a difficult task due to two major drawbacks: high installation costs and poor conversion efficiency of PV modules, which ranges from 9 to 17 percent. A lot of research is being done to reduce the cost of cell material in order to lower the installation cost [8]. The non linear I-V and P-V characteristics of PV modules are the primary cause of low conversion performance, and output power is mainly dependent on atmospheric conditions such as temperature and irradiance. To address this issue, a solar PV system should be run at its maximum power point. The phenomenon of partial shading [9][10] occurs when solar irradiance is not evenly distributed across the PV surface, resulting in low efficiency. when solar irradiance is not uniformly distributed, multiple peaks are generated, with only one peak containing the maximum power. This peak is known as the global maximum power point (GMPP). The non-uniformity of solar irradiance on certain PV modules is caused by clouds, building shadows, trees, and other factors, and it is the duty of the maximum power point tracker to ensure that the PV system is operated on the GMPP rather than the local maximum power point (LMPP).

To get the maximum power from the PV system, the maximum power point tracker regulates the duty ratio of the dc-dc converter. After reviewing a considerable amount of literature on solar PV array MPPT[2][3][6][7][11], it was discovered that many traditional, soft computing-based techniques, such as perturb and observe (P&O)[12], incremental conductance (INC)[13], hill climbing (HC)[14], fractional open circuit voltage (FOCV)[15], and others, have been used to obtain the GMPP in recent years. Among all these technique P&O and INC techniques are widely used due to their simplicity and ease of execution. Perturb and Observe is an iterative method for MPPT tracking it uses operating voltage for perturbation and the sign of change in power is used to determine whether the operating voltage should increase or decrease if the power increases by increasing the operating voltage, then voltage will be more perturbed in the same direction otherwise reverse the direction of perturbation. However, the problem with this technique is that operating point oscillates around the MPP results in power loss. These oscillations can be minimised by reducing the step size, but this decreases the system's speed. Several improved P&O techniques based on variable step size have been proposed in the literature to address this problem[16][17][18]. The HC technique is similar to the P&O technique, with the exception that HC uses duty cycle perturbation rather than operating voltage perturbation. INC technique removes the P&O constraint of oscillation around MPPT during rapidly changing atmosphere by contrasting instantaneous panel conductance with incremental panel conductance until the slope of the PV curve is zero. As a result, these methods, P&O and INC, can be used in uniform or without PSCs. These techniques are unable to distinguish GMPP from multiple MPPs in partial shading conditions and remain stuck at the first peak or first maxima, regardless of whether it is GMPP or LMPP. Apart from the techniques described above, there are several other traditional techniques such as Ripple correlation factor (RCF)[19], Current sweep (CS), Lookup table[20], and many others, but none of them are capable of tracking GMPP under partial shading conditions. To track the GMPP under partial shading conditions, researchers proposed an intelligent controlling based MPPT consisting of fuzzy logic control (FLC)[21] and artificial neural networks[22]. These techniques can find GMPP under PSCs as well as in rapidly changing atmosphere, but they need a lot of computation and put a lot of strain on the processor because they need a lot of data for training the artificial neural network and fuzzification and de-fuzzification in the fuzzy logic controller. Yet, the ANN requires a comprehensive training process demanding more advanced microcontroller with higher cost, and the FL-based MPPT controller is extremely dependent on the designer knowledge and experience about the PV system. Researchers were drawn to the Evolutionary algorithm (EA) because of the problems with the above-mentioned techniques. Due to their simplicity, flexibility, gradient free-mechanism and ease of execution, the EA can easily find GMPP under PSCs with very little computation and does not put a lot of strain on the processor. Among several EA techniques Particle swarm optimization (PSO)[23][24], Artificial bee colony (ABC)[25], Differential evolution (DE)[26], Ant colony optimization (ACO)[27], Grey wolf optimization (GWO) are the some popular EA techniques to find GMPP.

Grey wolf optimization (GWO)[28] was developed by the Mirjalili in 2014 which is based on the hunting behaviour of grey wolves that searching for the optimal way to hunting the preys. The social hierarchy and hunting mechanism of grey wolves served as inspiration for GWO. During the search process, the current position of the solution is determined by the three best solutions, such as omega wolves updating their position according to alpha wolf, beta wolf, and delta wolf, which is an advantage over the swarm intelligence algorithm[24], which determines the current solution by just one solution. GWO algorithm has many advantages over other algorithms, including simplicity, fast convergence speed, and the ability to find global maxima with a small number of iterations. It is also easy to implement for engineering problems, as shown by Mohanty's implementation of GWO[29][30] to track the GMPP for a PV system. GWO, on the other hand, works well for finding global maxima, but when GMPP and LMPP are really close to each other, GWO gets confused and stagnates on LMPP. Several modified GWO techniques are suggested to improve GWO's searching ability are described in literature [31][32][33][34]. Since these improved GWO techniques were introduced recently, and after a thorough analysis of the literature, it is clear that they are not being used to design MPPT.

In this paper a new and improved hybrid MPPT algorithm is proposed using two evolutionary algorithm that is Grey wolf optimization with a new and improved convergence factor based on sigmoid function that enhance the searching ability and convergence speed of GWO and Differential evolution with a dynamic scaling factor whose value is higher at initial stages which prevents algorithm to fall into local optima whereas at final stages the value of scaling factor is reduced and enhance the speed of algorithm. Furthermore, the proposed IGWO-DE MPPT method is able to find a GMPP under partial shading condition and can automatically select the different GMPP under the large fluctuation in irradiance levelThis work also includes the design and simulation of a standalone PV battery system with a flyback converter that provides isolation between the input and output sides. The bidirectional converter, in combination with a battery controller, can be used to connect the battery storage system to the PV system, allowing the battery to be charged and discharged properly. The following is how the rest of the paper is organised: Section II provides an explanation of the GWO method, Section III provides an overview of the conventional DE algorithm, and Section IV covers the proposed IGWO-DE algorithm. Section V implements the proposed algorithm to find and track the GMPP for a PV system, Section VI presents the simulation results of GMPP tracking for different algorithms, Section VII presents the design and analysis of a standalone PV battery system using a flyback converter, Section VIII discusses the simulation results for given system, and Section IX concludes.

II. OVERVIEW OF GWO TECHNIQUE:

Swarm intelligent algorithms are algorithms in which the hunting patterns of animals and birds are mathematically modelled to find global maxima and minima for optimization problems. These algorithms are commonly used to solve real-valued, non-linear, multi-modal objective functions, and they are often used for many engineering problems. The GWO algorithm is one of the SI algorithms that is based on grey wolves' social hierarchy and hunting mechanism. Mirjalili first suggested mathematical modelling of grey wolf social hierarchy and hunting process in 2014. Wolves are classified into four groups for mathematical modelling of the social hierarchy of grey wolves as shown in Fig 1: alpha wolf, which is the leader wolf and has the greatest knowledge of prey, beta wolves, delta wolf. The alpha, beta, and delta wolves are followed by the omega wolves in order to catch prey. Similarly, in optimization problems, the solutions are divided into four categories: alpha, which is the best solution, beta, which is the second best solution, delta, which is the third best solution and remaining solutions are considered as omega. Grey wolves hunting mechanism is divided into three part:

A) Encircling of prey
B) Hunting
C) Attacking

A. ENCIRCLING THE PREY:

Grey wolves are the most effective predators in the food chain since they catch their prey in groups and encircle them while hunting. Mirjaali suggested the following equation to mathematically model the encircling behaviour:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_p}(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \overrightarrow{X_p}(t) - \vec{A} \cdot \vec{D} \tag{2}$$

