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A Metaheuristic Optimization Technique for Maximum Power Extraction in Solar Photovoltaic Systems under Partial Shading

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ABSTRACT

One of the main problems with a solar photovoltaic (PV) system is the partial shading condition (PSC). This results in a significant reduction of the output power of a solar PV system. This paper mainly aims at proposing and validating a novel optimization technique namely the Genetic Algorithm (GA) for Maximum Power Point Tracking (MPPT) in case of PSC. In this study, an experimental examination utilizing a PV emulator highlights the effect of PSC on PV system performance. PSC was found to result in a 37% decrease in maximum power, a 38% decrease in fill factor, and a 60% decrease in efficiency. Meta-heuristic techniques for P-V curves with several peaks can be used to track the maximum power point (MPP). GA is based on a metaheuristic methodology that has been applied to solve optimization problems in a variety of systems, such as PV systems with MPPT. With a convergence time of less than 2 ms, the suggested system can track the global MPP with 99% tracking efficiency. This demonstrates the improvement in tracking time and accuracy over traditional MPPT techniques. Additionally, the suggested system can also accomplish steady operation in dynamically changing environmental conditions and reduce the oscillations around MPP.

1. INTRODUCTION

Due to the world's increasing population and the industrial sector's massive increase in energy consumption, there is currently an energy crisis. According to the Annual Energy Outlook reports, it won't take many decades for conventional energy sources like oil, gas, coal, and uranium to run out [1]. The gap between energy output and demand will soon continue to widen. Alternative energy sources are required to meet the energy demand. Over the past 20 years, renewable energy sources such as biomass, solar, wind, and others have been used [2]. A PV system's power generation is highly dependent on solar radiation [3]. The economic feasibility of the implementation of on-grid and off-grid solar PV systems is studied by the authors. The system is simulated for studying an economic analysis of the implementations. The on-grid system is found better in energy production as compared to off-grid systems [4]. Many issues, such as PSC, small defects, diode failure, etc., limit the power output of the PV system. A few of these issues can be diagnosed. But some things are unavoidable, like hotspots and some shade [5]. The effect of dust accumulated on PV panels in solar PV systems as well as Concentrated Solar Power (CSP) systems is discussed by the authors. The degradation in the performance is found more in the case of CSP as compared to PV systems. Dust accumulation can significantly reduce the power extraction from the system [6]. PV panels that are partially shaded lose some of their maximum power output and run the risk of damaging their PV cells from hot spots. The incorporation of MPPT in PV systems is a critical aspect in solving the problem of energy crisis, particularly in the context of renewable energy systems like solar PV, where it optimizes the energy extracted from the sun. The MPPT ensures that the PV system always operates at the optimum level by adjusting the operating point to the MPP under varying levels of solar irradiance. The design of highly efficient, faster, and robust MPPT is a key factor in the efficient utilization of PV systems. The selection of the proper MPPT is required to ensure the maximum power extraction from the system. This results in a reduced payback period and better Return on Investment (ROI). The selection of MPPT also impacts the maintenance requirements. Utilizing the efficient MPPT also helps to predict energy production and performance forecasting. The MPPTs also contribute to sustainable and environmental goals.

MPPT methods can be categorized as Conventional MPPTs, Soft computing MPPTs, Optimization-based MPPTs, and Hybrid MPPTs based on their operational principles and approach. Conventional methods include the Perturb and Observe (P&O) and Incremental Conductance (IC). These techniques use iterative processes to track the MPP by adjusting the duty cycle. Soft Computing Techniques use intelligent algorithms, such as Artificial Neural Networks (ANNs) and Fuzzy Logic uses prior training and knowledgebased rules to track the MPP. Optimization-based algorithms include Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE), and Genetic Algorithms (GA). These methods use a global search process to track the MPP, especially under complex scenarios like partial shading. Hybrid Techniques combine multiple methods, such as combining soft computing with optimization or conventional methods, to use the benefits of each and improve the performance in complex scenarios. Each category has different challenges, such as accuracy, speed, and handling nonlinearity or dynamic conditions. Appropriate MPPT can reduce the impact of PSC [7].

