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RESEARCH ARTICLE

Design & Development of MPPT Using PSO With Predefined Search Space Based on Fuzzy Fokker Planck Solution

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ABSTRACT Production of clean, green solar PV (SPV) power in developing countries now becomes a trend because of their economic and technical benefits. Therefore, generating maximum power out of the SPV is a key searchable area. The SPV must produce power at its terminal at their maximum possible power. To reach to the maximum possible power, maximum power point tracker(MPPT) is used in conjunction with SPV. Extracting maximum power from SPV under varying partial shading condition is one of the important factor in performance improvement of SPV. The characteristics of classical MPPT controller is not acceptable under variable shading condition. A clear distinction between global maxima power point from global minima using MPPT technique must be needed for extracting maximum power. This paper proposes a P&O MPPT based particle swarm optimization with improved search space, optimised through Fuzzy Fokker Planck solution. The pre-defined search space has been introduced to provide fine tune to membership function used in Fuzzy logic controller. The partial shading performance has been examined under four different condition such as active partial shading, colour spectrum, dust level and green house gas (GHG) concentration. Both hardware and simulation studies has been carried out for the proposed techniques. The MATLAB simulation result and that of proposed MPPT, offer more and better performance in terms of algorithm convergence by enhancing the efficiency of system under varying shading condition.

INDEX TERMS Algorithm, fuzzy, MPPT, PSO, solar panel, search space.

I. INTRODUCTION

Harvesting power from green source of energy is the only solution in 21st century to avoid pollution. Among the various available renewable energy resources solar power is abundantly available everywhere. It has been observed from the literature survey that, if all the space available on the earth is covered with solar PV cell, then the amount of power that it will generate will last for next 50 years. Therefore, the solar power can be compared with fossil fuel in terms of market penetration. According to the central electricity authority report 2021, the per capita electricity consumption in kwh has reached up to 1208 kwh which is 32% higher against a decade ago. The increase in the energy demand due to change in people life style has dragged the attention of many power energy resources installed capacity in India has increased from 69022 Megawatt in 2017-18 to 87028 Megawatt in 2019-2020. Out of 100 Gigawatt solar energy target the total installed capacity has increased up to 40.1 Gigawatt as of December 2021. Similarly, number of standalone solar power

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plant has increased up to 214565 kWatt as of December 2021. Therefore, it is observed that there is a sharp increase in renewable energy harvestment throughout the India to nurture sustainable development [1].

Production of grid level power, so as the make it comparable with conventional energy resources in terms of per unit generation is really a challenge in terms of efficiency improvement. As per the 2021 bidding process, it has been observed that the solar power per unit generation cost is about 2.52 rupees against 4.37 rupees in 2015. This clearly shows that the generation cost can be brought down only if the maximum power can be extracted from the solar PV System. It is worthwhile to mention here that the per unit generation cost of the solar is still at higher side against the per unit generation cost for hydro power and thermal power [5]. Efficiency improvement in the solar cell at the laboratory is a critical challenge because of the restriction on the material selection [6].

Two types of design are generally used in the solar PV Design such as monocrystalline and polycrystalline having designed efficiency of 22% and 27%. So roughly calculating the efficiency of solar PV with hydro turbine the efficiency is about 50% in SPV. Therefore, power estimation from solar PV can be enhanced only through power electronics-controlled technique such as maximum power point technique and solar tracker [4]. Actually, maximum power point technique is an algorithm where the algorithm always tries to operate the PV at its maximum capacity under varying whether condition such as solar isolation and operating temperature region. Solar tracker is a light sensing device where it will measure the line of sight of the sun so as to keep the solar cell towards sun facing for extracting power from the sun energy.

Again, from literature survey it can be found that various MPPT algorithm has been proposed by various researchers to extract maximum power from solar PV by varying the duty cycle of the converters. Incremental Conductance algorithm compares the slope of the curve if it comes negative then downward movement in the operating point on PV curve and if it comes positive then upward movement in the operating point in the PV curve [7]. Perturb and observe (P & O) algorithm compares the voltage value and will perturb to new voltage level unless it reaches maximum point on the PV Curve [8], [9].

Artificial Neural Network (ANN) works on weighted sum i.e. predefined load assigned to each node based on the memory of network and experience to select the best operating point on the PV curve [10]. One drawback of the artificial neural network is the involvement of complexity in getting a decision about the variable weather condition and the crisp variable at the input node back propagation in the ANN algorithm zone times stuck in the hidden layer due to unavailability of information [14]. This will happen because of intermittent nature of solar energy [11], [12]. Therefore, ANN based algorithm suffers from limited use [13].

Constant Voltage method is the advanced MPPT Technique in terms of Tracking maximum power at the MPP in a PV curve [15]. The operating point of the solar PV Cell basically located at the intersection of IV curve. Through constant voltage method the operating point will be made fixed at the intersection of IV Curve [16]. However, this method requires more than one sensor to track the voltage variation and it also suffers from lesser accuracy as compared to P and O algorithm [5].

The partial shading condition in a solar cell, make the solar cell to act as a load. Thus, results in generating local hot spot. This reduces the solar efficiency by 23%. This can be avoided by connecting a bypass diode in the reverse order across the non -shaded solar cell or PV Module. This arrangement sometimes alters the characteristics of solar PV Module, resulting into multiple power peaks. In order to find the best solution two types of optimization algorithms are usually applied such as deterministic approach and metaheuristic approach. All the traditional MPPT algorithms such as hill climbing method, P & O Method, gradient search method, modified gradient search method, modified gradient search method with two slope uses single point solution and will act as a blue point for iteration under partial shading condition these algorithms may not differentiate between local maximum power point and global maximum power point. During partial shading condition, the global maximum power point becomes proportional to three dependent variable such as voltage, cell temperature and shading condition. Therefore, it could be anywhere in the PV Plane.

Therefore, Ramadan *et.al.* [29] have proposed a population-based eagle strategy optimizer with chaotic. This will evaluate the static and dynamic model parameters fir 5-parameter and 7-parameter model under 2-diode modelling of solar cell. Root mean square (RMS) error has been used for 30 iterations to compare the robustness of the algorithm. A hybrid marine predators slime mould algorithm has been proposed by Yousni *et.al.* [30], where parameter estimation was also achieved for one diode and 2- diode model based on RMS error value.

Rezk *et.al.* [31] in their paper have studied global MPPT techniques for shaded PV system. About 20 Global MPPT algorithm for statistical and Dynamic Parameter estimation has been investigated. The robustness of the algorithm was tested using relative error, RMS error, mean absolute error (MAE), standard deviation and successful rate estimation. Hosseini *et.al.* [32] in their paper has proposed about shaded tolerant (ST) based global maximum power point. According to them, PV curve can be divided into two groups, such as left-hand side MPP and right-hand side MPP, and as majority of MPP will occupy the left-hand side so ST method will scan the right-hand side of MPP. The proposed method reduces the search space and thereby increases the iteration speed.

Bozelepe *et.al.* [33] have developed a voltage window search method based on power operating triangle to find the search space between Vmin and Vmax. As the method uses negative slop optimization algorithm, therefore global maximum power point is generated inside the search space. Wang *et.al.* [34] have presented specific region identification algorithm based on search skip judge for partially shaded condition. Here the objective is to discard the region where minimization can be discarded. Funtado *et.al.* [35] have introduced maximum power trapezium algorithm to deal with partial shading under light dust to heavy dust condition followed by different color spectrum. According to the algorithm, the maximum voltage step size, must be equal to the minimum step difference between two adjacent points. Here the adjacent point represents the maximum power point.

Soft computing based static and dynamic parameter evaluation is easier as compared to statistical method, here referred as classical method. The soft computing method can be broadly categorized into 3 groups such as brain inspired computing, chaos and meta-heuristic algorithm. Again, meta-heuristic algorithm can be further classified into swarm intelligence, bio-inspired, evolutionary algorithm, physical phenomena based and analytical based search. Several analytical searches based on jaya algorithm, binary search, teaching-learning based optimization has been proposed. All these algorithms provide immediate solution to search space to identify maximum power point.one of the best advantages of the analytical model is that it is based on mathematical formulation and mathematical model, not inspired by biological model. However, the disadvantages is that it must require a prior knowledge in the field of mathematical calculation and parameter optimization. Therefore, to address this issues hybrid global maximum power point, optimization technique has been adopted, where both hybrid conventional techniques and hybrid soft computing techniques can be brought together to settle down the MPP inside the search space.

Fuzzy Based MPPT algorithm is another soft computing-based algorithm where the main objective is to change the PV module voltage. The fuzzy logic controller (FLC) upon sensing a voltage variation at the input side [17]. Basically, gaussian membership function were used because of their smoothness and concise. However fuzzy logic suffers from a drawback regarding if the data are outside the lower and upper range limit then fuzzy logic controller may fail to operate [18]. Therefore, it is noticed in the literature that fuzzy logic has been used in conjunction with PI controller for generating the gating sequence for DC-DC converter [19], [20]. This additionally increases the complexity of the system.

Bio – Logically inspired algorithms such as metaheuristics algorithms, particle swarm optimization is some of the most popular algorithm in terms of maximum power tracking in a PV curve [21]. All those metaheuristic algorithms have their own characteristics in meeting their criteria for tracking maximum power [22].

P & O is the least complex and complicated algorithm and is more prone to local oscillation at the maximum power point [23]. One solution to damp out the oscillation is by creating a search space in the PV curve for the P & O algorithm [24]. Another method is to create a Gaussian plane with loss factor evaluation to reach the maximum power point [25].

The author [26] have introduced about artificial evolution algorithm by providing global search space. The developed prototype can track the maximum power point with in 2 sec and with an accuracy of 99%. The developed method is able to damp out the oscillation along with improvement in the steady state error as compared to the conventional P& O algorithm [27].

In regard to the way people consume energy, much of the world is still highly reliant on fossil fuels. It has reached a point where we have taken advantage of the world we live in and time to step up and fight to find a change. Extraction of green source of energy is the only solution in 21st century to avoid pollution.

There are several long-term issues with the use of damaging energy sources like fossil fuels and they include, but are not limited to Climate Change, Public Health and Safety and they are not reusable. Among the various available renewable energy resources solar power is abundantly available everywhere. It has been observed from the literature survey that, if all the space available on the earth is covered with solar PV cell, then the amount of power that it will generate will last for next 50 years. Therefore, the solar power can be compared with fossil fuel in terms of market penetration. Due to the economic and technical benefits, production of clean and green solar PV (SPV) power in developing countries has become a trend. Hence generating maximum power out of the SPV is a key searchable area. As per the 2021 bidding process, it has been observed that the solar power per unit generation cost is about 2.52 rupees against 4.37 rupees in 2015. This clearly shows that the generation cost can be brought down only if the maximum power can be extracted from the solar PV System.

Based on the extensive literature survey it can be found that various MPPT algorithm has been proposed by various researchers to extract maximum power from solar PV by varying the duty cycle of the converters. Of all the MPPT algorithm presented in literature survey, P & O is the least complex and complicated algorithm and is more prone to local oscillation at the maximum power point. One solution to damp out the oscillation is by creating a search space in the PV curve for the P & O algorithm. Another method is to create a Gaussian plane with loss factor evaluation to reach the maximum power point. Considering all the drawbacks in the literature, it was found that a clear distinction between global maxima power point from global minima using MPPT technique must be needed for extracting maximum power.

