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Rat Swarm Versus Particle Swarm Intelligent Optimization Algorithms for Maximum Power Point Tracking in Designing Energy-Efficient Solar Systems

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***Abstract* — Recently, Photovoltaic (PV) devices generate electricity directly from sunlight, so their integration into urban infrastructure will not only generate energy but also reduce carbon emissions. Due to those advantages, solar energy plays a crucial role in developing smart cities. However, the efficiency of PV systems is heavily dependent on their ability to operate at the Maximum Power Point (MPP), which represents the bias potential at which the solar cell outputs the maximum net power. This paper employs an intelligent optimization algorithm, RAT Swarm, to find the optimal voltage the PV system can operate to produce maximum power. MATLAB software is used to model and simulate the system using the Rate Swarm algorithm. The simulation results show that the RAT based MPPT has been capable of achieving the capability to precisely track the maximum power point and to maximize the power output of the PV system. Furthermore, the same software is employed to implement and simulate the well-known particle swarm optimization algorithm for comparison. Convergence speed, trading accuracy as well as the stability of power, voltage and current under both uniform and time varying irradiance conditions are also considered in the comparison. Comparative evaluation indicates that RSO is a viable option for PSO owing to faster convergence. Nevertheless, the stability of RSO and the absence of an oscillation in the power output have to be investigated. These improvements would enable RSO to become optimally effective, achieving fast convergence and stable output power for energy capture from PV systems.**

Keywords—MPPT, Intelligent Optimization Algorithms, Rat Swarm Optimization, PV System, Clean Energy

I. INTRODUCTION

Solar energy has been extensively used in many applications including smart homes, electric cars, as well as power electronic devices because solar energy is clean and the most abundant renewable energy source [1]. That is, one major challenge is to extract maximum power from PV systems to increase efficiency. However, the MPP voltage can be drifty with various variables, including temperature, irradiance intensity, and degradation. A technique known as maximum power point tracking (MPPT) achieves the maximum power that the PV module will provide by adjusting the operating point to the Values (MPP) [1, 2]. Solar power system performance is optimized using several MPPT algorithms. It has been shown, that traditional MPPT methods such as the Constant Voltage method, Perturb and Observe (P&O), Incremental Conductance (IncCond), Fractional open-circuit voltage (FOCV) and Fractional short-circuit current (FSCC), are widely used. Efficiency and consideration of the variable environmental conditions in the finished structure has been increased with development of advanced algorithms such as those based on artificial intelligence and/or optimization techniques.

II. RELATED WORKS

The use of photovoltaic (PV) systems is widespread in many applications. However, several more issues prevent their widespread adoption including the extraction of maximum power. A high output performance of a PV system can be provided via ensuring maximum power output of a PV system. Common methods for maximum power point tracking include Perturb and Observe (P&O), Incremental Conductance (IncCond), Fractional Open-Circuit Voltage (FOCV), and Fractional Short-Circuit Current (FSCC). The Incremental Conductance method identifies the Maximum Power Point (MPP) by equating incremental conductance of PV module to that of its instantaneous conductance [1, 3, 4]. However, this technique is highly effective but relies on delicate and expensive circuits, which constitute a serious drawback [5-7]. The Fractional Open Circuit Voltage (FOCV) method determines the Maximum Power Point (MPP) by multiplying the system's open-circuit voltage by a predefined constant [8, 9, and 10]. Likewise, the Fractional Short Circuit Current (FSCC) approach generates an MPP using a corresponding current-voltage relationship under certain environmental conditions at any one time [11].

Though these standard methods are often used, they typically present performance limitations due to oscillatory performance around the MPP, resulting in a reduction of efficiency and loss of power. In addition, common MPPT techniques suffer to overcome problems ensuing in PV systems under changing environmental conditions. These challenges have been overcome through alternative optimization strategies, with researchers leveraging artificial intelligence (AI) methods, in particular. Examples of these include artificial neural networks (ANN) [12] and fuzzy logic control (FLC) [13-14]. Significant among these is the FLC which is capable of handling nonlinearities and imprecise inputs well and as such despite the lack of a rigorous mathematical model [15]. However, AI based approaches tend to require ample training data, a prior knowledge of the PV system and large memory storage.

