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A performance analysis of a hybrid golden section search methodology and a nature-inspired algorithm for MPPT in a solar PV system

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Abstract: This research presents a comparative study for maximum power point tracking (MPPT) methodologies for a photovoltaic (PV) system. A novel hybrid algorithm golden section search assisted perturb and observe (GSS-PO) is proposed to solve the problems of the conventional PO (CPO). The aim of this new methodology is to boost the efficiency of the CPO. The new algorithm has a very low convergence time and a very high efficiency. GSS-PO is compared with the intelligent nature-inspired multi-verse optimization (MVO) algorithm by a simulation validation. The simulation study reveals that the novel GSS-PO outperforms MVO under uniform irradiance conditions and under a sudden change in irradiance.

Key words: hybrid optimization, golden sections search, multi-verse optimization algorithm, maximum power point tracking, perturb and observe, photovoltaic (PV)

1. Introduction

The use of renewable energy sources has extended hastily for many reasons, including the dwindling conventional energy sources, environmental issues, and fossil fuel price dispersion.

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Solar-based photovoltaic (PV) arrays represent one of the most promising renewable energy sources. An MPPT is used to extort the maximum power out of the PV module (PVM) and transfer it to the load. Various researches are done to boost the efficiency of the PV system. Many methods of tracking the MPP of a PVM have been developed to resolve the drawback of efficiency [1–5].

MPPT controller (MPPTC) controls the DC-DC converter (DDC) that acts as an interface between the PVM and the load [6]. This converter has a simple structure [7–12]. Several MPPT algorithms have been reviewed in the literature such as conventional perturb and observe (CPO) [13], fuzzy logic control (FLC) [14], incremental conductance (INC) [15, 16], golden section search (GSS) [17], grey wolf optimization (GWO) [18–20] and multi-verse optimizer (MVO) [21]. These techniques can be classified according to their complexity, convergence speed, and efficiency.

From the literature review, it is observed that the simplest MPPT algorithm is the PO algorithm, due to its ease of implementation and easiness of application with different types of PV arrays. Also, the oscillation in the output power of the converter can be considered as the main disadvantage of this algorithm, along with the low convergence time. On the other hand, the golden section search (GSS) is found to be an algorithm with advantages like noise and signal fluctuations immunity, fast convergence as compared to many other MPPT algorithms. Hence, this paper proposed a novel golden section search assisted PO (GSS-PO) technique. The fusion of the new technique relays on the advantages of the GSS of fast convergence time and the advantage of the CPO with a very small step size to track the MPP with higher accuracy and very low oscillations. The GSS-PO hybrid algorithm is then compared to a nature-inspired MVO algorithm (MVO). The comparative study proposed by this work is approached with a simulation validation.

2. Multi-verse optimization algorithm (MVO)

In [21] Mirjalili *et al*. have developed an algorithm known as MVO. This algorithm is encouraged by nature. This employ the concepts of white and black holes in order to explore search spaces by MVO. On the contrary, the wormholes support MVO in exploiting the search spaces. It is assumed that each result is corresponding to a universe and each variable in is an object in that universe. Besides, each solution is assigned an inflation rate, which is proportional to the corresponding fitness function value of the solution. During optimization, the following rules are applied to the universes of MVO:

– The probability of having a white hole is high, if the inflation rate is high.
– The probability of having black holes is low, if the inflation rate is high.
– Universes with a higher inflation rate send objects through white holes.
– Universes with a lower inflation rate receive objects through black holes.
– Despite the inflation rate, objects in all universes may have random movement towards the best universe through the wormholes.

The conceptual model of the proposed algorithm is illustrated in Fig. 1.

In Fig. 1, white points show transferred objects through the wormholes. It is observed that the wormholes randomly alter the objects of the universes without concerning their inflation rates. With the aim of presenting local changes for each universe and have a high probability

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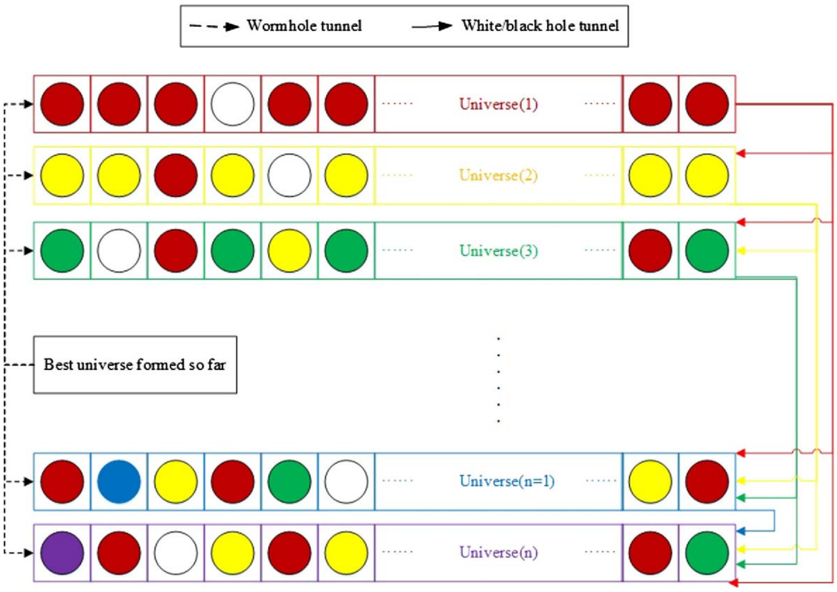

Fig. 1. MVO model

of improving the inflation rate using wormholes, we assume that wormhole tunnels are always established between a universe and the optimum universe formed thus far.

