Abstract—Inclusion of bypass diodes at the output terminal of the PV array mitigates the effect of partial shading (PS) but causes multiple peaks of power at the output. The conventional hill climbing and perturb and observe algorithms cannot track the optimal point during partial shading phenomena for multiple peaks corresponding to the different shading pattern on the Power-Voltage (P-V) curve. Fuzzy logic controller and artificial neural network-based methods for Maximum Power Point Tracking (MPPT) provide satisfactory results but at the cost of increased memory and computational burden. Recent work to incorporate exploration and exploitation phenomena of nature-inspired algorithms to track optimal power point have shown encouraging results by preventing convergence to local maxima and posing less burden on the processor. However, due to performance variation between different algorithms of this category newer algorithms with improved performances are still a requirement. In this paper, a novel most valuable player algorithm (MVPA) has been used to track the optimal operation point for extracting maximum power from a solar PV system. The algorithm’s performance is compared with the commonly employed particle swarm optimization (PSO) and the recently proposed Jaya algorithm’s modified form. It is observed that the proposed algorithm outperformed both the algorithms with a considerable improvement in terms of tracking speed, power tracking efficiency, robustness, faster decision for convergence after tracking the maximum power and lesser number of power fluctuations for different shading patterns.

Keywords—Partial shading, Maximum power point tracking (MPPT), PV System, Most valuable player algorithm (MVPA), Metaheuristic Algorithms.

I. INTRODUCTION

The requirement of a clean and sustainable source of energy has driven the power sector across the world to explore the possibility of bulk generation of power using sun and wind as sources of energy. Electrical energy generation from the sun has seen a considerable boost and is one of the fastest growing resource for electric energy generation with many countries in the world adopting this as a source of electricity generation [1-2]. Also, the solar energy provides the highest power density among all the renewables [3]. The Solar based generation wherein the sunlight is directly converted into electricity has picked up in the market with an exponential reduction in energy generation cost over a few decades. Serious research in material and production technology to increase the efficiency and robustness of PV cells have contributed to the popularity. Understanding the behavior of PV modules under changing atmospheric conditions and designing suitable algorithms to track the available power has been the endeavor of the researchers for the last three decades. The non-linear I-V characteristics of a Solar PV module has a unique point where maximum power is available. The point changes with insolation and temperature. The characteristics start exhibiting multiple power peaks when subjected to multiple insolation conditions. Incorporating bypass diodes to mitigate the partial shading effect introduced multiple peaks on the PV curve [4]. The presence of multiple peaks at the output makes it difficult for an algorithm to decide the global maximum power point/peak (GMPP) among the available ones. The classical algorithms which were developed in [5-7] do not have satisfactory performance for partial shading conditions due to the convergence to the P-V curve’s local peak. Moreover, in hill climbing and perturb and observe (P&O) methods, the algorithm oscillates around the MPP resulting in power loss [8]. A double stage technique was proposed in [9] to eliminate the issue of convergence to local maxima. During the first stage, all the available local MPPs are tracked. In the second stage, the Global MPP evaluation is done using P&O. Although the efficiency was improved, the computational time due to the complete search space exploration was increased, thereby resulting in the slower convergence. Fuzzy logic control (FLC) [10-11] and artificial neural network (ANN) [12] based algorithms were designed to resemble human thinking behavior. The algorithms are trained by feeding in with adequate information. In [13] a combined ANN and FLC was employed to track Global MPP. These soft computing methods provided desirable performance in tracking maximum power. But the complexity of these algorithms increases with the increase in data that is fed. Also, the huge data that is fed increases the storage burden [14]. Over the last few years metaheuristic algorithms have been applied in a variety of optimization problems. Due to their efficient convergence characteristics they have become quite popular in solving multivariable non-linear problems. A variety of metaheuristic algorithms ranging from mimicking the food foraging behavior, hunting methods, reproduction and breeding properties of plants and animals have been reported in literature. Various nature inspired algorithms are listed in Fig.1. Some of the more popular methods include particle swarm optimization, genetic algorithm, differential evolution, whale optimization, ant colony optimization, etc. They have also been applied to solve the optimal power point tracking in PV generation system [14-
These algorithms due to their exploration property traverse the complete search area and then decides the best value thereby avoiding local peaks. Moreover, no specific data is required in their training process hence poses lesser burden on processor memory. Nevertheless, all metaheuristic algorithms cannot provide identical performance and vary based on different performance defining parameters. Hence, it is an open area for research where better-performing algorithms are accepted. The need for newer algorithms arises from the fact that an algorithm is a software-based entity and improving its performance will have no additional cost implications. Thus, overall performance of the system will be increased with no additional costs. Performance of MPP tracker is judged based on different parameters like settling time rate, number of fluctuations, etc. In this work the parameters desirable for designing a well-performing MPPT controller which can produce power in an economical way has also been discussed. These parameters are settling time, number of power fluctuations, robustness, higher efficiency, and faster decision for convergence after tracking the MPP and are described as follows.

- Faster convergence: Time taken for settling to the MPP is a significant factor in MPP tracker performance since higher settling time will result in in non utilization of available PV power for greater time. The effect will be more profound for algorithms producing large size fluctuations.
- Lesser fluctuations: Large size fluctuations which implies larger drops in power also results in large power losses, hence are undesirable.
- Robustness: During a long duration of operation, large number of PS patterns are produced where some may be simple, while others may be very complex. However, an algorithm should be capable of giving stable performance and do not produce undesirable results in any PS condition.
- Higher Efficiency: An algorithm should be able to track power at higher efficiencies to give the maximum possible power output.
- Faster decision making: Faster decision for final convergence is also important. Once the true MPP is known it is desirable to converge to it with lesser fluctuations to avoid unnecessary power losses.

