INTERNATIONAL JOURNAL OF CIRCUITS, SYSTEMS AND SIGNAL PROCESSING
DOI: 10.46300/9106.2023.17.10 Volume 17, 2023

New MPPT Hybrid Controller based on Genetic Algorithms and Particle Swarm Optimization for Photovoltaic Systems

E. Mammeri[1], A. Ahriche[1*], A. Necaibia[2], A. Bouraiou[2]
1 Applied Automation Laboratory, Department of automation and electrification of industrial process,Faculty of Hydrocarbons and Chemistry, University of Boumerdes, Algeria
2 Unité de Recherche en Energie Renouvelables en milieu saharien, URERMS, Centre de Développement des Energies Renouvelables, CDER, 01000, Adrar, Algeria
* Corresponding author's Email: a.ahriche@univ-boumerdes.dz

Received: August 17, 2022. Revised: January 18, 2023. Accepted: February 20, 2023. Published: March 6, 2023.

Abstract- Traditional Maximum Power Point Tracking (MPPT) techniques are unable to reach high performance in photovoltaic (PV) system under partial shading conditions because of the multi-peaks present in the Power-Voltage curve. For that, particle Swarm Optimization (PSO) and genetic algorithms (GA) have been combined in recent years. However, these algorithms demonstrate some drawbacks in tracking accuracy and convergence rates, which impair control performance. In this paper, a new controller based on hybridization of PSO and GA is introduced to track the global maximum power point (GMPP). The proposed algorithm (HPGA) increases the balance rate between exploration and exploitation due to the cascade design of GA and PSO. Thus, the GMPP tracking of both algorithms will be improved. Simulations are carried out based on ISOFOTON-75W PV modules to prove the high performance of the proposed algorithm. From the obtained results, we conclude that HPGA shows fast convergence and very good tracking accuracy of GMPP in PV system even under different shading patterns.

Keywords- Photovoltaic, MPPT Techniques, Metaheuristic algorithms, Partial shading conditions, Particle swarm optimization.

I. Introduction

PHOTOVOLTAIC energy sources are growing rapidly, and their uses are expanding, from powering small electronic gadgets to enormous power plants connected to medium and low voltage grids. The PV cell is the basic element in a PV system, it has nonlinear relation with climate conditions such as irradiance and temperature[1]. This nonlinearity implies the use of maximum power point tracking (MPPT) techniques. In literature, Hill climbing algorithms such as perturb and observe [2] and incremental conductance[3, 4] are widely used because of their simplicity and efficiency in tracking the MPP. However, in complex PV systems under partial shading conditions, when multiple peaks are present, they can't distinguish between local maximum power points (LMPPs) and the global one (GMPP)[5, 6, 7].

To overcome this issue, several global maximum power point tracking (GMPPT) techniques are proposed in the literature. Meta-heuristic algorithms and hybrid approaches that combine multiple optimization algorithms are widely addressed for GMMPT[8, 9, 10, 11]. Meta-heuristic algorithms include swarm intelligence that mimics the behavior of some living creatures such as Particle swarm optimization PSO, ant colony [12], artificial bee colony [13], and salp swarm optimization [14], in addition to evolutionary-based algorithms which imitate the rules of the natural evolution [15].

Particle swarm optimization PSO is commonly used for general optimization problems because of its simplicity and effectiveness[16]. PSO, though, faces initialization issues that might cause an incorrect velocity update which slows down the convergence rate. Additionally, PSO has a propensity to prematurely converge on local maxima [17, 18, 19]. On the other hand, GA is a deep-rooted algorithm that is contently evolving to this date[20, 21, 22]. GA varieties can be divided into two families, the binary coded GA and the real coded GA, and each family has different operators for selection, crossover, and mutation. The real-coded version of GA is proving to be effective for various optimization problems nowadays. However, it shows low convergence speed when used in GMPPT controller [18, 23].

Hybrid approaches which are built by combining at least two optimization algorithms or an optimization al-

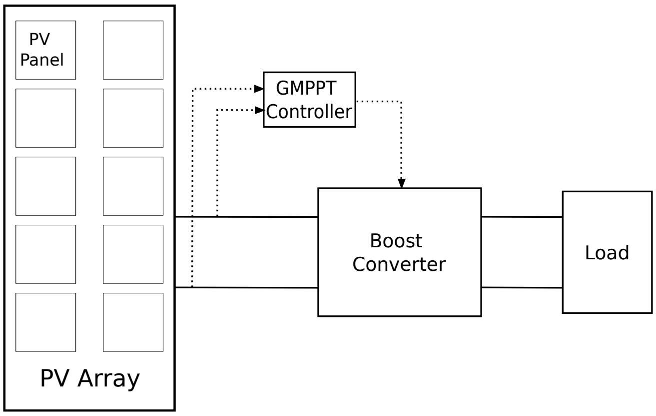

Fig. 1: PV system

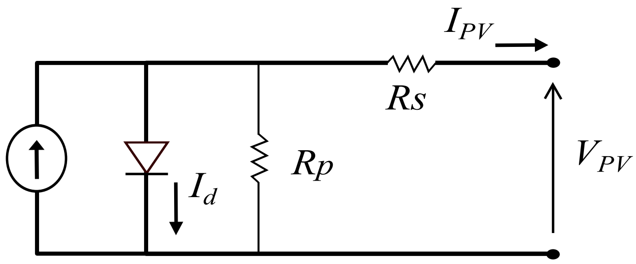

Fig. 2: the single diode model of a PV cell

gorithm with a conventional method have been introduced by researchers to solve complex optimization problems. In the literature, Hybrid approaches have proved to ameliorate the performance of the algorithms used for hybridization [24, 25, 26, 27]. However, the first barrier to building a hybrid approach is the selection of the algorithms to be combined. If we intend to implement a hybrid method, we must take into account several factors, including the advantages and drawbacks of each algorithm besides the characteristic of the system. The hybrid methods must aim to benefit from the advantages of each algorithm to overcome the drawbacks and improve optimization performances [6, 25].

