IEEE Access
Multidisciplinary ⁝ Rapid Review ⁝ Open Access Journal

Received December 26, 2019, accepted January 5, 2020, date of publication January 8, 2020, date of current version January 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2964759

A Novel Bat Algorithm Strategy for Maximum Power Point Tracker of Photovoltaic Energy Systems Under Dynamic Partial Shading

ALI M. ELTAMALY[1,2,3], **(Member, IEEE), M. S. AL-SAUD**[1,4], **AND AHMED G. ABOKHALIL**[5,6]

[1]Saudi Electricity Company Chair in Power System Reliability and Security, King Saud University, Riyadh 11421, Saudi Arabia
[2]Sustainable Energy Technologies Center, King Saud University, Riyadh 11421, Saudi Arabia
[3]Electrical Engineering Department, Mansoura University, Mansoura 35516, Egypt
[4]Electrical Engineering Department, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
[5]Electrical Engineering Department, Majmaah University, Al Majma'ah 11952, Saudi Arabia
[6]Electrical Engineering Department, Assiut University, Asyut 71515, Egypt

Corresponding author: Ali M. Eltamaly (eltamaly@ksu.edu.sa)

This work was supported by the Deanship of Scientific Research at King Saud University, Riyadh, Saudi Arabia, under Grant RG-1439-66.

ABSTRACT Power versus voltage curves of partial shading photovoltaic (PV) systems contain several local peaks (LPs) and one global peak (GP). Most conventional maximum power point tracker (MPPT) techniques may not follow the GP under partial shading conditions (PSC). The use of metaheuristic techniques such as the bat algorithm (BA) and particle swarm optimization (PSO) can overcome these obstacles. All problems inherent in the using of BA as MPPT of PV systems has been discussed and solved in this paper. The first problem is the random initial values of bats that may cause premature convergence. Therefore, the initial values of bats were modified to be close to the anticipated positions of peaks to reduce the convergence time and improve the chance of capturing the GP. The second problem occurs when shading pattern changes the value and position of the GP which is not configurable because all bats are concentrated at the previous GP; this can be resolved by BA re-initialization. The the third problem is the GP memorized in the execution of the BA code forces the PV system to work at the duty ratio of the highest GP ever seen, which may not be the real GP. This problem is solved by updating the memorized GP. This paper also proposes a new criterion for selecting the optimal swarm size against number of peaks to reduce the convergence time and improve the chance of capturing the GP. To the authors' knowledge, most of these problems inherent in the BA have hitherto not been addressed in the literature. The simulation and experimental results obtained from the proposed modified BA (MBA) with re-initialization have been compared to the PSO and grey wolf optimization (GWO) techniques which show the superiority of using MBA strategy in the MPPT of partial shading PV systems.

INDEX TERMS Bat algorithm, boost converter, dynamic global peak, maximum power point tracker, partial shading conditions, PV system.

I. INTRODUCTION

Photovoltaic (PV) energy systems have attracted attention in the last few decades because they are renewable and environmentally friendly. The power generated from PV array is a function of irradiance, temperature, and the terminal voltage of the PV array. A DC/DC converter such as a boost converter can be used to control the terminal voltage to extract the maximum available power from a PV system as shown in Fig. 1. The power versus voltage (P-V) characteristics of a PV array has only one peak in the case of uniformly distributed irradiance which makes conventional maximum power point tracking (MPPT) techniques well-suited to following the maximum power point. In the case of partial shading, however the P-V characteristics contain several local peaks (LPs) and only one global peak (GP) where, the number of peaks equals the number of parts (modules) in series having different irradiances. Fig. 2 shows the power versus duty ratio P-d curves for different numbers of peaks or shaded modules. Fig. 3 shows the P-d ratio of

The associate editor coordinating the review of this manuscript and approving it for publication was Zhilei Yao.

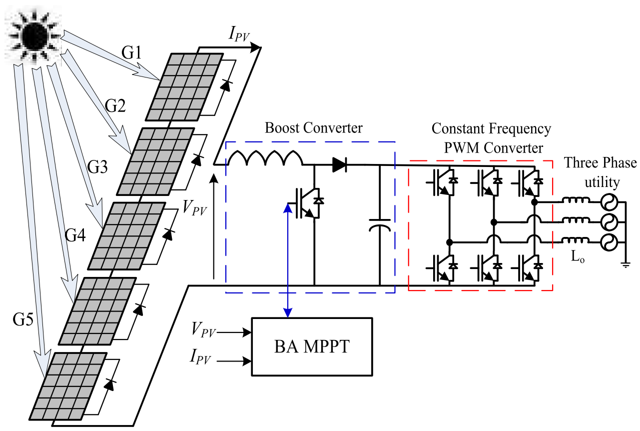

FIGURE 1. **The PV energy system with a BA-based MPPT.**

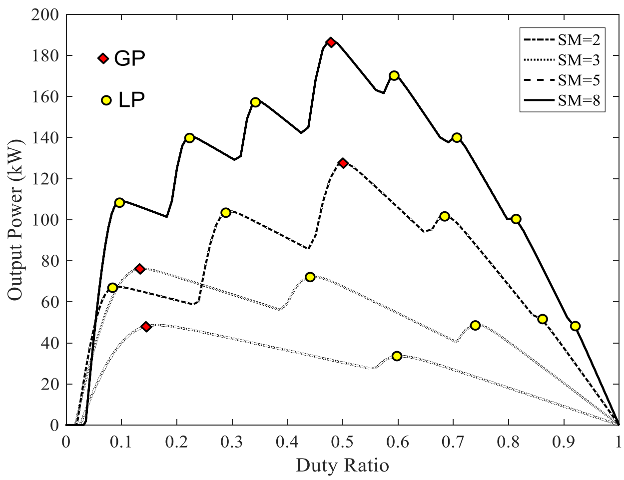

FIGURE 2. **P–V curves of PV array under different number of peaks.**

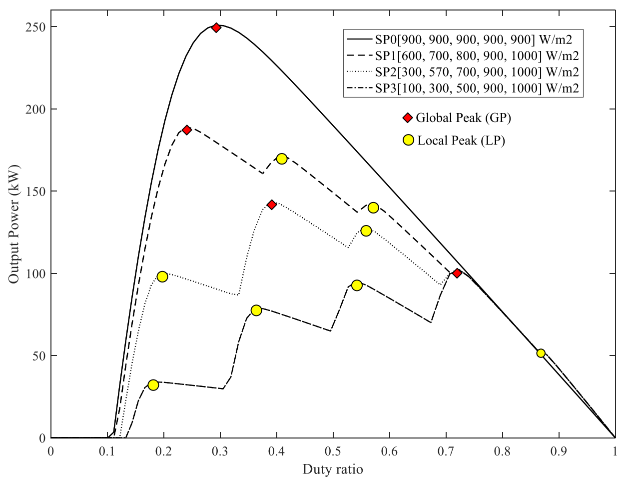

FIGURE 3. **Power vs duty ratio of boost converter with five modules in series having different irradiances.**

a boost converter with five modules in series having different irradiances.

Conventional MPPT techniques like perturb and observe [1], hill climbing [2], [3], fuzzy logic controller [4], and incremental conductance [5] maybe trapped at one of the LPs of the P-V curves which is one of the biggest problems associated with these techniques. Metaheuristic techniques provide significant advantages compared to these conventional techniques such as, simple implementation, the ability to follow the GP under different operating conditions, and faster convergence. MPPT of PV systems is implemented using many metaheuristic techniques like particle swarm optimization (PSO) [6], gray wolf optimization (GWO) [7], cuckoo search [8], and bat algorithm (BA) [9], [10]. Some papers introduced hybrid optimization where two different techniques were used together to gain the benefits of both techniques under different operating conditions [7], [11]. Many papers compared the application of these techniques in MPPT of PV systems [12], [13]. Most of these papers did not address the problems inherent in metaheuristic techniques such as dynamic variation of the shading pattern and the optimal initialization for duty ratio of the DC/DC converter to reduce the convergence time and increase the output energy. The BA is generally regarded as one of the best metaheuristic techniques in terms of convergence time and avoidance of premature convergence.

The BA was first introduced in 2010 [14]. It is generally regarded as an improvement over the PSO technique, and for this reason has been used in this paper. The BA was used as an MPPT technique for PV energy systems for the first time in late 2015 [15]. This paper [15] introduced the BA as an MPPT of PV systems supplying synchronous reluctance motors using a buck-boost DC/DC converter. The results were compared to similar results obtained from using PSO under the same conditions [15]. The BA showed better performance than the PSO in the PV MPPT applications [15]. This paper [15] did not discuss the problems associated with partial shading or the dynamic variation of shading patterns of PV systems. The first use of BA as an MPPT of off-grid PV systems under partial shading was in 2017 by Kaced *et. al.* [9]. This paper introduced initialized values that depended on the load values and DC/DC converter parameters, but it did not address the problem of initialization of bats when the shading pattern changed. Another paper using the BA as an MPPT of PV systems, also in 2017 [10], used a buck-boost converter to control the generated power from the PV system, and the results obtained from the BA were compared to those obtained from the PSO algorithm. Later in 2018 another paper used the BA as an MPPT of off-grid partial shading PV systems [16]. This paper did not address how to deal with the effect of the dynamic variation of shading patterns on the performance of the BA, nor how to reinitialize the BA upon variation of the shading pattern. Another paper [17] used the BA as an MPPT of PV systems with a single-ended primary-inductor converter. This paper suggested re-initialization after any sudden change in generated power above certain value.

