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HYBRID METAHEURISTIC ALGORITHMS MPPT UNDER PARTIAL SHADING CONDITION

Hayder **A**hmad **H**amad*, **H**anan **M**ikhael **D**. Habbi**, **A**faneen **A**nswer **a**bbood***
*College of Engineering, Salahddin University-Erbil, Kurdistan Region - Iraq
**College of Engineering, University of Baghdad, Baghdad- Iraq
***Dept. of Communication Engineering, College of Technology, Baghdad-Iraq

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ABSTRACT

This paper investigates the effectiveness of a hybrid metaheuristic optimization approach to achieving the maximum power from PV solar systems under partial shading. Stochastic metaheuristic optimization is utilized to guarantee the identification of optimal solutions within constrained timeframes. The proposed algorithms combine the Firefly Optimization Algorithm (FOA) and Salp Swarm Algorithm (SSA). Metaheuristic optimization proves advantageous due to its ability to tackle complex problems regardless of their structure. In this paper, settling time, speed convergence overshoot, and efficiency are considered under different values of irradiance. The sample time is carefully chosen to reach the optimal tracking time, making dynamic optimization the selected approach. The incorporation of FOA harnesses the search capability of SSA, leading to power outputs that closely align with those of the PV system. The utilization of SSA simplifies optimization complexity by utilizing a single control parameter. Additionally, the integration of FOA enhances the search capability of SSA, resulting in power outputs closely aligned with the PV system. A dc-dc boost converter is employed to achieve the desired output dc voltage. Matlab/Simulink is used to simulate the proposed system. The simulation results demonstrate satisfactory performance and the ability to achieve optimal Maximum Power Point (MPP) under partial shading conditions.

KEYWORDS: Heuristic optimization; salp swarm algorithm; firefly optimization algorithm; maximum power point tracking; PV solar

1. INTRODUCTION

Despite the advantages of renewable energy sources, which are friendly environments, there are some problems that are required to search on (Kumar et al., n.d.; Rigatos, n.d.). These problems are related to the weather conditions of renewable generating sources. One challenge is obtaining the maximum power from renewable energy sources (Abdul Hussain & Habbi, 2018; Kulkarni* & Deshmukh, 2019). This optimization process involves considering factors such as the amount of sunlight or wind available, partial shading conditions, and other relevant parameters that influence power production. By exploring and understanding these factors, researchers can devise strategies to improve power extraction from renewable sources.

Furthermore, achieving maximum power from renewable energy systems has implications for both grid-connected and off-grid applications. For grid-connected systems, it enables a more reliable and stable integration of renewable energy into the existing power grid. In off-grid scenarios, it enhances the autonomy and self-sufficiency of energy systems, reducing the dependence on non-renewable energy sources.

As renewable energy systems, such as solar and wind, rely on variable and intermittent sources, it becomes crucial to devise effective strategies to ensure the maximum utilization of these resources. The objective is to extract the highest possible power output under diverse environmental conditions. This optimization process requires the development of efficient algorithms and techniques to overcome the limitations imposed by weather conditions.

The maximum power tracking from the PV solar system under partial shading is presented (Aguila-Leon et al., 2023; Lyden & Haque, 2016; Millah et al., 2021, 2022). The researchers have utilized various algorithms to calculate the maximum power (Dutta & Gupta, 2022; Isknan et al., 2023). Some of these methods which are the traditional methods are dependent on constant parameters such as perturb and observe method (Bhattacharyya et al., 2021; Swaminathan et al.,

hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq

2022), incremental inductance method (Bhattacharyya et al., 2021), and model predictive control (Elzein & Petrenko, 2017). Other methods use artificial intelligence algorithms such as neural networks (Singh et al., 2022), fuzzy control(Zhong, 2022), evolutionary algorithms, and machine learning (Zhong, 2022).

Recently, approximate solutions inspired by natural processes have been utilized to get maximum power such as Grasshopper optimization (Jumani et al., 2018), ant colony optimization (Kreishan & Zobaa, 2022), and so on. A hybrid optimization algorithm is developed to calculate the maximum power from the PV solar system (Elzein & Petrenko, 2017; Pervez et al., 2022; Sher et al., 2015; Singh et al., 2022). These optimization algorithms are the Salp Optimization Algorithm (SOA)(Isknan et al., 2023; Pervez et al., 2022), and the Firefly Optimization Algorithm (FOA) (Ranjitha et al., 2021). The FAO is used to store energy fron renewable energy sources regarding the energy demand, and this will lead to balancing the power system requirements.

