

Article

New Gen Controlling Variable Using Dragonfly Algorithm in PV Panel

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Abstract: In the present scenario the depletion of conventional sources causes an energy crisis. The energy crisis causes load demand with respect to electricity. The use of renewable energy sources plays a vital role in reducing the energy crisis and in reduction of CO₂ emission. The use of solar energy is the major source of power in generation as this is the root cause for the development of wind, tides, etc. However, due to climatic condition the availability of PV sources varies from time to time. Hence it is essential to track the maximum source of energy by implementing different types of MPPT algorithms. However, use of MPPT algorithms has the limitation of using the same during partial shadow conditions. The issue of tracking power under partial shadow conditions can be resolved by implementing an intelligent optimization tracking algorithm which involves a computation process. Though many of nature's inspired algorithms were present to address real world problems, Mirjalili developed the dragonfly algorithm to provide a better optimization solution to the issues faced in real-time applications. The proposed concept focuses on the implementation of the dragonfly optimization algorithm to track the maximum power from solar and involves the concept of machine learning, image processing, and data computation.

Keywords: dragonfly optimization algorithm; maximum power tracker; PV panel



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1. Introduction

In the present situation the upcoming problems in the real-time environment is increased compared to the past situation. This led the present researchers to develop more effective solutions by means of optimization technique. The extensive search of these optimization techniques led the researcher to develop sustained solution by understanding the natural characteristics of swarms in nature. Many algorithms were developed by many of the researchers by understanding the characteristics, behaviors, reactions, and properties of swarms in nature. The upcoming research in the real world applications is the use of methodologies inspired by nature. The use of methodologies needs intelligence in computational techniques to solve complex problems. The ICT (intelligence in computational techniques) involves ANN (artificial neural network), FLS (fuzzy logic system), and MLA (multi-layer algorithm). The ICT addresses the real-time application issues that involve discrete or continuous time problems or combination of both. The recent trend in computational process is the use of SI (swarm intelligence) and the algorithms developed using SI attracted many researchers to develop solutions for complex

engineering real-time problems. The methodology is used to ensure the solutions in SIA are fast, robust, and flexible [1]. The biological sensing network and the concept of neural system is the great motivation in developing the SI based algorithm and each of these types of algorithm, resembles the natural behavior of animals and swarms. Among different types algorithm framed by SI (swarm intelligence), PSO (particle swarm optimization) proposed by Kennedy and Eberhart is the most popular type. In this, many agents together form a population and each agent in the population interacts with the naturally-framed systems and the environment [2,3]. Marco Dorigo developed a thesis and examined the optimization process using ACO (ant colony optimization) a nature-inspired algorithm [4]. The multi-objective optimization has many issues and the set of issues framed in MOO is a POS (Pareto optimal set), and these sets have better trades in between the objectives. The MOO algorithm is developed and carry forward to obtain the complete solution under the worst and best conditions of the current POS. The solution to POS is obtained by means of iteration and the probability of each set of iteration is utilized for process selection [5]. Power can be generated either by using conventional/non-conventional sources. The use of conventional sources for generation increases CO₂ emission and the depletion of conventional sources causes an energy crisis.

To avoid the energy crisis and to reduce the effect of CO₂ emission NCES (non-conventional energy sources) is utilized for power generation. Solar is the main source of NCES as it is the main root source for the development of wind and tides. The use of solar for power generation varies from time to time due to the variation in ecological conditions. Therefore, maximum power has to be absorbed from the available source. This is done by using a smart tracking technique. Among the available different tracking techniques the P and O MPPT (maximum power point tracker) tracker is highly efficient. For varying irradiance variable P and O MPPT is discussed in [6] to track maximum energy. The variable P and O comprises of an amalgamation of current and adaptive perturbation control techniques. The adaptive technique implied in MPPT fix the operating point in terms of PV source operating current and irradiance to validate the performance and stability under dynamic conditions. The genetic technique is implied in the MPP-P and O algorithm to trace the power under different ecological conditions and partial shadow conditions [7]. Hadeed Ahmed Sher proposed the tracking technique, which implies the combination of a short circuit method and a conventional P and O technology, named as fractional MPP with P and O and short-circuit current algorithm. In this the PV source short circuit current is taken as a reference to fix the operating point and, later, it is followed by the conventional P and O MPP [8]. The V-I and P-V characteristics of PV is non-monotonic. During the complete 24 h in a day there are many local points to trace the maximum power. A novel technique is proposed to search the point of maximum energy in the overall distribution of power. PSO is one such technique to develop this novel overall distribution algorithm [9]. The peak point of power available in a day has a multi-objective function. Among these multiple peak-point PSO with P and O is proposed to fix one operating point among the global power points [10].