Conventional MPPTs can track the MPP in normal conditions. But these methods have few limitations [8]. These algorithms are slower in tracking the MPP and also have less tracking efficiency. In PSC, multiple local MPPs are present on the power-voltage (P-V) curve of the system. The conventional methods are trapped at local MPP instead of GMPP. These methods are not able to handle nonlinearities due to PSC and high dynamics in PV systems. Conventional MPPTs use fixed step sizes. Convergence speed can be increased by a larger step size, but it decreases accuracy. On the other hand, the smaller step size increases the accuracy but reduces the convergence speed. To overcome these issues, optimization techniques are needed for MPPT. Optimization strategies can track the GMPP effectively under PSC. These methods can dynamically adjust the step size to balance the convergence speed and accuracy. The optimization algorithm can also handle non-linearities in the PV system caused by the PSC. These methods can explore the entire search space and can increase the power extraction from the PV system. The conventional strategies are combined with optimization techniques such as Particle Swarm Optimization (PSO), NN, ACO, ANN, and Cuckoo search [9]. The dynamics of unpredictable operational conditions affect the MPPT. Numerous researchers have examined soft computing strategies for solving this issue. This paper examines the impact of PSC on the PV system using a PV Emulator. The system is analyzed at different levels of PSC. In the later part of the paper, an optimization technique using GA is proposed for MPPT. The proposed system uses the GA algorithm to track the MPP under PSC. The statistical analysis using Standard Deviation (SD) at different levels of PSC is also done to focus on the stability of the system. The GA-based MPPT accurately tracks the MPP with more than 99% efficiency at a larger tracking speed having a response time of less than 2ms. The system also reduces the problems of oscillations around MPP and stability issues in complex PSC.

2. RELATED WORK

Various MPPTs have been developed by numerous researchers. The authors' new linear tangent-based Perturb and Observe (P&O) MPPT was able to produce a better dynamic and steady-state response, reduced oscillations, increased accuracy, and enhanced efficiency [10]. The researchers conducted a thorough analysis of the various hardware options to maximize power under partial shading. The research presented the difficulties and economic feasibility of the several alternatives [11]. A redesigned P&O-based MPP tracking system is demonstrated and assessed in both step and ramp irradiation scenarios. Under rapidly changing conditions, it tracks the MPP [12]. A thorough analysis of module-level and sub-module-level distributed MPPT approaches has been completed. Distributed MPPT (DMPPT) is emphasized in their work. A comprehensive examination and assessment of pertinent literature has been carried out [13]. The active power control techniques have been reviewed by Mahato et al. [14]. They looked at several active power control techniques, including variable and fixed horizons [14]. Another method based on non-linear function-based PSO techniques and ordered excitation (OE) was developed. The global extreme seeking's steady state and transient responses are improved by both the NF-PSO and OE algorithms [15]. From all these studies in the literature about conventional MPPTs, it is found that these systems are inefficient in tracking the MPPT in several aspects such as accuracy, stability, and convergence speed. The P&O systems in the literature highlight the limitations of the algorithm in tracking the GMPP in PSC. It also shows less efficiency and instability under a complex environment. The PSO-based systems exhibit slower convergence and higher dependence on the input parameters.

The researchers designed an MPPT design under the PSC using swarm intelligence. It was discovered that the suggested Teaching learning-based artificial bee colony (TLABC) technique performs better than alternative studied approaches [16]. Pal and Mukherjee [17] optimized PV array power under various climate conditions with an Improved Chaotic PSO (ICPSO). Nassef et al. [18] used the Honey-Badger algorithm (HBA) to create a modified MPPT. High dimensionality issues can be successfully solved by the HBA method. Additionally, a few other optimization techniques have been used to raise MPPT algorithm performance. For MPPT, Premkumar et al. [19] have employed the Whale optimization (WO) method that despite its rapid convergence speed and subpar tracking efficiency, seeks to identify the global peak. The authors presented another GMPPT that made use of the teaching-learning approach. Concerning tracking efficiency and steady-state oscillations, the proposed method outperforms the shortcomings of the existing conventional MPPT tracking schemes [20]. The Grey Wolf Optimization (GWO) and a tuned adaptive fuzzy PID (AFPID) controller optimized the parameters of the AFPID controller designed for power system frequency regulation using a GWO technique [21]. The authors have assessed various optimization techniques to find the sizing of a standalone hybrid energy system (HES). The MATLAB/Simulink is used for the simulation of the system to analyze the dynamic systems. The different results of sizing for various optimization methods are obtained from the study. The study focuses on the importance of the selection of suitable optimization techniques [22].

