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A New Improved Variable Step Size MPPT Method for Photovoltaic Systems Using Grey Wolf and Whale Optimization Technique Based PID Controller

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ABSTRACT

In this work, we have developed two new intelligent maximum power point tracking (MPPT) techniques for photovoltaic (PV) solar systems. To optimize the PWM duty cycle driving the DC/DC boost converter, we have used two optimization algorithms namely the whale optimization algorithm (WOA) and grey wolf optimization (GWO) so we can tune the PID controller gains. The oscillation around the MPP and the fail accuracy under fast variable isolation are among the well-known drawbacks of conventional MPPT algorithms. To overcome these two drawbacks, we have formulated a new objective fitness function that includes WOA/GWO based accuracy, ripple, and overshoot. To provide the most relevant variable step size, this objective fitness function was optimized using the two aforementioned optimization algorithms (i.e., WOA and GWO). We have carried out several tests on Solarex MSX-150 panel and DC/DC boost converter based PV systems . In the simulation results section, we can clearly see that the two proposed algorithms perform better than the conventional ones in term of power overshoot, ripple and the response time.

1. INTRODUCTION

Recently, the energy consumption has reached unexpected high levels, in which it surpassed all expectations, besides, continuous increasing demand and the high cost of conventional energies have forced many countries and institutions to find and develop new energy source able to replace the fossil energy gradually with better performance especially in term of abundance, pollution, price, efficiency, etc. Hence, the most researchers have opted to investigate the renewable energy as an alternative solution, which can be the most promising option while it renewable and naturally replenished. Renewable energy is the energy produced from natural resources like geothermal, wind turbines, tides, rain, and sun [1].

In this context, many studies have demonstrated that photovoltaic (PV) energy can be considered as one the most important renewable energy sources while it exhibits better performances, which is clean, free and abundant in the most part of the world as well as simplicity in design, low maintenance and low cost. However Photovoltaic still suffer some limitations particularly its low conversion efficiency which is only in the range of 9 - 17% [2] and the nonlinear characteristics. Hence, several studies and researches on the subject of the development and improvement of PV systems have been updated continuously in term of efficiency, cell materials, DC/DC converters, MPPT methods, etc.

In many studies, to increase the efficiency of PV systems, the focus was on maximum power point tracking MPPT algorithms [3, 4]. Two main categories exist: the conventional and intelligent methods. Perturb and observe (P & O) [5], Incremental Conductance (IC) [6], Hill Climbing (HC) [7], fractional open circuit voltage [8], fractional short circuit current [9] are all conventional methods, where the intelligent methods use neural network [10], fuzzy logic, grey wolf optimization (GWO) [11], and genetic algorithms [12], Particle Swarm Optimization PSO [13].

The oscillation around the MPP and the poor accuracy under fast variable atmospheric conditions are among the well-known drawbacks of MPPT algorithms. In this study, two optimization algorithms namely the whale optimization algorithm (WOA) and grey wolf optimization (GWO) are used to tune the variable step size providing the adaptive duty cycle of the DC/DC boost converter. A comparison between those two algorithms was done by considering a boost converter connected to a Solarex MSX-150 model. To check the efficiency of the proposed techniques, we have considered many scenarios and schemes for temperature and irradiation.

The rest of the paper is organized as follows: Section 2 and section 3 describe respectively the modeling of PV cell and P&O MPPT method. Section 4 gives a short background on bio-inspired algorithms in which Grey-Wolf Optimizer (GWO) and Whale Optimization Algorithm have been presented with details. Section 5 then presents the proposed variable step size MPPT algorithm using GWO and WOA. Section 6 shows the obtained results in which a comparative study has been carried out. Finally, Section 7 provides some conclusions and directions for future work.

2. PHOTOVOLTAIC CELLS' MODELING

Photovoltaic system (PV) is the conversion of light into electricity using semi conducting materials where the photovoltaic effect is exhibited. In Figure 1, we show the equivalent model of a PV cell. It consists of a light generated current source, a single diode, a series resistance Rs and a shunt resistance R_{sh} [3, 14-16].

One can express the solar cell terminal current in the form of a function of photo-generated current, diode current and shunt current.

$$I_o = I_{ph} - I_d - I_{sh} \tag{1}$$

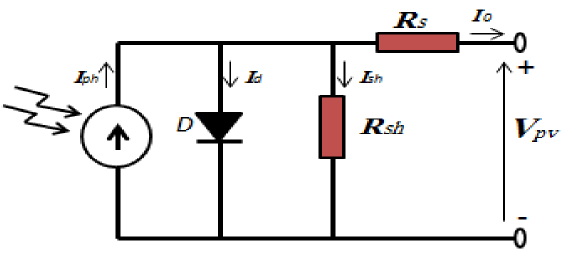


Figure 1. Model of a photovoltaic cell

The following equation gives the output current of a PV array.

$$I_0 = N_p I_{ph} - N_p I_{rs}\left[e^{\frac{q(V+R_s I_o)}{AkTN_s}} - 1\right] - N_p \frac{q(V+R_s I_o)}{N_s R_{sh}} \tag{2}$$

The following equation relates the generated photo-current I_{ph} to the solar irradiation.

$$I_{ph} = \frac{G}{1000}\left(I_{sc} + k_i(T - T_r)\right) \tag{3}$$

3. PERTURB & OBSERVE (P&O) METHOD

Currently, photovoltaics can be considered as the most relevant secondary energy source. Due to its nonlinear characteristics and low efficiency, the maximum power point tracking (MPPT) of a photovoltaic array is considered as an essential part of a PV system. Many MPPT techniques including perturb and observe [17, 18], incremental conductance [19], parasitic capacitance [6], constant voltage [20], can be tracked in literature.

The observation of the change in module output power and the perturbation of the module operating point are essential points to be considered in the mechanism of any classical P&O technique. The direction of the coming perturbation can be defined using the polarity of the module output power.

