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A novel global maximum power point tracking based on flamingo search algorithm for photovoltaic systems

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ABSTRACT

Due to the high dependency of photovoltaic (PV) solar cell's output on solar irradiance and, the ambient temperature. Maximum power point tracking (MPPT) algorithms are used extensively to operate the system at its full potentials. Moreover, being installed in outdoor spaces, PV modules are inevitably subjected to partial shading conditions, where different parts of the system are receiving different amounts of solar irradiance. In case of occurrence of partial shading conditions on a PV module that is equipped with bypass diodes, the power-voltage (P-V) curve will have multiple peaks. This multi-peak curve requires using an advanced algorithm which track the global maximum power point (GMPP) instead of being deceived and trapped in a local maximum power point. In this paper, the flamingo search algorithm (FSA) is adapted for GMPP tracking for a PV system under partial shading conditions. The FSA algorithm fetch for the GMPP by reading the PV panel power and setting accordingly the duty cycle of the buck converter. To investigate model validity, simulation is performed using the MATLAB/Simulink platform and results demonstrate good tracking performance and fast response that prove the robustness of the system against rapid variations in solar irradiance levels.

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1. INTRODUCTION

Nowadays, fossil fuels are still the main source of energy [1]. This type of resource is non-renewable and exploiting it is considered as main cause of pollution. To help mitigate the pollution and decrease the fast depletion of these fuels, many alternative renewable energies are adopted, and research efforts are made to improve its efficiency. Among the promising renewable energies, solar energy is harvested, mostly through the use of photovoltaic (PV) technology and that is thanks to its maintenance-free and noiseless characteristics.

The relatively poor conversion efficiency of the modern solar cells [2] requires development low cost yet efficient solutions to control the PV system. In addition, the nonlinearity in current-voltage (I-V) characteristics curve of the solar cell and its reliance on climate conditions such as temperature and solar irradiance, these challenges demand design of smart and fast response control schemes. By changing the output impedance seen by the PV system via a direct current to direct current (DC-DC) converter, the operating point of the system can be controlled, and the goal of the maximum power point tracking (MPPT) algorithm is it to track the MPP and operate at its vicinity.

When PV cells of a given module are receiving the same irradiance level, the power-voltage (P-V) curve of the system will have one single peak, a single operating point at which power is at its highest level. In this case, classical algorithms such as incremental conductance (IC) [3], perturb and observe (P&O) [4], and hill climbing (HC) [5] can be implemented to track maximum power point (MPP). Moreover, the efficiency of the PV cells is highly dependent on the level of solar irradiance and on the ambient temperature and in case of rapidly changing atmospheric conditions, the aforementioned algorithms may diverge from the optimal solution [6].

If the basic P&O MPPT algorithm is implemented, a step value has to be chosen before running the system. The algorithm will converge slowly to the MPP, if the step value is too low, otherwise if the step value is set too high, the algorithm converges rapidly but high fluctuations in output power will arise. To help overcome this problem, variable step P&O is suggested by Yadav *et al.* [7].

In order to protect PV cells against overheating due to shading, bypass diodes are connected across each group of cells. However, in case of occurrence of partial shading, where these groups of PV cells are receiving different irradiance amounts, the involvement of bypass diodes will cause the P-V curve to have multiple peaks [8] and therefore, makes it challenging to track the MPP. Therefore, the additional cost of bypass diodes must not worsen the system performance and that is achievable by designing a smart control scheme that tracks the optimal point which leads to full exploitation of system potentials.

Deterministic algorithms such as P&O and IC cannot always guarantee tracking the MPP as these algorithms once converging to a specific solution it stop looking for better solutions in the search space, in other words, under partial shading conditions, these algorithms are prone to local optima entrapment [9]. Entrapment in local optima relates to the inability of the algorithm to decide whether the found solution in a local region in the search space is the optimal solution in the entire search space. Since real engineering problems have a very large number of local solutions, one cannot rely on deterministic algorithms for finding the global optimum.

For solving optimization problems where the search landscape contains several peaks, metaheuristic algorithms demonstrated excellent substitution to the deterministic algorithms. Thanks to the randomness introduced the search for the global optimal value, metaheuristic algorithm can check for even better solutions even after finding a good solution in a specific region in the search space. it can search at the vicinity of the found best solution which increase the chance of finding the global optimal solution in the overall search space [10].

In the last two decades, researchers have proposed many types of algorithms by imitating natural phenomena. A wide number of researchers exploited metaheuristic algorithms to track the global maximum power point (GMPP) [11]. Thanks to its fast convergence and simplicity of implementation, several studies in [12]–[14] suggested the particle swarm optimization to fetch for the GMPP. Hadji *et al.* [15] presented an MPPT algorithm using the genetic algorithm. Differential evolution algorithm [16], snake optimizer algorithm [17] and grey-wolf algorithm [18] are exploited as well in the development of efficient MPPT algorithms especially for rapidly changing atmospheric conditions.

