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Cuckoo Search Optimization Technique Based MPPT Design for PV System Under partial Shading Condition

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Abstract:

This study uses a Cuckoo Search optimization algorithm technique to offer a maximum power point tracking (MPPT) design for Photo Voltaic system. A powerful optimization approach is urgently needed to capture the global peak of partially shaded solar arrays rather than the local peaks because many peaks are created in the power to voltage characteristics of such arrays. The necessary optimization technique needs to converge quickly and correctly identify the global peak. Multiple Local Maximums (LM) and a Global Maximum (GM) could been seen on the P-V and I-V curves when partial shading (PS) is present. Cuckoo Search optimization algorithm can provide outstanding dynamic response and also a rapid convergence speed by dynamically switching between both the exploratory and exploitative phases all through the Maximum power point tacking process. For different shading patterns, numerous simulations were conducted in the Matlab/Simulink system to evaluate the viability of the proposed approach. The simulation results show how accurate the suggested plan is for managing the energy that is available at the photovoltaic panels' output. Results from experiments support the suggested approach's effectiveness in tracking global peaks and its maximum reliability in handling partial shading.

Keywords —**Cuckoo Search optimization algorithm (CSO), maximum power point tracking (MPPT), Photovoltaic (PV), Partial shading (PS**

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I. INTRODUCTION

Renewable energy sources like wind and solar have made significant expansions into a wide range of engineering applications as a result of environmental concerns associated with the use of conventional energy generation sources. The potential for non-conventional energy sources is considerable, and they have several advantages over traditional energy sources. Numerous sources, including solar, wind, geothermal, biomass, and water, are used to provide renewable energy. They are able to generate power in big amounts over an extended period of time without releasing greenhouse emissions. Both direct and indirect uses are possible for the sun's renewable energy sources [1]. Two different technologies are related to the direct use of solar energy through sensors: the first, solar thermal energy, which provides calories, and the second, photovoltaic energy, which generates electricity. The most promising renewable energy technology is photovoltaic (PV) technology. The configurations of photovoltaic systems include standalone, grid-connected, and hybrid systems [3]. The majority of the time, photovoltaic (PV) devices capture light from sun. The output of PV systems is heavily influenced by the weather. The results could vary depending on the building and cloud colour [5]. In order to aspire the MPP, the duty cycle of the DC-DC converter is increased or decreased. To attain this goal, the MPPT is necessary to get the most out of PV systems. PV systems behave differently in various weather scenarios.

Multiple Local Maximums (LM) and a Global Maximum can be seen on the I-V and P-V curves when partial shading (PS) is present (GM). Usually, partial shading is caused by clouds, shadows, or uneven illumination. Depending on utilisation, regulated DC electric power is sent to loads using a DC-DC converter. The pulse signal, also known as the duty cycle, provides the control action. To achieve the intended improvement, the controller is built to optimise the duty cycle [8]. We test the performance of the adaptive fuzzy logic controller using four shading patterns (AFLC).

The general features of PV generators vary and depend on a number of variables, particularly the meteorological circumstances, such as solar radiation and ambient temperature as well as the ageing of the PV cells, PS, and uneven lighting [14]. When PV modules are exposed to constant sunshine, a single point of MPP results in a uni-modal P-V characteristic. Some weakly lit cells become reverse bias and transform into receiving elements when a portion or the entire module is illuminated unevenly. These cells may be destroyed as a result of this "hot spot phenomenon.

To solve this problem, solar modules feature switching devices that protect the cells that become passive [19]. Since bypass diodes are built inside solar modules, partial shadowing causes the P-V characteristic to alter and just become multimodal [17]. The P-V characteristic is characterised by the formation of multiple peaks, including some of the local maximum power points (LMPPs) & one global maximum power point (GMPP). The dispersion of sunshine on the solar power system, the amount of parasitic elements integrated into each photovoltaic module, and the shadow (either uniform or partial) always have an effect on the number of peaks [11].

The electrical efficiency of solar cells is still low despite efforts to improve their technology. Additionally, partial shade has a significant impact on the amount of electricity delivered. Several strategies are provided in the literature to decrease losses brought on by partial shadowing and boost solar panel efficiency. These tactics include system architectures, converter topologies, PV array designs, & MPPT techniques [7]. Adding extra materials makes the system further complicated and consequently more costly, notwithstanding the gains that can be accomplished utilising the very first three techniques. Therefore, by creating MPPT approaches that can manage the partial shade, a fair cost-efficiency compromise can be reached.