For positive polarity, the next voltage perturbation can increase or decrease in the voltage, the same as that for the previous perturbation. For negative polarity, the on the Improvements of Perturb and Observe Based MPPT [21].

Since it is simple and easy to implement, perturbation and observation is one of the most commonly used MPPT methods [22-24]. In this method, we need to slightly disturb (increase or decrease) the array voltage then we compare the actual value of the power P(k) to the previous obtained value P(k-1). If the disturbance caused an increase-in power panel, the following disturbance will have the same direction. In Figure 2 [25], we show the flowchart of this method.

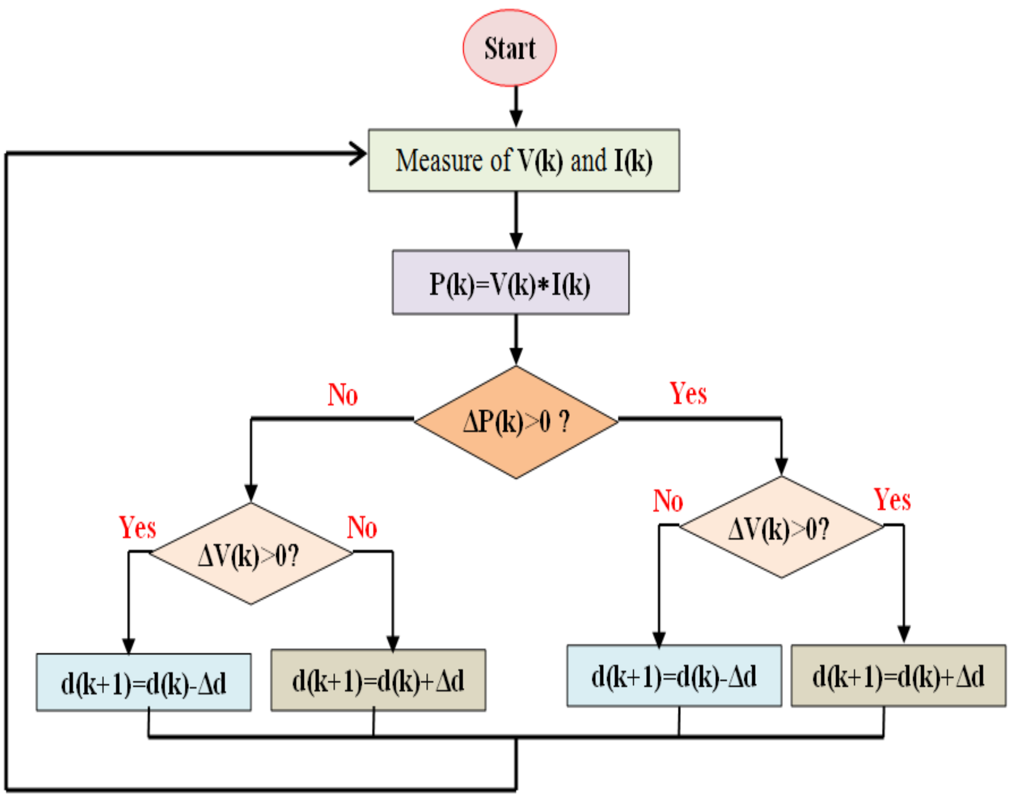


Figure 2. Flowchart of the conventional P&O algorithm [25]

4. BACKGROUND ON BIOINSPIRED ALGORITHMS

In the last decennium, the interest in bio-inspired optimization approaches has increased [26]. Hundreds of algorithms that proved their efficiency in various applications in many domains have been developed. Grey Wolf Optimizer [27-29] (GWO) and Whale Optimization Algorithm [30] (WOA) are two recently developed algorithms inspired by grey wolfs and whale behaviors, respectively. This section will summarize the main inspiration and the mathematical model of GWO and WOA.

4.1 Grey wolf optimizer

To mimic the natural leadership hierarchy and the hunting strategy of grey wolves, GWO is used. It consists of a stochastic algorithm and it was developed by Mirjalili et al. [31]. Grey wolves groups have a special hunting mechanism which has inspired the researchers who has developed this technique. Naturally, wolves prefer to be in a pack with a steady hierarchy. To help in the process of hunting, and based on the mission of each individual, each pack is divided into four categories named alpha, beta, delta and omega. During the hunting, the feeding, and the migration, the leader of the group who is responsible for guiding and directing the whole group is called alpha (α). Beta (β) wolf stands on the second level of social pyramid. This category can substitute α when they are killed or cannot lead the group anymore [32]. The next class is delta wolves (δ) and the rest of population is called omega (ω). When we design the GWO and as a mathematical model for the social hierarchy of wolves, the first three that have the fittest solutions in the population are regarded as: α, β and δ. We declare the rest of search agents as ω. In order to find the best optimal solution and during the optimization process, process ω group is guided and directed by α, β and δ toward the promising search space.

Basically, the mathematical model of GWO is described in three main phases which are: encircling, hunting and attacking the prey and they are detailed as follows:

4.1.1 Encircling

Start iterating (t=1) when we find a prey. Therefore, α, β and δ wolves leads the rest of search agents to pursue and eventually encircle the prey, this behavior of grey wolves is expressed as:

$$\vec{X}(t+1) = \vec{X}_p(t) + \vec{A}.\vec{D} \tag{4}$$

where, $\vec{X}$ is search agents (wolves) positions, $\vec{X}_p$ referenced the prey position. I is the iteration number. And $\vec{A}$ is a vector of coefficient at the (t+1)th iteration, Whereas, $\vec{D}$ is another coefficient that can be described as following:

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) \quad \vec{X}(t)\right| \tag{5}$$

The parameters $\vec{A}$ and $\vec{C}$ are combinations of controlling parameters a and random numbers and $\vec{r}_2$ which can be mathematically expressed as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 \tag{6}$$

$$\vec{C} = 2.\vec{r}_2 \tag{7}$$

where, components of $\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0,1].