Many metaheuristic algorithms have been suggested in literature. According to no free lunch theorem stated in [19], none of such algorithms can solve all optimization problems with the same efficiency, if one of these algorithms performs well for given optimization problem it may lead to poor solutions for another problem. In that regard, flamingo search algorithm [20] is suggested to track the GMPP in a PV system. Numerous benchmark tests were conducted to prove the superiority in performance of this algorithm over numerous popular metaheuristic algorithms. In addition, the algorithm has been already exploited in different fields. To name a few of its uses, It is used to find optimal routes in computer networks [21], implemented in cloud computing field to schedule tasks for internet of things device [22] and, suggested to forecast rainfalls [23] and to detect cancer via image processing [24]. This paper is organized as follow: solar cell modelling and partial shading conditions are examined, impact of selection of DC-DC converter on the system is discussed afterword, and next, the flamingo search algorithm is explained briefly, then, the use of this algorithm to track GMPP under different scenarios. Finally, simulation is conducted to check the tracking performance and to observe the influence of population size on the behavior of the algorithm.

2. METHOD

In the following subsections, the main components involved in our model will be examined. In addition, the partial shading condition and the inspiration of the algorithm will be discussed briefly. Adaptation of the FSA algorithm for MPPT is explained in a form of a flowchart. Finally, the electrical characteristics of the used PV module along with simulation model are presented.

2.1. The partial shading phenomena

Given that the PV system is installed in outdoor spaces, it is occasionally subjected to partial shading conditions, where different parts of the system receive different levels of solar irradiance. In other words, if the PV panel is partially shaded, the large current generated by the cells receiving the highest irradiance level will pass through the PV cells exposed to lower irradiance levels and therefore the latter cells will be acting as a resistive load, this latter will heat up leading probably to its irreversible damage. To help address this issue, an alternative route for the current is provided by connecting each group of cells to a bypass diode.

Moreover, the integration of bypass diodes across each group of cells will be causing the overall P-V curve to have multiple peaks [25], where only one peak will lead to extraction of highest power for the system and it is referred as the GMPP while the other lower peaks are referred as local maximum power point (LMPP). The maximum possible number of peaks in the P-V curve is equal to the number of bypass diodes. In the typical PV panel, three bypass diodes are used [26]. Being under partial shading conditions, Figure 1 illustrates the different resulting P-V curves of the system with and without bypass diodes.

Simulation will be carried out on the commercial Jinko solar JKM190M-72B module whose max power at the standard running conditions is 190 W at a voltage of 36.6 V. When the module is subjected to the shading scenario depicted in Figure 2(a) and whose corresponding P-V curve is shown in Figure 2(b). It is worth noting that GMPP location is strongly dependent on the shading pattern.

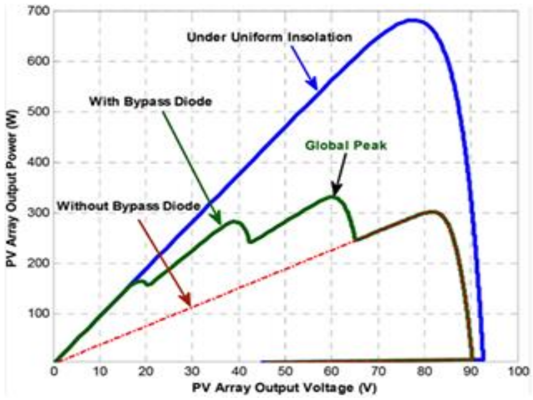
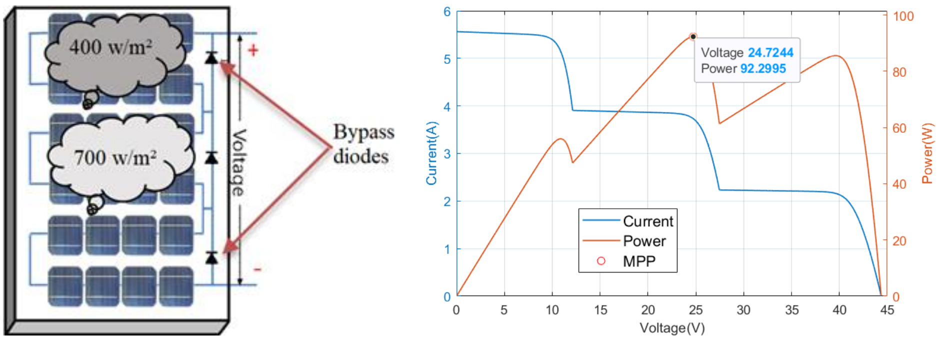


Figure 1. Effect of bypass diode on the resulting P-V curve



(a) (b)

