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A Novel MPPT Technique based on Hybrid Radial Movement Optimization with Teaching Learning Based Optimization for PV System

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Abstract— Because of its pure and plentiful accessibility, solar power is a remarkable resource of energy for the generation of electrical power. The solar photovoltaic mechanism transforms sunlight striking the photovoltaic solar panel or array of photovoltaic panels directly into non-linear DC power. Due to the nonlinear characteristics of solar photovoltaic panels, power must be tracked for their effective usage. When the photovoltaic arrays are shaded, the problem of nonlinearity becomes more pronounced, resulting in large power loss and intensive heating in a few areas of the photovoltaic arrangement. The tracking challenge is made more difficult by the fact that bypass diodes, which are used to completely eradicate the shading effect, generate numerous power peak levels on the power vs. voltage (P-V) curve. Traditional methods for tracing the global peak point are unable to examine the entire P-V curve as they frequently get stuck at the local peak point. Recently, machine learning or optimization algorithms have been used to determine the global peak point. Because these algorithms are random, they search the entire search area, reducing the possibility of being caught in the local maximum value. This article proposes a hybrid of two optimization approaches: radial movement optimization and teaching-learning optimization (HRMOTLBO). The proposed MPPT method was thoroughly investigated and tested in a wide range of photovoltaic partial shading combinations. The recommended HRMOTLBO MPPT approach outperforms and is more reliable than a recent Jaya-based MPPT approach in terms of tracing time and power variation under dynamic and static partial shading conditions. Experimental as well as simulation outcomes demonstrate that the proposed MPPT successfully traces the global peak point in less time and with fewer fluctuations during various partial shading conditions.

Keywords- Maximum Power Point Tracking (MPPT), Particle Swarm Optimization (PSO), Radial Movement Optimization (RMO), Teaching-Learning Based Optimization (TLBO), Partial Shading Conditions (PSC), Photovoltaic model(PVM).

I. INTRODUCTION

Due to the obvious impairment loss of existing traditional fossil resources, renewable resources are imposing a considerable imposition. Amongst the many renewable resources, solar photovoltaic technology has attracted a lot of attention because of its ecologically responsible nature, personal protection, cleanliness, and portability as well as unlimited access provision [1]. According to a recent study by Solangi [2], the contributed capacity of solar power plants to electricity production caused approximately 14,000 MW in 2010 and is expected to reach 1, 00,000 MW by 2023. Even though the solar photovoltaic system is a neat and tidy, green resource that is simpler to utilize, its performance is inferior when compared with of competitive alternative energy sources [3]. When solar particles hit the surface of a solar cell, charged particles begin to move, leading to the generation of DC power. The power extricated from the photovoltaic panel is influenced by environmental conditions, which eventually cause variations in power under changing operating conditions [4].

The most common semiconducting material chosen in photovoltaic technology for the manufacturing of solar cells is crystalline silicon. This crystalline silicon solar cell typically achieves an efficiency of 15-20% in field conditions. To increase the power production ability of a solar photovoltaic system, many numbers of solar photovoltaic modules are arranged in series and parallel configurations. However, ineffective tracing of peak power creates a decline in the production of electrical power, which becomes apparent due to changing solar irradiance circumstances.

PSC caused by residential structures, bird drops, tree branches, clouds, and other objects casting dark spots on the photovoltaic system at specified intervals during the day is the primary cause of power loss. [5]. Because of this partial shading impact (just on one cell) the overall performance of the solar array may suffer. Partial shading causes a cell to begin functioning as a load, consuming excess energy and delivering it as thermal energy. This is referred to as the hot-spot phenomenon [6]. Recent photovoltaic systems are installed with bypass diodes that can minimize this hot-spot phenomenon; As a consequence, the photovoltaic system has several local maxima and one global maximum in its power versus voltage (PV) characteristic. The intervention creates several power peak values at the array's output, making tracing the peak power point tricky.

However, as previously stated, one of the most challenging issues with photovoltaic is the cost involved. The impairment to the control structure, in addition to the investment costs of the photovoltaic modules, has a substantial effect on the overall cost of the photovoltaic arrangement. In addition, the governing system has a significant impact upon the system's productivity and effectiveness, which indirectly contributes to the system's price. Hence, it is imperative to have an appropriate governing structure in conjunction with the photovoltaic structure. One of the significant concerns affecting photovoltaic system efficiency is the output energy's reliance on the efficiency as well as the stability of the system's governing technique, particularly under PSC. An inadequate approach may lead to a significant reduction in overall energy generated under PSC or unexpected climate conditions. As a result, an intelligent control technique is integrated into the photovoltaic system arrangement for performance improvement.

The control scheme, sensing elements, and certain other accompanying ancillary circuits in the system influence the initial outlay. The control scheme, sensing elements, and certain other accompanying ancillary circuits in the system influence the initial outlay. Furthermore, the efficiency and dependability of the control module developed for MPPT influences the operational costs. Various factors of a photovoltaic structure, such as resource consumption, system layout, and an the effective MPPT approach, are viewed as essential factors affecting cost reduction. As a result, studies have been undertaken to investigate the significance of the governing structure employed by the MPPT controller's algorithm with respect to photovoltaic system efficiency.

Many investigations were involved designing a simple and fast MPPT approach for photovoltaic systems operating during uniform irradiance and temperature levels. Such MPPT approaches have been explored in research, including Perturb & Observe (P&O) [7], Hill Climbing (HC) [8], and Incremental Conductance (INC) [9]. Nevertheless, such traditional approaches are negatively affected by changing atmospheric conditions as well as by the incorporation of a bypass diode in the photovoltaic system arrangement. the majority of traditional MPPT strategies are vulnerable to PSC failure. Several approaches have been adopted to develop an adequate MPPT approach to mitigate the effects of the PSC. For the maximum energy extraction from renewable sources of energy, intellectual approaches such as fuzzy logic and neural networks are often used [10]. These approaches have not progressed under varying solar radiance and partial shading scenarios due to the complicated fuzzification guidelines and massive trained data requirement.

Various Meta - heuristic optimization approaches were used to trace the global peak point under PSC in the nonlinear power vs. voltage characteristics. The previous research has reviewed Particle Swarm Optimization (PSO) [11], Firefly Algorithm (FA) [12], Artificial Bee Colony (ABC) [13], Flower Pollination Algorithm (FPA) [14], Gray Wolf Optimization (GWO) [15], and other evolutionary algorithms. The main drawbacks of PSO are the substantial number of data points needed for convergence, the uncertainty of accelerated particles, and the lengthy computation time. However, the aforementioned strategies are not capable of performing a quick search of global peak power with faster convergence speed, lower computational burden, and expensive processor. When compared to the PSO and ABC approaches, the Jaya-based MPPT has a quick tracing capability of global peak point with minimal dispersion along this juncture and has expedited searching performance [16]. However, in the Jaya-based approach, the search time was much longer in the case of significant power oscillations at the outcome, leading to substantial power loss [17].

The TLBO approach has been developed, and it usually requires simulating student and teacher teaching-learning action in order to improve student effectiveness —the training of students is enhanced by two methods: teacher sessions and constructive conversation with other students [18]. Even though TLBO initially surpassed several state-of-the-art algorithms, later evaluation at higher dimensional space affected computational efficiency; so many advancements were integrated into the proposed approach to improve its effectiveness. Researchers proposed a two-step reconfiguration of TLBO [19] by incorporating self-study and intelligent lectures into traditional TLBO to optimize effectiveness. A comprehensive radial movement optimization (RMO) approach is suggested as well as implemented towards MPPT challenge. It is not necessary to carry information about the position of the existing particle onto the following iterative process because the particle movement does not cover the entire search area.

In terms of reliability parameters such as compactness, performance, and tracing speed, RMO outperforms INC, particle swarm optimization, modified PSO, and GWO [20]. The preliminary analysis of the current literature revealed that an effective Photovoltaic system requires a hybrid combination of MPPT control mechanisms.. As a result, this manuscript developed a new approach called radial movement optimization (RMO) in combination with a teaching-learning based optimization (HRMOTLBO), which has been found

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useful for MPPT due to quick traceability time and reduced power oscillations. According to the results, the proposed approach outperformed Jaya in aspects of accelerated tracing time and smaller output power fluctuations. Minimal fluctuations and a faster settling period both contributed to the system's energy productivity being improved.

The performance was obtained including both static and dynamic PSC; in the first case, the solar irradiance has remained unchanged throughout, whereas in the second case, solar irradiance was significantly changed with time. The second case was developed to demonstrate how well the suggested method performs in the real-world, because of rapidly passing clouds and changes in the direction of the sun. It has been proven that the suggested approach achieves robust and considerably better outcomes than Jaya under all scenarios, making it one of the more suitable approaches for tracing of global peak value under PSC. The proposed method is depicted schematically in Fig. 1. The primary goals for this proposed work are

- **To create a novel HRMOTLBO combinational MPPT approach for effective global peak point tracing that includes both static and dynamic PSC.**
- **MATLAB simulation and experimental results are used to assess the efficacy of the proposed combinational MPPT approach.**
- **The Suggested HRMOTLBO MPPT approach is referenced with the more recent JAYA MPPT.**

Chapter 2 of this work discusses mathematical analysis of photovoltaic arrays and the impact of PSC on power vs. voltage characteristics; Chapter 3 discusses RMO based MPPT approach; Chapter 4 explores TLBO based MPPT approach; Chapter 5 demonstrates suggested novel HRMOTLBO MPPT strategy; The simulation and experimental results of the proposed HRMOTLBO MPPT strategy are presented in Chapter 6.; and Chapter 7 summarizes the proposed work.

