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RESEARCH ARTICLE

AN IMPROVED BAT ALGORITHM FOR MORE EFFICIENT AND FASTER MAXIMUM POWER POINT TRACKING UNDER PARTIAL SHADING CONDITIONS

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ABSTRACT

Power and voltage characteristic curves (P-VCC) for PV array modules under Partial Shading Conditions (PSC) will have multiple peaks. The output power of the PV array modules will be extraordinarily decreased if the maximum power point (MPP) is not occurred. To solve this problem, Maximum Power Point Tracking (MPPT) control methods have been designed. By using Metaheuristic Approach (MHA) to observe the Global Maximum Power Point (GMPP) is one substitute. The Bat Algorithm (BA), a novel MHA, has newly shown promising results in the MPPT. However, when there are some Local Maximum Power Point (LMPP) around the GMPP, BA might not be able to track the GMPP. In addition, a further improvement in tracking time by reducing it, is required to account for the rapidly changing irradiance. Hence, it is suggested to combine BA with Cuckoo Search's (CS) abandoning mechanism to enhance BA's tracking capabilities. The suggested technique, when compared to BA, offers higher accuracy, and can enhance convergence speed by roughly 35% according to simulation data.

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INTRODUCTION

Lately, the realization of renewable energy sources like wind, solar, tidal, etc has been gradually increased. Among all these, solar is commonly used source. In practice, the solar modules are connected in series. When some of the modules are partially shaded due to cloud, building, etc, then the shaded solar modules limit the current and voltage of the entire PV module which can reduce the efficiency of the system. Some methods are already used to track the maximum power point such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Great Wolf Optimization (GWO) etc. However, they fail to explain the Global maximum power point of the shaded solar panel efficiently. As per the International Energy Agency's (IEA) market prediction, solar energy is expected to expand at the highest rate and constitute approximately one-third of the world's total power generation by 2023. As a result, it is now driving the growth of renewable energy Systems for producing photovoltaic power convert solar energy into electrical energy. Single photovoltaic (PV) modules have a nonlinear voltage-current relationship, which results in a set of maximum power points that change with temperature and irradiance. PV modules are connected in series in real-world applications. Some of these modules will limit the current and voltage of the entire PV panel when they are partially obscured by clouds, buildings, and other objects, which significantly lowers the system's efficiency. Hot spots will develop in partially shaded areas under PSC, which will accelerate component aging. Between every PV module, to minimize. Nevertheless, this approach will result in several peaks on the overall P-V characteristic curve (P-VCC). Thus, under different situations (with or without PSC), the goal of MPPT controller is to extract the GMPP. Creating advanced control algorithms (ACA), which are divided into deterministic-based MPPT and artificial intelligence-based (AI) MPPT, is one popular.

The deterministic-based MPPT category includes popular industrial algorithms including incremental conductance (InC), hill climbing (HC), and perturb and observe (P&O). P&O offers the benefits of quick tracking and simple installation. It cannot be guaranteed to attain the GMPP under PS, though, as it tends to swing about the maximum power point. The oscillation can happen quickly if the perturbation magnitude is not selected carefully. Reducing oscillation around the maximum power point (MPP) has been the subject of numerous attempts. One strategy to enhance P&O is to switch from a fixed step size to an adjustable one, as described in. In contrast to the conventional P&O approach, an adaptive P&O is based on the derivative of power concerning voltage, which has faster dynamics and better stability. In addition, the trigonometry rule is coupled with the InC approach to shorten the time it takes to reach GMPP. Even still, the GMPP of P-VCCs with numerous peaks remains unattainable with these refined techniques. To achieve GMPP for P-VCC with numerous peaks, AI-based MPPT is a potential method. The three types of AI-based MPPT are artificial neural networks (ANN), fuzzy logic (FL), and meta-heuristic approaches (MHAs). The duty cycle is calculated using the FL approach in conjunction with InC, taking into account the input variables and the rule base. Determining the linguistic words, membership functions (MF), and rule basis is necessary before building the FL. The quantity of linguistic terms affects accuracy. The results will be more accurate the more linguistic terms that are employed. However, there is a computational overhead associated with using more linguistic terms Furthermore, designers need to be somewhat familiar with the P-VCCs that need to be tracked to comply with the requirements of the MF and rule base. An ANN to monitor the GMPP under PS was presented by Kota et al. This approach demonstrates an impressive tracking time. Nonetheless, the training data has a significant impact on this method's accuracy. Additionally, additional data collection is required for other PS situations.

The MHA is made to fully adjust to every problem by solving an optimization problem. Since P-VCCs are typically unknown in advance, an MHA is ideally suited to solve the GMPP problem under PS conditions. Two traits are shared by all MHAs:

- They draw inspiration from nature, utilizing concepts from physics, biology, and ethology.
- To get out of local optimal locations, they employ stochastic components.