The literature presents a number of MPPT methods to address the multimodal P-V characteristic under partial shading circumstances. The intricacy of these methods, the types and numbers of sensors employed, and the implementation tools used differ. MPPT is crucial for maximising the electricity that PV can provide. The algorithms employed in MPPT fall under the categories of primary and secondary power controllers. The first merely optimizes mechanical energy without taking electrical power into account, but the other directly manages the electrical output [10]. The MPP is discovered using the sensorless Hill climbing search (HCS) and incremental conductance (INC), direct power controller methods that use a preset curve to assess power variation. The HCS that is most frequently applied is called perturb & observe (P&O).

In-depth research has done to create a controller that would get the most power possible out of the PV system. These methods include a modest, regular increase in output power. To identify whether an operation is positive or negative, a comparison with the reference voltage is made, and power samples of the current position and its consequences are used. Until the target MPP is reached, this process is repeated. These methods lack the capacity to detect Global Maxima and are less efficient with considerable steady state inaccuracy (GM) [12].

Below is a summary of the study's main contributions.

- For the solar PV system, a unique MPPT technique is presented to address the PS and CPS problem. Under PS and CPS circumstances, it can successfully track the GM. Additionally, it takes less iterations to approach GM and avoid energy loss.
- Experiments and statistical analyses comparing the suggested technique to previous meta-heuristic MPPT techniques verify its applicability. With the suggested method, we are able to tackle CPS with 100% GM tracking capability and power conversion efficiency up to 99.7%.

The remainder of the paper is structured as follows. The introduction and related material are in Section 1. Section 2 introduces the electrical characteristics of PV models. CS MPPT is suggested in Section 3. The optimization formula for the suggested Cuckoo Search optimization algorithm approach is applied in Section 4. Results of suggested algorithms are done in section 5, along with discussions of connected topics. Some closing thoughts are presented in Section 6.

II .PROPOSED SYSTEM

2. PV model characteristics for partial shading

2.1. PVArray Model

A detailed PV model is necessary to optimise the core design of a PV system by considering the effects of climate, irradiation ratios, thermal dissipation of Solar array, as well as the interconnection of series - parallel module to build an array. Figure 1 shows the circuitry of a photovoltaic cell. The section outlined by red dotted line represents the perfect PV cell, which acts as a Dc voltage source. In a standard method of the PV cell, the interface resistant and resistance value of a diode are mixed in series - parallel to imitate the PV cell's real behaviour. Using a single diode model, the analogous circuit of a PV cell is displayed in Fig. 1.

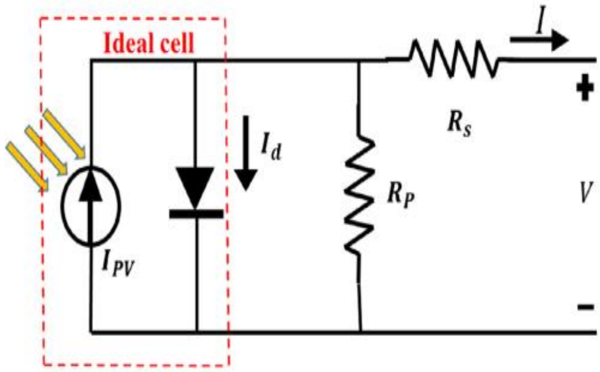

fig.1. PV cell equivalent circuit single-diode model

A PV system is composed of numerous PV modules connected in series and parallel, respectively, to increase voltage and boost current. Owing to the presence of bypass diodes, the P-V characteristic curve in PSCs exhibits several peaks, also known as local and global maximum points. Each PV module's parallel placement of bypass diodes lessens the risk of hot spots in PSCs. when the shadowed modules acts as a demand rather than providing power.