3. MVO MPPTC

With the weather conditions deviation (irradiance and temperature), the voltage, current, and power output of the PV module varies constantly. MPPTC is used to extort the maximum power out of the PVM. MVO is used as an MPPT algorithm. The universes here are the duty cycles of the MPPTC. For each universe (duty cycle) the MPPTC measures the PV volt, current through the sensors and calculate power (inflation rate) of each universe.

At the MPP, the duty cycle is maintained at a constant value which reduces the steady-state oscillations that exist in CPO MPPT techniques and lastly, the power loss due to oscillation is reduced resulting in higher system efficiency. The flowchart of the projected MVO MPPT is shown in Fig. 2. The main purpose is to acquire the MPP from the PV array considering duty ratio d as the decision variable. The objective function is formulated as follows:

max.: $P(d)$

Subjected: $d_{\min} < d < d_{\max}$

Initialization

Initialize population (duty cycles) in search space between the minimum limit, 0.1 and maximum limit, 0.9 of the duty ratio.

Evaluation of inflation rates

Calculate the inflation rate (PV power) of each population.

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Updating the search agent's positions

The positions of the universes d_i are updated. Powers are then calculated for updated positions.

Termination criterion

The algorithm ends when it reaches the maximum number of iterations and outputs the optimal duty ratio at maximum power.

Reset

The algorithm reinitializes search if any variation in solar irradiation is sensed.

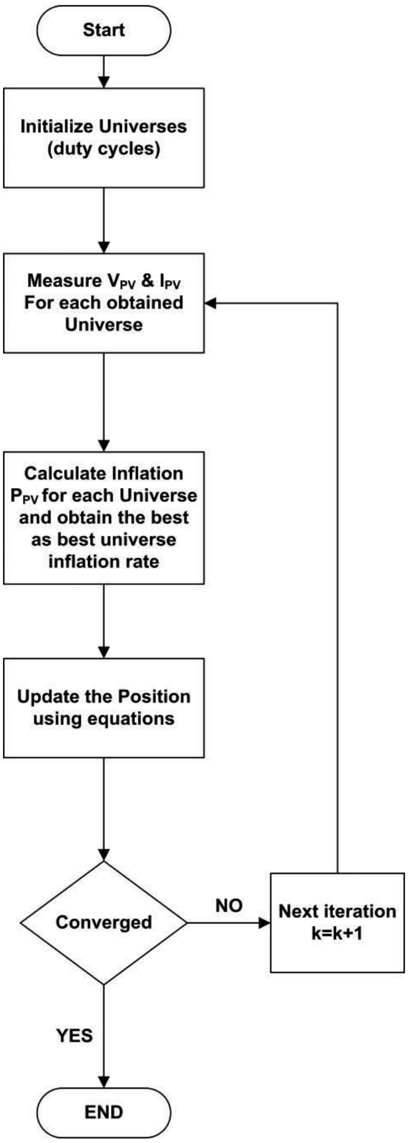

Fig. 2. MVO flowchart

During uniform irradiance, the P-V curve is categorized by only one peak, as shown in Fig. 3. It is to note that when the MVO finds the MPP, their associated coefficient vectors become almost equal to zero.

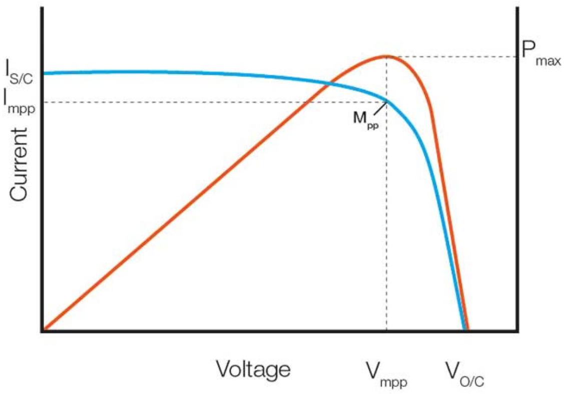

Fig. 3. I-V, P-V curves of PV module

4. Golden section search

One of the simplest methodologies of finding the local maximum is the equal interval method. Let's limit our debate to find the local maximum of $f(x)$ where the region in which the local maximum occurs is $[a, b]$. The GSS is utilized for finding the maximum or minimum of a unimodal function. The main intend is to find the maximum value of $f(x)$ within the input interval $[a, b]$. Two points, x_1 and x_2, are selected in the interval $[a, b]$ and function $f(x)$ is evaluated at these points. The points, x_1 and x_2, are such selected that each point subdivides the interval into two parts such that:

The length of a whole line/length of a larger fraction is equal to the length of a larger fraction/length of a smaller fraction. Assume a line segment [0, 1] as shown in Fig. 4(a) and Fig. 4(b), then we have:

$$1/r = r/1 - r. \tag{1}$$

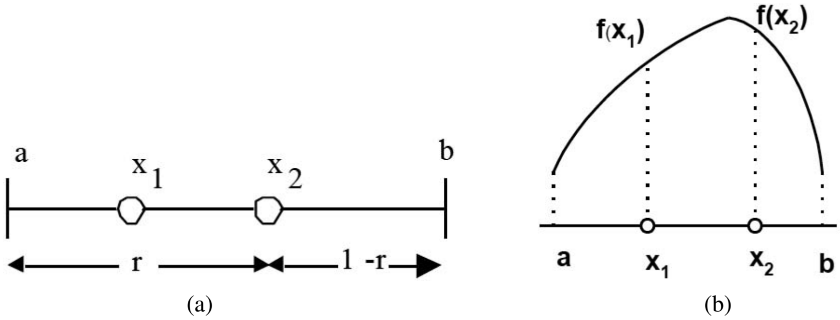

Fig. 4. GSS illustration diagrams (a), (b)

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From the above ratio, it is observed that $r = 0.618$. Hence we can derive an expression of the places of x_1 and x_2 from a and b

$$x_1 = b - r(b - a), \tag{2}$$

$$x_2 = a + r(b - a). \tag{3}$$

When the GSS is applied to a photovoltaic system for maximum power point tracking, the P-V characteristics is the operating characteristics wherein $f(x)$ corresponds to power whose maximum value has to be tracked, and x_1 and x_2 correspond to array voltage. The range of operation is from zero to open circuit voltage (V_{oc}). $a = 0$ and $b = V_{oc}$. The flow chart of this algorithm is shown in Fig. 5.

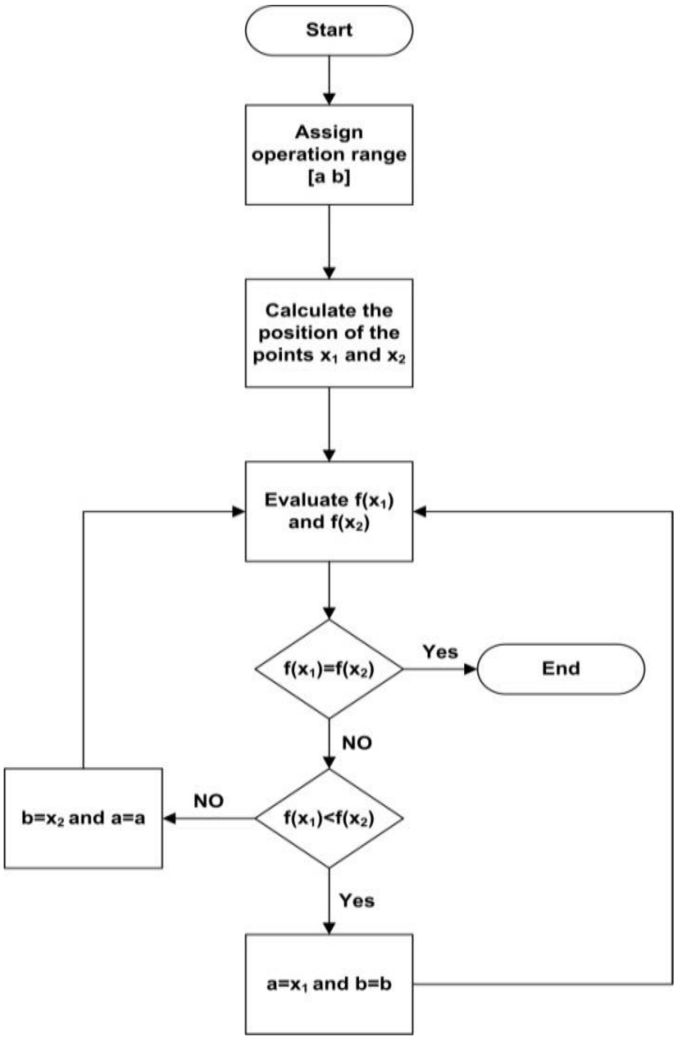

Fig. 5. GSS algorithm flowchart

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5. CPO algorithm

A CPO algorithm has been widely used due to the ease of implementation. This is a constant course of perturbation and observation till convergence at the MPP. The algorithm compares the power and voltages of a point (k) with the sample at a point (k–1). Miniature voltage perturbation changes the power of the PVM if delta power is positive, duty cycle perturbation is continued in increasing. But if delta power is negative, the duty cycle perturbation is decreased to reach the MPP. Fig. 6 shows the flowchart of a CPO. Many researchers have proposed modifications to the CPO algorithm to overcome the response time problem and steady state oscillations [4].