Thus, an algorithm capable of providing all the above benefits will result in an efficient and economical MPPT controller that can be suitable for residential, commercial, and industrial use. A very commonly used metaheuristic algorithm in literature is the particle swarm optimization (PSO). The algorithm has been used for MPPT with various modifications in literature [15-19] and gave satisfactory results. As it is stochastic in nature due to its dependency on random coefficients it was able to track the Maximum Power Point (MPP) under various shading patterns. However, the stochastic nature of algorithm poses some issues while the algorithm is in search of maxima. The social and cognitive coefficients of PSO when kept at lower values, may result in a continuous perturbation, thus demanding a higher number of iterations to get stable at optimal operating point [15]. The higher number of iterations result in an increase in settling time and possibly large size fluctuations thereby resulting in power losses. Apart from that, PSO cannot make rapid decisions for convergence due to large difference between solutions (particles / duty ratio) because of unnecessary diversifications. Another problem in PSO is its premature convergence due to its stochastic behavior. In [18], the PSO hybrid with differential evolution algorithm (PSO-DV) was proposed to reinitialize solution sustained at constant value for a few iterations to avoid local convergence. However, the convergence time and the power oscillations became significantly higher thereby creating high power losses. In [16] an adaptive PSO was proposed to avoid the local convergence issues by estimating the optimal initial duty ratio values using the open circuit and DC link voltages. Apart from avoiding getting stuck on local peaks, it also improved the convergence time and power oscillations. Nevertheless, output power fluctuations were still higher. Moreover, due to slow decisive power for convergence, steady state oscillations were also observed which made the convergence slower thereby increasing power losses. In [27], flower pollination algorithm (FPA) variants were proposed. Authors instead of generating random values used chaotic maps for exploring the search area. A significant improvement in the performance of the FPA was observed in terms of tracking time and reduced oscillations. Nonetheless, none of the variants provided the stable results as for different PS patterns the convergence time varied significantly. Moreover, the number of large size oscillations were higher that increased power losses. In [23, 37], a newly developed Jaya algorithm was proposed for MPPT whose equation contain only two factors. One which enhances its search towards the best solution (best enhancing component (BEC)) and the other which keeps it away from bad solutions (worst avoiding component (WAC)). The algorithm due to its fast MPPT tracking with accelerated search and less deviation was found useful in MPPT applications [37]. Nevertheless, the presence of worst avoider component in its updating equation especially for smaller optimal solution (duty ratio) results in extensive diversification in each iteration leading to large settling time and causing high power losses. Apart from increasing oscillations and settling time it also reduces stability thereby making algorithm less robust and hence less reliable. In this study, an improved version of the jaya algorithm proposed in [38] is used by incorporating time varying coefficients (TVC) in its equations for making its decisions more rapid. As discussed above, the WAC component in jaya results in large exploration of the solution thereby making the algorithm slower for convergence towards the maxima. The time varying coefficients are designed such that during the initial iterations they nullify the effect of WAC component thereby avoiding huge diversifications. Hence, within a few iterations the worst value reaches much nearer to the best value leading to much faster convergence compared to the conventional jaya thereby reducing power losses. Even though the performance of the modified jaya (Mjaya) was significantly better than the conventional jaya, large size fluctuations, larger settling time, lesser efficiency and slow decisive power were still a problem. Therefore, in this paper, a new algorithm known as the Most Valuable Player Algorithm (MVPA) [39] is proposed for MPPT. The algorithm is found to be very efficient in removing the shortcomings in the conventional, AI, and other
metaheuristic algorithms. In a single iteration, there are only two updating equations. In its first equation, which is the individual competition phase, there are two components, one which enhances its solution towards the region around the best value (BEC) while the other component moves its solution towards the best solution in a group of solutions (franchise enhancing component (FEC)). This dual-action ensures enough diversification around the global MPP along with keeping the solution in the reduced search space. In other words, the solution will be sufficiently explored while being nearest to the optimum global value. This avoids premature convergence and helps in faster exploitation towards the true global maxima and maintaining power tracking efficiency. In the next phase, the team competition phase, the algorithm further updates a particle's value in the optimally explored search space created during the individual competition phase to become closer to the global best. This increases the robustness of the algorithm by avoiding unnecessary diversifications and making convergence more rapid. Moreover, due to this dual-action all the solutions (duty ratios) remain within a closer limit, resulting in lesser power fluctuations and enhancing the decisive power for convergence once the MPP is tracked. Moreover, for both these equations to work effectively a novel search space limiting strategy is proposed in this work. This strategy brings all the duty ratios much nearer to the global optimal solution and avoid bad solutions to a large extent. Hence, overall, the proposed algorithm outperformed other state-of-the-art techniques in terms of the following parameters:

- faster tracking time
- No large size fluctuation
- Robustness
- higher efficiency
- faster decision-making capability for final convergence.