Particle swarm optimization (PSO) is the most widely used MHA for MPPT because of its simple implementation. But for vast search spaces, PSO suffers from a long tracking time.

Nevertheless, this process necessitates figuring out a few constants depending on the relationship between maximum power and duty cycle. Other MHAs for MPPT are now being sought after by researchers. The GMPP under PS is obtained by the artificial bee colony (ABC) algorithm, which performs better at convergence than PSO. But in a situation where there are not many bees, ABC will become stuck in a local maximum power point (LMPP). Jiang and Maskell created the ant colony optimization (ACO) protocol utilized in MPPT. When tested in both uniform and shade pattern situations, ACO's performance is comparable to that of PSO.

Tey et al have presented an improved differential evolution for obtaining GMPP under PS. This method's reduced control parameter count allows for quick convergence and easy implementation. Nevertheless, the particle lacks a memory system for the positions and motions it has encountered thus far in the program. The tendency is for it to remain at the local maximum. Inspired by the introspective habits of Cuckoo, Xin-She Yang and Suash Deb presented the Cuckoo Search (CS) in 2009. In comparison to PSO, the algorithm was shown to be more successful. Its pace of convergence is sluggish, nevertheless. The echolocation method used by bats serves as the inspiration for Xin-She Yang's proposed Bat Algorithm (BA). Before reaching the GMPP, particles can exhibit better dynamic behaviour and fewer oscillations because of the combination of global exploration and local search mechanisms. Reports in detail the application of BA for MPPT to reach GMPP under PS. It has been established that BA performs better for MPPT than PSO and P&O. The disadvantage of BA is that, in some situations, it can be readily trapped in an LMPP, which can lower the PV system's output power. Therefore, this paper's primary contribution is to increase the tracking duration and tracking efficiency for MPPT, thereby improving the performance of the original BA approach. The abandoning mechanism from CS and BA are combined in the proposed modified bat algorithm (MBA). It is verified by both simulation and experimental data that the suggested approach may considerably increase the convergence time and accuracy when compared to the original BA. This paper is organized as follows. The fundamentals of BA will be briefly introduced in the next section. The third portion will provide an overview of the MBA approach. In the fourth section, the simulation findings and parameter choices will be further explained. The experimental results are shown in the fifth section. Lastly, the sixth section contains the conclusion.

MATERIALS AND METHODES

BAT ALGORITHM: BA is a nature-inspired Metaheuristic Optimization Algorithm (MOA) developed by Xin-She Yang in 2010. It is inspired by the echolocation behaviour of bats and resolve optimization problems. In nature, bats use echolocation to navigate and hunt for prey. They emit ultrasonic pulses and listen to the echoes to detect objects in their environment. This process involves emitting pulses at a certain frequency, listening to the echoes, and adjusting their flight path based on the feedback received. The BA mimics this behaviour by modelling each bat as a potential solution to an optimization problem. The algorithm starts with an initial population of bats, each representing a potential solution. These bats fly randomly in the search space, emitting ultrasonic pulses at a certain frequency. The frequency of the pulse determines the distance the bat travels in the search space, and the intensity of the pulse represents the quality of the solution associated with that bat. In the context of the Maximum Power Point Tracking (MPPT) technique, the bat algorithm can be employed to optimize the operation of photovoltaic (PV) systems by continuously adjusting the operating point of the PV panels to extract maximum power from the solar irradiance. The bat algorithm helps in dynamically tracking the maximum power point (MPP) under varying environmental conditions like changes in solar radiation and temperature.

- The bats fly in position $X_n$with speed V_n, and they regulate the pulse emissivity $r_n$in the internal of [0, 1] as stated by the degree of proximity to the prey and automatically regulate the frequency of the pulse.
- The loudness emitted by the bats compared to the initial loudness A_0 to minimum A_{min} gradually reduce by increasing the number of iterations.

From the above rules, the pulse frequency of the nth bat, $f_n$is defined as

fn= fmin+ (fmax− fmin)δ, (1)

where f_{min} and f_{max} refer to the minimum and maximum frequencies, respectively, and δ is a random number in the range between 0 & 1.

The speed $V_n$for the nth bat is expressed as (2).

Vni= Vni−1 + (Xni−1 − Xbest) fn, (2)

wherek is the iteration number, X_{best} is the current global optimal value, and $X_n^i$is the position of n th bat in the ith iteration, and it is updated based on (3) and (4).