From the above introduction, it can be seen that the use of a BA as an MPPT of PV systems has been used in only a few papers, which did not give this powerful tool the credit it deserves as one of the best optimization algorithms.

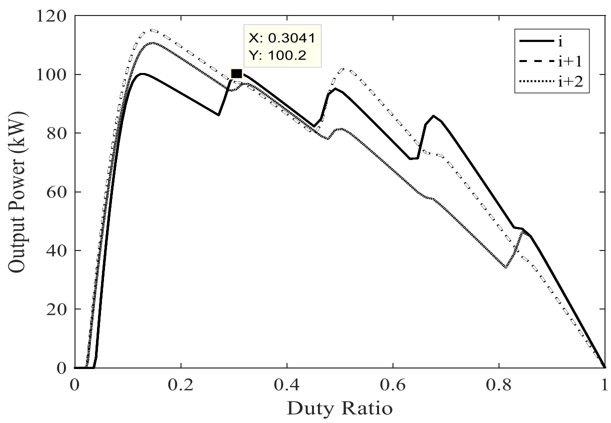

FIGURE 4. Three shading patterns for three consecutive iterations.

This paper is intended to fill this gap and to solve the problems of using the BA as an MPPT of PV systems under conditions of dynamic variation of shading patterns. As with all other metaheuristic techniques, the BA suffers from an inability to follow the GP in dynamic variation of shading patterns. This has been solved in the PSO technique by reinitializing the particles' positions at the places of the anticipated peaks [11] and has also been done with the BA in this paper for reinitializing the bats' positions. Reinitialization of the BA was performed when there was a considerable change in the generated power, which can be viewed as an indication of shading pattern variation.

The tracking of the GP with a metaheuristic technique occurs online which needs a short convergence time and high reliability to ensure the efficiency and stability of the system. This is achieved by initializing the duty ratio (initial bats' positions) to be at the anticipated locations of the LPs. This modification reduces the convergence time considerably and increases the likelihood of catching the GP compared to the random initialization of duty ratios which is used with PSO [18] and GWO [7]. It also avoids premature convergence that may also occur with random initialization, and for those reasons it was used in this paper for the BA.

When there is a reduction in irradiance with the same shading pattern, the new GP will be lower than the previous one, however the BA will keep the previous GP instead of the new GP. This will give sub-optimal values for the duty ratio of the boost converter resulting in less power being generated than is available from the PV system. For a better understanding of this problem, assume that the shading pattern for three consecutive iterations i, $i+1$, and $i+2$ results in the power curves shown in Fig. 4. In the case of iteration i, the generated power for GP_i is [100.2 kW, 0.3041] and all bats work at this peak. When the shading pattern changes to $i+1$, the power at duty ratio 0.3041 is less, at 99.8 kW. The logic will keep the peak of i (0.3041) at 99.8, however the true GP for that shading pattern is GP_{i+1} = [114.3 kW, 0.1387]. The generated energy is reduced by (114.3-99.8)/99.8*100 = 14.53% less than the available maximum power. When the new shading pattern changes to $i+2$, the generated power at the bats position is about 97.2 kW. As for the case of shading pattern $i+1$, the true GP is GP_{i+2} = [110.9KW, 0.1325]. Again the generated energy is reduced by (110.9-97.2)/97.2*100 = 14.1% less than the available maximum power. This problem has never been addressed in any of the literature. In this paper, the stored GP in the BA is replaced with the current maximum value if it is unchanged for two consecutive iterations. The detailed results from this modification are shown in the simulation results section of this paper.

The higher the number of bats in the BA, the longer the convergence time, however the possibility of premature convergence is reduced. So, a trade-off between the shortest convergence time and lowest premature convergence rate (PCR) is needed. This gives rise to the question

"What is the optimal number of bats for the lowest convergence time and PCR?"

To the knowledge of the authors, there is no research published a criterion for selecting the optimal number of bats in the BA as a PV MPPT technique [9], [10], [15]–[17]. This problem has been discussed in this paper and a novel criterion has been introduced to determine the optimal number of bats versus number of peaks to reduce the convergence time with the lowest PCR. Similar study is performed for PSO and GWO for comparison. This represents an important innovative element in this paper.

This paper has the following structure:

Section II discusses the modeling of the PV system;

Section III shows the BA and the improvement strategies introduced to alleviate the problems associated with the conventional BA when used as an MPPT of the PV system;

Section IV shows the simulation results and the improvements in comparison with the conventional BA and PSO techniques; Section V shows the details of experimental setup and results, Section VI discusses the conclusions from this work.

II. MODELING OF PV SYSTEM

The configuration of the proposed PV system is shown in Fig. 1. This system consists of five PV module groups connected in series, a boost converter, DC-link capacitor, and a three-phase pulse width modulation (PWM) inverter to be connected to the electric utility. The proposed BA is used to control the PV terminal voltage for MPPT of the PV system to force it to work at its maximum available power. The control system for the PWM inverter is used to keep a constant voltage at the DC-link by controlling the modulation index and power angle of the control signal of the PWM inverter.

The performance of the PV system under partial shading conditions (PSC) has been discussed and modeled in [19]. Shading on the PV system generates multiple peaks on the P-d curve of the PV array as explained above and is shown in Fig. 2 and Fig. 3. The maximum number of peaks in the P-d curve is equal to the number of modules in series when each module is exposed to irradiance that is different to the others [11], [6]. In the proposed system shown in Fig. 1, five groups are connected in series, which creates five different peaks in the case where a different amount of irradiance falls on each group. The shading patterns (SPs) introduced in the P-*d* curves shown in Fig. 3 are SP0, SP1, SP2, and SP3. These four shading patterns are corresponding to the following irradiances:

SP0 = [900,900,900,900,900] W/m^2
SP1 = [600,700,800,900,1000] W/m^2
SP2 = [300,570,700,900,1000] W/m^2
SP3 = [100,300,500,900,1000] W/m^2.

Each of the five elements of irradiance in each pattern corresponds to the irradiance falling on each of the five PV groups shown in Fig. 1. It is clear from Fig. 3 that the SP0 is the SP corresponding to a uniform distribution which shows only one peak, and which allows the conventional MPPT techniques to capture the GP effectively. The other shading patterns (SP1, SP2, and SP3) are the SPs corresponding to the partial shading which shows one GP and four LPs in different locations. SP1, SP2, and SP3 have GPs in the 1st, 2nd, and 4th places of the P-*d* curves. The main observation to be made from the curves shown in Fig. 3 is that, the peaks shown in each place have similar duty ratio. For this reason, it is better to reinitialize the bats at the duty ratios of these peaks to reduce the convergence time and increase the possibility of the premature conversion, and this was done in this paper. The approximate relationship between the optimal duty ratio ($d^{(k)}$) at each peak and the open circuit and DC voltages is shown in the following equation [18]:

$$d^{(k)} = 1 - \frac{(n-k+1) * k_V}{n} * \frac{V_{OC}}{V_{DC}} \tag{1}$$

where, V_{DC} is the DC-link voltage, V_{oc} is the open circuit voltage, n is the total number of peaks (total number of modules in series), k is a counter to represent the order of each duty ratio, the constant k_V has a value between 0.76 and 0.82 [20].

This equation is very important because it can be used to determine the approximate value of the optimal duty ratio at each peak. This equation shows that this value is a function of two constant values (V_{OC} and V_{DC}). The equation is used to determine the values of initial duty ratios at the starting points to be sure that these values are close to all of the LPs, which will shorten the convergence time and reduce the premature conversion rate (PCR) considerably. Using the calculated duty ratios as starting points of bats reduces the time taken to search for the GP which reduces the instability time of the PV system and increases the generated energy and efficiency of the PV system. These benefits are illustrated, discussed and evaluated in the simulation results' section.