During the recent years, BI algorithms have increasingly been used for their ability to closely track the MPP in renewable energy systems. However, algorithms like the Genetic

Algorithm (GA) [16], Differential Evolution (DE) [17] and Adaptive Jaya [18] have been shown to work, although their training can be long, their calculations demanding, and their parameter tuning necessary. Moreover, swarm based optimization methods have been explored extensively, including Gray Wolf Optimization (GWO) [19], Bat Algorithm (BA) [20–21] , Particle Swarm Optimization (PSO) [22–23] , Salp Swarm Optimization (SSO) [24] , Artificial Bee Colony (ABO) [25] , Animal Colony Optimization (ACO) [26] and Grasshopper Optimization (GHO) [27]. Under varying weather and partial shading conditions (PSCs), these approaches are particularly effective. Current research indicates that use of bio-inspired MPPT schemes provides superior efficiency, accuracy, and speed in tracking the MPP. The advantages confer to them a high propensity to handle the dynamic and complex tasks encountered in modern PV systems. The key part of this study is to use a RAT Swarm intelligent optimization algorithm for MPPT in PV systems. Furthermore, Particle Swarm Optimization, which is extensively used due to its simplicity and ease of using, is performed as a performance comparison for the Rat Swarm algorithm results as well. Convergence speed, tracking accuracy, and power, voltage and current waveforms' stability under uniform and time varying irradiance conditions are compared.

III. METHODOLOGY

A. PV System Model

A photovoltaic system is modeled by a single diode model, which has a current source (photocurrent), a diode, and series (and parallel) resistances. The output current (I) of the PV cell is given by [28]:

$$I = I_{ph} - I_s\left(e^{\frac{V+IR_S}{nV_t}} - 1\right) - \frac{V+IR_S}{R_p} \qquad (1)$$

Where V denotes the output voltage, I_{ph} is the photocurrent, n is the diode ideality factor I_s is the reverse saturation current, and V_t represents the thermal voltage. The electrical behavior of a PV cell can be described accurately using this model as shown in Fig. 1. The objective function to optimize PV system's overall power output under both uniform and time-varying irradiation conditions is:

$$maxP_{total} = \max(\textstyle\sum_{i=1}^{N} V_i I_i) \qquad (2)$$

Where P_{total} is the total power output, N is total number of PV modules in the system, $V_i \; and \; I_i$ is the voltage and current of each module.

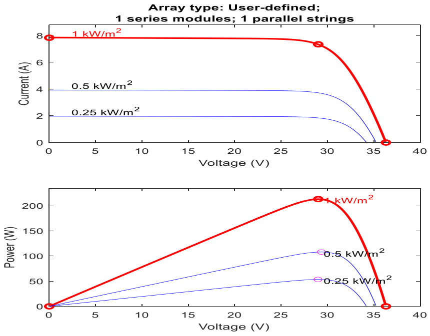

Fig. 1. VI and PV Curve

It is possible to formulate the objective function such that the maximum power output can be achieved, by finding the optimum operating point that gives the maximum sum of $(V_i I_i)$ for each module. The system is able to adapt under uniform irradiance and time varying irradiance over the modules such that their output power changes based on the irradiance level, maximizing efficiency under these conditions. There is a search for the MPP using advanced algorithms like PSO and RSO that adjust their operating voltage and current in each section. Therefore, these algorithms make use of iterative techniques to steer through the complex PV.