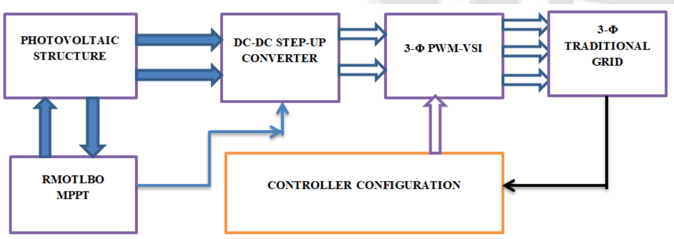

Fig 1. Schematic representation of a 3-Φ grid-connected HRMOTLBO-based PS solar system

II. NUMERICAL REPRESENTATION OF PHOTOVOLTAIC LAYOUT AND THE IMPACT OF PSC ON POWER VS. VOLTAGE CHARACTERISTICS:

2.1. Mathematical representation of photovoltaic layout:

The interface that transforms light into energy is known as the photovoltaic cell. A P-N junction in every photovoltaic cell converts solar radiation into electricity. There are two types of PVMs: double diode and single diode. Although the single diode model is less realistic than the others, it is preferred because of its simplicity. A widely viable silicon photovoltaic cell generates a current ranging from 28 mA/cm2 to 35 mA/cm2. By incorporating photovoltaic cells in series - parallel, current and voltage ratings can be increased. A photovoltaic array is a group of cells. While designing the PVM, climatic data (irradiation level and temperature) must be used as input parameters [21]. The output could be in the form of voltage, current, and power. Track the characteristics of current vs. voltage (I-V) and power vs. voltage (P-V) requirements of these three variables. When every change in the input parameters leads to a change in the output parameters. As a result, it is essential to use a precise PVM. Fig. 2 depicts an only one diode five parameter framework that is considered in this proposed approach. Those five parameters are current from the light (Iph), ideality factor of the diode (mD), shunt resistance (Rp), series resistance (Rse), and saturated current (Isat).

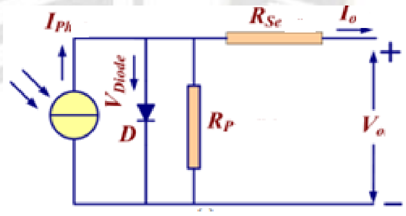

Fig 2. Single diode model of photovoltaic cell

The mathematical expression that describes the PVM is as follows [1]:

Eq. 1 calculates the output current (I_o) of each photovoltaic cell

$$I_O = I_{ph} - I_D - I_P \quad (1)$$

Where I_{ph} denotes the current produced by the solar light; Ip designates the current passing through the shunt resistance(R_p) is given by Eq. 2

$$I_P = \frac{V + IR_{Se}}{R_P} \quad (2)$$

I_D is the current passing through the diode given by Eq. 3,

$$I_D = I_{sat}\left[e^{\left(\frac{V_D}{m_D K_{TH}}\right)} - 1\right] \quad (3)$$

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Where, I_{sat} is the saturated current that flows through the diode.

Voltage across the diode (V_D) is given by Eq. 4

$$V_D = V_o + I_O R_{se} \quad (4)$$

K_{TH} is the temperature coefficient calculated by Eq. 5, and m_D is the ideality factor.

$$K_{TH} = \frac{K_B T_{AB}}{q_{electron}} \quad (5)$$

Where, K_B is Steafen -Boltzmann constant and $q_{electron}$ is the electron's charge

2.2. Effect of PSC on power-voltage characteristics:

Generally, a photovoltaic system is formed by connecting several PVMS in series or parallel, while the power of the photovoltaic system can be a total of the power obtained from every PVM. When three PVMs are linked in series, the power vs. voltage characteristics has 3 peak points under PSC [22]. The photovoltaic cells in PSCs are caused by radiation from the sun obstruction in certain parts of the PVM [23]. Analyzing that the impact of these darkness diminishes the power generated, continues to raise the heat dissipation, and resulting in damage to PVMs due to the resulting hot-spot. In Fig. 3, two series-connected PVMs are shown, one of which is partially shaded. The shaded PVM consumes energy and dissipates heat. This phenomenon can be explained by the I-V characteristics of each PVM, as shown in Figure 4.

The shaded PVM is driven to perform in the reverse bias condition, if the operating current of the photovoltaic system that consists of two series coupled PVMs is at Ia. As a result, it functions as a load demand rather than a source of energy [24]. Because of the concentrated energy dissipation, the shading PVM would be deteriorated over time. As a result, the bypass diodes indicated in Fig. 3 are included to prevent heating of the PVMs under PSC. Due to the fact that these bypass diodes are reverse biased, they're having no influence under uniform solar irradiance. When the PVM is shaded, the parallel bypass diode is attached to it exhibits forward bias, so current flows through the diode rather than the PVM. However, employing bypass diodes has the drawback of causing several peak points to emerge among the P-V characteristics during PSCs illustrated in figure 5. Up to 70% of energy loss could be minimized if the network works at the global maxima to harvest the maximum amount of energy from the photovoltaic system [25]. It results from the fact that, in the presence of PSCs, an effective and productive MPPT approach should be employed to discriminate between a global maxima and a local maxima. Because traditional MPPT techniques like Perturb and observe and INC finish searching once they locate the very first maximum value, they can't differentiate between global maxima and local maxima. As a result, a hybrid MPPT approach i.e. HRMOTLBO is developed and tested in this paper with many different conditions and found that the global maxima is met at all instances.

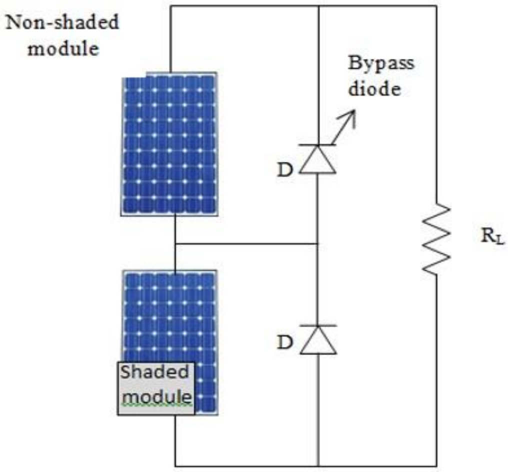

Fig 3. Two PVMs connected in series and one PVM is shaded

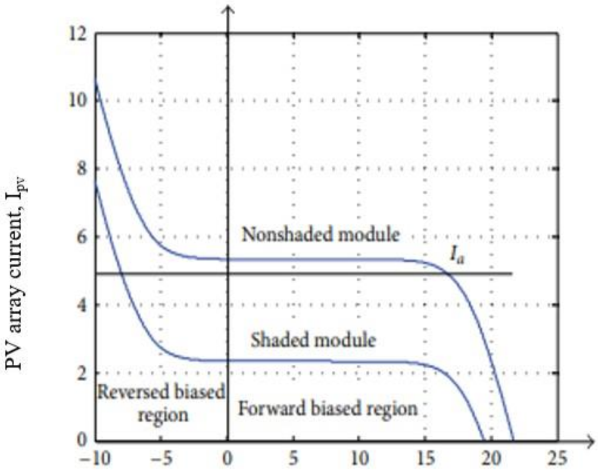

Fig. 4. I-V characteristics of PVMs

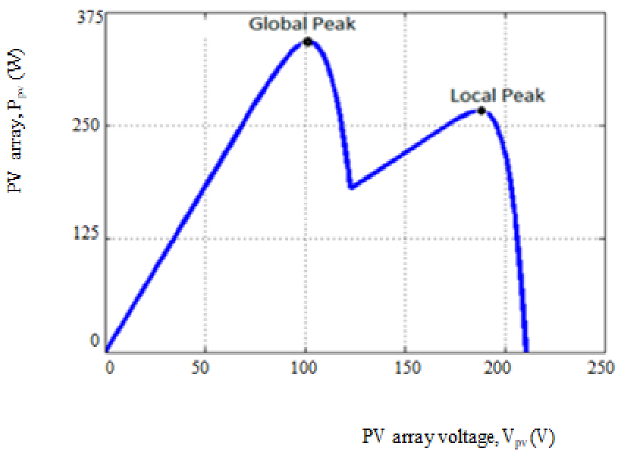

Fig 5. Power vs. voltage characteristics of photovoltaic system when one PVM is shaded.

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III. RADIAL MOVEMENT OPTIMIZATION (RMO) BASED MPPT:

The population-based deterministic heuristic algorithm known as Radial Movement Optimization (RMO) is analogous to PSO and DE. [26]. Each particle in the RMO search area has a position variable that signifies a suitable solution under investigative process. RMO moves particles differently than other optimization techniques. They are distributed from a centralized point and are regularly evolving at each step of the proposed approach. In a three-dimensional area, the concept is to allocate particles at various speeds along its vicinity of a space. A fitness function analyses the position of every particle in order to restore the fitness value and as a result, the location of the global optimum, concluded that the type of movement of the particles and regular updating improves system vulnerabilities by significantly expanding the search area. Aside from improved solution search, the RMO needs minimal memory access throughout the implementation and operation. Unlike other methodologies, where the space complexity expands in proportion to the severity of the problem. RMO updates particles at each step, eliminating the need for position and pace transition between the steps. The particles are moving from the moment that is revised with each step. There is a vector of global best alternatives to protect the optimization technique from being trapped in sub optimal positions.

Initial population: Create an array Y at random of size mp by mv, where mp and mv are the number of elementary particles and components (variables) respectively. The following expression can be used to analyse the components of the array Y given by Eq. 6:

$$Y_{(i,j)}=Y_{(min,j)}+rand(0,1)*(Y_{(max,j)}-Y_{(min,j)}) \quad (6)$$

From Eq. 1, i=1,2,3,4,5…mp and j=1,2,3,4,5…mv, $Y_{min,j}$ and $Y_{max,j}$ are the maximum and minimum bounds of the jth component. In this case, rand (0, 1) is a system can produce at random around "0" and "1" using the statistical model.