III. THE BA IN PV MPPT APPLICATIONS

Swarms are characterized by self-adoption of their performance during foraging or socializing. The swarms use trial-and-error to search for the best position in a complex problem by interacting with each other. The BA is one of the fastest convergence swarm intelligent optimization techniques that was first developed by Yang [14]. The BA imitates the echolocation of bats to find prey using different levels of pulses and loudness [14]. Bats search for prey in a three-dimensional axis by echo recognition. The time difference between the echo and the transmitted sound pulse identifies how far away the prey is. The intensity difference of the echoed sound pulse identifies the size, and the evaluation of the pitch difference identifies the moving speed of the prey, and whether the prey is moving towards or away from the bat. The bats emit loud sound impulses with very short time durations usually 10-100 times per second [14]. After transmitting the pulses and receiving the echo, bats translate the data into useful information to gauge the direction of the prey and how far the prey is from the bat's position. The BA is the ideal choice for use with low-dimensional engineering optimization problems, but due to its tendency to converge very fast at initialization, its performance is limited when used for high-dimensional engineering optimization problems. The MPPT of PV systems has only one variable (duty ratio) which is a very low-dimensional engineering optimization problem; this makes the BA ideal for use with it. The implementation of the BA represents the behavior of bats as equations and logic to be implemented in computer code to track the GP of any engineering optimization problem. The rate of pulses is set in the range between 0 and 1, where 0 means that there is no pulse emission and 1 means that the number of pulses per second is at a maximum. Yang [14] used generalized rules when implementing the BAs as shown in the following points [14], [21]:

1- The bats differentiate between food and obstacles and their distances using the echolocation;
2- Bats use their current position d_i to fly randomly with velocity v_i emitting pulses with varying wavelength (λ) and loudness A_0 at a fixed frequency f_{min} when searching for food;
3- Depending on the proximity of food, bats can adjust their frequency, wavelength, and rate of transmitting sound pulses r between 0 and 1;
4- The loudness of the transmitted sound pulse is assumed to vary from a large positive A_0 to a minimum constant value A_{min};
5- The frequency and wavelength of transmitted sound pulses are functions of each other due to the fact that the value of their product should be constant (λf = constant); this means that the frequency range of [$fmin$; $fmax$] corresponds directly to a range of [λmin; λmax] of wavelength;
6- In the initialization of searching of the BA, a wavelength with a large value should be selected and be reduced to lower values with each search step.

The logic showing the BA when it is used as an MPPT of PV systems with the proposed modifications is shown in Fig. 5 and explained in the following sections.

A. BAT ALGORITHM INITIALIZATIONS

In the initialization, the bats' position $d_0^{1:n}$ is suggested in the conventional BA [9], [15], [17], [21], [22] as having random values between 0 and 1, but in the modified BA (MBA),

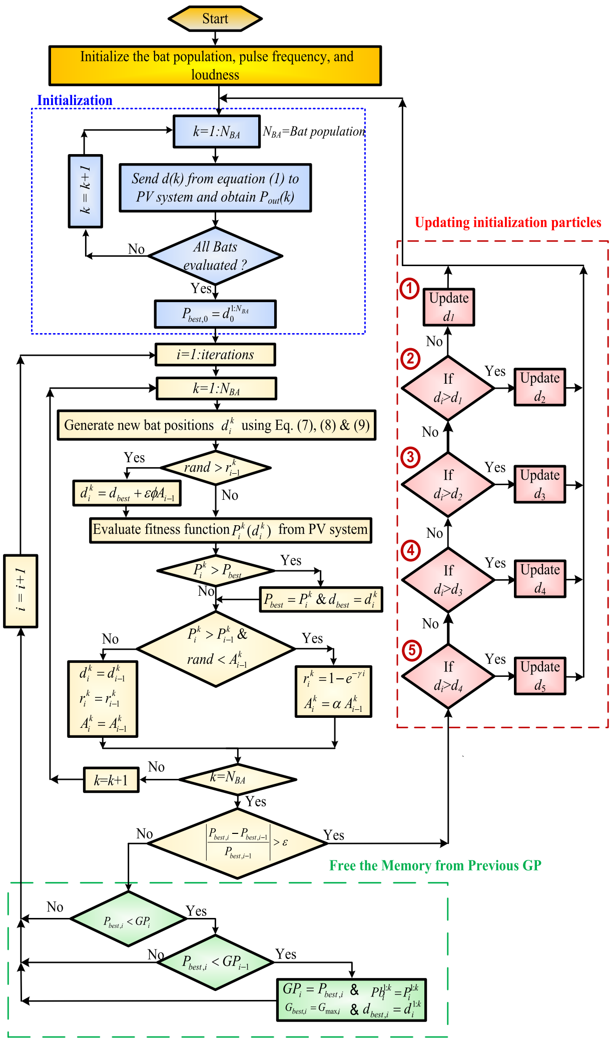

FIGURE 5. **The flowchart of the Bat Algorithm used for MPPT of PV systems.**

the bats get their initial values from the duty ratio calculated from equation (1). The other initial values are:

Speed of each bat $v_0^{1:n} = 0$;

Pulse frequency $f_0^{1:n} = 0$;

Pulse rate $r_0^{1:n} = 0$;

Loudness $A_0^{1:n} = 1$;

The bats' values are used in the PV system one by one to get the corresponding fitness value of each bat $P_0^{1:n}$. The highest power generated is determined from $P_{best} = \max(P_0^{1:n})$. The duty ratio at the P_{best} is determined, d_{best}., where n is the total number of bats (swarm size).

B. BATS TRACKING THE GLOBAL PEAK

The velocity for each bat at the iteration number i, $v_i^{1:n}$ and the new position $d_i^{1:n}$ of bats can be obtained from the following equations:

$$f_i^{1:n} = f_{\min} + (f_{\max} - f_{\min})\,\beta \tag{2}$$

$$v_i^{1:n} = \omega\, v_{i-1}^{1:n} + \left(d_{best} - d_{i-1}^{1:n}\right) f_i^{1:n} \tag{3}$$

$$d_i^{1:n} = d_{i-1}^{1:n} + v_i^{1:n} \tag{4}$$

where, the values of f_{min} and f_{max} are chosen to be 0 and 100, respectively [14]. β is a random value, $\beta \in [0, 1]$, and ω is called the inertia weight factor which is used to limit the speeds of the bats and has value $\omega = 0.5$ [22].

The new position for each bat should be updated using a random walk around the position determined from equation (4). The new positions of bats can be obtained from the following equation [9], [21]:

$$d_i^{1:n(new)} = d_i^{1:n(old)} + \varepsilon\phi A_i^{1:n} \tag{5}$$

where, ε is a random number, $\varepsilon \in [-1, 1]$ [9], [21], and ϕ is a positive constant used to limit the random walk. This constant is set to be 0.05 [9], while A_i^k is the loudness of each bat k at iteration i. The normal practice is to set the loudness (A_i) decreasing from high to low when the bat approaches its prey. The rate of pulse transmission r_i behaves opposite to the loudness (A_i), where r_i is increasing when the bats approach their prey. Normally, the value starts close to $r_0 = 0$ and at the end of iterations it approaches $r_i = 1$. With this logic, the value of these two parameters should be controlled during the iterations of the BA [14] as shown in the following equations:

$$A_i^{1:n} = \alpha A_{i-1}^{1:n} \tag{6}$$

$$r_i^{1:n} = r_0^{1:n}\left[1 - \exp(-\gamma i)\right] \tag{7}$$

where, $\alpha = \gamma = 0.9$ [21].

The new values of the duty ratios, $d_i^{1:n}$ will be fed into the PV system one by one to get its corresponding power $P_i^{1:n}$. These values will be used to update the best GP and the best LP values of each bat with the following logic:

For $k = 1: n$, if $P_i^{1:n} > P_{best}$ then $P_{best} = P_i^k$ and $d_{best} = d_i^k$

which can then update the GP.

The privet peaks can be updated from the following logic: if $P_i^k > P_{i-1}^k$& $rand < A_{i-1}^k$ then

$$r_i^k = 1 - e^{-\gamma i}\, \&\, A_i^k = \alpha A_{i-1}^k$$

Otherwise, $d_i^k = d_{i-1}^k$, $r_i^k = r_{i-1}^k$, and $A_i^k = A_{i-1}^k$.

After performing the above logic, the next iteration, i can be performed unless there is no need for re-initialization as shown in the simulation section. The logic will perform the reinitialization when the power changed with certain limit (5%) as shown in (8).

$$\left|\frac{P_{best,i} - P_{best,i-1}}{P_{best,i-1}}\right| > \varepsilon \tag{8}$$

where, $P_{best,i}$ is the GP at iteration i and ε is the allowable limit to reinitialize the swarm technique.

IV. SIMULATION RESULTS AND DISCUSSION

The simulation of the MBA is implemented in co-simulation between Matlab and Simulink, where the code of the MBA is implemented in Matlab and the PV system, DC/DC converter, and PWM are implemented in Simulink. The simulation of the system has been compared to the PSO technique [18].

TABLE 1. Specifications of PV module used in this study.

Specifications	Value
P_{max} *per* each module	185.22 W
Cells per PV Module	54
V_{OC}	32.2 V
I_{SC}	7.89 A

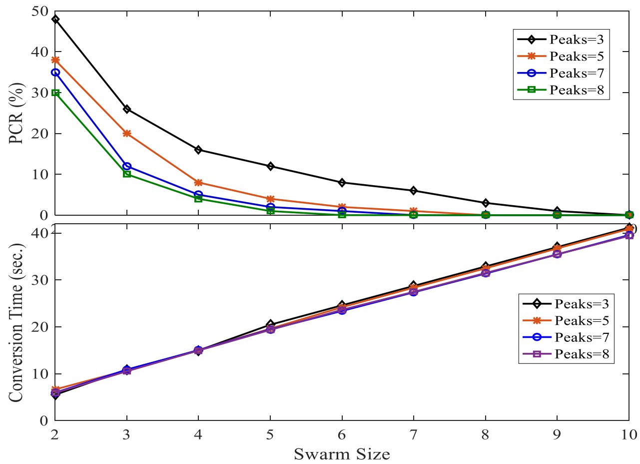

FIGURE 6. The variation of PCR and Convergence time against swarm size of PSO for 3, 5, 7, and 8 peaks in P-V curve.