Xni= Xni−1 + Vni, if rni≤ δ_1 (3)

Xni= Xbest+ 5 Ai−1, if rni>δ_1, (4)

In the iteration i, when r_n is the nth bat's pulse emissivity located A^i is the average loudness of the bats in the ith iteration, δ_1 is a random number between -1 and 1, and $\boldsymbol{\alpha}$ is a random value between 0 and 1. When bats enter the local search, it is indicated by $r_n^i>\delta_1$. The more iterations there are, the more the pulse's emissivity and loudness are changed. The loudness drops and the pulse emissivity rises when the optimal solutions remains higher to the present solution and A^i_n is greater than the random number δ_2. When the pulse emissivity and loudness are updated, it shows that the bat is looking for prey, and getting closer to it. Therefore, the loudness and pulse emissivity of the nth bat in the ith iteration are

$A^i_n = \beta A^{i-1}_n$, $r_n^i = r_n^0[1 - \exp(-\Gamma i)]$, (5)

whereβand Γare constants. The use of α in the BA is similar to the cooling factor of the simulated annealing algorithm [51], [52]. The value ranges are defined as 0 <β<1 and Γ>0, respectively. The trend of loudness and pulse emissivity with the increased number of iterations can be expressed as follows:

Ani→ Amin,rni→ ri0, as i→ ∞ (6)

It is achievable to draw various conclusions from (3) to (6). Bats will more easily enter global exploration in the early stages. Bats will explore in the opposite direction of the optimum solution at the point, which is important for them to leap out of the local optimal solution. Bats are more likely to show up in the local search later on. At this point, the search range will gradually converge in accordance with the loudness, beginning with the current global best solution.

The convergence criterion as defined in (7) is checked to ensure that the global maximum point (GMP) is reached:

$|X_{best}- X_n^i| \leq \varepsilon$, n = 1...N, (7)

Where εis the tolerance value and N is number of bat. The convergence condition is achieved when the gap between each bat and the current best position is less than the ε. In an MPPT case, the voltage V is the bat position X and the power P is the fitness of bat f (X). The flowchart of BA is shown in figure 1

PROPOSED MODIFIED BAT ALGORITHM

The proposed bat algorithm refers to any modifications or enhancements made to the original bat algorithm to improve its performance or adapt it to specific optimization problems. Researchers often propose variations of the bat algorithm by introducing new mechanisms, parameters, or strategies aimed at addressing limitations or enhancing its effectiveness for certain applications. These modifications can involve changes in the echolocation behaviour, frequency tuning, or movement strategies of the bats. In the context of the MPPT technique, a proposed bat algorithm would involve adapting the original bat algorithm to specifically target the optimization of maximum power point tracking for photovoltaic systems. To shorten the tracking period, this technique combines the CS abandoning mechanism with BA. Here, the CS algorithm is briefly reviewed to provide a better grasp of the abandoning mechanism. CS draws inspiration from its unique approach to brooding. To boost the likelihood that their eggs will hatch, cuckoos lay their eggs in the nests of other birds. Nevertheless, the host bird may discover the cuckoo's eggs and may either kill or abandon them.