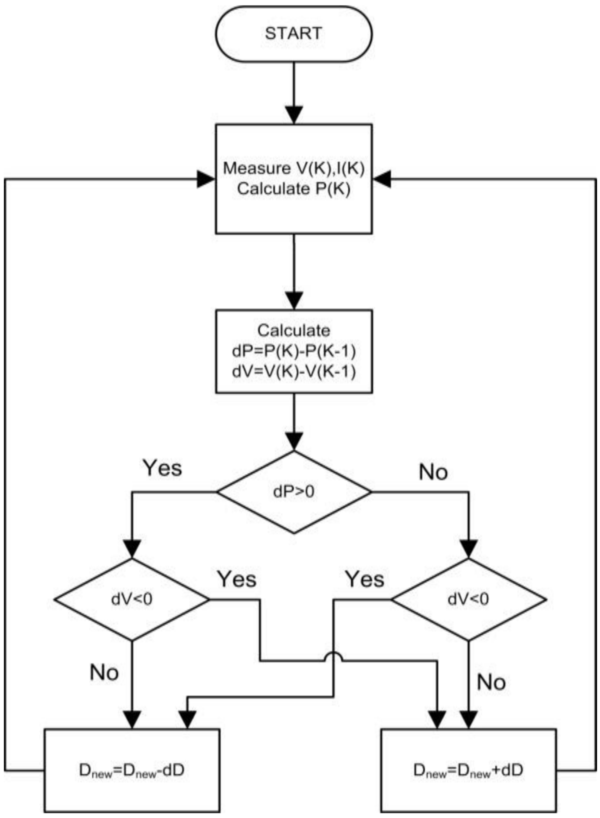


Fig. 6. CPO algorithm flowchart

6. Hybrid algorithm GSS-PO

The hybrid GSS-PO is presented in the following flow chart as shown in Fig. 7. The nature of the GSS algorithm makes it rapidly tracks the MPP and then the PO refines the tracking point. The PO algorithm uses a very small step size to lower the oscillations and to ultimately obtain the MPP.

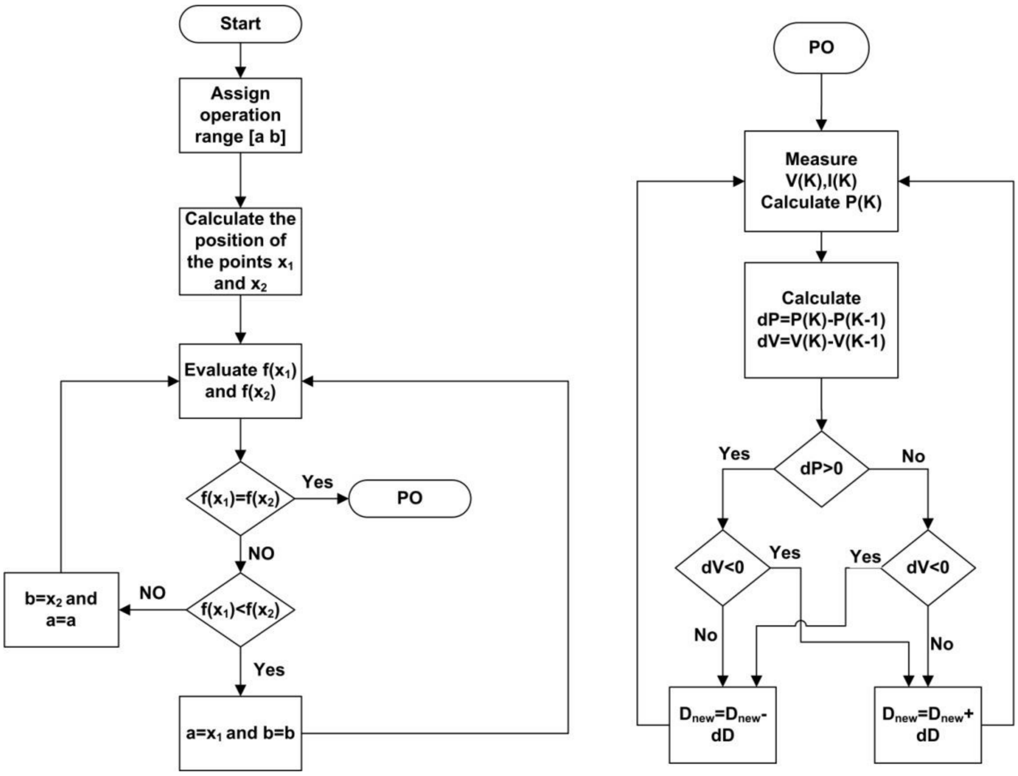


Fig. 7. GSS-PO hybrid algorithm flowchart

From the PV characteristics, it is observed that under uniform irradiance the PVM has only one peak of a maximum power of 30.0009 W under STC, as shown in Fig. 8(a) and Fig. 8(b) for the I–V and P–V curves, respectively.