IV. IMPLEMENTED OPTIMIZATION ALGORITHMS

A. Rat Swarm Optimization (RSO)

Rat Swarm algorithm proposed by Gaurav in 2020 [29] is a bio inspired optimization based on rat hunting and territorial behaviors. Rats are known for their social intelligence and have been seen chasing, jumping or fighting other rats in order to overpower their prey. The behaviors described provide the basis for the RSO algorithm, an approach to solve global optimization problems in a manner similar to those natural traits. The search space is described, each rat is initialized with a random position inside search space. The location of ith rat at iteration k is computed as shown in Eq. 3:

$$x_i(k) = M_k + rand \times (N_k - M_k) \qquad (3)$$

Where M_k and N_k shows the lower and upper bounds for the rat's position, and rand is a random number between 0 and 1. After the rats are initialized, the fitness of each rat's position is evaluated. This is done by comparing the rat's current position $x_i(k)$ with the best-known position $x_{best}(k)$, which is the position of the best-performing rat in the swarm as in equation 4:

$$F_i(k) = A.x_i(k) + C.(x_{best}(k) - x_i(k)) \qquad (4)$$

Here, A controls exploration by decreasing over time, and C is a random number that influences the movement of the rat. These constants guide the search process, encouraging the rats to discover the search space and exploit the best-known positions.

The equilibrium between exploration and exploitation is controlled by parameter A, which decreases as the algorithm progresses. This decrease in A encourages the rats to shift from exploring the search space to exploiting the best-known positions as per equation 5:

$$A = 2 - \frac{2.k}{MaxIter} \qquad (5)$$

Where k is the present iteration, and MaxIter is total iterations. This allows algorithm to focus on refining the solution as it converges.

In the next step, the rats simulate a combat process to refine their positions. The rats compare their current positions with the best-known position, and their locations are modified based on the fitness function $F_i(k)$. The modified location of the ith rat is given by:

$$x_i(k+1) = |x_{best}(k) + F_i(k)| \qquad (6)$$

Equation (6) allows the rats to move toward the best known position adjusting their positions based on the calculated fitness. The rats are placed in a position and it is repeated for many iterations, and then the position of the rats is refined again and again. As the rats update their locations by watching the best known location, the swarm collectively converge to preeminent solution. The algorithm runs until a stopping state is met, for example, when no more than the maximum allowed iterations, or when there is sufficient convergence. Fig 2 shows the flowchart to explain the working of RSO.