The faster tracking time of MVPA is due to the dual combination of the algorithm’s updating equations and the search space limitation of the duty ratios. The search space limitation (SSL) is the author’s own idea incorporated in the algorithm. To the best of author’s knowledge, this limitation strategy not been proposed before. Using the SSL, all the duty ratios were brought nearer to the most optimal solution. The SSL is applied only once during the initialization phase. After that, the dual combination of MVPA updating equations as explained above when applied to the reduced space, brings the solution much nearer to the optimal solution. Thus, in the first iteration only those solutions become much closer to the optimal value which significantly reduces the tracking time. The similar is the reason for the small fluctuations. The duty ratio remains much closer to each other along with maintaining diversification to avoid the local convergence. The robustness of MVPA is due to the SSL. This closeness of the duty ratios avoids the large size fluctuations. The SSL works such that for almost any PS condition the duty ratios automatically align themselves in the region close to the most optimal duty ratio. This ensures similar rapid search for almost any PS condition thereby making the results robust and non-deviating. Efficiency is ensured if the search region is well explored. The search space limitation was in itself much effective in reducing the search region to the extent where the duty ratios remain much nearer to the true optimal solution. This avoids bad solutions that may result in the local convergence. The diversifying equation of the MVPA (individual competition phase equation) then explores the reduced search space effectively such that it ensures efficiency along with the faster tracking time. The faster decision-making capability for final convergence is due to the very small difference between duty ratios. This is achieved because of the reduced search space combined with the MVPA equations. As soon as one particle tracks the MPP the other particles are so close that they start converging to this...
value which makes the decision-making capability of the algorithm faster once it tracks the MPP. Co-relating the proposed algorithm with the performance parameters clearly signifies the ability of the algorithm of making a desirable MPP tracker that is capable of producing power at a higher efficiency and reliability along with keeping the cost of the overall system same as the other less performing trackers. For proving the proposed algorithm’s performance an experimental analysis was conducted where it was compared with PSO [26] and the MJaya algorithm [38] which is the modified version of the very recently proposed jaya algorithm [23, 37]. The following sections are divided as follows: In Section II the effect of partial shading on a PV module is explained, Section III introduces the proposed algorithm (MVPA) and its working, Section IV describes the implementation of MVPA for MPPT, Section V describes the experimental results of the proposed algorithm and the comparative results with MJaya and PSO and Section VI is the conclusion of the whole paper.

II. PV ARRAY UNDER PARTIAL SHADDED CONDITION

To enhance the power handling capability of the PV generation system, PV panels are connected in series and parallel. Panels connected in series receiving unequal insolation results in negative voltage appearing across the panel receiving receiving lesser insolation. Also, the lesser insolation on a fraction of PV array causes the unshaded modules to operate in reverse bias thus leading to high power losses within the module and consecutive rise in temperature [40-41] as shown in Fig. 2. If left unattended it can cause permanent damage to the lower shaded panel [42]. To mitigate this problem, diodes are connected across panels which will ensure bypassing of current during voltage reversal phenomena. Although, bypass diodes mitigate the problem, they result in multiple peak formation on the PV curve with a unique global maximum as illustrated in Fig.3. The MPPT thus becomes more challenging with conventional, such as hill climbing, based algorithms getting stuck in local peaks thus leading to power losses as shown in Fig.3.

III. MOST VALUABLE PLAYER ALGORITHM

MVPA is a metaheuristic algorithm which was proposed by Boucekara in [40]. The algorithm owing to its exploration and exploitation properties exhibit similarities with other stochastic search based algorithms. Set of population (solution set) in this case is the number of players having different individual skillset which decides their performance. Different skills define different dimensions of the problem. The algorithm works on the concept of sports competition where different teams compete. The players compete individually in a team in order to be the franchise player of that team. After that team wise competition is done, the player exhibiting best skills is considered the most valuable player (MVP). The MVP is considered to be the optimal solution to the problem. Each player with a different skill set can be represented as eq. (1).

\[ \text{player}_1 = [\text{Skl}_{11}, \text{Skl}_{12}, \ldots, \text{Skl}_{12}] \]  

(1)

Where \( \text{Skl}_{11}, \text{Skl}_{12}, \ldots, \text{Skl}_{12} \) are the skills of the \( t^{th} \) player and \( z \) is the problem size or the total dimensions. The \( v^{th} \) team which is composed of a particular group of players is denoted as eq. (2).

\[ \text{Team}_v = \begin{bmatrix} \text{player}_1 \\ \text{player}_2 \\ \vdots \\ \text{player}_{PS} \end{bmatrix} \]  

(2)

Where \( PS \) denotes the size of players for a particular team. Also, the \( v^{th} \) team can be represented as eq. (3).

\[ \text{Team}_v = \begin{bmatrix} \text{Skl}_{11}, \text{Skl}_{12}, \ldots, \text{Skl}_{12} \\ \text{Skl}_{21}, \text{Skl}_{22}, \ldots, \text{Skl}_{2z} \\ \vdots \\ \text{Skl}_{PS1}, \text{Skl}_{PS2}, \ldots, \text{Skl}_{PSz} \end{bmatrix} \]  

(3)

Fig.4 shows the flowchart for the working of MVPA. Initially, a population of players equal to player’s size is generated. The team is then formed after the player’s formation. Players are randomly distributed in different teams. Any number of teams can be chosen. MVPA has a flexibility of accommodating different number of players in different teams.
Hence, for a fair comparison with other algorithms any number of players can be chosen. The team formation is done as follows. The total number of teams are divided into two as $mT_1$ and $mT_2$. In first $mT_1$ teams, as in eq. (6), $mP_1$ players are accommodated, as in eq. (4). Remaining $mT_2$ teams, as in eq. (7), will have $mP_2$ players as in eq. (5).

\[ mP_1 = \text{ceil} \left( \frac{\text{Player Size}}{\text{Teams Size}} \right) \]  
\[ mP_2 = mP_1 - 1 \]  
\[ mT_1 = \text{PlayersSize} - mP_2 \times \text{TeamsSize} \]  
\[ mT_2 = \text{TeamsSize} - mT_1 \] (7)

$\text{PlayersSize}$ and $\text{TeamsSize}$ respectively denotes the total number of players and teams in a league. The number is round off to the lowest following integer. Competition phase comes after the team formation. This phase has individual and team mode of competition.