The recent computational technology implemented in control action involves swarm intelligence. The system performance and its efficiency are affected with the discrete behavior of the swarm particles. In [11] the PSO with swarm particle algorithm is proposed to improve the transformation and crossover operation of the system. The proposed concept in this paper focuses both on single- and multi-objective problems. The PSO algorithm comprises of 'n' dimensional membership variables and each variable has been assigned with its own weight depending on the velocity. In [12] during the process of evolution of each of the individual flies, the solution to the optimization issue is resolved by frequently updating the weight based on the velocity and position. The best optimization solution is obtained in [12] with a uniformly-distributed random vector, 0 and 1. In [13] the non-linearity and the complexity of the problem is addressed with the recent approach of involving the characteristics of swarm particles. This algorithm is proposed as it is flexible and simple to implement. The challenging problems are addressed in this manuscript.

The DA (dragonfly algorithm) is a unique solution for better optimization. The recent technologically-advanced empirical optimization procedure is the dragonfly by Mirjalili. The proposed algorithmic procedure in [14] has exposed its ability to address various real-world issues. The algorithm in [15] is proposed with the natural flying behavior of dragonflies and it implies the concept of LFM—Levy flight mechanism. The use of LFM has cons, such as the swarming of the search area and disruption of nonsystematic flights. This paper proposes the DA algorithm study known as Brownian motion, which improves the randomization stage of the DA.

In the work proposed earlier, for any variation in the geographical condition and any variation in atmospheric situation, the output from a solar PV system varies abruptly. This causes fluctuations at its output and the dynamic response and the system efficiency is going to get affected very badly in [8–10]. Hence, to track the maximum amount of power many methods and algorithm have been proposed. However, swarm optimization is one of the best methodologies to be implemented in solar PV systems to trace the maximum amount of power. Though we have many more swarm optimization technologies, like PSO and firefly, the proposed dragonfly in MPPT produces the best result in terms of tracking the maximum power under all conditions. This includes partial shading conditions, as well. The proposed work identifies and incorporates a new controlling variable along with the dragonfly algorithm in MPPT to track the maximum amount of power under all conditions.

The concept of randomization is considered to be an important factor in optimization to solve the issues effectively. The random movement of the particle ensures that there are many ways to solve the problem. The solution obtained in optimization can be even more accurate by increasing the number of iterations. If the concept of randomization is not considered then the optimization is analyzed only in the confined region. To improve capacity of the concept at each and every point in space, the concept of randomization is important. The LFM is the new method that provides solution to hybrid optimization algorithm. In [16] the author proposed the LFM technique to analyze and validate the concept of a stochastic algorithm theoretically to obtain the global optimization. The algorithm examined in [17] proposed the concept of optimization towards the transmission of light. The author in [18] implements the concept of LFM in a cuckoo search technique that depends on the parasitic behavior of certain cuckoo classes in combination with the behavior of LFM. In [19] the firefly algorithm is adapted in LFM, and proved that the proposed one is superior in system performance when compared with the existing algorithm. For estimating the parameter in non-linear dynamics the bat algorithm technique is proposed along with LFM in [20]. The dragonfly algorithm concept is proposed by [21] to improve the result of optimization from its initial random population and converge towards global optimization.

2. Dragonfly Algorithm in PV System

The dragonfly algorithm developed by [21] is one of the best optimization techniques that involves nature-inspired algorithms. The DA (Dragonfly Algorithm) originated from the swarming behavior of flies under static and dynamic conditions. Exploration and exploitation are the two basic behaviors of swarming particles. The movement of dragonflies are isotropic in nature and it is modeled using LFM. The movements of the flies are random in nature and the distance it moved can be small or large.

If the flying behavior overflows, and if any distance gets interrupted due to the movement of the flies to a larger distance, the use of LFM causes disadvantages due to larger searching steps. The concept of the dragonfly is implemented in the MPPT algorithm. The general concept of DA is shown in Figure 1. The pivotal behavioral characteristics of the dragonfly are (i) separation, (ii) alignment, and (iii) cohesion. The genetic property of dragonfly neurons is utilized to trace and traject the highest range of temperature from a solar panel. The trajectory path is computed as an objective function for all values of the traced parameter until the required temperature is captured and is a maximum. The

cohesion property of dragon implemented in the algorithm helps and focused to collect similar range of temperature at all points in the solar panel.