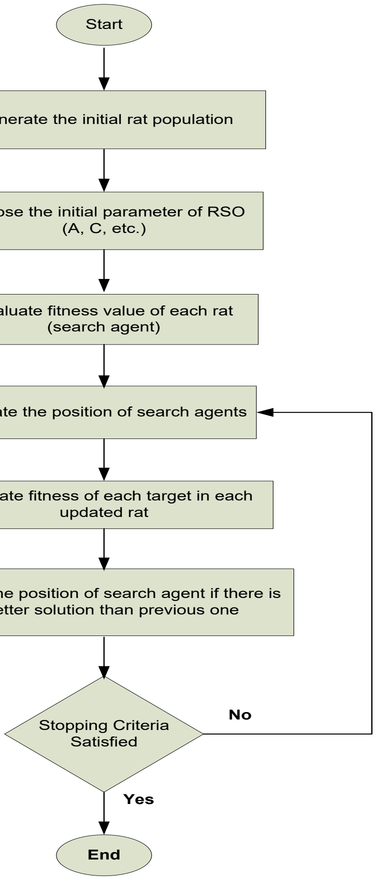

Fig. 2. Flow chart for RSO

B. *Particle Swarm Optimization (PSO)*

Kennedy and Eberhart first suggested PSO as a new swarm intelligence optimization algorithm in 1995 [30], and it has been evolving quickly over the last 20 years. This model is based on how flocks of birds behave. The population, often called the particle, is initialized in this algorithm [31]. In a problem with n dimensions, N particles move through the solution space. The location of the j^{th} particle at i^{th} iteration is indicated by the equation $X_j(t) = (X_{j1}, X_{j2}, \dots \dots, X_{jm})$ and the value of $x_{j,m} \, \varepsilon \, [L_m, U_m]$, $1 \leq m \leq N$, where L_m and U_m refer the lower and upper bound, respectively. The best position found by the j^{th} particle, known as P_{best}, is indicated by the formula$P_j = (P_{j1}, P_{j2}, \dots \dots, P_{jm})$. Ultimately, the swarm's global best position is determined to be global best (G_{best}) and is expressed as follows: $P_g = (P_{g1}, P_{g2}, \dots \dots, P_{gm})$. At iteration i^{th} the velocity vector is $V_j(t) = (V_{j1}, V_{j2}, \dots \dots, V_{jm})$. Finally, as indicated by Eq. 7 and 8, respectively, and as illustrated in Fig. 3, the particle's updated velocity and position variables for the subsequent iteration are determined.

$$V_j(t+1) = w.V_j(t) + r1.C1.\left(P_{best\,j}(t) - x_j(t)\right) + r2.C2.\left(G_{best\,j}(t) - x_j(t)\right), \quad (7)$$

$$x_j(t+1) = x_j(t) + V_j(t), \quad (8)$$

where w is inertia weight, r_1 and r_2 are arbitrary numbers among [0,1] [32], and the parameters C_1 and C_2 are acceleration coefficients. PSO technique provides a number of benefits, such as stability, ease of computation and implementation, and fewer complicated calculations than GA (such as coding/decoding, mutation, and crossover) [33]. The flowchart in Fig. 4 illustrates how PSO operates.

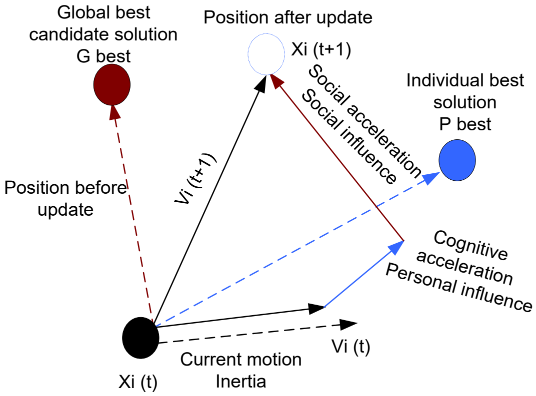

Fig. 3. Particles movement in PSO [34]

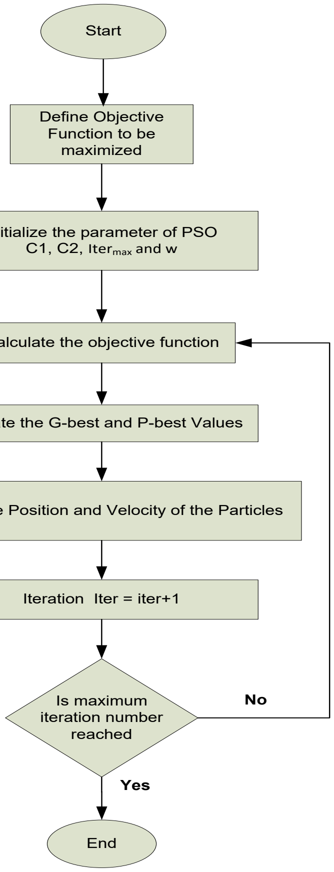

Fig. 4. Flow chart for PSO

V. RESULTS & DISCUSSION

This section evaluates and compare the performance of the Rat Swarm Optimization and Particle Swarm algorithms in achieving MPPT for a photovoltaic, as simulated in MATLAB/Simulink and illustrated in Fig. 5. The comparison focuses on convergence speed, tracking accuracy, and the stability of power, voltage, and current waveforms under both uniform and dynamically changing irradiance conditions. The RSO-based MPPT method, designed to adapt to rapid changes in irradiance, is discussed first, followed by a comparison with the conventional PSO.