Figure 2. The Jinko solar JKM190M-72B (a) simulated shading pattern on and (b) characteristics curves when subjected to partial shading conditions depicted in Figure 2(a)

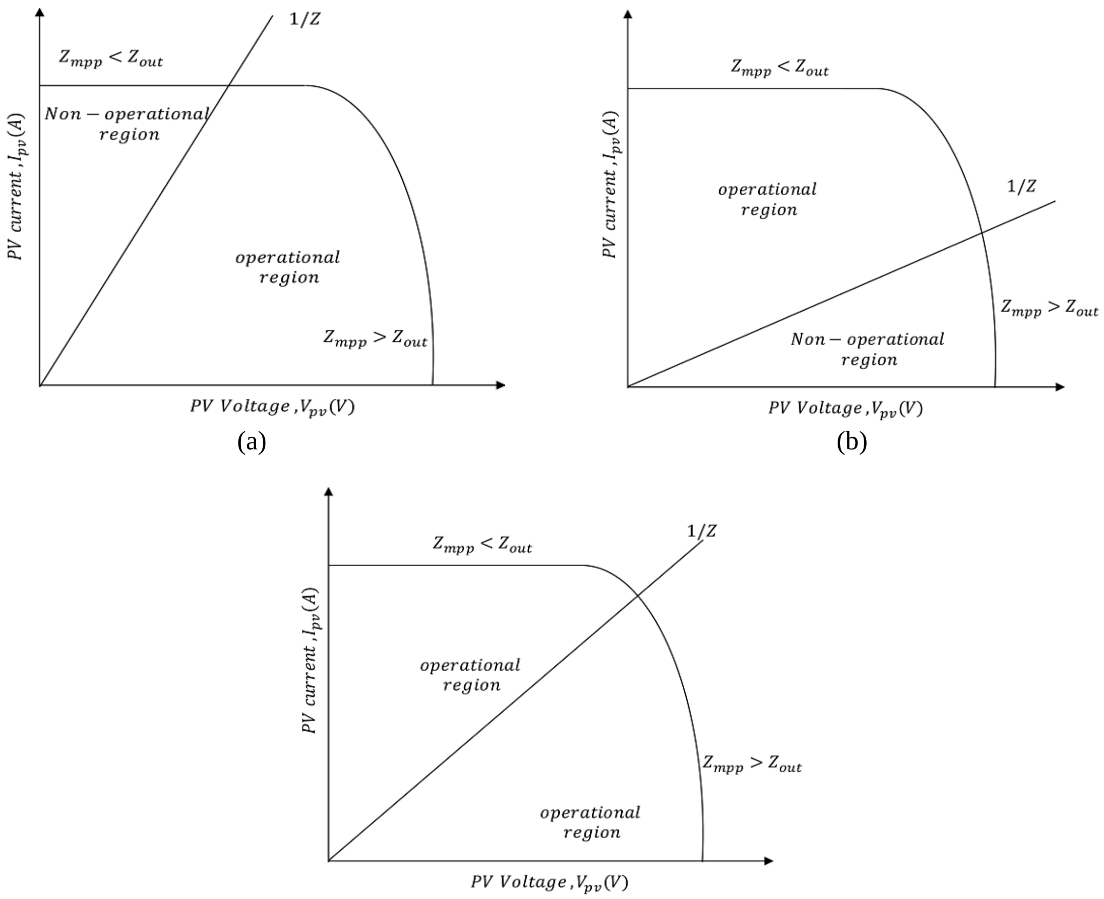
2.2. DC-DC converter selection criteria

In order to be able to control the operating point and eventually reach the MPP, the load must be connected to the PV system via a DC-DC converter. The DC-DC converter output voltage is controlled via a semiconductor switch. For a given load impedance Z_L, the value of duty cycle at which this switch is operated will define the value of converter's input impedance Z_{in}. This input impedance seen by the PV system as Z_{out}, will lead to operation at a given operating point in the PV-curve. In other words, to ensure operation at the MPP, this input impedance should match the Z_{mpp} which is equal to the ratio of V_{mpp} over I_{mpp}. In addition, the range of possible values of input impedance depends on the type of DC-DC converter, the input impedance value can be deduced as the ratio of voltage and current. Table 1 shows the values of current, voltage and input impedance depending on some types of DC-DC converters.