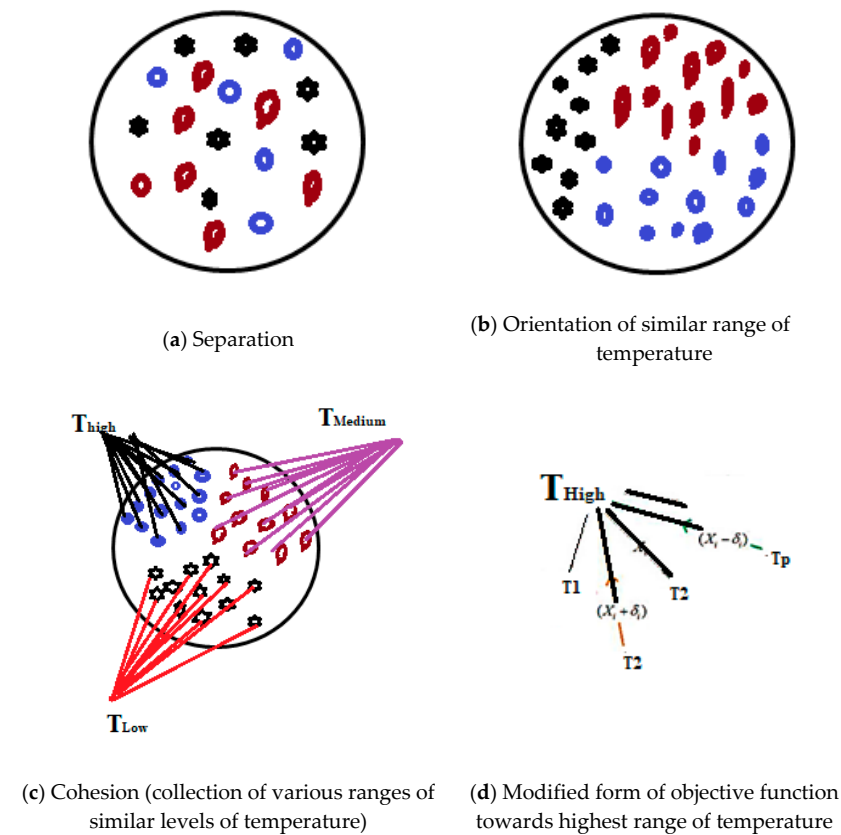


Figure 1. General concept of the DA algorithm in a PV system.

As the temperature of the solar system varies from time to time and pixel to pixel, the iridescence property implemented in DA helps to discover and catch the highest temperature range and remove the unwanted low temperature levels. All of the above said processes takes place in DA as the nature of similar flies has to be segregated. The populations of similar flies are grouped together and form as agents. Each of these agents interacts with the naturally-framed system and the environment.

The general concept of the DA algorithm implemented in the solar system is shown in Figure 1. As an initial step different ranges of irradiation is sensed and considered as a primary input as shown in Figure 1a. The light sensitive characteristic of the dragonfly separates the different ranges of irradiation factor as shown in Figure 1b. Later similar ranges of temperature are grouped together as shown in Figure 1c,d with the notation T_{high} , T_{low} , T_{medium} . The parameter x_1 and x_i represent the current position and neighboring position of the i^{th} individual. The objective function describing the concept for the Figure 1 is given in Equation (1):

$$\partial f_0 = \partial f_{01}^1, \partial f_{02}^2, \partial f_{03}^3, \dots, \partial f_{0p}^{dv}, S_i, C_i, T_i, P_i \tag{1}$$

Equation (1) shows the different levels of the objective function as $\partial f_{01}^1, \partial f_{02}^2, \partial f_{03}^3, \dots, \partial f_{0p}^{dv}$, where ∂f_0 is the objective function at various stages of temperatures like $T_1, T_2, T_3, \dots, T_p$. T_p is the temperature under partial shading conditions, S_i represents the segregation of temperature levels like low, medium, and high, C_i is the collection of similar range of irradiation factor, P_i is the partial radiation constant in the incident i -th radiation and T_i is the orientation of levels of temperature. Before starting the iteration process, the different levels of temperature are considered as population members and its minimum

and maximum level is initialized. The population members are initialized as shown in Equation (2):

$$\partial f_i^j = \partial f_i^1, \partial f_i^2, \partial f_i^3, \dots, \partial f_i^{dv} \quad (2)$$

where ∂f_i^j is the j -th range of temperature in i -th level iteration of the DA and dv is the problem verdict term. The objective function is iterated continuously at any time $t_{i+1} = t_i + D_t$ (t_i is a current moment, t_{i+1} is a next moment and D_t is a time step) until the maximum temperature is tracked. The temperature is traced as a function of velocity and position that helps in maintaining synchronization and the same is responsible for sharing the information as change in temperature level.