Where t denotes the t-th iteration, $\vec{A}$ and $\vec{C}$ represent the coefficient vectors, $\overrightarrow{X_p}$ depicts the prey's location vector, and $\vec{X}$ represents the grey wolf's position vector The following equation can be used to evaluate the vectors $\vec{A}$ and $\vec{C}$:

$$\vec{A} = 2a \cdot \overrightarrow{r_1} - a \tag{3}$$

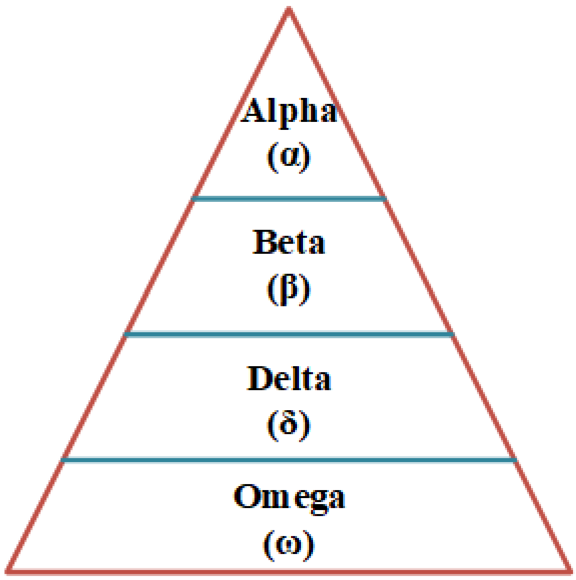


FIGURE 1: Social hierarchy of grey wolves

$$\vec{C} = 2 \cdot \overrightarrow{r_2} \tag{4}$$

Where $\overrightarrow{r_1}$, $\overrightarrow{r_2}$ are the random vectors in [0,1] and a is a vector that decrease from 2 to 0 as we increase the no of iteration and it can be calculated as follows :

$$a = 2 - 2t/t_{max} \tag{5}$$

Where a is the current iteration and t_{max} is the maximum number of iteration.

B. HUNTING

Grey wolves have the ability to recognise the position of prey and encircle them. The hunt normally led by the alpha. Hunting can be done by the beta and delta on occasion. However, In an abstract search space we have no idea where the optimum (prey) is located. In order to mathematically model the hunting behaviour of grey wolves, let us consider that alpha, beta and delta have better understanding about the location of prey. As a result, we save the three best solutions we've found so far as alpha, beta, and delta, and the other solution, omega, updates their positions based on alpha, beta, and delta. Mirjali proposed the following equation for updating the positions:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \vec{X}\right| \tag{6}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1} \cdot \left(\overrightarrow{D_\alpha}\right) \tag{7}$$

$$\overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X}\right| \tag{8}$$

$$\overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \cdot \left(\overrightarrow{D_\beta}\right) \tag{9}$$

$$\overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X}\right| \tag{10}$$

$$\overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_\delta}\right) \tag{11}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{12}$$

Where $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$, $\overrightarrow{X_\delta}$ and $\vec{X}$ are the positions vectors of alpha, beta, delta and the current solution respectively and $\vec{X}(t+1)$ is the final position vector of current solution for next iteration.

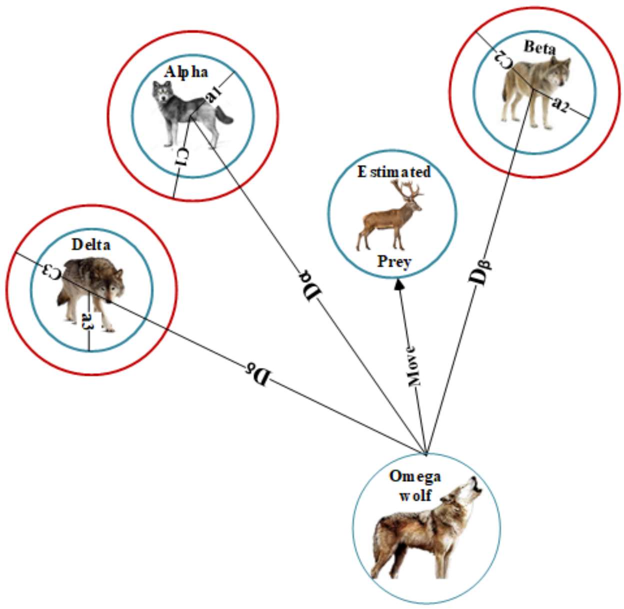


FIGURE 2: Position updating in GWO

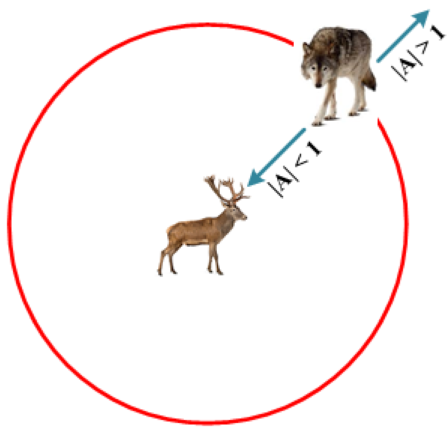


FIGURE 3: Attacking or searching for prey

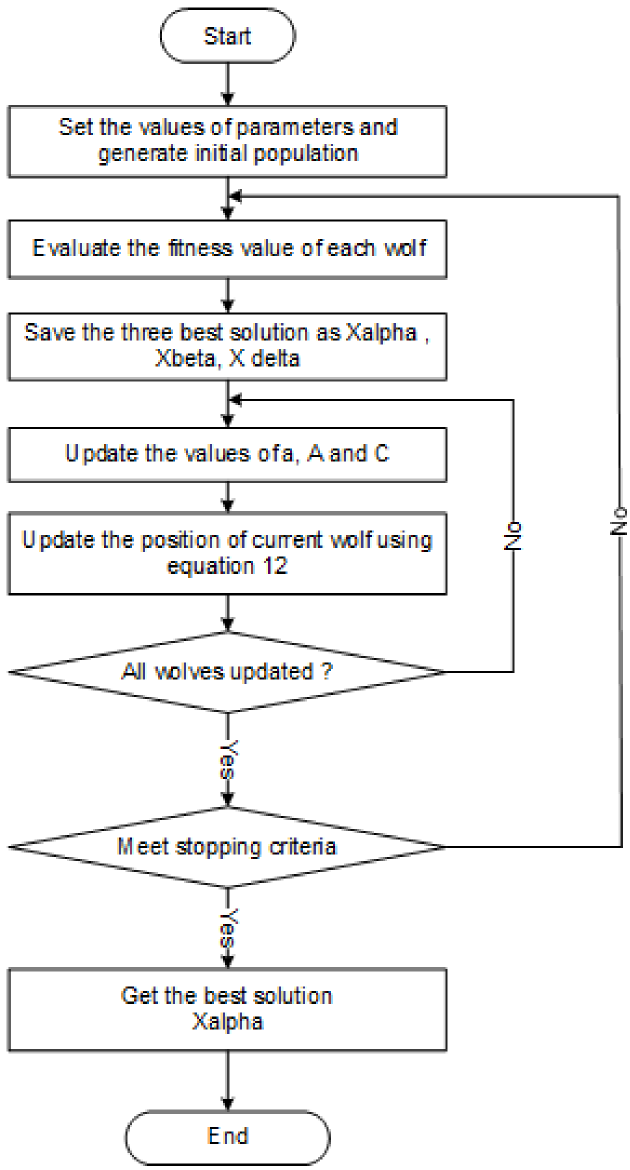


FIGURE 4: Flowchart of GWO technique

C. ATTACKING

Grey wolves mostly search according to position of alpha, beta and delta they diverge from each other to search for prey and converge to attack prey. Exploration is GWO's ability to explore new areas, which improves its global searching ability, while exploitation is GWO's ability to search in the same direction in greater depth. To achieve a reasonable equilibrium between exploration and exploitation, $\vec{A}$ and $\vec{C}$ are the two parameters that can be used. The wolf (solution) deviates from its path and searches in a new direction if $|\vec{A} > 1|$ and converge towards the prey (optimum solution) if $|\vec{A} < 1|$, and $\vec{A}$ is a random vector in the interval $[-2a, 2a]$ where a decreases from 2 to 0 over the course of iteration. When the value of $\vec{C}$ is greater than one, the $\vec{C}$ often favours exploration, and when the value of $\vec{C}$ is less than one, it favours exploitation. $\vec{C}$ is not linearly decreased in contrast to $\vec{A}$, so this parameter is very useful to avoid the local optima stagnation, particularly in the final iteration.