In this paper we propose a novel hybridization of PSO and GA, called HPGA, to overcome the drawbacks of PSO and GA algorithms in tracking the GMPP in PV systems under partial shading conditions. The hybrid algorithm employs a cascade configuration between GA and PSO, where GA is the master algorithm and PSO work on the initialized chromosomes to benefit from the advantages of both algorithms. This combination allows availing from exploration capabilities of GA algorithm due to crossover and mutation operators which generate better solutions every iteration, and from the convergence speed of PSO algorithm due to the tendency of particles to follow the global best value. simulation results exhibit the capability of HPGA algorithm to track rapidly the GMPP. It shows fast convergence with high tracking accuracy despite the complexity of the PV system under partial shading conditions.

II. Photovoltaic system

Figure 1 presents the schema of the stand-alone PV system used in this paper. The PV array is connected in series with a controlled boost converter to allow changing the voltage on the PV array terminals. while the MPPT controller measures the output voltage/current of the PV array and generates a duty cycle for the boost converter in order to track the GMPP.

A. Photovoltaic cell model

The basic element of a photovoltaic system is the PV cell, it is a semi-conductor able to convert photon's energy to electrical energy. The energy produced by the PV cell is relational to the irradiance amount and temperature. A DC generator combined with an antiparallel diode can model the PV cell effectively in ideal conditions. for realistic modeling, a series resistor and shunt resistor are added to model the optical and electrical losses. In literature, this type of modeling is called the single diode model [1]. The electric schema of this model is shown in Figure 2. The single diode is described mathematically by the following equations:

$$\begin{aligned} I_{PV} &= N_P.I_{ph} \\ &- N_p.I_s.\left\{exp\left[\frac{q.\left(V_{pv}+R_s.I_{pv}\right)}{N_s.A.K.T}\right]-1\right\} \\ &- N_p\frac{q.\left(V_{pv}+R_s.I_{pv}\right)}{R_p.\ N_s} \end{aligned} \tag{1}$$

The photo-current is influenced by the irradiance amount falling on the surface and the temperature. Equation 2 shows the mathematical expression of photo-current.

$$I_{ph} = \left[I_s + k_i.\left(T - T_r\right)\right].\frac{S}{100} \tag{2}$$

Where I_s is the current passes by the series resistor, given by :

$$I_s = I_{so}.\left(\frac{T}{T_r}\right)^3.exp\left[\left(-\frac{q.E_g}{A.K}\right).\left(\frac{1}{T_r}-\frac{1}{T}\right)\right] \tag{3}$$

The ideality factor A is given as follows:

$$A = \frac{q.\left(V_{pv}+R_s.I_{pv}\right)}{N_s} \tag{4}$$

A PV panel is a combination of several cells connected in series and parallel. The I-V and P-V characteristic of a PV panel is shown in Figure 3. The power produced by the panel varies depending on the voltage in its terminal and the current flowing through. There is one point from the graph where the power is at its maximum called maximum power point MPP. Therefore, several maximum power point tracking techniques are used to capture this point.