$$M_{si(t_{i+1})} = M_{si(t_i)} + rand^* (rand - M_{si(t_i)}) \quad (3)$$

The Equation (3) depicts the modified form of DA $M_{si(t_{i+1})}$ by Brownian motion and it shows the transformation that captures the actual range of temperature as population formations, and making sure that the captured values are nearly having the same number of iteration function and this is genetically related to the dragon flies and, furthermore, the analysis is extended by using $rand()$. The movement of the dragonfly is random. This is related to the concept of irradiance that was spread over the specified time with the normal distribution. The sudden variation in temperature of the solar panel is considered as a random variable while calculating the modified form of the DA $M_{si(t_{i+1})}$.

3. DA-Based MPPT Algorithm with a Novel Controlling Variable

In all the previous research analysis MPPT is mainly utilized to track maximum power in the solar PV systems. Among different types of MPPT algorithm the MPPT—P and O algorithm is the most common method used to track maximum power. However, this seems to be ineffective in tracing the maximum power under partial shading condition. To improve the power tracking in an effective way at all environmental condition this manuscript proposes the dragonfly concept in MPPT. The characteristics of the dragonfly can be utilized to track the effective sun's energy. The solar energy varies from time to time and also the temperature of the solar system varies frequently. This variation is tracked effectively by means of implementing the dragonfly characteristics. The reason for choosing this algorithm in tracking the sun is the dragonfly flies fast both forward and backward. Likewise for any variation in temperature from solar energy, the dragonfly algorithm is capable of tracing the highest level of temperature by moving forward and backward. Additionally, the implementation of this algorithm understands the present climatic condition and adapts itself to the present environment to self-realize and track the highest temperature to produce the highest power at its output. The abrupt change in the weather, geographical change and shadow causes sudden change in the I-V and P-V system characteristics. This sudden change in the characteristics causes system instability. Adjusting only the PI controller gain alone will not stabilize the entire system. Therefore, a new controlling variable 'R' is introduced as shown in Equation (4) by taking the instantaneous value of PV system voltage v_{pv} and current i_{pv} as a reference.

$$R = C_0 + C_1 i_{pv} - C_2 v_{pv} \quad (4)$$

where C_0, C_1 & C_2 are constants. The selection of C_0, C_1 & C_2 causes R_{ref} to be in the range of specified range of operation for any amount of variation in the input parameter like irradiance and temperature. The inclusion of new controlling variable R_{ref} causes the system to maintain stability. In VI characteristics the V and I vary inversely and, hence, R_{min} & R_{max} are calculated as a function of R as given in Equation (5):

$$f(x(R)) = \begin{cases} C_0 - C_2 v_{oc(PV)}, & R < 0 \\ C_0 + C_1 i_{sc(PV)}, & R \geq 0 \end{cases} \quad (5)$$

The VI and VR characteristics' different ranges of illumination and PV temperature are shown in Figures 2 and 3. After including the controlling parameter R the solar V-I characteristics are compared with the V-R characteristics. For different ranges of illumination the maximum power point is represented as a dotted line. This holds well under all ranges of illumination and even under partial shading conditions. The proposed method tracks the maximum amount of power in all conditions with the inclusion of the novel controlling term R with the minimum and maximum worst conditions in the MPPT-DA algorithm. The dreadful condition is obtained at an extreme point of $C_0 - C_2v_{oc(PV)}$ and a minimum of $C_0 + C_1i_{sc(PV)}$ $C_0 - C_2v_{oc(PV)}$ is the maximum at a minimum value of $v_{oc(PV)}$ and $C_0 + C_1i_{sc(PV)}$ is the minimum at the zero value of $i_{sc(PV)}$ as given in Equation (6).

$$f(x(R)) = \begin{cases} \max(C_0 - C_2v_{oc(PV)}) @ v_{\min-oc(PV)} \\ \min(C_0 + C_1i_{sc(PV)}) @ i_{sc(PV)} = 0 \end{cases} \quad (6)$$