The PV cell's characteristics have nonlinear electrical performance; therefore, it should adopt a guarantee of accuracy to consider the nonlinear system. Taking into consideration choose an algorithm that does not require excessive mathematical calculation and is easy to implement and fast response. SOA and FOA are capable to implement independently of the system parameters (Mansoor et al., 2020).

In certain daytime scenarios, the surface solar panel may be obstructed by external factors, resulting in a decrease in the power generated by the solar cells. This paper considers two cases: the variation of irradiance and partial shading conditions. The simulation results are validated using Matlab/Simulink. The duty cycle, current, voltage, and power from the PV system are illustrated to identify important features such as settling time, convergence speed, and PV efficiency.

2. METHODOLOGY

2.1 Salp Swarm Algorithm (SSA)

Swarming is the most interesting behavior of the salps. Salps achieved a good movement using rapid coordinated changes and it can divide as a leader and followers. Initially, a set of random solutions are formed into two stages exploring and exploiting to explore the search space and exploiting the neighborhood respectively. The updating position for the salp swarms equation is given as:

$$X_j^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases} \tag{1}$$

Where X_j and Fj indicate the positions of the leader and the feeding sources in jth respectively. ubj and lbj denote the upper and lower bounds, and c_2 and c_3 are the random floats between [0,1].

$$c_1 = 2e^{-(\frac{4l}{L})^2} \tag{2}$$

c_1 is the effective parameter in SSA to balance the exploration and exploitation and L represents the maximum number of iterations. This parameter assists the algorithm to axplore thesearch space at the beginning and exploits it at the final space.

The SSA results would depend on the its parameters such as threshold, scale, rate level, and salp backoff. The updated position for the follower's equation is given as:

$$X_j^i(t+1) = \frac{X_j^i(t) + X_j^i(t)}{2}, i = 2, \ldots, N \tag{3}$$

The main merits of the SSA are that it cannot be wiped out even if the entire population deteriorates, and the salp leader often explores and exploits the better space. Moreover, there is a gradual movement for the salp depending on the leading position. The flow chart of the SSA is shown in Fig. 1.

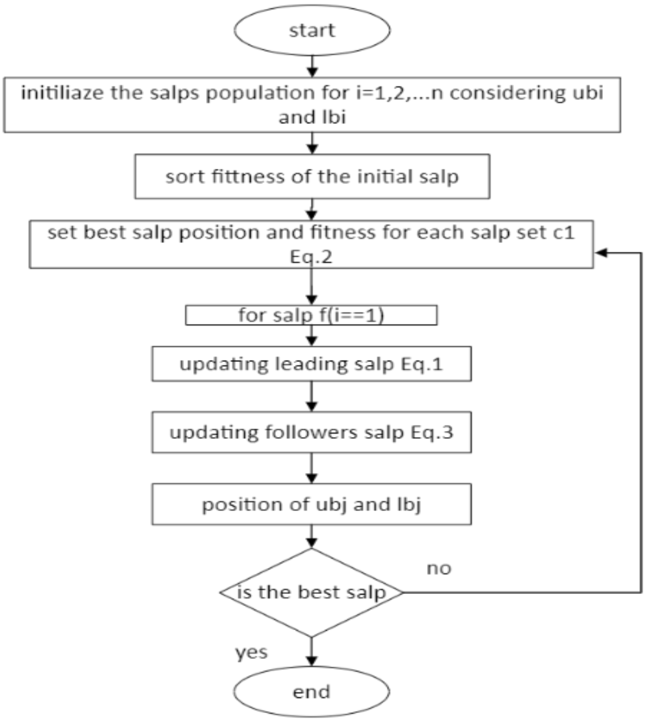

Fig.(1):- SOA flow chart

2.2 Firefly Optimization Algorithm (FOA)

The FOA flow chart is shown in Figure 2(b). The main feature of the FOA is that the firefly moves toward the attractive firefly. The distance between firefly increases whenever the attractiveness decreases. Therefore, the firefly at X_i moves to X_j when the firfly located at X_j is more attractive than a firefly at X_i. the update firefly position is given in Eq.4.