III. OVERVIEW OF DIFFERENTIAL EVOLUTION:

Differential evolution[35] is a stochastically population based technique proposed by Storn and Price in 1997. The DE method is used for practical problems because of the simplicity of the algorithm, which uses only a few parameters to handle nonlinear, multidimensional, and non-differentiable functions. DE begins with initialization to generate a target vector at random under bounding conditions, then the target vector undergoes mutation to create a donor vector, then the donor vector is used to generate the trial vector, and finally the target vector and trial vector are greedily selected. Let $\vec{X}_i^t = \left[x_{i,1}^t, x_{i,2}^t, x_{i,3}^t \ldots .., x_{i,d}^t\right]$ be the target vector of population size N_p with vector dimension d then this target vector undergoes for following operations :

A. MUTATION

Mutation operation is an important feature of DE which is used to produce donor vector $\vec{V}_i^t = \left[v_{i,1}^t, v_{i,2}^t, v_{i,3}^t, \ldots \ldots, v_{i,d}^t\right]$ from a target vector using various mutation strategies such as DE/rand/1, DE/best/1, DE/rand/2, DE/best/2 and so on. Among the various mutation strategy DE/rand/1, is the most basic mutation strategy which can be described as follows:

$$\vec{V}_i^t = \vec{X}_{R1}^t + F * \left(\vec{X}_{R2}^t - \vec{X}_{R3}^t\right) \tag{13}$$

Where R_1,R_2, R_3 are randomly chosen indices from $[1, 2, 3, \ldots ., N_p]$ such that $R_1 \neq R_2 \neq R_3 \neq i$. And F is the scaling factor ranges from 0 to 1, is used to govern the scaling of differential vector. The most popular strategy among the various types of mutation strategies is DE/best/1, which can be described as follows:

$$\vec{V}_i^t = \vec{X}_{\text{best}}^t + F * \left(\vec{X}_{R2}^t - \vec{X}_{R3}^t\right) \tag{14}$$

Where $\vec{X}_{\text{best}}^t$ is the best candidate solution as far.

B. CROSSOVER

Crossover operation is applied to generate the trial vector $\vec{U}_i^t = \left[u_{i,1}^t, u_{i,2}^t, u_{i,3}^t \ldots .., u_{i,d}^t\right]$ by recombining the target vector $\vec{X}_i^t$ and donor vector $\vec{V}_i^t$. While there are many crossover operators in the literature, the binomial and exponential crossover operators are the most widely used. Binomial crossover can be described as follows :

$$U_{i,j}^t = \begin{cases} V_{i,j}^t, \text{ if } \operatorname{rand}(0,1) \leq CORj = \delta \\ X_{i,j}^t, \text{ if } \operatorname{rand}(0,1) > CRANDj \neq \delta \end{cases} \tag{15}$$

Where δ is the randomly selected variable location such that $\delta \in \{1, 2, 3, \ldots \ldots, d\}$ to ensure that at least one variable is obtained from the donor vector and CR, the crossover rate or crossover probability which is generally kept high ranges from 0 to 1. If CR is high results in more contribution from the donor vector and if CR is low results in more contribution from the target vector.

C. SELECTION

To determine which trial vectors should replace the target vector and which should not, the selection operation is used, There are lot's of selection strategies such that tournament selection, rank based selection , fitness proportional selection and greedy selection. Among various selection strategies the most commonly used strategy is greedy selection. The greedy selection for maximization problem is described as follows :

$$\vec{X}_i^{t+1} = \begin{cases} \vec{U}_i^t, & \text{if } f\left(\vec{U}_i^t\right) \geq f\left(\vec{X}_i^t\right) \\ \vec{X}_i^t, & \text{if } f\left(\vec{U}_i^t\right) \leq f\left(\vec{X}_i^t\right) \end{cases} \tag{16}$$

Where f is the fitness function, $\vec{X}_i^{t+1}$ is the target vector for next generation or iteration. The above expression shows that if the value of the fitness function for the trial vector is greater than the value of the fitness function for the target vector, the trial vector replaces the target vector, and vice versa.

IV. ALGORITHMIC DESCRIPTION

GWO's searching ability is based on two principles : exploration and exploitation. Exploration refers to the process of exploring new areas or mathematically, the process of looking for a solution as much as possible in a search space in order to prevent local optimum stagnation. On the other hand exploitation refers to looking in the same direction in greater depth or mathematically, searching for a solution with high precision. Using the GWO algorithm to find the global optimum with high efficiency necessitates achieving the proper balance between exploration and exploitation. These two abilities are governed by two parameters, A and C, as described in section 2. As compared to other swarm intelligent techniques, GWO algorithms perform well in finding global optimum for high dimensional problems, but not so well in finding global optimum for low dimensional problems. As the problem in our case is only one dimensional, we need to find a GMPP among various MPPs for a solar PV array that is partially shaded. So while there's no assurance that GWO will find GMPP, it's possible that it will stick with the LMPP. To address this issue, a donor vector from a differential evolution technique is used, which adds randomness to the GWO technique and allows it to escape out of the local optimum and look in a new direction for the global optimum. Because the DE technique is based on complete random initialization, it outperforms to find the global optima, but it has a limitation in that it lacks a parameter that is directly related to algorithm convergence, so the speed of convergence is very slow and provides power oscillation around the global optima. As a result, the flaw in one approach is offset by other method. Therefore, a new algorithm called Improved grey wolf optimization and differential evolution (IGWO-DE) is proposed in this paper, which combines the GWO algorithm with a better convergence factor and the DE algorithm with a dynamic scaling factor with the help of a DE crossover operator. The initialization of a random vector of population size N_p with dimension d under boundary conditions is the first step in the IGWO-DE method. Where d denotes the problem dimension or the number of variables in the problem, and this random vector is referred to as the target vector, which can be described as follows:

$$\vec{X}_i^t = \left[x_{i,1}^t, x_{i,2}^t, x_{i,3}^t \ldots .., x_{i,d}^t\right] \tag{17}$$

Where i $\in \{1,2,3,\ldots\ldots N_p\}$, and t is the current value of iteration and each individual can be calculated as follows :

$$x_{i,j}^{1} = x_{lb} + \mathrm{rand}(0,1) * (x_{ub} - x_{lb}) \tag{18}$$

Where x_{ub}, x_{lb} are the upper bound and lower bound vectors with d individuals respectively. Similar to GWO, the three best solutions in IGWO-DE are saved as alpha $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$, and $\overrightarrow{X_\delta}$ solutions from the target vector. Following the saving of the solutions, the target vector is subjected to mutation in a manner similar to the DE technique. In our proposed algorithm, the donor vector $\overrightarrow{V}_i^t$ is generated from the target vector $\overrightarrow{X}_i^t$ using a DE/best/1 mutation strategy with a dynamic scaling factor F', which provides more randomness in the initial stages, preventing the algorithm from falling into a local optimum, while the value of F' decreases in the final stages, increasing the algorithm's convergence speed. So, the donor vector can be expressed as follows:

$$\overrightarrow{V}_i^t = \vec{X}_\alpha^t + F' * \left(\vec{X}_{R1}^t - \vec{X}_{R2}^t\right) \tag{19}$$