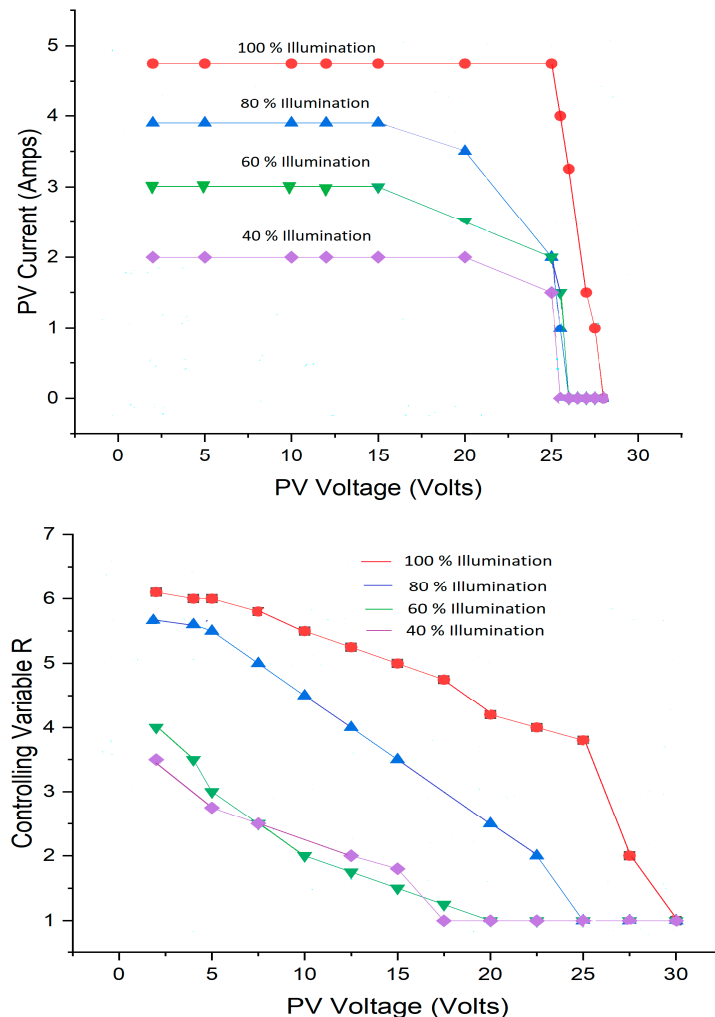


Figure 2. V-I and V-R characteristics for different illuminations.

The proportional values of the constants C_0, C_1 & C_2 are generated from the schematic shown in Figure 4. It is the simple voltage divider circuit designed to identify the new controlling variable 'R' as given in Equation (7).

$$R = \frac{R_2R_3}{R_1R_2 + R_2R_3 + R_3R_1}v_{const} - \frac{R_2R_3K_{vg}}{R_1R_2 + R_2R_3 + R_3R_1}v_{pv} + \frac{R_1R_3K_{ig}}{R_1R_2 + R_2R_3 + R_3R_1}i_{pv} \quad (7)$$

On Comparing Equation (4) with Equation (7), the constants C_0, C_1 & C_2 can be identified as given in Equation (8):

$$\begin{aligned}
 C_0 &= \frac{R_2 R_3}{R_1 R_2 + R_2 R_3 + R_3 R_1} v_{const} \\
 C_1 &= \frac{R_1 R_3 K_{ig}}{R_1 R_2 + R_2 R_3 + R_3 R_1} \\
 C_2 &= \frac{R_2 R_3 K_{vg}}{R_1 R_2 + R_2 R_3 + R_3 R_1}
 \end{aligned}
 \tag{8}$$

For different ranges of irradiance and temperature variation the value of v_{pv} & i_{pv} varies abruptly. This abrupt variation causes the constants in the controlling variable R to vary. In the third term in Equation (7) K_{ig} is the current gain (i_{out}/i_{pv}). Therefore, the third term in Equation (7), K_{ig} is replaced with (i_{out}/i_{pv}) and if it is substituted in the third term of Equation (7), we obtain ($R_1 R_3 i_o / R_1 R_2 + R_2 R_3 + R_3 R_1$). Here, $R_3 i_o$ gives the units of voltage. Based on this variation the population membership functions are initialized as given in Equation (2). Then the objective function, as shown in Equation (1), is iterated continuously until the maximum amount of power is tracked irrespective of temperature variation, irradiance, and partial shading condition. The simulation test results showing the variation of R with an increase or decrease in the value of constants.