$$X_i^{t+1} = X_i^t + \beta_o e^{-\gamma r_{rj}^2}\left(X_j^t - X_i^t\right) + \alpha_t \epsilon_i^t \quad (4)$$

X_i^t *is the p* osition of the firefly is $\beta_o e^{-\gamma r_{rj}^2}\left(X_j^t - X_i^t\right)$ *is the* attractiveness at position j, and $\alpha_t \epsilon_i^t$ is Levy distribution, $\epsilon_i^t = rand - 1/2$. In this paper, the FA parameters were taken as: β_o =2*rand, $\alpha \in [0,1]$ $\gamma =$ 1/S^2 ,$\gamma \in [0, \infty]$ $\gamma = 0.2 * 0.95^{iter}$ and the maximum iterations is 100. Since the parameters of FAO can be adjusted such as the attraction β which addresses the strength of attraction between fireflies. Whenever the attraction is increased the β will be higher. The absorbation parameter γ is controlled the rate of absorption of light, therefore when this papaerter increased then the light intensity reduced rapidly (Ewees et al., 2021; Satapathy et al., 2016).

The random value α represents the amount of randomization in the firefly's movement, with the randomness reduced when a lower value of α is used. The main factor in FAO is the population, which affects the optimization convergence. Therefore, in this paper, a population of 5 is chosen.

hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq

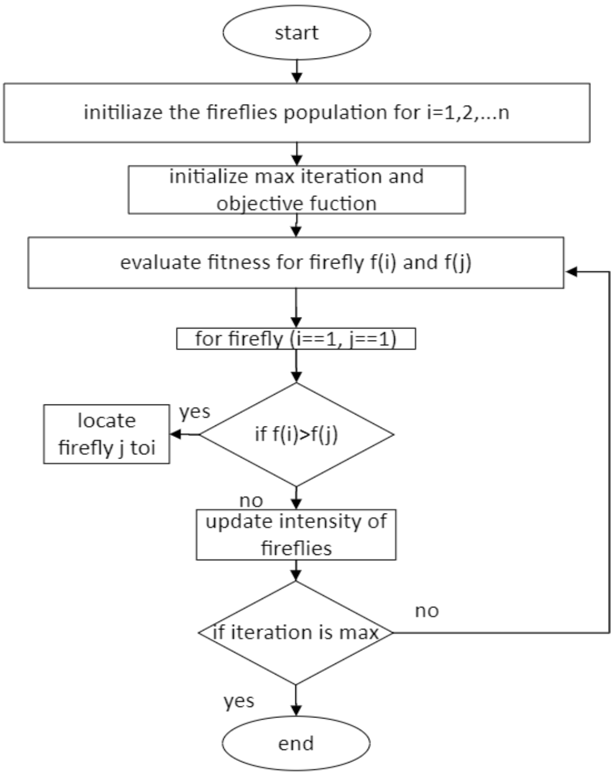

Fig.(2):- FOA flow chart

2.3 Proposed Method

The proposed method is a hybrid Heuresitic optimization of SSA and FOA as expressed:

- determine the parameters of SSA and FOA
- set the fitness function (smallest C_{max})
- calculate $X_i^t, i = 1,2, \ldots N$
- select the best X_i^t
- calculate the probability value $= fit_i / \sum_{k=1}^{N} fit_k$
- if the probability >0.5 then start FA
- elsewhere update X_i^t

3. Boost DC-DC converter Model Based MPPT

The equivalent circuit of the PV cell is shown in Figure 3.

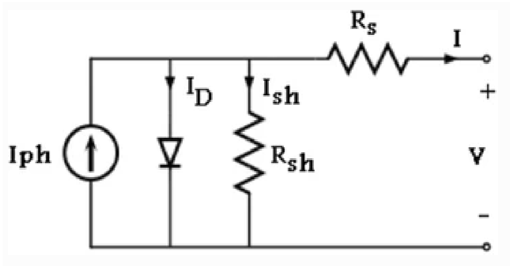

Fig.(3):- PV cell equivalent circuit

The mathematical equations are given as,

$$I_o = I_{sh}/[\exp\left(\frac{qV_T}{N_s knT}\right) - 1 \quad (5)$$

$$I_{sh} = \frac{V \times {}^{N_p}/_{N_s} + IR_s}{R_{sh}} \quad (6)$$

Where R_{sh} is the shunt resistance, R_s is the series resistance, i_D is the diode current and i_{ph} is the photocurrent of the PV cell. The Matlab/ Simulink model for the boost converter is shown in Fig. 4 with MPPT algorithm. MPPT algorithms Efficiency is calculated by Eq.7.