Where $\vec{X}_\alpha^t$ is the alpha solution or best candidate solution as far and $\vec{X}_{R1}^t$, $\vec{X}_{R2}^t$ are the randomly selected solution from the target vector and F' can be expressed as follow:

$$F' = \frac{2}{\left(1 + e^{\left(k*\left(\frac{t}{t\max}\right)\right)}\right)}; k \in [8,14] \tag{20}$$

GWO's searching ability is primarily determined by the vectors $\vec{A}$ and $\vec{C}$, where $\vec{C}$ is a randomly generated vector ranging from 0 to 2, the wolves favour exploration if $\vec{C} > 1$ and exploitation if $\vec{C} < 1$, and $\vec{C}$ plays no role in GWO's convergence speed. Now, the only vector that is important in convergence is $\vec{A}$, but the value of $\vec{A}$ is determined by the convergence factor or a, and the value of a decreases linearly from 2 to 0 over the course of iteration. We need to modify the convergence factor to improve the speed of the algorithm. This paper proposed a new non linear convergence factor based on a sigmoid function that improves the speed of the algorithm, which can be expressed as follows.:

$$a = \frac{2}{\left(1 + e^{\left(k*\left(\frac{t}{t_{\max} - \frac{1}{2}}\right)\right)}\right)}; k \in [8,12] \tag{21}$$

Using this improved convergence factor, the updated position of the wolves can be calculated using equations on the basis of the position of the best wolves. Let us consider the i-th position vector of wolves in the t-th iteration as $\vec{W}_i^t = \left[w_{i,1}^t, w_{i,2}^t, w_{i,3}^t \ldots, w_{i,d}^t\right]$ which can be calculated using equation. Now these two vectors are combined using a binomial crossover operator to generate a position vector for next iteration. The new position vector can be described as follows:

$$X_{i,j}^{t+1} = \begin{cases} V_{i,j}^t, \text{ if } \mathrm{rand}(0,1) \le CR \text{ OR } j = \delta \\ X_{i,j}^t, \text{ if } \mathrm{rand}(0,1) > CR \text{ AND } j \ne \delta \end{cases} \tag{22}$$

V. IMPLEMENTATION OF IGWO-DE

To extract the maximum power from a solar PV system, the proposed algorithm is applied to a maximum power point tracker. The proposed MPPT algorithm is used to find and track the GMPP among various LMPPs under partial shading conditions. MPPT regulates the duty ratio of the converter to vary voltage and current sensed by the sensor in order to get the maximum power from the PV system, as shown in the Fig 5. In order to implement our IGWO-DE algorithm for tracking the MPP, we need a dc-dc converter, a solar PV array, a load, and a control system which is used to implement MPPT algorithm. As previously discussed, the first

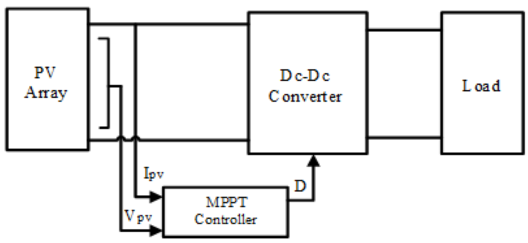


FIGURE 5: Block diagram of PV system with MPPT controller

step of the IGWO-DE technique is to initialise the random vector under the boundary conditions, so for implementation of IGWO-DE in MPPT algorithm, the random duty ratio vector d_i^t with population size Np of dimension one can be expressed as follows because there is only one variable.

$$X_i^t = d_i^t = \left[d_1^t, d_2^t, d_3^t, \ldots .d_i^t\right] \tag{23}$$

Where $i \in [1, N_p]$, t is the current iteration and the objective of MPPT algorithm is to get maximum power from a solar PV system by varying duty cycle mathematically, the objective function can be expressed as:

$$P\left(d_i^t\right) > P\left(d_i^{t-1}\right) \tag{24}$$

Flowchart of IGWO-DE based MPPT as shown in Fig 6 consist several steps which can be described as follows:

Step 1: Initialise parameter including maximum iteration, population size, minimum (d_{min}) and maximum $(d_{max}$ value of duty cycle.

Step 2: Generate a set of duty cycle values ranging between d_{min} and d_{max}

Step 3: Using sensors, sense the current and voltage of the PV array, and then calculate the power of a PV panel corresponding to each search agent (duty cycle)

Step 4: Determine the best three solutions as alpha, beta and delta solution by comparing the fitness value P_{pv} for each search agent (d_i^t).

Step 5: When all search agents' fitness values are calculated, the position vector of the search agent for the next iteration is determined using the binomial crossover operator of differential evolution, which can be described as follows:

$$X_i^{t+1} = d_i^{t+1} = \begin{cases} V_i^t, \text{ if } \mathrm{rand}(0,1) \leq CR \\ W_i^t, \text{ if } \mathrm{rand}(0,1) > CR \end{cases} \quad (25)$$

Where $d_i^{t+!}$ is the duty cycle of the i-th agent for the next iteration,V_i^t is the donor vector borrowed from the DE/best/1 mutation strategy described above in equation (19)(20), and W_i^t it is the vector obtained using the position update strategy of the GWO technique with an improved convergence factor described in equation (6-12), (21).

Step 6: The IGWO-DE technique will terminate when the convergence criteria are met, i.e. when the number of iterations equals the maximum number of iterations. The position of a search agent (duty cycle) obtained is the position of the alpha solution (best duty cycle).

Step 7: When the environmental conditions change, the MPP of a PV system changes as well. In order to find the MPP again, the algorithm is reinitialized, and a set of new search agents begins searching for the new MPP. So, in order to determine whether or not the environmental condition has changed, we have to check whether or not the following condition is satisfied:

$$\frac{|P_t - P_{t-1}|}{P_{t-1}} \geq \Delta P \quad (26)$$

Where P_t, P_{t-1} are the powers corresponding to the current iteration and previous iteration respectively. So, when the change in power is more than the decided ΔP then the algorithm will reinitialized and search for a new MPP.

VI. SIMULATION RESULT OF MPPT TRACKING FOR DIFFERENT ALGORITHMS:

The proposed method is implemented in MATLAB/SIMULINK software to observe the effectiveness of proposed IGWO-DE based MPPT method and compare with the popular conventional algorithms that is GWO, DE and PSO based MPPT method under two different partial shading conditions. In order to put the MPPT algorithms into practise, Consider the PV array, a conventional boost converter, an MPPT controller, and the load across the output terminal of a boost converter shown in Fig 7. In order to generate desire output voltage and output current, four PV modules are connected in series with a parallel connected bypass diode which prevents the probability of hot-spot during partial shading conditions .The specification of each PV module and boost converter are given in the table 1 and table 2 respectively.

