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Rapid and Robust Adaptive Jaya (Ajaya) Based Maximum Power Point Tracking of a PV-Based Generation System

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ABSTRACT When subjected to partial shading (PS), photovoltaic (PV) arrays suffer from the significantly reduced output. Although the incorporation of bypass diodes at the output alleviates the effect of PS, such modification results in multiple peaks of output power. Conventional algorithms—such as perturb and observe (P&O) and hill-climbing (HC)—are not suitable to be employed to track the optimal peak due to their convergence to local maxima. To address this issue, various artificial intelligence (AI) based algorithms—such as an artificial neural network (ANN) and fuzzy logic control (FLC)—have been employed to track the maximum power point (MPP). Although these algorithms provide satisfactory results under PS conditions, a very large amount of data is required for their training process, thereby imposing an excessive burden on processor memory. Consequently, this paper proposes a novel optimization algorithm based on stochastic search (random exploration of search space), known as the adaptive jaya (Ajaya) algorithm in which two adaptive coefficients are incorporated for maximum power point tracking (MPPT) with a rapid convergence rate, fewer power fluctuations and high stability. The algorithm successfully eliminates the issues associated with existing conventional and AI-based algorithms. Moreover, the proposed algorithm outperforms other state-of-the-art stochastic search-based techniques in terms of fewer fluctuations, robustness, simplicity, and faster convergence to the optima. Extensive analysis of results obtained from MATLAB® is done to prove the above performance parameters under static insolation conditions (using a three, four and a five-module series-connected PV system), under dynamically varying insolation (using a four-module series connected system), by changing the PV module rating (using a four-module series connected system) and using an IEC standard.

INDEX TERMS Adaptive jaya (Ajaya), maximum power point tracking (MPPT), metaheuristic algorithms, conventional algorithms, photovoltaic (PV).

I. INTRODUCTION

The increasing demand for energy at the global level has placed pressure on the power sector to provide enough electricity that can fulfill the growing requirements due to population growth, and increased deployment of electrical and electronic technology. This demand places further pressure on conventional sources of energy, which are also damaging to the environment and to human health. Consequently, researchers have focused on the extraction of energy through renewable sources such as wind, biomass, solar, and geothermal.

Among these, solar is the most popular technique owing to its clean, cost-effective, and efficient energy production. However, partial shading (PS) conditions that occur as a result of cloud shading, bird drops, shading due to a building, etc.

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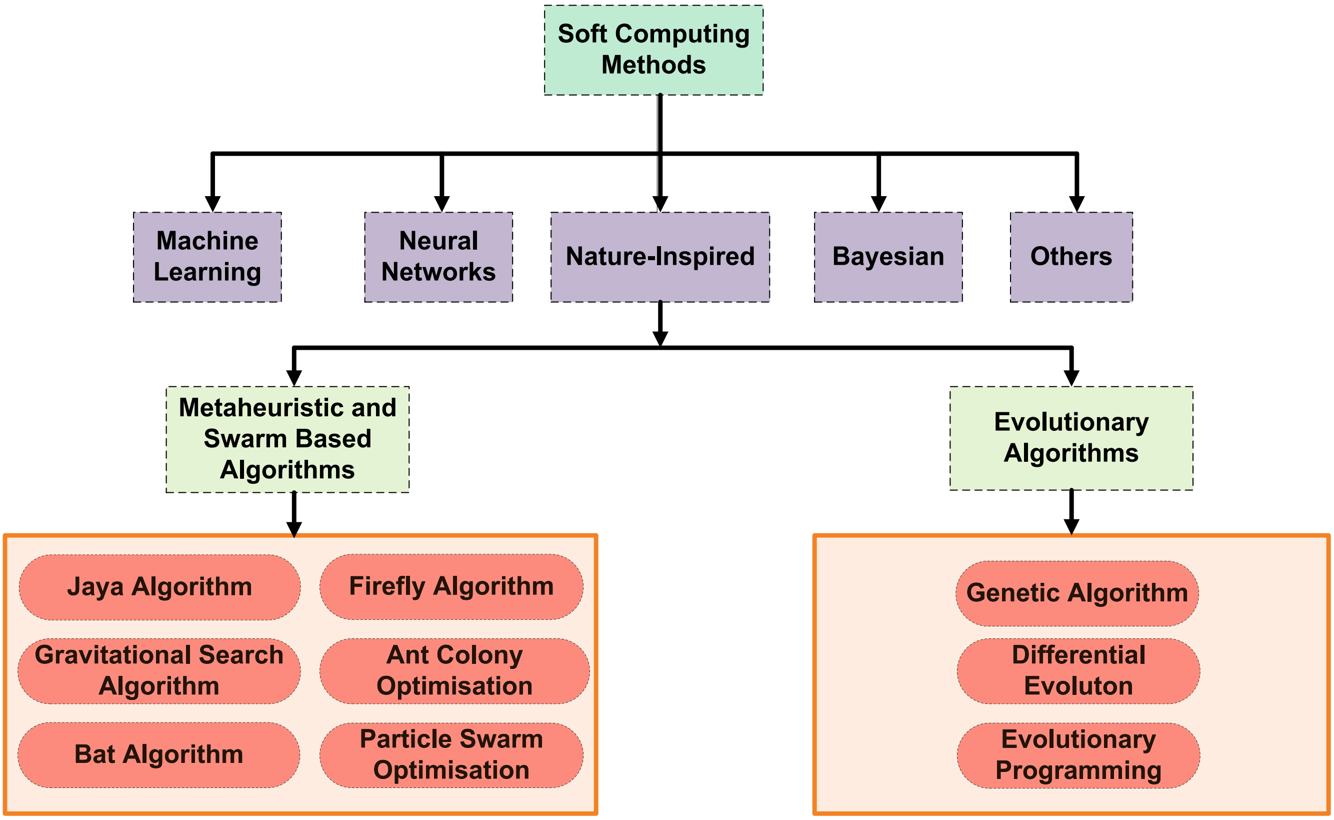


FIGURE 1. Soft computing techniques.

can drastically reduce the power output from a photovoltaic (PV) array. Moreover, PS can cause hotspots which may damage the PV module due to excessive heating at one point. To mitigate the variation in output power caused by PS, bypass diodes are connected in parallel with the PV module at its output terminal. Since the use of bypass diodes produces multiple peaks of power at the output of the array, various optimization techniques have been proposed in the literature to find the maximum value among the available peaks. Fig.1 illustrates a general overview of the available soft computing techniques in the literature.

Conventional algorithms such as [1]–[3] have been used for maximum power point tracking (MPPT). These algorithms successfully track the maximum power point (MPP) under full insolation conditions but can become stuck at local maxima under PS conditions. To avoid such issues, AI based algorithms such as [4]–[6], which use their past experiences as the basis for search criterion, were employed for MPPT. Although these algorithms were very useful in tracking the maximum power under shading range of PS conditions, they had a few limitations like their training process requires very large amounts of data to be fed to the processor, which imposes an excessive burden on its memory, unavailability of historical data may hinder the training process, anomalies in given data may lead deviated results. Consequently, metaheuristic algorithms based on stochastic search method have been proposed for MPPT. These techniques take their inspiration from natural phenomena such as bird swarm, ant colonies, and flower pollination. Various such nature-inspired techniques have been proposed in the literature and most of them have been employed for MPPT [7]–[31]. Moreover, they have also been hybridized with the AI-based algorithms in various literature for MPPT [32]–[35]. The MPP tracker developed using these techniques was proven useful in various practical applications [32]–[38]. In [32], a hybrid of particle swarm optimization (PSO) and adaptive neuro-fuzzy inference system (ANFIS) was proposed for integrating a PV MPP tracker with grid supply. A hybrid of flower pollination algorithm (FPA) and ANFIS was proposed in [33] for motor pumping applications using a brushless DC motor specifically at remote places with no stand-alone grid system. The same authors, considering the negative aspects of a brushless DC motor used a switched reluctance motor (SRM) for water pumping applications using a PSO hybrid with the gravitational algorithm (GSA) in [36]. Considering these aspects calls for a necessity to work further in this area and develop the most economical and efficient MPP tracker for serving humanity. The advantage of using the metaheuristic algorithms is their stochastic nature due to which they complete their search process by exploring the search space. After that the algorithm exploits to the best solution in that space. However, the performance of these algorithms varies based on time taken for settling to the MPP, the number of power fluctuations while tracking the MPP, efficiency with respect to the true MPP, the burden it poses on processor memory, and various other parameters. There is, therefore, a need for algorithms with better performances and simple structure (fewer variables to be saved by the processor memory) that can further improve existing MPP trackers and make them cost-effective. An ideal system is the one where the cheapest possible components are used without affecting the performance of the system. An algorithm with a simple structure will cause least burden on the processor memory and hence will be the most suitable one for cheaper processors, unlike complex algorithms with too many equations involved in the updating process that might lead to malfunctioning of the less expensive processors, thereby forcing to opt for an expensive solution. Thus, an ideal algorithm is the one that poses the least burden on the processor, along with enhancing the performance of the system in terms of the above-mentioned parameters like tracking time, efficiency, etc. Hence, there is a need for continuous research in this area by employing simple structured algorithms that can fulfill all the requirements of an ideal algorithm, thereby making the system cheaper and reliable. Particle swarm optimization (PSO), owing to its simple structure, is a choice for many researchers and has been applied with various modifications for MPPT [8]–[12]. These modifications were due to the unsatisfactory performance of conventional PSO for MPPT. In [12], a PSO without the random coefficients called deterministic PSO (DPSO) was proposed to improvise the performance of conventional PSO but, due to the lack of stochastic behavior, it was unable to converge to MPP for all shading patterns. A hybrid of PSO with P&O was proposed in [11] with P&O as the initiator for the search of maxima. However, initialization of search using P&O was not suitable [7]. In [16], [38], the jaya algorithm, due to its simpler structure, was found suitable for tracking the MPP. The algorithm has two components in its updating equation, one that takes it nearer to the best value (best enhancing component (BEC)) and another that keeps it away from the worst solutions (worst avoiding component (WAC)). At smaller values of global best, the WAC becomes very large and keeps the solution far away from the true global best, thereby increasing the tracking time and the number of fluctuations which cause power losses. Moreover, it was also observed that for certain irregular solar (insolation) conditions, mostly when the MPP is at the left most position in the power versus voltage (P-V) curve the tracking time and number of fluctuations in jaya were significantly increased thereby showing the unpredictable behavior of the jaya. In [19] three variants of chaotic-flower pollination algorithm (C-FPA) were proposed: namely logistic, sine and tent. All three variants successfully tracked the MPP at higher efficiencies. However, tracking time varied significantly for different PS conditions showing a lack of robustness in each of these algorithms. Hence, in this paper an adaptive jaya algorithm is proposed which keeps the initial weightage of WAC much lower using the adaptive coefficients (AC) introduced based on [39]. In each iteration the WAC value is nearer to the BEC, thereby reducing large diversifications leading to a much faster convergence compared to the simple jaya.

Apart from incorporating the AC further improvement in the algorithm's performance was observed when the initial optimal value (value at first iteration) is larger than the true optimal value (duty ratio in this case). Therefore, it was programmed such that on detecting a situation where the initially found optimal duty ratio value is smaller than the true optimal duty it reinitializes all the duty ratios such that the initial optimal duty ratio becomes greater than the true optimal duty. Duty ratios are reinitialized between initial optimal duty and its increment of 0.2 and the power corresponding to the latter is then evaluated. If the evaluated power is smaller the duties are reinitialized between a minor increment and an increment of almost 0.1 in the initial optima. It was achieved using *if* and *else* statements and no extra equation was involved.

In this paper, comparison of the proposed algorithm was undertaken with the jaya algorithm, the PSO algorithm and the C-FPA variants introduced in [19] based on tracking speed, fluctuations in the power output, robustness and simplicity. The results illustrated a significant improvement in the performance of Ajaya compared to the simple jaya algorithm in terms of tracking time, lesser fluctuations and robustness. The necessity for improvement in the performance of the simple jaya was due to its simple structure which poses less burden on the processor memory especially when a cheap controller is employed. Nevertheless, apart from enhancing the performance of the simple jaya algorithm the improvement was so profound that it outperformed other state-of-the-art techniques in terms of various parameters thereby becoming an ideal algorithm for MPPT applications as explained above. To summarize, the following advantages were observed in the proposed algorithm:

- Significant improvement in terms of tracking time.
- Fewer fluctuations in the power output.
- Robustness (non-deviating performance in changing conditions).

Hence, besides comparable to other algorithms like C-FPA, Jaya and PSO in terms of simplicity, the proposed algorithm exhibits other desirable advantages over them too. Thereby, the Ajaya meta-heuristic approach is becoming an ideal algorithm to solve many practical applications.