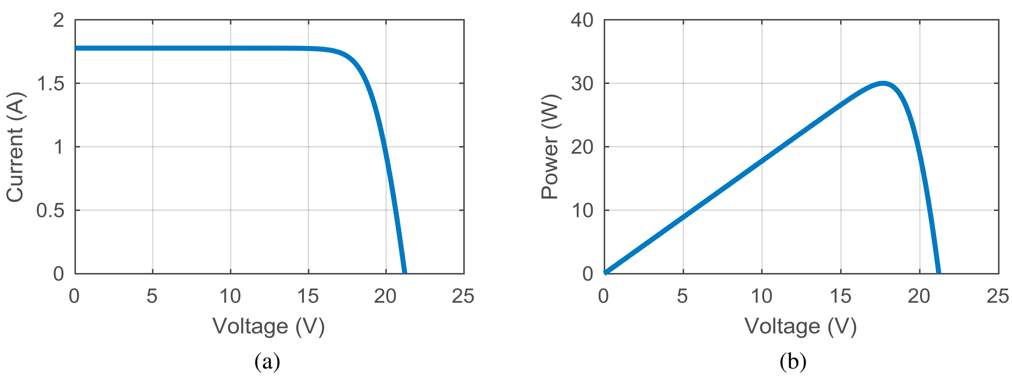
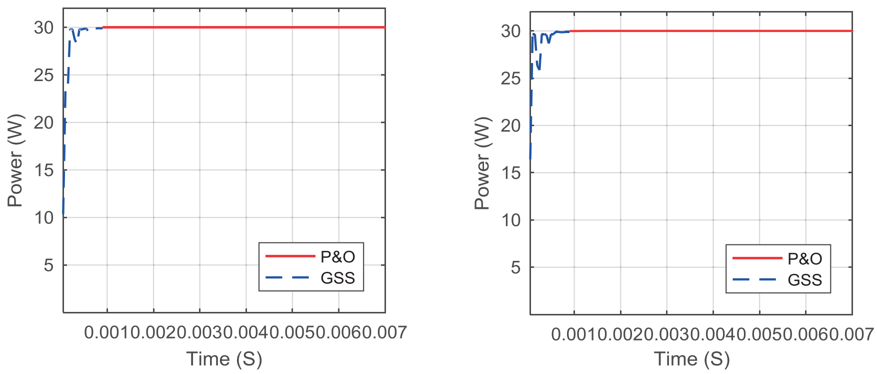


Fig. 8. I-V curve of the module used (a), P-V curve of the module used (b)

7. Performance results

7.1. GSS-PO

The GSS-PO is implemented in the MATLAB package to verify the algorithm efficiency. The simulation used a 30 W PV module with a maximum power of 30.0009 W, V_{oc} = 21.2, I_{sc} = 1.77. The module characteristics are shown in Fig. 8 and an ideal boost converter is used along with the module and resistive load. The following results are observed from the simulation in Fig. 9(a) and Fig. 9(b).



(a) (b)

Fig. 9. GSS-PO output at 18 Ω (a), GSS-PO outputs at 28 Ω (b)

The first test of Fig. 9(a) is done with a resistive load of 18 Ω, and the second test in Fig. 9(b) with a resistive load of 28 Ω. As observed, the GSS algorithm operates until the MPP is reached, and then the PO algorithm gives a refine continuous operation with very low oscillations. The algorithm has a very high efficiency of 99.9% because of the very high accuracy of the GSS methodology. The GSS algorithm obtains a maximum power of 29.9 W in only 8 iterations. Then the PO continues the tracking till it oscillates around 30.0008 W in a very low interval [30.0075, 30.0085]. The oscillation behavior is shown below in Fig. 10.

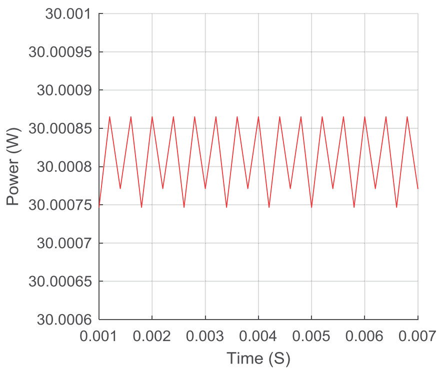


Fig. 10. GSS-PO oscillations around MPP

7.2. MVO

For the assessment of the new hybrid system, GSS-PO is compared to MVO. MVO is one of the promising algorithms utilizing the MPPT application. It has very high efficiency and low convergence time. But also it's more complex and requires more calculations. The MVO is implemented in the MATLAB package to compare the algorithm efficiency with the hybrid GSS-PO. The simulation used a 30 W PV module with a maximum power of 30.0009 W, $V_{oc} = 21.2$, $I_{sc} = 1.77$, the load is varied to identify the tracking efficiency under load variation. First, we use a load of 18 Ω then a load of 28 Ω is used. The module characteristic is shown in Fig. 10 and an ideal boost converter is used along with the module and resistive load. The following results are observed from the simulation of the MVO in Fig. 11 and Fig. 12.