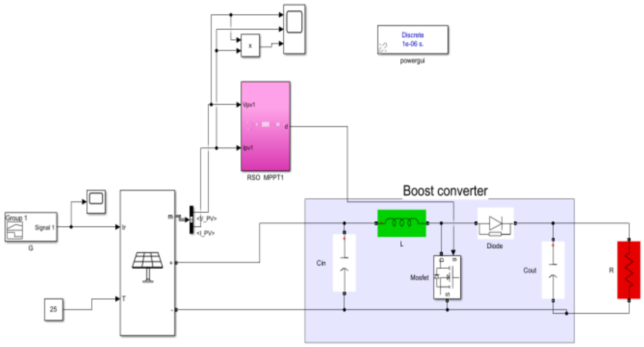

Fig. 5. MPPT based PV System

C. Performance Comparison under Uniform Irradiance

The behavior of PSO and RSO algorithms in tracing the MPPT for PV systems varies for uniform irradiance environments. Figure 7 highlights the superior convergence speed of the RSO-based PV curve to the Maximum Power when contrasted with PSO method. The faster convergence can be attributed to the distinct search mechanism of the RSO, where positions are dynamically adjusted centered on social agonistic performance observed in rats within swarm. Although RSO achieves quicker MPP tracking, it introduces slight oscillations in the power waveform, as seen in Figure 6. This oscillation presents a trade-off: while RSO provides a quicker response, it sacrifices some stability in the waveform smoothness compared to the slower, but more stable PSO response.

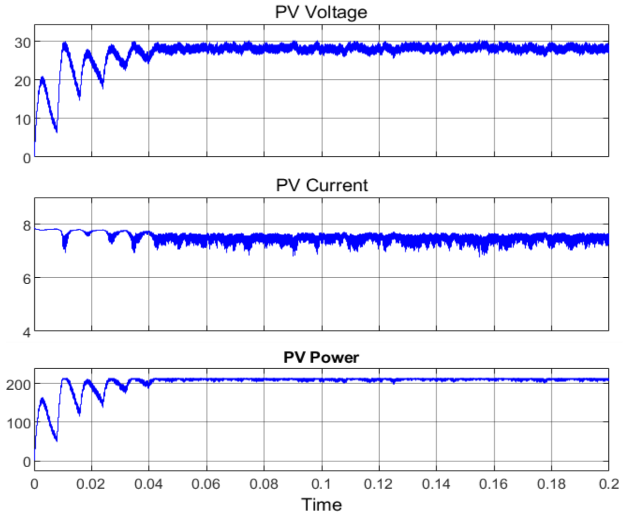

Fig. 6. RSO based Power, Voltage and Current Waveform

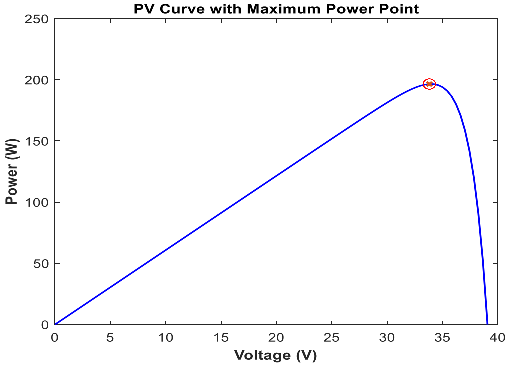

Fig. 7. RSO based PV Curve with MPP

On the other hand, as depicted in Figure 8 the PSO-based PV curve with MPP tracking provides stable power output as shown in Fig. 8 but it requires more iterations to converge to the MPP as shown in Fig. 9. This is primarily due to the influence of random values in the velocity update, which can slow down the convergence rate and lead to potential inefficiencies. When the random values are small, PSO's convergence is slow; conversely, if these values are large, PSO may overshoot the MPP and exhibit delayed convergence.