A. Individual Competition

In this mode each player competes with other players of the same team and the best player of the team is its franchise player. Hence, for $v^\text{th}$ team, the player’s skills are updated as eq. (8). Where $\text{Franchise}_v$ is the best player of $v^\text{th}$ team, $\text{MVP}$ is the best player in the whole league, $\text{Team}_v$ denotes the skill of a player in a team $v$ and $\text{rand}$ is some random number.

\[ \text{Team}_v = \text{Team}_v + \text{rand} \times (\text{Franchise}_v - \text{Team}_v) + 2 \times \text{rand} \times (\text{MVP} - \text{Team}_v) \] (8)

B. Team Competition

In this mode different teams that have taken part in a league compete with each other. A particular $\text{Team}_v$ competes with some $\text{Team}_u$. Either of the two teams may win and the fitness is updated as follows:

Let us say that two teams $\text{Team}_j$ and $\text{Team}_k$ are playing against each other. Then the probability of $\text{Team}_j$ beating $\text{Team}_k$ is $j$ and probability of $\text{Team}_k$ beating $\text{Team}_j$ is $k$. In MVPA for all teams, the fitness values are normalized. Hence, for a given team the normalization of fitness can be given as in eq. (9).

\[ \text{fitN(Team}_v) = \text{fit(Team}_v) - \text{min}(\text{fit(AllTeams)}) \] (9)

Then the probability of $\text{Team}_j$ beating $\text{Team}_k$ becomes as in eq. (10).

\[ \text{Probb(Team}_j \text{ Beats Team}_k) = 1 - \frac{(\text{fitN(Team}_j))^{p}}{(\text{fitN(Team}_j))^{p} + (\text{fitN(Team}_j))^{p}} \] (10)

If $\text{Probb(Team}_j \text{ Beats Team}_k)$ is found greater than $\text{Probb(Team}_k \text{ Beats Team}_j)$ it means $\text{Team}_j$ wins. But in a real league even at the last moment other team may win. Hence, in order to give this algorithm, the characteristics like reality, a random number is generated. If this number is greater than the probability of $\text{Team}_j$ then $\text{Team}_k$ wins, otherwise $\text{Team}_j$ wins. Also, in case of a draw a random number is generated. If the Random number is greater than 0.5, $\text{Team}_j$ wins otherwise $\text{Team}_k$ wins. Finally, if $\text{Team}_j$ is selected and it wins against $\text{Team}_k$ the player’s skills of $\text{Team}_j$ are updated as in eq. (11) otherwise as in eq. (12).

\[ \text{Team}_j = \text{Team}_j + \text{rand} \times (\text{Team}_j - \text{franchise}_k) \] (11)

\[ \text{Team}_j = \text{Team}_j + \text{rand} \times (\text{franchise}_k - \text{Team}_j) \] (12)

Finally, after all these processes, application of greediness is applied in which the comparison is done between the fitness values before and after the competition phase. If fitness before competition is better than the fitness acquired after competition, it is replaced by the previous value. Greediness is followed by the application of elitism where the best players are replaced by the worst players. After that if two players in the population exhibit same skills then one is replaced by the another. Finally, the algorithm stops as soon as the termination criterion is satisfied.
IV. MPPT USING MVPA

The maximum power is achieved at a particular optimal combination of voltage and current which corresponds to the optimal duty ratio given to the DC-DC converter. The MVPA was embedded into the microcontroller which then receives the voltage and the current from the PV source as its input and produces the corresponding duty ratio value. The duty ratio here is analogous to a player’s skill in the MVPA. The MVPA compiled into the microcontroller updates the duty ratio in each iteration in a similar fashion as it updates the performance of each player. The power was compared in each iteration with the previous value and the duty ratio corresponding to greater power was stored. At power difference smaller than 5% or duty ratio difference smaller than 2% only the optimal duty ratio was sent to the switch. MVP is the value of duty ratio corresponding to which the maximum power at the output is achieved. Although the MVPA was experimentally tested for different initial duty ratios for static insolation results, the most recommended values are the ones given below for the best performance as they include the limited search. The complete description of MPPT using MVPA is given in the flowchart in Fig.5. A step wise description of MVPA for MPPT is given below.

The objective function used is:

\[ F(D) = \text{Power} \]  \hspace{1cm} (13)

D denotes the duty ratio and hence corresponding to a duty ratio value power output of the boost converter is calculated.

**Initialization**

*Step1:* Assign 4 initial duty ratios between 0.2 and 0.8 as \( D_1 = 0.2, D_2 = 0.4, D_3 = 0.6, D_4 = 0.8. \) \hspace{1cm} (14)

*Step2:* Form different teams

Team\(_1\) = \{\(D_3, D_1\)\}.

Team\(_2\) = \{\(D_4, D_2\)\}. \hspace{1cm} (15)

*Step3:* 3rd and 4th steps explain the limited search strategy.
Trigger all initial duty ratios to the switch and find the corresponding power. The maximum of the calculated power is called the initial optimal power and the corresponding duty ratio is called the initial optimal duty ratio. Increase the duty ratio by a small value and evaluate power corresponding to that increment.

**Step 4:** This step is explaining an if-else statement used in the program. The if-else code was created using the OR operator. In the following description of this command the word “OR” is used to clarify where the OR operator has been used in the code.

If the power corresponding to the incremented duty ratio is greater than the initial optimal power OR the initial optimal power corresponds to the lowest initialized duty ratio, redistribute duty ratios between the initial optimal and the next higher initialized duty else redistribute it between the initial optimal and the previous smaller initialized solution.

**Objective function evaluation and comparison**

**Step 5:** Compare the newly generated power with the old value.

Save new power if greater and its corresponding duty ratio.

**Updating duty ratio using MVPA**

**Step 6:** Perform individual competition using eq. (8); however, the factor “2” is to be replaced with “1.2” as described in the upcoming section.

**Step 7:** Find normalized fitness and probability using eqs. (9) and (10).

**Step 8:** Perform team competition using eqs. (11) and (12).

**Step 9:** Trigger switch using the updated duty ratio values.

**Step 10:** Find corresponding new power. At power difference between solutions smaller than 5% or duty ratio difference smaller than 2% send only the optimal value to the switch until the insolation change or the end of runtime.

**Step 11:** If the difference between the current and the previous power is less than 1% (insolation change) reinitialize all duty ratios and other parameters and return to step 3, else move to step 12.