The output in the form of current is given by Eq. (1)

$$I = I_{pv} - I_0\left(\exp\left(\frac{V+R_S I}{V_t \alpha}\right) - 1\right) - \frac{V+R_S I}{R_S} \quad (1)$$

The following definitions pertain to the symbols used in the model:
I_{PV} : PV source current;
R_S : The total resistance caused by all the elements in the course of a current should be as minimal as possible;
R_P: to depict the leakage out across P-N junction, that should ideally be as wide as feasible;
I : difference between both the diode current ID and the photocurrent I_{PV}

When T is the temperature coefficient and G is the irradiation level, equations (2), (3), and (4) are used to calculate the PV cell current, saturation current, and thermal voltage.

$$I_{pv} = \left(I_{pv,n} + K_1(T - T_n)\right)\frac{G}{G_n} \quad (2)$$

Saturation current is given as,

$$I_0 = \frac{(I_{SC}+K_1(T-T_n))}{\exp\left(V_{OC}+\frac{K_v(T-T_n)}{aV_t}\right)-1} \quad (3)$$

Thermal voltage is given as,

$$V_t = \frac{N_sKT}{q} \quad (4)$$

PV systems are made up of a grid of PV cells. Current I is improved by the parallel cell combination while voltage V is added by the series cell arrangement. The number of parallel cells is Np, whereas the number of series cells is Nm. Eq.(1) is transformed into Eq.(5).

$$N_pI_{pv} - N_pI_o(\exp\left(\frac{V+R_{seq}I}{N_MV_Ta}\right) - 1) - \frac{V+R_{seq}I}{R_{peq}}$$

(5)

Table 1: The specifications of the components used in solar systems.

S. No	Parameters	Values
1	V_{DC}	330 V
2	L	2.85 mH
3	C_{OUT}	$120\mu F$
4	C_{IN}	$47\mu F$
5	V_{UG}	220 V
6	f_S	10 KHz
7	ΔV_{DC} and ΔV_{MP}	1 %
8	t_S	0.01S

The primary issue with PV MPPT approaches has been partial shading (PS), which considerably lowers the system's efficiency. MPPT methods are developed to address this issue. Global and local maxima cannot be distinguished by conventional gradient-based MPPT techniques like P&O and IC. These methods can only be used on a single point, and the decision is made solely based on whether the gradient is positive or negative. The effectiveness of these gradient-based approaches is severely hampered by PS's many peak locations on the curves. The GM can be located using bio- The

Table 2: characteristics of "SunPower SPR-315EWHT-D

Description	SunPower SPR-315E-WHT-D
Maximum power (P_{MAX})	315.072 W
Voltage at MPP (V_{MAX})	54.7 V
Current at MPP (I_{MAX})	5.76 A
Short Circuit Current (I_{SC})	6.14 A
Open circuit Voltage (V_{OC})	64.6 V
Temperature coefficient of V_{OC}	-0.176mV/K
Temperature coefficient of I_{SC}	3.5mA/K
Temperature coefficient of power	-0.38%/K
Peak Efficiency	19.30%

The GM can be located using bio-inspired optimization approaches, which have been successfully used to PV MPPT applications. The electric properties of the "SunPower SPR-315EWHT-D" PV array are shown in Table 1.

A system with four modules connected in series (4S configuration) and two distinct shading styles for their P-V curves is shown in the figure 2.

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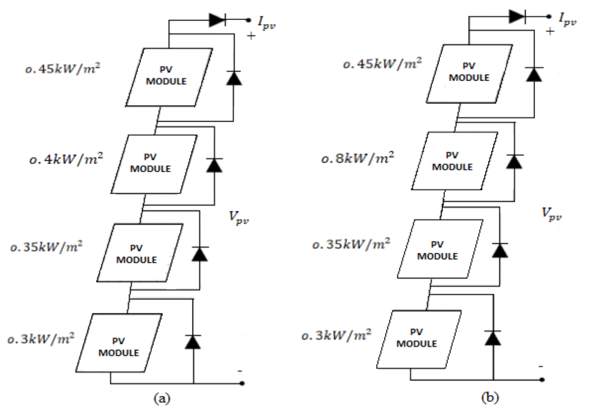

Fig.2. 4S configuration under different shading patterns.

3 Cuckoo Search optimization algorithm overview

The Cuckoo Search optimization algorithm (CSO) was based on the Archimedes principle, which is regarded as a fundamental law of physics. The weight of the fluid expelled from the body is equal to the upward force (known as buoyancy) produced by the liquid on the body. The immersed items in CSO are regarded as the population's people (candidate solutions). The method starts by populating a population with objects, and each object's position is initialised randomly inside the issue search space. After that, the associated fitness function is determined.

Algorithms that maintain their clarity, convenience of use, and desire to prevent local optima generally stand out from the competition. This illustrates why just a few number of new meta - heuristic algorithms continues to have been of attention to the academic world while others frequently vanish despite the increased introduction of new ones. Among other things, optimization methods always need to achieve a balance between exploitation and exploration. The successful algorithms are those that successfully balance a wide range of optimization challenges. But any metaheuristic algorithm's general process can be described as Algorithm1.