4.1.2 Hunting the prey

Grey wolves hunting behavior change position of each pack in the group by approaching to the prey, this behavior is mathematically described as follows: α is considered as the leader and the finest solution, β and δ are expected to know more information about prey's possible positions. Therefore, ω pack will pursue them and obliged to change locations in the light of α, β and δ in the next iterations. Position updating or hunting behavior is described by the-following-equations:

$$\vec{D}_\alpha = \left|\vec{C}_1^t.\vec{X}_\alpha^t \quad X^t\right|, \vec{D}_\beta = \left|\vec{C}_1^t.\vec{X}_\beta^t \quad X^t\right|, \vec{D}_\delta = \left|\vec{C}_1^t.\vec{X}_\delta^t \quad X^t\right| \tag{8}$$

$$\vec{X}_1^t = \vec{X}_\alpha^t \quad A_1^t.\vec{D}_\alpha^t, \vec{X}_2^t = \vec{X}_\beta^t \quad A_2^t.\vec{D}_\beta^t, \vec{X}_3^t = \vec{X}_\beta^t \quad A_3^t.\vec{D}_\beta^t, \tag{9}$$

$$X^{t+1} = \frac{X_1^t + X_2^t + X_3^t}{3} \tag{10}$$

4.1.3 Attacking the prey

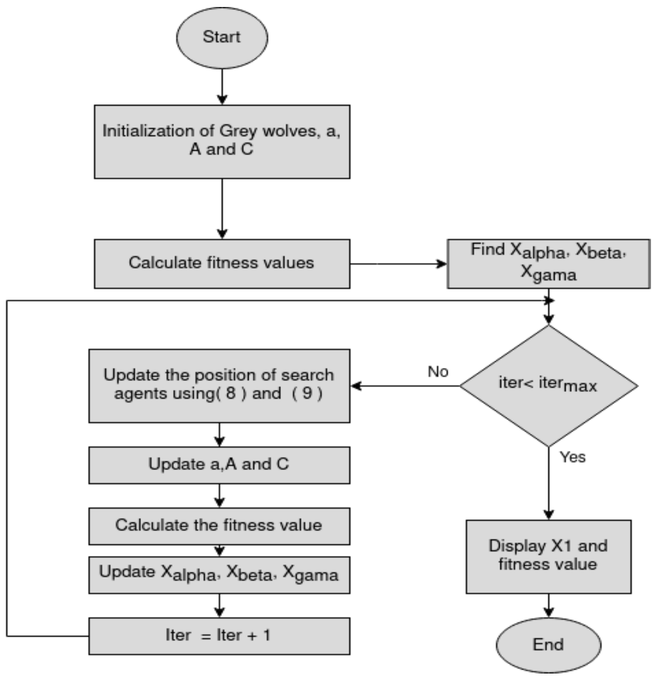


Figure 3. Flow chart of GWO algorithm

The attacking process is controlled by the parameter $\vec{a}$ changes the vector $\vec{A}$ and conduct the omega wolves to approach or run away from the prey (solution), theorically, if $|\vec{A}| > 1$ wolves run a way to explore more search space. Else, they approach to dominants which mean that omega wolves will follow the dominants which exploit the small search space. $\vec{a}$ are linearly decreased from 2 to 0 over the-course of iterations are cried on:

$$\vec{a} = 2(1 \quad t/N) \tag{11}$$

where, N is the total number of iterations and t is the current iteration number.

The basic steps of the grey wolf optimization can be shown Figure 3 [27-32].

4.2 Whale Optimization Algorithm

Mirjalili et al. [33] developed a new stochastic population algorithm named Whale Optimization Algorithm (WOA) [34]. The social behavior of the humpback whales is behind the inspiration of this algorithm. More directly, the WOA is a mimic of the bubbles net feeding in the foraging behavior of the humpback whales. This behavior is illustrated in Figure 4.

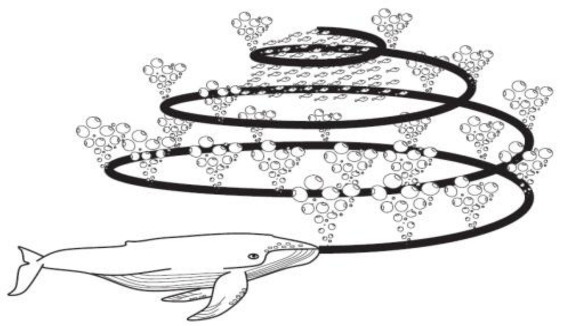


Figure 4. Bubble net feeding behavior of humpback whales

Two main phases are required to compose the algorithm namely exploitation phase (which contains two steps: the encircling prey, and the bubble-net attacking) and the exploration phase (which consists of the Search for prey). In the following section, we describe the mathematical model of WOA.

4.2.1 Exploitation phase (Encircling *prey, Bubble-net attacking*)

The mathematical model of the encircling behavior of the humpback whales is given in Eqns. (12) and (13).

$$\vec{D} = \left|\vec{C}.\vec{X}'(t) \quad \vec{X}(t)\right| \tag{12}$$

$$\vec{X}(t+1) = \vec{X}'(t) \quad (\vec{A}).\vec{D} \tag{13}$$

where, *t* indicates the current iteration, *X'* represents the best solution obtained so far, *X* is the position vector. Eqns. (14) and (15) are used to calculate the coefficient vectors A and C.

$$\vec{A} = 2\vec{a}.\vec{r} \quad \vec{a} \tag{14}$$

$$\vec{C} = 2.\vec{r} \tag{15}$$

where, a decrease linearly from 2 to 0 over-the course of iterations (in both exploration and exploitation phases) and r is a random vector generated with uniform distribution in the interval of [0,1]. search agents update their positions based on the best known solution. The solution location is controlled by the adjustments of A and C values.