Many simulation studies have been performed to show the importance of the modifications added to the BA, compared to PSO, and GWO. The first simulation study determines the optimal number of bats, particles, and wolves for a given number of peaks that can be generated in the P-V characteristics. The second study shows the importance of reinitialization of bats, particles and wolves when the generated power changed with certain limit. The third study shows the superiority of starting the particles, wolves, and bats at the duty ratios of anticipated peaks and the importance of updating it during the execution of the logic. The fourth study is showing the need for updating the memorized GP in all techniques under study if it is not changing for two consecutive iterations. The last study shows the performance of the MBA for gradual and acute changes of the shading conditions.

The PV module used in this simulation is (Sunperfect Solar CRM185S156P-54) [23] and its specifications are shown in Table 1. The PV system consists five groups each group having 300 modules placed in 60 parallel branches with 5 modules in series in each branch. The boost converter parameters are $L = 0.5$ mH and $C = 200\ \mu$F.

A. OPTIMAL NUMBER OF PARTICLES, WOLVES AND BATS

As has been discussed in the introduction section, the higher the number of particles, bats or wolves the longer the convergence time will be and the lower the PCR is. The question raised in the introduction section; "What is the optimal number of bats, particles, or wolves for the lowest convergence time and PCR?" will be answered using the results shown in Fig. 6, Fig. 7, Fig. 8, and Fig. 9. Owing to the

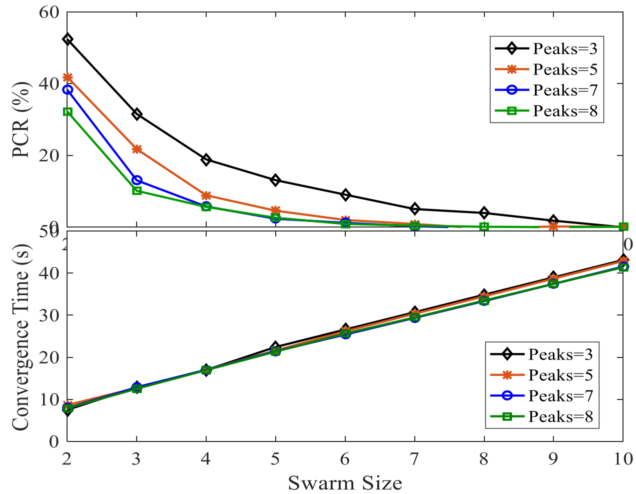

FIGURE 7. The variation of PCR and Convergence time against swarm size of GWO for 3, 5, 7, and 8 peaks in P-V curve.

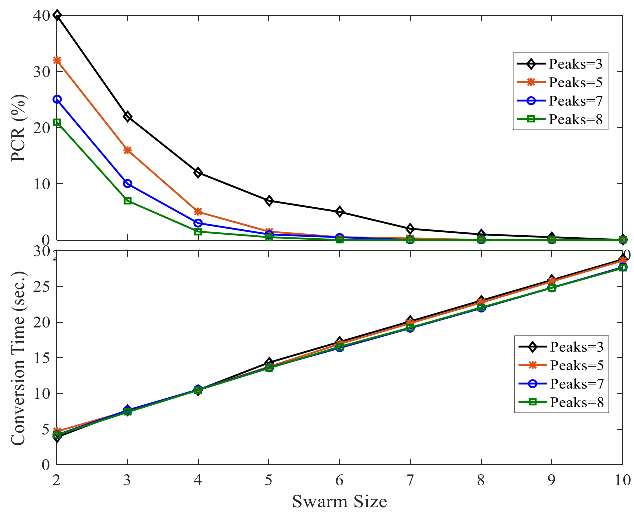

FIGURE 8. The variation of PCR and Convergence time against swarm size of the BA for 3, 5, 7, and 8 peaks in P-V curve.

knowledge of the authors, this study never introduced in the literature. The simulation has been performed for the BA, PSO, and GWO with random initial values for the number of bats, particles, and wolves, respectively. Fig. 6 shows the convergence time and PCR for different numbers of particles with random initial values when using the PSO technique. Fig. 7 shows the convergence time and PCR for different numbers of wolves with random initial values when using the GWO technique. Fig. 8 shows the same information for different numbers of bats with random initial values when using the BA technique. Fig. 9 shows the PSO, GWO, and BA techniques compared to one another. Due to the stochastic nature of the swarm techniques under study, the simulation was performed 1000 times to get the average of convergence time and PCR. The calculation of convergence time and PCR are dictated by equations (9) and (10), respectively. The convergence time is calculated when the condition shown

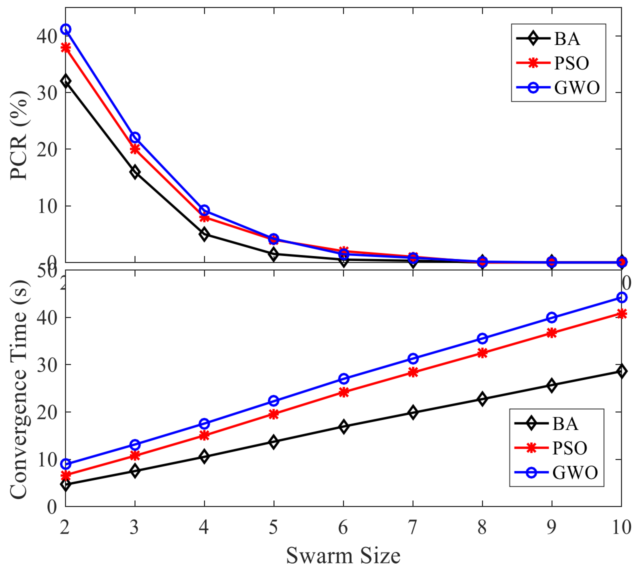

FIGURE 9. The variation of PCR and Convergence time against swarm size of the BA, PSO, and GWO for 5 peaks in P-V curve.

in equation (9) is valid. The highest and lowest values of particles, wolves, and bats are subtracted from one another and should be lower than $\varepsilon_1 = 0.001$ to confirm that convergence has occurred. The number of occurrences of premature convergence is calculated when all the particles are attracted to any local peaks under the condition shown in (9). After executing the simulation for the PSO, GWO and BA 1000 times for different numbers of particles, wolves, and bats the values of PCR calculated from equation (10) are shown in Fig. 6 to Fig. 9. These figures showed unexpected results. The literature concludes that the best number of bats is equal to the number of peaks of the P-V curve [18] which is not the result obtained from this study as discussed below. The upper trace of Fig. 6 shows the change in PCR (%) for the PSO technique for different swarm sizes for 3, 5, 7, and 8 peaks. This figure shows that the PCR is inversely proportional to the swarm size for the same number of peaks. Moreover, the PCR for a specific swarm size is inversely proportional to the number of peaks. The lower trace of Fig. 6 shows the convergence time (the time for all particles to be concentrated at one peak) for different swarm sizes. It is clear from this trace that, the convergence time is linearly proportional to swarm size and the convergence time is the same regardless of the number of peaks. The PCR is more important than the convergence time in terms of generated power because the higher the value of the PCR, the higher the probability that the particles, wolves, and bats are working at an LP (rather than the GP) which means the generated power is less than the maximum available. Meanwhile, the convergence time only affects the power during initialization which takes only a few seconds. The aim is to get the lowest value of PCR with the shortest possible convergence time. It is clear from Fig. 6 that, if a PCR = 5% is an acceptable value, the optimal swarm sizes for PSO are 7, 5, 5, and 4 for peaks equal to 3, 5, 7, and 8, respectively. Similar to PSO, From Fig. 7, the GWO optimal number of wolves (swarm size) are 8, 5, 5, and 5 for peaks equal to 3, 5, 7, and 8, respectively. Similar to PSO and GWO, for PCR = 5%, the optimal swarm sizes for BA shown in Fig.8 are 7, 5, 4, and 4 for peaks equal to 3, 5, 7, and 8, respectively. For the rest of this study, the swarm size = 5 were used in PSO, GWO, and BA because there are 5 peaks maximum in the P-V curve as discussed before. As shown in Fig.9, for the PSO, the PCR and convergence time values are 3.9% and 18 s, respectively. Also, for the GWO, the PCR and convergence time values are 4.1% and 22 s, respectively. Finally, for the BA, the PCR and convergence time values are 2.2% and 11 s, respectively. It is clear from Fig. 9 that, the BA has the lowest value for PCR and convergence time compared to PSO and GWO which proves its better performs than PSO and GWO in this regard.