Elementary particle movement: After determining the centre point, the particles are distributed in horizontal plane from the centre along the radius r determined by the velocity profile (V). This array has the same order as Y, which is mp by mv. The components of velocity profile can be calculated using Eq. 7:

$$V_{(i,j)}=rand(0,1)*V_{(max,j)} \quad (7)$$

Where, i=1, 2, 3…mp and j=1, 2, 3…mv, and $V_{(max,j)}=(Y_{(max,j}-Y_{(min,j)})/i$. The variable i is an absolute value chosen by the controller. An inertial weight (Wk) helps to control convergence and reduces as the number of iterations increases. An inertial weight (WK) can be calculated using Eq.8

$$W_K=W_{max}-((W_{max}-W_{min})/G_{max})*G_K \quad (8)$$

Wmax and Wmin are typically assumed to be 1 and 0, respectively. These two reference values of WK analyze the effect of different velocities on movement of the elementary particles. Thus, Eq. 7 can now be re - written and included the effect of WK and represented by Eq. 9

$$V_{(i,j)}=W_K*rand(0,1)*V_{(max,j)} \quad (9)$$

The strength of each elementary particle is examined by utilizing the objective function after all of the elementary particles have been strewn about. The overall best outcome is saved in Rpeak along with the particle's placement. Gpeak (global peak) is an attribute that accumulates the highest value and its placement among all Rpeak values from the earlier iterations. The centre point is adjusted using this Gpeak and the modified vector, according to the formulae given by Eq 10 & Eq. 11:

$$centre_{new}=centre_{old}-update \quad (10)$$

$$update=K_1*(G_{peak}-centre_{old})+K_2*(R_{peak}-centre_{old}) \quad (11)$$

Before applying the RMO approach, the coefficients K1 and K2 are fixed. After the centre point has been modified, the process is rehashed with the updated centre point till a termination criterion (such as in the allowable maximum amount of repetitions or the prespecified lowest value Gpeak) is happened to meet. Figure 6 also depicts the two major stages of the RMO-based MPPT approach.

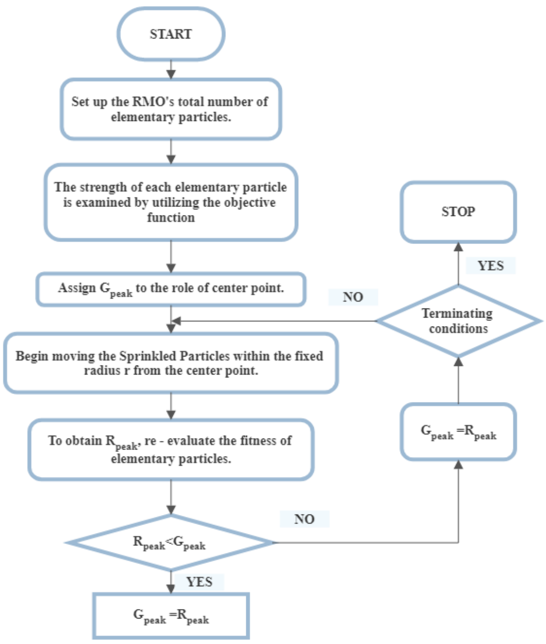

Fig 6. Flowchart of MPPT based on RMO

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IV. MPPT TRACKING USING TEACHING-LEARNING BASED OPTIMIZATION (TLBO):

TLBO, formed by the researchers of [28], mimics the teaching learning methodology in the school environment. Fig. 7 shows the solar modules array's MPPT system layout based on the suggested TLBO. The population is denoted by the students who have the area of study designated to them. The fitness function can be expressed by the grade levels of the students, whereas the optimized solution is represented by the teacher in each stage. The algorithm is divided into two phases: students and teachers. Effective teaching or sharing of knowledge by the teacher improves the average scores of the students in class while in the teacher step. Conversation among students improves grades during the student phase. In the following step, the greatest learner is promoted to teacher. When applied to the MPPT challenge, the duty cycle of the DC-DC power converter can be chosen as the students, whereas the output power of PVS is regarded as the fitness value. During the teacher phase, the duty cycle of the DC-DC converter is revised using Eq. 12.

$$\delta(k+1)=\delta(k)+r*(\delta_{k,best}-T_{F}\,\delta_{k,averge}) \qquad (12)$$

Where, $\delta(k+1)$ is the duty cycle at (k+1)th iteration and $\delta(k)$ is the present duty cycle

$\delta_{k,best}$ is the teacher's value

$\delta_{k,average}$ is the average value of students.

T_F is the factor of teaching given by Eq. 13

$$T_F=\delta_{k,average}/\delta_{k,best} \qquad (13)$$

During the student interaction phase, two randomly selected students, δy and δz, interact to generate a new duty cycle value represented by Eq. 14 & Eq.15

$$\delta_{new}=\delta_{old}+(\delta_z-\delta_y) \text{ if } [P_{PVS}] \text{ at } \delta_z>[P_{PVS}] \text{ at } \delta_y \quad (14)$$

$$\delta_{new}=\delta_{old}+(\delta_y-\delta_z) \text{ if } [P_{PVS}] \text{ at } \delta_z<[P_{PVS}] \text{ at } \delta_y \quad (15)$$

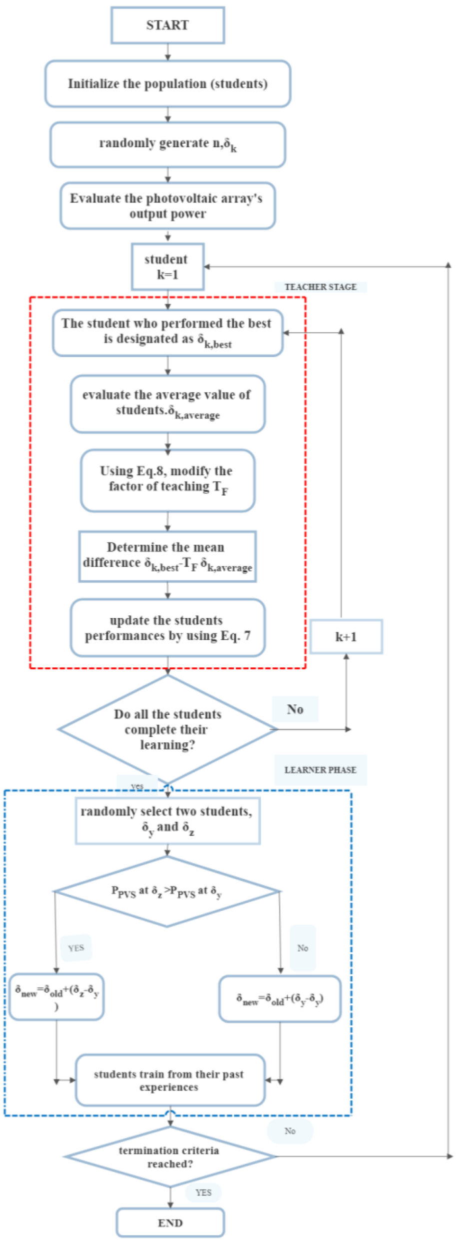

Fig. 7 TLBOMPPT's flow diagram

V. HRMOTLBO-BASED MPPT TRACKING:

5.1. Hybrid RMO with TLBO:

In this proposed work, the elementary particle location has been further modified by employing a transitioning possibility between attempting to bring the value closer to the optimum value and the learner phase of TLBO proposed in [28]. This additional enhancement contributed to the convergence to a better outcome. The pseudo code for HRMOTLBO is as follows:

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if rand<t

$$\delta_i^q(k+1) = \delta_i^q(k) + r_i^q(k+1)$$

else

if $g\left(\delta_y^q(k)\right) > g((\delta_z^q(k))$

$$\delta_i^q(k+1) = \delta_i^q(k) + \mathrm{rand}(\delta_y^q(k) - \delta_z^q(k))$$

else

$$\delta_i^q(k+1) = \delta_i^q(k) + \mathrm{rand}(\delta_z^q(k) - \delta_y^q(k))$$

In this suggested work, rand is a random variable between zero and one, t is the transition possibility considered, y and z are the two elementary particles selected randomly in addition to the existing elementary particle.

5.2. MPPT Implementation with HRMOTLBO:

A DC-DC boost converter served as a conduit for MPPT between the traditional power grid and the PVS. In order to send the voltage and current corresponding to the maximum power value at the output, the STEP-UP converter's duty cycle was adjusted for a specific solar irradiation condition. Here, the duty cycle was exactly equivalent to that of the HRMOTLBO elementary particle. The hybrid HRMOTLBO's structural flow diagram is described in Fig. 8.

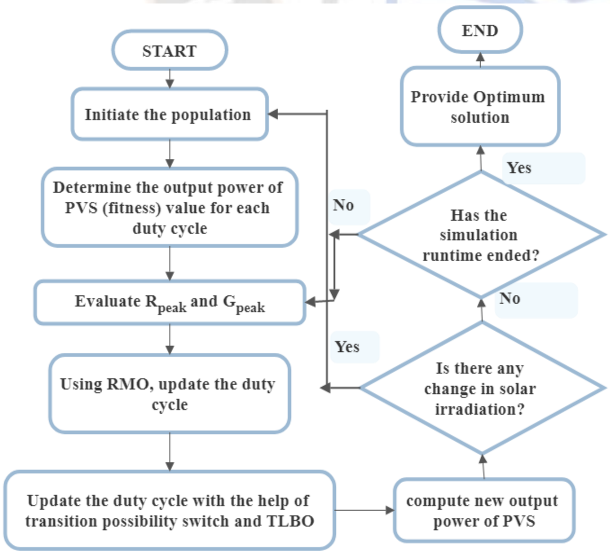

Fig 8. Flow chart of proposed HRMOTLBO

The duty cycle in this case was comparable to that of the elementary particle in HRMOTLBO. The MATLAB Simulink was used to capture real-time simulated results. HRMOTLBO was written in MATLAB C function block, which functions similarly to a microcontroller. In each time step, power pertaining to five initial duty cycle values (0.1, 0.2, 0.3, 0.6, and 0.9) was first observed, and then all four duty cycle values were adjusted using the HRMOTLBO formulas. The procedure was repeated until the simulation runtime terminated. Figure 8 depicts a flowchart of HRMOTLBO operation.

VI. SIMULATION & EXPERIMENTAL RESULTS OF THE SUGGESTED HRMOTLBO:

In this section, a comparison of HRMOTLBO is made with the very recently proposed Jaya algorithm [29]. The comparison is made based on the time taken for convergence to the GMPP and the average number of power pulsations. The parameters of the photovoltaic panels used in the MATLAB simulation and experimental implementation are listed in Table 1. The outcomes are divided into 2 parts. In the first part, the results for lightly PSCs were taken (fewer or no photovoltaic modules were shaded). Various cases of heavily PSCs (8 out of 10 panels are partly shaded) have been presented in the second part to prove the tracing capabilities of the suggested algorithm.