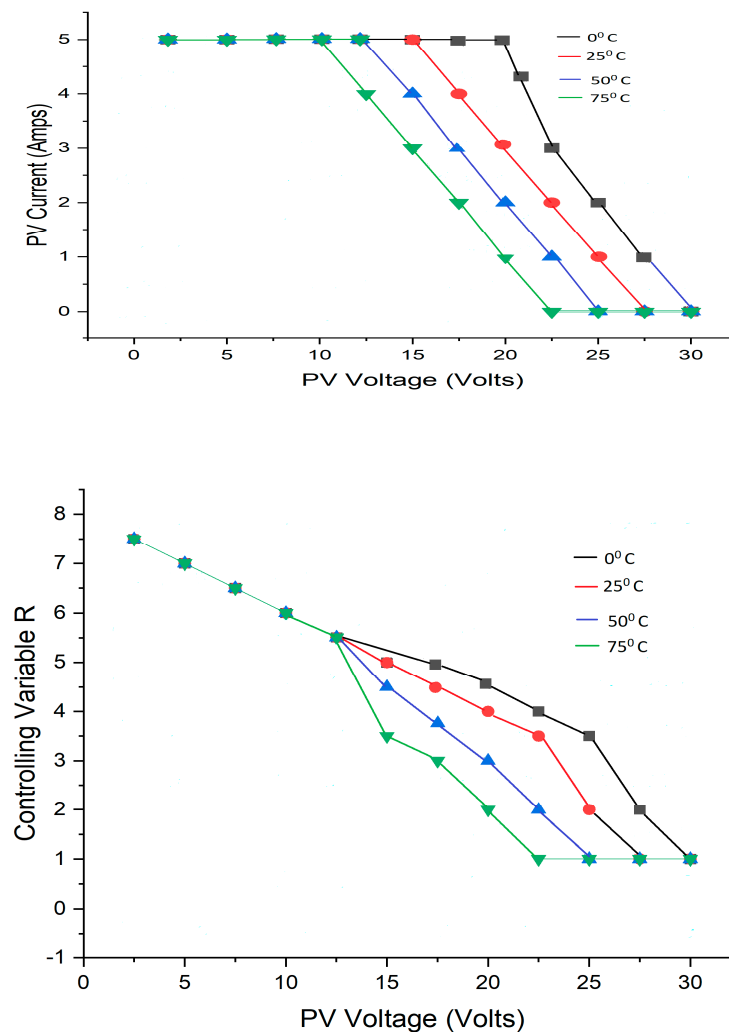


Figure 3. V-I and V-R characteristics for different PV temperature.

With the continuous iteration of the objective function framed by using Equation (1), the range of operation of controlling variable R is identified. Within this range of operation

the complete system is simulated to trace maximum amount of power even under partial shading condition.

These characteristics of dragonfly are taken into account along with the MPPT algorithm to develop a new dragonfly MPPT forward and reverse algorithm. The flowchart shown in Figures 5 and 6 represents the implementation of the concept of dragonfly concept in MPPT forward-reverse algorithm. The evaluation of DA in MPPT is done in MATLAB R2017 to obtain the solution of single and multi-objective problems. The hunting and relocation strategies of dragon flies are implemented in PV technology to track maximum source of power. The hunting strategy is implicated for static flies and it can be flied and traced within the limited distance.

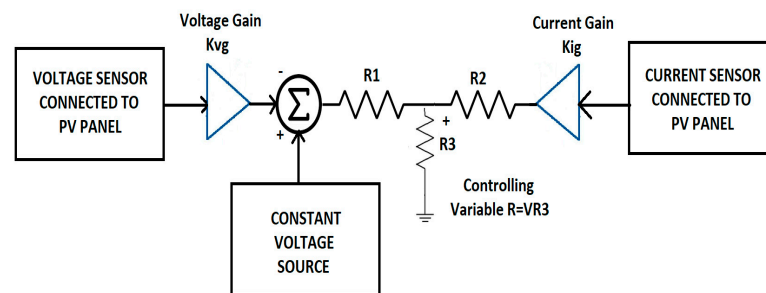


Figure 4. Circuit to generate the controlling variable R.