Algorithm 1 Pseudo-code of a metaheuristic algorithm

procedure *METAHEURISTIC(params)*
initialize population of candidate solutions
evaluate the initial solutions and remember the best
one
while *termination criteria not met* ***do***
generate new solutions by modifying existing ones
evaluate new solutions
if *new solutions are better than existing* ***then***
update population
end if
remember the best solution found so far
end while
return *the best solution found*
end procedure

While some of the previously stated metaheuristic algorithms are complex, some are also basic yet effective. While some of these algorithms are successfully being updated for better search efficiency, others have a shown track record of solving multiple optimization problems. Additionally, when applied to challenging and highly non-linear optimization situations, fresh concepts are always competing with established techniques like SA, PSO, ABC, and ACO. One algorithm or approach cannot perform better than another on all optimization problems, so there is always opportunity for improvement in current methods as well as opportunities to propose new ones. Because certain algorithms will perform well for some tasks while performing poorly for others.

A successful metaheuristic algorithm, however, may be defined as one that solves most problems satisfactorily or at least well enough. One cannot, however, ensure that a method has been extensively tried and tested due to the broader variety of optimization problems. However, we can verify a metaheuristic's effectiveness using a set of tests that everyone agrees upon. Based on the rationale, this research also makes use of a test environment that is frequently utilised for experimenting and assessing how well the proposed Cuckoo Search optimization algorithm performs.

In Cuckoo Search optimization algorithm, people are the submerged items that make up the population. These things have characteristics like density, volume, and acceleration that are crucial to an object's buoyancy. By using a large test-bed of constrained engineering design issues and unconstrained benchmark functions, we looked at how well CS performed and discovered that its global search capability makes it effective. The procedure of initialising all objects is carried out using the following formula:

$$O_i = l_i + rand \times (u_i - l_i), i = 1,2,3 \ldots \ldots, N \quad (6)$$

where N represents the number of objects, l_i and u_i represent the i^{th} object's lower and upper bounds, respectively. Each object's volume and density can be initialised as follows:

$$den_i = rand, vol_i = rand \quad (7)$$

where rand is a D-dimensional vector having values between [0, 1]. The following formula can be used to determine each object's acceleration:

$$acc_i = lb_i + rand \times (ub_i - lb_i) \quad (8)$$

The baseline fitness performance is calculated, and the item with the best fitness is given the designations $x^{best}, den^{best}, vol^{best}$ and acc^{best}.

Based on the following formula, the updating procedure for an i^{th} object's density and volume is carried out:

$$\mathrm{den}_i^{t+1} = \mathrm{den}_i^t + \mathrm{rand} \times (\mathrm{den}^{\mathrm{best}} - \mathrm{den}_i^t) \quad (9)$$

$$vol_i^{t+1} = vol_i^t + rand \times (vol^{best} - vol_i^t) \quad (10)$$

where rand is a random number and t is the current iteration. An initial collision between the items is followed by an attempt by the object to reach the equilibrium condition. The transfer operator used in this action aids in the transition from the exploration phase to the exploitation phase. The following can be used to write the transfer operator formula:

$$TF = exp\left(\frac{t-t_{max}}{t_{max}}\right) \quad (11)$$

The maximum number of iterations is indicated by t_{max} .

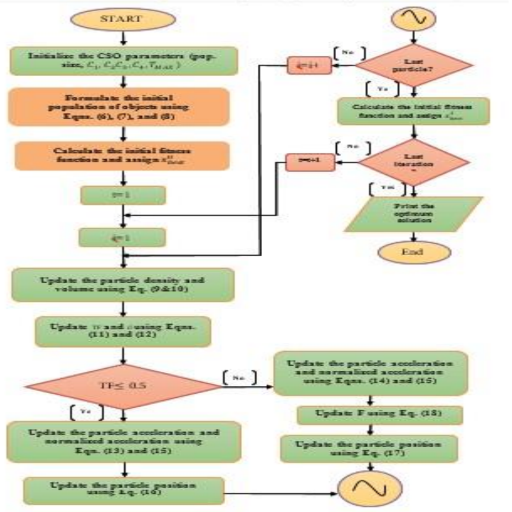

Fig 3. The flowchart of Cuckoo Search optimization algorithm

In this case, TF's value is raised progressively through iterations until it approaches unity. Another component that aids CSO in switching from global to local search is the density lowering factor, which can be expressed as follows:

$$d^{t+1} = exp\left(\frac{t-t_{max}}{t_{max}}\right) - \frac{t}{t_{max}} \quad (12)$$