Substantial analysis of results was done to prove the above qualities of the proposed algorithm first under static insolation conditions (insolation do not vary with time) using different series-connected module configurations (three, four and a five-module system), after that a real-world phenomenon was chosen where the insolation varies with time due to either movement of clouds or sun's changing positions throughout the day. Then, the module rating was changed based on [19] to compare the proposed algorithm with the algorithms in [19] and to show its robustness under changing conditions. Finally, the International Electrotechnical Commission (IEC) standard curves as described in [40], [41] were chosen to prove

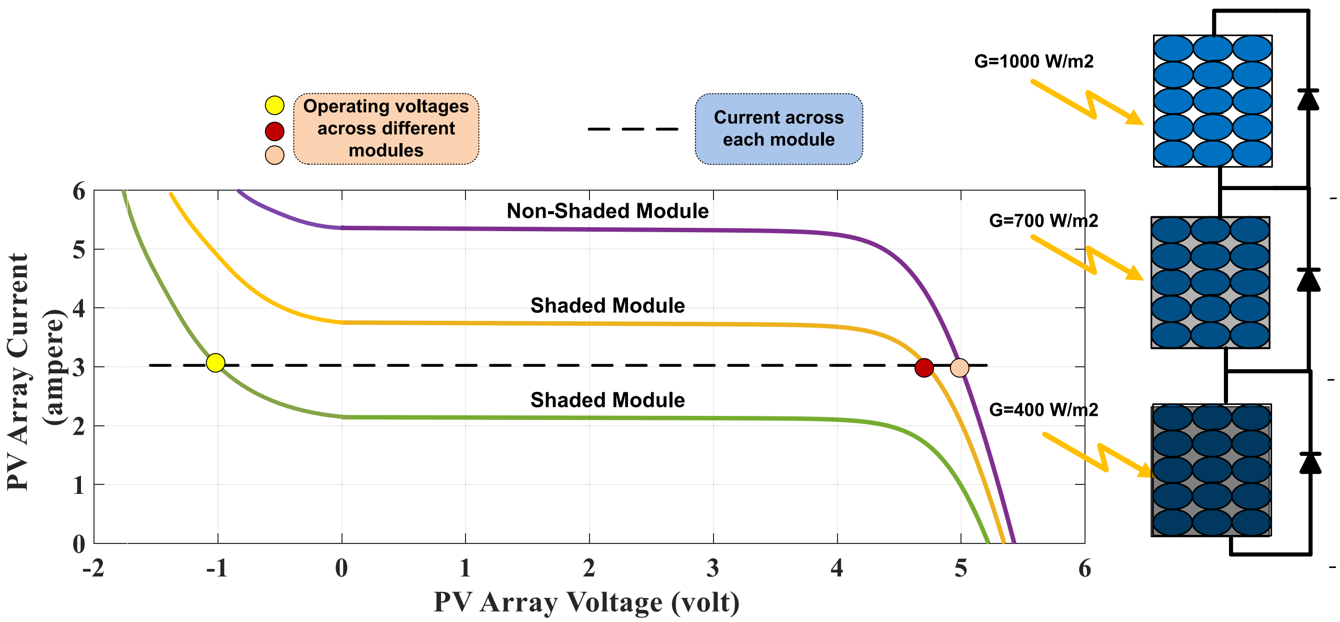


FIGURE 2. I-V characteristics curve under partially shading conditions.

the proposed algorithm's performance. Owing to all these features, especially robustness and lesser burden on processor, the algorithm can be trusted for being employed in industrial, commercial, and residential use as described in the upcoming sections thereby making the overall MPP tracker an ideal one. The remainder of this paper is divided as follows: in section II PS on a PV array is described, section III describes the working of the proposed algorithm, in section IV employment of the proposed algorithm for MPPT is described, section V is the illustration of results, section VI describes the managerial implication of the proposed work and section VII concludes the paper.

II. PARTIAL SHADING ON A PV ARRAY

PV cells, which convert the incident solar radiance into electricity, are connected in two major arrangement categories, namely: series arrangement and parallel arrangement. Due to irregular incident solar radiation (insolation) in a series-connected system, the panel, which receives lesser insolation, will tend to have a negative voltage surging across the panel, thereby acting against the overall system producing high temperatures and huge power losses [42], [43]. By way of analogy, consider the constant flow of blood through arteries to be analogous to the current flow through the circuit. If the artery is clogged due to fat deposition or a blood clot, the flow of blood constricted; similarly, if a part of the panel in a string is shaded (that is, it has lower insolation), it forces the unshaded part (with more insolation) to work less efficiently, thereby increasing the losses. Such an arrangement can cause irreparable damage to the panels which have a lower shading [44].

Fig. 2 shows the reverse bias effect due to PS on a three-module system. In order to avoid these losses modifications to the panel array can be made to use bypass diodes, module level power electronics, or microinverters. For this paper we focus only on the use of bypass diodes, which helps the current to skip over the area with less insolation (the shaded area), thereby allowing the higher current of the area with more insolation (the unshaded area) to pass around the shaded area, thus reducing the losses. However, this arrangement causes multiple peaks to form on the PV curve, leading to multiple global maxima. Fig. 3 illustrates the effect of PS on the power-voltage (P-V) characteristics for a five-module system. It is clear that, due to the PS effect, multiple peaks of power are created. This poses a challenge when using conventional algorithms such as the hill climbing algorithm (HC) or incremental conductance (InC) due to their convergence on local peaks; however, the Ajaya algorithm, being stochastic in nature, eliminates this challenge.

III. THE AJAYA ALGORITHM

A. JAYA AND IT's WORKING

The Jaya Algorithm is one of the many nature-inspired algorithms used for the purpose of deriving optimized solutions to complex problems. The Jaya meta-heuristic is an efficient nature-inspired algorithm and tends to use low processor power to compute optimum results [16]. The Jaya Algorithm takes its name from the Hindi Language word "JAYA" meaning "VICTORY", and the algorithm works on the principle of eliminating the worst choices, continually improving the results during the entire simulation operation. The final result is the best possible solution to the problem, in this case, for the maximum solar power point tracking.

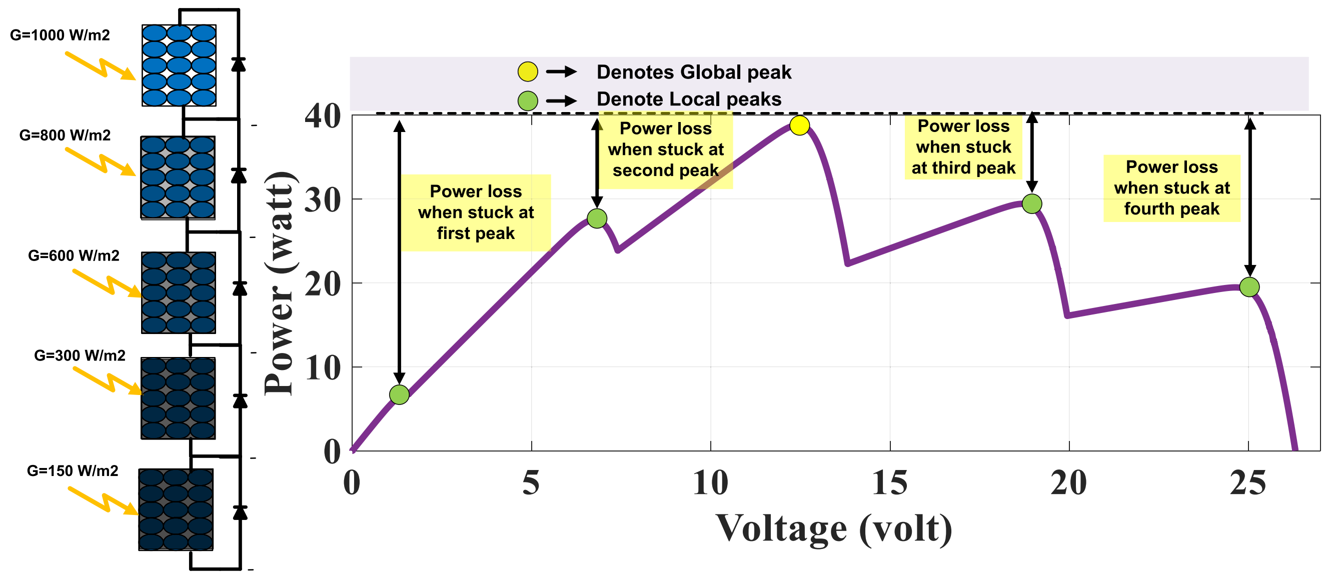


FIGURE 3. **P-V characteristics curve under partially shaded conditions.**

Equations involved in the implementation of the jaya algorithm are as follows:

$$X_v^{i+1} = X_v^i + rand_1^i \left(X_{\text{best}}^i - \left|X_v^i\right|\right) - rand_2^i \left(X_{\text{worst}}^i - \left|X_v^i\right|\right) \tag{1}$$

where X_v^i denotes the fitness of v^{th} particle at i^{th} iteration, X_{best}^i and X_{worst}^i respectively denotes the best and the worst solution among all particles. Hence, only one equation is involved in its updating step which is the reason for its simplicity.

B. AJAYA AND ITS WORKING

An improvement in the simple version of jaya algorithm was done by incorporating AC based on [39] in eq. 1 to make it adaptive such that in each iteration based on values of the worst and the best components, it adaptively adjusts the equation for faster convergence, unlike the jaya, which leads to large diversifications, thereby resulting in larger convergence times.

Moreover, it was observed that Ajaya performs better when the initial optimal value identified is greater than the true optima. Therefore, it was programmed such that for cases where the true optima are greater than the initially found optima all the duty ratios are reinitialized to make the initially found optima greater than the true optima. The following equations are used in implementing the Ajaya algorithm.

$$X_v^{i+1} = X_v^i + c_1^i \times rand_1^i \left(X_{best}^i - \left|X_v^i\right|\right) - c_2^i \times rand_2^i \left(X_{worst}^i - \left|X_v^i\right|\right) \tag{2}$$

where, $\boldsymbol{c_{1i}} = \boldsymbol{c_{2i}} = 1$, $\boldsymbol{c_{1f}} = 0.5$ and $\boldsymbol{c_{2f}} = 0$

The AC in each iteration are varied as follows:

$$c_1^i = c_{1i} - (c_{1i} - c_{1f})\frac{i}{i_{max}} \tag{3}$$

$$c_2^i = c_{2f} - (c_{2f} - c_{2i})\frac{i_{max} - i}{i_{max}} \tag{4}$$

where, i is the present iteration value and i_{max} is the total number of iterations performed. The coefficient c_2^i attached with the WAC remains initially too small thereby reducing the initial effect of the WAC on the equation which is responsible for larger diversifications. The coefficient c_1^i attached to the BEC initially remains high to bring the solution much closer to the optimal solution. After this initial combined action of both the coefficients all the solutions become closer to the optimal value thereby reducing the difference between the best and the worst value. Now, because the WAC has been reduced and will no more cause large diversifications, c_2^i in the next iteration is increased to make its effect a bit more profound and c_1^i is correspondingly decreased such that the combined effect updates the solution to bring it nearer to optima and keeps away from the worst solution.

IV. MPPT USING AJAYA

The main objective is to send the highest power at the output load corresponding to an insolation combination. A DC-DC boost converter is employed as an interface between the PV array and the load. The switching of the boost converter decides on the combination of voltage and current corresponding to which produces the maximum power. The duty ratio, in this case, is analogous to the particles, which are the solution for a problem. The duty ratio value varies with varying insolation and hence, for each changing insolation pattern on PV modules, a new optimal duty ratio must be calculated using the Ajaya updating equations. Initial power and four random duty ratios are first assigned to the Ajaya compiled in a microcontroller. The algorithm then triggers the switch using all the initial duty ratio values through a gate driver circuit. The new combination of voltage and current generated is read by the microcontroller using voltage and current sensors, respectively, and the newly calculated power is compared with the previous value. The duty ratio corresponding to the higher power is saved in each iteration, and the global best and worst of the Ajaya are the duty ratio values corresponding to which the power was the highest and the lowest, respectively. The Ajaya then explores each duty ratio around the global best value and try to keep it away from the worst value using BEC and WAC attached with AC respectively in each iteration. The process continues until the simulation run time is over. Working of the Ajaya algorithm for MPPT is shown in fig. 4. The complete setup of a boost converter based MPPT controller is shown in fig. 5.

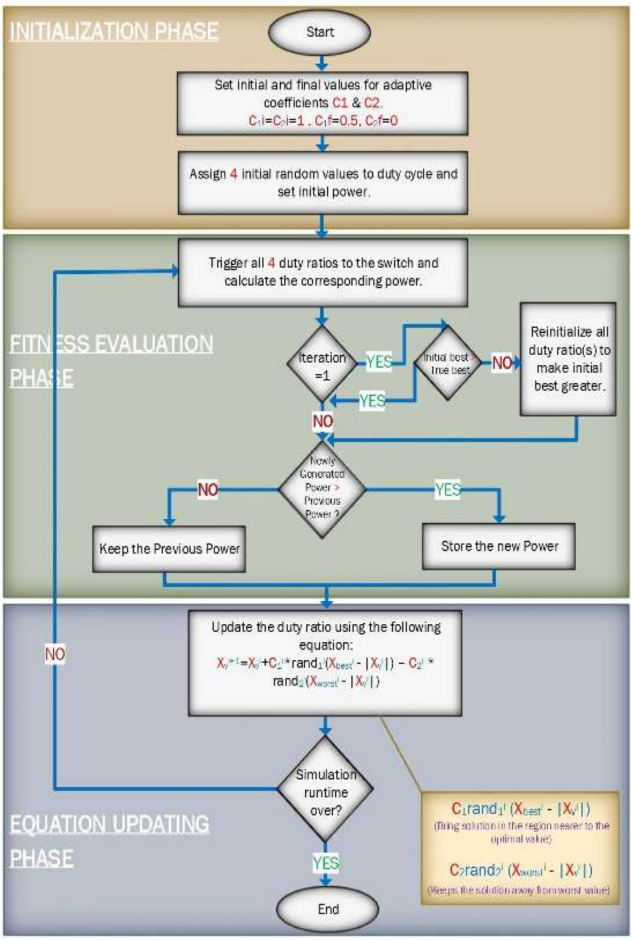


FIGURE 4. Flowchart for MPPT using Ajaya.

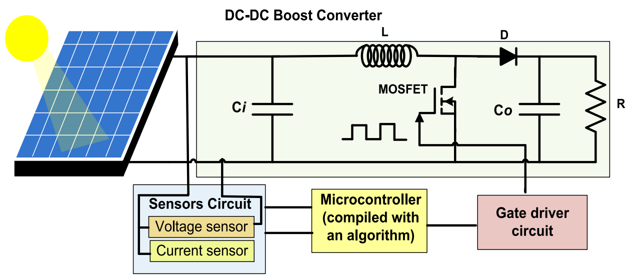


FIGURE 5. Boost converter based MPP tracker.