TABLE 1: Specification of PV module

Open circuit voltage	Short circuit current	Maximum current	Maximum voltage	Peak power
22.5V	5.57A	5.13A	18.52V	95W

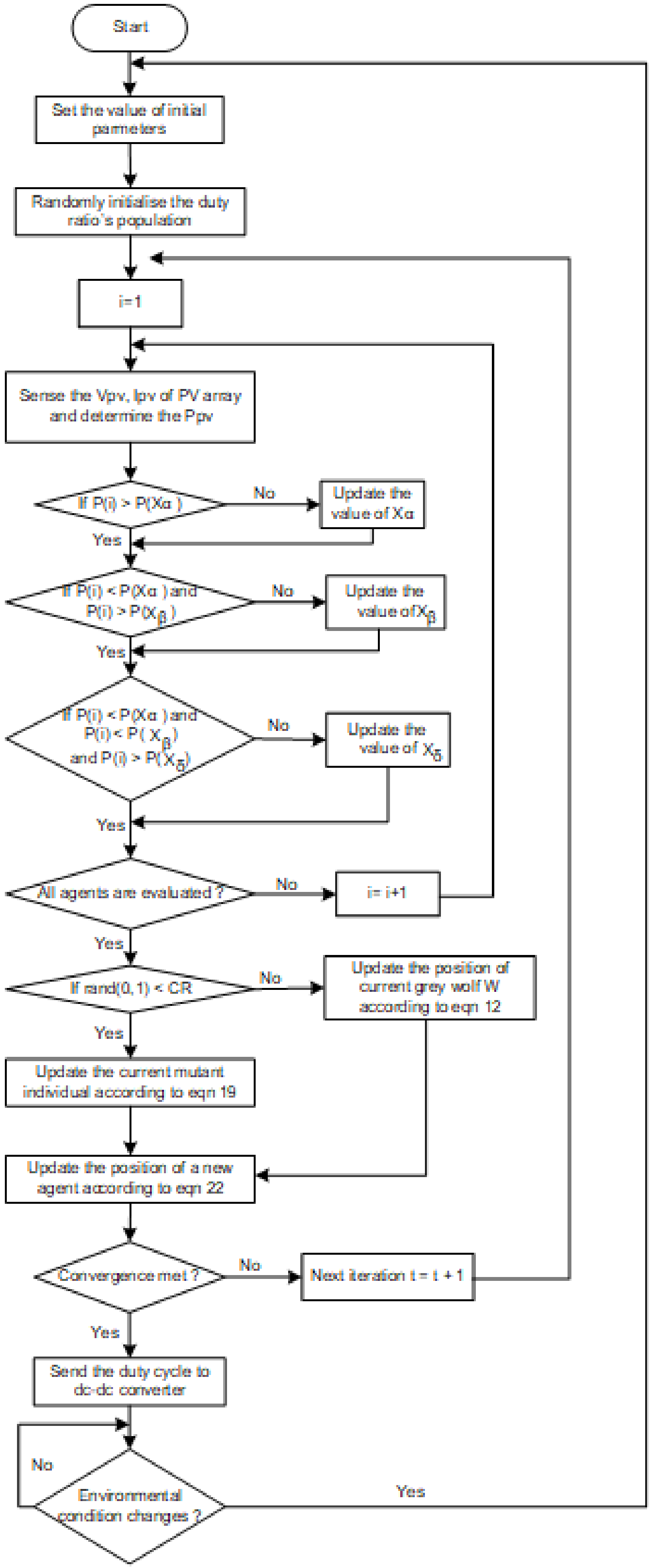


FIGURE 6: Flowchart of IGWO-DE

A. CASE 1:

Two out of four PV panels are partially shaded in this case and two peaks are observed. The GMPP is located at the rightmost position in PV- characteristic of PV array. The

TABLE 2: Specification of boost converter

Parameters	L	C	Cin	Switching Frequency
Value	4mH	300uf	20uf	25Khz

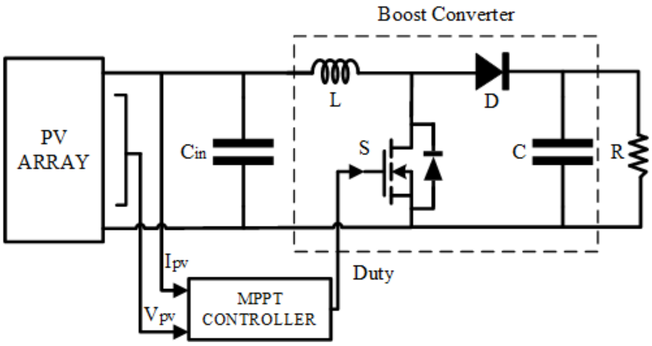


FIGURE 7: A PV system using boost converter

power associated to the GMPP and LMPP are 235W at 59V and 190W at 37V respectively. Figure 8 depicts the I-V and P-V characteristic curves for Case 1, while Figure 9 illustrates the simulation results for GWO, DE, and the proposed method.

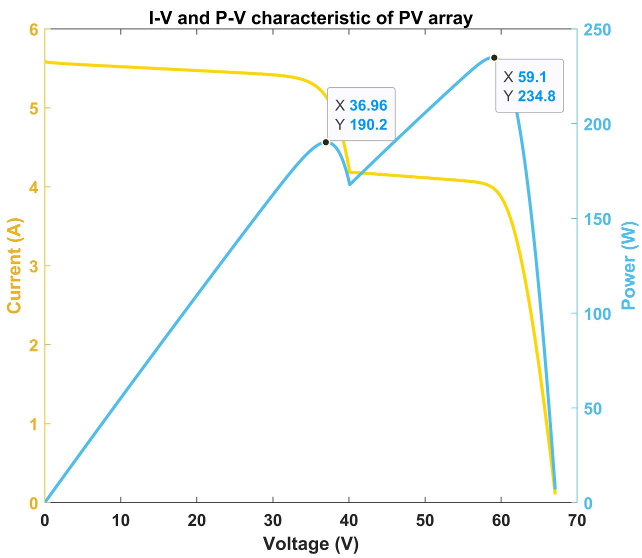
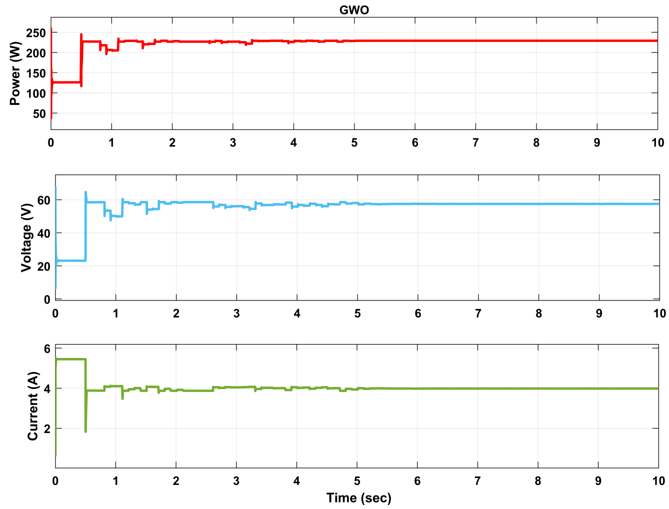
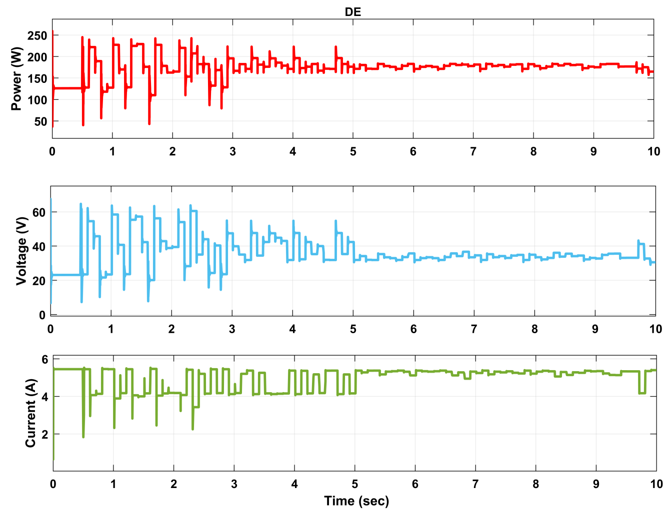