The value of d^{t+1} declines over time, and effective assignment of this variable aids in striking a balance between supply and demand. Whenever the transference operator is 0.5, the exploring phase represented by the collision of the objects—is taken into account. By choosing a random material,the acceleration of the i^{th} object at iteration t + 1 is given as follow:

$$acc_i^{t+1} = \frac{den_{mr} + vol_{mr} \times acc_{mr}}{den_i^{t+1} \times vol_i^{t+1}} \quad (13)$$

where the concentration, capacity, and velocity of randomized stuff are denoted den_{mr}, vol_{mr} and acc_{mr} .Whenever the value of the transfer operator is higher than 0.5, the exploiting phase of the CS is performed. This phase does not evaluate any object collisions. The following formula can be used to calculate an object's acceleration during the evaluation stage:

$$acc_i^{t+1} = \frac{den_{best} + vol_{best} \times acc_{best}}{den_i^{t+1} \times vol_i^{t+1}} \quad (14)$$

Where the finest object's intensity, capacity, and velocity are denoted by den_{best}, vol_{best} and acc_{best} respectively. Normalizing each particle's acceleration is crucial since it affects the amount each particles will vary in steps. It is possible to express the normalised acceleration as follows:

$$acc_{i-norm}^{t+1} = u \times \left(\frac{acc_i^{t+1} - \min(acc)}{\max(acc) - \min(acc)}\right) + l \quad (15)$$

where l and u are given the values 0.1 and 0.9, respectively, to represent the normalisation range. When an object is distant from the global optima, the acceleration value will be high; this is when the exploration phase is started; else, the exploitation phase is displayed. The formula: is used to modify the path of the i^{th} particle during the exploration phase.

$$x_i^{t+1} = x_i^t + C_1 \times rand \times acc_{i-norm}^{t+1} \times d \times (x_{rand} - x_i^t) \quad (16)$$

On the other hand, the following diagram illustrates how the positions of the particles are updated during the exploitation phase:

$$\mathrm{x}_i^{t+1} = \mathrm{x}_i^t + \mathrm{F} \times \mathrm{C}_2 \times \mathrm{rand} \times \mathrm{acc}_{i-\mathrm{norm}}^{t+1} \times \mathrm{d} \times (\mathrm{T} \times \mathrm{x}_{\mathrm{best}} - \mathrm{x}_i^t) \quad (17)$$

where x_{best} is the coordinates of the best particle, C_1 and C_2 are user-defined constants, T is a variable that relies on the transference operator ($T = C_3 \times TF$), C_3 is a fixed value, and F is the flag used to alter the particle's motion direction.

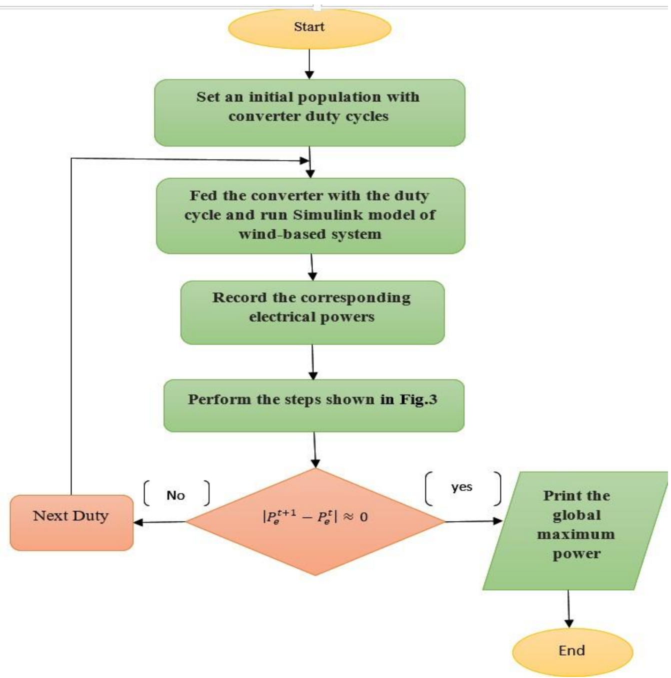

fig.4. flowchart illustrating the processes that would be taken in the planned CSO to create the MPPT

The following formula can be used to calculate the value of F:

$$F = \begin{cases} +1 & P \leq 0.5 \\ -1 & P > 0.5 \end{cases} \quad (18)$$

0

where the operator assigns a random value for P. The optimal solution is then reported after computing the fitness function at the sites of the upgraded particles.