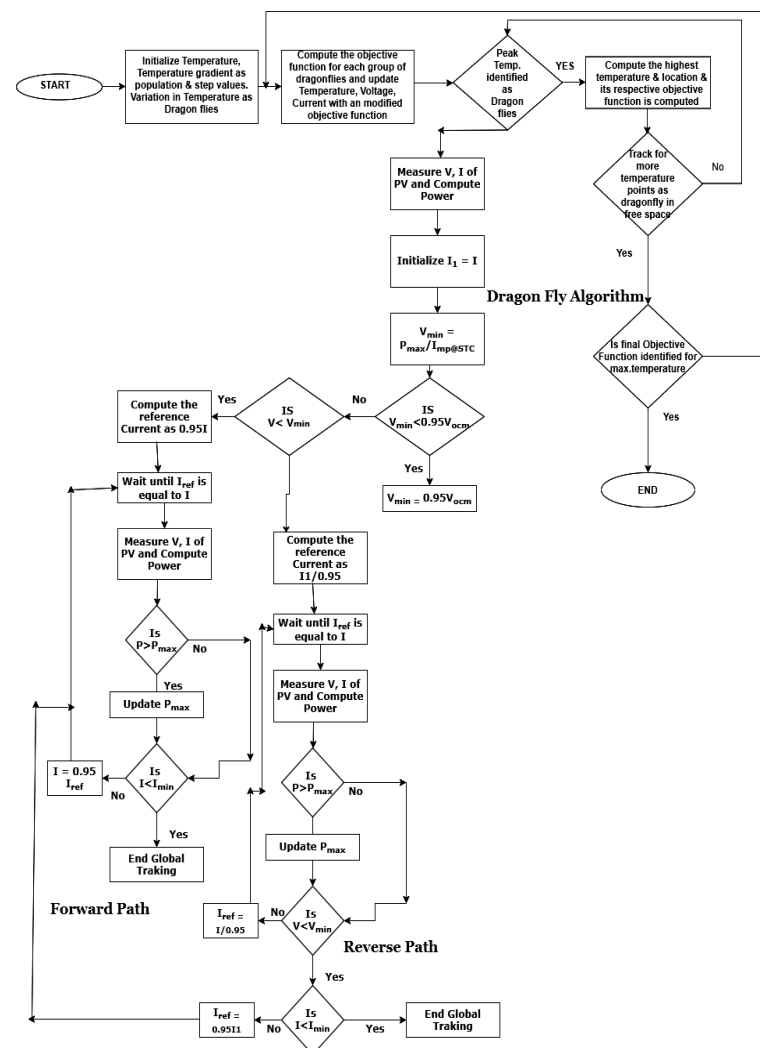


Figure 5. Flowchart of the dragonfly MPPT forward and reverse algorithm.

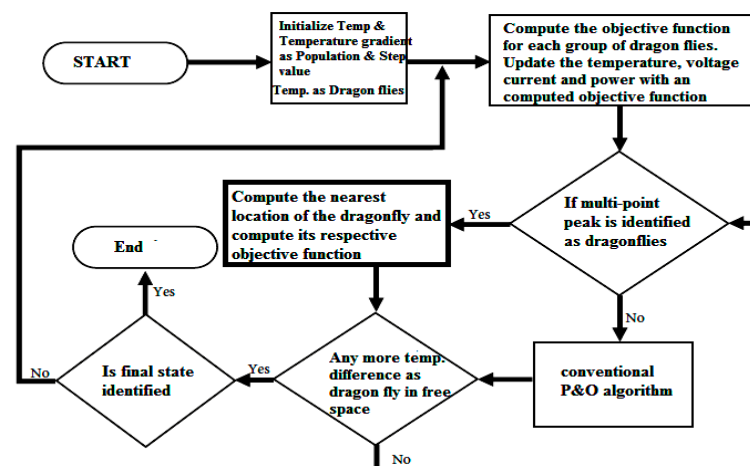


Figure 6. Flowchart of the dragonfly algorithm.

4. Pseudo Code of the Dragonfly MPPT-FR Algorithm

The proposed algorithm shown in Figure 7, and the temperature tracing strategy using DA is shown in Figure 8. It states that the dragonfly characteristics are limited to shorter distances. Within the short span of distance the different ranges of temperature are traced at a faster rate and collected as a membership functional population. The different range of distances is shown as small geometric hexagonal shapes. A sample of space is taken as references and the temperature is measured at different positions and is simulated in MATLAB. The dragonfly algorithm is implemented along with MPPT-forward and reverse algorithm for tracking and routing the various ranges of temperature as shown in Figure 9. This output is shown for the sampled distance of 100 m.

```

Function
[max_temp,panel_pos,velocity] =
DA(SearchAgents_no,Max_iteration, Si,Ci,Ti,Pi) display ('DA is
optimizing the problem'); velocity = zeros(1,Max_iteration); if
size(upper,2) = 1
Upper = ones(1,dim)*upper;
Lower = ones(1,dim)*lower; end
Initialize different values of temperature as dragonflies
X = initialization(SearchAgents_no,dim,upper,lower);
F = zeros(1,SearchAgents_no);
DeltaX = initialization(SearchAgents_no,dim, upper, lower);
Segregate the similar dragon flies
Align all the similar dragon flies
While the final state is not satisfied
Compute the objective function for each group of dragon flies using
an Equation (1), Equation (2), and Equation (3)
Update the temperature, voltage current and power with an
computed objective function
If multi-point peak is identified
{Compute the nearest location of the dragonfly and compute its
respective objective function} else follow MPPT-FR (MPPT-forward and
reverse) algorithm
If only one range of temperature is identified {Find the new range of
function by applying Brownian motion} else follow conventional P and
O algorithm end while
  
```

Figure 7. Dragonfly MPPT-FR Algorithm.