FIGURE 8: : I-V and P-V characteristic for case 1

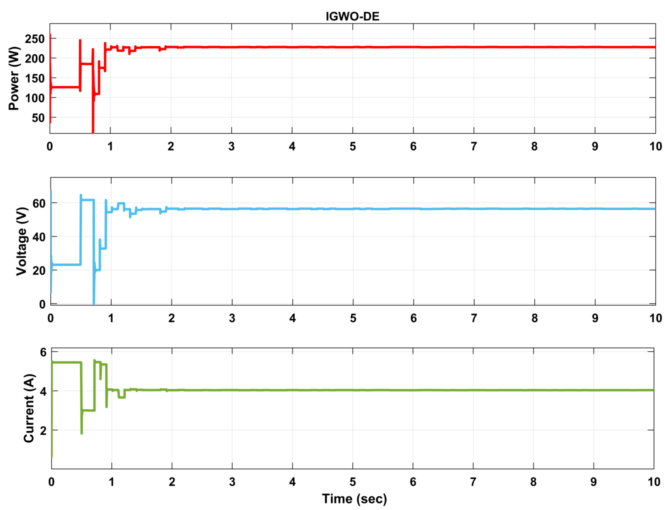
According to Fig 9, the GWO, DE, and proposed IGWO-DE based MPPTs take 3sec, 7sec, and 2sec, respectively, to stabilise properly. As can be seen in Fig 8, there is a significant difference between GMPP and LMPP, making it simple to find GMPP for GWO with proper initialization and less power oscillation. DE will find MPP, but there is a significant power loss due to large power oscillations around MPP. This is due to the complete random initialization of particles, which reduces DE's efficiency. Furthermore, in conventional DE, there is no parameter that directly affects the algorithm's convergence speed, which is why the DE



(a) GWO



(b) DE



(c) IGWO-DE

FIGURE 9: : Simulation results for case 1

algorithm's convergence speed is slow. As a result, we can infer that the proposed IGWO-DE approach is highly efficient due to low power oscillations and the ability to find GMPP quickly as compared to other techniques.

B. CASE 2:

In Case 2, each of the four panels is partially shaded, resulting in four peaks. The GMPP is the second peak from the left of the four peaks, and the power associated with it is 132W at 39V. This case differs from Case 1 in that it has four peaks, and one of the local maxima is very close to the GMPP, which has an associated power of 128W at 60V. Figure 10 depicts the I-V and P-V characteristic curves for Case 2, while Figure 11 depicts the simulation results for GWO, DE, and the proposed method for this case.

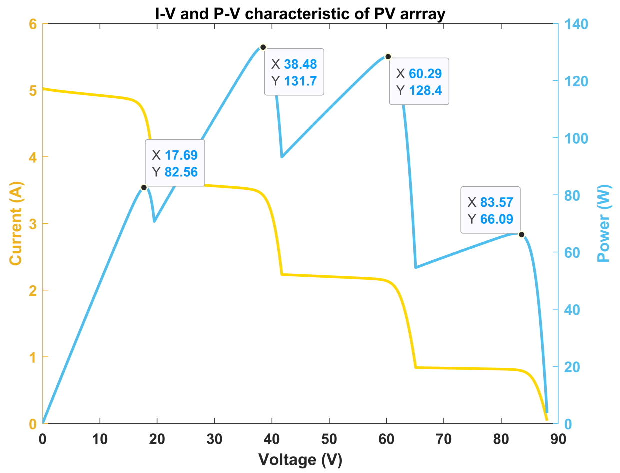
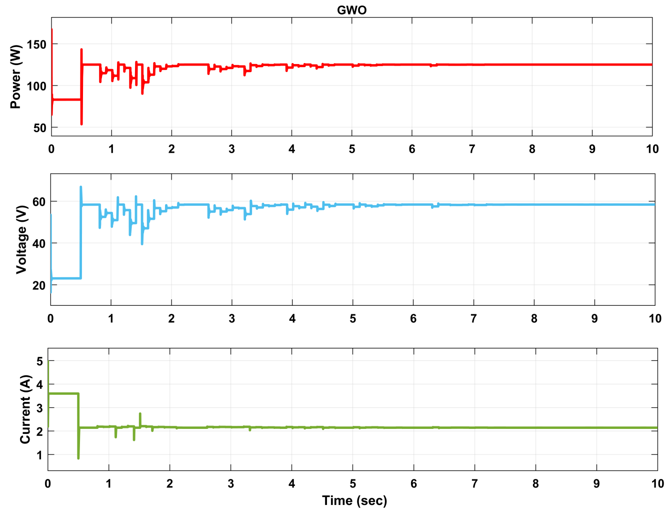
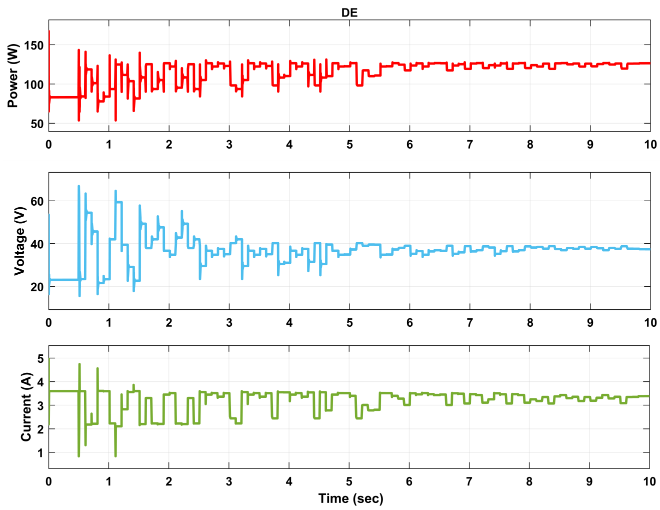


FIGURE 10: I-V and P-V characteristic for case 2

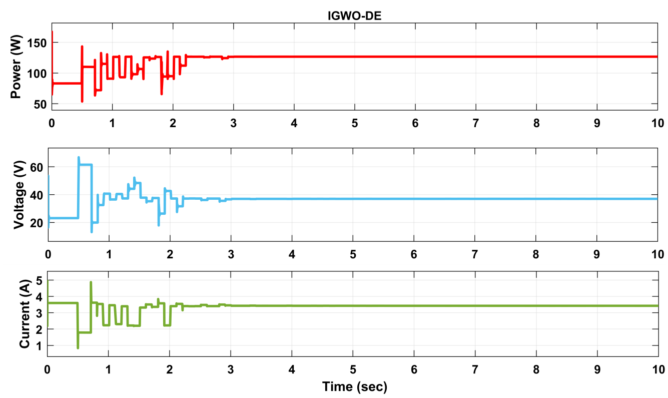
According to Fig. 11, the GWO technique is unable to find a GMPP and is stuck on the LMPP, resulting in power loss and decreased efficiency. Because of the slight gap of just 4W between the nearest LMPP and GMPP, it only takes 5 seconds to converge to the local maxima. However, GWO can be used in this case by limiting the search area, making it case specific and unable to find the GMPP in other PSCs. Whereas the simulation results shown that DE cannot get a stable point until 9 seconds but it is able to find the GMPP with large amount of power oscillation resulting in power loss. While the proposed IGWO-DE-based MPPT takes only 3 seconds to obtain the GMPP with the least amount of power oscillations, this is due to the improved convergence factor and dynamic scaling factor proposed in this paper, the values of which are large in the initial iterations to prevent IGWO-DE from stuck into LMPP and small in the final iterations to provide the minimum oscillations. As a result of Fig 11, it is possible to conclude that the IGWO-DE based MPPT can find the GMPP in any PSC with greater efficiency and speed than other methods.