With all the above-mentioned drawbacks and persistent issues in the MPPT area, required for an intervention and solution, which were the main elements of motivation to carry out the work on the proposed MPPT based particle swarm optimization (PSO) with improved search space, optimized through Fuzzy Fokker Planck solution (FFPS). Here the pre-defined search space has been introduced to provide fine tune to membership function used in Fuzzy logic controller.

The partial shading performance has been examined under four different condition such as active partial shading, color spectrum, dust level and GHG concentration. Both hardware and simulation studies has been carried out for the proposed techniques. The MATLAB simulation result and that of proposed MPPT, offer more and better performance in terms of algorithm convergence by enhancing the efficiency of system under varying shading condition.

The paper has been organized as per the following details section – 1 represents the introduction to MPPT techniques and literature review in terms of latest state of the art practices followed by section – 2. About the problem formulation and solution methodology section – 3 represents about the modelling of solar cell and conventional P & O algorithm with modified P & O algorithm section – 4 represents about hardware setup and results analysis has been describer under section -5. A brief conclusion about the model is presented in section – 6 followed by reference.

II. MODELLING OF SOLAR CELL

To investigate the performance of the solar cell equivalent circuit is needed. Therefore in literature there are two types of solar photovoltaic model like one diode model and two diode models. The physics of semiconductor describes about the diode modelling. Diode is represented by a current source in parallel with two numbers of diodes. Diodes basically represent the current escaping due to diffusion and charge recombination process. This charge recombination process can be represented by a two diode model. Internal resistance of the photovoltaic module is represented by a parallel resistance i.e. Rp . The contact resistance of the system is represented by a series resistance i.e. Rs. Generally the series resistance of the system is less as compared to the parallel resistance. The value of the resistance is measured by the curve fitting technology or by means of graphical techniques. According to designing point of view the two resistances are considered on an approximate basis. If the minority carrier of the cell is neglected then the two diode model can be converted into the single diode model as shown in Fig. 1. Assuming the current through the diode D2 is very small the designing parameter can be made less.

$$I = I_{ph} - I_d \tag{1}$$

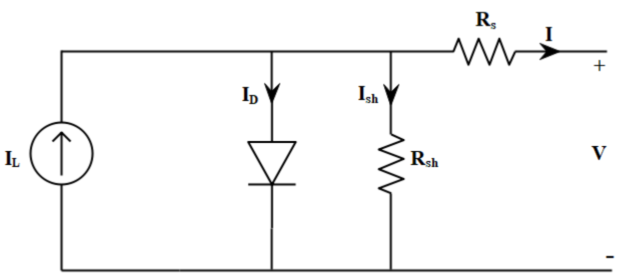


FIGURE 1. One diode model of solar cell.

Diode current for the system becomes

$$I_d = I_0[exp(\frac{qV}{\alpha kT}) - 1] \tag{2}$$

By putting the eq.(1) in eq.(2) the net current becomes

$$I = I_{ph} - I_0[exp(\frac{qV}{\alpha kT}) - 1] - \frac{V + R_s I}{R_p} \tag{3}$$

To investigate the electrical restraints, solar cells are modelled usually using P-N Junction. For the ideality factor n, single diode equations assume a constant value. During the recombination in the device at high voltage, which is being dominated by surfaces, the ideality factor is close to one in the bulk regions. But during the low voltage ranges, the recombination in the junction dominates and ideality factor increases to two. This junction recombination is modelled by adding a second diode in parallel with existing first one and ideality factor is set to two. Due to the lack in recombination, which is ignored in the single diode model, it leads to inaccuracy in the PV model parameters. To overcome the existing issue, a double diode or two diode model is chosen to represent the physical form is the solar PV cell as shown in the Fig.2.

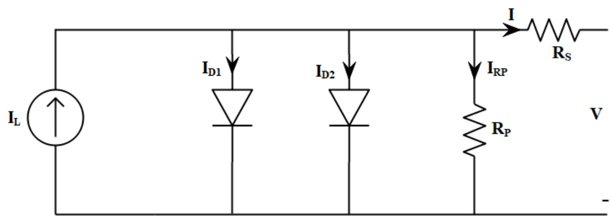


FIGURE 2. Two diode model of solar cell.

From two diode model

$$I = I_{ph} - I_{d1} - I_{d2} \tag{4}$$

$$I_d = I_{01}[exp(\frac{qV}{\alpha_1 kT}) - 1] \tag{5}$$

$$I_d = I_{02}[exp(\frac{qV}{\alpha_2 kT}) - 1] \tag{6}$$

So an exact model of two diode solar PV model is achieved by considering the Recombination loss. By using of the double diode, the diffusion current is focused on P-N junction material. While the other is accounted for recombination loss. With two diode model a more accurate model can be developed. The seven parameters namely, I_{ph}, I_{01}, I_{02}, α_1, α_2, R_S, and R_P can be calculated using the eq.(7)

$$I = I_{ph} - I_0 1[exp(\frac{qV}{\alpha_1 kT}) - 1] - I_0 1[exp(\frac{qV}{\alpha_2 kT}) - 1] - \frac{V + R_s I}{R_p} \tag{7}$$

The diode ideality factors α_1 and α_2 represent represent the diffusion and recombination currents. In accordance with Shockley's diffusion theory, α_1 must be unity.

TABLE 1. Comparative analysis of Computational Intelligence (CI) & Meta Heuristic (MH) MPPT controller based on P&O and Incremental Conductance (IC).

Criteria	P&O					IC				
	ANN	FLC	GA	PSO	FLC+PSO	ANN	FLC	GA	PSO	FLC+PSO
Tracking Speed	Low	Medium	Fast	Fast	Meddium	Low	Low	Medium	Fast	Medium
Type	CI	CI	MH	MH	CI+MH	CI	CI	MH	MH	CI+MH
Cost	High	Medium	High	Medium	Medium	High	Medium	High	Medium	High
Oscillations	No	No	No	No	No	No	No	No	No	No
Efficiency	Low	Medium	Low	High	Medium	Medium	Medium	Medium	High	Medium
PV Array Dependancies	Yes	Yes	No	No	Yes	Yes	Yes	No	No	Yes
Complexity in Configuration	Medium	Medium	High	Low	Low	Medium	High	High	Low	High
Sensors	VIG	VI	VI	VI	VI	VIG	VI	VI	VI	VI

III. PROBLEM FORMULATION

The maximum power point tracking using P& O algorithm suffers from local oscillations. Fig.3 & Fig.4 shows the PV and IV curve on a single diagram. In the Fig.3 P_{max1} and P_{max2} represents the lower and upper limit of operating point and that of P_{max1}, P_{max2} and P_{max3} is shown in Fig.4. This shows that system behaves an uncertain dynamic system, which can be analyzed interms of fuzzy initial problem.Let the fuzzy initial problem be

$$P'_{VI}(t) = f(t, v), P(t_0) = p_0 \in F_R \tag{8}$$

In eq.(8) P(t) represents the fuzzy unknown power output function and $f : [0, T]XF_R \to F_R$ is a c continuous surface function. In order to apply Fuzzy Euler method to find solution to eq.(8), let a partition $A_N = [O = t_0 < t_1 < \ldots.. < t_N = T]$ lies in the interval $[0, T]$. The step size $S = \frac{T}{N}$ inside the search space, with assumption that all the segmented points lies on the curve. Here four different cases may arise depending upon the solution assumption.

A. CASE-1: ASSUMING SOLUTION AS ($\dot{d}$-vI)

Here it is assumed that the function $P'_{vI}(t)$ has only one solution $(\dot{d} - vI)$, which is differentiable and does not change in boundary $[t_1, t_2]$, where t_1 represents initial point and t_2 represents the final point. Therefore the fuzzy Taylor expression becomes

$$P(t_{k+1}) = P(t_k) \oplus \dot{P}_{((d)-vI)} \odot (t_{k+1} - t_k) \oplus \ddot{P}_{(\dot{(d)}-vI)}(\eta_k) \odot \frac{(t_{k+1} - tk)^2}{2!} \tag{9}$$

Again for same point,

$$\eta_k \in [t_k, t_{k+1}], s = t_{k+1} - t_k \tag{10}$$

putting eq.(10) in eq.(9)

$$P(t_{k+1}) = P(t_k) \oplus s \odot \dot{P}_{(\dot{(d)}-vI)}(t_k) \oplus \frac{s^2}{2!}\ddot{P}_{(\dot{(d)}-vI)}(\eta_k) \tag{11}$$

or

$$P(t_{k+1}) = P(t_k) \oplus s \odot f(t_k, p(t_k)) \oplus \frac{s^2}{2!} \odot \ddot{P}_{(\dot{(d)}-vI))}(\eta_k) \tag{12}$$

Approaching the step size to "0" and deriving eq. (12) the fuzzy Euler error function can be written as

$$D_s(P(t_{k+1}), P(t_k) \oplus s \odot f(t_k.P(t_k)) \oplus \frac{s^2}{2!} \odot \ddot{P}_{(\dot{(d)}-vI))}(\eta_k) \leq D_s(P(t_{k+1}), P(t_k) \oplus s \odot f(t_k.P(t_k)) \oplus D_s(0, \frac{s^2}{2!} \odot \ddot{P}_{(\dot{(d)}-vI))}(\eta_k)) \tag{13}$$

or

$$\begin{cases} D_s(P(t_k + a), P(t_k) \oplus s \odot f(t_k, P(t_k))) \to 0 \\ D_s(0, \frac{S^2}{2!} \odot \ddot{P}_{(\dot{(d)}-vI)}(\eta_k)) \to 0 \end{cases} \tag{14}$$

Now equating $s \to 0$, eq. (14) can be reduced to a iteration function of

$$\begin{cases} P_{k+1} = P_k \oplus s \odot f(t_k, P_k), k = 0, 1, 2 \ldots N - 1 \\ P_0 \in F_R \end{cases} \tag{15}$$

Therefore, the maximum power point becomes a function of instantaneous power with a scalar product with power and time.

B. CASE-2: ASSUMING SOLUTION AS ($\ddot{d}$-vI)

Here it is assumed that the function $P'_{vI}(t)$ has double derivative at ($\ddot{d}$-vI) which is differentiable and does not change inside boundary $[t_1, t_2]$, where t_1 represents the initial point and t_2 represents the final point. Therefore, the fuzzy Taylor expression becomes,

$$P(t_{k+1}) = P(t_k) \ominus S_{-1}s \odot \ddot{P}_{((d)-vI)}(t_k) \ominus s_{-1} \frac{s^2}{2!} \odot \ddot{P}_{((d)-vI)}(\eta_k) \tag{16}$$

as $P_{(\ddot{(d)}-vI')}(t) = f(t, P(t))$, therefore,

$$P(t_{k+1}) = P(t_k) \ominus S_{(-1)}s \odot f(t_k, P(t_k)) \ominus s_{(-1)} \frac{S^2}{2!} \odot \ddot{P}_{(\ddot{(d)}-vI)}(\eta_k) \tag{17}$$

eq.(17) is clearly compatible with eq.(8), therefore eq.(17) can be analysed in terms of iteration function and will take a form of eq.(8) i.e.

$$\begin{cases} P_{k+1} = P_k \oplus s.f(t_k, P_k), k = 0, 1 \ldots N-1 \\ P_0 \in F_R \end{cases} \tag{18}$$

Therefore, the double derivative also holds good to the hypothesis and the methodology fits to be compatible with P&O algorithm in tracking the maximum power for the system.