INTERNATIONAL JOURNAL OF CIRCUITS, SYSTEMS AND SIGNAL PROCESSING
DOI: 10.46300/9106.2023.17.10 Volume 17, 2023

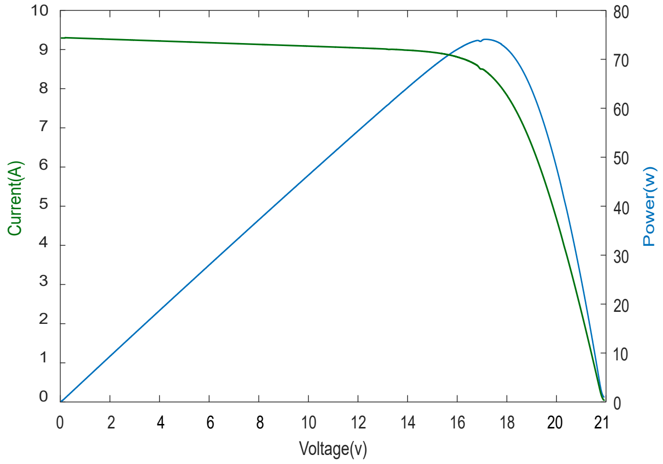

Fig. 3: P(V) and I(V) graph of a PV module

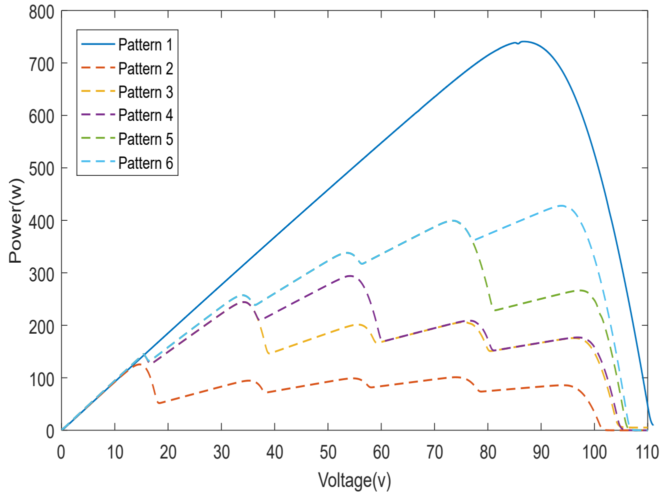

Fig. 4: P(V) and I(V) graph of a PV module

B. *Partial shading conditions*

When more significant power levels are necessary, a PV array is built utilizing many PV panels coupled in a particular arrangement depending on the intended power requirements. When a PV panel in an array receives less irradiance than the other panels owing to shade, the voltage changes to negative and the panel becomes a load on the other panels[28, 29]. In this phenomenon, known as the hot-spot, the shaded panel is subject to degradation because of the reverse current imposed on it by the unshaded panels. In order to prevent hots-pots, a bypass diode is installed in parallel to each panel to provide an additional path for the current if the panel voltage drops due to partial shading conditions. Under uniform irradiance, the characteristics of a PV array are identical to those of a PV panel. However, the power exhibits many peaks under the partial shading conditions due to the bypass diodes, as shown in Figure 4 patterns 2-6. The highest peak is called the global maximum power point whereas the other peaks are called local maximum power points. Traditional MPPT algorithms are more likely to fall in local MPP and ignore the global MPP. Thus, specific MPPT techniques are required to distinguish the global MPP from the local MPPs.

III. Global MPPT algorithms

A. *Genetic algorithm*

GA is an optimization algorithm inspired by natural selection and genetics principles; it was originally proposed by Holland with three essential operators, namely crossover, mutation, and natural selection [30]. Population individuals are called chromosomes in this algorithm. Traditionally, chromosomes are represented in binary form and their variation is bounded according to the binary word length and crossover is performed by alternating a randomly selected part of parents' word to get new offspring, while mutation happens by switching the stat, from 1 to 0 or vice-versa, of a randomly selected bit [30]. However, Binary representation suffers from precision loss and lack of convergence when dealing with high-dimensional or high-precision problems. Consequently, a real coded genetic algorithm is developed to overcome this issue [31]. This last uses real numbers instead of binary strings in solution representation which opens a wide probability for crossover and mutation types leading to fast convergence with high resolution. There are different operators for each phase, in this paper, we use tournament selection, simulated binary crossover, and polynomial mutation operators because of their effectiveness.

B. *Particle swarm optimization*

Particle swarm optimization (PSO), Introduced by Kennedy and Eberhat [32], is a metaheuristic algorithm that mimics the swarming behavior of birds and fishes while discovering new nourishment sources or avoiding predators. It is used for optimization problems with large parameters number by exploring social cooperation and self-experience of particles to attend to the optimum solution in a given search space[19]. Each particle updates its position according to its velocity, which is calculated using the best solution attended by the particle (PBest) and the best solution attended so far (Gbest) by the algorithm. Equations 5, and 6, show the evolution of PSO particles during optimization:

$$\begin{aligned} V_i\,(k+1) = w.V_i\,(k) + c_1.r_1.\,(x_i\,(k) - Pbest_i) + \\ + c_2.r_2.\,(x_i\,(k.) - Gbest) \end{aligned} \tag{5}$$

$$X_i\,(k+1) = x_i\,(k) + V_i\,(k+1) \tag{6}$$

Where X_i, V_i are, respectively, the position and the velocity of particle i. $Pbest_i, Gbest_i$ are, respectively, the personal best and the global best of particle i.w is the inertia weight. c_1, c_2 are, respectively, the memory factor and the cooperation factor and $r_1, r_2 \epsilon [0, 1]$ are random numbers.

C. *Proposed algorithm*

As mentioned before, GA has a good exploration phase due to its various operators, especially mutation.

While PSO has a better exploitation phase because of the influence of the global best solution included in the velocity equation. In this paper, we propose a hybrid GMPPT method that aims to benefit from the exploration phase of GA and the exploitation phase of PSO. Unlike the previously proposed hybridization of these two algorithms [24], in this paper PSO and GA are used separately in a cascade configuration, GA will be the master optimization algorithm while PSO will help to ameliorate the position of some chromosomes every iteration which increases the exploitation capabilities. PSO factors are modified in a manner to give fast convergence toward the global best solution. In the final step of PSO, the personal best of each particle is added to the offspring population generated by GA algorithm. In addition, a stopping criterion is added to HPGA algorithm to increase convergence speed and prevent the algorithm from generating new chromosomes after finding the GMPPT which is the case in traditional GA algorithms. The pseudo-code of HPGA is represented in Figure 5. By using GA as a master algorithm, we benefit from the capability of GA to generate new possible solutions every iteration. Crossover and mutation operators are the same as the traditional GA. Crossover chooses randomly two parents' chromosomes and generates two offspring While mutation takes one offspring and generates a new mutated chromosome. At this stage the next offspring generation of GA is ready. The population is ranked according to the associated fitness from high to low power. Chromosomes with high, medium, and worst fitness are selected for PSO algorithm which is performed for 5 iterations. The memory factor of PSO is reduced to decrease the influence of the personal best on the new particles. While the cooperation factor is raised to increase the dependency of new particles on the global best solution. Then the convergence state (η_s) of the optimization is calculated. η_s is the difference between the best fitness Pb and the worst fitness P_b divided by the average fitness. HPGA will stop if η_s is equal to or less than 1%. the convergence state η_s is calculated using the following equation:

$$\eta_s = \frac{P_b - P_w}{(P_b + P_w)/2} \tag{7}$$

Algorithm 1: HPGA Algorithm

1. Set HPGA parameters (Pc, Pm, w, c1, c2).
2. Initialize n chromosomes randomly.
3. Generate chromosomes as duty cycle (d) and record the produced power by the PV array.
4. While t< tmax
5. Select n parents using tournament selection.
6. Perform crossover and mutation on parents and obtain offspring population.
7. Rank offspring population and select the best, medium, and worst chromosomes.
8. Perform PSO on the selected chromosomes.
9. Combine and rank the offspring population with the personal bests of each PSO particle.
10. Calculate the difference in power (ΔP) between the best and the worst particle.
11. t=t+1;
12. If ΔP <1 W; break while loop.
13. end while
14. Output the best chromosome as the duty cycle.