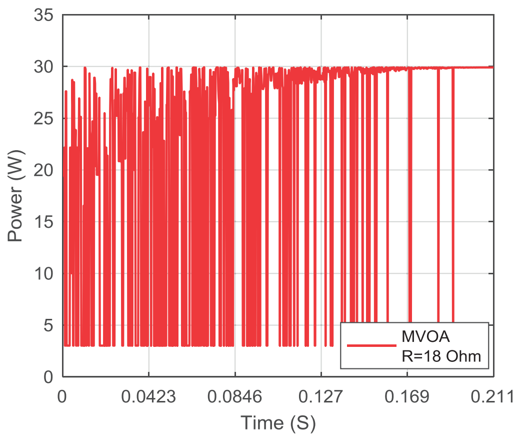


Fig. 11. MVO output at 18 Ω

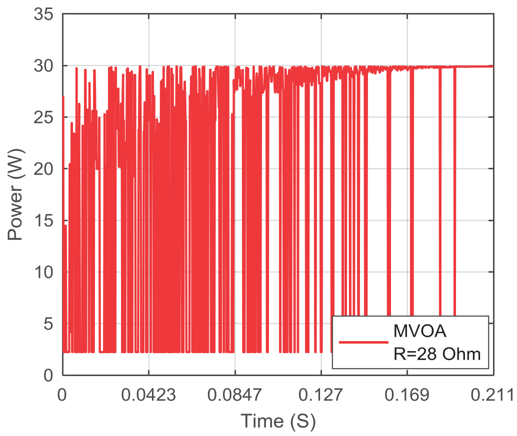


Fig. 12. MVO output at 28 Ω

From the above results, it is clearly observed that the MVO has very high efficiency (99.99%) in comparison to the proposed hybrid algorithm GSS-PO, but it is much more complex in

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calculations. The GSS-PO has a higher convergence speed (lower time) because the GSS algorithm has a lower number of iterations. Also, the GSS-PO suffers from steady state oscillations despite it is very low. Unlike the MVO which doesn't experience steady state oscillations. But the GSS-PO is very simple for hardware implementation, unlike the complex MVO. The next figure validates the GSS-PO and MVO algorithms under sudden irradiance change. The irradiance changed from 1 000 to 500 and the output power is changed as observed in Fig. 13 and Fig. 14. The two algorithms successfully track the MPP after a sudden change in irradiance. The MPP_{500} from the PV curve is obtained as 14.8757 W. The MVO tracks the MPP at a power of 14.7756 W and the GSS-PO tracks the MPP at 14.87, which gives a tracking efficiency of 99.99%.

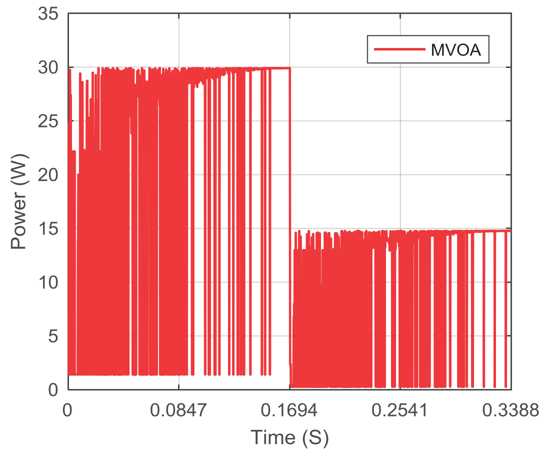

Fig. 13. MVO under irradiance sudden change from 1 KW/m^2 to 0.5 KW/m^2

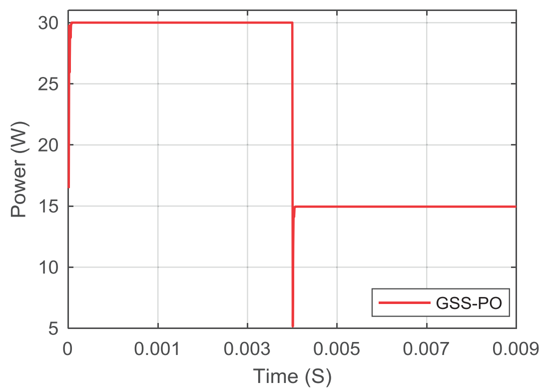

Fig. 14. GSS-PO under irradiance sudden change from 1 KW/m^2 to 0.5 KW/m^2

The study also comprises the CPO algorithm, though it has been covered in many researches before, but this is for comparison purposes. The CPO is widely used because of its ease of implementation and the low implementation costs. Despite, if it is implemented with a small step size, it will suffer from a very high convergence time, but with low oscillations. On the other