C. CASE-3: SWITCHING INTERMITTENT WITH SINGLE DERIVATIVE ($\dot{P}(t)$)

As the solar energy is intermittent in nature, therefore the hypothesis or algorithm has to satisfy the switching intermittent (P_t) in the interval of [0,T].

Switching intermittent are like impulse function i.e. it may last for fraction of changes, therefore the step size inside the interval [o,T] can be assumed to be zero. Again eq.(17) can be further reduced to eq.(18) with continuous iteration function as shown in eq.(19)

$$\begin{cases} P_{k+1} = P_k \oplus S \odot f(t_k, P_k) \\ P_{k+1} = P_k \ominus H_{(-1)S \odot f(t_k, P_k)} \\ P_0 \in F_R \end{cases} \tag{19}$$

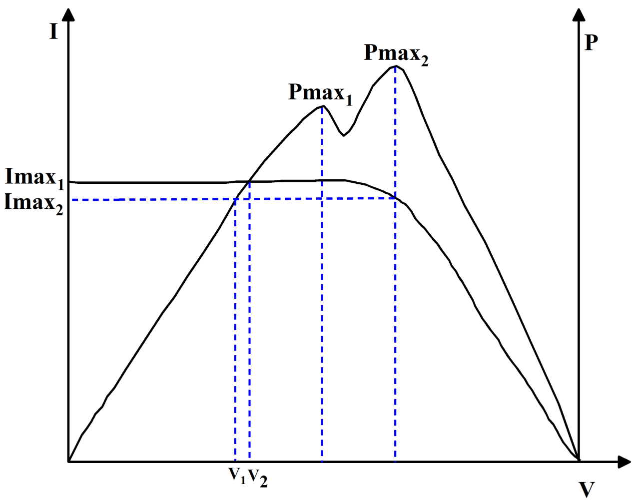


FIGURE 3. Perturb and observe MPPT technique.

D. CASE-4: SWITCHING INTERMITTENT WITH DOUBLE DERIVATIVE $\ddot{P}$

Assuming the sace with switching intermittent with double derivative $\ddot{i}$, the step $s \to 0$, therefore the solution becomes,

$$\begin{cases} P_{k+1} = P_k \ominus S_{(} - 1)s \odot f(t_k, P_k) \\ P_{k+1} = P_k \oplus s \odot f(t_k, P_k) \\ P_0 \in F_R \end{cases} \tag{20}$$

Based on the above solution methodology, it can be understood that the P&O algorithm can be modified with specified search area in order to reduce the search space, search time and step size. Reduction in step size will also results in better convergence. The nest section presents a detailed discussion about P&O algorithm implementing the hypothesis.

Most of the optimization algorithm uses local and global minima to reduce system dependencies. However, most of the algorithm depends on multiple peak and none of them address about the MPPT failure under dynamic irradiance changes [28]. In this research work, in accordance with eq. (15), the MPP becomes a scalar product of power and time against vector in classical P&O algorithm. Again eq. (19) and (20) represents single derivative & double derivative of switching intermittent under continuous irradiance fluctuation. This two equation clearly shows that, the proposed model will reduce the MPPT failure rate under dynamic changes of environmental parameter.

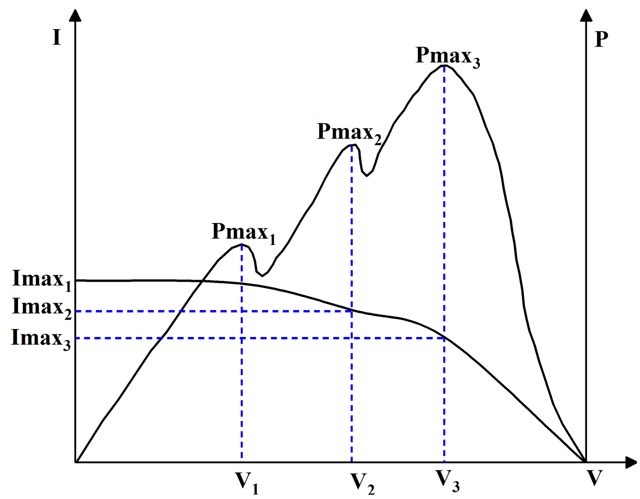


FIGURE 4. Perturb and observe MPPT technique.

IV. BENCH MARKING MODEL

In order to check the efficiency and robustness of the proposed model, three bench marking model has been considered for comparison of model. The bench marking modes are Fuzzy logic based MPPT, Particle swarm based MPPT and classical PI controlled MPPT.

A. CASE-1: PI CONTROLLED MPPT

Perturb and Observe method is used for tracking MPP. Here a small perturbation is introduced to for causing a power change in the PV Module. Output of the PV Module is constantly measured and compared with previous value. This control strategy revolves around relationship between PV output power and voltage. Panel voltage and current are two important parameter which needs to measure instantaneously. The PV output power is periodically measured and is compared to previous power. If the PV out power increases, then the perturbation is continued, else it is reversed. The controller changes its output power in a very small steps at each control cycle. The step size usually considered is constant or variable. Voltage and current are either considered as control parameter. Maximum power Condition is given by eq.(21)

$$\frac{dP}{dV} = 0 \qquad at \quad MPP \tag{21}$$

dP is the differential change in output power of PV panel and also known as operating point.

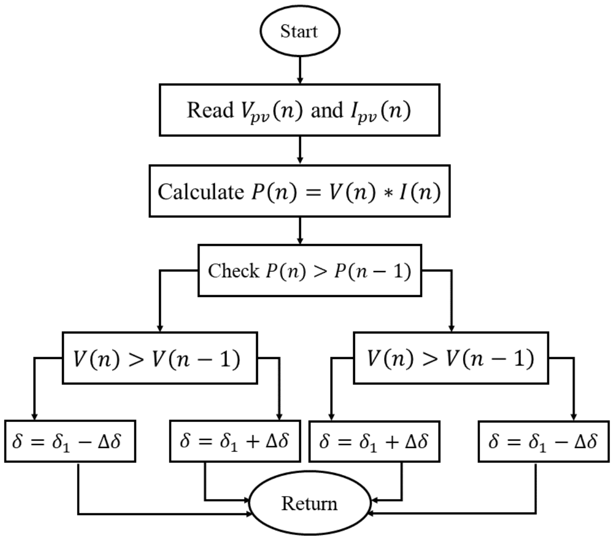


FIGURE 5. Perturb and observe MPPT technique.

dV is the differential change in output voltage of PV panel

The increase and decrease in the PV module voltage is based on whether the power is increased or decreased. If there is an increase in the voltage, it leads to increase in power, this points to the fact that the operating point of the Module is on the left side of the MPP [11], [14]. Thus, further perturbation is needed towards the right to reach the MPP. But if the increase in voltage leads to decrease in power, which indicates that the MPP is on the right side and needs perturbation towards left side. The Fig. 5 shows the flow chart for perturb and observe MPP technique. MPPT operated charge controller is connected between the PV panel and battery, which measure the PV and battery voltage. The technique measures the battery voltage, it checks if the battery is fully charged or not, if its fully charged then it stops charging to further prevent the battery from over charging. But if the battery is not fully charged then it activates the DC-DC converter. The existing power Pnew is calculated by the microcontroller at the output by measuring the voltage and current and then compare the calculated power with the previous measured power Pold. Thus, if the Pnew is found to be greater than the Pold, PWM duty cycle is increased there by extracting maximum power from the PV panel. But if it found that If Pnew is less than Pold, then the Duty cycle is reduced to ensure system slides to earlier maximum power and drift far from MPP. This MPPT technique is simple and easy to implement, the implementation cost is also less with high accuracy [2], [3]

B. CASE-2: FUZZY LOGIC MPPT

Fuzzy based MPPT method is a non linear controlled method to work on heruistic variables based on the knowledge and past experience. The entire fuzzy logic consists of four operational block namely fuzzyfication, de-fuzzyfication and inference with rule designer.The basic fuzzy controller is shown in Fig.6

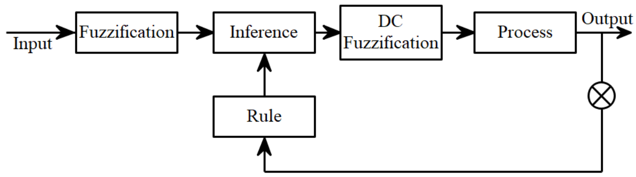


FIGURE 6. Basic fuzzy controller with process feedback.

The fuzzyfication block process the input signal and it will assign a fuzzy value. It will convert the crisp data into linguistic variable. The inference system will make a decision with rules to provide suitable output. Defuzzification will again convert back the linguistic variable into machine level variables. The performance can be evaluated based on error(e) and change in error ($\triangle e$). The mathematical expression for error becomes,

$$E(k) = \frac{P(k) - P(k-1)}{v(k) - v(k-1)} = \frac{\triangle P}{\triangle V} \tag{22}$$

and that of change in error becomes,

$$\triangle e(k) = E(k) - E(k-1) = \triangle E \tag{23}$$

Here E(k) represents the slope of PV curve and acts like an input to the system, where as $\triangle E(k)$ represents the movement of operating point related to MPP in the direction of slope. Similarly, the duty cycle becomes,

$$D(k) = D(k-1) + \triangle D(k) \tag{24}$$

Combining eq. (22),(23) and (24), the membership function table becomes,

TABLE 2. Fuzzy membership variable arrangement.

	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NM	NM	NS	NS	ZE
NM	NB	NM	NM	NS	NS	ZE	PS
NS	NM	NM	NS	NS	ZE	PS	PM
ZE	NM	NS	NS	ZE	PS	PM	PS
PS	NS	NS	ZE	PS	PM	PS	PB
PM	NS	ZE	PS	PM	PS	PB	PB
PB	ZE	PS	PM	PS	PB	PB	PB

Table-2 shows the fuzzy membership arrangement. Here 7 membership function has been taken into consideration for designing of controller. The fuzzy rule inference is shown in Fig.7,

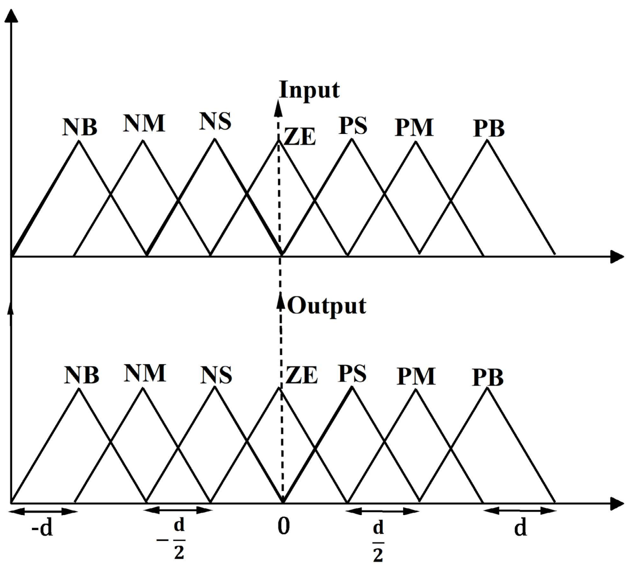


FIGURE 7. Fuzzy rule inference.