Fig. 5: Pseudo-code of HPGA algorithm

Algorithm	**Parameters values**				
PSO	w	c1	c2		
	0.9	1.5	1.5		
GA	Pc	Pm			
	0.8	0.3			
ABC	Employed	Onlooker			
	5	5			
HPGA	Pc	Pm	w	c1	c2
	0.8	0.3	0.4	1.2	1.2
HGAPSO	pc	pm	w	c1	c2
	0.8	0.3	0.9	1.5	1.5

Table 1: Configuration parameters of algorithms

IV. Results and discussions

In order to reveal the advantages and disadvantages of the proposed algorithm. We compare five algorithms in this paper, three metaheuristic algorithms PSO[16], GA[20], and ABC [13], besides two-hybrid approaches, the proposed HPGA algorithm, and another hybrid genetic algorithm and particle swarm optimization [24] (HGAPSO) from the literature. The algorithms are coded to function as described beforehand. Table 1 summarizes the configuration parameters for the five algorithms. The common parameters between GA and HPGA are the same as GA algorithm is the master algorithm to observe the influence of hybridization on tracking performances. However, PSO parameters in HPGA are modified to increase convergence speed.

Simulation of the algorithms mentioned before was performed in a MATLAB environment. A computer with an AMD Ryzen 7 processor and 8 GB RAM was used to code these algorithms and to run the simulation. The main parts of the PV system are a PV array, a DC-DC boost converter, and a GMPPT controller. We used an array consisting of 10 ISOFOTON-75W PV modules. The PV array is built on a 5-series, 2-parallel (5S-2P) configuration to allow getting various complex partial shading patterns when changing the irradiation intensity for each PV module. In the 5S-2P configuration, the voltage of the PV array is five times the voltage of a single module and Its current is two times the current of a single module. The characteristics of the module used in this work in standard climatic conditions is given in

Parameters	ISOFOTON 75W
Technology type	Single–crystal Si
Maximum power	75 W
Open-circuit voltage	21.6 V
Short-circuit current Isc	4.67 A
Maximum power voltage	17.5 V
Maximum power current	4.34 A
Number of cells in series	36

Table 2: characteristics of the PV module

Table 2.

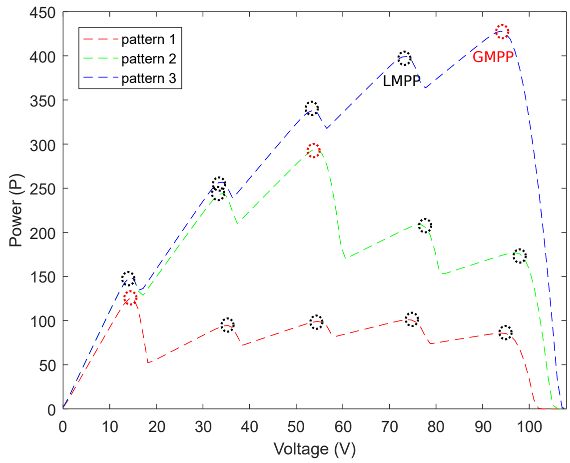

Fig. 6: P(V) curves of a PV array under different partial shading patterns.

Simulation results are presented in Figure 97,and 8. At every simulation, the power and voltage progress of the system is recorded, and the results of the algorithms are combined according to the pattern case.

The performance of HPGA algorithm is observed under three partial shading conditions patterns depending on the location of GMPP, see Figure 6. We choose patterns with four LMPPs and only one GMPP to increase the complexity of the system. The patterns considered for the PV array simulation are as follows: pattern 1: each 5 modules in series receive the following irradiations (1000w/m2- 700 w/m2- 200 w/m2-150 w/m2-100 w/m2). The GMPP in this pattern is located in the first peak with a maximum power of 125.6 w. The peaks are approximately similar which will make it difficult for the algorithms to distinguish the GMPP from the LMPPs. pattern 2: each 5 modules in series receive the following irradiations (1000w/m2- 800 w/m2- 600 w/m2-200 w/m2-100 w/m2). The GMPP in this pattern is located in the middle with a maximum power of 294.2 w. pattern 3: each 5 modules in series receive the following irradiations (1000w/m2- 800 w/m2- 650 w/m2-500 w/m2-400 w/m2). The GMPP in this pattern is located in the last peak with a maximum power of 427.95 w. From