From the literature study on optimization methods for MPPT, it is found that many such systems are highly complex and need intense computations. These systems also pose the problem of early convergence.

Various reconfiguration strategies have also been used in recent MPPT research developments to track the GMPP. Physical relocation methods require a lot of labor; thus, they are difficult. Achieving the optimal switching matrix design for electrical array reconfiguration remains a challenging task. The authors performed a thorough analysis and compared the performance of several reconfigurations [23]. For GMPPT, Patro and Saini [24] used static array reconfiguration. It has been found that the output power of a static PV array using a

Total Cross Tied (TCT) arrangement, and a bypass diode may be increased to 1.14 kW. Social Learning Differential Evolution (SLDE) is used in the MPPT technology to execute an inspection approach, hence improving tracking capabilities [24]. Adaptive-JAYA optimization, another novel metaheuristic approach, is utilized to determine the optimal PV array reconfiguration with less memory [25]. The PV array reconfiguration techniques need connections switching of PV panels to control the current or voltage levels. This requires additional hardware such as relays or switches. This increases the cost and maintenance of the system. The time required for the reconfiguration process reduces the speed and the efficiency of the system. These systems may fail to track the GMPP under complex PSC.

Under PSC, choosing the appropriate MPPT technology is essential for solar PV systems.

3. EXPERIMENTAL ANALYSIS OF THE EFFECT OF PARTIAL SHADING USING PV EMULATOR

The PV Emulator was used to examine the impact of PSC. The hardware setup used for the experiment is shown in Figure 1. The SPVE001 PV Emulator model is used for the experimentation. It is connected to the laptop having the software Labview, SPVE001 application software, NI VISA 17.0, and USB to Serial driver installed. Two operating modes i.e. 1kW and 2kW are available in this model. The 1 kW mode with 25℃ temperature is selected for this study.

Steps for the PV Emulator-based work:

1) Select the COM Port for the Emulator.

2) Set the values of input parameters and solar irradiance as per the requirement and run the system.

3) The system gets emulated according to the input parameters; plots the performance curves on the screen and displays the output parameters such as MPP, fill factor, and efficiency.

The accuracy of the PV Emulator is already verified by using the actual hardware setup.

The PV Emulator's parameters were set up as indicated in Table 1 and the performance parameters were noted under four levels of PSC. Using a PV Emulator, Figure 2 shows the P-V curves in four distinct PSCs. A summary of these observations can be seen in Table 2.

Table 1. PV emulator configuration parameters

Sr. No.	Parameter	Value
1	V_{oc}	36.3V
2	I_{sc}	7.84A
3	T_c	0.102
4	A	0.98117
5	R_s	0