Table 1. Input and output relationship of some DC/DC converters

Type of converter	Voltage equation	Current equation	Impedance equation
Buck	$V_{in} = \frac{1}{D}.V_{out}$	$I_{in} = D.I_{out}$	$Z_{in} = \frac{1}{D^2}.Z_L$
Boost	$V_{in} = (1-D).V_{out}$	$I_{in} = \frac{1}{1-D}.I_{out}$	$Z_{in} = (1-D)^2.Z_L$
Buck-Boost	$V_{in} = -\frac{1-D}{D}.V_{out}$	$I_{in} = -\frac{D}{1-D}.I_{out}$	$Z_{in} = \frac{(1-D)^2}{D^2}.Z_L$

In order to know the operational region of each converter, values of Z_{mpp} and Z_{out} must be compared [27]. For instance, for a buck converter, if Z_{out} is less than Z_{mpp}, it is impossible to operate the system at the MPP. In essence the selection of converter is based on size of load impedance seen by the PV panel and on PV panel itself, maximum power point impedance. From Figure 3(a) it is noticed that the buck converter should be operated at a low duty cycle to ensure a high voltage at its input port. Conversely, from Figure 3(b), it is mandatory for boost converter to be operating at high duty cycle to track the MPP. Operating conditions of buck-boost converter is similar to that of the buck converter as can be seen from Figure 3(c).



(c)

Figure 3. Operational regions according to values of Z_{mpp} and Z_{out} for: (a) buck converter, (b) boost converter, and (c) buck-boost converter

For the buck converter the minimum value which ensure operating in the continuous mode is expressed in (1) [28].

$$L_{min} = \frac{R(1-D)}{2f} \tag{1}$$

The capacitor of the buck converter serves as smoother of the output voltage, its value is chosen on the basis of the rate of acceptable ripples in the voltage waveform. R is the load resistance value and it has a considerable effect on the operating point of the system as discussed earlier. In addition, the switching frequency of the semiconductor switch of the converter is selected as high as the switch can support.

2.3. The flamingo search algorithm

Flamingo search algorithm (FSA) is a new swarm intelligence optimization algorithm. It is inspired from the migratory and foraging behaviors of flamingos. Flamingo birds are social migratory animals that feed mostly on underwater plants and insects, Figure 4 shows a group of these animals.

Figure 4. A group of flamingo birds

The Flamingo birds live in areas rich in food. After exhausting the food in that area, flamingos population move elsewhere when the food in the region is decreased to a quantity that is not enough for the group [29]. The flamingo search algorithm demonstrate a good tradeoff between exploitation and exploration operations and tests on this algorithm, proved the superiority of the FSA over many popular optimization algorithms [20].

When the swarm of flamingo birds are foraging for food, the bird finding a source of food in the region will sing to inform for the availability of food in its location. While remaining immobile and thanks to its long neck and using its beak, this bird will start scanning the neighborhood for a location richer in food and may move its body toward direction with abundant food, this behavior inspires the exploitation part of the algorithm. When a flamingo bird finds a source of food in its current location, its foraging behavior consists of scanning slowly the neighboring space by moving its feet, one at the time and by scanning the underwater with its beak. In (2) simulate the movement of the i^{th} individual in the j^{th} dimension.

$$x_{ij}^{t+1} = (x_{ij}^{t} + \varepsilon_1 x_j^t + G_2|G_1 Xbest_j^t + \varepsilon_2 x_{ij}^t|)/K \tag{2}$$

To account for randomness of direction of movement of its feet and to represent the random beak trajectory, random parameters $\varepsilon_1, \varepsilon_2, G_1$ and, G_2 are introduced. Another random K parameter is introduced to consider the physical differences between the birds, such as length of feet and beak. $Xbest_j$ represents the current best location in the j^{th} dimension.

When food diminish in the present living area, the flamingo group travels towards a new area richer in food. Supposing that the position of that new area in the j^{th} dimension is $Xbest_j$ and adopting the random parameter w to take into consideration the randomness in the decision of each bird, the formula of the migration of the i^{th} flamingo bird is stated in (3). w parameter is a Gaussian random number used to expand the search space during the migration of flamingos and account for the arbitrary behaviors of each bird in the specific migration process.

$$x_{ij}^{t+1} = x_{ij}^{t} + w * (Xbest_j^t - x_{ij}^t) \tag{3}$$

In summary, the population of birds, initially, will be subdivided into a foraging group and migrating group. Fitness values of birds are obtained, birds with lower fitness value will join the migrating group and the ones having higher fitness values will join the foraging group. The position of each bird will be updated according to the group to which it belongs. The position of best individual which represents the optimal solution is stored for the next iteration. The process is repeated until stop criteria is met or until all iterations are performed and elite is given as solution. The flow chart below depicted in Figure 5 demonstrates these steps.