Table 1. Specifications of the PV Panel

Panel Parameters	**Rating**
Temperature Range	-40 to 85 C
Operating current	5.8A
Operating voltage	16.8V
Maximum voltage	1000V DC
No. of panels	10
No.of photovoltaic modules	5
Total no of series cells	36
Cell area	125 mm x 31.25mm
Converter parameters	**Rating**
Switching frequency	10kHz
Capacitors C_1, C_2	$1000\mu F$, 10 μF
Inductors L_1 L_2	10mH/10A
Diode	FR207

6.1. Circumstances of stable PSCs:

This paper analyses the effectiveness of the HRMOTLBO-based MPPT methodology for different PSC circumstances. Given the stochastic nature of partial shaded scenarios, there are countless potential weather patterns. In order to verify the system's dependability, it is crucial to test how it performs in diverse circumstances .Under these circumstances, the PS situations were maintained constant across the whole duration of the simulation and experimental run time. The results have been obtained under two distinct circumstances: mild PSCs and intensive PSCs are discussed in the following.

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6.1.1. Mild PSCs:

Three distinct scenarios were considered, each with complete and partial shading. In the first scenario, all five photovoltaic modules received uniform solar insolation under the condition of full irradiance. Another two scenarios were picked in such a way that a total of four and three photovoltaic modules received 100% irradiance, respectively. Table 2 provides an overview of all the patterns for these circumstances.

Table 2. Overview of the patterns under mild PSCs

Shading strategies	Solar irradiation passing through the photovoltaic modules (W/m^2)				
	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5
Mild PSC-1	1000	1000	1000	1000	1000
Mild PSC-2	1000	1000	1000	1000	900
Mild PSC-3	1000	1000	1000	900	800

6.1.2. Intensive PSCs:

In this instance, the effectiveness of the suggested hybrid MPPT technique was evaluated using two distinct heavy PSCs. Two modules in each of these two situations received full sun irradiation of 1000W/m2, while the remaining three panels were significantly shadowed and operated under various solar illumination circumstances, as stated in Table 3.

Table 3. Overview of patterns during intensive PSCs

Shading strategies	Solar irradiation passing through the photovoltaic modules (W/m^2)				
	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5
Intensive PSC-1	1000	1000	800	750	700
Intensive PSC 2	1000	1000	700	650	400

6.2. Circumstances for dynamic PSC:

This section's comparative investigation takes into account a realistic situation. In everyday practice, the shaded pattern on a PV array fluctuate due to changing climate variability like as passing cloud cover, continuously changing amount of solar energy and orientation, and so on. As a result, a method relies on these conditions must be tested for a more detailed study. We chose two distinct variable shading criteria. The shading was expected to be lower in the initial instance and subsequently raised in the next, and vice versa listed in Table 4 and Table 5.

Table 4. Overview of patterns during dynamic PSC-1

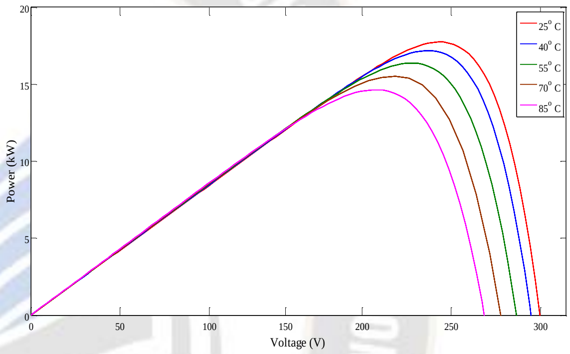
Shading strategies	Solar irradiation passing through the photovoltaic panels (w/m^2)				
	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5
Instant 1	1000	1000	600	500	300
Instant 2	1000	1000	1000	700	500

Table 5. Overview of patterns during dynamic PSC-2

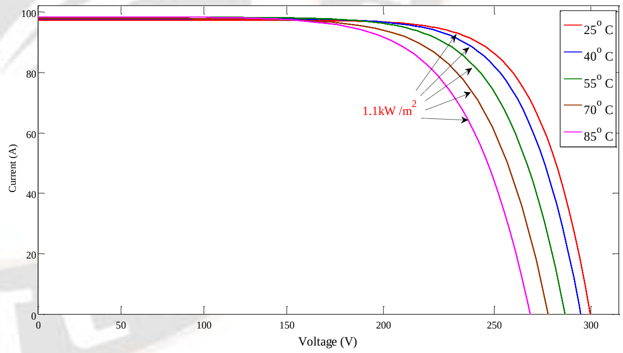
Shading strategies	Solar irradiation passing through the photovoltaic panels (w/m^2)				
	Panel 1	Panel 2	Panel 3	Panel 4	Panel 5
Instant 1	1000	1000	1000	800	600
Instant 2	1000	1000	600	500	200

6.3. Simulation results and discussion:

Analytical and simulation studies were conducted to assess the effectiveness of HRMOTLBO based MPPT. The insolation ranges from 500 to 1100 kW/m2, and the cell temperature ranges from 85 to 25 degrees Celsius. Figures 9 and 10 depict the module's I-V and P-V characteristics as cell temperature and irradiance change. These characteristics serve as a framework for the network training.



(a)



(b)

Fig 9. (a) P-V characteristics of PV array (variable temperature) (b) I-V characteristics of PV array (variable temperature)

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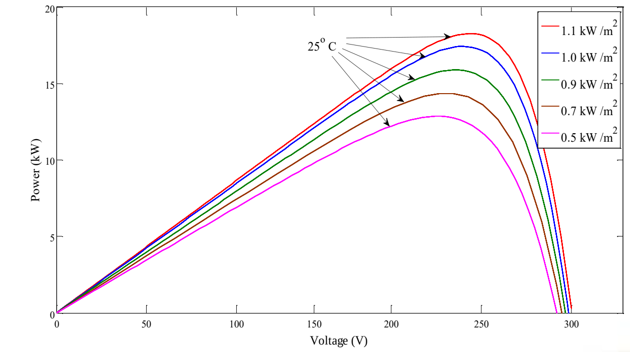
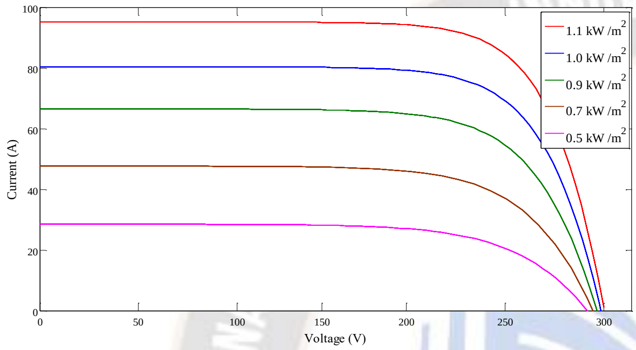
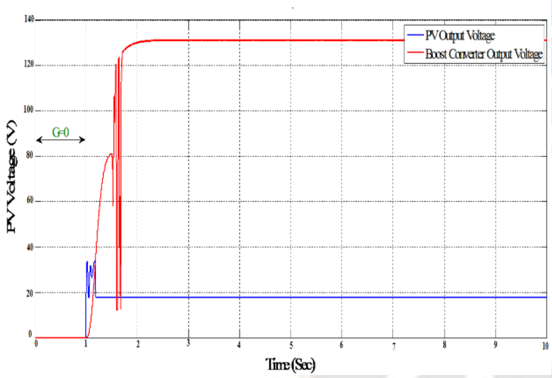


(a)

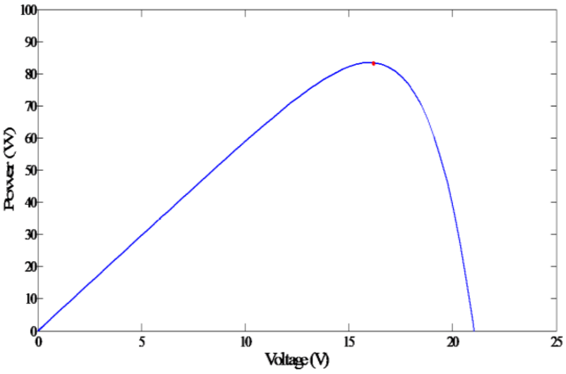


(b)

Fig 10. (a) P-V characteristics of PV array (variable irradiance W/m^2)
(b) I-V characteristics of PV array (variable irradiance W/m^2)



(a)



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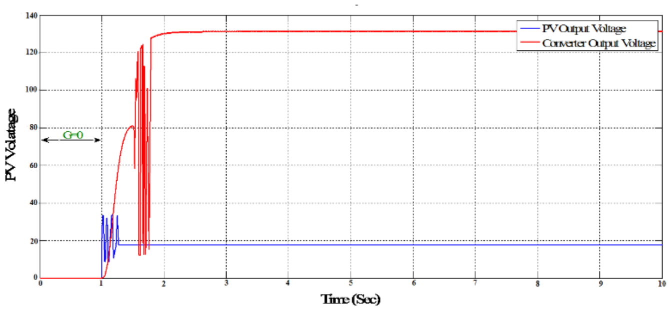
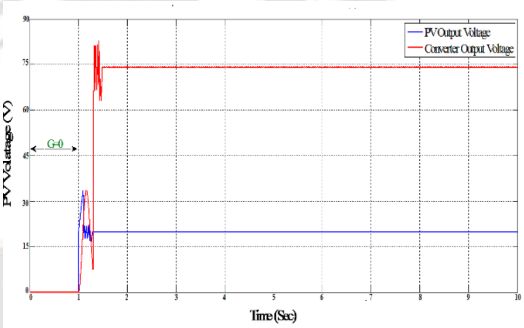


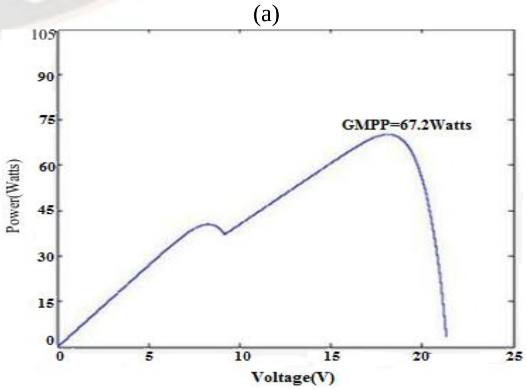
(c)

Fig 11. Under mild PSC-1:
(a) simulated photovoltaic output voltage with hybrid HRMOTLBO MPPT,
(b) P-V characteristics of photovoltaic array
(c) Photovoltaic output voltage with recent Jaya algorithm based MPPT

Figures 11 (a), (b), and (c) depict the comparative simulated evaluation under mild PSC-1. The suggested hybrid MPPT technique traces the MPP of 85.5W in 0.8 seconds. The recent Jaya algorithm traces the MEP in1.7 seconds. It is evident that the recommended methodology clearly accessed the Maximum power point more quickly. Furthermore, the proposed algorithm produced relatively lesser oscillations at the output voltage than the recent Jaya method, which produced a greater amount of larger oscillations, which led to significant power losses. The lowered tracing time as well made a significant contribution to power efficiency, significantly improving the effectiveness while compared to the case while recent Jaya had been used.