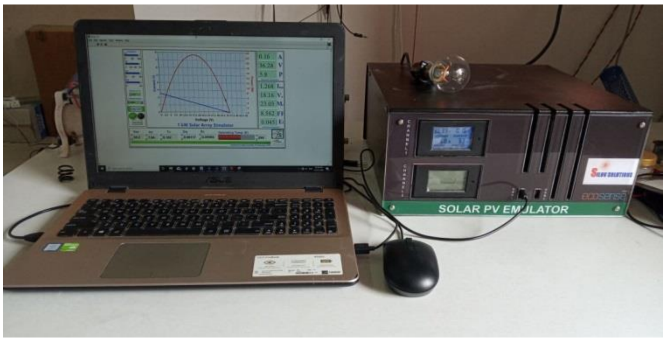

Figure 1. The experimental setup using PV emulator

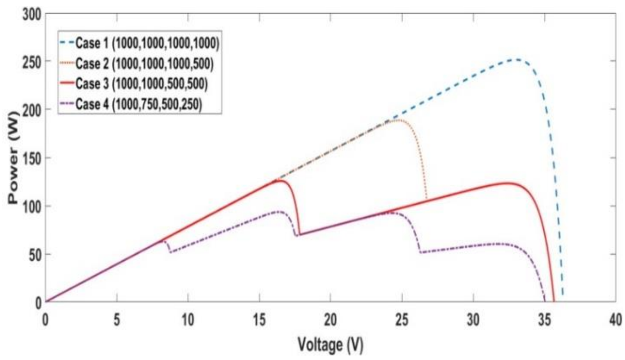

Figure 2. PV curves using PV emulator

The system generates an MPP of 251.6 W with constant solar irradiation across all PV panels, as case 1 illustrates. In further experimentation in cases 2, 3, and 4; the maximum power decreases as the solar irradiation non-uniformity increases. There are more local maxima in addition. The results of the experiment validate the impact of PSC on the PV system's maximum power and local maxima.

Table 2. PV array performance under partial shading using PV emulator

Case	Irradiance Levels (W/m^2)	I_{MPP} (A)	V_{MPP} (V)	MPP (W)	Fill Factor	Efficiency
1	1000, 1000, 1000, 1000	7.618	33.02	251.6	88.37	0.4006
2	1000, 1000, 1000, 500	7.620	24.77	188.7	67.46	0.3432
3	1000, 1000, 500, 500	7.618	16.50	125.9	44.98	0.2671
4	1000, 750, 500, 250	5.713	16.39	93.52	34.03	0.2384

4. PROPOSED MPPT METHOD USING GENETIC ALGORITHM

A genetic algorithm (GA) is a method for solving constrained and limited optimization problems that mimic biological evolution through natural selection. The method modifies a population of unique solutions over time. A genetic algorithm generates a population of possible solutions, also known as individuals, creatures, organisms, or phenotypes, to an optimization problem in the direction of better solutions. Each potential solution's attributes, such as its chromosome makeup or genotype, are changeable. While binary strings of 0s and 1s are the traditional way that solutions are expressed, there are several possible encodings.

Evolution, as depicted in Figure 3, starts with a population of randomly generated individuals and continues iteratively, with the population of each iteration being referred to as a generation. Every generation evaluates the fitness of every member of the population; the value of the objective function in the optimization problem under consideration is frequently used to quantify fitness. The fitter individuals are selected at random from the current population and have their genomes modified (recombined and may be randomly mutated) to produce a new generation. The new set of possible solutions is then used in the subsequent algorithm iteration. When a maximum number of generations have been generated or the population reaches a suitable fitness level, the algorithm typically comes to an end.

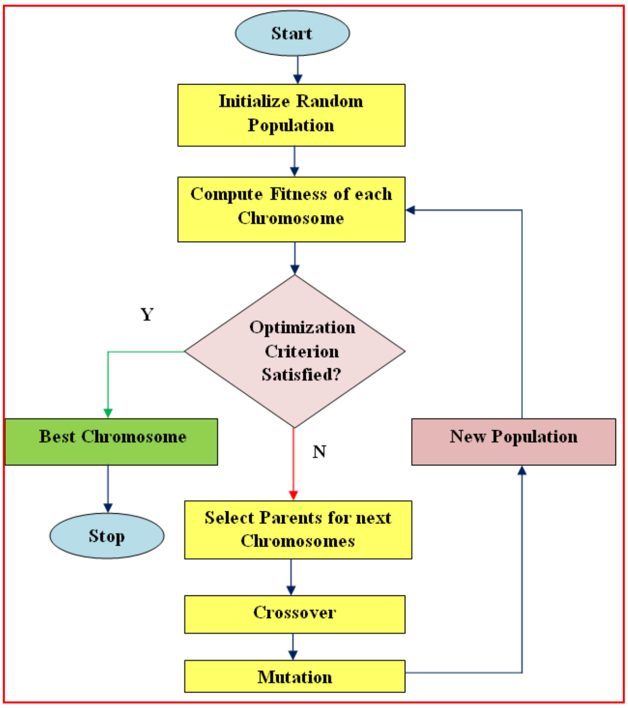

Figure 3. Flowchart for GA

4.1 Initialization

A randomly generated binary matrix makes up the initial population. It has N individuals i.e. photovoltaic current encoded on S bits and m variables:

$$Population\ (I) = \begin{bmatrix} I_1 \\ \cdot \\ \cdot \\ I_N \end{bmatrix} \quad (1)$$

$$I_{max} = I_{sc} = 111 \ldots 11 \quad (2)$$

$$Population\ (I) = \begin{bmatrix} x_{1,1} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,m} \end{bmatrix} \quad (3)$$

where, $x_{i,j}$ is the j^{th} variable of i^{th} individual.

Every individual of the generated population will have their power (fitness) assessed.

4.2 Evaluation

The evaluation is a critical process that guarantees the survival of the best possible individual. The fitness function, which is a positive function that optimizes an individual for its maximum value, can accomplish this. Since the PV power serves as the fitness function in this instance, the ideal individual provides the maximum power. Based on the associated power, a PV current evaluation is provided for each individual.

$$P = V.I \quad (4)$$

The single diode cell model is used to evaluate the power of each individual (fitness function).

The output voltage equation of the cell will be:

$$V = V_T\ L_n \left[\left(1 - \frac{I}{I_{sc}}\right) \left(e^{\left(\frac{V_{OC}}{V_T}\right)} - 1\right) + 1 \right] - R_s I \quad (5)$$

Finally, according to Eq. (6) and Eq. (7), the power is calculated as:

$$P = \left(V_T\ L_n \left[\left(1 - \frac{I}{I_{sc}}\right) \left(e^{\left(\frac{V_{OC}}{V_T}\right)} - 1\right) + 1 \right] - R_s I\right).I \quad (6)$$

This equation is used to determine each individual's power, or fitness function, which is then employed in genetic operations to form a new population (generation), which is then implanted into the parent population based on that population's fitness function.

4.3 Genetic operations

The foundation of GAs is genetic operations, which produce very intriguing findings but do not rule out probability theories.

These operations are:

1) Selection: In nature, only those individuals who are better adapted to their surroundings will survive. Choose a portion of the population that corresponds to the optimum fitness at a rate of T_{sel} (%). The process of a roulette wheel selection is employed.

2) Crossover: Pairs of individuals are crossed to carry out natural reproduction.

3) Mutation: Following crossover, a mutation is applied with a tiny probability Pm.

4) Insertion: To create a new generation with the same number of individuals, the new population will be merged with the old one to replace those with the lowest fitness function.

The procedure produces new, ideal individuals. We get a constant execution time because it terminates after a predetermined number of iterations. To select an iteration number that strikes a compromise between processing time and ideal results, numerous tests were run.

Figure 4 depicts the GA-based MPPT applied to PV system under partial shading. MPPT controls the working of DC-DC converter to keep the power at maximum level.

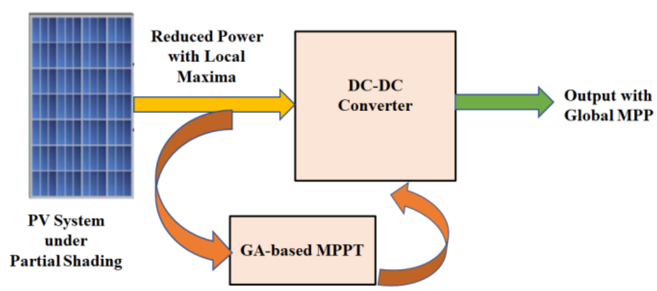

Figure 4. GA-based MPPT

5. RESULTS AND DISCUSSION

The proposed MPPT was tested in a MATLAB SIMULINK environment. The system used the PV array having four series connected “Tata Power Solar Systems TP250MBZ” PV modules, each module with the specification as shown in Table 3.