V. RESULTS AND DISCUSSION

Results are divided into four sections: for static insolation condition, for dynamic insolation condition, for a condition when panel rating is changed, and for performance evaluation under real atmosphere. A standard PV module at a rated MPP of 21.837 W was chosen and joined in series to make an array of 3, 4, and 5 modules for static insolation conditions. The DC-DC boost converter was used as an interface between the PV array and the load to send the optimal power at the output. A general boost converter based MPPT controller is shown in fig. 5. The input and the output capacitance (C_i and C_o) of the converter are 47 and 470 μF respectively, inductance (L) is 1.15 mH, and the output resistive load (R) is of 10 Ω. Initially, all the results for the static and the dynamic condition were taken using the PV array described above. After that, to verify the robustness of the proposed algorithm and to compare it with the C-FPA variants in [19], another array of 36 W rating described in [19] was chosen and the results were taken for the same PS patterns as described in [19]. The boost converter parameters were chosen as in [19]. The parameters for PSO were chosen as $C_1 = 1.2$, $C_2 = 1.6$ and $w = 0.4$ [31]. Finally, to give an approximate idea of the proposed algorithm's robustness and its efficient performance under real atmospheric conditions, the International Electrotechnical Commission (IEC) data was used to generate the P-V curves.

A. STATIC INSOLATION CONDITION

In this case, algorithms are compared for different PS conditions that do not vary with time and remain the same throughout the simulation run time. All comparisons are made for different numbers of modules. Firstly, the comparison is made for a three-module system, then for a four- and a five-module system. These many-module configurations were chosen to show that in any case, the proposed algorithm performs better than the other algorithms. For each of these configurations, a full insolation condition and three different shading scenarios were chosen. These patterns were chosen to show that the proposed algorithm can track the MPP for any peak position unlike the conventional algorithms that can only track for a certain peak. The shading patterns can be described as follows:

1) STATIC PS 1

For each configuration of PV array the shading pattern with the MPP at the right-most position is said to be static PS 1. The shading patterns will be different for each configuration, but the peak will reside at the right-most position.

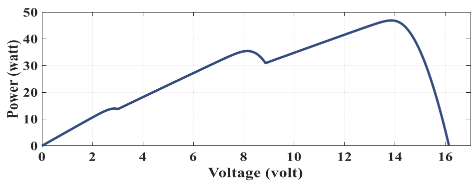
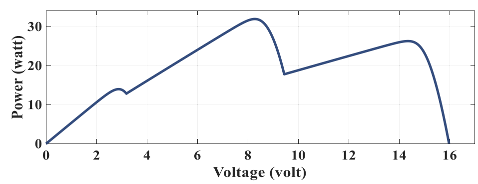
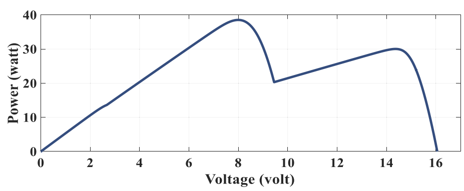
2) STATIC PS 2

For each configuration of PV array the shading pattern with the MPP at the middle position is said to be static PS 2. Like the static PS 1 the shading patterns will be different for different configurations, but the peak will always reside in the middle.

3) STATIC PS 3

For each configuration of PV array the shading pattern with the MPP at the left position is said to be static PS 3. Again, the shading patterns will be different for different configurations, but the peak will always reside to the left. Details of all the shading cases for PV arrays comprising 3, 4 and 5 modules are summarized in tables 1, 2 and 3 respectively. Figs. 6-8 show the comparative analysis of all the algorithms for static PS conditions.

TABLE 1. Insolation Summary, P-V Curve Positions Insolation Summary, P-V Curve Positions & MPP of a Three-Module PV System Under Partial Shading.

<table>
<tr><th>NUMBER OF MODULES</th><th colspan="3">INSOLATION ACROSS EACH MODULE (W/m^2)</th></tr>
<tr><td rowspan="7">3</td><td>MODULE 1</td><td>MODULE 2</td><td>MODULE 3</td></tr>
<tr><td>1000</td><td>850</td><td>650</td></tr>
<tr><td colspan="3">Peak position: Right
MPP: 46.9 W
</td></tr>
<tr><td>1000</td><td>750</td><td>350</td></tr>
<tr><td colspan="3">Peak position: Middle
MPP: 31.88 W
</td></tr>
<tr><td>1000</td><td>950</td><td>400</td></tr>
<tr><td colspan="3">Peak position: Left
MPP: 38.51 W
</td></tr>
</table>

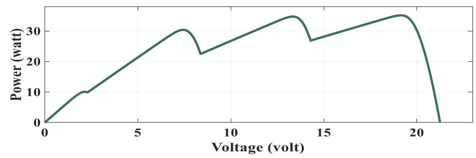
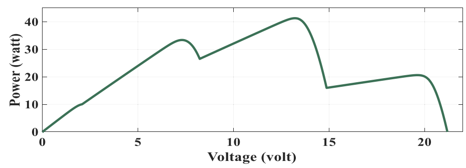
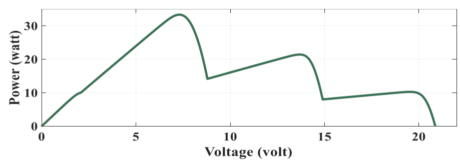
4) THREE-MODULE SYSTEM

Fig.6(a-d) shows the comparison of the proposed algorithm with other algorithms for this configuration.

In fig.6(a) performances of the InC, PSO, jaya and Ajaya are shown for full insolation.

- InC successfully tracked the MPP of 65.267 W. The time taken by the algorithm was 0.637 seconds with an efficiency of 99.04 %.
- PSO successfully tracked the MPP of 65.388 W. The time taken by the algorithm was 1.539 seconds with an efficiency of 99.22 %.

TABLE 2. Insolation Summary, P-V Curve Positions Insolation Summary, P-V Curve Positions & MPP of a Four-Module PV System Under Partial Shading.

<table>
<tr><th>NUMBER OF MODULES</th><th colspan="4">INSOLATION ACROSS EACH MODULE (W/m^2)</th></tr>
<tr><td rowspan="7">4</td><td>MODULE 1</td><td>MODULE 2</td><td>MODULE 3</td><td>MODULE 4</td></tr>
<tr><td>1000</td><td>800</td><td>500</td><td>350</td></tr>
<tr><td colspan="4">Peak position: Right
MPP: 35.15 W
</td></tr>
<tr><td>1000</td><td>900</td><td>600</td><td>200</td></tr>
<tr><td colspan="4">Peak position: Middle
MPP: 41.3 W
</td></tr>
<tr><td>1000</td><td>900</td><td>300</td><td>100</td></tr>
<tr><td colspan="4">Peak position: Left
MPP: 33.9 W
</td></tr>
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- Jaya successfully tracked the MPP of 65.379 W. The time taken by the algorithm was 0.581 seconds with an efficiency of 99.20 %.
- Ajaya successfully tracked the MPP of 65.382 W. The tracking time of the algorithm was 0.574 seconds. The efficiency of the algorithm was 99.21 %.

It is seen that under full insolation InC successfully converged to MPP and at good efficiency. PSO for this condition took longer in the final convergence. However, the time difference between jaya and Ajaya is small. The percentage decrease in settling time with Ajaya with respect to PSO and jaya was found to be 168.1 and 1.21%, respectively.

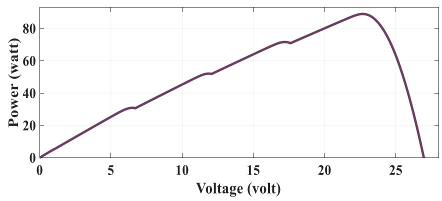
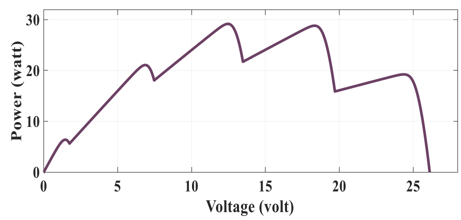
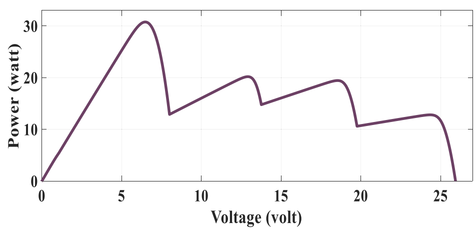
In fig.6(b), performances of InC, PSO, jaya and Ajaya are shown for static PS 1.

- InC tracked the MPP of 46.72 W. The time taken by the algorithm was 0.248 seconds with

an efficiency of 99.61%.

- PSO tracked the MPP of 46.85 W. The time taken by the algorithm was 1.334 seconds, with an efficiency of 99.89 %.

TABLE 3. Insolation Summary, P-V Curve Positions & MPP of a Five-Module PV System Under Partial Shading.

Number of modules	Insolation across each module (W/m^2)				
	Module 1	Module 2	Module 3	Module 4	Module 5
	1000	950	850	800	750
	Peak position: Right MPP: 88.97 W 				
5	1000	600	450	300	150
	Peak position: Middle MPP: 29.19 W 				
	1000	950	300	200	100
	Peak position: Left MPP: 30.77 W 				

- Jaya tracked the MPP of 46.845 W. The time taken by the algorithm was 1.181 seconds, with an efficiency of 99.88 %.
- Ajaya tracked the MPP of 46.84 W. The tracking time of the algorithm was 0.698 seconds, which shows much faster tracking than the other algorithms. The efficiency of the algorithm was 99.87 %.

It is seen from the static PS 1 results that, even though it is a PS condition, InC tracked the MPP at higher efficiency. Moreover, PSO and jaya successfully tracked the MPP but took much longer in finally converging to the MPP. Other than that, the number of fluctuations in search for the MPP are also much larger in the case of PSO and jaya, thereby causing excessive power losses.

On the other hand, the proposed algorithm settled to the MPP in much less time and with minor fluctuations thereby avoiding power losses. The percentage decrease in settling time in Ajaya with respect to PSO and jaya was found to be 91.1 and 69.2%, respectively.

In fig.6(c) the performances of PSO, jaya and Ajaya are shown for static PS 2.

- InC tracked the MPP of 31.62 W. The time taken by the algorithm was 0.761 seconds with an efficiency of 99.19 %.
- PSO tracked the MPP of 31.82 W. The time taken by the algorithm was 1.717 seconds with an efficiency of 99.825 %.
- Jaya tracked the MPP of 31.81 W in 1.717 seconds with an efficiency of 99.784%.
- Ajaya tracked the MPP in of 99.824 W in 0.908 seconds with an efficiency of 99.824%.

From static PS 2 results once again, it is concluded that the proposed algorithm shows a significant improvement in terms of settling time and fewer fluctuations while tracking the MPP. Moreover, it is also observed that, for this case the performance of the jaya algorithm is further reduced, thereby causing larger fluctuations and slower settling time. However, the proposed algorithm produced stable results without increasing the number of fluctuations, proving its robustness over jaya. Although an increase in the settling time of Ajaya is observed, it was due to a minor fluctuation, which does not have a significant impact on the efficiency of the converter. Other than that, InC again successfully tracked the MPP even though it is a PS condition. The percentage decrease in settling time in the Ajaya with respect to PSO and the jaya was the same in this case and equal to 89.09%.

In fig.6(d) the performances of PSO, jaya, and Ajaya are shown for static PS 3.

- InC tracked the MPP of 29.93 W. The time taken by the algorithm was 0.376 seconds, with an efficiency of 77.72%.
- PSO tracked the MPP of 38.44 W. The time taken by the algorithm was 1.334 seconds, with an efficiency of 99.819 %.
- Jaya tracked the MPP of 38.43W with the time taken for convergence to be 1.797 seconds and an efficiency of 99.79 %.
- Ajaya tracked the MPP of 0.908 W with the time taken for convergence to be 0.908 seconds and efficiency of 99.817 %.

Again, an additional advantage of using the proposed algorithm is observed in the static PS 3 results. The performance of jaya is further reduced and produced higher fluctuations with slower settling time compared to the previous cases. However, the proposed algorithm provided more stable results with smaller fluctuations and faster settling time thereby proving its robustness over jaya. The percentage decrease in settling time in the Ajaya with respect to PSO and the jaya was found to be 46.91 and 97.9%, respectively.