(a)



(b)

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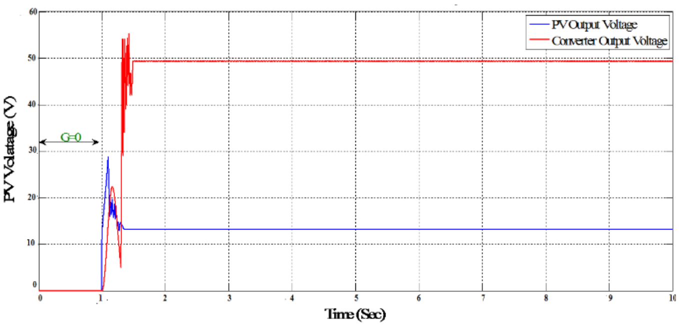
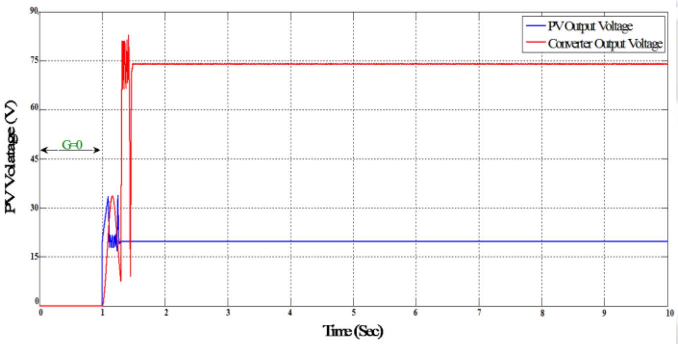


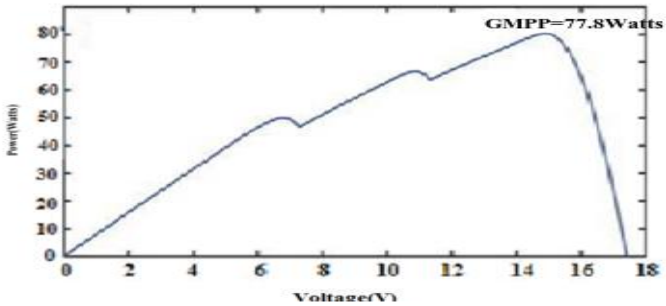
(c)

Fig 12. Under mild PSC-2:
(a) simulated photovoltaic output voltage with hybrid HRMOTLBO MPPT,
(b) P-V characteristics of photovoltaic array
(c) Photovoltaic output voltage with recent Jaya algorithm based MPPT

When only one module was shaded, Figures 12 (a), (b), &(c) demonstrated the comparative analysis outcomes under mild PSC-2. In 1.7 seconds, the suggested algorithm tracked the 67.5 W MPP. The Jaya was tracked for 1.8 seconds at 67.2 W. As a result, the suggested technique traced the MPP more quickly. The outcomes of the simulation also show that the oscillations in voltage were much less with HRMOTLBO, which also raises the total effectiveness of the photovoltaic system.



(a)



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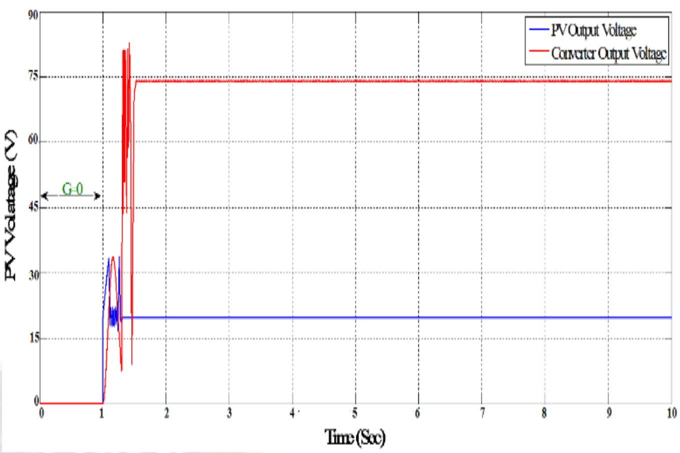
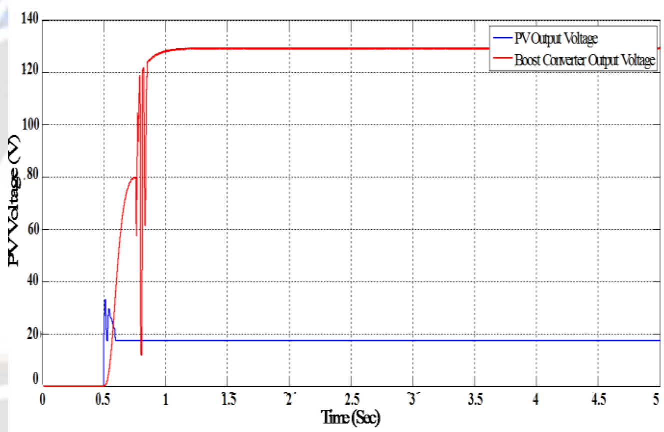


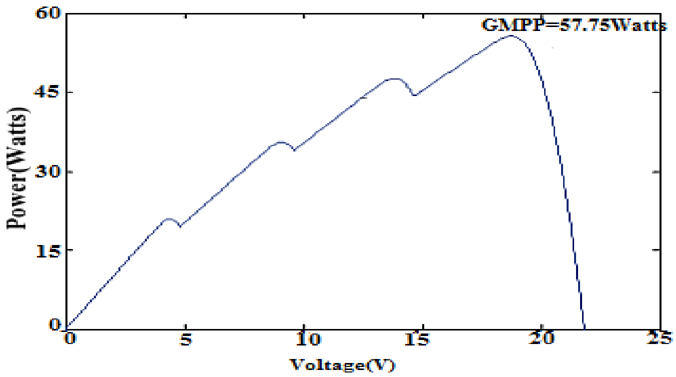
(c)

Fig 13. Under mild PSC-3 (a) Simulated photovoltaic output voltage with hybrid HRMOTLBO MPPT,
(b) P-V characteristics of photovoltaic array
(c) Photovoltaic output voltage with recent Jaya algorithm based MPPT

Under the mild PSC-3, two modules had been obscured, and Figure 13(a), (b), &(c) displayed the comparison results. The suggested approach tracked the MPP of 77.8 W within 1.3 seconds. Recent Jaya's tracing duration was 1.5 seconds. Again the suggested technique traced the MPP more quickly. HRMOTLBO's overall efficiency was increased by the fact that there were a lot fewer output fluctuations.



(a)



(b)

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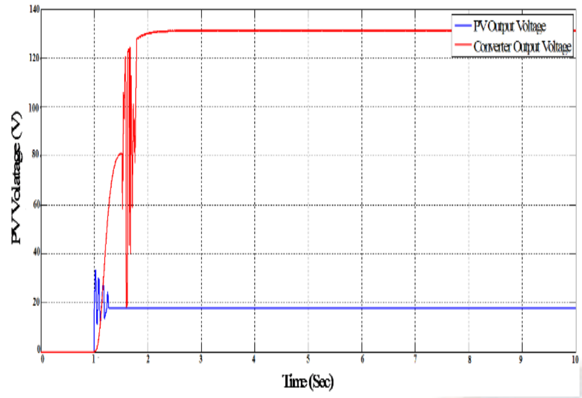
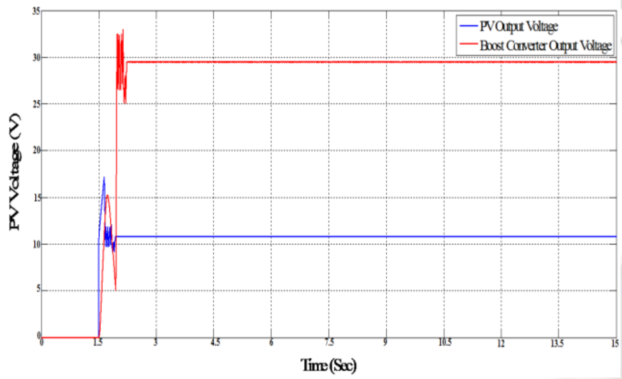


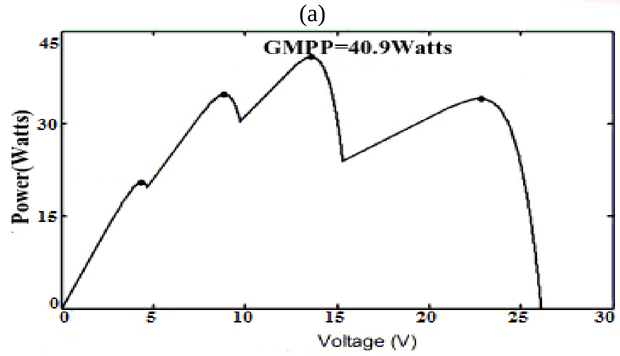
(c)

Fig 14. Under intensive PSC-1 (a) simulated photovoltaic output voltage with hybrid HRMOTLBO MPPT,
(b) P-V characteristics of photovoltaic array
(c) Photovoltaic output voltage with recent Jaya algorithm based MPPT

The correlation results under intensive PSC-1 are shown in Figure 14(a), (b), &(c). The suggested methodology traced the GMPP in 0.75 seconds at 57.75 W. The recent Jaya's methodology attains GMPP in 1.55 seconds at a power of 57.7 W.As a result, when compared to the recent Jaya algorithm; the proposed algorithm traced the GMPP with a much quicker speed and with considerably fewer large size oscillations under intensive PSC-1. As a result of the simultaneous ability to contribute of lower oscillations and quicker tracing as common, overall effectiveness is improved.