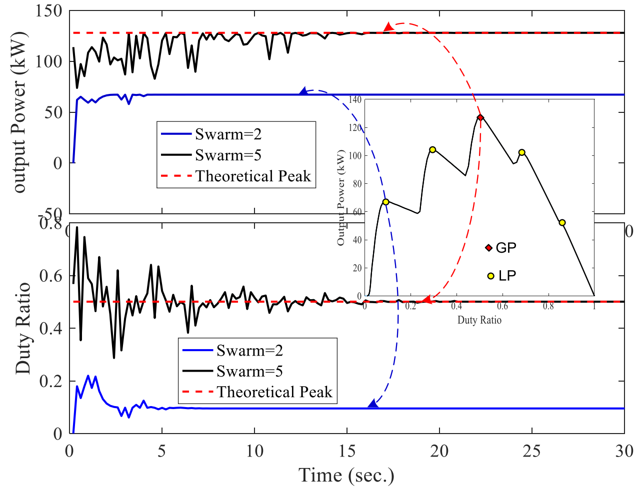

FIGURE 10. The performance of PV system having 5 peaks using 2 and 5 particles in PSO with random initialization.

$$d_h - d_l < \varepsilon_1 \tag{9}$$

where, d_h and d_l are the particles, wolves, or bats with highest value and lowest value during the swarm of the current iteration, respectively, ε_1 is the acceptable range of distance between particles/bats ($\varepsilon_1 = 0.001$) to judge the end of the re-initialization period.

$$PCR = N_{PC}/N_T \tag{10}$$

where, N_{PC} is the number of occurrences of premature convergence and N_T is the total number of simulation times.

For the system under study having 5 peaks in the P-V curve, the performance of this system when using swarm sizes of 2 and 5 particles, wolves, or bats for the PSO, GWO and the BA are shown in Fig. 10, Fig. 11 and Fig. 12. It is clear from Fig. 10 that, the PSO captured the GP when using 5 particles with 129 kW power, but it trapped at one LP with 64 kW when using 2 particles only which reduces the generated energy to about half of its available power from the PV system. It is also clear from Fig. 10 that, the convergence times are 18 s and 4 s for PSO having 5 and 2 particles, respectively. Similar to the PSO, the GWO simulation results

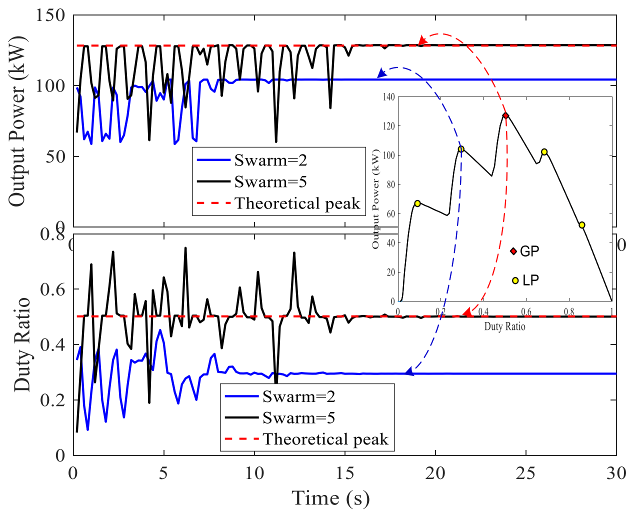

FIGURE 11. The performance of PV system having 5 peaks using 2 and 5 particles in GWO with random initialization.

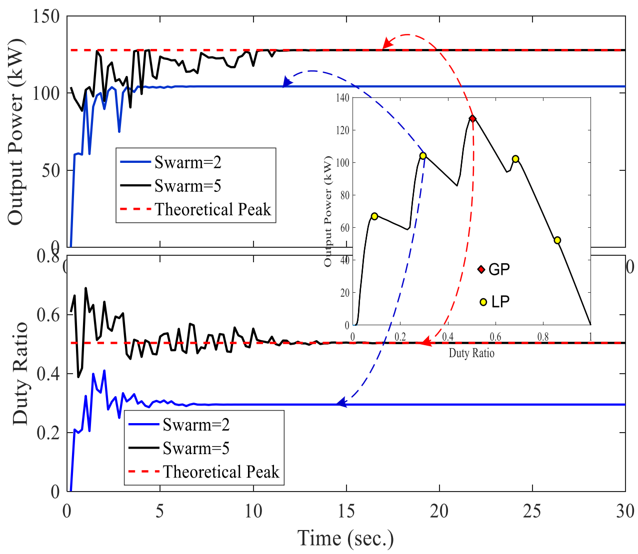

FIGURE 12. The performance of PV system having 5 peaks using 2 and 5 bats in BA with random initialization.

for 2 and 5 wolves are shown in Fig. 11 where the the GWO captured the GP when using 5 wolves with 129 kW power, but it trapped at one LP with 64 kW when using 2 wolves only which reduces the generated energy to about half of its available power from the PV system. It is also clear from Fig. 11 that, the convergence times are 22 s and 4.5 s for GWO having 5 and 2 wolves, respectively. Fig. 12 shows the same results for the BA where again the BA captured the GP when using 5 bats, but with 2 bats the bats trapped in another LP but at generated power = 101 kW. In addition, the convergence times are 11 s and 3.5 s for the BA having 5 and 2 bats, respectively.

B. OPTIMAL INITIALIZATION OF PSO, GWO, AND MBA

As has been shown in the previous section the optimal swarm size for the maximum number of peaks (the number of series

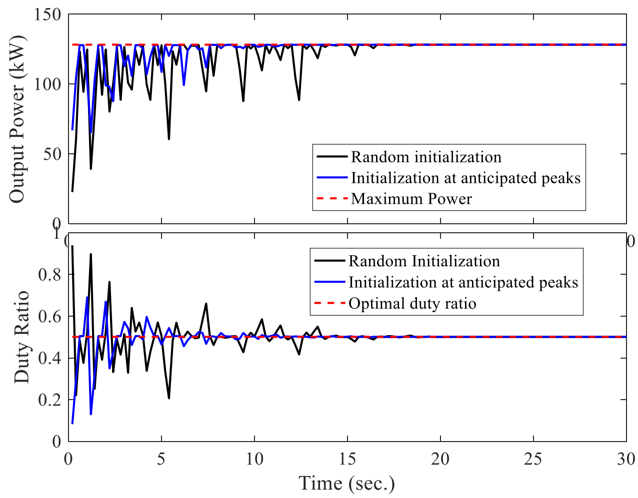

FIGURE 13. The starting period with random start (Case-1) and particles at peaks position (Case-2) for PSO.

modules/group modules) is 5. To show the importance of using anticipated values of duty ratios obtained from equation (1) to be used as initial particles/bats' positions, six different cases have been used as follows:

Case-1: PSO with random initialization;

Case-2: PSO with initialization using anticipated values of duty ratios (from equation (1));

Case-3: GWO with random initialization;

Case-4: GWO with initialization using anticipated values of duty ratios (from equation (1));

Case-5: BA with random in initialization;

Case-6: MBA with initialization using anticipated values of duty ratios (from equation (1)).

The first two cases (Case-1 and Case-2) are shown in Fig. 13, two cases (Case-3 and Case-4) are shown in Fig. 14, and the last two cases (Case-5 and Case-6) are shown in Fig. 15. It is clear from Fig. 13 and Fig. 14 that initialization with the random values of particles of PSO and GWO (Case-1 and case-3) takes about 15 s to converge while it takes only 7 s to converge when initialization uses anticipated places of peaks as initial values of particles of PSO (Case-2 and case-4). In addition, the PCR will be less when initializing using particles at anticipated peaks instead of random initialization. Fig. 15 shows that, for the BA the convergence times are about 10 s and 6 s for Case-5 and Case-6, respectively. Therefore, it is recommended that, the particles, wolves, and bats should be initialized to the values of the anticipated peaks obtained from equation (1). Fig. 13, Fig.14 and Fig. 15 also show that, the BA is the best compared to the PSO and GWO in terms of convergence time and PCR. Therefore, it is recommended that, the BA be used as the MPPT of PV energy systems. It is also important to note that, the use of the anticipated duty ratios at peaks as initial values of particles, wolves, and bats reduces the PCR considerably because the random values may be concentrated in places distant from the GP and the particles, wolves, and bats will tend to only look around the LPs and may therefore miss the GP. The reduction

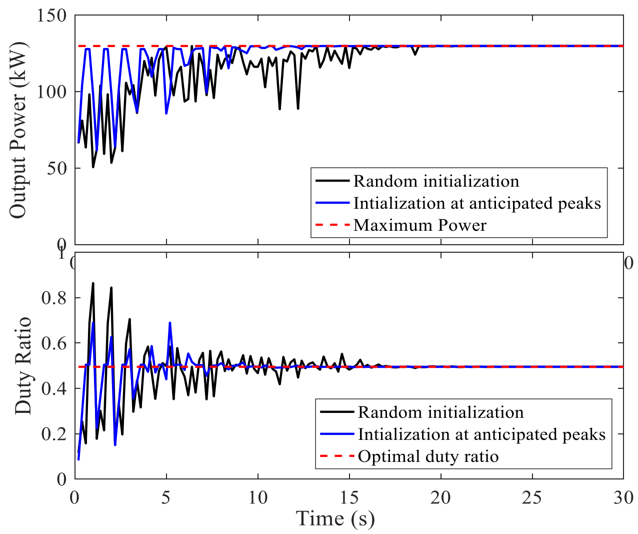

FIGURE 14. The starting period with random start (Case-3) and wolves at peaks position (Case-4) for GWO.