The system was applied with four different levels of solar irradiance. The results show that an efficiency of 99.94%, 99.96%, 99.93%, and 99.96% was obtained in four cases. The maximum powers tracked are shown in Figure 5, Figure 6, Figure 7, and Figure 8. The proposed system was able to avoid oscillations and achieve stable performance.

The performance parameters noted for all four cases are noted in Table 4.

As can be seen from the results, the proposed GA-based MPPT system can track the GMPP with improved accuracy and less convergence time. The performance of GA-based MPPT is compared with other conventional MPPT methods in Table 5.

As shown in Figure 9 and Figure 10, the proposed GA-based MPPT outperforms in terms of efficiency and convergence speed compared to conventional MPPTs.

The stability of the GA-based MPPT under different shading patterns can be found by the statistical analysis of the above results using Standard Deviation (SD) technique. The steps for SD-based analysis are as follows:

Step1: Data Collection

The output power at every second for 10 minutes duration in each shading pattern is recorded.

Step2: Calculate Standard Deviation (SD)

SD is then calculated by using the formula as:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}} \tag{7}$$

where,

xi = Power output at each interval.

μ= Mean power output over the 10-minute duration.

n = Number of intervals.

The value of n is taken as 600 because output power is recorded every second for 10 minutes.

Table 3. PV array specifications

Sr. No.	Parameter	Value
1	Maximum power	249 W
2	Cells per module	60
3	V_{oc}	36.8 V
4	I_{sc}	8.83 A
5	V_{MPP}	30 V
6	I_{MPP}	8.3 A
7	R_s	0.2914 Ω
8	R_{sh}	314.7646 Ω

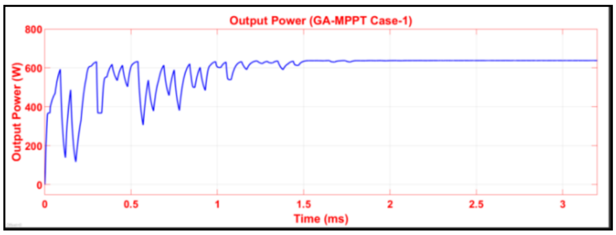

Figure 5. Maximum power tracked (Case 1)

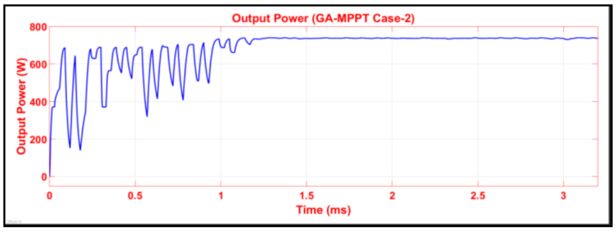

Figure 6. Maximum power tracked (Case 2)

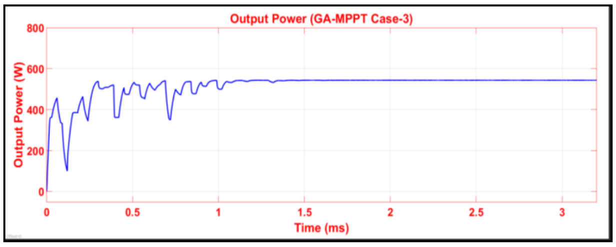

Figure 7. Maximum power tracked (Case 3)

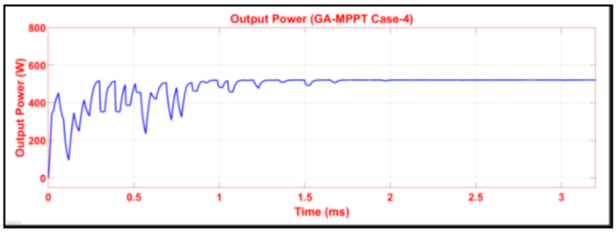

Figure 8. Maximum Power Tracked (Case 4)