From these results it is also observed that the InC converges to the local MPP. From all the above results it is now finally concluded that InC may track MPP for some cases of PS, but this does not guarantee convergence for all PS cases

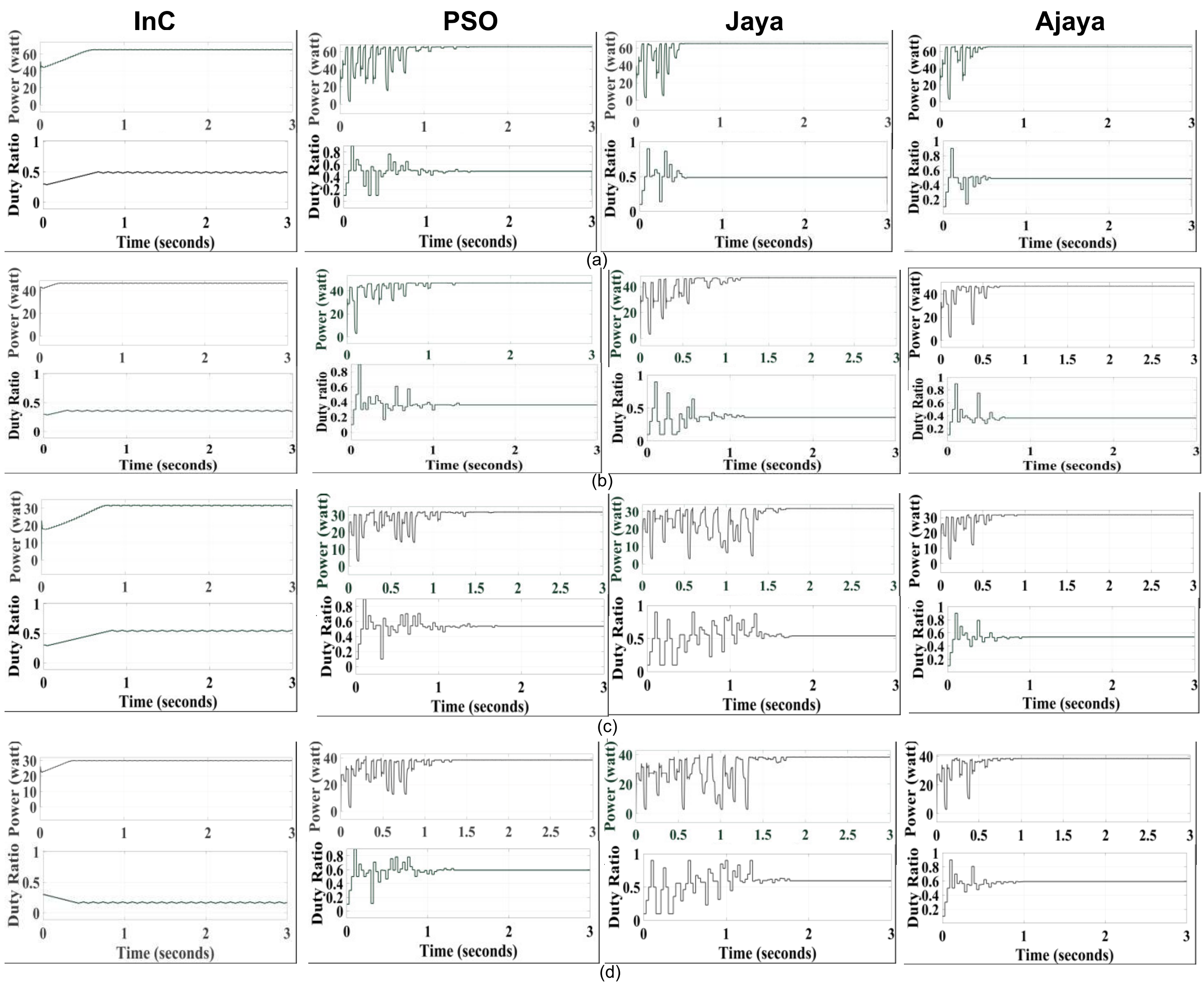


FIGURE 6. Comparison graphs for a 3-module system under (a) full insolation (b) static PS1 (c) static PS2 (d) static PS3.

and the algorithm may become stuck in local MPP for certain cases. Hence, for the upcoming module configurations the results for only the metaheuristic algorithms have been shown.

A comparison summary of Ajaya in terms of its settling time and percentage reduction in settling time is shown in table 4.

5) FOUR-MODULE SYSTEM

Fig.7(a-d) shows the comparison of the proposed algorithm with other algorithms for this configuration.

In fig.7(a) the performances of PSO, jaya and Ajaya are shown for full insolation.

- PSO tracked the MPP of 87.19 W. The time taken by the algorithm was 1.784 seconds with an efficiency of 99.41%.
- Jaya tracked the MPP of 87.19 W with the time taken for convergence to be 1.114 seconds at an efficiency of 99.41 %.
- Ajaya tracked the MPP of 86.716 W with the time taken for convergence to be 0.694 seconds at an efficiency of 98.867 %.

The above results show that although the efficiency of the proposed algorithm is a bit lower in this case, it tracked the MPP in much less time along with reduced oscillations. Moreover, in the three-module system the tracking speed of the jaya was faster but, when employed on four-module, the speed is reduced unlike Ajaya which has the usual tracking time. The percentage decrease in settling time for Ajaya with respect to PSO and jaya was found to be 157.06 and 60.5%, respectively.

In fig.7(b) the performances of PSO, jaya and Ajaya are shown for static PS 1.

- PSO successfully tracked the MPP of 34.73 W. The time taken by the algorithm was 1.18 seconds with an efficiency of 98.8 %.
- Jaya successfully tracked the MPP of 34.728 W. The time taken by the algorithm was 1.386 seconds with an efficiency of 98.79 %.

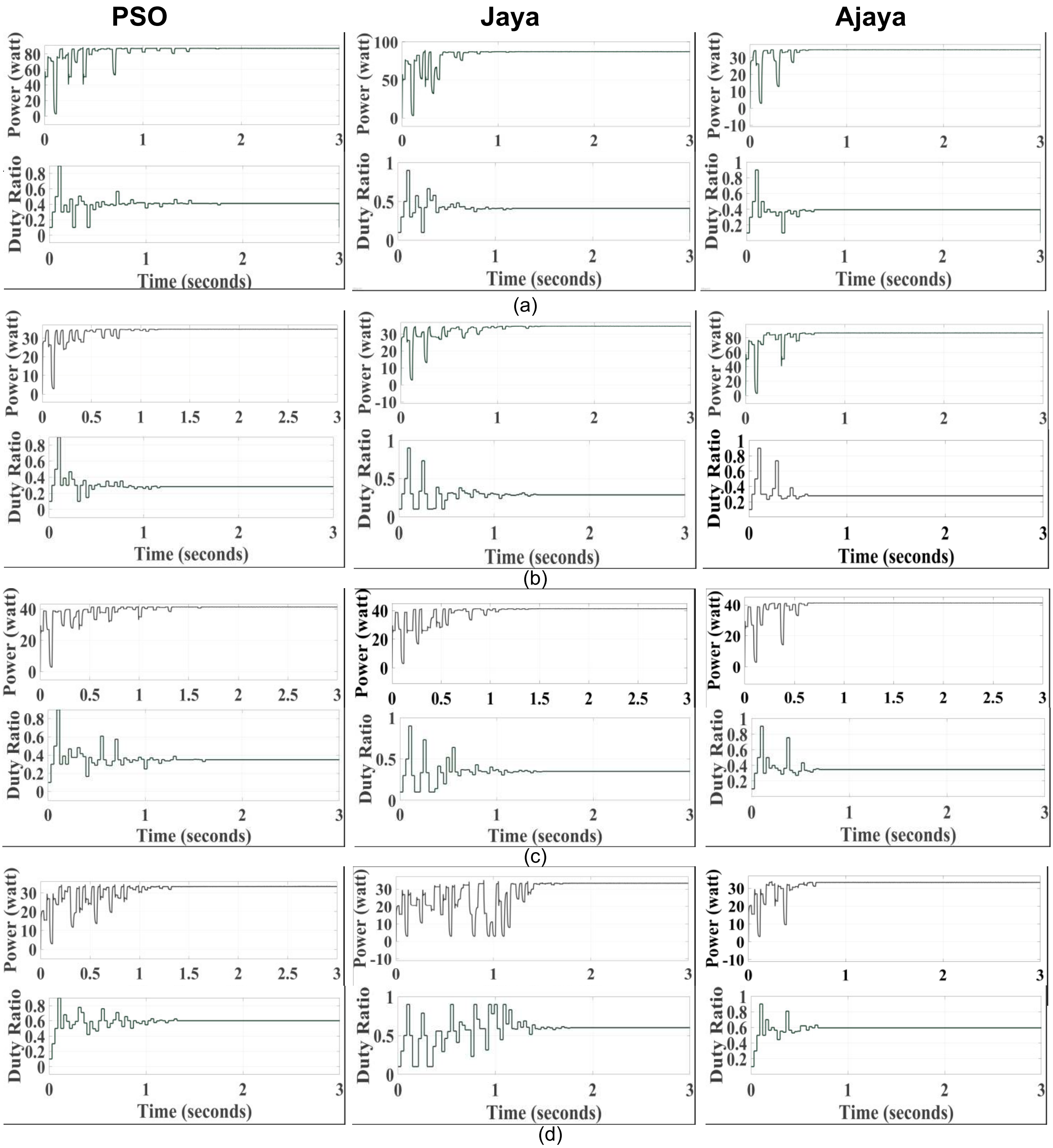


FIGURE 7. Comparison graphs for a 4-module system under (a) full insolation (b) static PS1 (c) static PS2 (d) static PS3.

- Ajaya successfully tracked the MPP of 34.691 W. The tracking time of the algorithm was 0.615 seconds with an efficiency of 98.695 %.

Like the three-module configuration, for four-module configuration of the static PS 1 it is concluded that although PSO and jaya successfully tracked the MPP, they took much longer to finally converge to the MPP. Moreover, the number of fluctuations for both the algorithms were higher thereby causing excessive power losses.

On the other hand, the proposed algorithm settled to the MPP in much lesser time with less fluctuations thereby avoiding power losses. The percentage decrease in settling time for Ajaya with respect to PSO and jaya was found to be 91.86 and 125.36%, respectively.

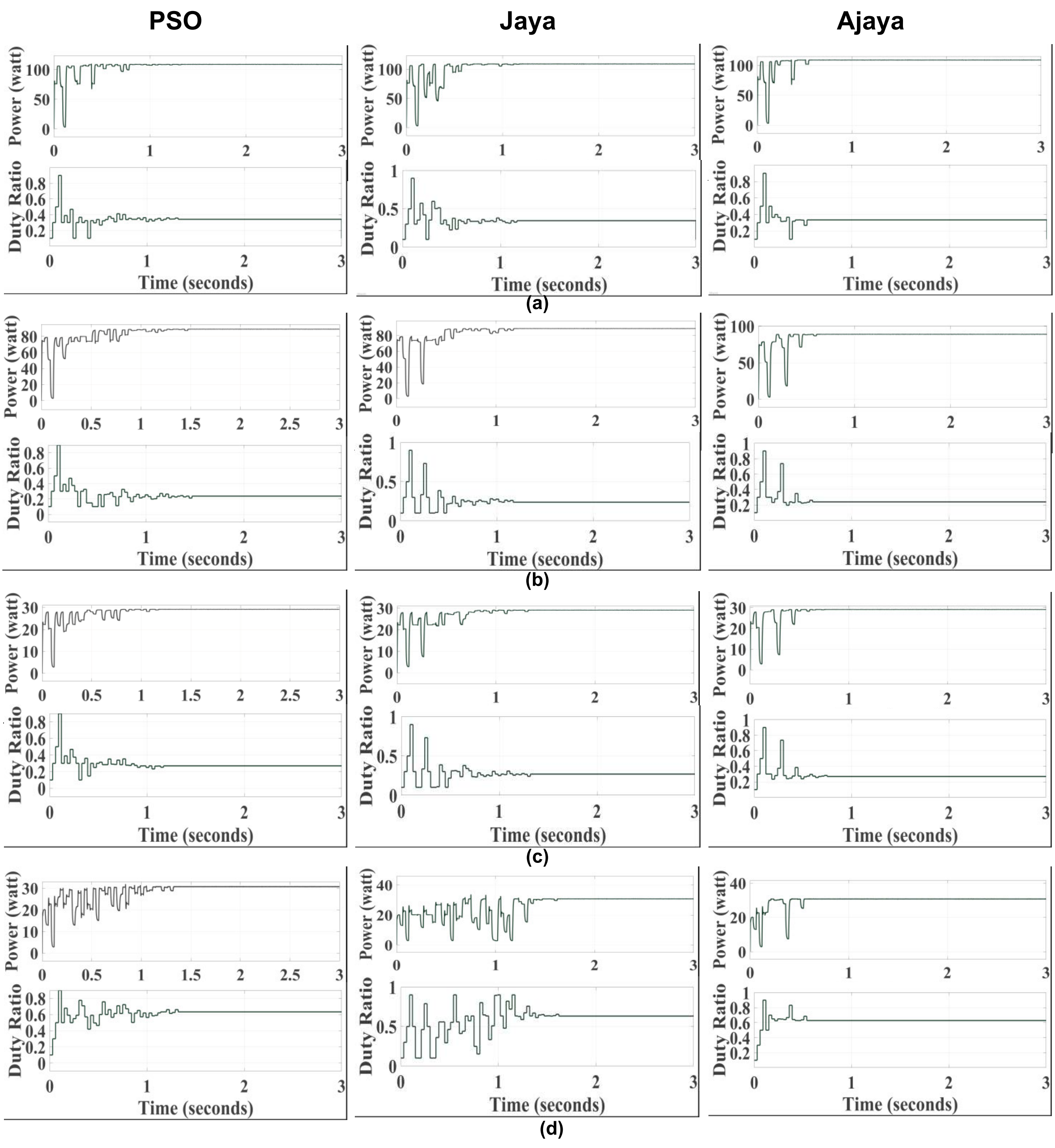


FIGURE 8. Comparison graphs for a 5-module system under (a) full insolation (b) static PS1 (c) static PS2 (d) static PS3.

In fig.7(c) the performances of PSO, jaya and Ajaya are shown for static PS 2.

- PSO tracked the MPP of 41.25 W. The time taken by the algorithm was 1.636 seconds with an efficiency of 99.88 %.
- Jaya tracked the MPP of 41.25 W. The time taken by the algorithm was 1.396 seconds with an efficiency of 99.88 %.
- Ajaya tracked the MPP of 41.23 W. The tracking time of the algorithm was 0.648 seconds with an efficiency of 99.84 %.

TABLE 4. Summary of settling time of all algorithms and percentage reduction in settling time of the proposed algorithm for different module configurations.