$$\eta_{MPPT} = \frac{\int_0^t P_{PVmax}(t)dt}{\int_0^t P_{PVMPPT}(t)dt} \quad (7)$$

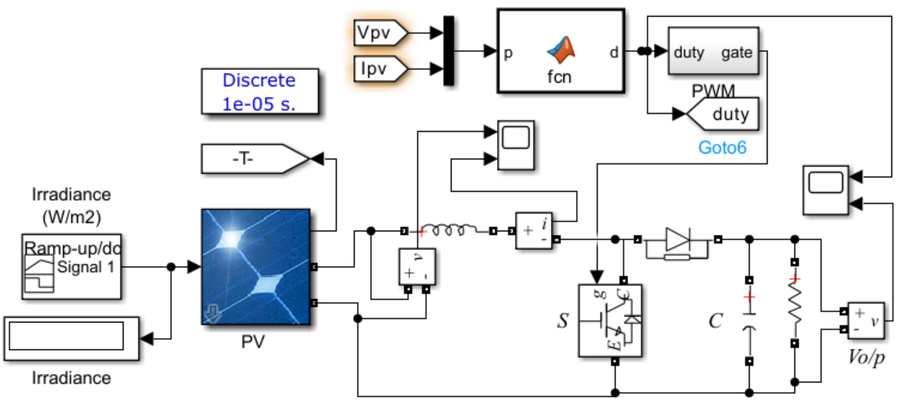

Fig.(5):- Matlab/Simulink Boost converter with proposed MPPT

hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq

4. RESULTS AND DISCUSSION

The tested PV is Suntech STP270S-24_Vb with 5 series connected modules per string and 66 parallel strings. The PV specification is given in Table 1. The boost parameters are given in Table 2. There are two cases have been considered in this paper to validate the performance of the proposed MPPT. Case 1: when the irradiance is maintained constant 1000W/m^2 then it changed to 500W/m^2 at t=0.5s. Case 2: when the irradiance is maintained constant 1000W/m^2 from 0 to 0.4s then it changed to 800W/m^2 then at t=0.6s is changed back to 1000W/m^2. The sampling time is 0.2ms

Fig. 5 shows the I/V and P/V characteriestics under different irradiance of the tested PV.

Table(1):- PV specifications

parameter	Value
Open circuit voltage	44.499V
Short circuit current	8.1998A
Voltage at maximum power point	35V
Current at maximum power point	7.709A
Temperature coefficient of Voc	-0.1504V/C°