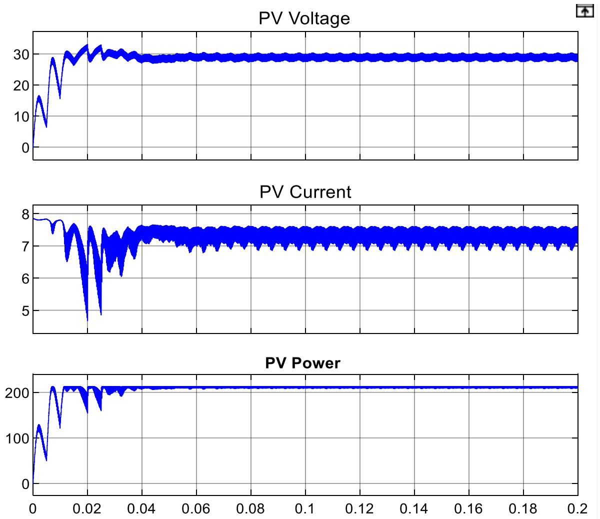

Fig. 8. PSO based Power, Voltage and Current Waveform

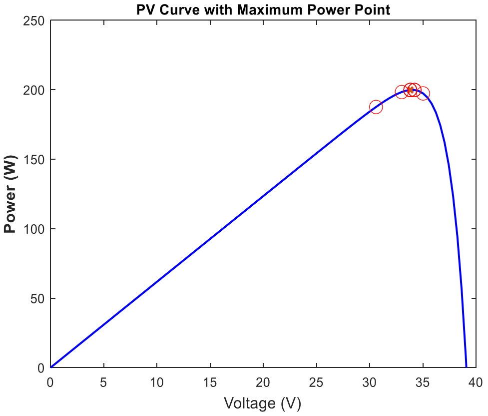

Fig. 9. PSO based PV Curve with MPP

D. *Performance Under Time-Varying Irradiance*

The effectiveness of any MPPT algorithm is significantly influenced by irradiance conditions experienced by the photovoltaic (PV) system. The irradiance curve used in this study is shown in Fig. 10.

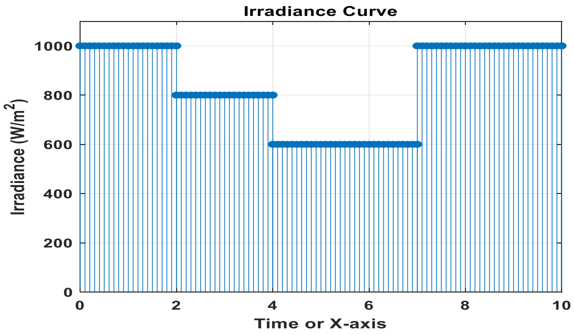

Fig. 10. Irradiance Curve

Both algorithms were further evaluated under time-varying irradiance to observe their adaptive capabilities. In the case of RSO demonstrates enhanced responsiveness under time-varying irradiance, adjusting to irradiance fluctuations with a quicker convergence rate. Figure 11 illustrates how RSO's power, voltage, and current waveforms adjust dynamically to the changing irradiance. However, this swift responsiveness brings about minor oscillations in the waveform, while these oscillations are small they show that RSO sacrifices waveform stability for speed of convergence. It is likely that this feature may need to be improved for applications where waveform stability is critical, but this can be a useful feature in other situations where quick response to changing environmental conditions may be necessary.

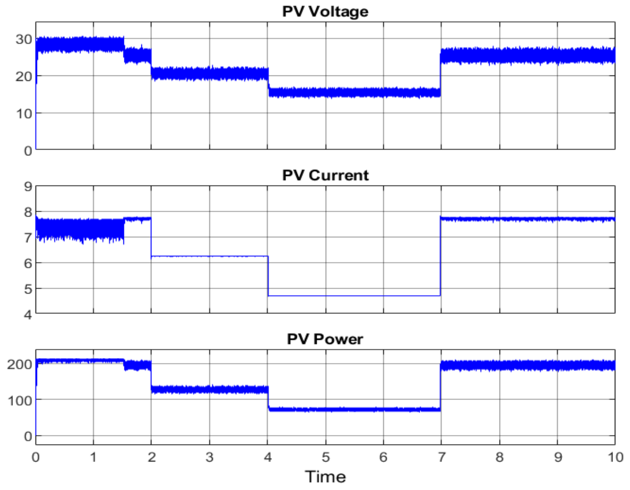

Fig. 11. RSO based Power, Voltage and Current Waveform

In contrast, the PSO method effectively follows the MPP but shows a tendency toward delayed adaptation when the irradiance intensity varies. This is seen in Figure 12, which displays steady but steady PSO-based changes in power, voltage, and current waveforms in response to varying irradiance. This more gradual approach lessens sudden oscillations, but it results in a delayed response to rapid irradiance changes, which could affect power output efficiency overall.