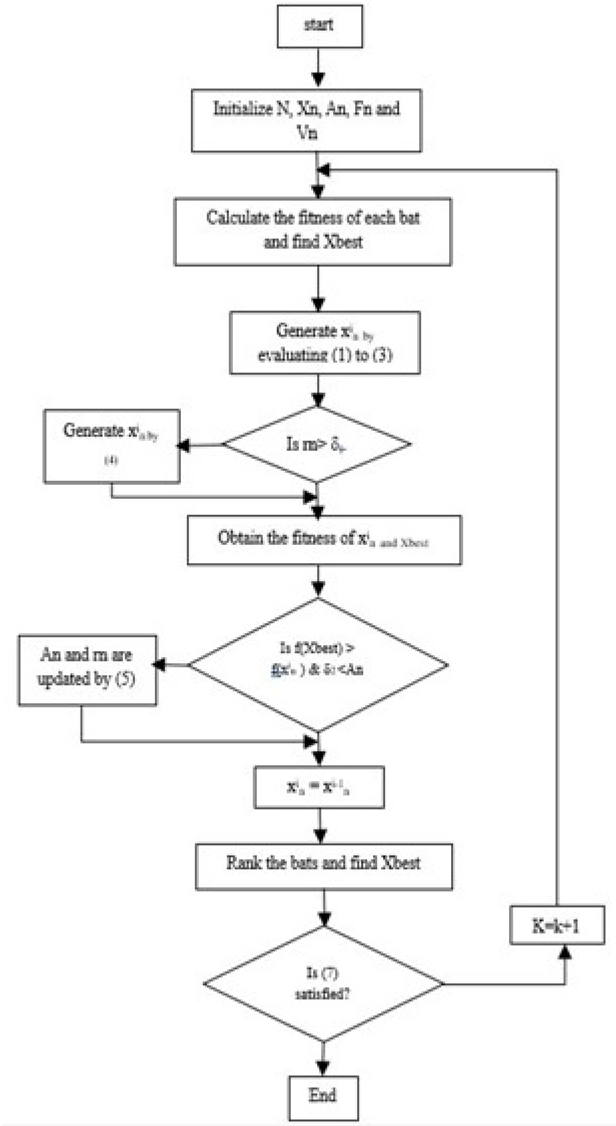

Fig 1. BA flowchart

There are a fixed number of host nests in the ecosystem and the probability of alien eggs being discovered by the host bird is $P_a \in[0,1]$. The nest will be destroyed if the host bird locates the alien eggs. The host bird then constructs a new nest somewhere else. It should be noted that new solutions can be used to approximate this by switching a fraction (P_a) of N nests. Whenever BA particles has been updated using step (1) through (5), the abandonment mechanism is activated instantly. First, the order of $X_n$is sorted in ascending order in the abandoning mechanism. Afterward a number of N_r ($N_r = P_a \times N$) particles are dropped. To restore and equal quality of particles, we first calculate the distance between the global best position $X_{best}$and the abandoned bat position X_{an}, ΔX_a, which is defined in (8)

$$\Delta Xan= |Xbest-Xan| \tag{7}$$

The value of ΔX_{an}will be compared with a tolerance value, ε_1. If $\Delta X_{an}$is equal to or smaller than ε_1, it implies that $X_{an}$is very close to X_{best}. Hence, the replenishing particle, $X_{n,new}$is set to X_{best}. On the other hand, if $\Delta X_{an}$is larger than ε_1, it implies that $X_{an}$is far away from X_{best}. Hence, we proposed to set the replenishing particles to have the form of (9)

$$Xn, new= Xbest\pm \Delta Sn \tag{8}$$

$S_n$is defined in (10).

$$\Delta S_n= \Delta X_{an}\cdot N_c\cdot \delta_3, \tag{10}$$

whereδ_3 is the random number in the range between 0 and 1 and $N_c$is a cooling factor, whose formula is defined as (11).

$$N_c=1/n \tag{11}$$

To determine whether ΔS_nshould be added to or subtracted from X_{best}, the following criteria are evaluated. Assume that X_{nb}represents the best solution of the current iteration. If $X_{best}>X_{nb}$, it means $X_{nb}$is at the left side of X_{best}. Hence, the replenishing particle, $X_{n,new}$is set as (12)

$$Xn,new= Xbest- \Delta Sn \tag{12}$$

placing the replenishing particle $X_{n,new}$according to (12), all the particles are constrained at the left subspace, which can potentially speed up when $X_{best}\leq X_{nb}$, it means $X_{nb}$is at the right side of X_{best}. Therefore, $X_{n,new}$is set as (13) to explore the right side of X_{best}

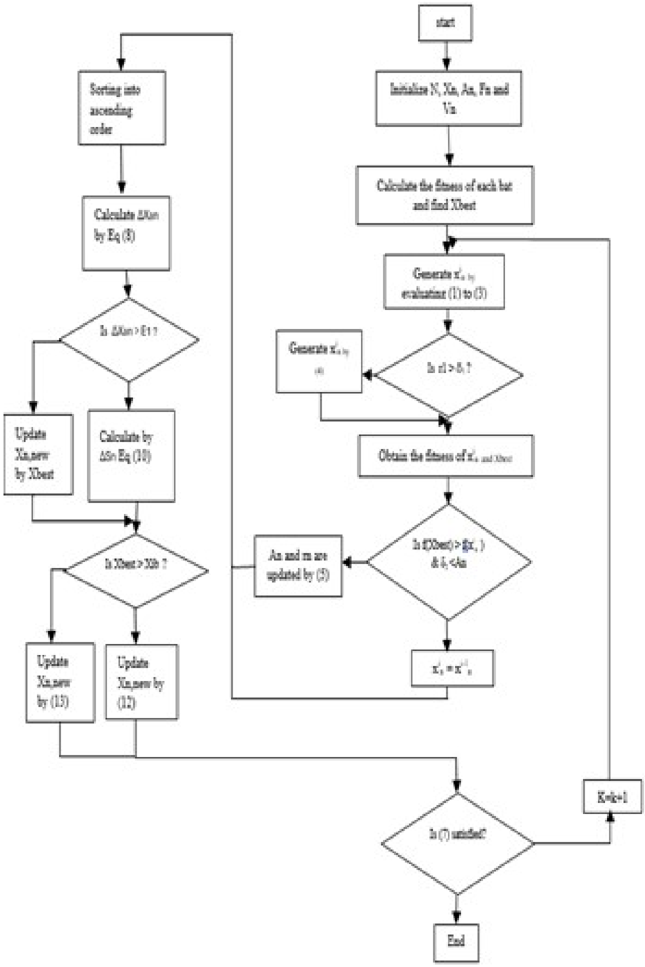

Fig. 2. MBA flowchart

$$Xn, new= Xbest+ 4Sn \tag{13}$$

Maximum Power Point Tracking: Maximum Power Point Tracking (MPPT) is a technique used in photovoltaic (PV) systems to ensure that the solar panels operate at their maximum power output under varying environmental conditions such as changes in sunlight intensity and temperature.