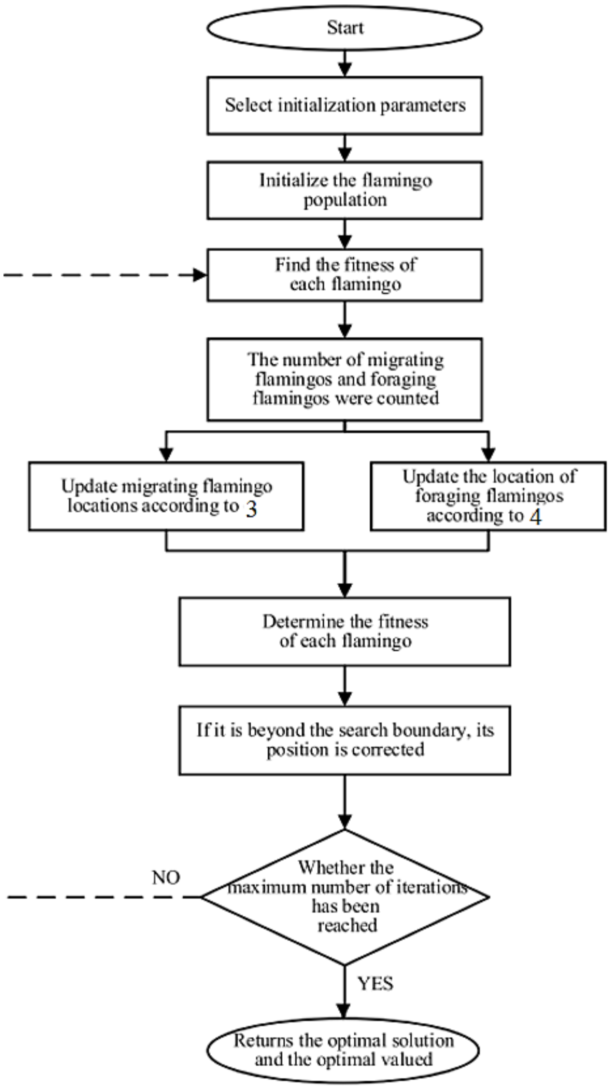


Figure 5. Flowchart of the FSA

2.4. Adaptation of FSA for MPPT application

The suggested MPPT based on the FSA is implemented for battery-charging application where a PV panel is charging a battery via a DC-DC buck converter. Each flamingo bird represents the value of duty cycle. The area with plentiful food corresponds to the operating points at the vicinity of the MPP.

The bird position represents a duty cycle value ranging between 0 and 1. The corresponding fitness value is the measured power obtained by testing the system with the given duty cycle. The same process is repeated for positions of the other remaining birds “duty cycles.” The duty cycle leading to the highest output power will be assigned as the best position. Next, bird positions will be updated according to their fitness values and the system will be evaluated with the new positions. When the relative error of powers ΔP of elite values decreased below the set value, this indicates that the latest best duty cycle will lead to operation at MPP. Relative error ΔP is calculated in (4).

$$\Delta P = \frac{|P^{t}-P^{t-1}|}{P^{t-1}} * 100\% \quad (4)$$

System will be kept operating with this duty cycle, if shading conditions changes, the MPP will change its location in the PV curve causing the relative error in power to increase beyond the set value, therefore, the FSA will run again. Simplicity of equations involved in the FSA algorithm, leads to fast response of the system. The flow chart below illustrated in Figure 6 demonstrates the MPPT-FSA algorithm.