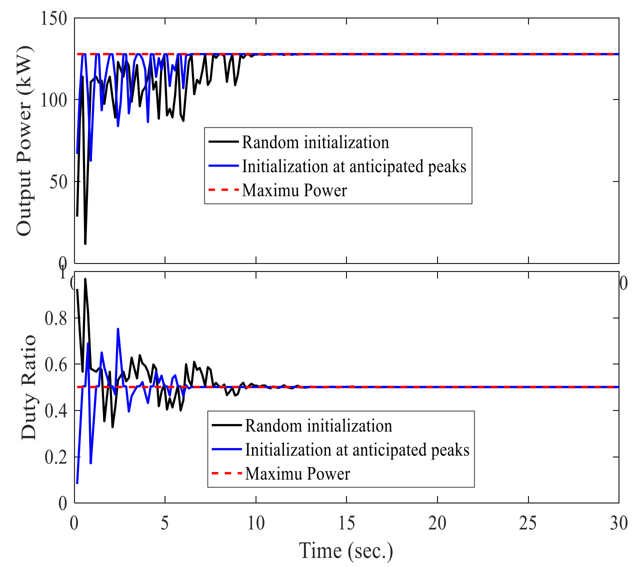

FIGURE 15. The starting period with random start (Case-5) and bats at peaks position (Case-6) for the BA.

of the convergence time will reduce the system instability and increase the generated energy and efficiency of the system.

C. UPDATING THE GP MEMORIZED VALUE

The effectiveness of the PSO, GWO, BA and all other meta-heuristic techniques is limited by the fact that the memorized GP is the highest ever value of the maximum power. When the irradiance changes and the maximum power is lower than the memorized GP, the logic will not use the new maximum power and its corresponding duty ratio, because it is lower than the memorized value of GP. The system will be forced to work at the duty ratio corresponding to the memorized GP which is not the optimal value under the new shading condition. This limitation is discussed in Section III and has not been addressed in the literature. The solution to this problem has been found to be to check the GP for two consecutive iterations, if it is unchanged, the code will replace the memorized GP with the current maximum power in the third iteration. To show this problem, the simulation of two different cases was performed as shown in the following instances. The PSO, GWO, and BA are treated as one case for this point because there is not much difference between them in the final result:

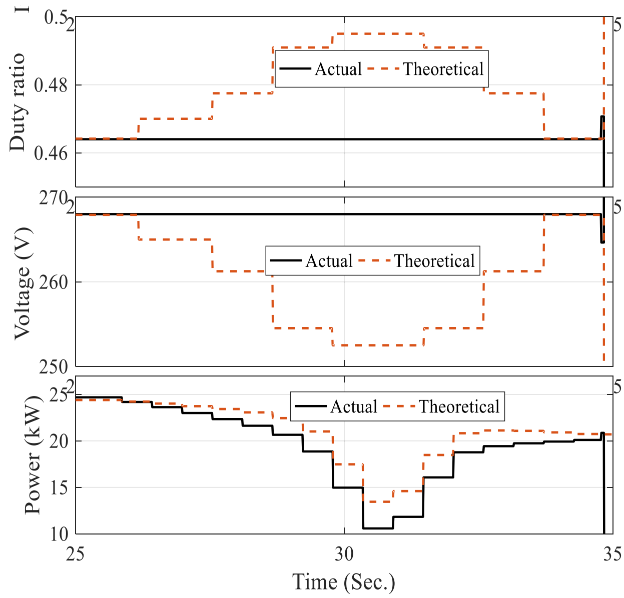

FIGURE 16. Case-1 results where the memorized value of the GP did not update.

Case-1: The PSO, GWO, and BA without updating the GP memorized value (Fig. 16).

Case-2: The PSO, GWO, and BA with updating the GP memorized value (Fig. 17).

It is clear from Fig. 16 that the GP was following the theoretical GP but once the real GP becomes lower than the previous one, the system works at the duty ratio of the memorized GP which is not the optimal duty ratio for the new GP. With the modified PSO, GWO, and BA (Case-2), the code checks the GP for two consecutive iterations. If it is unchanged it will use the peak of the current iteration which is the real GP of the current iteration as shown in Fig. 17. This modification will increase the generated energy and increase the PV system efficiency.

D. OVERALL SIMULATION OF MODIFIED BA

The simulation of the system has been carried out for 50 s where the irradiances are changing gradually in the first 25 s and it has one acute change at $t = 25$, 33, and 42 s as shown in Fig. 18 to show and evaluate the performance of the MBA for different types of operating conditions. As has been shown in Section IV (C), the MBA has a shorter convergence time (6 s) in initialization. After making the modifications introduced in this paper into the MBA, the initialization time became very short (2.5 s) and followed the GP with the lowest PCR under all operating conditions.

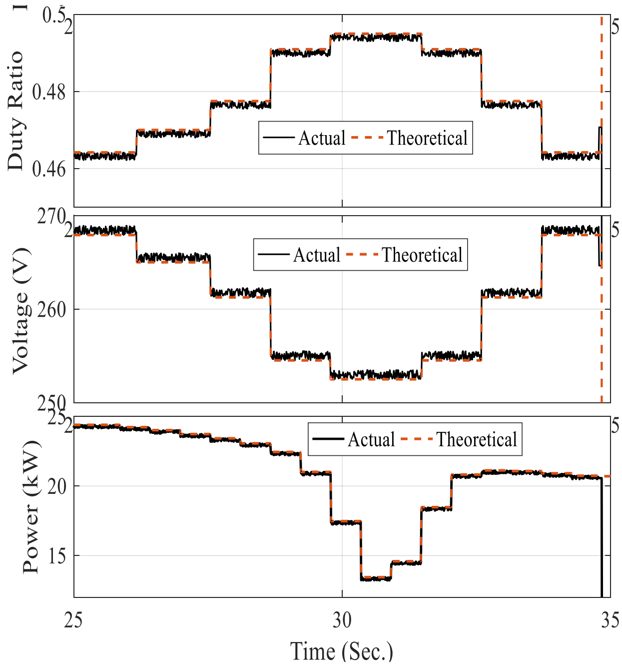

FIGURE 17. Case-2 results where the memorized value of the GP updated every two iterations.

In the first 25 s, the irradiance changes gradually but the GP changes its positions in $t = 5, 12, 16,$ and 22 and the system detected this change in generated power according the condition shown in (8) and the BA reinitialized at these instants to search again for the GP and it captured it effectively. It is worth noting here that, the bats reinitialized again at $t = 25$ s because of the validation of the condition shown in equation (8). In addition, the convergence time in initialization was 5 s but after the acute change in irradiance it became less than 2.5 s because the accurate positions of peaks are updated as discussed above. Moreover, the output power followed the theoretical maximum power available when the maximum power is gradually reduced due to the updating criteria of the GP discussed in Section IV (C).

The MBA is the superior technique for following the GP of the PV system under all operating conditions when the modifications introduced in this paper are taken into consideration as shown in Fig. 18.

V. EXPERIMENTAL WORK

A. HARDWARE SETUP

Experimental setup has been built in the lab to validate the correct operation of the MBA compared to the PSO and GWO. These techniques built in Matlab/Simulink environment where the code for each metaheuristic technique is built in Matlab m-file and the circuit contains the pulse generator and ADC/DAC are built in Simulink. dSPACE (DS1104 hardware card) is working as interface circuit between the computer and the power circuit as shown in Fig. 19. Fig. 20 shows the picture of the experimental setup. dSPACE uses "control desk" software which allows the graphical user interface (GUI) which can observe and record the response of the

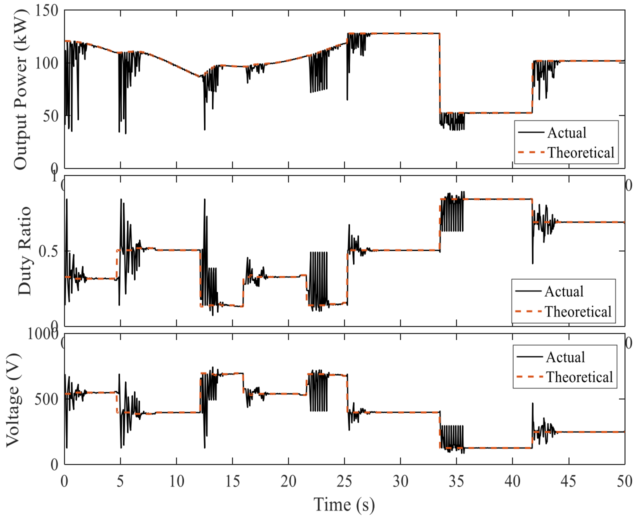

FIGURE 18. The output results for the MBA for different operating conditions.