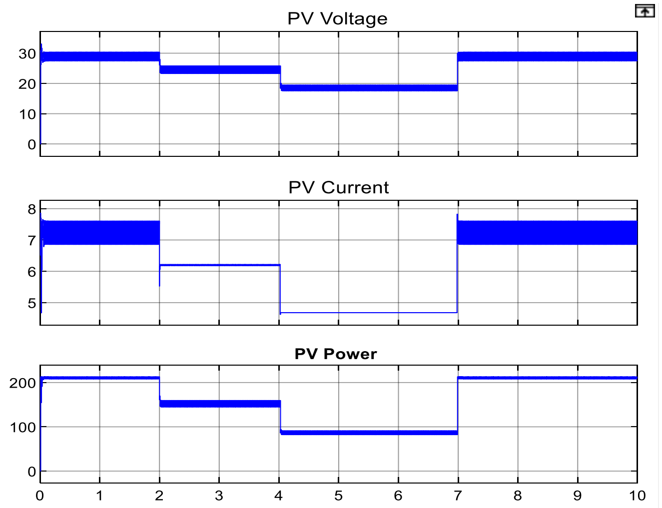

Fig. 12. Power, Voltage and Current Waveform for PSO

E. *Comparative Performance Analysis*

In this study the RSO algorithm is presented as an alternative to the MPPT in PV systems with different advantages when compared to the well-known PSO regarding convergence speed. Fig. 6 demonstrates an optimization of RSO structure and function to track the MPP more quickly with fewer iterations, a desirable feature in applications constrained by fast response times. However, the RSO algorithm's rapid convergence introduces a notable trade-off: Likewise, the power waveform exhibits slight oscillations, which might compromise stability in some applications.

The PSO algorithm is then compared with RSO to contextualize RSO's advantages and challenges. PSO has been proven particularly stable in MPP tracking (as shown in Fig. 8), but has a slower convergence rate. This weakness of the PSO algorithm in its velocity update process has been beneficial for searching for multiple MPPs, but at the expense of delayed convergence. Smaller values of the random are stabilising PSO's progress speed, but potentially loose speed in overshooting the global peak, introducing inefficiency worsens to the process.

Results show the comparative evaluation that RSO is a promising alternative to PSO and that its faster convergence might be a clear advantage when adaptability and fast MPP tracking are required. Nevertheless, improvements to RSO's stability and elimination of oscillations of the power output are suggested. These improvements could make RSO optimally effective, capturing fast convergence and stable output power which are needed for efficient energy capture in PV systems.

VI. CONCLUSION

This paper implements RSO algorithm to find the optimal voltage for extracting maximum power from PV system. MATLAB is used to simulate system with RAT Swarm algorithm. The simulation results highlight the efficacy of the RSO-MPPT in accurately tracing the MPPT and enhancing the PV system's power output. Moreover, the well-known particle swarm optimization algorithm is implemented and simulated using the same software for comparison. Convergence speed and power, voltage, and current waveform stability under uniform and time varying irradiance conditions are compared. Convergence speed, tracking accuracy, power, voltage and current stability under uniform and time varying irradiance conditions is compared. By comparing with RSO, we found that RSO is a splendid alternative to PSO on the ground of fast convergence. Nevertheless, RSO stability improvements and absence of power consumption oscillations require further investigation. If these improvements are made, the RSO could become optimally effective for fast convergence and stable output power required for efficient energy capture in PV systems.

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