**Step 12:** If runtime is over, stop the controller, else keep on sending the best duty ratio to the switch.

### A. MVPA Parameter Tuning

The constant value “2” in eq. (8) of MVPA is tunable for a particular problem to give a better performance. The duty ratio is a very small value and a small change in this value can lead to a drastic change in the power output. The random number defined in the updating equations of the algorithm can change the duty ratio value significantly thereby increasing convergence time. Hence, after a thorough experimental analysis the constant value was set to 1.2 in this study. This constant value limited the range of duty ratio to optimal search space by decreasing the region around the global best thereby reducing the convergence time and maintaining higher efficiency. Although the algorithm can track by keeping the value to 2, the region around the global best will increase which increases the convergence time. Therefore, in this study the value is kept as 1.2.

### B. Illustration of particle movement in the MVPA

In this section a thorough working of MVPA is illustrated representing significance of different parameters like franchise player, teams, etc. Fig. 6 represents the particle movement in MVPA while in search of maximum power. Let us consider a four peak P-V curve with the maximum power peak in the middle as shown in fig.6. Insolation values on 4 panels were kept as 1000, 750, 500 and 250 W/m² respectively. The green dot denotes team 1 while the red denotes team 2. In fig. 6 in the initialization step different particles are at different positions of the P-V curve. Among them the franchise player of team 1 is nearest to the optimal peak value and the rest are at local peaks.
The algorithm then detects the duty ratio closest to the optimal value and considers it as the MVP, and then redistributes the search space as defined above. Next, in iteration 1 using the individual phase equation, the algorithm searches the area around the initially found best value. This equation has MVP and franchise components which push a solution towards the best as well as the franchise value. This combined effect along with the search space redistribution avoids large diversifications and hence an initial step towards avoiding premature convergence. However, for some unpredictable values of random numbers and current solution one solution might get largely diversified thereby increasing the convergence time. Nevertheless, the next equation of team competition phase solves this purpose in which the franchise value of one team is compared with that of another team. The duty ratio of a team then gets closer or farther from the franchise duty ratio of another team depending upon its fitness. Moreover, it is clear from fig. 6 that in first iteration only the particles become much closer to each other. Thus, the dual action of individual and team competition phase avoids large and unnecessary diversifications thereby avoiding local solutions along with keeping the duty ratio values near which produces small oscillations. The particles in this iteration becomes even closer with the franchise player of team 2 serving as the MVP. In iteration 2 only one particle of team 2 is away from the peak and franchise player of team 2 becomes MVP with other particles equivalent to it in their fitness. In iteration 3 that particle becomes even closer and by iteration 4 all were converged.

Fig. 9 MPPT Performance of different algorithms for shading condition 2. (a) PSO, (b) MJaya and (c) MVPA

Fig. 10 MPPT Performance of different algorithms for shading condition 1. (a) PSO, (b) MJaya and (c) MVPA
Fig. 11 MPPT Performance of different algorithms for shading condition 3. (a) PSO, (b) MJaya and (c) MVPA

V. EXPERIMENTAL TESTS AND DISCUSSIONS

A. Experimental Setup

The complete experimental setup is shown in Fig. 7 for evaluating the real time performance of the proposed algorithm and to compare it with the other state of the art algorithms. The MVPA is compared with the PSO and the MJaya algorithm. The parameters of PSO are selected as $C_1 = 1.2, C_2 = 1.6$ and $w = 0.4$ based on [26]. The experimental setup consists of a Solar Array Simulator (SAS) used to create different partial shading (PS) conditions, DC-DC boost converter, and Dspace (D1104) is used a controller to send Pulse Width Modulation (PWM) signals to the gate driver. The boost converter configuration is shown in Fig. 8 with

the rating of its components parameter as: $C_1 = 47 \mu F, C_2 = 470 \mu F, L = 1.5 mH \text{ and } R = 20 \Omega$. Depending upon the application the load can be reduced up to almost 8 $\Omega$ for which the MVPA was tested in this study. The Chroma 62150H solar PV array simulator was used for providing input voltage and current to the DC-DC boost converter. A PV array consisting of four modules connected in series was set with the help of SAS GUI. The ratings of PV emulator were chosen corresponding to the standard PV module as: maximum power ($P_{MP}$) = 21.837 W, voltage at MPP ($V_{MP}$) = 4.35 V, current at MPP ($I_{MP}$) = 5.02 A, open circuit voltage $V_{OC} = 5.425$ V and short circuit current $I_{SC} = 5.34$ A. The input voltage and current were sensed using a voltage (LEM LV-25-P) and a current sensor (LEM LA-25-NP) and the combination was then sent to dSpace ADC pins. The frequency was kept at 20 kHz with a sampling time of 50 ms. The updated duty ratio in each iteration was then sent to the gate driver in the form of modulated pulses which then triggered the switch and the corresponding optimized power as a product of optimized voltage and current was sent at the output load. In the next section, the comparison of the proposed algorithm is done with the other state of the art algorithms for different partial shading (PS) conditions.

B. Different Partial Shading (PS) Conditions testing

Various PS conditions were chosen to prove the performance of the proposed algorithm. In the first shading condition, the power peak resides at the right most of the P-V curve. In the second shading condition, the power peak resides at in the middle and finally a complex shading condition was chosen where the difference between the local and global maxima is less than 2 watts. Table I gives a brief overview of all shading patterns.

1) Condition 1

In this PS condition, the insolation of 1000, 900, 800 and 700 W/m² was set at the modules 1, 2, 3 and 4. Fig. 9(a) shows the performance of PSO. The PSO due to its exploration capabilities successfully tracked the MPP. However, the tracking time along with the large size fluctuations was higher as evident from the figure. This gives rise to larger dips in power received at the output load for longer periods which causes large power losses thereby reducing the efficiency. The first large size fluctuation is not considered since it is due to duty ratio initialization and has nothing to do with the algorithm performance. Moreover, even though the MPP was tracked early, algorithm produced additional fluctuations before final convergence. This is due to larger differences among the four duty ratios and lack of faster convergence capability. This causes unnecessary additional power losses and thus reduces the overall system efficiency. The settling time for PSO was found to be 1.85 seconds at the convergence efficiency of 99.42%.