4. The proposed optimization formula

The electrical energy obtained from the PV system is regarded as the fitness function to be maximised when employing the design technique of MPPT installed with the PV system used in this study as an optimisation issue. The following is how the objective function is stated

$$Maximize\ P_e(t) = (\frac{V_{out}(t)}{n} \times (1 - D_{s1}) * I_{in}(t))$$

(19)

where $I_{in}(t)$ is the converter's input current at instant t and $V_{out}(t)$ is the load terminal voltage at instant t. By modifying the duty cycle D_{s1}, the PV system's output power can be managed. The duty cycle is related to the relevant restriction in the following way:

$$D_{s1,min} \leq D_{s1} \leq D_{s1,max} \quad (20)$$

where $D_{s1,min}$ and $D_{s1,max}$ are designated as 0 and 1, respectively, for the minimum and maximum boundaries of the Transistor duty cycle. In order to reflect the MPPT that is preinstalled on the system, we selected a modern meta-heuristic optimizer of the Cuckoo Search optimization algorithm. CSO is chosen because it is straightforward to implement and has fewer governing parameters. It also features a balance between exploration and exploitation, which aids in the algorithm's ability to extract the global optimum. Then, the Suggested CSO's proposed stages for designing the MPPT equipped with a PV system are shown in Fig. 3.

The proposed approach for CSO starts by instantiating a populace using converters switching frequency depending on the superior and inferior limitations specified by the user and then moves on to the following phase. After that, a duty cycle is applied to the converter MOSFET, and the resulting electrical power is noted as P_e^t. The power produced is recorded as P_e^{t+1} after applying the iterative approach depicted in Fig. 3. Based on Eqs. (16) and (17), the duty cycle is altered when $P_e^{t+1} > P_e^t$ (17). The iterative process is continued until the difference between current power and that acquired in the accurate definition converges to zero. Then, the greatest power in the universe is printed.

III. Results and Discussions

As a result, the suggested research project is built to operate under either partial shade or reduced shade conditions. The four PV modules are arranged in series connections. The DC-DC boost converter is used to connect the PV array arrangement, and the MPPT is used to control and optimise it. PID controllers are used in the controlling and optimization techniques, respectively. Through the MPPT, which is linked to the EPSO and PID controller, the maximum power point is monitored. Following optimization, the PID will give the MPPT a controlling function and track the power peak. The bypass diode is used in a PV array with series connections.

Time domain simulation for photovoltaic System MPPT under four shading patterns are carried out using Matlab/Simulink. Results will be compared to FLC and conventional P&O methods to show how much better the proposed adaptive fuzzy logic controller method (ALFC). Three MPPT algorithms' tracking efficiency, tracking speed, and steady-state performance are compared for each shade pattern. Four shading patterns that integrate different shading effects were taken into account for the current work. The positions that the shading patterns are assumed to occupy include the first, second, and third peaks of the global MPP. Under various irradiance patterns, Figure 5 & 6 displays the output power of the SPVS for P&O, FLC, and AFLC methods.

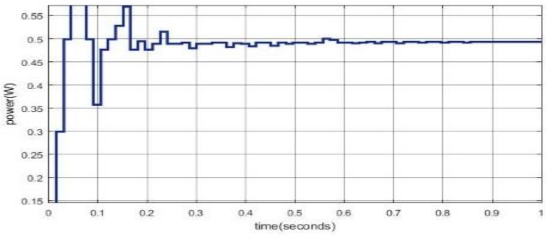

Fig. 5.1characteristics curve of time and power

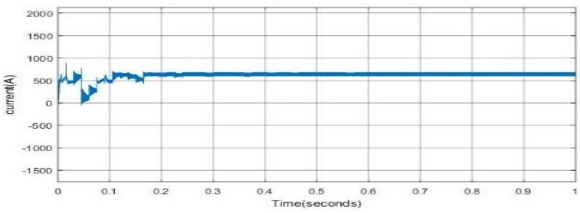

Fig .5.2 characteristics curve of MPPT

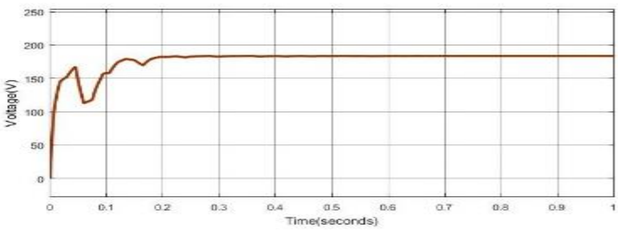

Fig . 5.3 characteristics curve of time and voltage

In the figure 5.3 represent the characteristics curve of time and voltage. The voltage reaches the peak value after that the voltages flows the constant. Time domain simulation for photovoltaic System MPPT under four shading patterns are carried out using Matlab/Simulink.