The goal of MPPT is to continuously adjust the operating voltage and current of the PV array to maintain it at the maximum power point (MPP), where the product of voltage and current is maximized. MPPT is crucial for optimizing the energy harvest from solar panels and improving the overall efficiency of PV systems. Without MPPT, the output power of the solar panels would vary widely with changes in environmental conditions, leading to energy losses and suboptimal performance.

Global Maximum Power Point: In MPPT of PV systems under partial shading conditions, the global maximum power point refers to the optimal operating point at which the overall power output of the photovoltaic array is maximized, considering the effects of partial shading on individual solar cells or panels. Unlike traditional MPPT techniques that assume uniform irradiance across the entire PV array, addressing partial shading requires identifying the global maximum power point by considering the complex interactions between shaded and unshaded regions. The global maximum power point under partial shading conditions may shift dynamically due to changes in shading patterns, solar angles, and environmental factors. Therefore, MPPT algorithms must be adaptive and capable of quickly responding to variations to ensure optimal performance and maximize energy harvest from the PV system.

Local Maximum Power Point: In MPPT techniques for PV systems under partial shading conditions, the concept of local maximum power point refers to the optimal operating points within individual shaded regions or segments of the PV array. Locating local maximum power points under partial shading conditions is crucial for maximizing the overall energy harvest from the PV system.

Since shaded areas may have different optimal operating points compared to unshaded regions, traditional MPPT techniques may struggle to accurately track these local maxima. Advanced MPPT algorithms tailored for partial shading scenarios utilize techniques such as dynamic perturbation and multi-objective optimization to identify and track local maximum power points effectively. These algorithms dynamically adjust the operating conditions of individual segments or bypass diodes within the PV array to optimize power output while mitigating the effects of shading. By identifying and optimizing local maximum power points, MPPT techniques for PV systems under partial shading conditions can improve energy harvest efficiency and mitigate power losses caused by shading effects.

SIMULATION AND RESULTS

Firstly, the proposed method is evaluated through MATLAB simulation. The number of bats (or ‘‘particles’’) is chosen to be ten. Since the converter only has one control parameter (i.e. the duty cycle) to be varied, these ten bats need to be executed sequentially for the applications of MPPT. For a fair comparison, all the initial voltage values of BA and MBA are set at 90%, 80%, 70%, 60%, and 50% of the open circuit voltage (215 V), respectively. Each waveform runs 200 times.