3 Module System			4 Module System			5 Module System		
Partial shading condition	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**
Full Insolation	Ajaya	0.574	Full Insolation	Ajaya	0.694	Full Insolation	Ajaya	0.552
	Jaya	0.581		Jaya	1.114		Jaya	1.181
	PSO	1.539		PSO	1.784		PSO	1.331
Percentage improvement in convergence time compared with (in %): Jaya: 1.21% PSO: 168.1%			**Percentage improvement in convergence time compared with (in %):** Jaya: 60.5% PSO: 157.06 %			**Percentage improvement in convergence time compared with (in %):** Jaya: 113.9% PSO: 141.1%		
Partial shading condition	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**
Static1	Ajaya	0.698	Static1	Ajaya	0.615	Static1	Ajaya	0.615
	Jaya	1.181		Jaya	1.386		Jaya	1.191
	PSO	1.334		PSO	1.18		PSO	1.481
Percentage decrease in convergence time compared with (in %): Jaya: 69.2% PSO: 91.1%			**Percentage decrease in convergence time compared with (in %):** Jaya: 125.36% PSO: 91.86%			**Percentage decrease in convergence time compared with (in %):** Jaya: 93.658% PSO: 140.8%		
Partial shading condition	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**
Static2	Ajaya	0.908	Static2	Ajaya	0.648	Static2	Ajaya	0.672
	Jaya	1.717		Jaya	1.396		Jaya	1.334
	PSO	1.717		PSO	1.636		PSO	1.181
Percentage decrease in convergence time compared with (in %): Jaya: 89.09% PSO: 89.09%			**Percentage decrease in convergence time compared with (in %):** Jaya: 115.43% PSO: 152.47%			**Percentage decrease in convergence time compared with (in %):** Jaya: 98.5% PSO: 75.74%		
Partial shading condition	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**	**Partial shading condition**	**MPPT algorithm**	**Time (seconds)**
Static3	Ajaya	0.908	Static3	Ajaya	0.698	Static3	Ajaya	0.563
	Jaya	1.797		Jaya	1.719		Jaya	1.629
	PSO	1.334		PSO	1.336		PSO	1.334
Percentage decrease in convergence time compared with (in %): Jaya: 97.9% PSO: 46.91%			**Percentage decrease in convergence time compared with (in %):** Jaya: 146.27% PSO: 91.4%			**Percentage decrease in convergence time compared with (in %):** Jaya: 189.34% PSO: 136.94%		

The results for the static PS 2 condition show that the proposed algorithm shows a significant improvement in terms of settling time and fewer fluctuations. The percentage decrease in settling time for Ajaya with respect to PSO and jaya was found to be 152.47 and 115.43%, respectively.

In fig.7(d) the performances of PSO, jaya and Ajaya are shown for static PS 3.

- PSO tracked the MPP of 33.32 W. The time taken by the algorithm was 1.336 seconds with an efficiency of 99.79 %.
- Jaya tracked the MPP in of 33.32 W in 1.719 seconds with an efficiency of 99.79 %.
- Ajaya tracked the MPP in of 33.27 W in 0.698 seconds with an efficiency of 99.64%.

Once again, the performance of the jaya algorithm is reduced for the static PS 3 condition. The number of fluctuations and the settling time are increased thereby causing power losses. Nevertheless, the proposed algorithm is more robust causing no such deviation from the actual performance. The percentage decrease in time for Ajaya with respect to PSO and the jaya was found to be 91.4 and 146.27 respectively.

6) FIVE-MODULE SYSTEM

Figs.8(a-d) shows the comparison of the proposed algorithm with other algorithms for this configuration.

In fig.8(a) the performances of PSO, jaya and Ajaya are shown for full insolation.

- PSO settled to the MPP of 108.997 W at a settling time of 1.331 seconds and efficiency 99.9%.
- Jaya settled to the MPP of 108.964 W at a settling time of 1.181 seconds and efficiency 99.87%.
- Ajaya settled to the MPP of 108.886 W at a settling time of 0.552 seconds and efficiency 99.8%.

The Ajaya algorithm tracked the MPP in a shorter time and with lesser fluctuations. Moreover, it is seen that under full insolation over a five-module system the jaya produced additional fluctuations compared to the three-module system under full insolation. However, as always, Ajaya has stable results and produced no additional fluctuations. The percentage decrease in settling time in the Ajaya with respect to PSO and jaya was found to be 141.1 and 113.9%, respectively.

In fig. 8(b) the performances of PSO, jaya and Ajaya are shown for static PS 1.

- PSO settled to the MPP of 88.88 W at a settling time of 1.481 seconds and efficiency 99.9%.
- Jaya settled to the MPP of 88.89 W at a settling time of 1.191 seconds and efficiency 99.91%
- Ajaya settled to the MPP of 88.91 W at a settling time of 0.615 seconds and efficiency 99.93%.

The proposed algorithm successfully outperformed PSO and jaya in terms of faster settling time. Apart from that the number of fluctuations were very less thereby resulting in least power losses before the MPP is finally tracked. The percentage decrease in settling time for Ajaya with respect to PSO and jaya was found to be 140.8 and 93.658%, respectively.

In fig.8(c) the performances of PSO, jaya and Ajaya are shown for static PS 2.

- PSO settled to the MPP of 29.16 W at a settling time of 1.181 seconds and efficiency 99.9%.
- Jaya settled to the MPP of 29.159 W at a settling time of 1.334 seconds and efficiency 99.895%.
- Ajaya settled to the MPP of 29.158 W at a settling time of 0.672 seconds and efficiency 99.892%.

Again, the proposed algorithm outperformed both the algorithms in terms of faster tracking time and lesser fluctuations. The percentage decrease in settling time for Ajaya compared to PSO and jaya was found to be 75.74 and 98.5%, respectively.

In fig.8(d) the performances of the PSO, jaya and Ajaya are shown for static PS 3.

- PSO settled to the MPP of 30.74 W at a settling time of 1.334 seconds and efficiency 99.87%.
- Jaya settled to the MPP of 30.744 W at a settling time of 1.629 seconds and efficiency 99.92%
- Ajaya settled to the MPP of 30.741 W at a settling time of 0.563 seconds and efficiency 99.91%

Once again it is seen that the performance of the jaya algorithm is further reduced which results in slower convergence and higher fluctuations. Nonetheless, as usual the Ajaya provided the stable performance. The percentage decrease in time in the Ajaya compared to PSO and the jaya was found to be 136.94 and 189.34%, respectively.

A final key observation for the static PS results can be drawn where it is clear that the proposed algorithm outperformed PSO and the jaya in terms of faster tracking time, lesser fluctuations and robustness. For all the PS cases the tracking of the proposed algorithm was at least 40% less than the other two algorithms. Under full insolation except for the three-module system the tracking time of the Ajaya was much faster than the other two algorithms. Moreover, it was also observed, especially when the MPP was at the left-most position, PSO and jaya took much longer to settle and produced larger fluctuations compared to their usual performance and in that case a clear percentage increase in the reduction in settling time of Ajaya was observed. A comparison summary for all the modules under static PS condition is given in table 4. The comparison is completed based on tracking speed and percentage reduction in tracking time of the proposed algorithm compared with the others.

B. DYNAMIC INSOLATION CONDITION

This condition was chosen to show that apart from static condition the proposed algorithm will give a better performance in a real-world scenario. To simulate a dynamic scenario the shading patterns were varied with time considering change in sun's position and cloud movement. The results were taken using a four-module configuration with each module of the same rating of 21.837. Two different cases are shown. The first case was drawn assuming that the shading pattern changes with time due to changes in proportion of insolation on different modules. In this case the sun's position was considered to be changing throughout the day with respect to a tree branch as shown in fig.9. The tree will remain fixed, but the sun will change its position throughout the day which will result in different shading patterns on a PV array due to tree branches working as a barrier. The shading pattern was changed every three seconds. This case is also defined as dynamic insolation (varying irradiance) in this paper.

Table 5 summarizes peak positions in P-V curve and MPP value for every instant of this case. In the next case the effect of shading was reduced with time which is similar to, say, a cloud that initially caused partial shading now moving forward with time and uncovering the surface of the PV array thereby reducing the partial shading as illustrated in fig.10. This case is also defined as dynamic insolation (PS attenuation). Table 6 summarizes peak positions in P-V curve and MPP value for every instant of this case. The results obtained for both conditions are described below. In the static PS results it is observed that the efficiency for all three

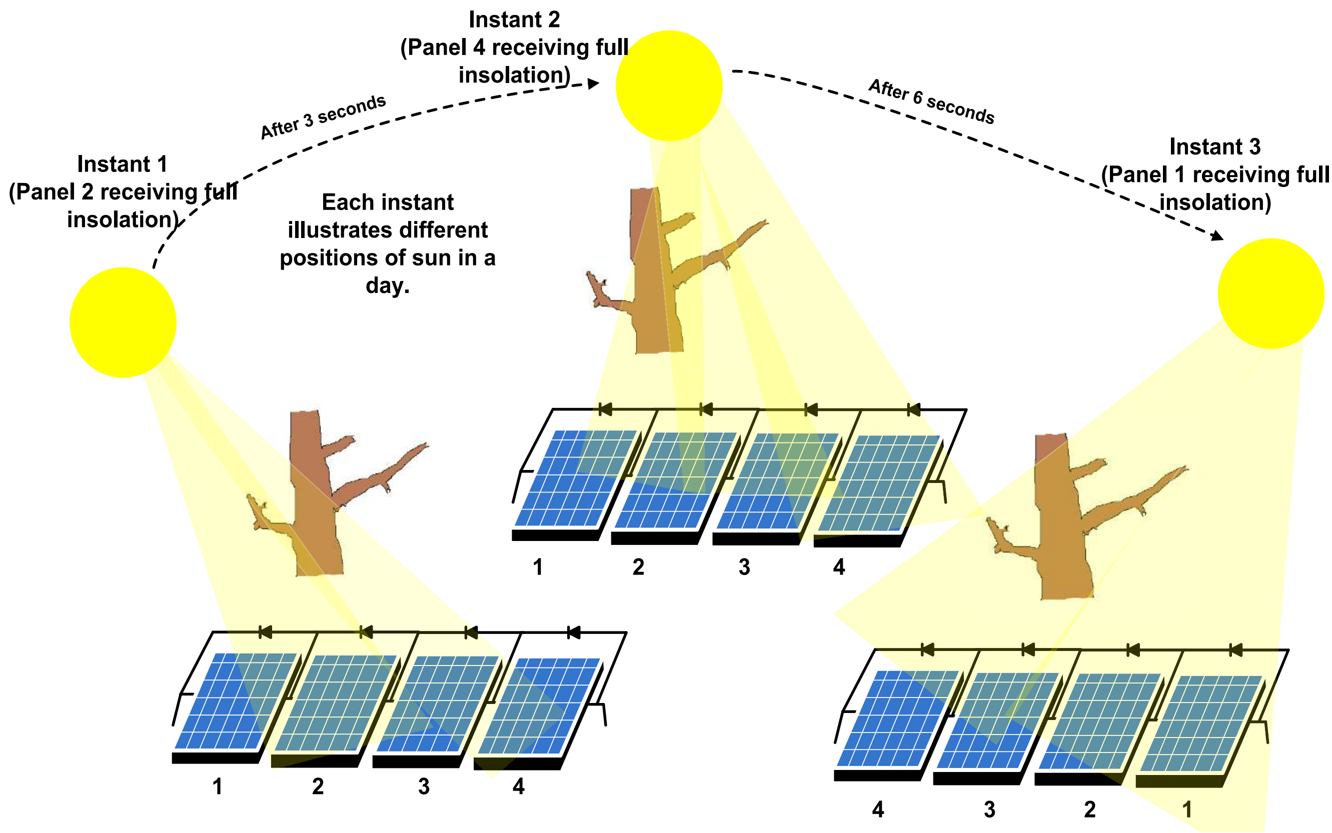


FIGURE 9. Dynamic insolation with varying insolation.

algorithms is almost the same. Hence, for this case only the tracking time is calculated.

1) DYNAMIC INSOLATION (VARYING IRRADIANCE)

Fig.11 presents the results for this case for all the algorithms. In fig.11 (a) the result for PSO is shown under dynamic insolation. It is seen that the PSO algorithm successfully tracked the MPP at all the instants, however, the time taken to converge and the number of fluctuations were higher at every instant. The convergence time was 1.476, 1.45 and greater than 1.832 respectively for instant 1, 2 and 3.

In fig.11(b) the result for jaya is shown under dynamic insolation. It is seen that the jaya algorithm successfully tracked the MPP for all the instants, however, the time taken to converge and the number of fluctuations for each instant were higher. Moreover, it was observed, at the third instant, the algorithm was unable to track the MPP and keeps fluctuating, thereby resulting in power losses. The convergence time was 1.34, 0.99, and greater than 3 seconds (unable to converge to MPP) respectively for instant 1, 2, and 3.

In fig.11 (c) the result for Ajaya is shown under dynamic insolation. It is seen that the Ajaya algorithm successfully tracked the MPP for all instants. Apart from that, for each instant the convergence time and the number of fluctuations were much lower compared to PSO and jaya.

The convergence time was found to be 0.608, 0.758, and 1.18 seconds, respectively for instant 1, 2 and 3. It is also seen that for the third instant, the jaya was unable to converge and produced large fluctuations. Nevertheless, the proposed algorithm tracked the MPP for all three cases in much lesser time, which clearly shows the advantage of modification.

Percentage decrease in tracking time with respect to PSO and jaya was found to be 142.76 and 120.4%, 91.3 and 30.6% and 55.25% and untracked, respectively for instants 1, 2 and 3. A summary of Ajaya in terms of its settling time and percentage decrease in settling time with respect to PSO and jaya is given in table 7 for this case.