Algorithm 1 Calculate perturb$\leq$ 0.2 Sec

Require: $Np \geq 0 \vee n \neq 0$
Ensure: function_defuzzification(MF_Data)
  if $NB > NMandNB > PB$ **then**
    output=calculate_crisp (NB,NM,NS)
  else if $PB > PMandPB > PS$ **then**
    output=calculate_crisp (PB,PM,PS)
  else if $ZE > NSandZE < PS$ **then**
    output=calculate_crisp (NS,ZE,PS)
  end if
  function_crispdata(Triangular)
  if $MF == Triangular$ **then**
    return 1
  else
    return 0
  end if

C. PARTICLE SWARM OPTIMIZATION BASED MPPT

Particle swarm optimization(PSO) is a bio inspired model closely resembles with bird flocks. The global convergence property of PSO has made it suitable to utilize in nonlinear, non-differential curve.The MPPT algorithm curve is highly non linear because of intermittent nature of source.

In PSO, generally cooperative points are used in an n-dimensional space to calculate global solution to optimization problem. Let assume that the particle position is P_i with initial velocity v_i. Each individual particle is characterised by P_best and as a group the best value id G_best. Therefore the approached velocity becomes

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_{best} - P_i^k) + c_2 r_2 (G_{best} - P_i^k) \quad (25)$$

and that of the position becomes

$$P_i^{k+1} = P_i^k + V_i^{k+1} \quad (26)$$

Algorithm 2 Calculate perturb$>$ 0.2 Sec

Require: $Np \geq 0 \vee n \neq 0$
Ensure: function_defuzzification(MF_Data)
  if $PB > PMandPB > NB$ **then**
    output=calculate_crisp (PB,PM,PS)
  else if $NB > NMandNB > NS$ **then**
    output=calculate_crisp (NB,NM,NS)
  else if $ZE < PSandZE < PMandZE > NS$ **then**
    output=calculate_crisp (PS,ZE,NS)
  end if
  function_crispdata(Trapezoidal)
  if $MF == Trapeziodal$ **then**
    return 0
  else
    return 1
  end if

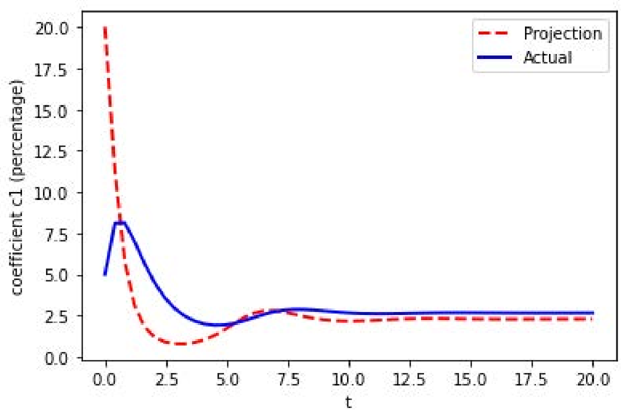


FIGURE 8. Performance of c1 against time in search space.

Here eq.(25) and eq.(26) represents the velocity and position of particle and their movement. Here the velocity depends upon the random variable r1 and r2. If random variable is less then, it will take more time to converge and if random variable is close to 1 then unintentional convergence may occur and that of k represents the number of iterations. ω is the initial weight.

In the present research, the velocity represents the size of duty cycle. So if the random number is close to 1 then unity duty cycle with fast operation can be achieved. In contradiction if duty cycle is less then sluggish operation may result. Therefore to achieve a good performance, the random variable has been given a search space [0.53,0.57]. This reduces the searching space and hence we can achieve global best value with minimum iteration.so eq.(25) and eq.(26) can be modified into

$$V_i^{k+1} = \omega V_i^k + c_1 \rho_1 (P_{best} - P_i^k) + c_2 \rho_2 (G_{best} - P_i^k) \quad (27)$$

and

$$P_i^{k+1} = P_i^k + V_i^{k+1} \quad (28)$$

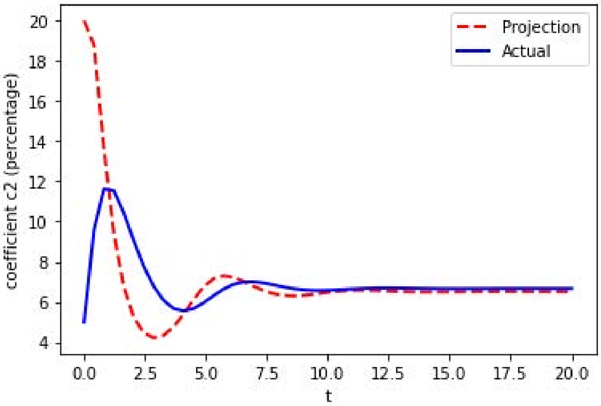


FIGURE 9. Performance of c2 against time in search space.

TABLE 3. Performance of swarm (sample) with different random variables against c1=0.5 & c2=0.4.

Sample	Np	Random No.	Time sec.	velocity	loss value	R^2 Error
SAP-1	10	0.53	3.041	0.071	287.49	0.81
SAP-2	12	0.53	3.392	0.073	293.66	0.78
SAP-3	14	0.53	4.814	0.087	299.03	0.79
SAP-4	10	0.55	3.338	0.068	243.55	0.64
SAP-5	12	0.55	3.457	0.068	266.03	0.69
SAP-6	14	0.55	5.035	0.076	288.21	0.69
SAP-7	10	0.57	3.630	0.064	218.41	0.13
SAP-8	12	0.57	3.985	0.069	222.51	0.15
SAP-9	14	0.57	5.415	0.069	247.86	0.21

Again, the performance of eq.(27) and eq.(28) depends on the size of particle. If the size of particle is more, then capability to find the best solution is more. A comparative analysis of sample size and random variable for different particle(swarm) no. has been shown in Table-1, implemented using MATLAB.

Performance of c1 and c2 against time in search space is shown in Fig.8 and 9. It can be found that the steady value c1 is about 0.22 and that of c2 is 0.78.Similarly, considering the 1st transient response c1 and c2 are 0.5 & 0.4 respectively.,

Table-3 shows the Performance of Swarm (Sample) with different random Variables against c1=0.5 & c2=0.4. Here it can be observed that with increase in random no. the velocity is decreasing and that of the loss value is decreasing for the objective function. in contrast the response time is increasing. similarly, Table-4 shows the Performance of Swarm (Sample) with different random Variables against c1=0.2 & c2=0.78. Here sample-7 to 9 the R^2 error is constant at 0.29. This shows that with neighbour coefficient of 0.2 and 0.87 and random no. of 0.57 there is no change in the convergence. This also shown in Fig,10. where for sample size 12 and 14 it seems to be divergent for some particle.

The result shown in Table-3 has been carried out in MATLAB with solar radiance of $1000W/m^2$ and temperature of $25°c$. It can be observed from Table-3 that loss value is decreasing with increase in random no. however the time for convergence has increased.

TABLE 4. Performance of swarm (sample) with different random variables against c1=0.2 & c2=0.78.

Sample	Np	Random No.	Time sec.	velocity	loss value	R^2 Error
SAP-1	10	0.53	2.987	0.055	185.42	0.52
SAP-2	12	0.53	2.938	0.059	184.97	0.55
SAP-3	14	0.53	3.427	0.082	194.23	0.53
SAP-4	10	0.55	2.251	0.053	183.99	0.50
SAP-5	12	0.55	2.339	0.067	184.01	0.58
SAP-6	14	0.55	4.127	0.067	204.82	0.56
SAP-7	10	0.57	2.632	0.054	177.08	0.29
SAP-8	12	0.57	2.671	0.058	181.57	0.29
SAP-9	14	0.57	3.993	0.061	199.29	0.29

TABLE 5. Detailed parameter of solar panel.

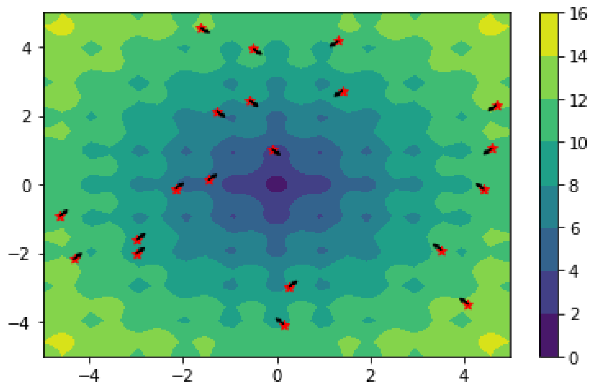
Sr. No.	Parameter	Symbl	Value	Unit
1	Maximum Power	P max	250	Watt
2	Maximum Voltage	Vmax	30.80	Volt
3	Maximum Current	Imax	8.12	Amp.
4	Open Ckt. Voltage	Voc	37.20	Volt
5	Short Ckt. Current	Isc	8.96	Amp.
6	Filter Inductor	L	0.6	mH
7	Filter Capacitor	C	3.2	mF
8	DC Capacitor	Cdc	330	mF
9	Temp. Coefficient	α	0.0681	%/oC
10	Temp. Coefficient	β	-0.2941	%/oC
11	Module Efficiency	η	15.40	%
12	Max. Series Fuse Rating		15	Amp.

V. EXPERIMENTAL SETUP AND RESULT ANALYSIS

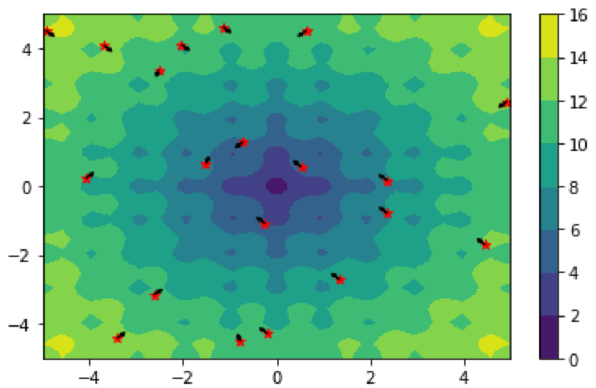
The effectiveness of the proposed MPPT algorithm has been tested with a developed prototype. To test the prototype two nos. of 250 Watt poly crystalline solar panel has been connected in series and a laboratory arrangement has been carried out with proper lighting arrangement. The detailed parameter of the solar panel is shown in table-5.

During the experiment, the panels were exposed to halogen light with intensity of $1012w/m^2$ and a room temperature of $32°C$ has been maintained for conducting the experiment. To measure the current and voltage of solar panel, WCS1700 hall current sensor with over current protection and $SM72442MTE/NO$ controller were used respectively. A clock frequency of 30MHz digital signal controller dsPIC30F4013 has been used to process the voltage and current to the computer compatible mixture interface board. A dual channel dSpace has been used to generate the necessary gate signal for PWM converter. The detail experimental setup as well as the technical specification were shown in Fig.13. and Table- 5 as shown, the maximum of solar panel is 30.80 watt and that of current is 8.12 Amp. Similarly open circuit voltage is 37.20V and SC current is 8.96 Amp. with an efficiency of 19%.