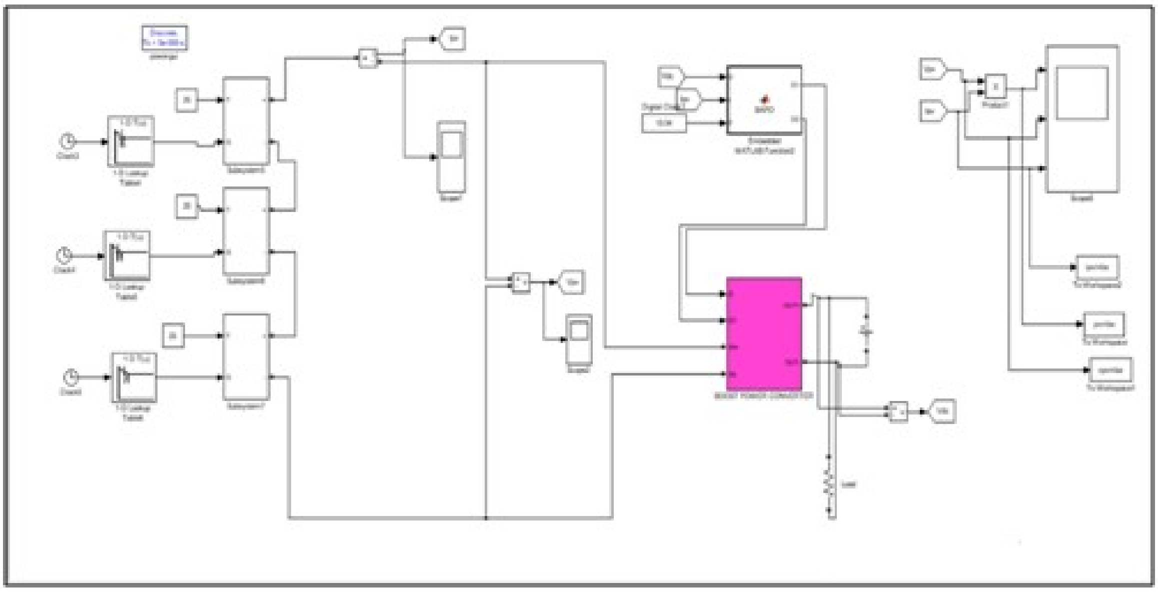

Fig 3. Simulation of Proposed algorithm

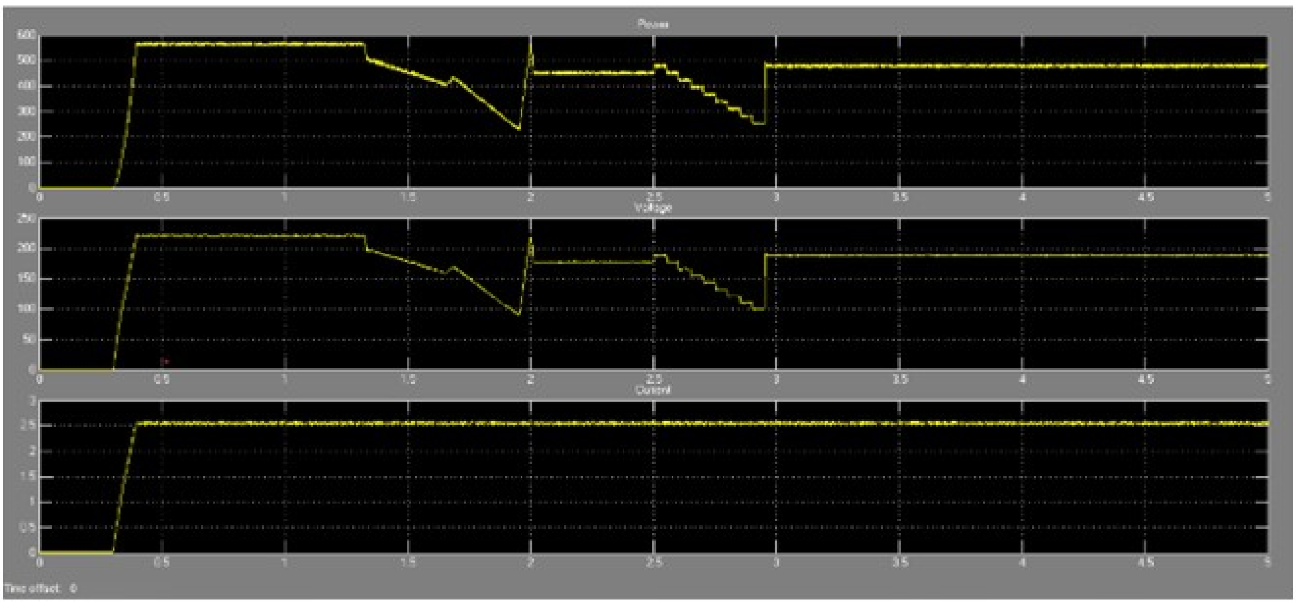

Fig 4. Output waveforms of Power, Voltage and Current Signals for BA

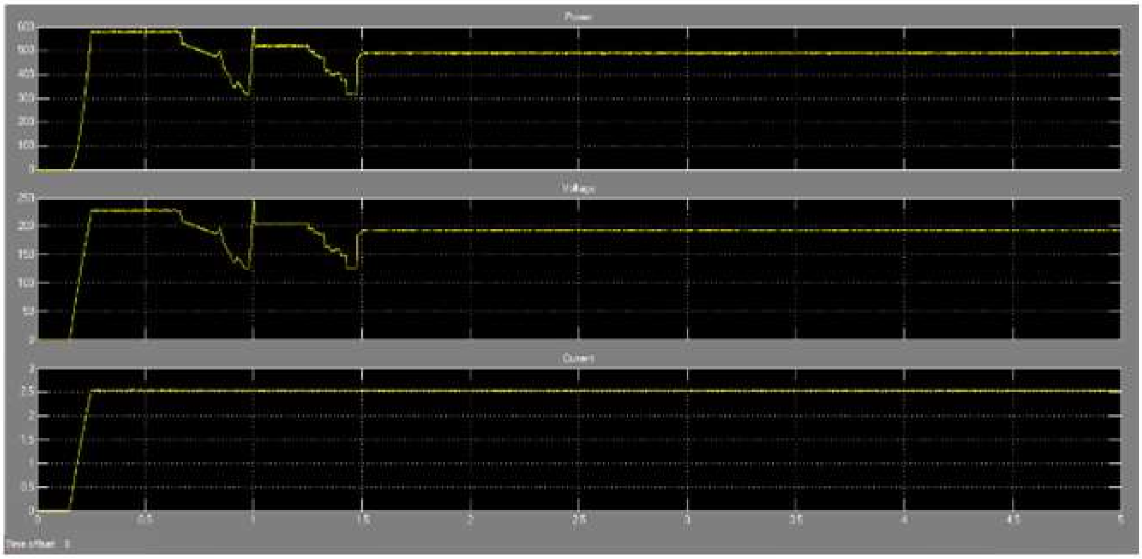

Fig 5. Output waveforms of Power, Voltage and Current for MBA

Table 1. BA and MBA power voltage characteristics comparison

Parameters	Voltage(volts)	Power(watts)	Stability time(sec)
MBA	175	420	1.5
BA	172.6	410	3.0