Fig.9(b) shows performance curve of the MJaya algorithm. The algorithm was able to track the MPP successfully but at the cost of large convergence time and higher large size oscillations. Like PSO, the combined effect of higher convergence time and a greater number of large size oscillations in the MJaya causes
large power losses and reduces efficiency. Also, it is observed that the MPP was tracked at very initial stages, but the algorithm took larger time to finally settle to MPP. This is due to large differences among duty ratios and lack of search space handling capability. The total convergence time of MJaya was found to be 1.59 seconds at an efficiency of 99.04%.

Finally, in Fig.9 (c) performance of the proposed algorithm is shown. The algorithm settled to the MPP with a very fast convergence rate and no large size oscillation thereby proving its ability to keep the solutions within a small search space. The first large fluctuation is due to duty ratio initialization and has nothing to do with the algorithm performance and hence is not considered as a fluctuation. Another benefit due to small and smart diversification was the faster decision for final convergence once the MPP is tracked thereby avoiding additional power losses. All these aspects contribute to significant utilization of power produced by the PV array thereby increasing the overall efficiency. The tracking time in case of MVPA was 0.718 seconds at a tracking efficiency of 99.4%. Percentage improvement in settling time compared to PSO and MJaya for this case was 257.6 and 221% respectively.

2) Condition 2

In this condition the insolation values were kept at 1000, 600, 500 and 200 W/m² respectively on the four modules of the PV array. Fig.10(a) illustrates the performance of PSO. Only for this case after finding MPP, very soon the algorithm converged to MPP thereby avoiding unnecessary power losses. However, the time taken for final convergence was higher along with a greater number of large size fluctuations which contribute to power losses. Convergence time of PSO was 1.06 seconds at a tracking efficiency of 99.8%.

Fig.10(b) shows performance of the MJaya algorithm. For this case, the settling time along with the number of large size fluctuations were higher compared to PSO. Moreover, the decision for final convergence to MPP after it was tracked was much slower. Hence, overall, the power losses are greater. The algorithm tracked the MPP at a tracking efficiency of 99.3% with the time taken for convergence to be 1.4 seconds.

Finally, in Fig.10(c) the performance of MVPA is evaluated. It is clear from the results; the convergence time is much lower and no large size fluctuation when compared with the PSO and the MJaya. Moreover, the decision for final convergence to the MPP was much rapid. Thus, overall, the efficiency is improved. The tracking time for MVPA was found to be 0.42 seconds at a tracking efficiency of 99.21%. Percentage improvement in settling time compared to PSO and MJaya for this case was 252 and 333% respectively.

### Table I

<table>
<thead>
<tr>
<th>Condition</th>
<th>Insolation Values (W/m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel 1</td>
<td>1000</td>
</tr>
<tr>
<td>Panel 2</td>
<td>900</td>
</tr>
<tr>
<td>Panel 3</td>
<td>800</td>
</tr>
<tr>
<td>Panel 4</td>
<td>700</td>
</tr>
</tbody>
</table>

### Table II

<table>
<thead>
<tr>
<th>Factors</th>
<th>Condition 1</th>
<th>Condition 2</th>
<th>Condition 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>1.83 s</td>
<td>1.06 s</td>
<td>3 s</td>
</tr>
<tr>
<td>MJAYA</td>
<td>1.59 s</td>
<td>1.4 s</td>
<td>1.689 s</td>
</tr>
<tr>
<td>MVPA</td>
<td>0.718 s</td>
<td>0.42 s</td>
<td>0.447 s</td>
</tr>
</tbody>
</table>

### Table III

<table>
<thead>
<tr>
<th>Shading condition</th>
<th>Percentage improvement with respect to PSO</th>
<th>Percentage improvement with respect to MJaya</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition 1</td>
<td>257.6%</td>
<td>221%</td>
</tr>
<tr>
<td>Condition 2</td>
<td>252%</td>
<td>333%</td>
</tr>
<tr>
<td>Condition 3</td>
<td>671%</td>
<td>377.8%</td>
</tr>
</tbody>
</table>
From Fig. 11(c) it is known that the performance of neither MJaya nor PSO is comparable to MVPA, which settled to the MPP at a very rapid convergence rate along with no large size fluctuation. Also, as usual, the final convergence to the MPP was very fast after finding the MPP. Hence, even for a complex PS condition the proposed algorithm due to its smart search space handling capability can sustain the power output without deviating from its usual performance. This fulfills the requirements of being reliable and efficient. The tracking time for MVPA was found to be 0.447 seconds with a tracking efficiency of 98.82%. Percentage improvement in settling time compared to PSO and MJaya for this case was 671 and 377.8% respectively.

Table II shows the comparison summary of all algorithms based on settling time and efficiency while table III is the comparison in terms of percentage improvement in tracking time of the proposed technique.