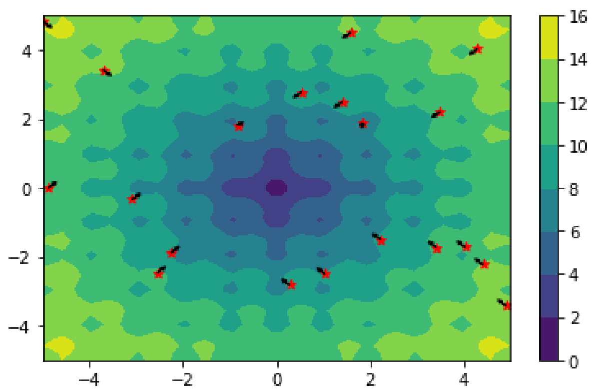
Again to validate the experiment result, MATLAB based simulink model was also developed. The two solar PV cell connected in series to a DC-DC boost converter. The getting sequence for switches was generated through a PWM converter using PI,PI+Fuzzy and PI+PSO for the identified bench marking model. The proposed algorithm was also tested with PI+PSO-SS under ODE25 with discrete step



(a) Sample Size (N_P)=10

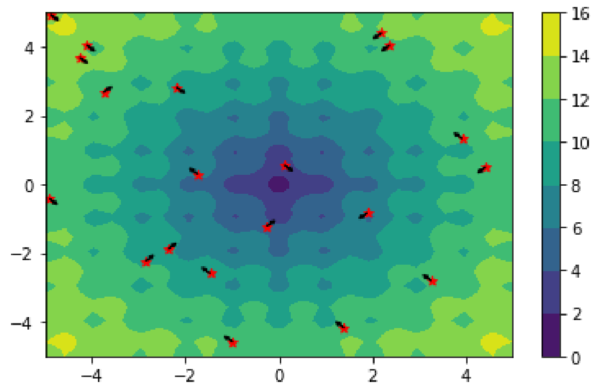


(b) Sample Size (N_P)=12

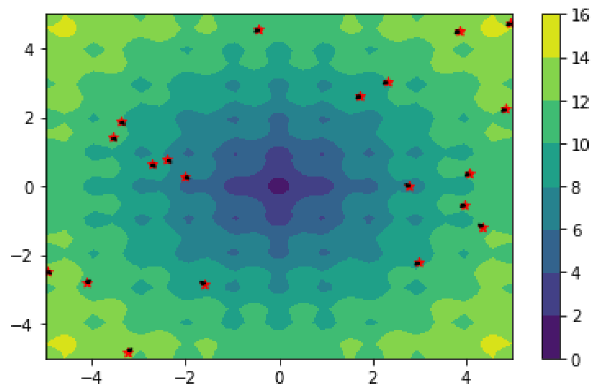


(c) Sample Size (N_P)=14

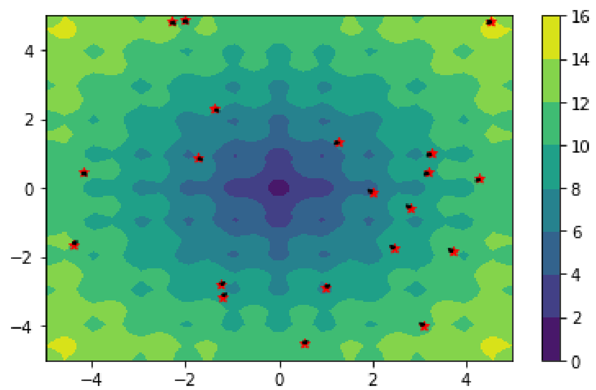
FIGURE 10. Movement of particles inside MPP search space against c1=0.5 & c2=0.4.



(a) Sample Size (N_P)=10



(b) Sample Size (N_P)=12



(c) Sample Size (N_P)=14

FIGURE 11. Movement of particles inside MPP search space against c1=0.2 & c2=0.87.

size. Technical specification for Boost Converter is shown in Table- 6.

Fig.12 shows the Solar Panel laboratory experimental Setup, Fig.13. and Fig.14. shows the experimental set up for partial shading and colour spectrum inside laboratory. The performance of bench marking model as well as the proposed MPPT has been tested under three different partial shading condition such as 25%, 50% and 75% respectively. Similarly colour spectrum has been analysed for three different colour such as RED, YELLOW and GREEN.

The model has been simulated under different testing conditions as stated in the above paragraph and performance Comparison of different MPPT techniques through MATLAB Simulink is shown in Table- 7. Fig.17. shows the output voltage waveform for PI+Fuzzy system. It can be observed that there are three transitions in the in the system representing three variations in the solar insolation namely, $600w/m^2$, $800w/m^2 and 1000w/m^2$. During the transition the system has under gone some oscillations to track the Maximum Power (MPP). However, when there is a transition at

TABLE 6. Boost converter simulink parameter.

Sr. No.	Parameter	Value	Units
1	Input Voltage	60	V
2	OutPut Voltage	100	V
3	Switching Frequency	25	kHz
4	Power Output	300	Watt
5	Ripple Voltage	5	%
6	Ripple Current	5	%
7	Capacitance	298	microFarad
8	Inductance	18	mH
9	Resistance	200	ohm

TABLE 7. Technical specification of MPPT set up.

Sr. No.	Name of Component	Type
1	MOSFET	IRF9520PMOS
2	MOSFET	IRF520NMOS
3	SMC	MSP430FS132IDA
4	ESD	TPDIEI0B06DPYR
5	Drift Current Sensor	WCS1700
6	Buck Regulator	RT6200
7	PWM Generator	4081IC

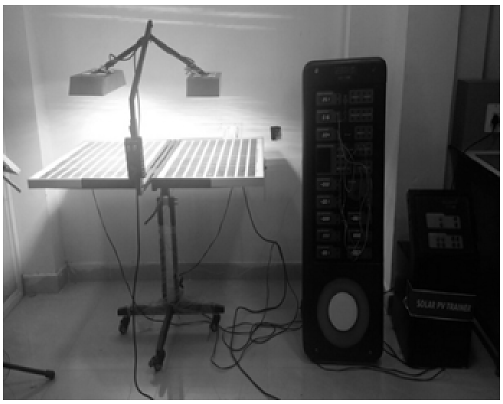


FIGURE 12. Solar Panel laboratory experimental setup.

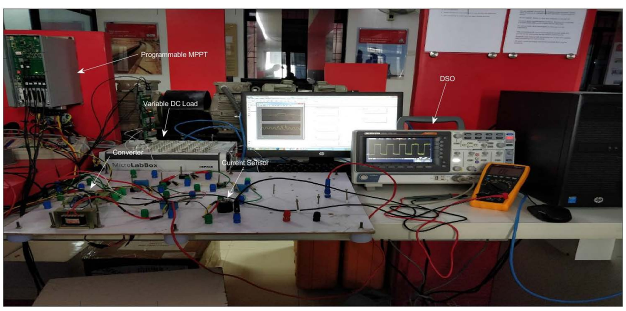


FIGURE 13. MPPT experimental setup for partial shading.

the higher solar insolation range this oscillation is minimum. Once the voltage reaches the cut in voltage of 32.3V, a very less perturb can be observed.Fig.15 shows the movement of particles inside MPP search space against with coefficient of c1=0.2 & c2=0.87. Similarly, Fig.15 shows the movement of particles inside MPP search space against with coefficient of c1=0.22 & c2=0.79. Table-8 shows the performance

FIGURE 14. MPPT experimental setup for color spectrum.

TABLE 8. Performance comparison of different MPPT techniques through MATLAB simulink.

MPPT Scheme	Efficiency	Response Time (Sec.)	Speed	Remarks (Cycles/Sec.)
P&O+PI	77.9	0.082	Sluggish	12.19
P&O+Fuzzy	81.87	0.081	Sluggish	12.34
P&O+PSO	92.34	0.063	Sluggish	15.87
P&O+PSO-SS	94.67	0.057	Moderate	17.54

comparison of different MPPT techniques through MATLAB Simulink, where efficiency comparison and MPPT response time(Sec.) has been evaluated for all the algorithm.With predefined search space an efficiency of 94.67 % has been achieved.

The comparative analysis between different MPPT under partial shading condition and color spectrum is shown in Table- 9 and Table- 10 respectively. With partial shading test it can be found that P&O+PSO-SS provides best tracking response of 0.057 for 75% and 25% of shading. This is 57% faster as compared to P&O+PSO. Similarly the proposed algorithm is 63.8% faster as compared to PI+Fuzzy. The tracking voltage has also increased from 36.14% in P&O+Fuzzy to 42.71% in P&O+PSO-SS. The proposed algorithm also increases the voltage from 93.56V to 104.7V. Similarly under color spectrum experiment it can be observed that the MPPT efficiency has increased from 76.8% in PI enabled MPPT to 85.46% in P&O+PSO-SS MPPT. Similarly the comparitive analysis between different MPPT under different dust level and GHG Concentration is shown in Table - 11 and Table - 12 respectively. with dust level test it can be found that P&O+PSO-SS provides best tracking response of 0.044 with $PM_{2.5}$ and efficiency of 93.86.

Again, the change in perturb can also be observed in Duty Ratio waveform as generated from MPPT for converter firing circuit. The duty ratio has undergone three different changes in a stepwise manner. The final duty ratio is 0.24 at an insolation of $1000 w/m^2$ under partial shading condition. Similarly a variation in the input resistance to converter is also noticed from the Fig.19. The change in resistance represents the effect of partial shading on MPP performance.

Fig.20 shows the output voltage waveform at the output of converter. Here PI+PSO algorithm has been used to track the changes and to improve the efficiency as compared to PI+Fuzzy. It can be noticed here that, as compared to Fig.17

TABLE 9. Performance comparison of different MPPT techniques under partial shading condition.

Type of MPPT	% of Shading	Irradiance Level (Watt/m^2)	Temp. Level (Surface)	Measured Power (Watt)	Response Time (Cycles/Sec.)	Max. Voltage(V)	Max. Current(A)	Efficiency (%)
P&O +PI	25	1000	37.7	147.24	0.082	18.48	5.68	60.03
	50	800	33.5	97.96	0.087	7.7	3.00	37.83
	75	600	31.8	93.56	0.091	3.69	2.03	25.97
P&O+Fuzzy	25	1000	38.1	151.25	0.0817	18.63	4.91	60.5
	50	800	36.7	137.14	0.083	16.63	4.38	54.37
	75	600	36.1	90.01	0.0899	11.08	2.92	36.14
P&O+PSO	25	1000	38.2	177.5	0.063	21.86	5.576	71.33
	50	800	36.3	145.00	0.066	17.86	4.70	58.19
	75	600	36.1	97.4	0.073	12.01	3.16	39.64
P&O+PSO-SS	25	1000	38.3	197.5	0.057	24.33	6.41	79.81
	50	800	35.8	157.5	0.056	19.404	5.11	63.55
	75	600	35.00	104.7	0.057	12.93	3.41	42.71

TABLE 10. Performance comparison of different MPPT techniques under different color spectrum.