Table 2. BA and MBA current characteristics comparison

Parameters	Current(amps)	Stability Time(sec)
MBA	2.35	0.2
BA	2.34	0.35

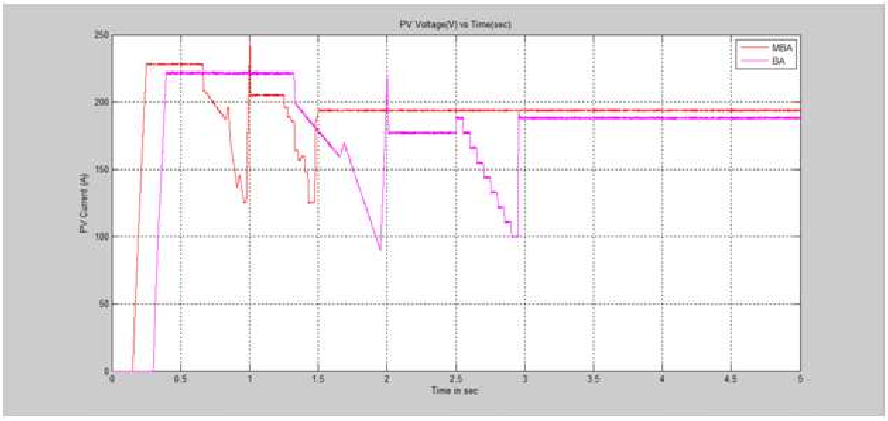

Fig 6. Comparison of Voltages of MBA and BA

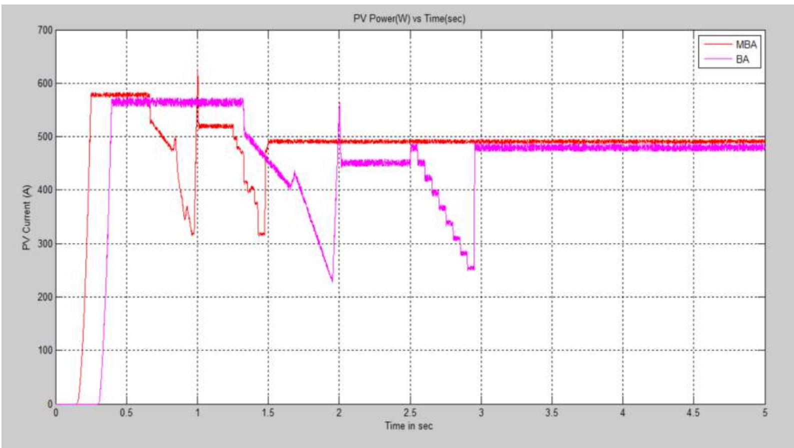

Fig 7. Comparison of Power for MBA and BA

The DC-DC converter is an interleaved boost converter that can reduce the ripple currents and increase efficiency and reliability. The MPPT algorithms are implemented at 'BAPO' block. The maximum input voltage is 215 V, and the load voltage is maintained at 450 V. The load is a resistive load and its voltage is regulated by a voltage source. Figure (3) shows the simulation of the proposed method by implementing the proposed MPPT algorithm that is MBA. This block control duty cycle and give accurate results and tracking time will reduce. Compared to BA, the MBA algorithm stable the voltage and power signals with in less time Fig (4) and (5) give shown as the output waveforms of Power, Voltage and Current signals of both MBA and BA.