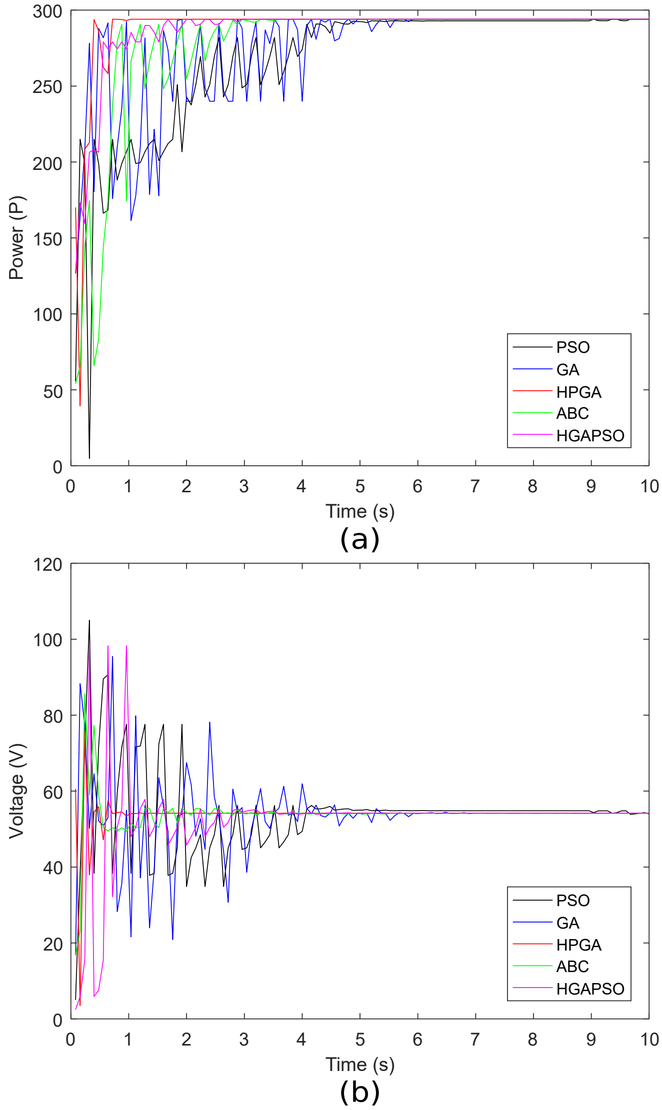

Fig. 7: Power (a) and voltage (b) variation in the second pattern.

Figure 6 we can notice pattern 1 is the most complex pattern as the GMPP and LMPPs are converged which make it difficult for the algorithms to capture the GMPP. While pattern 3 seems to be less complex than other patterns due to the wide spread of the MPPs. However, the wide difference between MPPs means that a weak convergence will lead to high power loss which will decrease the MPPT efficiency. we can classify the patterns according to their complexity in ascending order from the first pattern to the third.

To better evaluate the performance of the algorithms. Table 3 presents a summary of some parameters extracted from Figure 9,7,and 8. The extracted parameters are the maximum power achieved by each algorithm referred to by P_{mpp} the tracking time which is the required time to reach the MPP, and the tracking efficiency (η_{mpp}) which represents the percentage of the power achieved Pmpp against the power of the actual GMPP in each pattern (P_{gmpp}). The tracking efficiency is calculated according to Equation 8.

DOI: 10.46300/9106.2023.17.10

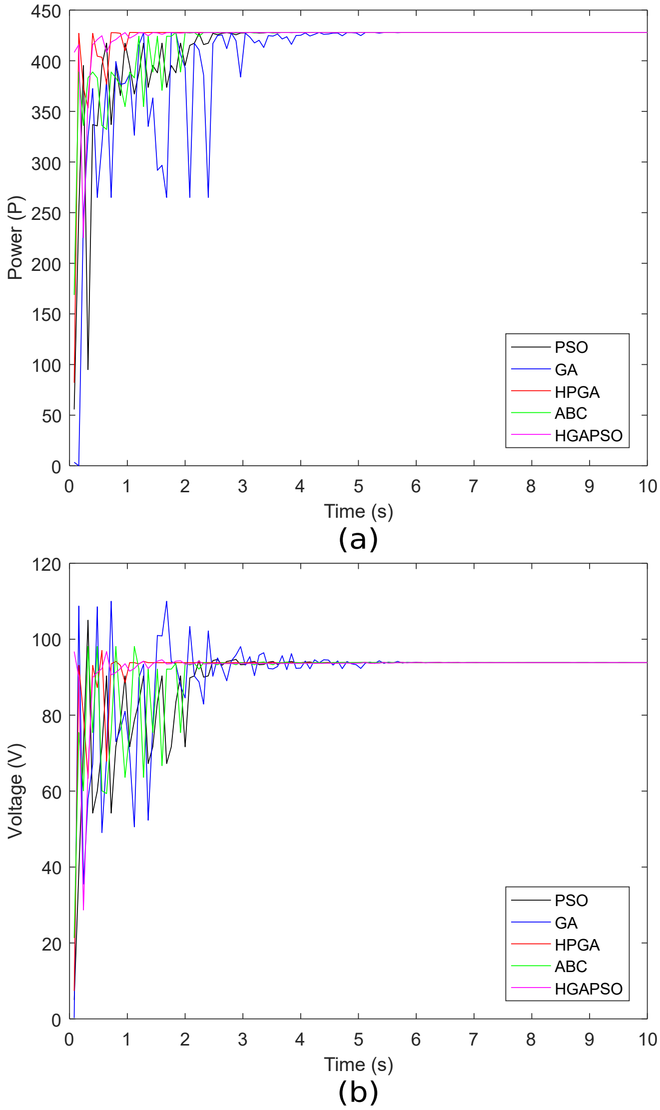

Fig. 8: Power (a) and voltage (b) variation in the third pattern.