(a)



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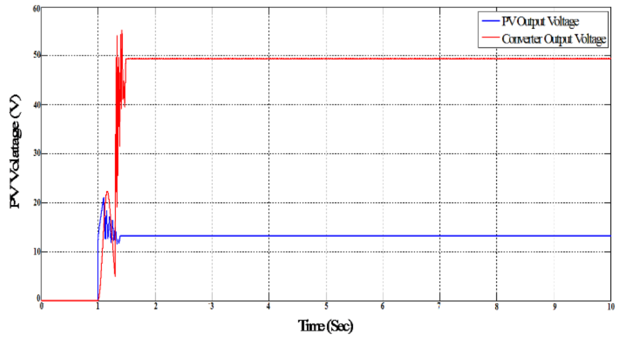

(c)

Fig 15. Under intensive PSC-2 (a) simulated photovoltaic output voltage with hybrid HRMOTLBO MPPT,
(b) P-V characteristics of photovoltaic array
(c) Photovoltaic output voltage with recent Jaya based MPPT

The comparative outcomes under intensive PSC-2 are shown in Figure 15 (a), (b), & (c) . At a power of 42 W, the proposed algorithm traced the GMPP in 1.75 seconds. The Jaya took 1.4 seconds to settle to the GMPP with a power of 40.9 W. This represents the only circumstance in which the recent Jaya methodology found the GMPP with much less time. However, the recent Jaya's large - sized oscillations remained a problem, decreasing the effectiveness of the system.

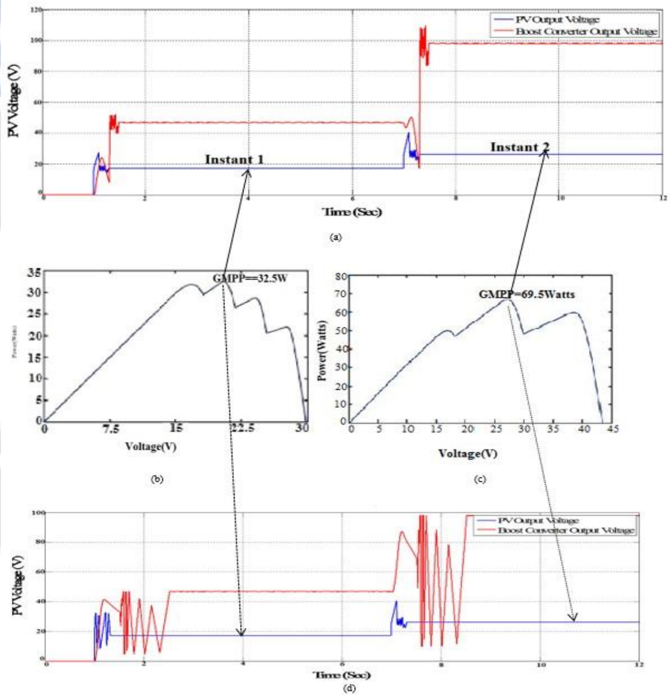

Fig 16. Under dynamic PSC-1 (a) Simulated output voltage with HRMOTLBO MPPT
(b) P-V characteristics of photovoltaic system during instance-1
(c) P-V characteristics of photovoltaic system during instance-2
(d) Simulated output voltage with recent Jaya based MPPT

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Table 4 encapsulates partial shaded patterns at various moments in this case. The outcomes for this scenario are shown in Figure 16(a),(b),(c),&(d). Each partial shaded instant persisted for 5.5 seconds. The results demonstrate that the recommended method traced the global maximum energy point from the photovoltaic system at instants 1 and 2 of 32.5 Watts 0.75 seconds and 66.96 Watts 0.55 seconds, respectively. Jaya measured the MPP at 32.5W in 1.2 seconds and 66.87Watts in 1 second At instants 1 and 2 respectively. As a result, it is evident that the suggested method outperforms recent Jaya in terms of monetary traceability and generating some less large - scale power oscillations.

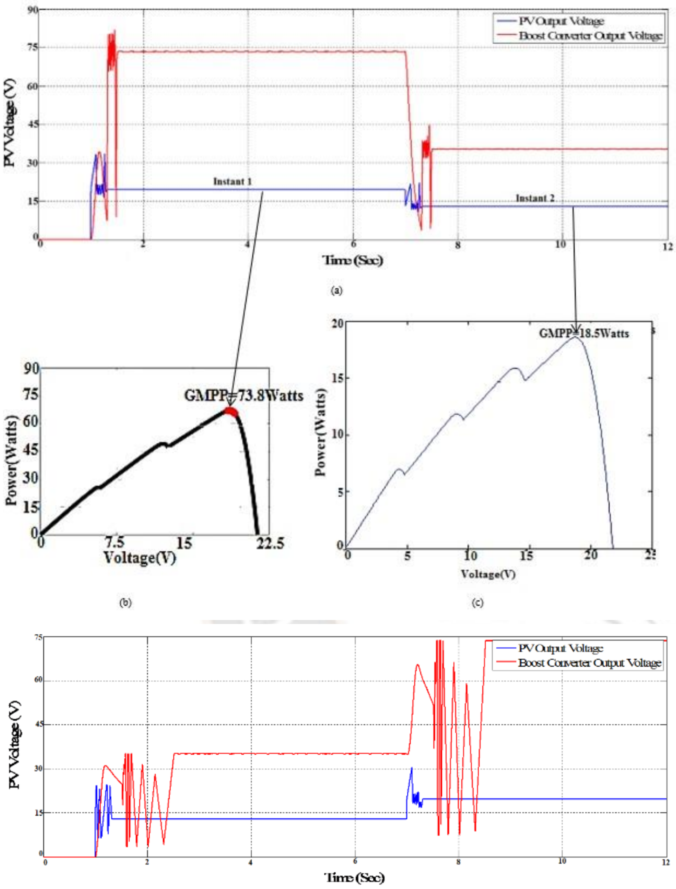

Fig 17. Under dynamic PSC-2 (a) Simulated output voltage with HRMOTLBO MPPT
(b) P-V characteristics of photovoltaic system during instance-1
(c) P-V characteristics of photovoltaic system during instance-2
(d) Simulated output voltage with recent Jaya based MPPT

The results are depicted in Fig. 17 an overview of partial shaded patterns during dynamic PSC-2 at numerous instances of time for this case. The suggested methodology traced the maximum power from the photovoltaic system of 73.8 W in 0.35 secs and 18.5 W in 0.95 secs at instances of time 2 and 1 respectively. For instance 2, recent Jaya traced the MPP of 73.8 W in 1.3 seconds; however, for instance 1, recent Jaya was able to trace the maximum power 2.2seconds with large oscillations from the photovoltaic system, demonstrating the ineffectiveness of the recent Jaya algorithm under dynamic fluctuations in solar irradiation. In contrast to recent Jaya, HRMOTLBO was capable of successfully trace the maximum power. As a consequence, it is evident that the suggested method achieves the recent jaya algorithm in terms of continuous tracing and producing a lower number of significant voltage fluctuations.

6.4. Experimental results and discussion:

Figure 18 depicts a pilot model created in this manuscript that demonstrates the effectiveness of the HRMOTLBO MPPT approach. A PV array, a DSPIC30F2010 processor, a DSPIC30F2010 connector board, a typical high DC-DC step-up converter, and a LC filter were used to create this experimentation arrangement. The PV array is made up of 10 PV modules connected in series. The suggested method is realized using a Micro electro mechanical DSPIC (DSPIC30F2010) as the MPPT controller. In this paper, a High step up DC-DC (RE-BOOST) Converter is presented to reduce harmonic components in power generation powered by solar renewable energy systems. The use of this converter can reduce ripples in low frequency components. The experiment was carried with the similar circumstances as in the MATLAB simulation. The IR2110 is a medium voltage MOSFET driver integrated circuit. In half-bridge and low bridge circuits, this can operate both low and high side switching. The switching frequency of the DC-DC step-up converter was set to 20 kHz. Solar (PV) panels or solar cells are connected to form Photovoltaic modules. They are made of semiconductor materials such as crystalline silicon. The working voltage and current ratings of solar panel are 16.8V and 5.8A accordingly.

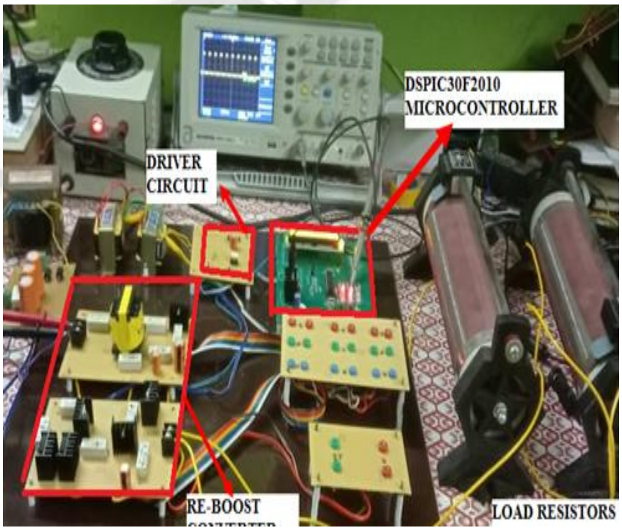

Fig 18. Hardware prototype of the suggested HRMOTLBO-based photovoltaic system.