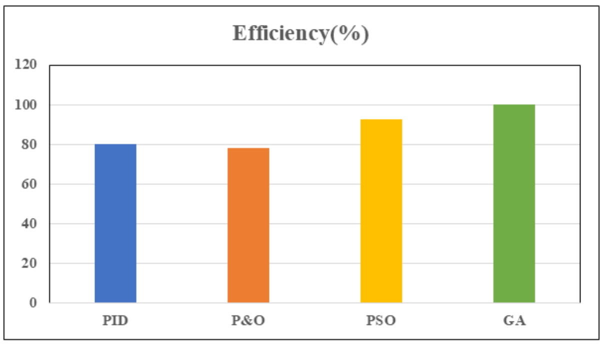

Figure 9. Comparison of efficiency

Table 4. Performance of proposed MPPT

Case	Solar Irradiance on Panel 1 (W/m²)	Solar Irradiance on Panel 2 (W/m²)	Solar Irradiance on Panel 3 (W/m²)	Solar Irradiance on Panel 4 (W/m²)	Output Power (W)	Tracking Efficiency (%)	Convergence Time (ms)
1	500	800	1000	1000	638	99.94	2.1
2	500	1000	1000	1000	740	99.96	1.51
3	500	500	1000	1000	544	99.93	1.42
4	500	500	500	1000	522	99.96	1.99

Table 5. Performance comparison of proposed MPPT with conventional MPPTs

MPPT	PID	P&O	PSO	GA
Efficiency (%)	80.22	78.23	92.5	99.94
Convergence Time (ms)	2.5	2.3	2.5	2.1
Complexity	Low	Low	Moderate	Moderate
Stability	Moderate	Moderate	High	High
Anti-interference Capability	Low	Low	High	High

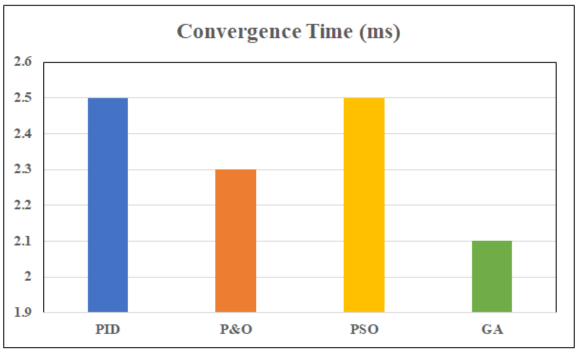

Figure 10. Comparison of convergence time

Table 6. Standard deviation calculation

Case	Output Power (W)	SD
1	638	7W
2	740	2W
3	544	16W
4	522	19W

The low value of SD in case 2 indicates that the GA-based MPPT provides consistent power in lower shading. The moderate value of SD in case 1 indicates the variations due to the adaptive nature of GA because of the increased level of PSC and possible switching process between local MPP and GMPP. The higher value of SD in case 3 and case 4 indicates the substantial fluctuations in the output due to the dynamic response of GA in an increased level of PSC (see Table 6).

GA-based MPPT adapts to varying irradiance and temperature by performing genetic operators like mutation and crossover. So, it provides high efficiency in energy extraction. The selection process prioritizes the fitter solutions i.e. exploitation. The operations of crossover and mutation generate exploration, giving a faster convergence. The GA-based MPPT is moderately complex as compared to conventional MPPTs. However, it is highly stable and has high anti-interference capability as compared to other MPTTs. Higher efficiency helps to minimize the energy losses, directly increasing the overall performance of the system and it makes the PV systems more economical, especially in off-grid systems or large-scale solar farms. In such applications, the weather conditions are not stable and there are problems like varying temperatures, partial shading, and rapid variations in solar irradiance. Higher convergence speed ensures minimal energy loss during transient conditions like rapid temperature fluctuations or passing clouds. A faster convergence process is extremely important in reducing the downtime in power tracking when the system is subjected to rapid variations in environmental conditions, especially for locations where the weather pattern is unstable. The higher stability of GA makes the system robust to frequent oscillations and increases the maximum power. It also reduces the stress on the PV components used in the system and thus extends the life of these components.