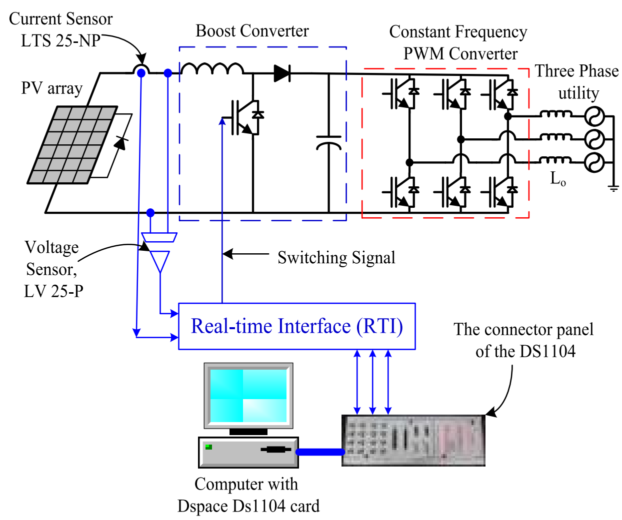

FIGURE 19. Schematic of hardware setup of the MPPT of PV system.

system to perform the bidirectional control. Real-time interface (RTI) circuit is built to provide a link between the power circuit containing the PV modules, boost converter, and PWM inverter.

The boost converter switch is MOSFET IRF540 having 100V and 25 A rating. A driver IC 74HC14 is used to drive this MOSFET. The switching frequency used in the experimental circuit is 20kHz.

The other hardware components used in the hardware setup is shown in the following points

- 5 PV modules (Sunperfect Solar CRM185S156P-54) [23] connected in series. As shown in the upper picture of Fig. 20. The partial shading done by covering the targeted module with semi-transparent sheets.
- Boost converter inductor and capacitor values are $L = 0.5$ mH and $C = 470$ μF.
- 2000 W single phase inverter to transfer the generated power to the electric utility.

FIGURE 20. The picture of the experimental setup.

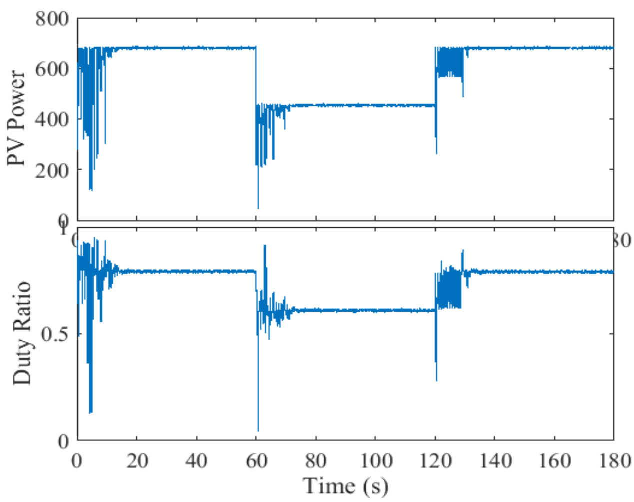

FIGURE 21. Experimental results for initialization of PV power and duty ratio for PSO.

- Current Sensors Part number: LTS 25-NP.
- Voltage sensor, Part number: LV 25-P.
- dSPACE (DS1104 hardware card) and the connector panel of the DS1104.

B. EXPERIMENTAL RESULTS

The resulting signals are plotted in the control desk of the dSPACE software as a graphical user interface (GUI) provided in dSPACE. Five particles, wolves, and bats have been used in the PSO, GWO, and BA in the experimental setup. The data captured for 3 min for each MPPT, where the first 1 min was working in normal irradiance, two modules were covered by semitransparent sheet for another 1 min then it is removed back for the last 1 min. The oscilloscope can capture the current, voltage, switching signal as shown

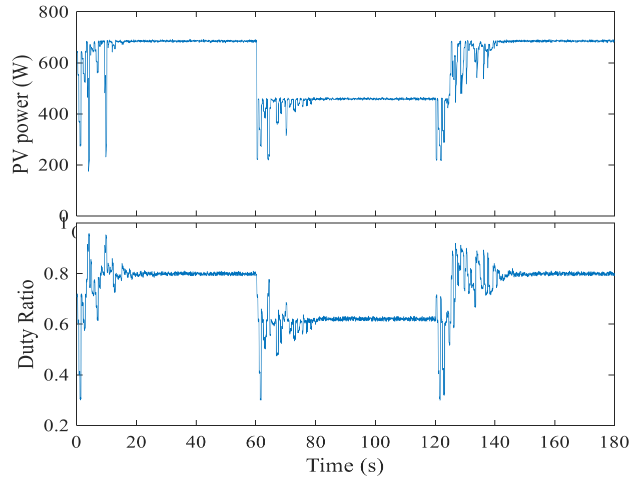

FIGURE 22. Experimental results for initialization of PV power and duty ratio for GWO, respectively.

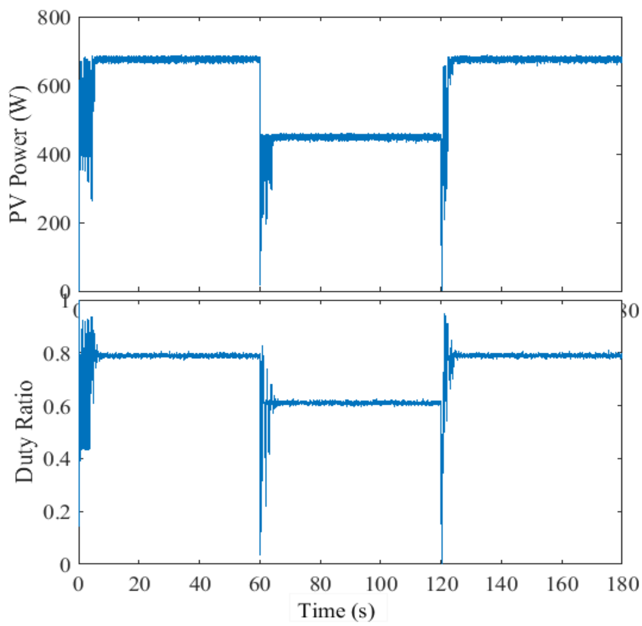

FIGURE 23. Experimental results for initialization of PV power and duty ratio for MBA.

in Fig. 20. Meanwhile, the recorded data for the 3 min operation will be recorded through the control disk software that come with dSPACE as shown in Fig. 21-Fig. 23. Also, the initialization period for each MPPT technique under study has been recorded. Fig. 21 shows the experimental results of PSO, where the upper trace shows the PV power and lower trace shows the duty ratio that can be obtained from dividing the PV terminal voltage over the DC-link voltage. Similarly, Fig. 22 shows the experimental results for GWO. Fig. 23 shows the experimental results for MBA. It is clear from the experimental results shown in Fig. 21 – Fig.23 that, the conversance time is about 11 s, 12 s, and 5 s for PSO, GWO, and MBA, respectively. The experimental results prove the better performance of MBA compared to

TABLE 2. Experimental results of reinitialization for Case-1 and Case-2.

Technique	Case-1		Case-2	
	CT (s)	PCR%	CT (s)	PCR %
PSO	18	20	9	0
GWO	21	30	11	0
BA	11	10	4	0

PSO and GWO in terms of conversance time and generated power from the PV system.

Experimental study has been performed for the PSO, GWO, and BA to show the importance of initialization at the duty ratio of anticipated peaks compared to the random initialization. The results have been collected for 10 times to get the average value of the convergence time and the PCR for each case and the results tabulated in Table 2 where;

Case-1: Random initialization.

Case-2: Initialization with the duty ratios at the anticipated peaks that can be obtained from (1).

It is clear from the experimental results shown in Table 2 that the conversion time (CT) for case-1 (random initialization) is twice the CT for case-2 (Initialization with the duty ratios at the anticipated peaks). Also, after 10 times of running the experimental circuit for random initialization, the PSO missed the GP two times out of 10 (PCR = 20%), similarly, GWO missed the GP 3 times (PCR = 30%), and the BA missed it only one time (PCR = 10%). Meanwhile, the initialization of all techniques at the duty ratios of anticipated peaks, they never miss the GP for 10 times (PCR = 0%). Therefore, it is easy to deduce that the initialization of all techniques at anticipated peaks (Case-2) reduced the conversion time to half compared to the random initialization (Case-1). Moreover, the initialization with the duty ratio at the anticipated peaks (case-2) never missed the GP, meanwhile random initialization missed it 2, 3, and 1 times out of 10 for PSO, GWO, and BA, respectively. These results proved the superiority of initializing all techniques with the duty ratios at the anticipated peaks. Also, it is clear that, the BA has the lowest conversion time and PCR compared to the other two techniques which proved the superiority of using BA in MPPT of PV systems.