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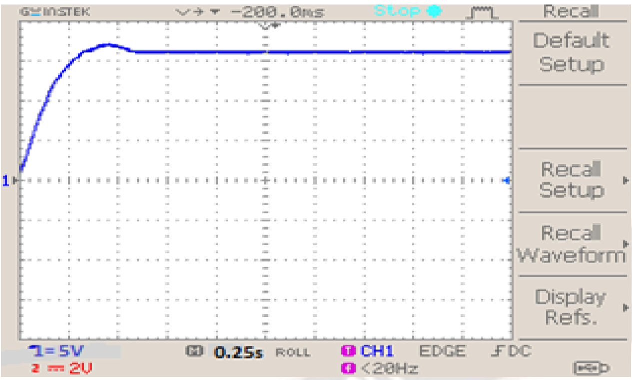
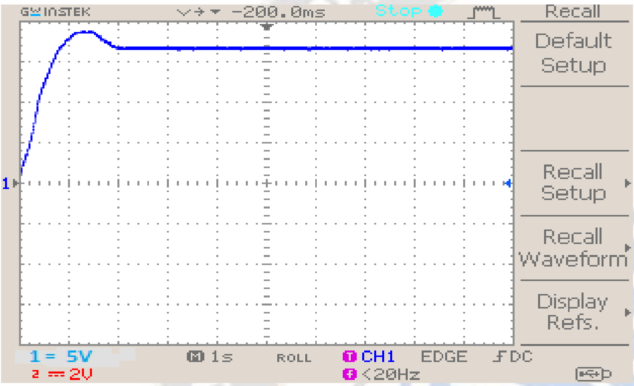
Mild PSCs: When all of the photovoltaic modules are at full sun insolation of 1000W/m^2, under mild PSC-1 the voltage across the photovoltaic system that uses HRMOTLBO and the most recent Jaya algorithm is illustrated.



(a)



(b)

Figure 19. Under mild PSC-1 (a) Experimental photovoltaic output voltage with hybrid HRMOTLBO MPPT
(b) Experimental Photovoltaic output voltage with recent Jaya algorithm based MPPT

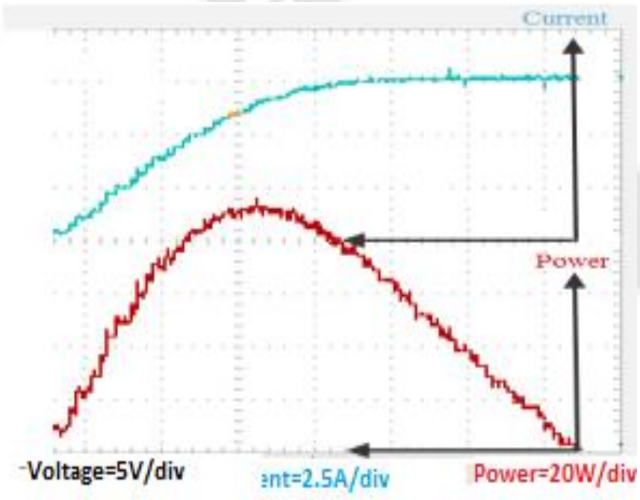
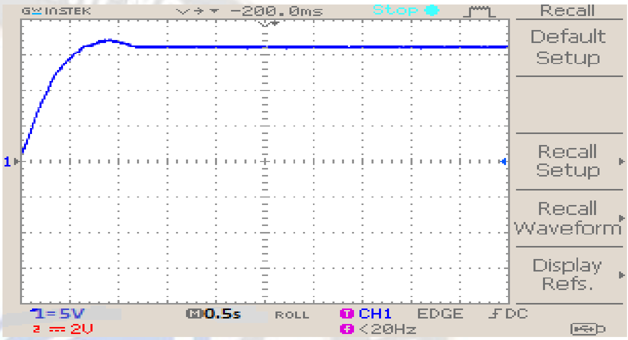
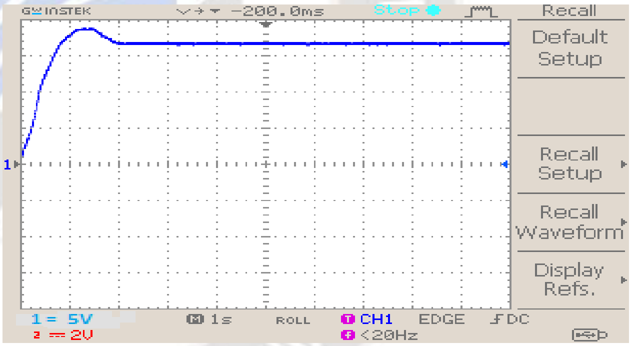


Figure 20. P-V and I-V characteristics of a photovoltaic system with all modules operating at 1000W/m^2 uniform radiation.

The experimental evaluation of photovoltaic output voltages with HRMOTLBO and the recent Jaya optimization technique under mild PSCs is shown in Figures 19 (a), (b). As shown in Figure 20, the hybrid MPPT method developed here traces the MPP of 87.5W in 0.75 seconds under full uniform solar irradiance conditions. The MEP is traced in 1.9 seconds by the most recent Jaya algorithm. As a result, the suggested method clearly accessed the MPP faster. The experimental analysis also shows that there are no oscillations in photovoltaic output voltage in both the proposed HRMOTLBO MPPT and the recent Jaya-based MPPT. However, with Jaya-based MPPT, there is a significant peak overshoot in the photo-voltaic output voltage waveform.



(a)



(b)

Figure 21. Under mild PSC-2 (a) Experimental photovoltaic output voltage with hybrid HRMOTLBO MPPT
(b) Experimental Photovoltaic output voltage with recent Jaya algorithm based MPPT

As shown in fig 21 (a) & (b) Under mild PSC-2, the suggested algorithm traced the 68 W MPP in 1.3 seconds. At 67 W, the Jaya was tracked for 2.1 seconds. As a result, the suggested methodology traced the MPP faster.

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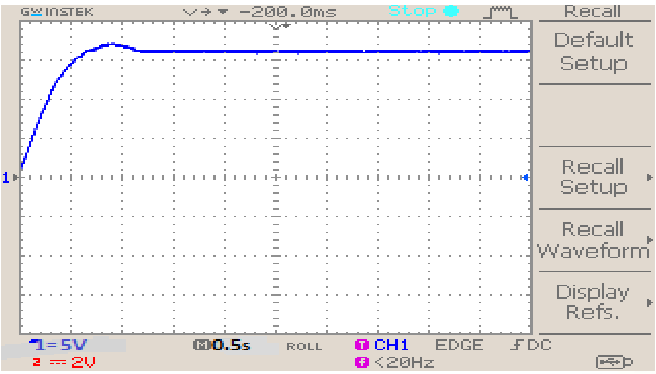
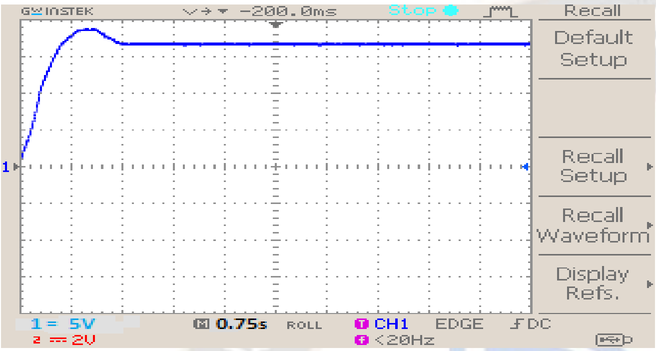


(a)

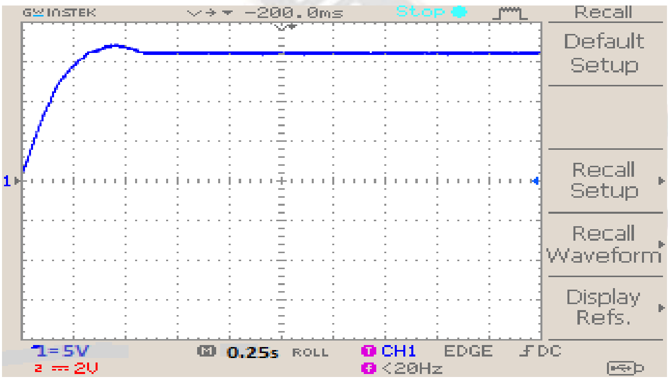


(b)

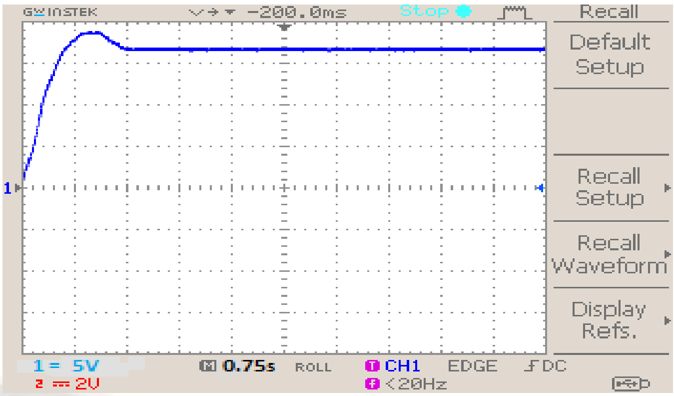
Figure 22. Under mild PSC-3 (a) Experimental photovoltaic output voltage with hybrid HRMOTLBO MPPT
(b) Experimental Photovoltaic output voltage with recent Jaya algorithm based MPPT

As shown in fig 22 (a) & (b) Under mild PSC-3, the suggested algorithm traced the 77 W MPP in 1.3 seconds. At 75.2 W, the Jaya was tracked for 1.6 seconds. As a result, the suggested methodology traced the MPP faster.

Intensive PSCs:



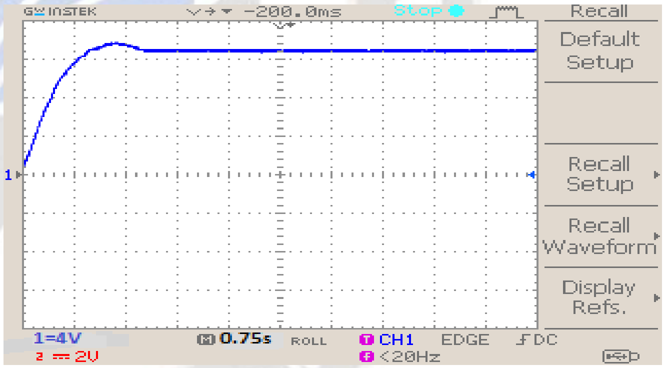
(a)



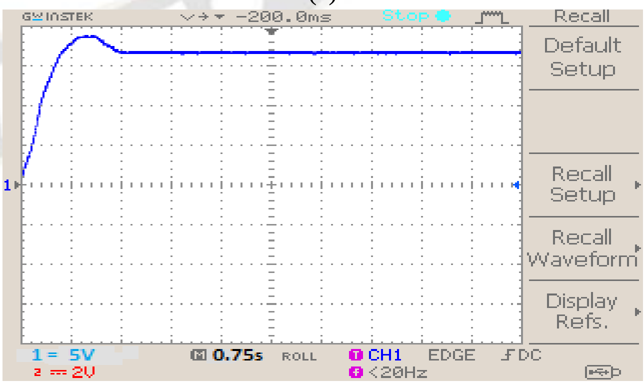
(b)

Figure 23. Under intensive PSC-1 (a) Experimental photovoltaic output voltage with hybrid HRMOTLBO MPPT
(b) Experimental Photovoltaic output voltage with recent Jaya algorithm based MPPT

The correlation results under intensive PSC-1 are shown in Figure 23(a), & (b). The suggested methodology traced the GMPP in 0.6 seconds at 56 W. The recent Jaya's methodology attains GMPP in 1.55 seconds at a power of 57.7 W. As a result, in comparison with the recent Jaya methodology; the one suggested traced the GMPP with a much quicker speed under intensive PSC-1.