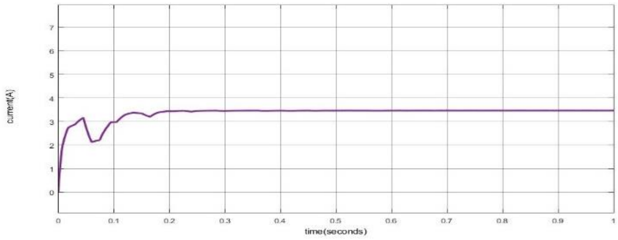

fig .5.3 characteristics curve of pv array

In the figure 5.3 represent the characteristics cure of PV array that drawn between the time and current.In the current reaches the peak value in 3.5A after the peak time the current flows through constant.

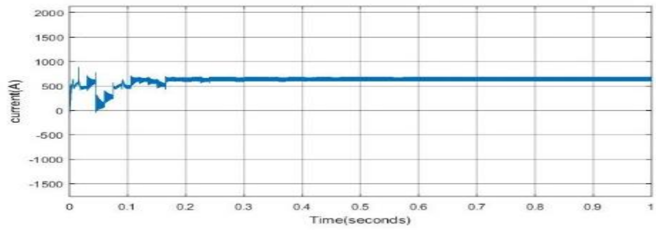

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Fig .5.4characteristics curve of MPPT

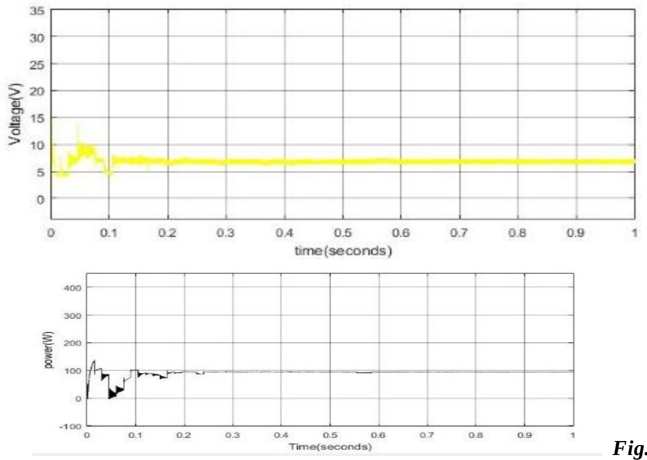

Fig. 5.5 CSO based tracking of simulated power and voltage curves for shading pattern 0.45, 0.8, 0.35, 0.3 kw/m2

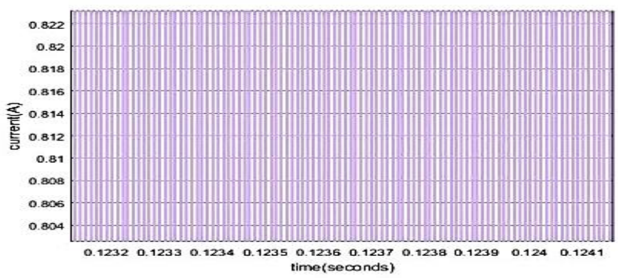

Fig .5.6 current and time curves for shading pattern

For PV modules, the solar irradiances to be taken into account are 0.45, 0.4, 0.35, and 0.3

kW/m2. This graph shows that all algorithms track GMPP quite effectively. Fig. 5 shows the entire simulated results (power, voltage, and current) of SPVS for several MPPT approaches using this pattern. With tracking times of 0.038 s and 0.05 s, respectively, AFLC and FLC achieve MPP. The simulation results demonstrate that the proposed AFLC reduces tracking time by 24% when compared to FLC.