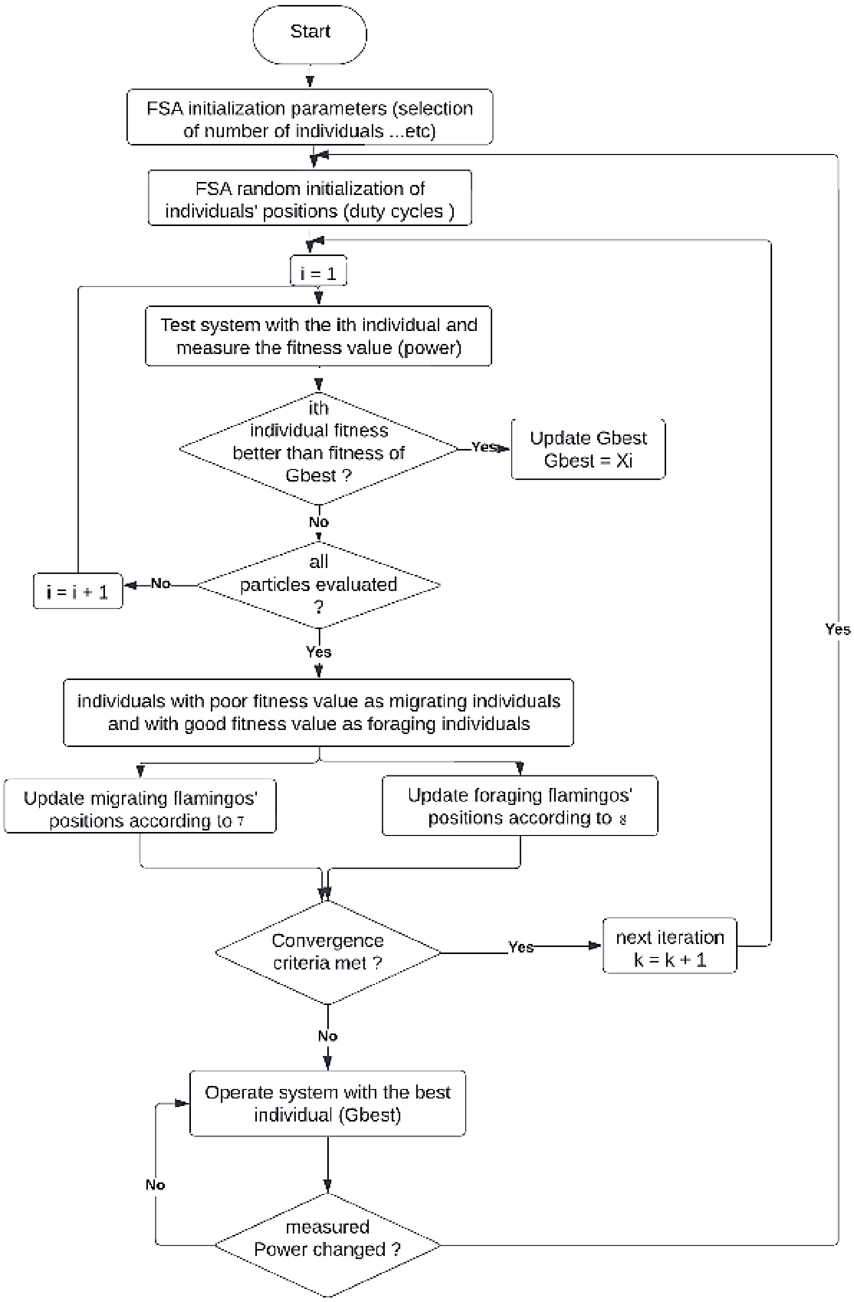


Figure 6. Flow chart of the proposed MPPT based on FSA

2.5. Simulation of the system

The PV panel characteristics are based on the commercial 250 W 72 cells The Jinko Solar JKM190M-72B module whose parameters are obtained from the National Renewable Energy Laboratory (NREL) system advisor model. The model accuracy is very high as stated in [30]. Table 2 show module electrical characteristics. Figure 7 illustrates the developed model in MATLAB/Simulink.

Table 2. Jinko solar JKM190M-72B module electrical characteristics

Parameter	Value
STC power rating	189.95 W
Number of Cells	72
I_{mp}	5.19 A
V_{mp}	36.6 V
I_{sc}	5.56 A
V_{oc}	45.2 V
Temperature coefficient of I_{sc}	0.0775%/°C
Temperature coefficient of V_{oc}	-0.3931%/°C

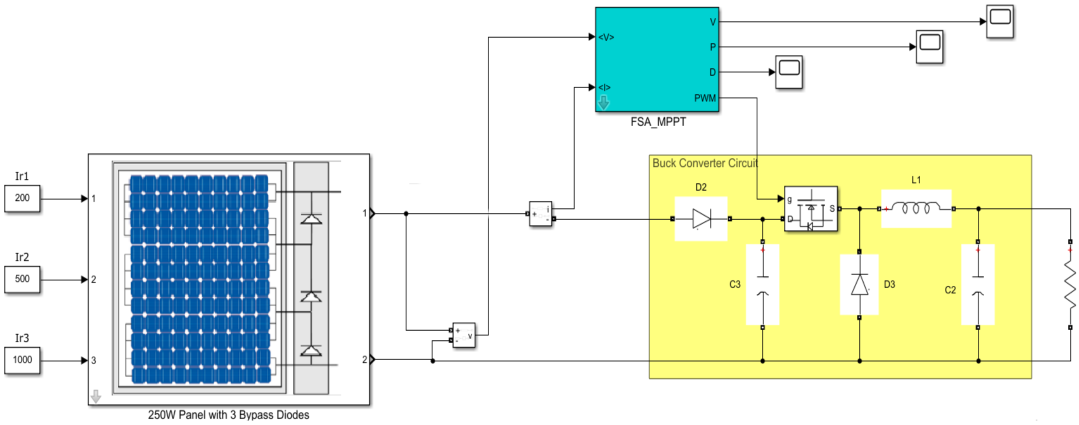


Figure 7. The MATLAB/Simulink model

3. RESULTS AND DISCUSSION

To assess tracking performance of the suggested technique, the PV system will be tested with two scenarios: i) when operating in normal conditions and ii) when operating under partial shading conditions. Initially, the size of population is set to 8 birds, the effect of population size is demonstrated in the subsequent section. It is worth mentioning that due to the randomness involved in the metaheuristic algorithms and due to the numerous parameters that has to be initialized for each algorithm, comparison of performances of these algorithm for such problems has little to no significance [31].