Table(2):- Boost parameters

parameter	Value
Inductor	5mH
Capacitor	0.012F
Switching frequency	5kHz

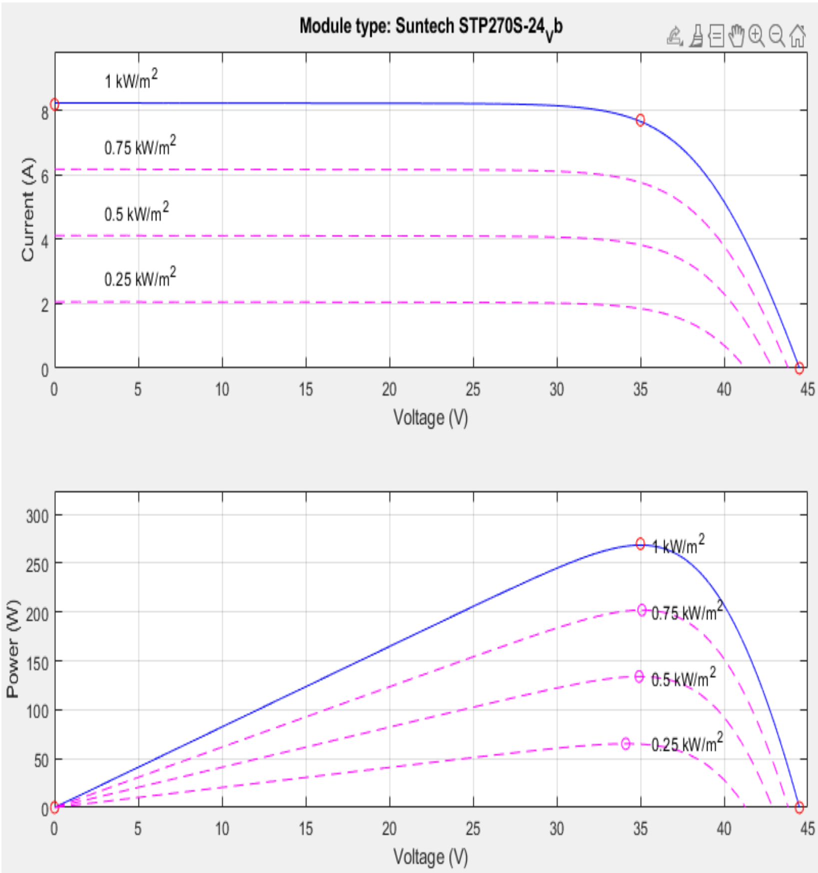

Fig.(5):- I/V and P/V characteriestics under different irradiance

hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq

Case 1: iraadiance varied 1000W/m^2 at t=0.5s to 500W/m^2

Fig. 6 shows the irradiance variation. The simulation results in this case are illustrated in Fig. 7. It can be shown the duty cycle response (Fig.7 a). the duty cycle has a global maximum when the irradiance is changed then the duty cycle is reduced according to the irradiance value. The current of the PV is affected by the variation of the irradiance therefore it is cleared to observe the overshoot as shown in Fig.7b. As well as the voltage of the PV system has a quite small oscillation as shown in Fig.7c. While the power respeonse from the PV has an oscillation during the irradince variation but it clears from Fig. 7 d that the maximum power can be obtained from the proposed optimization. In conclusion the system has a good dynamic optimization response.

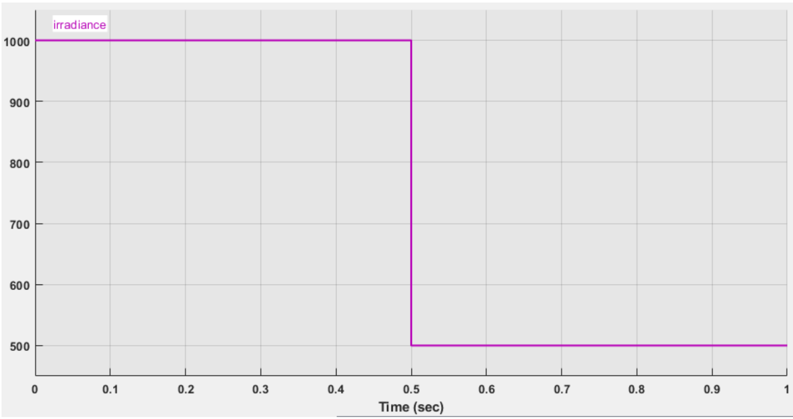

Fig.(6):- Irradiance variation (case 1)