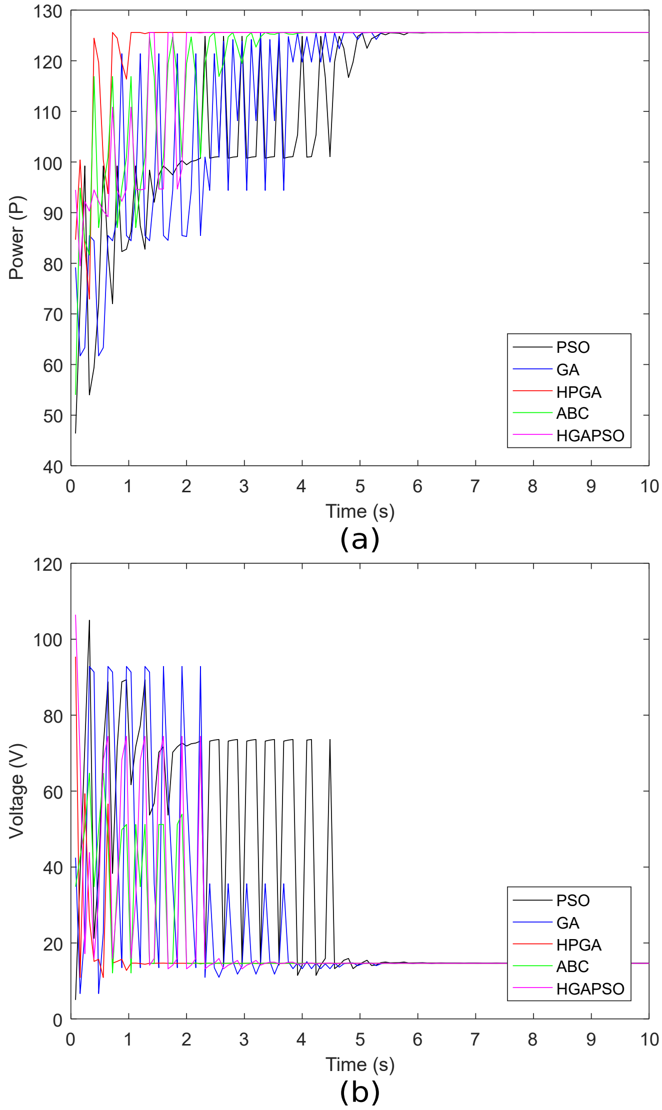

Fig. 9: Power (a) and voltage (b) variation in the first pattern.

$$\eta_{mpp} = \frac{P_{mpp}}{P_{gmpp}} * 100\% \quad (8)$$

From Figure 9,7, 8, and Table 3 we can notice that HPGA achieved the best GMPP with the lowest tracking time. However, PSO failed to track accurately the GMPP in patterns 1 and 3.

In the first pattern, GA, ABC, and PSO algorithms show slow convergence speed, 4s for GA and 4.5s for PSO, and low MPPT efficiency which is less than 90% for PSO and GA. It is worth mentioning that for PSO algorithm, the lack of convergence to GMPP as the power has not across the 100w in the first 2.3 s gives rise to this energy loss. GA presents high ripples count which may be caused by the mutated offspring that take random values in the working space. These mutated offspring help to explore new possible locations of the GMPP. However, they decrease the effectiveness of GA in the exploitation phase. On the other hand, the hybrid methods HPGA and HGAPSO show relatively low ripples after a short tracking period down to 1.2s for HPGA, which gives an MPPT efficiency more than PSO by 13%. While in the second pattern, all algorithms reach the GMPP and show relatively low ripples compared to the first pattern, especially for HPGA and HGAPSO. As a result, the GMPPT efficiency of all algorithms is increased compared to the first pattern, where GA shows a big increase with a difference of 3.36%. we can notice from Figure 8 that hybrid algorithms present better convergence toward the GMPP and achieve higher efficiency. The algorithms show the best convergence speed and MPPT efficiency in the third pattern specially HPGA as it converged to the GMPP with an efficiency of 98.61 in only 1.2s. However, the power in GA presents an unsteady response for 2.94s which is longer than the convergence time of HPGA by 145%.

We notice that the convergence speed and MPPT efficiency of algorithms are improved from pattern 1 to pattern 2, and then showed the best performances in

Pattern	Algorithm	Pmpp (W)	Tracking Time(s)	tracking efficiency (%)
1	PSO	125.41	4.96	87.35
	GA	125.60	4.72	89.03
	HPGA	125.60	1.28	98.07
	ABC	125.60	2.16	95.06
	HGAPSO	125.60	3.12	93.59
2	PSO	292.98	4.16	88.40
	GA	294.02	4.08	92.39
	HPGA	294.02	0.96	98.88
	ABC	294.02	2.24	96.05
	HGAPSO	294.02	2.8	93.93
3	PSO	427.95	2.24	95.69
	GA	427.95	3.6	92.57
	HPGA	427.95	1.2	99.04
	ABC	427.95	2	96.12
	HGAPSO	427.95	1.44	98.11

Table 3: Comparison of different used techniques

the last pattern. Therefore, we can say that the performance of algorithms is related linearly to the system's complexity. Also, hybrid methods present better performance compared to PSO, GA, and PSO, this superiority proves the effectiveness of using advantageous elements from multiple algorithms to increase their efficiency and reduce drawbacks.

V. Conclusion

This paper proposes an MPPT controller for PV systems under partial shading conditions based on a hybrid GA and PSO algorithm. The proposed algorithm HPGA is built on cascade form to gather the advantages of GA in the exploration phase and PSO in the exploitation phase. Also, it is provided with a stopping criterion to reduce the tracking time. In order to evaluate the performances of HPGA in tracking the GMPPT, it has been compared with four other metaheuristic algorithms. All algorithms have been tested on a PV system under different shading patterns. The HPGA shows superior capabilities in terms of tracking speed and efficiency, it presents an average of 98.66 in MPPT efficiency, and a tracking speed time down to 0.96s in the second pattern. Simulation results indicate that HPGA can be effective in tracking the GMPP in complex partial shading conditions.