3.1. System subjected to uniform irradiance

The irradiance of the three solar cell groups is set to be identical at a value of 1000 W/m², the resulting P-V curve, The output power, voltage and duty cycle are depicted in Figures 8. Clearly, it can be noticed that the algorithm operated the system with distinct duty cycle values while storing at each iteration the one leading to highest power. The algorithm will drive the system with the best duty cycle found if it is leading to almost the same power produced by the latest tested duty cycle. As shown in Figure 8(a), the MPP requires having around 36 volts across terminals of the PV module leading to generation of roughly 190 W. Figures 8(b) and 8(c) proves the speed and accuracy of FSA-based MPPT tracking. Figure 8(d) shows the several duty cycle values generated by the system before tracking the MPPT.

3.2. System under partial shading conditions

As mentioned earlier, three solar cell groups form our PV panel, the upper, middle and lower solar cells groups are assumed to be receiving insulations of 400, 700, and 1,000 W/m² respectively. The resulting 3 peaks P-V curve is represented in Figure 9(a), where the maximum power that can be harvested is around 92 Watts. The output power and voltage in addition to the generated duty cycle by the FSA are presented in Figures 9(b)-9(d) respectively.

3.3. Effect of population size on the system performance

To assess the effect of population size on the performance of system, the algorithm has been initialized with population size of 8 and then with population size of 4. Figure 10 shows the obtained results. Referring to the completely different two operating conditions, when comparing the obtained values of voltage and power with the values corresponding to the MPP, it can be clearly seen that the newly presented FSA-based MPPT algorithm exhibits fast and accurate tracking.

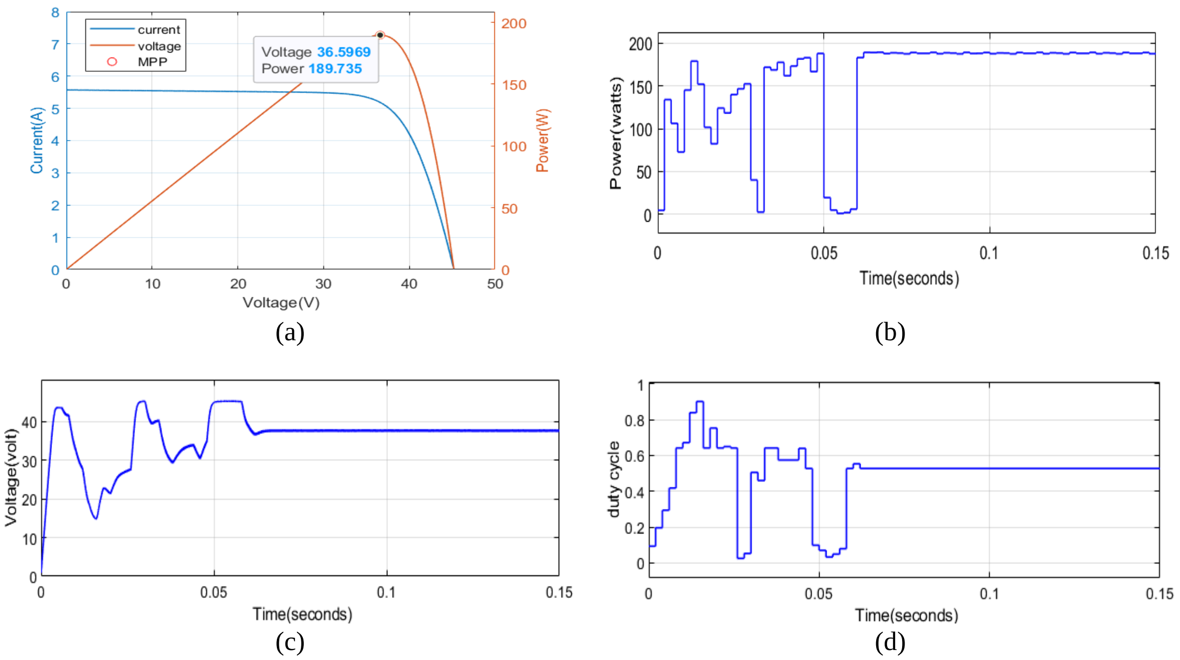


Figure 8. Under uniform irradiance (a) the module P-V and I-V curves, (b) module output power, (c) module output voltage, and (d) generated duty cycle