Type of MPPT	Type of Color	Irradiance Level (Watt/m^2)	Temp. Level (Surface)	Measured Power (Watt)	Response Time (Cycles/Sec.)	Max. Voltage(V)	Max. Current(A)	Efficiency (%)
P&O +PI	Red	1000	37.7	218.46	0.076	26.91	7.09	87.38
	Yellow	800	33.5	224.67	0.076	27.67	7.29	89.86
	Green	600	31.8	192.33	0.079	23.65	6.23	76.8
P&O+Fuzzy	Red	1000	38.1	221.79	0.083	27.10	7.14	88.3
	Yellow	800	36.7	225.46	0.079	27.72	7.33	90.02
	Green	600	36.1	203.04	0.081	24.94	6.57	81.37
P&O+PSO	Red	1000	38.2	219.97	0.071	26.79	7.06	87.37
	Yellow	800	36.3	225.03	0.068	27.72	7.33	90.03
	Green	600	36.1	211.80	0.068	25.87	6.82	84.38
P&O+PSO-SS	Red	1000	38.3	227.41	0.043	27.81	7.33	90.27
	Yellow	800	35.8	231.82	0.048	28.33	7.47	92.81
	Green	600	35.00	213.68	0.054	26.18	6.90	85.46

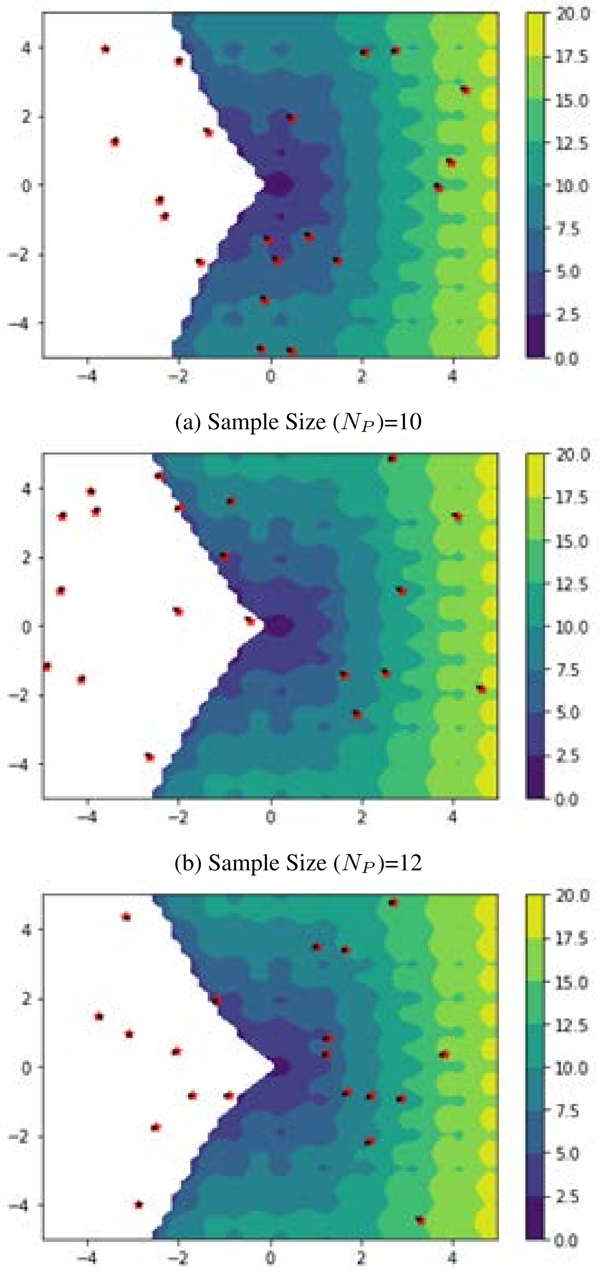
TABLE 11. Performance comparison of different MPPT techniques under different dust level.

Type of MPPT	Type of Dust	Wt.per sqcm	Irradiance (Watt/m^2)	Temp. Level (Surface)	Measured Power (Watt)	Response Time (Cycles/Sec.)	Max. Voltage(V)	Max. Current(A)	Efficiency (%)
P&O +PI	$PM_{2.5}$	2.0gm	1000	38.3	220.56	0.078	27.03	7.12	88.13
	$PM_{5.0}$	1.0gm	800	33.7	224.12	0.078	26.88	7.08	88.71
	PM_{10}	0.5gm	600	32.0	194.36	0.093	24.55	6.78	81.66
P&O+Fuzzy	$PM_{2.5}$	2.0gm	1000	38.3	222.04	0.078	27.55	7.37	89.49
	$PM_{5.0}$	1.0gm	800	33.6	225.07	0.077	27.03	7.38	89.00
	PM_{10}	0.5gm	600	32.1	200.83	0.079	25.68	6.94	83.71
P&O+PSO	$PM_{2.5}$	2.0gm	1000	38.2	221.57	0.069	27.69	7.49	89.61
	$PM_{5.0}$	1.0gm	800	34.1	228.92	0.071	28.37	7.44	90.33
	PM_{10}	0.5gm	600	32.3	209.63	0.071	25.04	7.26	87.08
P&O+PSO-SS	$PM_{2.5}$	2.0gm	1000	38.3	234.87	0.044	29.36	7.76	93.86
	$PM_{5.0}$	1.0gm	800	33.8	230.32	0.051	28.19	7.61	93.07
	PM_{10}	0.5gm	600	33.1	217.46	0.051	26.77	7.22	88.96

TABLE 12. Performance comparison of different MPPT techniques under different GHG concentration.

Type of MPPT	GHG	Irradiance Level (Watt/m^2)	Temp. Level (Surface 0_c)	Measured Power (Watt)	Response Time (Cycles/Sec.)	Max. Voltage (V)	Max. Current(A)	Efficiency (%)
P&O +PI	Co2	1000	37.9	129.42	0.078	24.14	6.63	78.51
	CH4	800	33.5	182.25	0.08	20.75	5.79	72.13
	NOx	600	31.8	160	0.087	17.29	5.01	61.47
P&O+Fuzzy	Co2	1000	38.1	198.36	0.069	24.42	6.47	79.43
	CH4	800	35.6	195.89	0.079	23.79	6.36	77.79
	NOx	600	34.7	164.6	0.083	20.56	5.47	67.07
P&O+PSO	Co2	1000	38.2	206.34	0.067	25.44	6.7	82.77
	CH4	800	35.5	199.65	0.068	24.65	6.49	52.51
	NOx	600	34.8	172.94	0.07	20.97	5.74	70.36
P&O+PSO-SS	Co2	1000	38.3	219.9	0.048	27.1	7.16	87.98
	CH4	800	35.1	206.5	0.051	24.64	6.73	83.14
	NOx	600	34.3	178.61	0.054	21.96	5.84	72.37

in Fig.20 the initial transition time is very less i.e. the system can achieve 0 to 78% of its final value in less than 2 sec where as in PI+Fuzzy it takes 4.03 sec. to track the changes. Similarly Fig.21 shows the duty ratio generated for switches using MPPT. In contradiction to PI+Fuzzy, in PI+PSO system behaves more oscillations during transient. Fig.22 shows

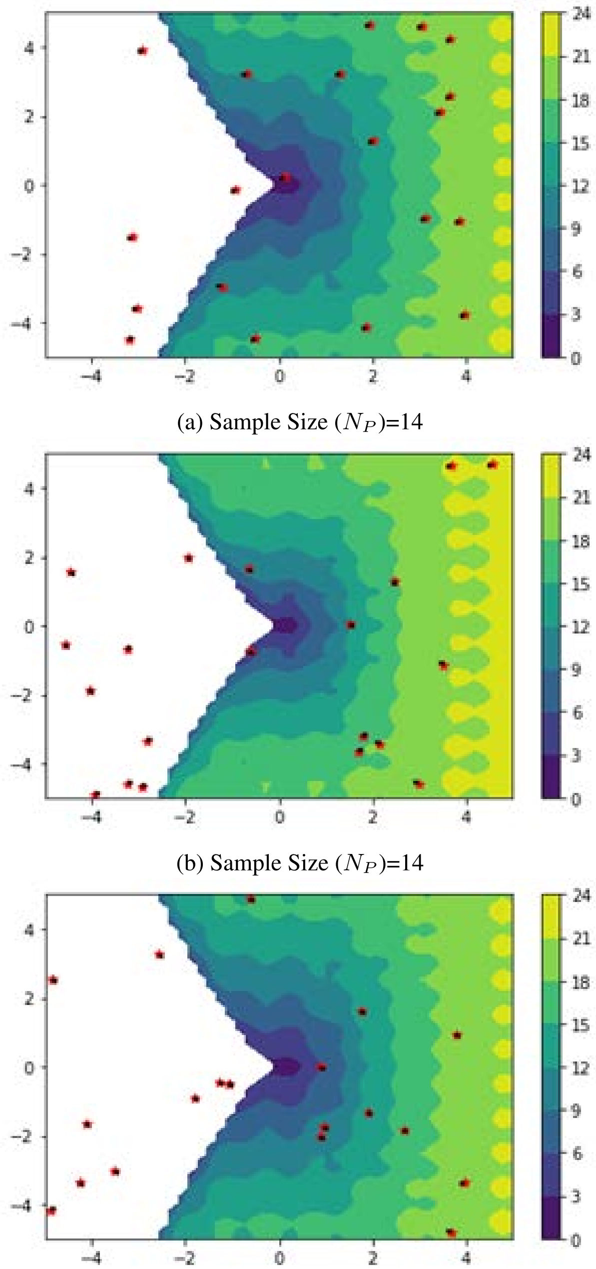


(a) Sample Size (N_P)=10

(b) Sample Size (N_P)=12

(c) Sample Size (N_P)=14

FIGURE 15. Movement of particles inside MPP search space against c1=0.2 & c2=0.87.



(a) Sample Size (N_P)=14

(b) Sample Size (N_P)=14

(c) Sample Size (N_P)=14

FIGURE 16. Movement of particles inside MPP search space against c1=0.2 & c2=0.87.

the variation in converter resistance due to change in duty cycle.

Figure 23-26 represents the performance of P&O + PI, P&O + Fuzzy, P&O + PSO and P&O + PSO - SS for four evaluation criteria such as efficiency, success rate, speed and track. All the four models have been normalized to the evaluation criteria. The standard model depicts the strength and weakness of proposed algorithm (P&O+PSO-SS) with reference to different shading conditions. It is observed that the proposed algorithm based on fokker plank solution (P&O+PSO-SS) will provide better performance at about 7.2% superior as compared to all the standard models. The detail intrusion can be summarized as follows:

- Figure 23(a) P&O + PI algorithm under 50% and 75% of shading shows better speed against efficiency rate. Similar type of things was also noticed under Figure 23 (c), where tracking rate is good as compared to speed of operation. However, with the proposed model 23 (d) of P&O + PSO – SS, for all the conditions of shading it will

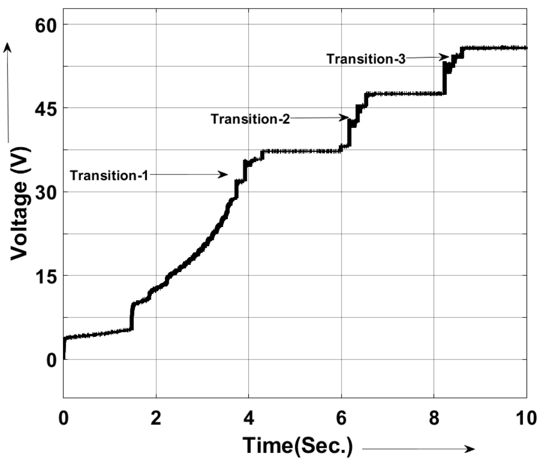


FIGURE 17. Output voltage waveform (fuzzy MPPT).