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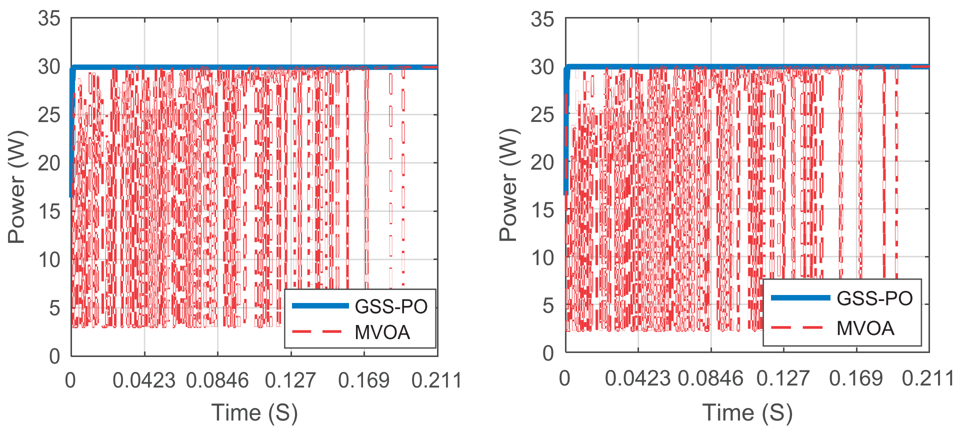
hand, if it is implemented with a high step size, the situation will be inverted (low convergence time and high oscillations). Overall, as observed from the above results, it's obvious that the overall efficiency of the MVO is equal to that of GSS-PO, but GSS-PO algorithm has a lower convergence time. Also, both algorithms have higher efficiency and lower time compared to the CPO. The obtained results where sorted in the following Table 1 to make it clear and simple to read. Table 1 shows a performance comparison of the proposed methods under load variation.

Table 1. Performance comparison

Load resistance (Ohm)	**Maximum power from PV curve (W)**	**Tracking method**	**Maximum power (W)**	**Maximum voltage (V)**	**Maximum current (A)**	**Efficiency (%)**
18	30.0009	CPO	28.8	18.2	1.58	96
		GSS-PO	30.008	18.01	1.66	99.99
		MVO	30.008	18.0	1.66	99.99
28	30.0009	CPO	28.7	18.25	1.57	95.6
		GSS-PO	30.0008	18.01	1.66	99.99
		MVO	30.0008	18.0	1.66	99.99

As observed, the variation between the simulation efficiencies of the GSS-PO and the MVO is almost zero. Also, load variation is used in both simulations, thus it was evaluated that the proposed algorithm successfully tracks the MPP even if the load changes and efficiency is almost the same. The overall performance of the GSS-PO and MVO algorithms is shown in the following figures: Fig. 15(a) and Fig. 15(b), for the first and second test, respectively.



(a) (b)

Fig. 15. MVO, GSS-PO comparison at 18 Ω (a), MVO GSS-PO comparison at 28 Ω (b)

As observed from Fig. 15(a) and Fig. 15(b), the GSS-PO has high efficiency and convergence time. This was achieved due to the fast convergence of the GSS algorithm addition to the tuning that has been accomplished by the PO algorithm. This fusion between the GSS and PO has a very powerful performance under uniform irradiance.

8. Performance discussion

In this section, a full discussion of the proposed GSS-PO and MVO has been provided. In the discussion, different perspectives were taken into consideration such as algorithm complexity, execution time, ranking, advantages, and disadvantages.

Computational complexity of any algorithm can be measured using different methods. One of these methods is the big O. In optimization algorithms, the big O is used to clarify algorithms according to how their running time or space requirements grow as the input size grows. In this section complexity for the proposed GSS-PO and MVO will be discussed.

8.1. GSS-PO complexity

Starting with an interval of length l, to reach an interval with length $\leq \varepsilon$, we need n iterations. Where ε is the algorithm's accuracy. Then we have:

$$n \log(1-\rho) \leq \log\left(\frac{\varepsilon}{l}\right),$$

where

$$\frac{\rho}{1-\rho} = 0.618.$$

So we can write the expression as follows:

$$n \log\left(\frac{1}{1-\rho}\right) \geq \log\left(\frac{l}{\varepsilon}\right).$$

From the above expression we can see that

$$n = \mathrm{O}\left(\log\left(\frac{1}{\varepsilon}\right)\right). \tag{4}$$

Thus from Eq. (4), it's clear that the GSS-PO time complexity depends on the number of iterations, which depends on the accuracy of the algorithm only, that makes the execution time low compared to other algorithms like the MVO, which is discussed in the following sub-section.

8.2. MVO complexity

MVO complexity can be obtained as mentioned in [21]. The computational complexity of the MVO depends on the number of iterations, number of universes, roulette wheel mechanism, and sorting mechanism. Therefore, the overall time complexity is:

$$\mathrm{O}\,(\mathrm{MVO}) = \mathrm{O}\left(l\left(n^2 + n \times d \times \log(n)\right)\right), \tag{5}$$

where n is the number of universes, l is the maximum number of iterations, and d is the number of objects (for MPPT $d = 1$). It is observed that MVO complexity depends on the number of universes and the number of iterations, so when these two numbers are large, the complexity increases and the execution time increases. Table 2 shows the effect of the increased number of universes on the execution time and the variation in accuracy effect on the execution time of the GSS-PO. The execution time is calculated using MATLAB. The iteration number is 500 for all trials to insure a fair comparison.