VI. CONCLUSION

Conventional MPPT techniques work effectively when tracking the GP of uniformly distributed irradiances due to there is only being one peak generated in the P-V curve of the PV array. In the case of partial shading, however, many peaks will be generated which may cause the conventional MPPT techniques to be trapped at one of the local peaks (LPs) and miss the global peak (GP). This problem has been solved by using metaheuristic swarm techniques like the PSO, GWO, and BA. The optimal swarm size for the PSO, GWO, and BA against number of peaks in the P-V curve has never discussed in the literature, and it is shown in this paper for the first time. The optimal swarm size is inversely proportional to the number of peaks of the P-V curve which is never concluded before in literature. The optimal swarm size used guarantees the shortest convergence time with the lowest possible premature convergence rate which can be translated into an increase in output power and efficiency of the PV systems. Initializing the particles, wolves, or bats at the duty ratios at anticipated peaks of the P-V curve reduced the convergence time and PCR considerably compared to using random initializations. This solution reduced the time taken to capture the GP from 8 s to 3 s. Updating the memorized GP if the GP is unchanged for two consecutive iterations forced the PV system to work at the duty ratio of the current GP rather than the duty ratio of the highest ever sensed GP which increased the output energy and efficiency of PV systems. These modifications in the PSO, GWO, and BA improved their superior performance as an MPPT of PV systems considerably. The simulation and experimental results showed the superiority of using the modified PSO, GWO, and MBA as MPPT techniques with better performance associated with the modified BA compared to the modified PSO and GWO in terms of convergence time and avoidance of the premature conversance.

REFERENCES

[1] J. Ahmed and Z. Salam, "An enhanced adaptive P&O MPPT for fast and efficient tracking under varying environmental conditions," *IEEE Trans. Sustain. Energy*, vol. 9, no. 3, pp. 1487–1496, Jul. 2018.

[2] W. Zhu, L. Shang, P. Li, and H. Guo, "Modified hill climbing MPPT algorithm with reduced steady-state oscillation and improved tracking efficiency," *J. Eng.*, vol. 2018, no. 17, pp. 1878–1883, Nov. 2018.

[3] T. Tuffaha, M. Babar, Y. Khan, and N. Malik, "Comparative study of different hill climbing MPPT through Simulation and experimental test bed," *Res. J. Appl. Sci., Eng. Technol.*, vol. 7, no. 20, pp. 4258–4263, Sep. 2016.

[4] Y.-Y. Hong, P. M. P. Buay, and A. A. Beltran, "Maximum power point tracking of photovoltaic system using Taguchi-based fuzzy logic control," in *Proc. IEEE Milan PowerTech*, Milan, Italy, Jun. 2019, pp. 1–6.

[5] A. Ilyas, M. Ayyub, M. R. Khan, A. Jain, and M. A. Husain, "Realisation of incremental conductance the MPPT algorithm for a solar photovoltaic system," *Int. J. Ambient Energy*, vol. 39, no. 8, pp. 873–884, Nov. 2018.

[6] K. Hu, S. Cao, W. Li, and F. Zhu, "An improved particle swarm optimization algorithm suitable for photovoltaic power tracking under partial shading conditions," *IEEE Access*, vol. 7, pp. 143217–143232, 2019.

[7] A. M. Eltamaly and H. M. Farh, "Dynamic global maximum power point tracking of the PV systems under variant partial shading using hybrid GWO-FLC," *Solar Energy*, vol. 177, pp. 306–316, Jan. 2019.

[8] J. Ahmed and Z. Salam, "Maximum power point tracking (MPPT) for PV system using cuckoo search with partial shading capability," *Appl Energy*, vol. 119, pp. 118–130, Apr. 2015.

[9] K. Kaced, C. Larbes, N. Ramzan, M. Bounabi, and Z. E. Dahmane, "Bat algorithm based maximum power point tracking for photovoltaic system under partial shading conditions," *Solar Energy*, vol. 158, pp. 490–503, Dec. 2017.

[10] M. Karagöz and H. Demirel, "Novel MPPT method for PV arrays based on modified bat algorithm with partial shading capability," *Int. J. Comput. Sci. Netw. Secur*, vol. 17, no. 22, pp. 61–66, 2017.

[11] N. Priyadarshi, S. Padmanaban, P. Kiran Maroti, and A. Sharma, "An extensive practical investigation of FPSO-based MPPT for grid integrated PV system under variable operating conditions with anti-islanding protection," *IEEE Syst. J.*, vol. 13, no. 2, pp. 1861–1871, Jun. 2019.

[12] H. M. Farh and M. Ali Eltamaly, "Maximum power extraction from the photovoltaic system under partial shading conditions," in *Modern Maximum Power Point Tracking Techniques for Photovoltaic Energy Systems*. Cham, Switzerland: Springer, 2020, pp. 107–129.

[13] A. M. Eltamaly, H. M. Farh, and M. S. Al-Saud, "Grade point average assessment for metaheuristic GMPP techniques of partial shaded PV systems," *IET Renew. Power Gener.*, vol. 13, no. 8, pp. 1215–1231, Jun. 2019.

[14] X. S. Yang, "A new metaheuristic bat-inspired algorithm," in *Proc. NICSO*, Berlin, Germany, 2010, pp. 65–74.

[15] A. Oshaba, E. Ali, and S. Abd Elazim, "MPPT control design of PV system supplied SRM using BAT search algorithm," *Sustain. Energy, Grids Netw.*, vol. 2, pp. 51–60, Jun. 2015.
[16] Z. Wu and D. Yu, "Application of improved bat algorithm for solar PV maximum power point tracking under partially shaded condition," *Appl. Soft Comput.*, vol. 62, pp. 101–109, Jan. 2018.
[17] M. Seyedmahmoudian, T. Kok Soon, E. Jamei, G. Thirunavukkarasu, B. Horan, S. Mekhilef, and A. Stojcevski, "Maximum power point tracking for photovoltaic systems under partial shading conditions using bat algorithm," *Sustainability*, vol. 10, no. 5, p. 1347, Apr. 2018.
[18] M. Ali Eltamaly, "Photovoltaic maximum power point tracking under dynamic partial shading changes by novel adaptive particle swarm optimization strategy," *Trans. Inst. Meas. Control*, vol. 2019, Aug. 2019, Art. no. 014233121986562.
[19] E. Avila, N. Pozo, M. Pozo, G. Salazar, and X. Domínguez, "Improved particle swarm optimization based MPPT for PV systems under partial shading conditions," in *Proc. IEEE Southern Power Electron. Conf. (SPEC)*, Puerto Varas, Chile, Dec. 2017, pp. 1–6.
[20] M. A. Husain, A. Jain, and A. Tariq, "A novel fast mutable duty (FMD) MPPT technique for solar PV system with reduced searching area," *J. Renew. Sustain. Energy*, vol. 8, no. 5, Sep. 2016, Art. no. 054703.
[21] N. M. Yahya, "Bats echolocation-inspired algorithms for global optimisation problems," Ph.D. dissertation, Dept. Electr. Eng., Sheffield Univ., Sheffield, U.K., 2016.
[22] Y. Lu and T. Jiang, "Bi-population based discrete bat algorithm for the low-carbon job shop scheduling problem," *IEEE Access*, vol. 7, pp. 14513–14522, 2019.
[23] Enf, USA. *Sun Perfect Solar Module*. Accessed: Oct. 2019. [Online]. Available: https://www.enfsolar.com/pv/panel-datasheet/crystalline/13433

ALI M. ELTAMALY received the B.Sc. and M.Sc. degrees in electrical engineering from Al-Minia University, Egypt, in 1992 and 1996, respectively, and the Ph.D. degree in electrical engineering from Texas A&M University, in 2000. He is currently a Full Professor with King Saud University, Saudi Arabia, and Mansoura University, Egypt. His current research interests include renewable energy, smart grids, power electronics, motor drives, power quality, artificial intelligence, evolutionary and heuristic optimization techniques, and distributed generation. He has published 15 books and book chapters. He has authored or coauthored more than 200 refereed journal articles and conference papers, and a number of patents with the U.S. Patent Office. He has supervised several M.Sc. and Ph.D. theses, and worked on number of technical projects. He received the Professor Award for Scientific Excellence, the Egyptian Supreme Council of Universities, Egypt, in June 2017. He has been awarded many prizes from different universities in Egypt and Saudi Arabia. In addition, he has chaired many international conference sessions. He participates as an Editor and an Associate Editor for many international journals.

M. S. AL-SAUD received the Ph.D. degree from McMaster University, Canada, in 2007. He is currently an Associate Professor with the Electrical Engineering Department, King Saud University. He is also the Director of the Saudi Electricity Company Chair in power system reliability and security. As part of his work at King Saud University, he has been involved in research and development activities in the areas of sustainable energy technologies, smart grid and renewable energy adoption, reliability and security assessment of power supply systems, design and operation of distribution systems, application of artificial intelligence in power system design, and load management.

AHMED G. ABOKHALIL received the bachelor's and M.S. degrees in engineering from Assiut University, Egypt, and the Ph.D. degree from the School of Electrical and Computer Engineering, Yeungnam University, South Korea, in 2007. In 2008, he joined the Rensselaer Polytechnic Institute, NY, USA, as a Postdoctoral Researcher, where he worked on a renewable energy project. From 2009 to 2010, he was a Postdoctoral Research Fellow with the Korean Institute of Energy Research, Daejeon, South Korea, working on photovoltaic power conversion systems. In 2010, he moved to Assiut University, Egypt, as an Assistant Professor. He currently works as an Associate Professor with the Department of Electrical Engineering, Majmaah University, Al Majma'ah, Saudi Arabia.