(a)



(b)

Figure 24. Under intensive PSC-2 (a) Experimental photovoltaic output voltage with hybrid HRMOTLBO MPPT
(b) Experimental Photovoltaic output voltage with recent Jaya algorithm based MPPT

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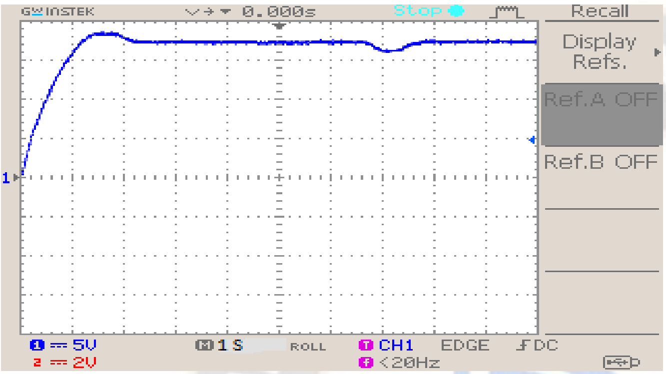
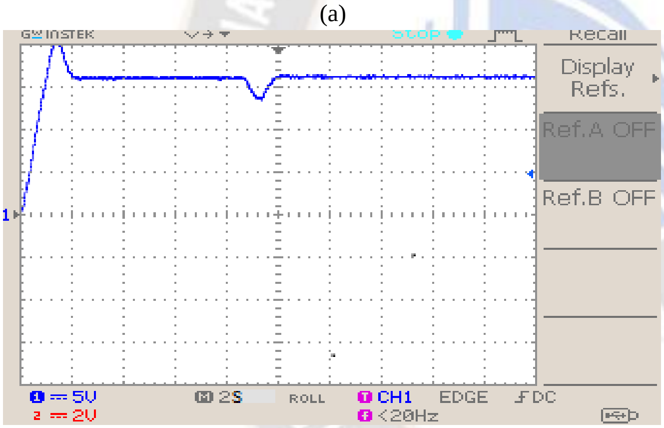
The comparative outcomes under intensive PSC-2 are shown in Figure 24 (a),& (b). At a power of 41 W, the suggested approach traced the GMPP within 1.7 seconds. The Jaya took 1.5 seconds to settle to the GMPP with a power of 40.9 W. It is the sole instance where the new Jaya methodology discovered its GMPP in less time. However, the recent Jaya's large - sized overshoot remained a problem, decreasing the effectiveness of the system. Table 8 depicts an overview of MPPT tracing at different PSCS together with simulation and experimental results.



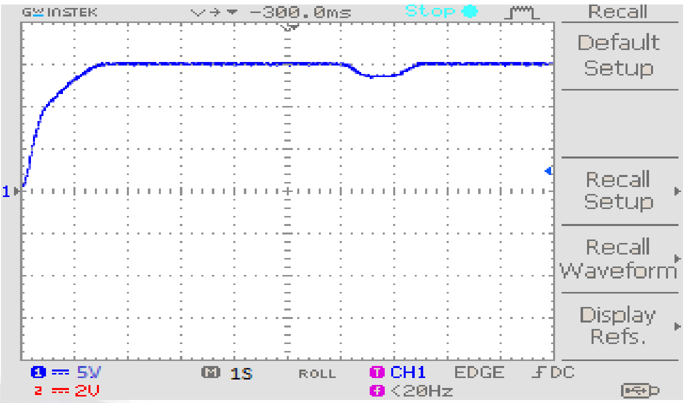
(a)



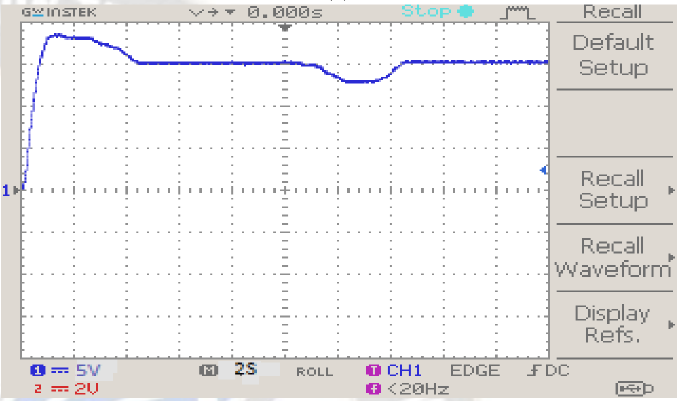
(b)

Figure 25. Under dynamic PSC-1 (a) Experimental photo-voltaic output voltage with HRMOTLBO MPPT
(b) Experimental photo-voltaic output voltage with recent Jaya based MPPT

Figures 25 (a), & (b) describe the experimental analysis of photo - voltaic voltages incorporating HRMOTLBO and the recently developed Jaya optimization algorithm under dynamic PSC-1. Table 4 summarizes different illumination patterns during dynamic PSC-1 at various points. Each instant of insolation lasted for 5.5 seconds. The extensive experiments show that the suggested HRMOTLBO method located the photovoltaic system's global maximum energy point at instants 1 and 2, which were 31 Watts for instant 1 in 0.95 seconds and 65.5 Watts for instant 2 in 0.6 seconds, respectively. At instants 1 and 2, Jaya measured the MPP at 31W in 1.6 seconds and 65.5Watts in 1.3 second, respectively with large overshoot in the photovoltaic output voltage.



(a)



(b)

Figure 26. Under dynamic PSC-2 (a) Experimental photo-voltaic output voltage with HRMOTLBO MPPT
(b) Experimental photo-voltaic output voltage with recent Jaya based MPPT

In Fig. 26, an overview of different illumination patterns during dynamic PSC-2 at various points in time for this case, the experimental results are shown. The suggested methodology traced the photovoltaic system's maximum power at instances 1 and 2, which was 18W in 2.2 seconds and 72.55 W in 0.95 seconds, respectively. In instance 1, recent Jaya was able to trace the maximum power in 2.2 seconds with large overshoot under dynamic variations in solar irradiation. In instance 1, recent Jaya traced the MPP of 72 W in 1.3 seconds.

Table 8 compares simulation and experimental results for various PSCs with HRMOTLBO MPPT and recent Jaya-based MPPT. In terms of voltage oscillations, overshoot, and tracing time, HRMOTLBO was able to successfully trace the maximum power, in contrast to the most recent Jaya.

Table 8. Comparisons of simulation and experimental results for various PSCs with HRMOTLBO MPPT and recent Jaya-based MPPT

Shading Strategies	Simulation results				Experimental results			
	HRMOTLBO MPPT		Recent Jaya based MPPT		HRMOTLBO MPPT		Recent Jaya based MPPT	
	GMPP (W)	Tracing time (s)	GMPP (W)	Tracing time (s)	GMPP (W)	Tracing time (s)	GMPP (W)	Tracing time (s)
Mild PSC-1	87.5	0.75	87.5	1.9	87.5	0.75	87.5	1.9
Mild PSC-2	67.5	1.7	67.2	1.8	68	1.3	67	2.1
Mild PSC-3	77.8	1.3	77.8	1.5	77	1.3	75.2	1.6
Intensive PSC-1	57.75	0.75	57.7	1.55	57.7	0.6	57.7	1.55
Intensive PSC-2	42	1.75	40.9	1.4	41	1.7	40.9	1.5
Dynamic PSC-1 (Instance 1)	66.96	0.55	66.9	1	65.5	0.95	65.5	1.3
Dynamic PSC-1 (Instance 2)	32.5	0.75	32.5	1.2	31	0.95	31	1.6
Dynamic PSC-2 (Instance 1)	18.5	0.95	18.5	2.2	18	0.95	18	2.2
Dynamic PSC-2 (Instance 2)	73.8	0.65	73.8	1.3	72.55	0.95	72.5	1.3

VII. CONCLUSION:

First, a partially shaded situation detection method is demonstrated in this paper, and its performance in diverse circumstances is investigated. This paper also describes a successful implementation of HRMOTLBO method for photovoltaic system to trace the global peak point within the lesser time and fewer power fluctuations. For various PSCs, effectiveness validation was completed for both steady state and even more plausible highly dynamic irradiance conditions. The suggested methodology outperformed the newly proposed Jaya technique with respect to tracing time, large-scale voltage oscillations and peak over shoot. According to simulation and experimental results, under mild PSCs and heavily shaded PSCs, the proposed HRMOTLBO-based MPPT traces the global peak power point at a much faster rate than the recent Jaya-based MPPT as shown in Table 8. The proposed hybrid methodology determines whether or not the system operates under uniform irradiance. An innovative simple and speedy methodology for MPPT under distinct PSCs is then presented, which operates as a direct control method and does not require feedback control of current and voltage. Quicker tracking time and very few oscillations on the load side are required because the fewer the oscillations and rapid tracking, the smaller the energy losses, which make significant contributions to the system's productivity, particularly during rapidly varying irradiance circumstances. As a result, the suggested methodology could be better alternative when developing a control scheme for residences, business, or manufacturing applications. In terms of tracking time, voltage oscillations, and overshoot, the outcomes of both experiments and simulations confirmed the concept of HRMOTLBO.

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