A stable system is crucial for standalone as well as grid-tied systems. High anti-interference capability confirms the system's ability to track GMPP in PSC. It also makes the system robust to noise and minor fluctuations. The PV systems in such applications can be customized by using efficient hardware systems, fine-tuning, and user-friendly interfaces. By employing such a customized way of design, the research prototype can be converted to an economical commercial solution to extract the maximum power.

The conventional MPPTs such as P&O and IC are not able to track the GMPP in PSC. This problem is solved by GA by using adaptive operations. Many optimization algorithms such as PSO and DE exhibit a slower convergence because of the excessive exploration of solution space especially in complex PSCs. GA has the balance in exploration and exploitation using bio-mechanisms that lead to faster convergence. Few optimization techniques such as PSO or Ant Colony Optimization (ACO) deeply depend on the input parameters such as inertia weight and learning factors that need proper tuning for varying environmental conditions. But GA is less sensitive to parameter tuning which makes it suitable for varying environmental conditions. Few optimization algorithms such as multi-objective or hybrid algorithms require very intense computations. But GA has a lesser computational requirement that makes it feasible for real-time MPPT with limited hardware. GA-based MPPT is highly adaptive to dynamic environmental conditions than other optimization methods. Many optimization-based MPPTs possess a problem of early convergence due to insufficient exploration bias. But GA-based MPPT provides a stable response and does have the problem of early convergence.

6. CONCLUSIONS

The experimental investigation of partial shading effects on PV system performance and the suggested GMPPT technique are mainly focused in this paper. The PV emulator-based experimentation was done to investigate the partial shading effects. Partial shading resulted in a 37% decrease in MPP, a 38% decrease in fill factor, and a 60% decrease in efficiency. The study suggested a new metaheuristic method for tracking the global MPP that makes use of the Genetic algorithm. We tested the method with various partial shading levels. In 2.1 ms, the suggested approach was able to reach 99% efficiency. In terms of efficiency and convergence speed, the genetic algorithm-based MPPT performs better than traditional MPPT techniques. The proposed MPPT is free from the oscillations around MPP in the tracking process. Such highly efficient MPPT makes the PV system suitable for small-scale to large-scale applications having rapid environmental parameters fluctuation. The stable performance of GA-based MPPT is crucial in noisy and complex environments. Such a system can efficiently handle the non-linearities in the PV system due to varying environmental conditions. The proposed system can be easily scaled up to large complex systems without significant tuning. Thus, the problems associated with the conventional MPPTs and other optimization techniques are solved by the GA-based MPPT.

The proposed system can be further improved by adapting various ways. GA-based MPPT can be integrated with other optimization strategies such as PSO or ANN to boost accuracy and convergence speed. Adaptive GA can be developed by dynamically adjusting the rates of mutation and crossover which can reduce the burden of intense computations and enhance the response speed. A more efficient hardware system with the utilization of a Graphics Processing Unit (GPU), Field Programmable Gate Array (FPGA), dedicated microcontrollers, advanced Digital Signal Processors (DSP), and Internet of Things (IoT) platforms for control and remote monitoring can be incorporated to enhance the performance of the MPPT system. Predictive models can also be utilized for energy forecasting along with GA-based MPPT to further optimize the power extraction.GA can be further extended to optimize other parameters also, such as battery management processing, energy storage process, and inverter efficiency enhancement. This can improve the overall performance of the system. A modular GA-based framework can be incorporated that can be utilized for various PV systems, from small stand-alone setups to large-scale solar farms, by adjusting the input parameters like population size, crossover rates, and search space.

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NOMENCLATURE

V_{oc}	Open-circuit voltage (V)
I_{sc}	Short-circuit current (A)
T_c	Temperature coefficient
R_s	Series resistance (Ohms)
R_{sh}	Shunt resistance (Ohms)
I_{MPP}	Current at Maximum Power (A)
V_{MPP}	Voltage at Maximum Power (V)
MPP	Maximum Power (Watts)
SD	Standard Deviation