The humpback hunting method is based on shrinking encircling mechanism and a spiral shaped path toward the prey. The shrinking behavior is formulated by the Eq. (16)

$$a = 2 \quad t\frac{2}{MaxIter} \tag{16}$$

where, t is the iteration number and MaxIter is the maximum number of allowed iterations. The distance between the actual solution and the best position is used to calculate the spiral-shaped path (see Eq. (17)),

$$\vec{X}(t+1) = D'\, e^{bl}.\cos(2\%PIl) + \vec{X}'(t) \tag{17}$$

where, $D' = \left|\vec{X}'(t) \quad \vec{X}(t)\right|$ and the distance of the whale from the prey (The best solution obtained so far) is described by Eq. (17). To make a choice between the two mechanisms (shrinking encircling mechanism and the spiral-shaped path) with probability of 50% during the optimization process, we use a random coefficient p in [0,1]. The shrinking encircling is used to update the position when p <0,5. The spiral-shaped path is used elsewhere.

4.2.2 Exploration phase (Search for prey)

When they are constructing bubble-network, whales have certain probability of searching for prey when. Mathematically, the search for a prey will enhance the WOA exploration. In this phase, we have to change the coefficient A. We update the distance data D randomly, if A exceeds the range of [-1,1]. At this moment, the algorithm will have certain global search ability since the whales will deviate-from the original optimal fitness (see Eqns. (18), (19))

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}} - \vec{X}\right| \tag{18}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}} - \vec{A}.\vec{D} \tag{19}$$

where, X_{rand} is random location information of a whale selected from this iteration.

Figure 5 depicts the flowchart of WOA technique. Moreover, the pseudo code of WOA can be expressed as the following:

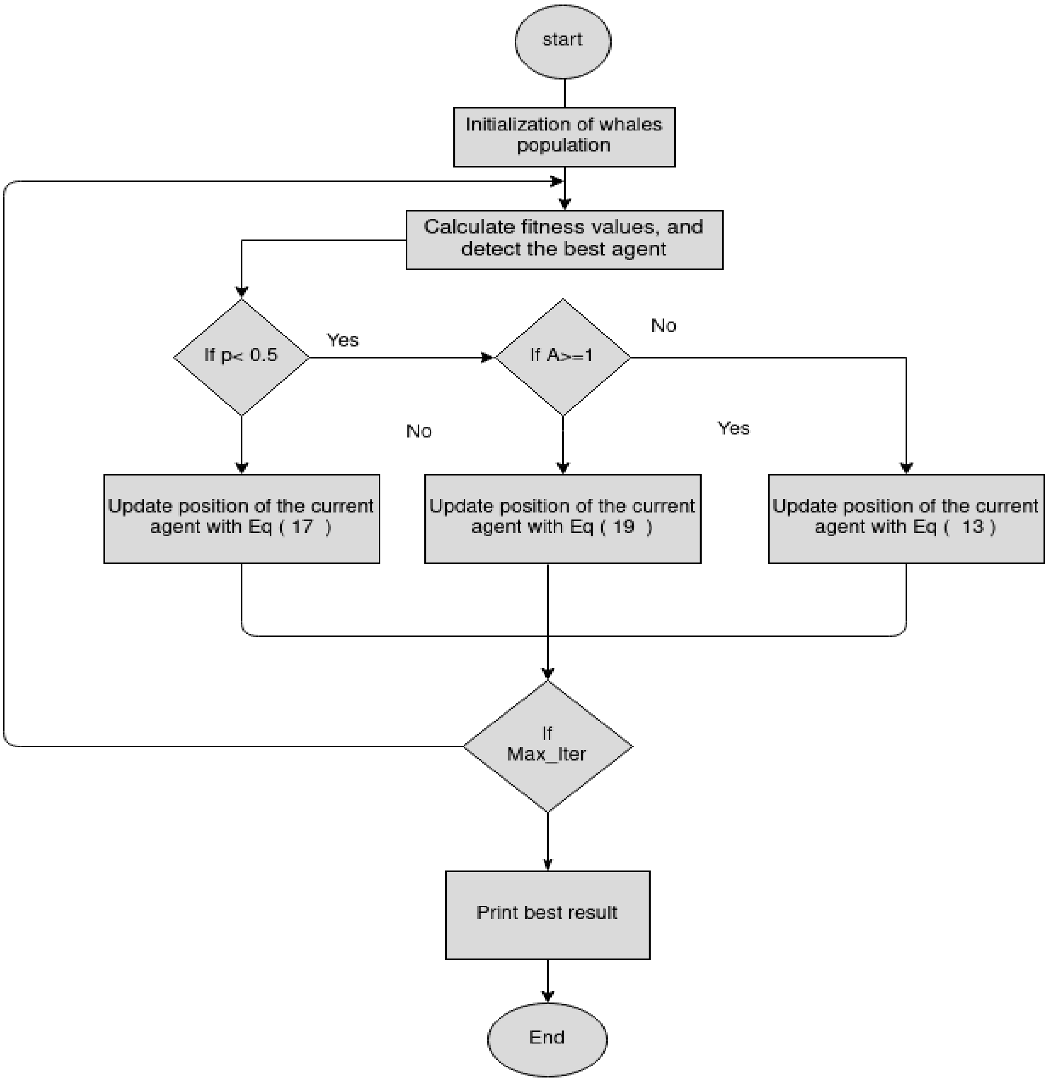


Figure 5. Flowchart of WOA technique, with a duty cycle Xi and the PV power as the fitness

5. VARIABLE STEP SIZE MPPT ALGORITHM USING GWO AND WOA

As aforementioned, with a fixed-step size, the conventional MPPT methods have good performance. However, the slow convergence, the oscillations around the MPP point and the failing to track the MPP point under rapidly changing atmospheric conditions are the most drawbacks. A speedy tracking can be achieved by considering larger step. The oscillations with slower dynamics can be reduced using smaller step size. Many contributions which used variable step size have been introduced and significant progress has been made to solve these dilemmas. In this approach, the step size is calculated automatically according to the PV array characteristics [1-4, 9, 25] by the algorithm. The step size should make a satisfactory tradeoff between the dynamics and oscillations, and this will depend on each operational condition. In this study, we propose a new variable step size MPPT algorithm characterized by more simplicity, faster response time and less oscillations.