References

[1] Y. Jiang, J. A. Abu Qahouq, and T. A. Haskew, "Adaptive step size with adaptive-perturbation-frequency digital MPPT controller for a single-sensor photovoltaic solar system," *IEEE Trans. Power Electron.*, vol. 28, no. 7, pp. 3195–3205, 2013.

[2] T. K. Soon and S. Mekhilef, "A fast-converging MPPT technique for photovoltaic system under fast-varying solar irradiation and load resistance," *IEEE Trans. Ind. Informatics*, vol. 11, no. 1, pp. 176–186, 2015.

[3] S. Necaibia, M. S. Kelaiaia, H. Labar, A. Necaibia, and E. D. Castronuovo, "Enhanced auto-scaling incremental conductance MPPT method, implemented on low-cost microcontroller and SEPIC converter," *Sol. Energy*, vol. 180, no. October 2018, pp. 152–168, 2019.

[4] F. Belhachat and C. Larbes, "A review of global maximum power point tracking techniques of photovoltaic system under partial shading conditions," *Renew. Sustain. Energy Rev.*, vol. 92, no. October 2017, pp. 513–553, 2018.

[5] B. Yang, T. Zhu, J. Wang, H. Shu, T. Yu, X. Zhang, W. Yao, and L. Sun, "Comprehensive overview of maximum power point tracking algorithms of PV systems under partial shading condition," *J. Clean. Prod.*, vol. 268, p. 121983, 2020.

[6] S. Motahhir, A. El Hammoumi, and A. El Ghzizal, "The most used MPPT algorithms: Review and the suitable low-cost embedded board for each algorithm," *J. Clean. Prod.*, vol. 246, 2020.

[7] F. Belhachat and C. Larbes, "Global maximum power point tracking based on ANFIS approach for PV array configurations under partial shading conditions," *Renew. Sustain. Energy Rev.*, vol. 77, no. September 2016, pp. 875–889, 2017.

[8] R. Sarkar, J. R. Kumar, R. Sridhar, and S. Vidyasagar, "A New Hybrid BAT-ANFIS-Based Power Tracking Technique for Partial Shaded Photovoltaic Systems," *Int. J. Fuzzy Syst.*, vol. 23, pp. 1313–1325, jul 2021.

[9] H. Rezk, A. Fathy, and A. Y. Abdelaziz, "A comparison of different global MPPT techniques based on meta-heuristic algorithms for photovoltaic system subjected to partial shading conditions," 2017.

[10] M. Naseem, M. A. Husain, A. F. Minai, A. N. Khan, M. Amir, J. Dinesh Kumar, and A. Iqbal, "Assessment of Meta-Heuristic and Classical Methods for GMPPT of PV System," jun 2021.

[11] S. Titri, C. Larbes, K. Y. Toumi, and K. Benatchba, "A new MPPT controller based on the Ant colony optimization algorithm for Photovoltaic systems under partial shading conditions," *Appl. Soft Comput. J.*, vol. 58, pp. 465–479, sep 2017.

[12] C. Gonzalez-Castano, C. Restrepo, S. Kouro, and J. Rodriguez, "MPPT Algorithm Based on Artificial Bee Colony for PV System," *IEEE Access*, vol. 9, pp. 43121–43133, 2021.

[13] A. F. Mirza, M. Mansoor, Q. Ling, B. Yin, and M. Y. Javed, "A Salp-Swarm Optimization based MPPT technique for harvesting maximum energy from PV systems under partial shading conditions," *Energy Convers. Manag.*, vol. 209, apr 2020.

[14] M. Z. Ali, N. H. Awad, P. N. Suganthan, A. M. Shatnawi, and R. G. Reynolds, "An improved class of real-coded genetic algorithms for numerical optimization," *Neurocomputing*, vol. 275, pp. 155–166, 2018.

[15] A. Ibrahim, R. Aboelsaud, and S. Obukhov, "Improved particle swarm optimization for global maximum power point tracking of partially shaded PV array," *Electr. Eng.*, vol. 101, pp. 443–455, jun 2019.

[16] A. Fathy, I. Ziedan, and D. Amer, "Improved teaching–learning-based optimization algorithm-based maximum power point trackers for photovoltaic system," *Electr. Eng.*, vol. 100, pp. 1773–1784, sep 2018.

[17] D. Fares, M. Fathi, I. Shams, and S. Mekhilef, "A novel global MPPT technique based on squirrel search algorithm for PV module under partial shading conditions," *Energy Convers. Manag.*, vol. 230, feb 2021.

[18] B. Ganeshprabu and M. Geethanjali, "Rigorous reduction of partial shading condition in grid connected solar PV system using discrete time-based PSO controller," *Soft Comput.*, vol. 24, pp. 18765–18775, dec 2020.

[19] A. Harrag and S. Messalti, "Adaptive GA-based reconfiguration of photovoltaic array combating partial shading conditions," *Neural Comput. Appl.*, vol. 30, pp. 1145–1170, aug 2018.

[20] P. Megantoro, Y. D. Nugroho, F. Anggara, A. Pakha, and B. A. Pramudita, "The implementation of genetic algorithm to MPPT technique in a DC/DC buck converter under partial shading condition," *Proc. - 2018 3rd Int. Conf. Inf. Technol. Inf. Syst. Electr. Eng. ICITISEE 2018*, pp. 308–312, 2018.

[21] A. F. Mirza, M. Mansoor, Q. Ling, M. I. Khan, and O. M. Aldossary, "Advanced variable step size incremental conductance mppt for a standalone PV system utilizing a ga-tuned pid controller," *Energies*, vol. 13, no. 6, pp. 1–24, 2020.