2) DYNAMIC INSOLATION (PS ATTENUATION)

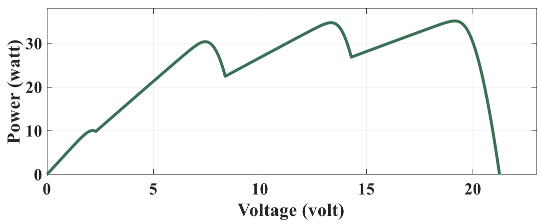
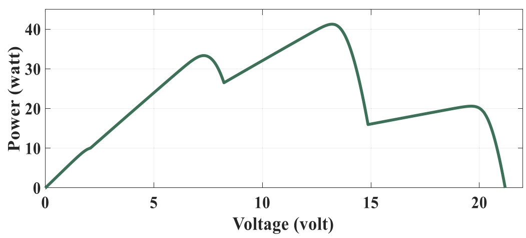
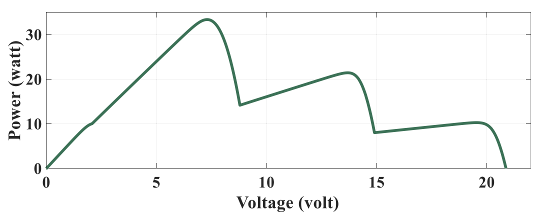
Fig. 12 shows the performance of all algorithms under this condition. Fig.12(a) illustrates the performance of the PSO algorithm. Convergence time was 1.476, 2.204, 1.443, and 1.783 seconds at instants 1, 2, 3 and 4 respectively.

Fig.12(b) illustrates the performance of the jaya algorithm under this condition. Convergence time was 1.123, 0.88, 1.93, and 1.184 seconds at instants 1, 2, 3 and 4 respectively.

Fig.12(c) illustrates the performance of the Ajaya algorithm. Convergence time was 0.611, 0.88, 1.19 and 1.034 seconds at instants 1, 2, 3 and 4 respectively.

The convergence time and the number of fluctuations were much lower compared to the jaya and PSO except for instant 2 and instant 4, which are the light partial shading and full insolation condition cases, respectively. The time difference between the jaya and the Ajaya was small for instant 4.

TABLE 5. Insolation Summary, P-V Curve Positions & MPP of for different instants of varying insolation dynamic PS condition.

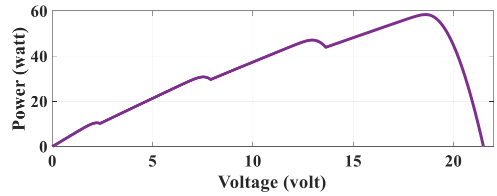
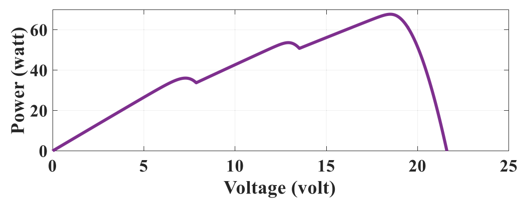
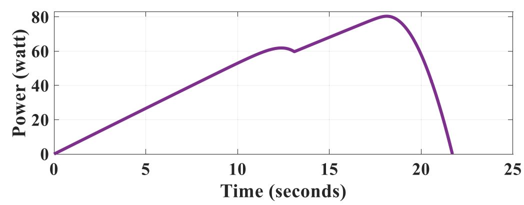
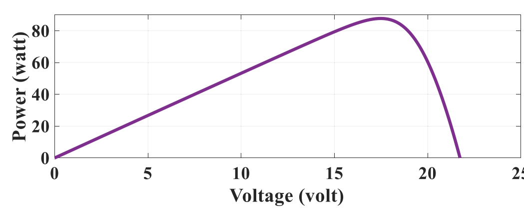
Insolation across each module (W/m^2)			
Module 1	Module 2	Module 3	Module 4
350	1000	800	500
Instant 1 **Peak position:** Right **MPP:** 35.32 W 			
200	600	900	1000
Instant 2 **Peak position:** Middle **MPP:** 41.58 W 			
100	300	900	1000
Instant 3 **Peak position:** Left **MPP:** 33.78 W 			

Instant 2 is the only case of PS and that also a light PS condition (only two panels partially shaded) among all results where the tracking time for the jaya and the Ajaya was the same. Percentage decrease in tracking time with respect to PSO and jaya was found

To be 141.57 and 83.8%, 150.45 and 0%, 21.26 and 62.18% and 72.437 and 14.5% respectively for instants 1, 2 and 3 and 4, respectively.

A summary of Ajaya in terms of its settling time and percentage decrease in settling time with respect to PSO and jaya is given in table 8 for this case.

TABLE 6. Insolation Summary, P-V Curve Positions & MPP of for different instants of attenuated insolation dynamic PS condition.

Insolation across each module (W/m^2)			
Module 1	Module 2	Module 3	Module 4
600	1000	800	700
Instant 1 **Peak position:** Right **MPP:** 48.51 W 			
800	700	1000	1000
Instant 2 **Peak position:** Right **MPP:** 67.76 W 			
850	1000	1000	1000
Instant 3 **Peak position:** Right **MPP:** 80.41 W 			
1000	1000	1000	1000
Instant 4 **Peak position:** Fixed **MPP:** 87.71 W 			

C. PV PANEL CHANGE

In this section, to further prove the robustness of the proposed algorithm and to compare it with the recently proposed algorithms in [19], the S36 PV module used in [19] was designed. The results were compared for pattern 1, 2 and 3 of [19]. The

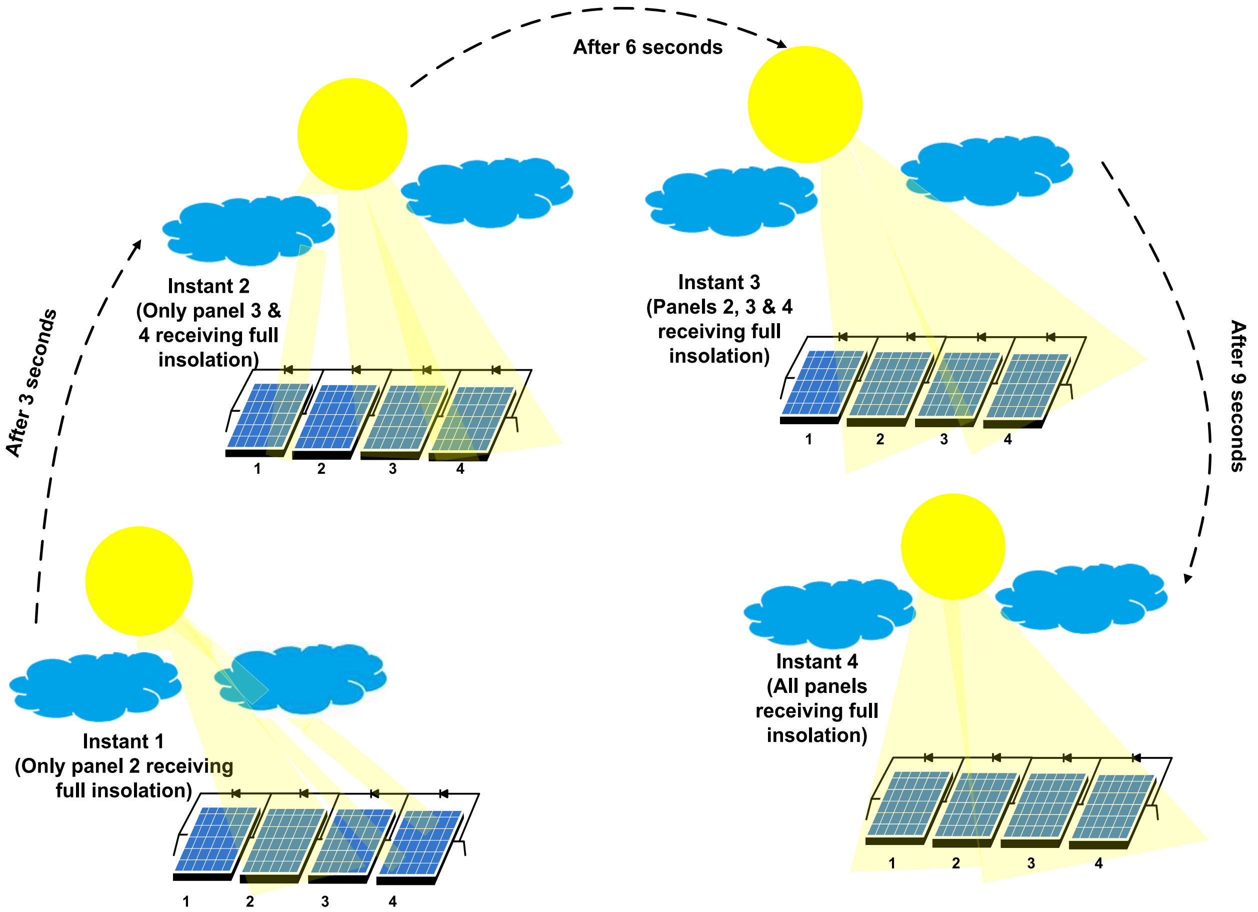


FIGURE 10. Dynamic insolation with PS attenuation.

insolation proportion for all these patterns is summarized in table 7. The PV module was designed based on the values given in table 3 of [19]. However, it was observed that the MPP in [19] was inaccurate. In table 3 of [19] the module is rated at 36 W. Under full insolation conditions, the MPP for a four-module series configuration should be nearly 144 W; nevertheless, in [19] it is 148.693 W, which is not too accurate. The module designed in the proposed literature using the values in Table 3 of [19] provided the MPP of 143.23 W under full insolation, which is much closer to the desired value of 144. In this case, apart from settling time, a number of fluctuations, and robustness, the proposed algorithm is compared from the algorithms in [19] in terms of efficiency.

1) PATTERN 1

Fig.13(a) shows the comparison of all algorithms for this condition.

- Tracking time of PSO for this condition was found to be 1.777 seconds at an efficiency of 99.98%.
- Tracking time of jaya for this condition was found to be 1.174 seconds at an efficiency of 99.98%.
- Tracking time of Ajaya for this condition was found to be 0.602 seconds at an efficiency of 99.927%.
- Tracking time of logistic-FPA for this condition was found to be 1.523 seconds at an efficiency of 99.8783% [19].
- Tracking time of sine-FPA for this condition was found to be 2.168 seconds at an efficiency of 99.8783% [19].
- Tracking time of tent-FPA for this condition was found to be 1.249 seconds at an efficiency of 99.8783% [19].

It is concluded from this pattern that the Ajaya algorithm tracked the MPP in the least time. The percentage reduction in time of the proposed algorithm compared to PSO, jaya, logistic-FPA, sine-FPA and tent-FPA was found to be 195.18, 95.01, 153, 260.1 and 107.47% respectively.

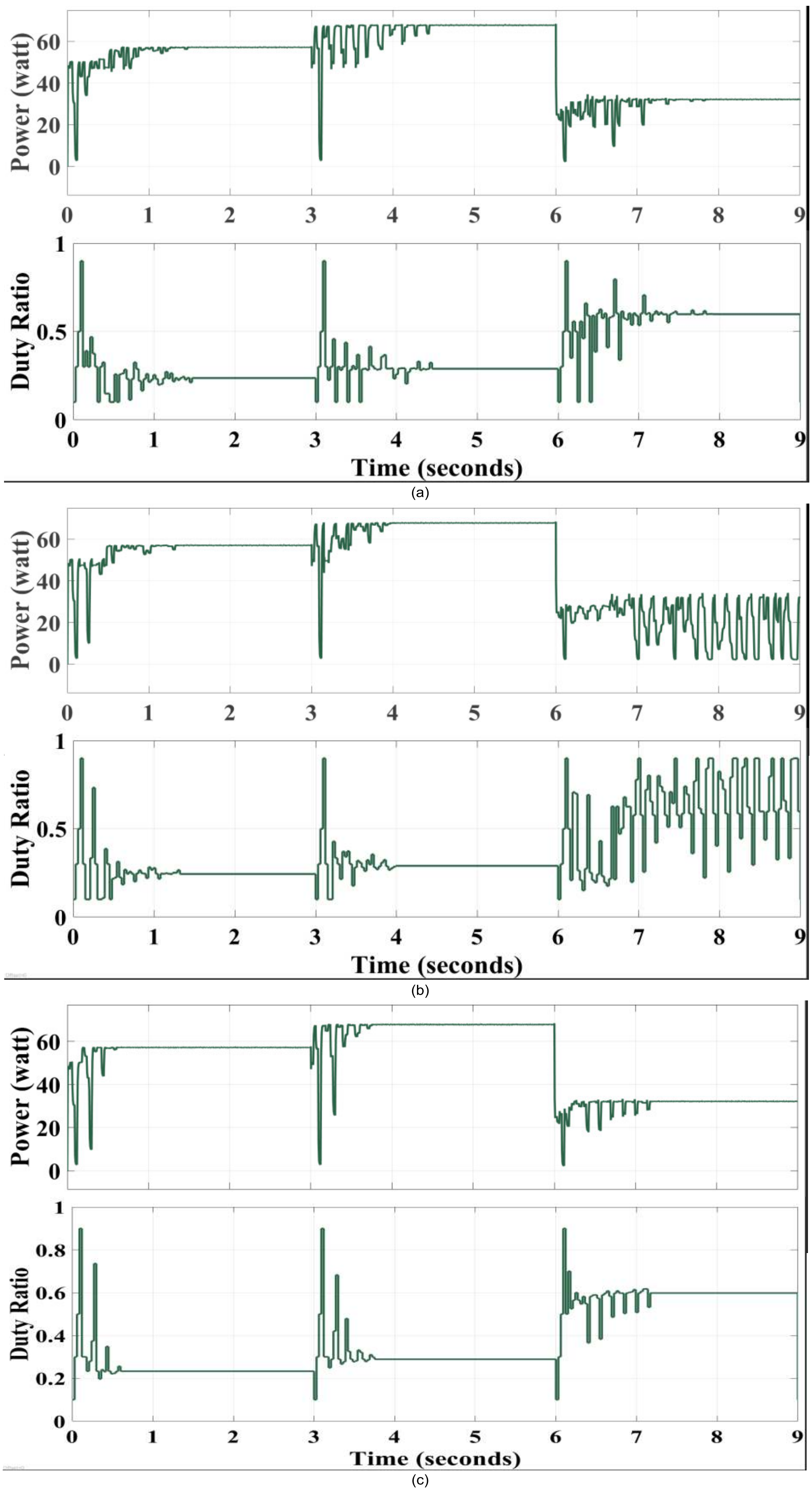
Moreover, except for PSO and jaya its efficiency was higher compared to all the C-FPA variants.