In Figure 7, we show the variable step MPPT developed using Simulink.

In the following equation, we give the proposed variable step size method.

$$D(k) = D(k-1) \pm N * dP \tag{20}$$

5.1 GWO/WOA based step size MPPT Tuning

To ensure optimal control MPPT performance at nominal condition for the PV, one can apply GWO/WOA to tune PID parameters gains (Kp, Ki and Kd). In Figure 6, we give the block diagram for the entire system.

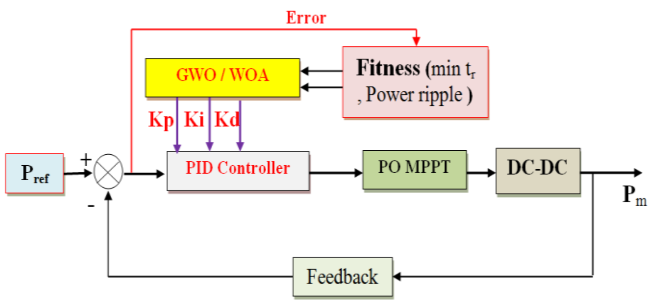


Figure 6. The proposed GWO/WOA Variable Step MPPT-PO

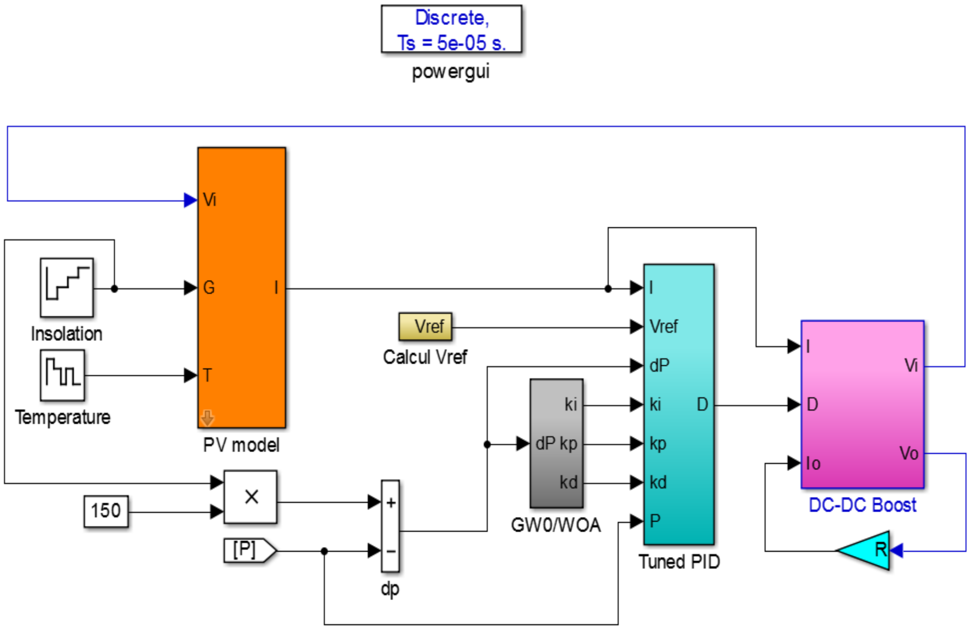


Figure 7. MPPT variable step PO-GWO/WOA implementation Matlab/Simulink

5.2 Objective function

In each optimization issue, the evaluation of the results can be performed using the objective function. In which, the evaluation measures are included. The successful choice of function means more accurate and better results. In this work, a combination of various criteria is introduced in the evaluation function, in order to be optimized and get the best gains in our main goals such as Ripple, Overshoot, and system response time. Firstly, integral square error (ISE) [29] criterion is given as a measure for ripple, in which the difference between the theoretical and produced power is calculated. ISE is given by the equation:

$$\int_0^{\tau} \left(P_{ref} - P_{out}\right)^2 dt \qquad (21)$$

also, the overshoot criteria employed as second part of the fitness function, which is defined as follows:

$$Overshoot = max(P_{out}) - Pref \qquad (22)$$

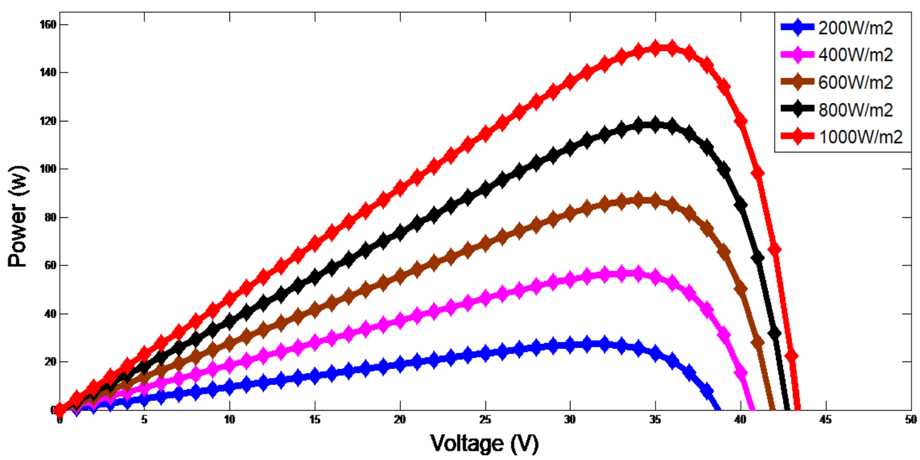
Based on these two measurements; we define our fitness function as follows:

$$F = \alpha . ISE + \beta . Overshoot \qquad (23)$$

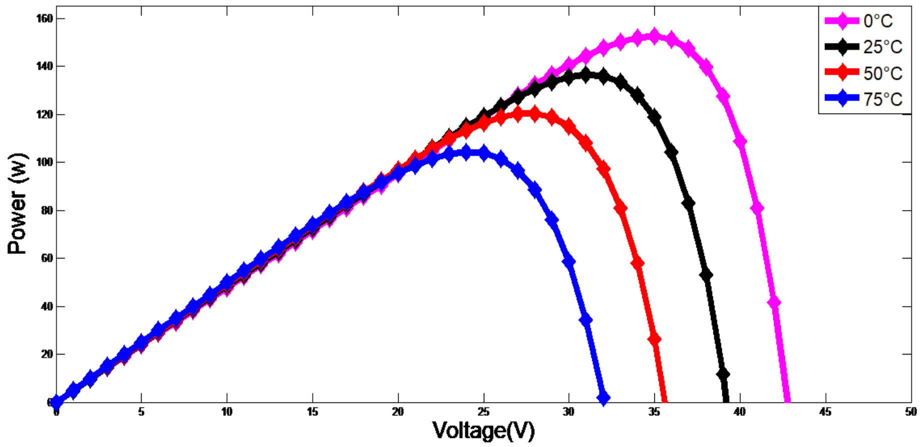
where, α and β are two empirical parameters used for balancing between the measurements. In our-case, there is no-preference between-the two-objectives, so (α=β=0.5) is chosen.

6. SIMULATION RESULTS AND DISCUSSION

To simulate and analyze the proposed method, we choose the Solarex MSX-150 photovoltaic module with 36 solar cells [4]. The Figure 8 shows the P-V characteristics of the PV cell from a typical Solarex MSX-150 PV panel. For more details; Figure 8(a) show the P-V voltage characteristics of the PV cell for different irradiation levels (0.2, 0.4, 0.6, 0.8, 1 KW/M²) at fixed temperature=25°C, respectively. Where, the Figure 8(b) reports the impact of the temperature variation (T=25, 50, 75, 100, 125 and 150°C) with constant irradiation (S=1 KW/M²) on the P-V voltage characteristics of the PV cell.



(a) P–Vacurves for various-irradiation-levels (Solarex-MSX-150, S= 0.25, 0.5,0.75, 1 Sun, T= 25)



(b) P–Vacurves for various temperatures. (Solarex-MSX-150, S=1 Sun, T=0, 25, 50, and 75)

Figure 8. Characteristics P-V and I-V under various insolation levels

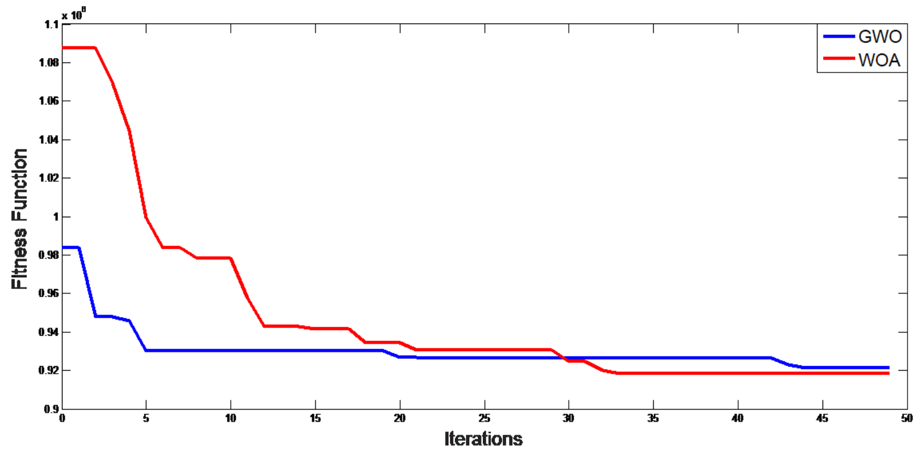


Figure 9. Evolution curves of the fitness value

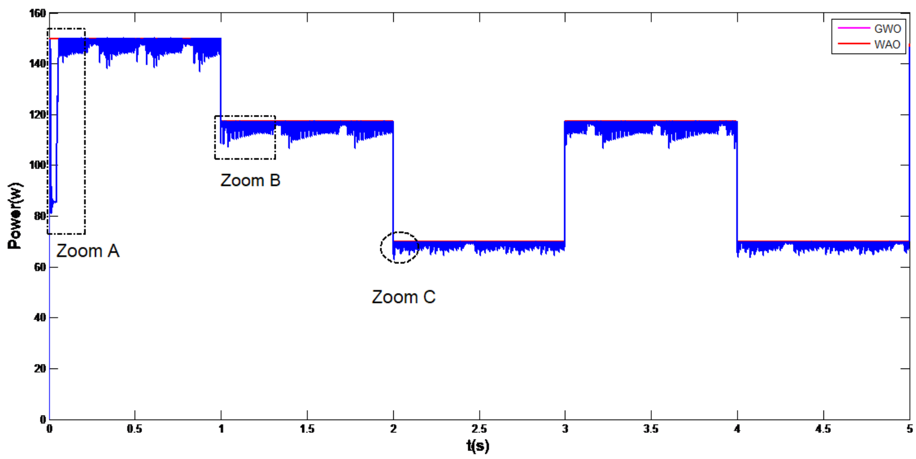


Figure 10. Output power of MPPT using GWO and WOA

Table 1. Test pattern signals

Irradiation (W/m^2)	Time (s)
1000	0-0.5
600	0.5-1
800	1-1.5
600	1.5-2
1000	2-2.5

In order to prove our proposals efficiency, with the quick variation of irradiation due to weather changing or cloud passing, three irradiation steps signals were simulated using a MATLAB/Simulink software as described by Table 1. The obtained results are compared to P&O classical algorithm and even compared between them.