(a) GWO



(b) DE



(c) IGWO-DE

FIGURE 11: simulation result for case 2

VII. STANDALONE PV BATTERY SYSTEM USING FLY-BACK CONVERTER:

As shown in Fig12 , a standalone PV battery system is made up of several components. A fly-back converter connects the

PV panel to the load, providing electrical isolation[36]. To get the maximum power out of the PV system, the maximum power point tracker adjusts the duty ratio of the fly-back converter. The battery controller uses a bidirectional converter to regulate the voltage across the load and tries to keep it constant in a quickly changing environment. The bidirectional converter is used to transfer power in either way between two DC sources and can be used to interface with a battery storage system[37].

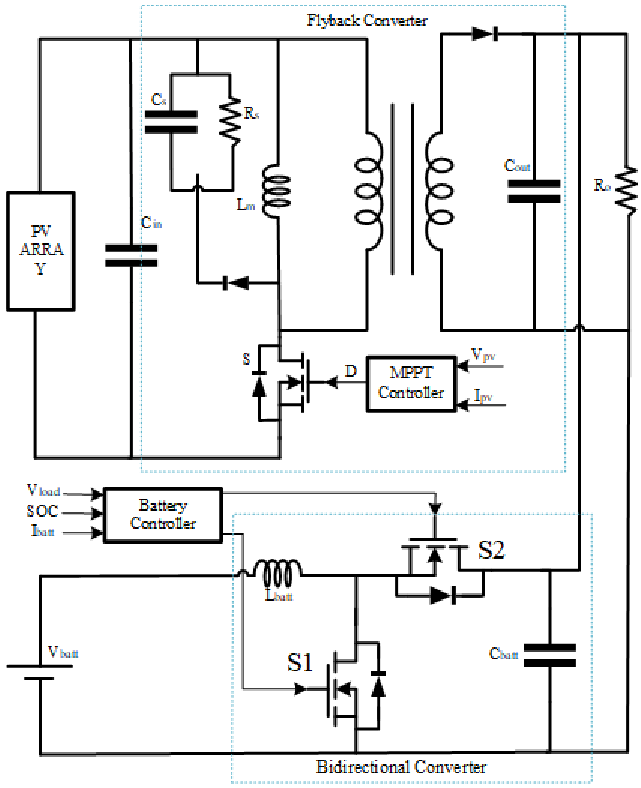


FIGURE 12: Standalone PV battery system using flyback converter

A. MODELLING OF FLYBACK CONVERTER:

Isolated and non-isolated Dc-Dc converters are the two types of Dc-Dc converters. The advantages and disadvantages of each converter are primarily determined by their applications. Because these converters do not provide isolation between the input and output terminals, there is an electrical connection between the drive and power circuits, making them unsafe in a fault situation. In general, we need a much higher voltage across the load than the PV panel, so there must be proper electrical isolation between the low voltage and high voltage sides, because if there is no electrical isolation, if a fault occurs, we can receive a severe shock while cleaning the PV panel during the rainy season. Isolated converters use a transformer to provide electrical isolation between the input and output terminals, as well as several outputs, which is a benefit over non-isolated converters. When all of these factors are taken into account, isolated converters are the better choice for PV system applications. Many isolated converters, such as fly-back and forward converters, are described in the literature[38].

Fly-back converters are buck-boost converters that may be used to step up or down a given input Dc voltage while simultaneously providing galvanic isolation via a transformer by storing energy and releasing it back to the load. There are two modes of operation for a fly-back converter. When the switch is turned on, the magnetising inductance stores the energy from the input Dc source, but there is no current in the secondary winding of the transformer because the diode acts as an open circuit, and the output capacitor distributes power to the load. In the second mode, when the switch is turned off and the diode begins to conduct, the magnetising inductance returns the energy to the secondary winding of transformer and starts feeding the load.

Assume the switching frequency of the converter is 25 KHz while developing the components of a flyback converter. We set the output voltage at 100V, however the input voltage for the converter from the PV panel varies with irradiance. For the calculations, we assumed that the input voltage and current are equal to the voltage and current at maximum power at 1 kw/m2. Now, using the following relationship, the ratio of transformer turns may be calculated:

$$n = \frac{V_{\text{out}} * (1 - D)}{V_{in} * D} \approx 2 \tag{27}$$

The amount of ripple in the current is determined by the value of magnetising inductance, but we cannot use a very large value of magnetising inductance because as the value of magnetising inductance increases, so does the leakage inductance, which causes a bigger problem than ripple. Let us assume that the current ripple is 50 percent of the average value of current, and that the value of magnetising inductance can be computed using the following equations:

$$I_m = I_{mpp} + \frac{V_{out}}{R_o} * n \tag{28}$$

$$\Delta I_m = 0.5 * 2 * I_m \tag{29}$$

$$L_m = \frac{V_{in} * D}{\Delta I_m * f_{sw}} = 204\mu H \tag{30}$$

And, assuming a 2 percent and 5 percent ripple in the output and input voltages, respectively, the output and input capacitance can be calculated as follows:

$$C \geq \frac{V_{\text{out}} * D}{R_o * \Delta V_{\text{out}} * f_{sw}} \qquad C \geq 11.62\mu\text{f} \tag{31}$$

$$C_{in} \geq \frac{I_{in}(1 - D)}{f_{sw} * 0.1 * V_{in}} \qquad C_{in} \geq 17.6\mu f \tag{32}$$

The snubber circuit, which is a parallel combination of resistance and capacitance along with a series diode as shown in fig, prevents overvoltage across the switch because leakage current requires a way to exit and this is only possible when the RC time constant of the snubber circuit is much greater than the time period of the switch as given in eqn 33. The following equation can be used to compute the resistance and capacitance of a snubber circuit:

$$R_s * C_s \gg \frac{1}{f_{sw}} \tag{33}$$

$$\begin{aligned} R_s &= \frac{2 * (V_{\text{out}}/n)^2}{0.03 * L_m * I_{\text{in}} * f_{sw}} = 13030\text{ohm} \\ C_s &> \frac{10}{f_{sw} * R_{\text{clamp}}} > 30.6\text{nf} \end{aligned} \tag{34}$$

TABLE 3: Modelling Parameters

Simulation Parameter	Value
n	2
R_o	43 Ω
f_{sw}	25 KHz
C_{in}	700 μf
C	50 μf
L_m	204 mH
C_s	200 nf
R_s	13030 Ω
$Nominal\ Voltage$	48 V
$Ampere-hour\ rating$	125 Ah
C_{batt}	200 μf
L_{batt}	7 mH

B. BATTERY CONTROLLER

The battery controller keeps the voltage constant across the load and delivers power from the battery when it's needed, all while staying below safe limits. This solar PV battery controller is a viable alternative for powering dynamic loads like solar vehicles, household loads and so on[39]. Because it converts the Dc voltage and Dc current for the power storage battery, the bidirectional converter is an essential component of a standalone PV battery system. Depending on the signal sent to its switches by the battery controller, the bidirectional converter can operate in either buck or boost mode. The bidirectional Dc-Dc converter's buck mode is used to charge the battery, while the boost mode is applied to discharge the system. For selecting the correct mode of operation, the bidirectional converter uses the control mechanism illustrated in fig 13. A PI controller with gain kp = 0.85 and ki = 10 is

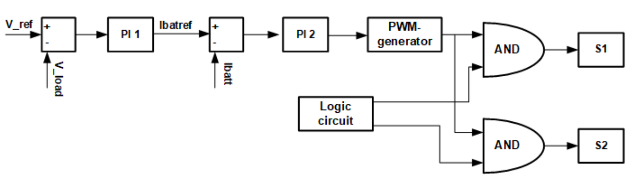


FIGURE 13: Control scheme

used to keep the 100V voltage constant throughout the load, and another PI controller with gain kp = 0.01 and ki = 10is used to regulate the battery current in the control scheme. The controller's output is sent to a PWM generator, which uses the Vo and SOC logic to trigger the switches of a bidirectional converter. The logic circuit is used to enable the correct mode of operation of the battery depending on SOC, PV panel power, and load power requirement. The top and lower limits of SOC were set at 90 percent and 30 percent, respectively, to prevent the battery from becoming profoundly drained. We also took into account the limit for Vo (99.5 Vo 100.5), which protects the battery from being charged and discharged unnecessarily. Keeping the above premise in mind, there are many modes of operation:

Mode 1: The PV output power exceeds the load power in this case, and the battery state of charge (SOC) is below the top limit, indicating that the battery has not been fully charged. In this situation, the battery is charged using a bidirectional converter in buck mode by turning on switch S1 and turning off switch S2.