[22] A. S. Oshaba, E. S. Ali, and S. M. Abd Elazim, "PI controller design using ABC algorithm for MPPT of PV system supplying DC motor pump load," *Neural Comput. Appl.*, vol. 28, pp. 353–364, feb 2017.

[23] L. G. K. Chai, L. Gopal, F. H. Juwono, C. W. Chiong, H. C. Ling, and T. A. Basuki, "A novel global MPPT technique using improved PS-FW algorithm for PV system under partial shading conditions," *Energy Convers. Manag.*, vol. 246, oct 2021.

[24] M. Pesaran H.A., M. Nazari-Heris, B. Mohammadi-Ivatloo, and H. Seyedi, "A hybrid genetic particle swarm optimization for distributed generation allocation in power distribution networks," *Energy*, vol. 209, p. 118218, 2020.

[25] S. A. Rizzo and G. Scelba, "A hybrid global MPPT searching method for fast variable shading conditions," *J. Clean. Prod.*, vol. 298, may 2021.

[26] K. H. Chao and M. N. Rizal, "A hybrid mppt controller based on the genetic algorithm and ant colony optimization for photovoltaic systems under partially shaded conditions," *Energies*, vol. 14, no. 10, 2021.

[27] J. Sarkar and S. Bhattacharyya, "Application of graphene and graphene-based materials in clean energy-related devices Minghui," *Arch. Thermodyn.*, vol. 33, no. 4, pp. 23–40, 2012.

[28] A. Bouraiou, M. Hamouda, A. Chaker, S. Lachtar, A. Neçaibia, N. Boutasseta, and M. Mostefaoui, "Experimental evaluation of the performance and degradation of single crystalline silicon photovoltaic modules in the Saharan environment," *Energy*, vol. 132, pp. 22–30, 2017.

[29] N. Padmavathi, A. Chilambuchelvan, and N. R. Shanker, "Maximum Power Point Tracking During Partial Shading Effect in PV System Using Machine Learning Regression Controller," *J. Electr. Eng. Technol.*, vol. 16, pp. 737–748, mar 2021.

[30] K. Deb and R. B. Agrawal, "Simulated Binary Crossover for Continuous Search Space The crossover operator is believed to be the main search operator in the working of a genetic," *Complex Systems*, vol. 9, no. 2, pp. 115–148, 1994.

[31] M. V. Pathan, S. Patsias, and V. L. Tagarielli, "A real-coded genetic algorithm for optimizing the damping response of composite laminates," *Comput. Struct.*, vol. 198, pp. 51–60, 2018.

[32] R. Eberhart and James Kennedy, "A New Optimizer Using Particle Swarm Theory," *Int. Symp. Micro Mach. Hum. Sci.*, pp. 39–43, 1999.

E. Mammeri received bachelor and master degrees (Automatic Control) from Boumerdes university in 2016 and 2018 respectively. He worked as an instrumentation engineer in Groupementtouat gas (GTG) company, Adrar. He is currently pursuing the Ph.D. degree with the Faculty of hydrocarbon and chemistry, university of boumerdes, Algeria. His research interests include renewable energies control, power system control, Photovoltaic energy conversion and storage, battery management systems, optimization methods.

A. Ahriche received his master and PhD degrees in Automatic Control from Boumerdes University in 2008 and 2014 respectively. He worked as Lecturer in the same university from 2008 till now. His research interests include renewable energies control, power sys-

tem control, Photovoltaic energy conversion and storage, battery management systems, optimization methods. He authored and co-authored more than 25 publications in academic journals and proceedings in the Scopus database.

A. Necaibia received Engineer (Automation) and Magister (electrical control) degrees from Annaba University in 2007 and 2009 respectively, and Ph.D. in 2016 from the Department of Electrical Engineering, "20 August 1955" University of Skikda, and the "Habilitation to supervise research" degree in electrical engineering from the Uiversity of Adrar in 2019. He has worked as an automation Engineer at in El Hadjar steel complex (ArcelorMittal), Annaba. He joined the Research unit in Renewable energies in the Saharan Medium URERMS/CDER, Adrar, Algeria in 2011 as an assistant researcher and, currently, he is working as a senior researcher "A". His research interest includes Fractional Order Control, Adaptive Control, Robust Control, Renewable Energy, Photovoltaic Conversion and monitoring, PV system reliability. He authored and co-authored more than 40 publications in academic journals and proceedings in the Scopus database.

A. Bouraiou received Engineer (Automation) and Magister (electrical control) degrees from Annaba University in 2007 and 2011 respectively, and a Ph.D. in 2018 from the National polytechnic school of Oran, and the "Habilitation to supervise research" degree in electrical engineering from University of Adrar in 2020. He has worked as an automation Engineer at Automation Department (Central Maintenance) in El Hadjar steel complex (ArcelorMittal), Annaba. He joined the Research unit in Renewable energies in the Saharan Medium URERMS/CDER, Adrar, Algeria in 2013 as an assistant researcher and, currently, he is working as a senior researcher "A". His research interest includes Renewable Energy Systems control and monitoring, PV system reliability, and industrial process automation. He authored and co-authored more than 40 publications in academic journals and proceedings in the Scopus database.

Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Author Contributions:

E. Mammeri has implemented HPGA Algorithm in addition to GA,PSO and ABC algorithms.
A. Aimad has wrote, reviewed and edited the manuscript.
A. Necaibia was responsible for the Simulation of the PV system
A. Bouraiou has investigate and validate the simulations.

Sources of funding for research presented in a scientific article or scientific article itself

the authors declare no source of funding