Table 2. Execution time comparison

Universes number (n)	**Execution time of MVO**	**Accuracy ε**	**Execution time of GSS-PO**
2	0.2167 S	0.2	0.0166 S
4	0.2590 S	0.1	0.0201 S
16	0.3901 S	0.05	0.0264 S
32	0.5269 S	0.025	0.0312 S

It's obvious that GSS-PO is much faster than MVO. In addition to that GSS-PO reaches 95% of the MPP in just a little number of iterations and then maintains the MPP.

8.3. Algorithm ranking

As stated in [22]. The absolute rating of the MPPT is calculated from the weighted mean formula as shown in the following equation.

$$\text{Ranking}_{\text{Uniform irradiance}} = (1 \times AC) + (1 \times HS) + (2 \times TS) + (2 \times SSE)/6. \tag{6}$$

Thus, as the PV system used in simulations works under uniform irradiance, Eq. (6) will be used, where *AC* is the algorithm complexity, *HS* is the hardware implementation, *TS* is the tracking speed, and *SSE* is the steady state efficiency of uniform irradiance only. Then, the rating of the proposed algorithm under the PS conditions can be calculated as follows:

$$\text{Ranking}_{\text{GSS-PO}} = (1 \times 2) + (1 \times 1) + (2 \times 1) + (2 \times 1)/6 = 1.33,$$
$$\text{Ranking}_{\text{MVO}} = (1 \times 4) + (1 \times 1) + (2 \times 3) + (2 \times 1)/6 = 2.16.$$

The overall rating of the GSS-PO is lower than that of the MVO. A lower ranking is better, which is a proof on the simplicity, accuracy and faster converging speed of the algorithm under uniform irradiance.

8.4. Advantages and disadvantages of GSS-PO

As observed from the above results it's obvious that the GSS-PO exhibits superior performance although it has some limitations and drawbacks like oscillations in the steady state period, even if it's very small due to the small step size of the PO. Moreover, it has not been tested under partial shading conditions as the MVO which will work for both uniform and partial shading conditions.

In addition, the main advantage of the fusion between the GSS and PO is that the PO will make the algorithm immune against the small changes in the PV system power, as it will track it and refine the output of the system to its maximum due to its small step size, and because the GSS-PO will not be reset until steady state power deviates more than ε (if irradiance or temperature changes). Also, the PO refines the MPP tracking as we choose an accuracy of $\varepsilon = 5\%$ for the GSS algorithm to have a rapid tracking. In other words, the GSS rapidly track the MPP region within 5% accuracy, then the PO refines the MPP tracking within the 5% interval. The GSS-PO will also be suitable for hardware implementation because of the low computational complexity and low requirements. A comparative study is shown in Table 3.

Table 3. Qualitative comparison between algorithms

Parameter	MVO	GSS-PO	CPO
Steady-state oscillation	Zero	Very low	Step size dependant
Tracking speed	Fast	Very fast	Slow
Computational complexity	High	Low	Low
Rank	High	Very low	Low
Execution time	Low	Very low	High
Efficiency	High	High	Less

8.5. Statistical analysis

The statistical performance analysis of GSS-PO and MVO MPPT algorithms is done by performing 50 trail runs for each algorithm. The 50 trails done on two irradiances to ensure a precise statistical analysis for each algorithm. In Table 4 it is observed that the proposed algorithm has a higher mean value of the power over the MVO algorithm.

Table 4. Statistical analysis of proposed algorithms

Irradiance (W/m^2)	Algorithm	Mean power value (W)	Standard deviation (W)	Max. power of PV panel (W)
1 000	GSS-PO	30.0005	30.00041	30.0009
	MVO	30.00045	30.00037	30.0009
500	GSS-PO	14.865	14.81	14.875
	MVO	14.792	14.77	14.875

From the 50 trials, it is observed that the GSS-PO doesn't have a large deviation because the GSS doesn't rely on randomization of the first population, as in the MVO. The GSS only rely on the golden ration, which is fixed. So the GSS-PO is much more accurate and has a very low standard deviation and a larger mean value than that of the MVO.

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9. Conclusion

This paper presents a novel GSS-PO hybrid method for MPPT. The accuracy of the proposed GSS-PO is assessed by a simulation study on a PV system. Comparative studies of the GSS-PO with a nature-inspired MVO technique to envisage that the proposed GSS-PO exhibits superior performance such as high tracking speed and faster convergence towards the MPP. The GSS-PO also has very low oscillations that almost don't affect the power. Comparative results are shown to illustrate the main difference between the GSS-PO and MVO on convergence MPP tracking efficiency. Thus, it could be confirmed that the proposed hybrid MPPT algorithm presents superior performance related to higher tracking speed, faster convergence towards the MPP, superior efficiency compared to other algorithms and lower oscillations at the MPP.

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