Mode 2: In this situation, the PV power exceeds the load power, and the SOC exceeds the top limit, indicating that the battery is fully charged. During this mode, battery is disconnected from the system by turning OFF both the switches of bidirectional converter.

Mode 4: This mode is activated when the PV panel is unable to satisfy the load demand and the battery is in charge condition, indicating that the SOC of the battery is between the limits. In this instance, the battery supplies the remaining power to meet the load demand by turning ON the switch S2 and turning OFF the switch S1 of bidirectional converter.

Mode 4: When the PV power is less than the load power and the SOC is lower than its lower limit means battery is deeply discharged. During this mode, battery is disconnected from the system by turning OFF both the switches of bidirectional converter.

VIII. SIMULATION RESULTS FOR STANDALONE PV BATTERY SYSTEM USING FLY-BACK CONVERTER:

This simulation was performed using the MATLAB SIMULINK software to analyze the output characteristics of a standalone PV battery system for DC loads utilising a conventional fly-back and bidirectional converter. And, to ensure that the system is operating at GMPP, the proposed algorithm is implemented in the MPPT controller for GMPP tracking. Figure 14 shows the simulation model:

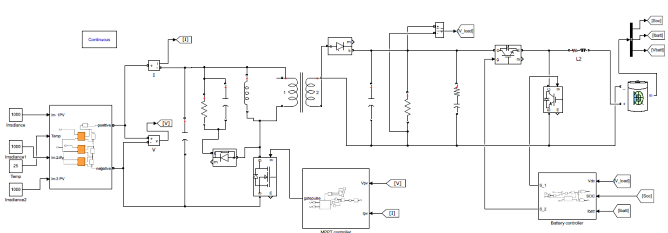
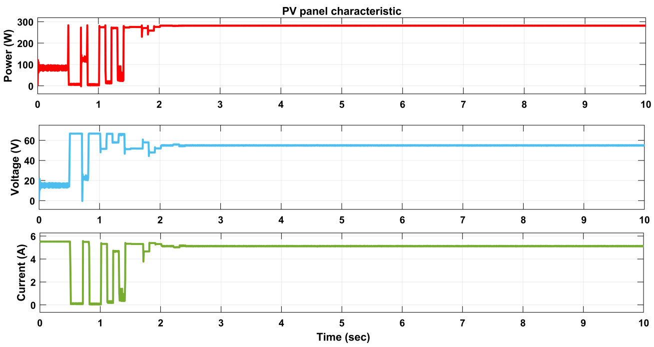


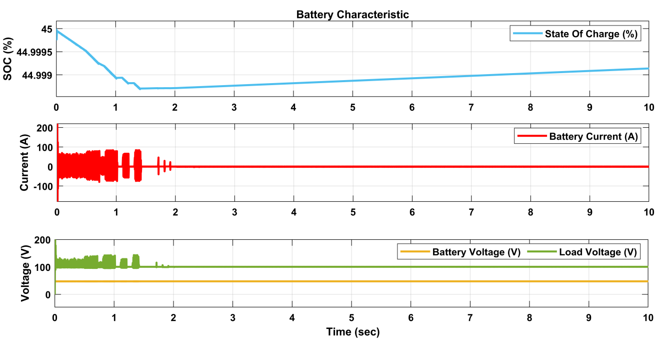
FIGURE 14: Simulation model of a standalone PV system

A. CASE 1: BATTERY IN CHARGING MODE

In this mode, all three panels receive uniform irradiance and provide an MPP of approximately 285W at 55V and 5.13A, which is greater than the load power, as seen in fig 15. When the generated power exceeds the load power, the excess power is used to charge the battery through bidirectional converter operating in a buck mode, maintaining a constant voltage of 100V and 48V across the load and battery respectively. It can be seen that there is a lot of ripple in the battery current when it initially starts, but once the algorithm finds the MPP, the ripple in the battery current reduces and starts charging by negative small current.



(a)

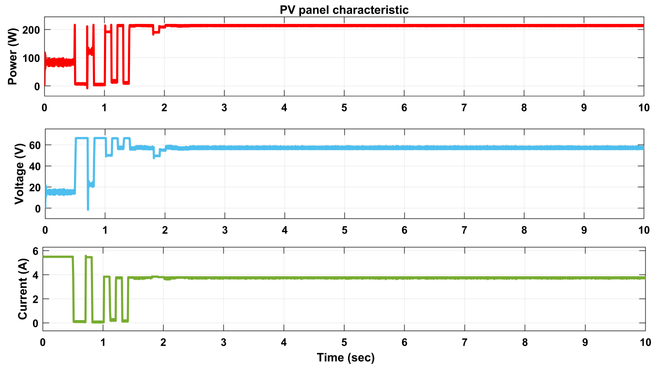


(b)

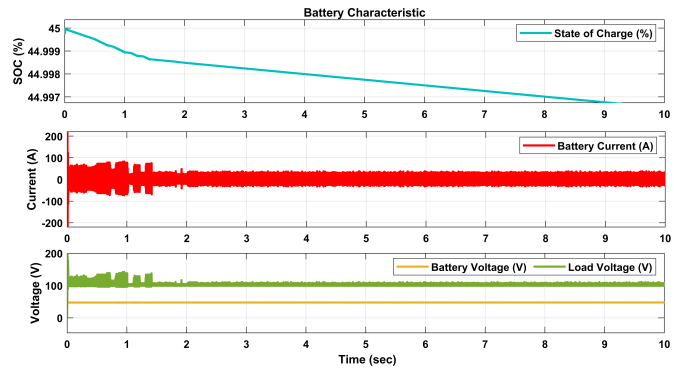
FIGURE 15: Simulation result for case 1 (a) PV panel characteristic (b) Battery characteristic

B. CASE 2: BATTERY IN DISCHARGING MODE

In this case, two of the PV panels receive uniform irradiance at constant temperature, while the remaining PV panel is partially shaded and provides GMPP of 215W, which is lower than the load power as shown in fig 16. If the PV system is unable to feed the load, the battery begins to discharge and sends the remaining power to the load, maintaining a constant voltage across the load of 100V. It can be observed that after discovering MPP, the ripple in the current has decreased and the battery is now being discharged by a high positive current at a constant voltage of 48V.



(a)



(b)

FIGURE 16: Simulation result for case 2 (a) PV panel characteristic (b) Battery characteristic

IX. CONCLUSION

In this paper, a novel hybrid MPPT algorithm based on GWO and DE is proposed to find GMPP in the presence of partial shading. The proposed algorithm has three main features 1) tracks the GMPP in various partial shading conditions; 2) provides a dynamic scaling factor and improved convergence factor to reduce oscillation around the MPP; and 3) easily adapts to sudden changes in the environment. The MATLAB/SIMULINK simulation results confirmed that the proposed MPPT algorithm can find GMPP with greater efficiency and speed than other conventional algorithms.This study also presents the modelling and simulation of a standalone PV battery system employing a fly-back converter, and the switching of a fly-back converter is also controlled by an MPPT controller. Also, based on the simulation results, it is possible to conclude that the voltage across the load is kept constant by the battery controller.

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