VI. COMPARISON UNDER DYNAMICALY VARYING INSOLATION

For a more practical analysis, the proposed method is compared with the other state-of-the-art techniques under dynamically varying insolation conditions. These conditions may be considered as either clouds moving with time and imposing different shading patterns on the PV array or the sun changing its position with time, etc. In this study, shading patterns are varied at six different time instants of 3 seconds each. For initial three instants, three different shading patterns were created. For the remaining three the shading was reduced until all the panels started receiving full insolation. This can be considered similar to a real phenomenon where moving clouds initially impose different shading patterns on a PV array by coming in front of the sun. After that they start uncovering the sun thereby reducing shading effect and increasing insolation on the PV surface which finally starts to receive full insolation. This process is shown in fig. 12 which is the comparison graph for all the three algorithms by dividing the graph into two sections. In the first section, because of cloud movement at different positions in front of the sun the power values are changing. In the second section, the power is continuously increasing due to increasing insolation on the PV panels. This increase in insolation is due to cloud uncovering the sun’s surface. The insolation pattern summary at different instants on different modules is shown in table IV. The results were taken on the software platform of the Typhoon-HIL hardware in loop (HIL) which produce real-time equivalent results. The Typhoon-HIL is advantageous to use since more complex waveforms can be created using it. Although MATLAB can also be used for producing complex results, it does not provide a good insight into the real-time results. The six instants of insolation change were possible through the typhoon HIL platform. Whereas on the real-hardware only three instants were possible due to the limitation of the solar PV simulator to the best of author’s knowledge. The comparison in fig. 12 is done based on different performance parameters that have already been explained in the previous section.

Fig. 12 (a) is the performance curve for the PSO. The time taken by the PSO for settling for all the six instants is 1.96, 1.36, 1.36, 2.16, 1.71, and 0.66 secs respectively which is higher and increase power losses. Although for full insolation it is faster, metaheuristic algorithms should perform well for PS conditions for which they are mainly used. Moreover, as evident from the figure there are several large size fluctuations (excluding the first one which is due to duty ratio initialization). This contributes to high power dips thereby increasing power losses. Other than that, the decision for final convergence after tracking the MPP is very slow for most of the instants of insolation change due to which there are additional unwanted fluctuations which results in unnecessary power dips and power losses.

Fig. 12 (b) is the performance curve for the MJaya. The time taken by the MJaya for settling for all the six instants is 0.958, 0.97, 0.97, 0.956, 0.97, and 0.948 secs respectively which is better compared to PSO. However, it is still higher and need significant improvements. Moreover, the number of large size fluctuations are comparatively lower compared to PSO. Nevertheless, having no large size fluctuation is a more desirable property since for small size fluctuation the power dip is small. Also, the decision for final convergence after tracking the MPP is faster in MJaya for all the instants of insolation change. Thus, MJaya is better than PSO in terms of different performance parameters.

Fig. 12 (c) is the performance curve for the MVPA. The time taken by the MVPA for settling for all the six instants is 0.464, 0.46, 0.66, 0.42, 0.66, and 0.55 secs which is much better compared to both the above algorithms thereby improving power losses. In addition, for all the instants of insolation change there is no large size fluctuation except for the last one which has only one large fluctuation. However, the PSO and the MJaya exhibit large size fluctuations for almost all of their instants. Also, the decision for final convergence after tracking the MPP is very fast for almost all the cases thereby creating either very small or no fluctuation between tracking and the convergence time period. The improvement especially when compared to PSO is much profound for all the cases. For full insolation although PSO do not have much fluctuation in between the power tracked and the power converged, MVPA is still better. When compared with the MJaya mostly the MVPA outperformed the MJaya. For the full insolation case the MJaya has a smaller fluctuation compared to MVPA in between the tracked and the converged time period. However, in terms of the overall performance for the full insolation case the MVPA is better than the MJaya since its convergence time and the number of fluctuations are much lesser. Moreover, for the second instant of insolation change, the MVPA exhibit an ideal feature which is to converge as soon as the power is tracked without
Varying power due to cloud movement in front of the sun at different positions

Increasing power due to cloud uncovering the sun's surface

Fig. 12 Comparison between (a) PSO, (b) MJaya and, (c) MVPA for dynamically varying insolation conditions
causing any fluctuation. Neither MJaya nor PSO show this behavior for any instant of insolation change. Note that a fluctuation causing a power dip of around 0.03 watt especially for 50mS is obviously insignificant and can be neglected. It is now clear from the results that the MVPA significantly outperformed both the MJaya and the PSO in different aspects thereby improving the system’s reliability and making it more power efficient. Table V is the comparison summary in terms of convergence time for different instants of insolation change.

Table VI illustrates the comparison of the proposed algorithm with the other state of the art algorithms based on various performance parameters. In table VII MVPA is compared with the other algorithms based on the computational complexity. A comparison was done considering the number of mathematical operations in the algorithm’s updating equations and its related equations. The table shows the number of times the operators are used in each iteration. Since, the total duty ratios were 4 in each iteration, each operator associated with an updating equation is multiplied by 4 to know about its total evaluations. From the table it is seen that the number of multiplication/division operations are the least in the MVPA. However, in terms of addition/subtraction it has higher operation. Nevertheless, in a microprocessor the most complex operations are multiplication and division. Therefore, even though it has higher number of addition/subtraction operations, the multiplication/division operations that are the most significant are the least.

### VII. Conclusion

The purpose of this paper was to develop an MPPT controller that will have higher tracking speed, higher efficiency, reliability and produce least number of fluctuations while tracking MPP at the output of a PV array. Following advantages were observed with the proposed algorithm: (A) Higher efficiency (B) Smaller tracking time (C) Least number of large size fluctuations at the output (D) Small diversifications between duty ratios which results in faster convergence after tracking the MPP, and (E) Faster exploitation due to double updating methods. The proposed algorithm was compared with the other metaheuristic algorithms (PSO and MJaya algorithm) under different partially shaded conditions. The proposed algorithm outperformed both the algorithms (PSO and MJaya) for all the above mentioned aspects. Also, the proposed algorithm maintained its robustness in tracking the MPP in a complex situation where the difference between the global and the local optima was very small. All these aspects illustrated significant advantages of using the proposed method over the other techniques in terms of efficiency and reliability thereby making it one of the ideal algorithms for developing an MPP tracker that can be employed in industrial, commercial and residential uses.

### Acknowledgements

The authors also acknowledge the financial support from Taif University Researchers Supporting Project Number (TURSP-2020/278), Taif University, Taif, Saudi Arabia.