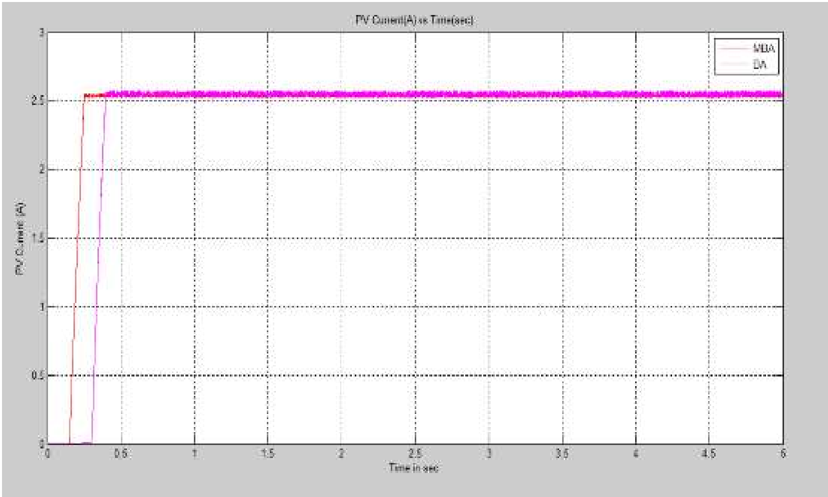

Fig 8. Comparison of Current for MBA and BA

CONCLUSION

This work uses the CS abandoning mechanism to enhance the PV system's BA for MPPT. The abandonment mechanism added to BA can reduce tracking time and raise the likelihood of exiting the LMPP by keeping the high-quality solution and discarding the subpar solution. The testing findings demonstrate that the suggested method's static tracking accuracy is higher than 99.08%. Furthermore, as compared to a BA, an MBA can improve dynamic tracking efficiency by about 2.5% and reduce tracking time by nearly 35%. These differences can be attributed to the following factors. When opposed to the BA, the MBA shows far reduced power and voltage variations. Furthermore, whenever a power change is detected, the MBA settles to the GMPP faster. This case study shows that the MBA can track the GMPP efficiently and in a lot less time.

ABRIVATIONAS

BA: Bat Algorithm
CS: Cuckoo Search
FSCC: Fractional Short-Circuit Current
GA: Genetic Algorithm
GMPP: Global Maximum Power Point
LMPP: Local Maximum Power Point
MBA: Modified Bat Algorithm
MPPT: Maximum Power Point Tracking
PAO-APO: Particle Swarm Optimization-Adaptive Perturb and Observe
PO: Perturb and Observe
PSO: Particle Swarm Optimization
PSC: Partial Shading Condition
PV: Photovoltaic system

REFERENCES

Ghasemi, M. A. A. Ramyar, and H. Iman-Eini, ''MPPT method for PV systems under partially shaded conditions by approximating I–V curve,'' IEEE Trans. Ind. Electron., vol. 65, no. 5, pp. 3966–3975, May 2018.

Bingöl O. and B. Özkaya, ''Analysis and comparison of different PV array configurations under partial shading conditions,'' Sol. Energy, vol. 160, pp. 336–343, Jan. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0038092X17310769

Li, H. D. Yang, W. Su, J. Lü, and X. Yu, ''An overall distribution particle swarm optimization MPPT algorithm for photovoltaic system under partial shading,'' IEEE Trans. Ind. Electron., vol. 66, no. 1, pp. 265–275, Jan. 2019.

Ishaque, K. Z. Salam, M. Amjad, and S. Mekhilef, ''An improved particle swarm optimization (PSO)–based MPPT for PV with reduced steady-state oscillation,'' IEEE Trans. Power Electron., vol. 27, no. 8, pp. 3627–3638, Aug. 2012.

Ghasemi, M. A. H. M. Foroushani, and M. Parniani, ''Partial shading detection and smooth maximum power point tracking of PV arrays under PSC,'' IEEE Trans. Power Electron., vol. 31, no. 9, pp. 6281–6292, Sep. 2016

Ahmed J. 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.

Ahmed J. and Z. Salam, ''A maximum power point tracking (MPPT) for PV system using cuckoo search with partial shading capability,'' *Appl. Energy*, vol. 119, pp. 118–130, Apr. 2014. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261914000026

Yang X. and A. Hossein Gandomi, ''Bat algorithm: A novel approach for global engineering optimization,'' *Eng. Computations*, vol. 29, no. 5, pp. 464–483, Jul. 2012, doi: 10.1108/02644401211235834.

Tey, K. S. S. Mekhilef, and M. Seyedmahmoudian, ''Implementation of bat algorithm as maximum power point tracking technique for photovoltaic system under partial shading conditions,'' in *Proc. IEEE Energy Convers. Congr. Exposit. (ECCE)*, Sep. 2018, pp. 2531–2535.

Kaced, K. C. Larbes, N. Ramzan, M. Bounabi, and Z. E. Dahmane, ''Bat algorithm based maximum power point tracking for photovoltaic system under partial shading conditions,'' *Sol. Energy*, vol. 158, pp. 490–503, Dec. 2017. [Online]. Available: http://www.sciencedirect.com/science/ article/pii/S0038092X17308599

International Energy Agency. According to Latest IEA Market Forecast. (2018). *Modern Bioenergy Leads the Growth of All Renewables to 2023*. [Online]. Available: https://www.iea.org/newsroom/ news/2018/october/modern-bioenergy-leads-the-growth-of-allrenewables-to-2023-accord-.ing-to-latest-.html

Nadeem, F. S.M.S. Hussain, P.K. Tiwari, A.K. Goswami and T. S. Ustun, ''Comparative review of energy storage systems, their roles, and impacts on future power systems,'' *IEEE Access*, vol. 7, pp. 4555–4585, 2019.

Koraki D. and K. Strunz, ''Wind and solar power integration in electricity markets and distribution networks through service-centric virtual power plants,'' *IEEE Trans. Power Syst.*, vol. 33, no. 1, pp. 473–485, Jan. 2018.

International Energy Agency. (2019). *The Latest Trends in Energy and Emissions in 2018*. [Online]. Available: https://webstore.iea.org/globalenergy-co2-status-report-2018

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