As stated in the background on bio-inspired algorithms section, the main advantages of GWO and WOA is the less number of parameter entered by the user. Mainly, three parameters are used in both algorithms, which are number of iterations, number of agents and optimized variables number, such as, the last one representing the PID parameters Kp, Ki and Kd in our model. Table 2 reports the utilized values for each parameter in the algorithms.

Table 2. GWO and WAO setup parameters

Description	Parameters	
	WAO	**GWO**
Number ofasearchaagents	10	10
Maximumanumber ofaiterations	50	50
Numberaof variable	2	2

Table 3. Optimum set of controllers gains

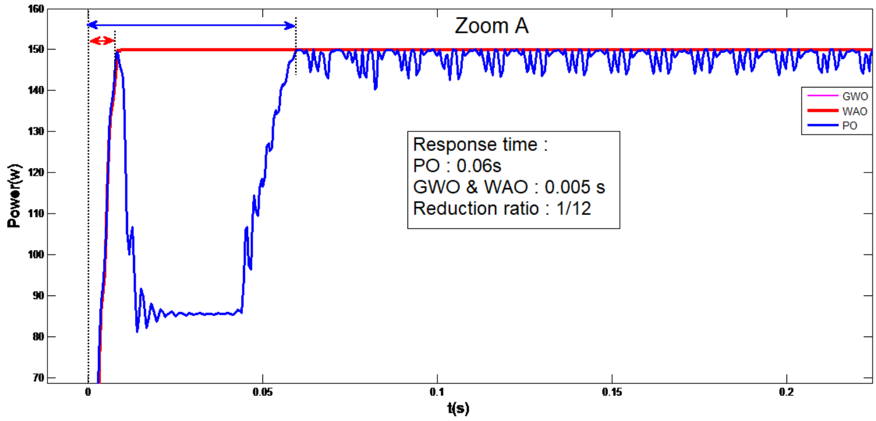
Algorithm		Ki	Kp	Kd
GWO	Test 1	45.381005	1077.134	0.028086226
	Test 2	33.342169	1300.6693	0.038502141
	Test 3	26.151597	1425.7115	0.038324656
	Test 4	58.341318	1470.8635	0.038500916
WOA	Test 1	81.273813	1097.8142	0.038562088
	Test 2	83.00539	1118.2084	0.039770502
	Test 3	65.992306	1095.0812	0.012762517
	Test 4	93.027473	1395.4121	0.037849931

As the first comparison, with the aim to forecast the best method that gives more minimization of the fitness function between GWO and WOA. Figure 9 reports the results of fitness function in terms of number of iterations. It's observed that whale optimization algorithm performs the Grey wolves optimization algorithm in terms of minimization, which means more efficiency in terms of overshoot and response time. This result is due to the good trad-off between exploitation and exploration in WOA. However, Gray wolves optimization algorithm starts with less fitness function in the first few iterations, which effect directly on the ripples in our model, due to the hierarchical search method that makes GWO algorithm powerful in terms of exploration. Table 3 give the results of 4 executions of the proposed methods with the same global objective with different performances (ripple, overshoot and response time). The best results, which will be used in the rest of our study, are highlighted in bold.

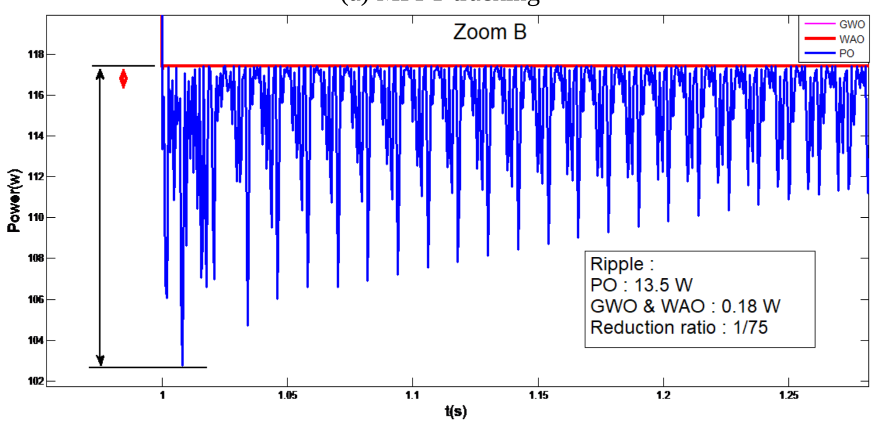
The efficiency of the proposed GWO-MPPT and WOA-MPPT methods, is illustrated through a comparative study between variable step size MPPT and MPPT-GWO/WOA have been illustrated. We have demonstrated three improvements: a) tracking accuracy, b) ripple. c) overshoot. Figure 10 shows the GWO and WOA performance in training offline step. While Figure 11 shows the obtained results using the trained optimal variable step size MPPT.

From simulation results we can see that:

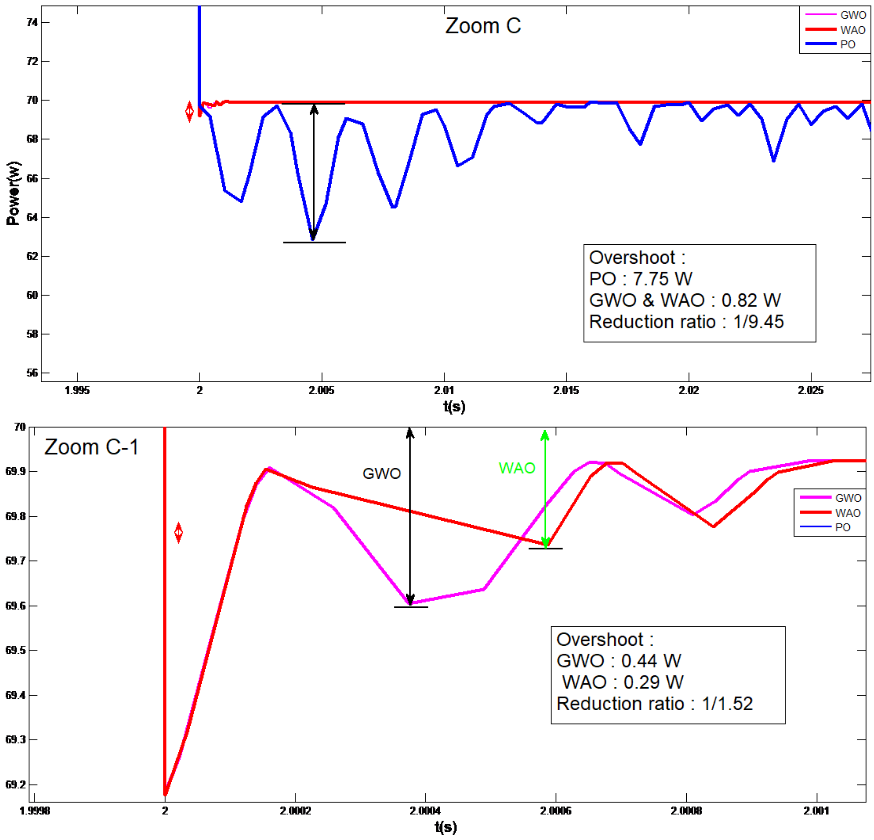
- **MPPT tracking:** fixed and variable step size MPPT algorithms both have acceptable accuracy. In both cases, the power values are very close to the theoretical value corresponding to irradiation levels (Figure 10 and Figure11A).
- **Ripple:** It is clear the variable step MPPT method gives improvement regarding the ripple. The quality of the output power P_{PV} (Ripple) with variable step GWO/WOA MPPT algorithm are obviously better than it with fixed step size MPPT algorithm (Figure 11B).
- **Overshoot:** the power peak value of the overshoot in case of suddenly changing atmospheric conditions is more important with the fixed value GWO/WOA MPPT compared to overshoot using the proposed variable step size GWO/WOA MPPT ontroller (Figure 11C).



(a) MPPT tracking



(b) Power ripple

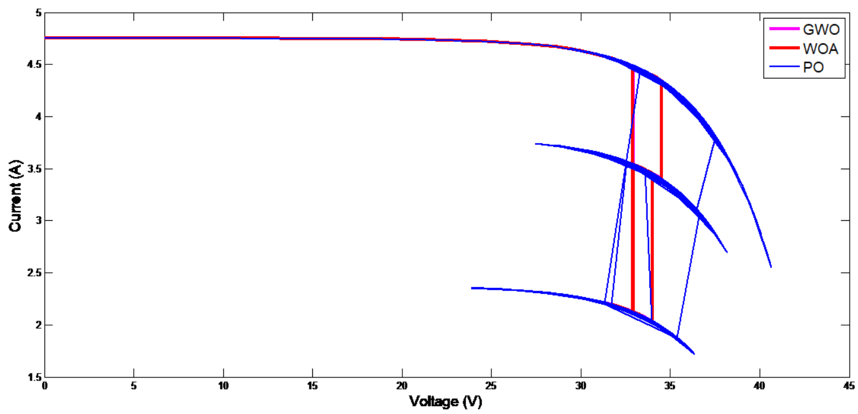


(c) Power overshoot

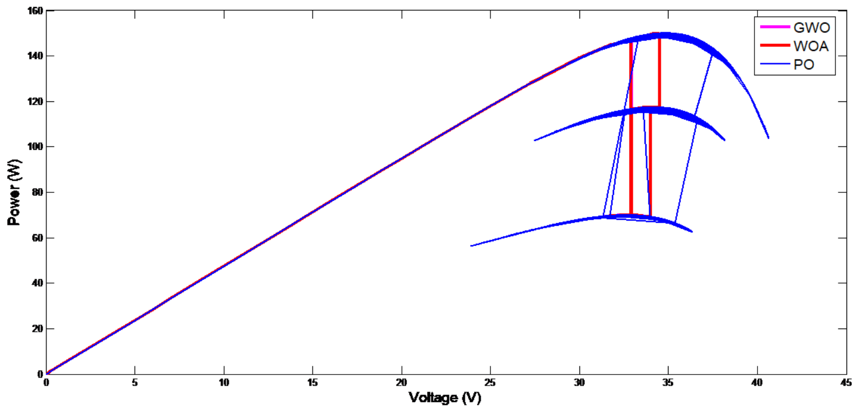
Figure 11. Zoom output power of MPPT using GWO and WOA

The MPPT point tracking by both algorithms (P&O and PO-GOW/WAO) is shown by Figure 12.

On can clearly see that due to the instability and the oscillation of the P&O algorithm especially around the MPPT point, in the proposed PO-GWO/WAO algorithms, the race of the MPPT point in most cases is less important.



(a) **I-V** characteristics



(b) **P-V** characteristics

Figure 12. Fixed step PO and GWO / WAO variable step MPP tracking

7. CONCLUSION

Two new intelligent maximum PowerPoint tracking (MPPT) techniques for photovoltaic (PV) solar systems have been developed in this study. To tune the PID controller gains, the whale optimization algorithm (WOA) and grey wolf optimization (GWO) algorithm are used .To address the challenges associated with rapidly changing insolation levels; we have used these two algorithms. To validate the performance and functionality of the proposed algorithms, simulation results are provided. To do simulation, we have used the Simulink environment and we have detailed different aspects of the model design and parameters. The simulation results were divided into transient, steady state, and dynamic response. The reduction of the ripple, the overshoot and the response time as well as the good ability of the roposed PO-GWO/WOA algorithms to follows the MPPT point especially in fast changing environment conditions, which resulting in an overall reduction of lost energy, are the main contributions in this work. In addition, we plan to extend the present work studying the biggest disadvantages of both proposed algorithms GWO / WAO when they used to optimize their parameters online and change the PID gains according the selected decisive criteria.

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