2) PATTERN 2

Fig.13(a) shows the comparison of all algorithms for this condition.

Tracking time of PSO for this condition was found to be 1.627 seconds at an efficiency of 99.97%.

Tracking time of jaya for this condition was found to be 1.771 seconds at an efficiency of 99.956%.



(a) (b) (c)

FIGURE 11. Comparison graphs under dynamic insolation with varying insolation for (a) PSO (b) Jaya (c) Ajaya.

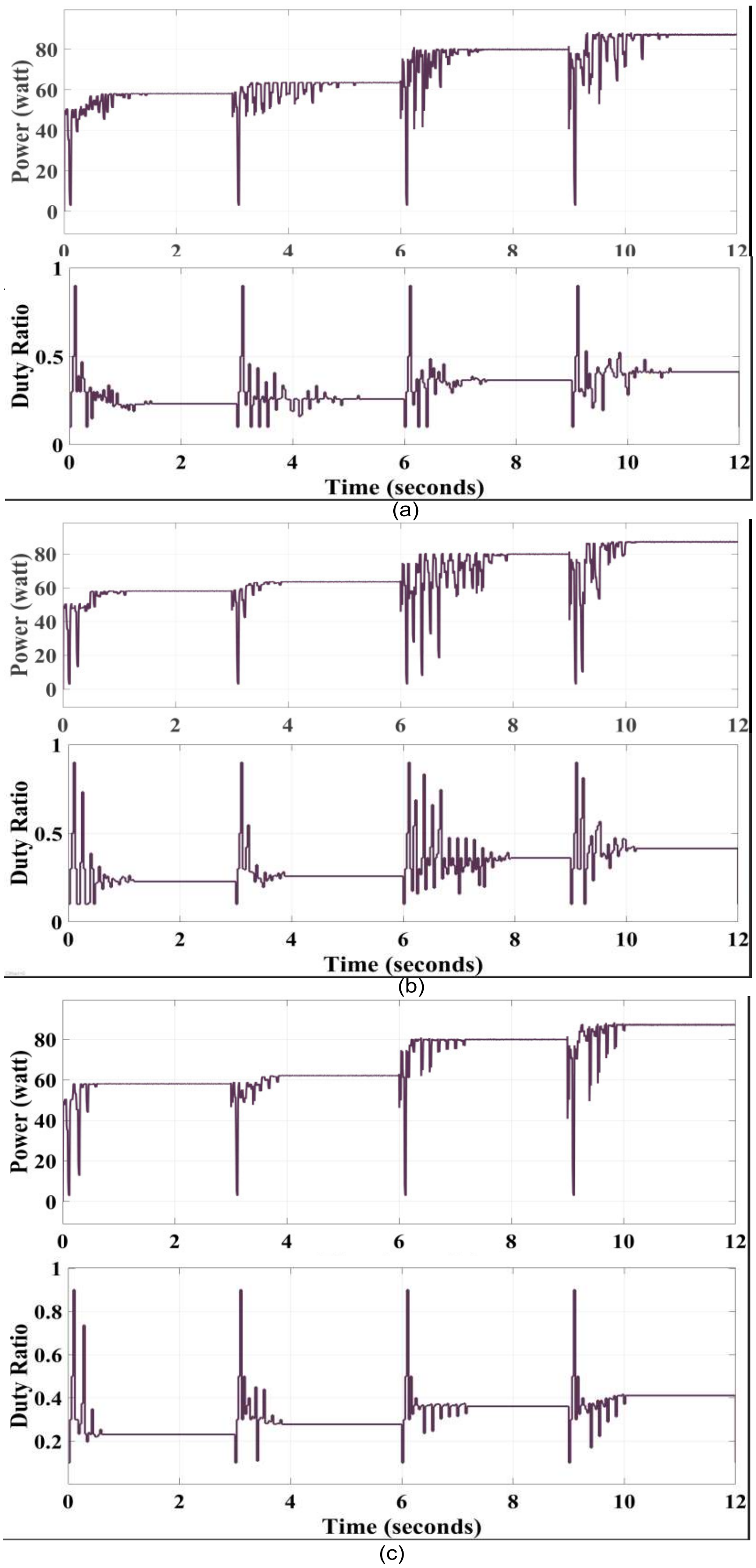


FIGURE 12. Comparison graphs under PS attenuation dynamic insolation condition for (a) PSO (b) Jaya (c) Ajaya.

TABLE 7. Insolation Summary, P-V Curve Positions & true and tracked MPP for different PS scenarios of S36 PV module.

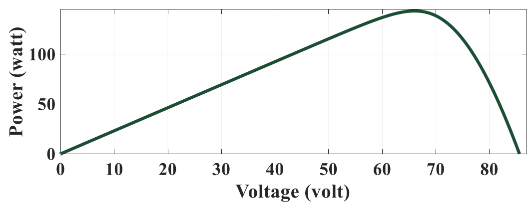
INSOLATION ACROSS EACH MODULE (W/m^2)			
MODULE 1	MODULE 2	MODULE 3	MODULE 4
1000	1000	1000	1000

Pattern 1

Peak position: Fixed
MPP: 143.23 W

MPP tracked (W):

PSO	143.2
Jaya	143.2
Ajaya	143.126



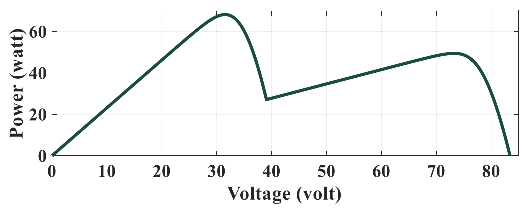
1000	1000	300	300

Pattern 2

Peak position: Left
MPP: 68.15 W

MPP tracked (W):

PSO	68.1295
Jaya	68.12
Ajaya	68.1295



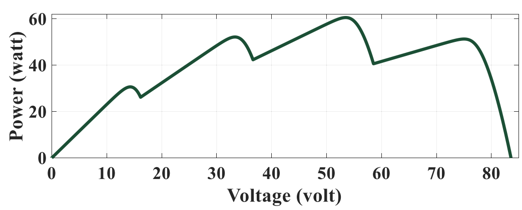
1000	700	500	300

Pattern 3

Peak position: Middle
MPP: 60.55 W

MPP tracked (W):

PSO	60.541
Jaya	60.5145
Ajaya	60.487



- Tracking time of logistic-FPA for this condition was found to be 0.995 seconds at an efficiency of 99.9527% [19].
- Tracking time of sine-FPA for this condition was found to be 1.316 seconds at an efficiency of 99.9541% [19].

TABLE 8. Comparison summary based on settling time and percentage reduction in settling time of the Ajaya algorithm.

4 Module System		
Partial shading condition	MPPT algorithm	Time (seconds)
Pattern1	Ajaya	0.602
	Jaya	1.174
	PSO	1.777
	Logistic-FPA [19]	1.523
	Sine-FPA [19]	2.168
	Tent-FPA [19]	1.249
Percentage decrease in convergence time compared with (in %): Jaya: 95.01% Logistic-FPA: 153% Tent-FPA: 107.47% PSO: 195.18% Sine-FPA: 260.1%		
Partial shading condition	MPPT algorithm	Time (seconds)
Pattern2	Ajaya	0.844
	Jaya	1.771
	PSO	1.627
	Logistic-FPA [19]	0.995
	Sine-FPA [19]	1.316
	Tent-FPA [19]	1.354
Percentage decrease in convergence time compared with (in %): Jaya: 109.83% Logistic-FPA: 17.9% Tent-FPA: 60.42% PSO: 92.77% Sine-FPA: 55.92%		
Partial shading condition	MPPT algorithm	Time (seconds)
Pattern 3	Ajaya	0.694
	Jaya	1.17
	PSO	1.473
	Logistic-FPA [19]	1.231
	Sine-FPA [19]	1.228
	Tent-FPA [19]	0.769
Percentage decrease in convergence time compared with (in %): Jaya: 68.58% Logistic-FPA: 77.37% Tent-FPA: 10.8% PSO: 112.24% Sine-FPA: 76.94%		

- Tracking time of tent-FPA for this condition was found to be 1.354 seconds at an efficiency of 99.9541% [19].
- Tracking time of Ajaya for this condition was found to be 0.844 seconds at an efficiency of 99.97%.

It is concluded from this pattern that the Ajaya algorithm tracked the MPP in the least amount of time spent.

The percentage reduction in time of the proposed algorithm compared to PSO, jaya, logistic-FPA, sine-FPA and tent - FPA was found to be 92.77, 109.83, 17.9, 55.92 and 60.42% respectively. For this case, efficiency of Ajaya was equal to PSO but greater than all the other algorithms.

3) PATTERN 3

Fig.13(a) shows the comparison of all algorithms for this condition.

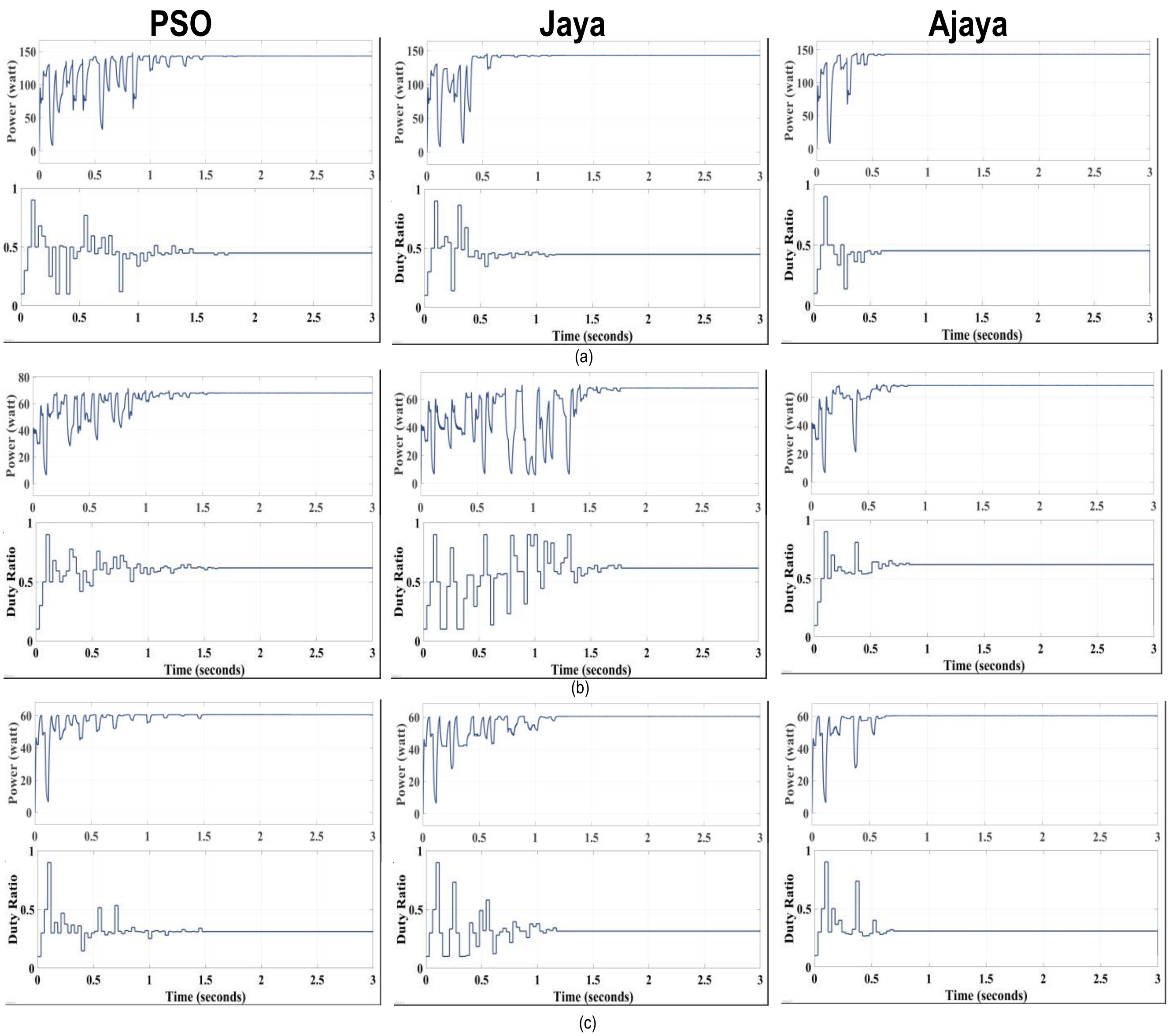


FIGURE 13. Comparison graphs for S36 PV module for (a) Pattern1 (b) Pattern 2 (c) Pattern 3.