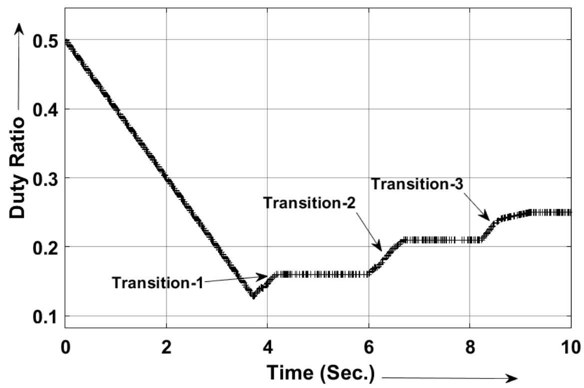


FIGURE 18. Duty ratio generated from MPPT for converter (fuzzy MPPT).

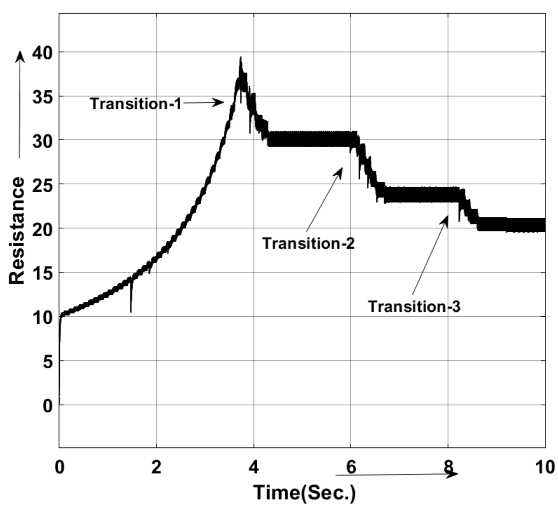


FIGURE 19. Variation in converter input resistance due to change in duty cycle (fuzzy MPPT).

provide better efficiency and speed without compromising with success rate and tracking speed.

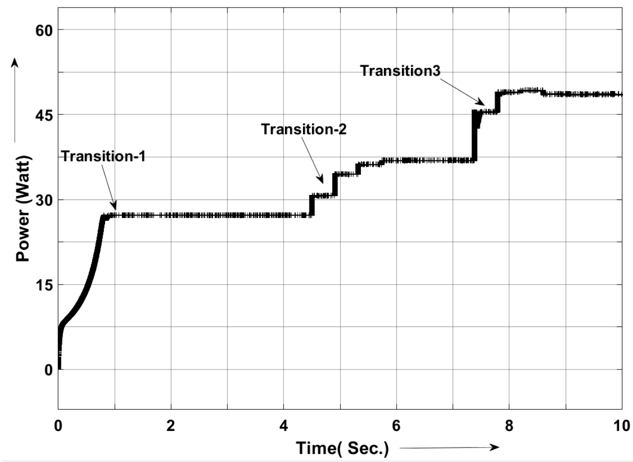


FIGURE 20. Output voltage waveform (PSO MPPT).

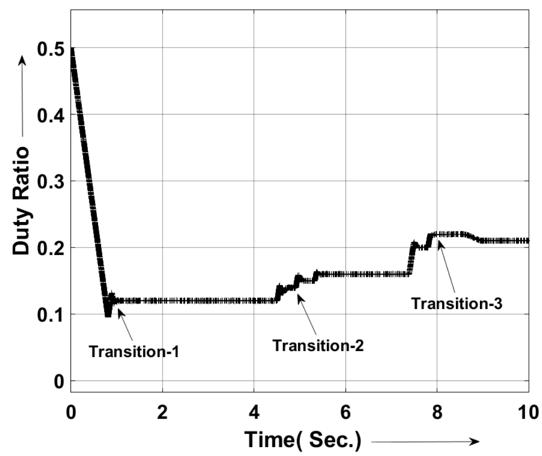


FIGURE 21. Duty ratio generated from MPPT for converter (PSO MPPT).

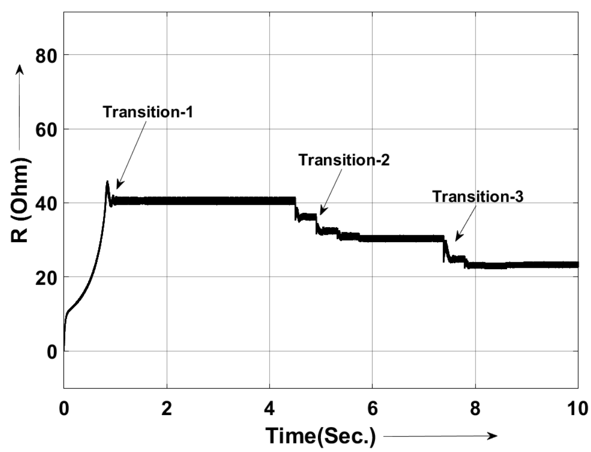


FIGURE 22. Variation in converter input resistance due to change in duty cycle (PSO MPPT).

- Figure 24 (b) P&O+ Fuzzy under red and yellow condition of shading provides superior speed as compared to

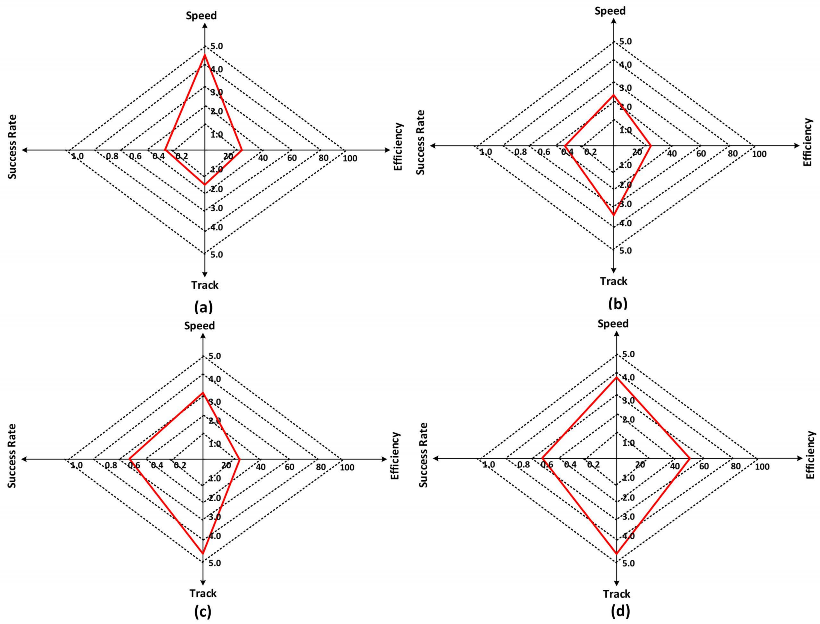


FIGURE 23. Efficiency, success rate analysisunder partial shading condition a) P&O+PI, b) P&O+Fuzzy, c) P&O+PSO, d) P&O+PSO-SS.

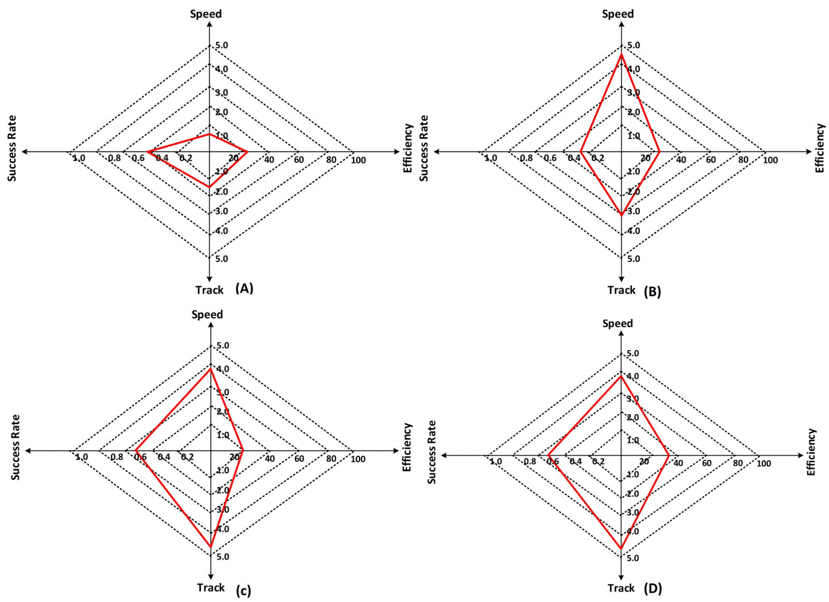


FIGURE 24. Efficiency, success rate analysis under different color spectrum a) P&O+P, b) P&O+Fuzzy, c) P&O+PSO, d) P&O+PSO-SS.

tracking and that of efficiency is almost same with success rate. Again comparison between Figure 24(c) and 24(d), Figure 24 (d) provides better efficiency and success rate. P&O+ PI, performance was not that much better as compared to others as shown under Figure 24 (a).

- Figure 25 (d), P&O + PSO-SS (Fokker Plank Solution) provides highest efficiency under particulate matter (PM_{10}) among other algorithm. Here the efficiency is around 88.96% with PM_{10} And 93.86% with $PM_{2.5}$. The success rate for PSO+PI (Figure 25(a)) is more than P&O +PSO (Figure 25(c)).
- Figure 26 (c), P&O + PSO provides increase in tracking speed and slight increase in efficiency. However, Figure 26 (d) P&O +PSO-SS shows better performance in track speed and searching speed as compared to all other algorithms.

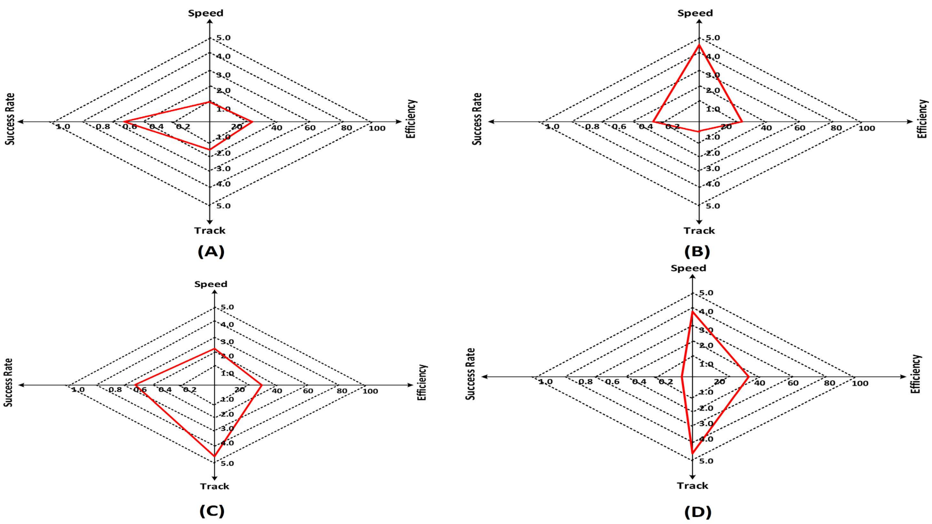


FIGURE 25. Efficiency, success rate analysis under different dust level a) P&O+PI, b) P&O+Fuzzy, c) P&O+PSO, d) P&O+PSO-SS.