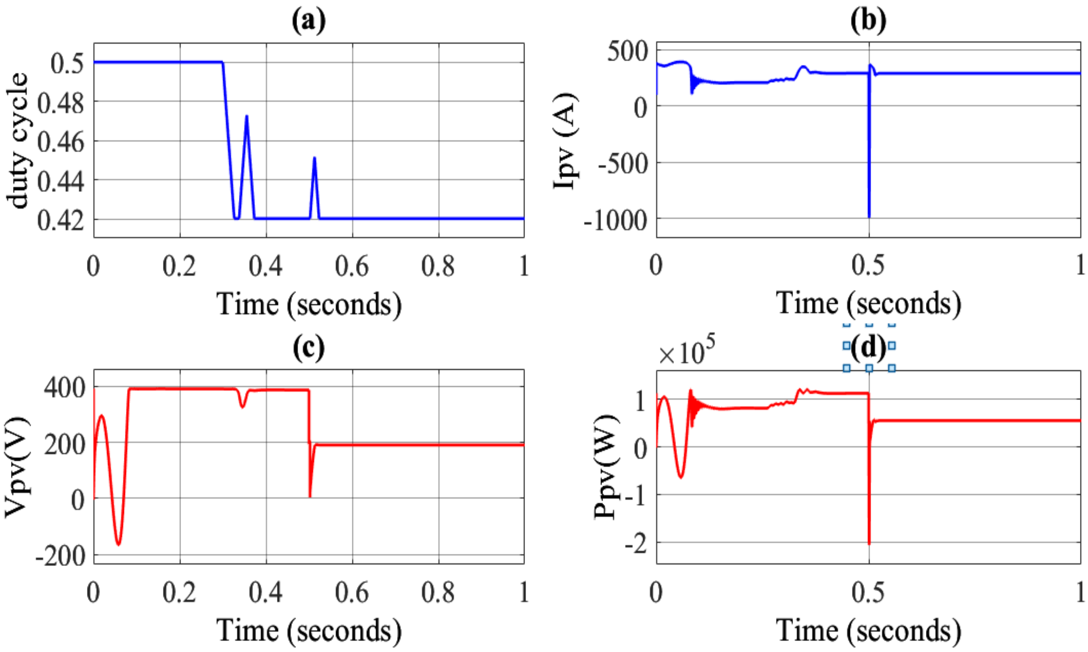

Fig.(7):- MPPT response for case 1 (a) duty cycle (b) Ipv , (c) Vpv and (d) Ppv

hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq

Case 2: iraadiance varied 1000W/m^2 at t=0.4s to 800W/m^2 then to 1000W/m^2 at t=0.6s

Fig. 8 shows the irradiance variation under partial condition. The simulation results in this case are illustrated in Fig. 9. It can be shown that the duty cycle response (Fig.9 a) has a global maximum when the irradiance is changed. The current of the PV is affected by the variation of the irradiance therefore it is cleared to observe the overshoot as shown in Fig. 9b. As well as the voltage of the PV system has a quite small oscillation as shown in Fig.9c and the Vpv is dropped when the irradiance value reduced. While the power respeonse from the PV has an oscillation during the irradince variation but it clears from Fig. 9 d that the maximum power can be obtained from the proposed optimization. The system has a good settling time and minimal overshoot. In addition, the iteration for FOA is selected to be 10.

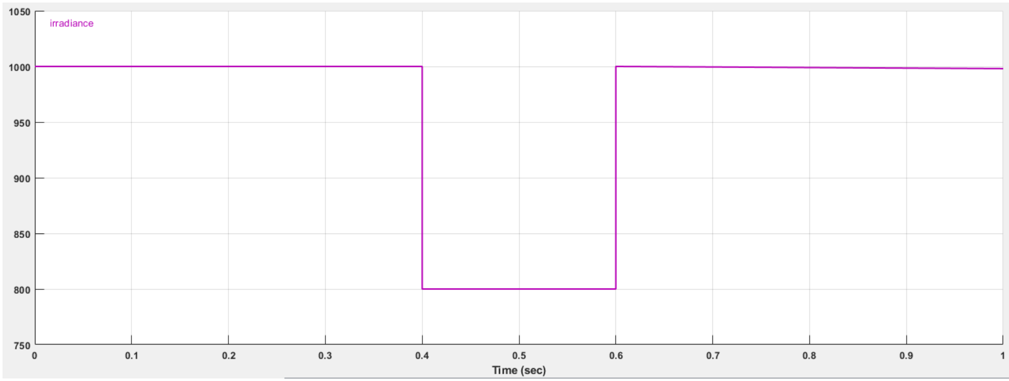

Fig.(8):- Irradiance variation (case 2)