- Tracking time of PSO for this condition was found to be 1.473 seconds at an efficiency of 99.985%.
- Tracking time of jaya for this condition was found to be 1.17 seconds at an efficiency of 99.94%.
- Tracking time of logistic-FPA for this condition was found to be 1.231 seconds at an efficiency of 99.4116% [19].
- Tracking time of sine-FPA for this condition was found to be 1.228 seconds at an efficiency of 99.7379% [19].
- Tracking time of tent-FPA for this condition was found to be 0.769 seconds at an efficiency of 99.7379% [19].
- Tracking time of Ajaya for this condition was found to be 0.694 seconds at an efficiency of 99.9%.

It is concluded from this pattern that the Ajaya algorithm tracked the MPP in the least amount of time spent. The percentage reduction in time of the proposed algorithm compared to PSO, jaya, logistic-FPA, sine-FPA and tent -FPA was found to be 112.24, 68.58, 77.37, 76.94 and 10.8 % respectively. In this case also the efficiency of the Ajaya was equal to PSO but greater than all the other cases.

It is observed from the above results that, even after changing the module rating and testing it for different patterns, there was no effect on the performance of the proposed algorithm giving the clear evidence of its robustness. However, none of the five algorithms described above exhibit this feature and their performance varied with varying insolation of this new rating module. Even the best performing C-FPA variant, the tent FPA's performance varied in terms of tracking time and number of oscillations with varying shading patterns. Hence, the proposed algorithm can be implemented for any

TABLE 9. P-V curves as per IEC standard data [40], [41].

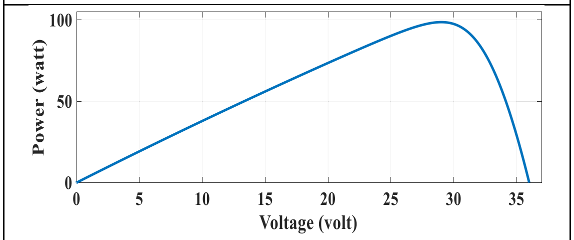
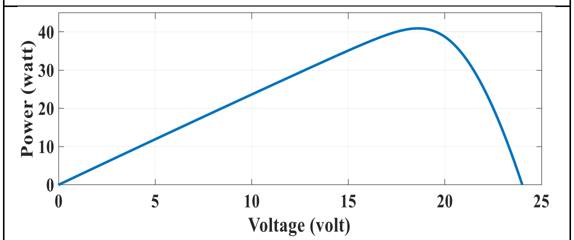
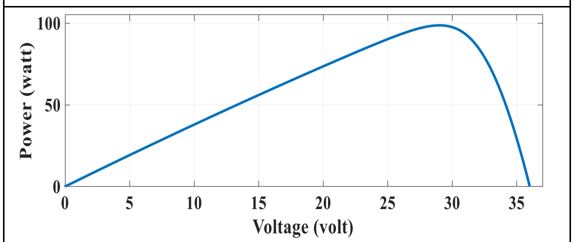
Curve 1	
	
$V_{oc} = 22$ $I_{sc} = 5.5$	$V_{MPP} = 16$ $I_{MPP} = 4.9$
Curve 2	
	
$V_{oc} = 24$ $I_{sc} = 2.4$	$V_{MPP} = 18.6$ $I_{MPP} = 2.2$
Curve 3	
	
$V_{oc} = 36$ $I_{sc} = 3.9$	$V_{MPP} = 29$ $I_{MPP} = 3.4$

TABLE 10. Settling time of all algorithms and percentage improvement in settling time of the Ajaya compared to others.

Curve 1	
MPPT algorithm	Time (seconds)
Ajaya	0.546
Jaya	1.034
PSO	1.325
Percentage decrease in convergence time compared with (in %): Jaya: 89.377%	PSO: 142.67%
Curve 2	
MPPT algorithm	Time (seconds)
Ajaya	0.546
Jaya	1.173
PSO	1.323
Percentage decrease in convergence time compared with (in %): Jaya: 114.8%	PSO: 142.3%
Curve 3	
MPPT algorithm	Time (seconds)
Ajaya	0.6997
Jaya	1.415
PSO	1.339
Percentage decrease in convergence time compared with (in %): Jaya: 102.2%	PSO: 91.367%

MPPT system without the fear of reduced performance or additional power losses due to variations in environmental conditions.

Table 8 is the summary of Ajaya in terms of settling time and its percentage decrease with respect to PSO, jaya and C-FPA variants.

D. PERFORMANCE VALIDATION UNDER REAL ATMOSPHERE USING IEC STANDARD

Commercially available PV modules tested at standard test conditions (STC) of 1000 W/m^2 and 25°C are not a good estimate for defining PV array performance under rapidly and unpredictably fluctuating atmosphere. During a day, a PV module may have to face various temperature and insolation changes that may drastically affect its performance. Hence, IEC define some specific insolation and temperature conditions for which a PV module is tested. This specified irradiance-temperature combination may not be equal to the real-world data; hence, IEC 61853-1 [45] used four procedures (three defined by the IEC-60891 [46] and one by the National Renewable Energy Laboratory (NREL)) [47] to approximate the real-world data to their standards. In this work, the performance of the proposed algorithm is validated using the curves corresponding to procedures 1 and 4 of IEC 61853-1.

1) PERFORMANCE VALIDATION USING THE IEC 61853-1 PROCEDURES

Figs.14(a-b) show the MPP tracking capability of all algorithms using the curves corresponding to the data of procedure 1 in [40] while fig. 14 (c) show results for the curves corresponding to the data of procedure 4 in [41]. The curves corresponding to two procedure 1 and one procedure 4 are defined as curve 1, curve 2, and curve 3 respectively. Summary of all the curves is given in table 9.

Fig. 14 (a) show the results of all algorithms corresponding to curve 1.

Convergence times for PSO, jaya and the Ajaya were recorded to be 1.325, 1.034 and 0.546 seconds respectively. It is clear that the tracking speed of the proposed algorithm was much faster compared to the other algorithms. Moreover, the number of large size oscillations were also much lesser compared to the other two algorithms thereby increasing the overall efficiency. Percentage improvement of Ajaya in terms

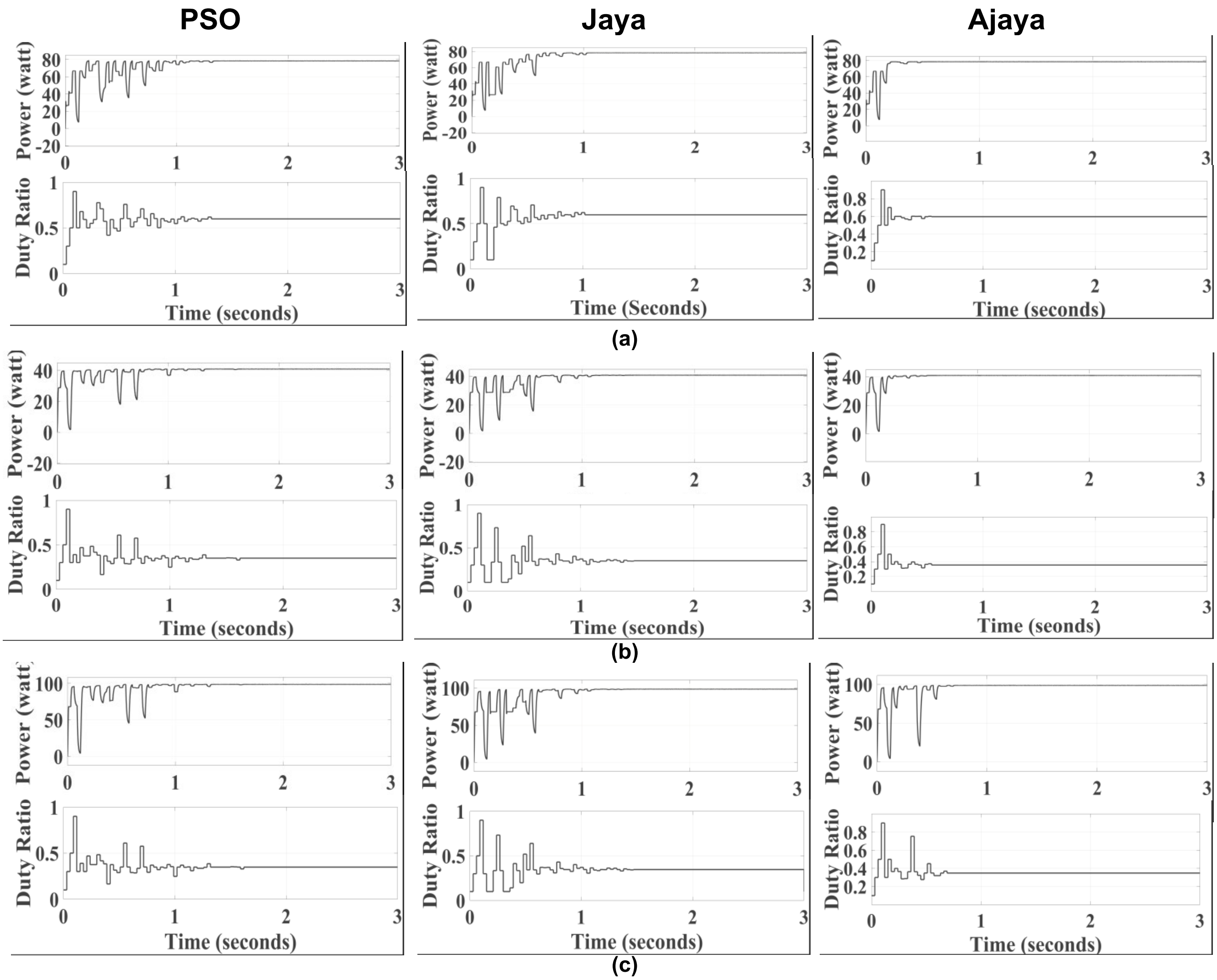


FIGURE 14. Comparison graphs for algorithms for IEC procedure (a) one,(b) one, and (c) four.

of tracking time compared to the PSO and the jaya was found to be 142.67 and 89.377 % respectively.

Fig. 14 (b) show the results of all algorithms corresponding to curve 2.

Convergence times for PSO, jaya and the Ajaya were found as 1.323, 1.173 and 0.546 seconds respectively. Again, the tracking speed of the proposed algorithm was much faster compared to the other algorithms along with very few oscillations. Percentage improvement of Ajaya in terms of tracking time compared to the PSO and the jaya was found to be 142.3 and 114.8 % respectively.

Fig. 14 (c) show the results of all algorithms corresponding to curve 3.

Convergence times for PSO, jaya and the Ajaya were recorded to be 1.339, 1.415 and 0.6997 seconds respectively. Finally, for procedure 4 also the tracking speed of the proposed algorithm was much faster compared to the other algorithms. Moreover, the number of large size oscillations were also much lesser compared to the other two algorithms thereby increasing the overall efficiency. Percentage improvement of Ajaya in terms of tracking time compared to the PSO and the jaya was found to be 91.367 and 102.2 % respectively.

Overall, it can be said that even for IEC standard curves the proposed algorithm worked much better compared to the other techniques in terms of faster settling time and lesser number of fluctuations in power thereby increasing the overall efficiency of the system. Moreover, its non-deviated performance reflects its reliability. Summary of convergence and its performance improvement for the Ajaya compared to others is shown in table 10.

VI. MANAGERIAL IMPLICATIONS

Although there is no 100% guarantee for any algorithm to give the best performance in any environment, the proposed algorithm after being tested with so many module configurations, shading scenarios and different rating modules gave such a stable performance that it can be trusted for being employed in industrial use. The stable performance of the proposed algorithm under different module configurations implied its use when a module change is required. For example, if the rating of an array has to be changed by changing the number of modules in that case without the need to buy a new MPP tracker, the tracker compiled with the Ajaya can be used. Apart from that its robustness after a change in the module rating implied that after years when a new PV array is installed the tracker compiled with Ajaya is not required to be changed since it will provide stable performance even after the rating is changed. Boost converter rating change based on [19] was to compare the proposed method with the techniques in [19]. The algorithm will give perfect results even if the old converter rating is employed. Apart from its robustness, owing to its simplicity due to the presence of a single updating equation the algorithm is well suited for being compiled on a low-priced controller. Moreover, its faster tracking and smaller fluctuations results in a decrease in power losses thereby increasing the overall efficiency of the system. Hence, Ajaya is an ideal algorithm exhibiting almost all desirable features to implement an inexpensive, efficient, rapid, and robust MPP tracker that can be employed as an economical solution for residential, commercial, and industrial use.

VII. CONCLUSION

In this literature pre-existing jaya algorithm wasincorporated with some changes to enhance its performance, in particular related to longer settling time and larger fluctuations which results in power losses and related to performance variation of an algorithm under different conditions that makes it less reliable for practical applications. Moreover, due to its simple structure the algorithm was found suitable to be implemented on a low cost controller. Hence, the main contribution of the proposed Ajaya algorithm was in terms of (A) settling time, (B) fewer fluctuations (C) simplicity and (D) robustness. Extensive analysis of the proposed algorithm's performance was done by using different module configurations and different shading scenarios for each of those configurations, dynamically varying insolation conditions, changing module's rating and using IEC standard curves. Such an analysis was done to validate the proposed advantages and assure the universal validity of the proposed algorithm. After validation, a much higher improvement in terms of all the above-mentioned aspects was observed in the Ajaya. Hence, the modification of the Ajaya was not only useful in enhancing the performance of jaya but performed much better compared with the other state-of-the-art techniques thereby increasing overall efficiency and stability of the system along with keeping it economical and becoming an ideal algorithm for residential, commercial, and industrial use.

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