The proposed CS is practised, and the outcomes are evaluated against electric charged particle optimization (ECPO), grasshopper optimization algorithm (GOA) and cuckoo search (CS) . The best outcomes in this situation are shown in Table 3. With a maximum electrical output of 102.2039 W at a duty cycle of 0.0911 delivered to the converter MOSFET, the proposed CS outperformed AOA, GOA, and ECPO. After feeding the converter with a duty cycle of 0.0975, GOA comes in second place with a maximum power of 101.1967 W. Maximum outputs of 63.5237 W and 78.3044 W were attained by CS and ECPO-based algorithms, respectively, with duty cycles of 0.2 and 0.1576. This demonstrates that local optima exist for both CS and ECPO.

	AOA	**GOA**	**ECPO**	**Proposed CSO**
$p_m(W)$	81.3745	143.816	89.237	143.829
$w_m(rad/sec)$	17.7283	30.373	21.816	30.421
duty	0.3001	0.0939	0.1572	0.0932
$p_{max}(W)$	73.134	103.885	81.214	103.418
$V_{MPP}(V)$	134.23	165.426	141.871	165.871
$I_{MPP}(A)$	0.2314	0.8754	0.2198	0.8934

Table:4 Comparison of various research methodology:

S. No	**Authors name and year**	**Methodology**	**Outcome**
1.	Muhammad Hamza Zafar et al. year: 2021	An innovative MPPT control method based on a new meta-heuristic optimization algorithm for PV systems operating under difficult partial shading conditions	The offered SRA control technique stands out for its durability, ease of implementation, and ability to track power with an efficiency of up to 97.93% in steady-state.
2.	Adeel Feroz Mirza et al. year:2020	For maximum energy extraction from PV systems while partially shaded, a Salp-Swarm Optimization-based MPPT technique is used.	Both transient and steady-state oscillations are successfully addressed by SSO. It has a minimal overshoot, and efficiency is typically above 98 percent under all working situations.
3.	Noman Mujeeb Khan et al. year 2021	Maximum power point tracking for solar systems under partial shade and complex partial shading scenarios using bio-inspired optimization algorithms	With the suggested technique, tacking times have decreased by up to 45% while efficiency has increased by more than 98.9 percent.
4.	Rakesh Kumar Phanden et al. year: 2021	A revolutionary maximum power point tracking controller for solar systems based on modified ant colony optimization	The performance of a modified ACO-based MPPT controller for MPPT tracking in a stand-alone PV system is shown through simulation results.
5.	Ali M. Eltamaly year:2021	Applying a unique musical chairs algorithm to PV system MPPT	The convergence time was slashed from five benchmark optimization procedures to 20–50% of the original value.
6.	N Shankar et al year 2020	Enhanced Particle Swarm Optimization Technique reduces the partial shade impact in a	A general examination reveals that SP-topology delivers 90% of the expected results at

		multiple PV array setup model.	400 volts, 8 amps of current, and 3200 watts of maximum power.
7.	Majad Mansoor et al. year 2020	Control of PV Systems with Partial Shading Using Harris Hawk Optimization	The proposed MPPT Technique improves tracking time by 10 to 30 percent and reduces random oscillations by more than 90 %
8.	Proposed	New MPPT Design For Photovoltaic System Under Partial Shading Condition Based on Archimedes Optimization Technique.	The suggested strategy yields static efficiencies above 98.9% in the majority of the tested cases and follows the GMPP with great accuracy.

IV. CONCLUSION

In this research, a brand-new CSO-based MPPT technique is suggested for obtaining the solar PV system's maximum energy output. In order to implement the MPPT integrated with a wind energy generation system and enhance its performance, this research provided a novel use of the Cuckoo Search optimization algorithm. PV is connected to PMSG in the generation system that is being demonstrated. To experiment with the proposed controller's performance, four shading patterns are used. The converter MOSFET's duty cycle is managed by the proposed Cuckoo Search optimization algorithm in a way that maximises the output power from the solar energy generation system. Since the Cuckoo Search method dynamically mixes the exploratory moves with the wide local search throughout the MPPT process, it can offer very speedy convergence and great accuracy. Simulations are run with extreme shading patterns to verify the effectiveness of the global search and the dynamic performance. According to the simulation results, the suggested method follows the GMPP with excellent accuracy and produces static efficiencies above 98.9% in the majority of the cases examined. The outcomes demonstrated the CSO -MPPT controller's reliability in providing the best solar energy generation system performance, outperforming all analysed optimizers. In the near future, the suggested method will be used to resolve a number of optimization issues for different renewable energy systems and smart grid.

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