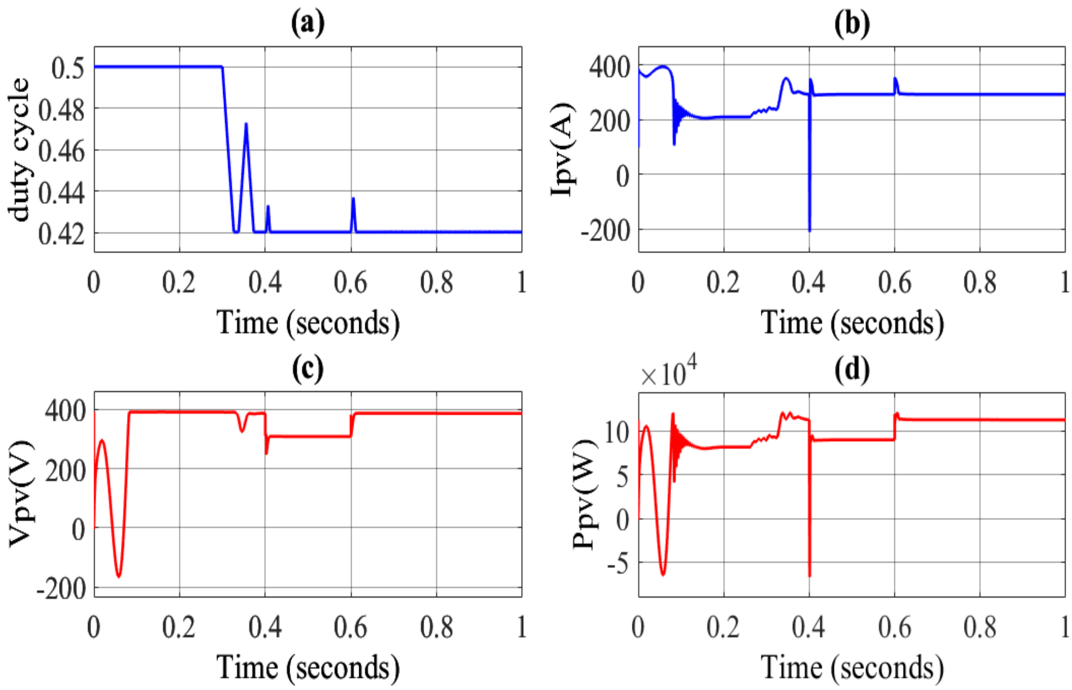

Fig.(9):- MPPT response for case 1 (a) duty cycle (b) Ipv , (c) Vpv and (d) Ppv

The comparison simulation results for the hybrid FOA and SSA are tabulated in Table 3. The table presents information on various performance results for a SSA with FOA. It includes settling time, overshoot, convergence speed, and pptimization efficiency percentage. According to the table, the settling time for the SSA with FOA method is 0.2 seconds. Settling time refers to the time it takes for a

hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq

system's response to reach and remain within a certain range of its final value. In this case, a settling time of 0.2 seconds indicates that the system reaches a stable state relatively quickly. The overshoot is described as "low" in the table. Overshoot refers to the extent by which a system's response exceeds its final desired value before reaching stability. A low overshoot indicates that the SSA with FOA method exhibits minimal deviation from the desired outcome. The convergence speed is listed as "moderate." Convergence speed refers to how quickly a system reaches a stable state or an optimal solution. A moderate convergence speed suggests that the SSA with FOA method achieves stability within a reasonable time frame.

Lastly, the optimization efficiency percentage is stated as 92%. Optimization efficiency reflects the effectiveness of the method in finding the best or most optimal solution. A higher efficiency percentage indicates that the SSA with FOA method is successful in achieving optimized results.

Table (3):- Simulation results

Method	Settling time (s)	Overshoot	Convergence speed	Optimization efficiency%
SSA + FOA	0.2	Low	Moderate	92

5. CONCLUSION

This paper has demonstrated the effectiveness of metaheuristic optimization, particularly the hybridization of Salp Swarm Algorithm (SSA) and Firefly Optimization Algorithm (FOA), in addressing the challenge of maximizing power output from renewable energy systems. The main advantage of metaheuristic optimization is its ability to solve complex problems regardless of the problem's structure. By combining SSA and FOA, the hybrid optimization approach achieves a minimum settling time error and demonstrates a high efficiency of up to 92%. The utilization of SSA reduces the optimization complexity by relying on a single control parameter, c1. The incorporation of FOA further enhances the search ability of SSA, resulting in power outputs that closely match those of the PV system.

However, it is important to note that the hybrid power optimization response may exhibit oscillations during partial shading conditions. To address this issue, future research could explore the implementation of an adaptive Maximum Power Point Tracking (MPPT) parameter. This adaptive approach could help mitigate the oscillations and further improve the performance of the hybrid optimization method.

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hayder.hamad@su.edu.krd
,hananhabbi@coeng.uobaghdad.edu.iq
afaneen.a.abbood@uotechnology.edu.iq