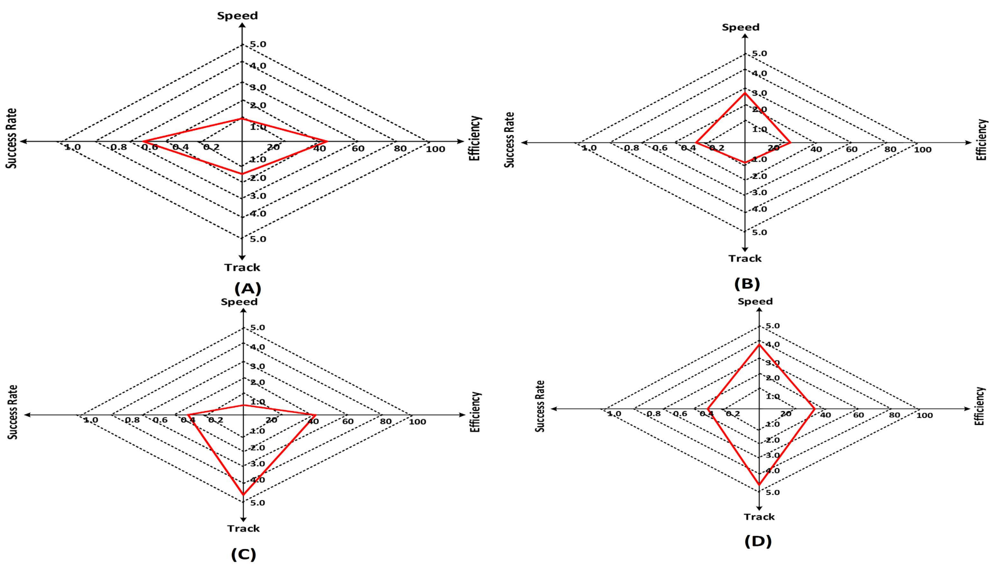


FIGURE 26. Efficiency, success rate analysis under different GHG level a) P&O+PI, b) P&O+Fuzzy, c) P&O+PSO, d) P&O+PSO-SS.

Standardize transient efficiency analysis for all the algorithm has been shown in the table 13-15. Hence all together 20 sample test, 5 from each category has been conducted individually for each partial shading condition under colour spectrum, dust and GHG with mix type concentration. A shading rate of 20% has been applied to all the model for making it standardized.

The transient efficiency has been evaluated on the basis of change in power from lower lapse time to upper lapse time with a minimum step size interval of 200ms to maximum 300ms. Again from table – 13, it is noticed that the maximum standardized deviation for transient becomes 5.78 and that of minimum is 5.69. Whereas for P&O + PSO the maximum and minimum deviation is 5.80 and 5.71 respectively. Therefore it can be understood that low deviation in transient efficient results in better voltage track and that of good tracking speed.

Table -14 shows the standardized transient mean efficiency change under different mix dust level. Here the change in dust level from one transition to other transition is 20% of the particulate matter (2.5, 5.0 and 10). It is observed that minimum mean deviation in efficiency change is for P&O +PSO – SS, 5.40. and that of maximum deviation is for P&O + PSO, 5.81. P&O +PI shows a change in voltage track length of 1.99V (aggregate). This reveals that the algorithm requires more step change to track the small change in voltage fluctuation.

TABLE 13. Standardized transient mean efficiency change under different mix colour spectrum (shading rate 20 % change).

Type of optimization	Test Sample	Time Elapse	P(i-1)	Pi	Voc 0.9Voc	Voc 0.85Voc	Voc 0.80Voc	Standardized Transient Mean deviation efficiency change
P&O+PI	1	0.01	285.00	283.00	33.19	31.34	29.44	5.59
	2	0.04	281.00	280.00	33.29	31.44	29.56	5.57
	3	0.05	277.00	271.00	32.79	30.94	28.96	5.66
	4	0.07	263.00	259.00	32.99	31.14	29.21	5.62
	5	0.11	261.00	259.00	33.19	31.34	29.44	5.59
P&O+Fuzzy	1	0.02	290.70	288.66	33.42	31.49	29.60	5.78
	2	0.05	286.62	285.60	33.54	31.61	29.72	5.75
	3	0.07	282.54	276.42	32.93	31.00	29.11	5.86
	4	0.08	268.26	264.18	33.17	31.24	29.35	5.82
	5	0.13	266.22	264.18	33.42	31.49	29.60	5.78
P&O+PSO	1	0.01	250.30	248.55	28.96	27.31	25.67	5.73
	2	0.04	246.79	245.91	29.06	27.41	25.77	5.71
	3	0.05	243.28	238.01	28.57	26.93	25.25	5.80
	4	0.07	230.98	227.47	28.77	27.12	25.46	5.76
	5	0.10	229.23	227.47	28.96	27.31	25.67	5.73
P&O+PSO-SS	1	0.01	260.57	258.74	30.15	28.43	26.72	5.71
	2	0.04	256.91	256.00	30.25	28.53	26.83	5.69
	3	0.05	253.25	247.77	29.74	28.03	26.28	5.78
	4	0.07	240.46	236.80	29.95	28.23	26.51	5.74
	5	0.11	238.63	236.80	30.15	28.43	26.72	5.71

TABLE 14. Standardized transient mean efficiency change under different mix dust level (shading rate 20 % change).

Type of optimization	Test Sample	Time Elapse	P(i-1)	Pi	Voc 0.9Voc	Voc 0.85Voc	Voc 0.80Voc	Standardized Transient Mean deviation efficiency change
P&O+PI	1	0.01	282.94	280.84	18.54	16.59	14.60	4.77
	2	0.04	278.74	277.69	18.64	16.70	14.73	4.75
	3	0.05	274.54	268.24	18.12	16.17	14.10	4.84
	4	0.07	259.84	255.64	18.33	16.38	14.36	4.81
	5	0.11	257.74	255.64	18.54	16.59	14.60	4.77
P&O+Fuzzy	1	0.02	288.93	286.78	18.78	16.75	14.76	4.96
	2	0.05	284.64	283.57	18.90	16.88	14.89	4.94
	3	0.07	280.36	273.93	18.26	16.24	14.25	5.05
	4	0.08	265.36	261.08	18.52	16.49	14.51	5.00
	5	0.13	263.22	261.08	18.78	16.75	14.76	4.99
P&O+PSO	1	0.01	255.31	253.52	29.06	27.38	25.73	5.81
	2	0.04	248.37	247.47	22.80	21.08	19.40	5.44
	3	0.05	244.74	239.28	22.26	20.54	18.85	5.53
	4	0.07	232.01	228.37	22.47	20.75	19.07	5.50
	5	0.10	230.19	228.37	22.69	20.97	19.29	5.47
P&O+PSO-SS	1	0.01	265.78	263.92	30.25	28.50	26.79	5.79
	2	0.04	258.56	257.61	23.74	21.95	20.19	5.40
	3	0.05	254.77	249.10	23.17	21.38	19.62	5.50
	4	0.07	241.52	237.74	23.40	21.60	19.85	5.46
	5	0.11	239.63	237.74	23.62	21.83	20.08	5.43

TABLE 15. Standardized transient mean efficiency change under different mix GHG concentration (Shading Rate 20 % Change).

Type of optimization	Test Sample	Time Elapse	P(i-1)	Pi	Voc 0.9Vov	Voc 0.85Voc	Voc 0.80Voc	Standardized Transient Mean deviation efficiency change
P&O+PI	1	0.01	280.78	278.57	17.22	15.10	13.01	5.15
	2	0.04	276.37	275.26	17.36	15.23	13.15	5.14
	3	0.05	271.96	265.34	16.68	14.56	12.47	5.22
	4	0.07	256.52	252.11	16.95	14.83	12.74	5.19
	5	0.11	254.32	252.11	17.22	15.10	13.01	5.15
P&O+Fuzzy	1	0.02	287.06	284.81	16.06	12.16	13.01	5.35
	2	0.05	282.56	281.44	16.21	12.30	13.15	5.33
	3	0.07	278.06	271.32	15.50	11.59	12.47	5.44
	4	0.08	262.32	257.82	15.78	11.88	12.74	5.39
	5	0.13	260.07	257.82	16.06	12.16	13.01	5.38
P&O+PSO	1	0.01	253.75	251.87	14.47	11.85	19.29	5.46
	2	0.04	246.61	245.66	14.59	11.97	12.19	5.25
	3	0.05	242.79	237.06	13.99	11.37	11.62	5.35
	4	0.07	229.43	225.61	14.23	11.61	11.85	5.31
	5	0.10	227.52	225.61	14.47	11.85	12.08	5.30
P&O+PSO-SS	1	0.01	264.16	262.20	15.87	12.99	15.05	5.42
	2	0.04	256.72	255.73	16.00	13.12	12.79	5.20
	3	0.05	252.75	246.79	15.34	12.47	12.15	5.30
	4	0.07	238.84	234.86	15.60	12.73	12.40	5.26
	5	0.11	236.85	234.86	15.87	12.99	12.66	5.25

Here open circuit voltage analysis has been carried out for three different fraction of Voc Level such as 0.9Voc, 0.85Voc and 0.80Voc. The proposed algorithm that is P&O+PSO-SS shows a state change of 4.22V as maximum and 3.53V as minimum deviation from Voc under 20-100 change in dust level. Similarly the convergence time (time elapse) is same for all the tested algorithm. Therefore it can be understood that with the proposed algorithm the tracking speed as well as Voc level can be maintained in superior way as compared to the existing algorithm.

Table -15 shows the standardized transient mean efficiency change under different mix GHG level. The minimum standardized efficiency deviation is 5.14 as observed in P&O+PI and that of maximum deviation is 5.46 in P&O+PSO. Here P&O+PSO-SS shows 94% efficient from that of P&O+PSO but in terms of voltage variation it is nearly 2.11 against 2.37 in P&O+PI.

VI. CONCLUSION

Solar PV technology has acclaimed global attraction from stand alone to grid connected system. Very soon the renewable grid interconnection will dominate the energy sector against fossil fuel. However the efficiency of extracting power from solar MPPT is a great challenge. In this regard the optimized allocation of power plays a very important role.

Solar PV efficiency, stability in tracking MPP without oscillation and reliability are some of the important thrust area for making solar PV to stand in the market. In this research a comparative analysis among conventional PI, fuzzy, PSO with P&O controller and that of proposed PSO-SS has been presented. All the models have been developed with respect to a common optimisation techniques. The main characteristics of each bench marking model has been discussed and compared with the proposed method to improve their efficiency under different shading condition. The drawbacks associated with the PI+Fuzzy, such as slow convergence response oscillation around MPP during transient shading makes it not suitable for operating MPPT at MPP. Hence the modified P&O +PSO-SS using Fokker Planck Solution has been proposed to address the issues.

The proposed algorithm uses the advantages of PSO and search space to converge under stochastic effect of solar irradiance and temperature. A remarkable decrease in processing speed has been noticed with higher output both in simulation and in hardware. No divergence in the MPP under four test bed such as partial shading, color spectrum, dust level and GHG concentration. The highest efficiency of the MPP has been recorded as 99.23% against 96.07% under Fuzzy+P&O algorithm. Rapid diminish in the steady state oscillation and improved transient response time have made it possible to track small changes occurring in the system.

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