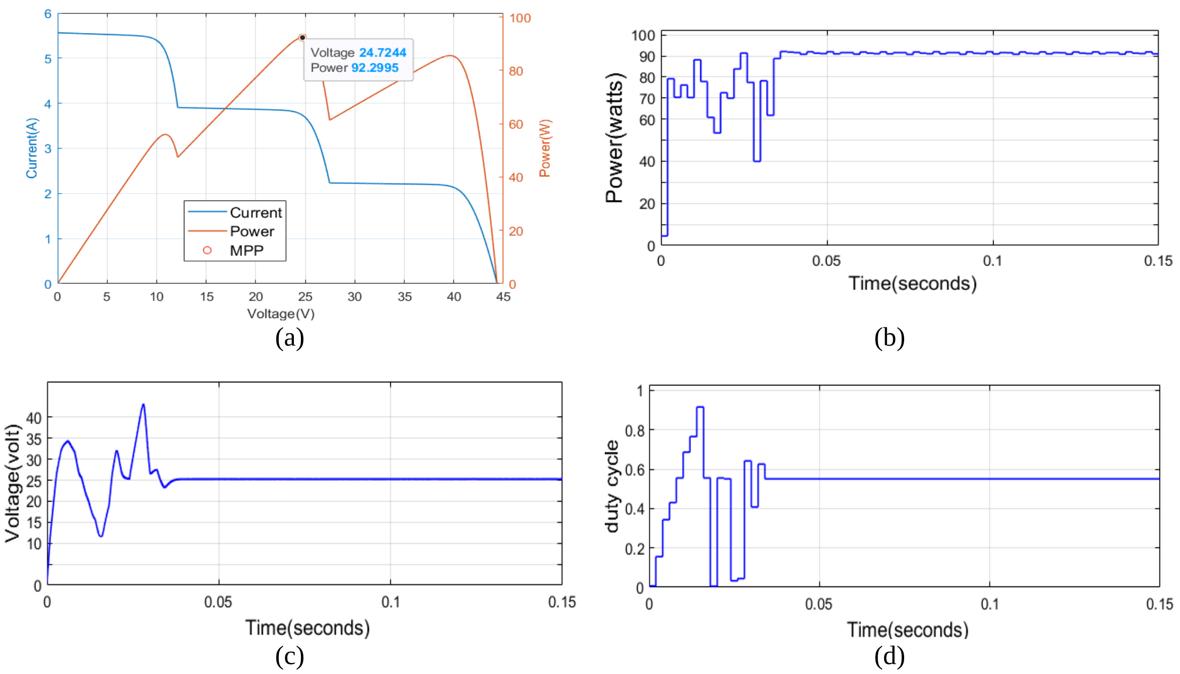


Figure 9. Under partial shading conditions (a) the module P-V and I-V curves, (b) module output power, (c) module output voltage, and (d) generated duty cycle

Given that the MPP location is changing frequently by various factors such as, air mass, ambient temperature, solar insolation and type and size of load, the system fast response proves the high reliability of the algorithm to be used for PV systems installed in regions with highly variable climatic conditions and it is valid also for dynamic loads. Referring to the duty cycle figures of the two operating scenarios, it is noticed that the system is tested with a successive distant duty cycle value, which may lead to harsh transient response. For that reason and in order to allow for transient response to pass, a delay unit should be integrated in the system to allow for accurate measuring of power corresponding to each tested duty cycle.

In case of uniform irradiance, the simpler algorithms such as P&O, HC and, IC tracks rapidly and with high accuracy the MPP, therefore, the suggested method can used hybridized with one of the simple algorithms at the expense of adding solar irradiance sensor at the center of each solar group composing the PV module. The selection of population size should be selected wisely. A too high value for this parameter will lead to unnecessary large numbers of tests of the system which is computationally expensive. A too low value set for this parameter will ensure fast convergence at the risk of the algorithm being stagnated at one of local maximum power points.

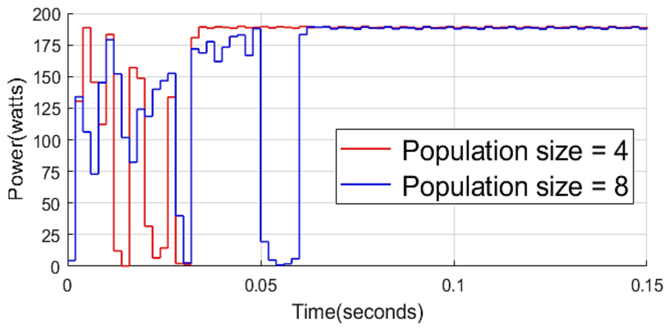


Figure 10. Effect of population size on the convergence speed

4. CONCLUSION

Although the integration of renewable energies has helped tremendously in reducing pollution and cost of electricity production, it has introduced new technical challenges. Among these challenges is the tracking of the optimal power point as it becomes a difficult task as the size of the PV system is growing day by day. Fast and Smart trackers that has the ability to distinguish GMPPT from the many LMPPT in a timely manner are required. The time variant and complex nature of P-V curve of the entire PV system demands a population-based metaheuristic algorithm among which the FSA has proved it effectiveness in the present paper. Thanks to the numerous MPPT algorithms suggested in literature, a more sophisticated algorithm can be implemented in real applications by exploiting the advantages of each technique.

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