The authors would like to acknowledge the technical support provided by the Hardware-In-the-Loop (HIL) Lab and Non-Conventional Energy (NCE) Lab, Department of Electrical Engineering, Aligarh Muslim University, India.

The authors also acknowledge the the technical support provided by Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, University of Malaya, Malaysia.

### References


### Table V

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Parameter</th>
<th>Instants</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO</td>
<td>Convergence Time</td>
<td></td>
<td>1.96</td>
<td>1.36</td>
<td>1.36</td>
<td>2.16</td>
<td>1.71</td>
<td>0.66</td>
</tr>
<tr>
<td>MJAYA</td>
<td>Convergence Time</td>
<td></td>
<td>0.958</td>
<td>0.97</td>
<td>0.97</td>
<td>0.956</td>
<td>0.97</td>
<td>0.948</td>
</tr>
<tr>
<td>MVPA</td>
<td>Convergence Time</td>
<td></td>
<td>0.464</td>
<td>0.46</td>
<td>0.66</td>
<td>0.42</td>
<td>0.66</td>
<td>0.55</td>
</tr>
</tbody>
</table>

### Table VI

<table>
<thead>
<tr>
<th>Qualities</th>
<th>InC [31]</th>
<th>MJaya</th>
<th>PSO</th>
<th>MVPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMPP tracking capability</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Efficiency</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Effect on performance with increased complexity</td>
<td>Cannot track GMPP</td>
<td>High</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Decision for convergence after MPP found</td>
<td>Oscillations Throughout</td>
<td>Slow</td>
<td>Slow</td>
<td>Very Fast</td>
</tr>
<tr>
<td>Reliability</td>
<td>Low</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Steady-state oscillations</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Tracking speed</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
<td>High</td>
</tr>
</tbody>
</table>

### Table VII

<table>
<thead>
<tr>
<th>Operator</th>
<th>MJaya</th>
<th>PSO</th>
<th>MVPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Multiplication/Division</td>
<td>20</td>
<td>20</td>
<td>18</td>
</tr>
<tr>
<td>Addition/Subtraction</td>
<td>20</td>
<td>16</td>
<td>30</td>
</tr>
</tbody>
</table>


Authors Affiliation:

Imran Pervez, Adil Sarwar and Mohd Tariq are with the Department of Electrical Engineering ZHCET, Aligarh Muslim University, Aligarh – 202002, India. (imranpervez7@gmail.com, adil.sarwar@zhcet.ac.in, tariq.ee@zhcet.ac.in)

Immad Shams is with the Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, Faculty of Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia. (immadshams@um.edu.my)

Saad Mekhilef is with the Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, Faculty of Engineering, University of Malaya, 50603, Kuala Lumpur, Malaysia and also with the School of Software and Electrical Engineering, Faculty of Science, Engineering and Technology, Swinburne University of Technology, Victoria, VIC 3122, Australia. (saad@um.edu.my)

Basem Alamri is with the Department of Electrical Engineering, College of Engineering, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia.

Corresponding author: Mohd Tariq (tariq.ee@zhcet.ac.in) and Saad Mekhilef (saad@um.edu.my)

Authors Biographies:

Imran Pervez has completed his bachelor’s in technology (B. Tech) in Electrical Engineering from Aligarh Muslim University (AMU), Aligarh, India in 2020. He has published various papers on Solar PV power optimization techniques in international journals and conference proceedings. In two of his proceeding he has got the best paper award.

Immad Shams received the M.Eng. (Electrical power) degree from the University of Technology Malaysia, Johor Bahru, Malaysia, in 2017 with best postgraduate student award. He is currently working towards his Ph.D. degree from the Department of Electrical Engineering, University of Malaya, Malaysia. He has been associated with Power Electronics and Renewable Energy Research Laboratory (PEARL) as a Graduate Research Assistant since 2018.

Saad Mekhilef received the B.Eng. degree in electrical engineering from the University of Setif, Setif, Algeria, in 1995, and the master’s degree in engineering science and the Ph.D. degree in electrical engineering from the University of Malaya, Kuala Lumpur, Malaysia, in 1998 and 2003, respectively. He is currently a Professor and the Director of the Power Electronics and Renewable Energy Laboratory (PEARL), Department of Electrical Engineering, University of Malaya, where he is also the Dean of the Faculty of Engineering. He is also a Distinguished Adjunct Professor with the School of Software and Electrical Engineering, Faculty of Science, Engineering and Technology, Swinburne University of Technology, VIC, Australia. He has authored or co-authored more than 600 publications in international journals and conference proceedings.

Adil Sarwar received the bachelor’s and master’s degrees in technology from Aligarh Muslim University, in 2006 and 2008, respectively, and the Ph.D. degree from Aligarh Muslim University, in 2012. He is currently an Assistant Professor with the Department of Electrical Engineering, Aligarh Muslim University, India. He has authored or co-authored several research papers published in reputed international SCI-indexed journals.

Mohd Tariq received the bachelor’s degree in electrical engineering from Aligarh Muslim University, Aligarh, the master’s degree in machine drives and power electronics from the Indian Institute of Technology (IIT)- Kharagpur, and the Ph.D. degree in electrical engineering with focus on power electronics and control from Nanyang Technological University (NTU), Singapore. He has authored more than 130 research papers in international journals/conferences including many articles in IEEE Transactions/Journals. He is also the inventor of 17 patents granted/published by the patent office, India.

Basem Alamri received the B.Sc. degree (Hons.) in electrical engineering from the King Fahd University of Petroleum and Minerals (KFUPM), the M.Sc. degree (Hons.) in electrical power systems from King Abdulaziz University, Jeddah, Saudi Arabia, the M.Sc. degree in sustainable electrical power from Brunel University, London, U.K., in 2007 and 2008, respectively, and the Ph.D. degree in electrical power engineering from Brunel University, in 2017. He is currently an Assistant Professor of Electrical Engineering with the College of Engineering, Taif University.