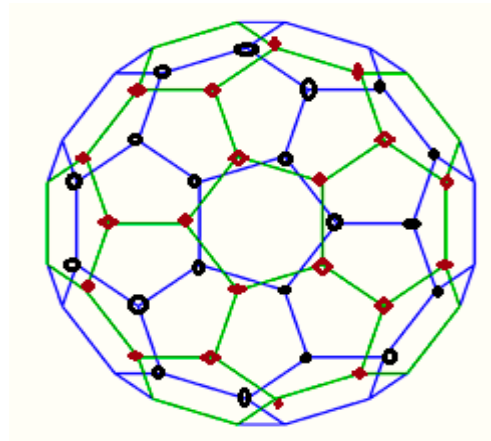


Figure 8. Temperature tracing strategy using DA.

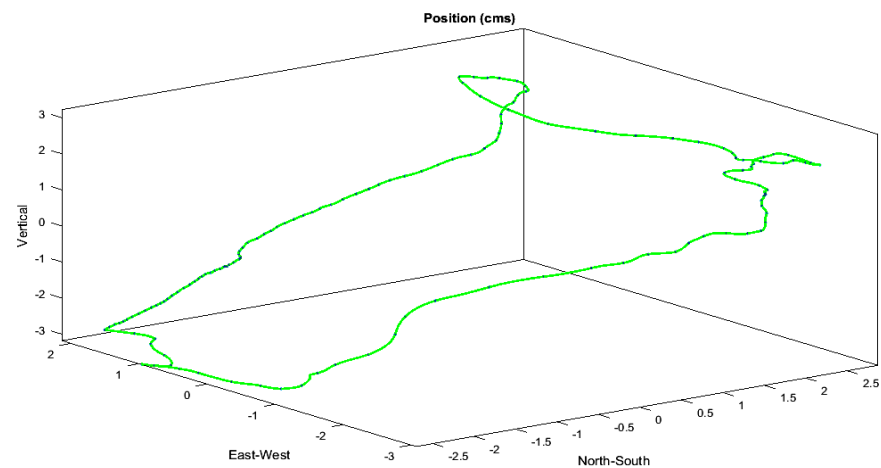


Figure 9. Dragonfly algorithm used for routing different ranges of temperature.

After the measurement of temperature at different location, new objective function is computed for various levels of temperature gradients as shown in Figure 10. The new objective function is computed by using an Equations (1)–(3) at different S_i , C_i , T_i , P_i and the respective voltage, current, and power values are updated to the traced maximum level of temperature and are shown in Figure 11. The proposed system is tested in MATLAB (Matlab 2017a) with lower number of sampled agents. In the above measured data—temperature, 80% of the dragonflies' data are utilized to train other samples, while 20% of data is utilized for testing purposes to trace the maximum power.

The simulated output is recorded as shown in Table 1 and its output graph is as shown in Figures 12 and 13. From the recorded output it is observed that the power drawn from the solar PV system is the maximum to a value of around 1046 Watts at $T = 145^\circ\text{C}$. For a continuous variation in temperature from solar insolation, the implemented dragonfly forward-reverse algorithm tracks the maximum amount of power. The characteristic of the dragonfly algorithm allows the designed system to trace the highest temperature with a minimum of processing time. Additionally, implementation of this algorithm understands the present climatic condition and adapts itself to the present environment to self-realize and track the highest temperature to produce the highest power at its output.

Performance Analysis of Proposed Algorithm

In general performance analysis of proposed algorithm can be verified using two different characteristics, which include (i) convergence and (ii) robustness. The purpose

of choosing convergence characteristics is to check how fast the algorithm yields local optimum solutions.

Figure 14 shows the convergence characteristics of proposed method where, solar power that is particular for projected method reaches the optimum solution within the 50th iteration. This is not conceivable for other existing algorithms as the amount of solar power is much higher and with such a large amount of power it is difficult to attain optimal solutions. Once the convergence characteristic of proposed algorithm is suitable for implantation unit then the quality of implantation should be checked. Figure 15 shows the robustness characteristics of proposed algorithm where, the quality is greatly improved when compared to existing methods. Even with smaller trial run the projected algorithm yields best quality and it is best for implementing even at larger run.

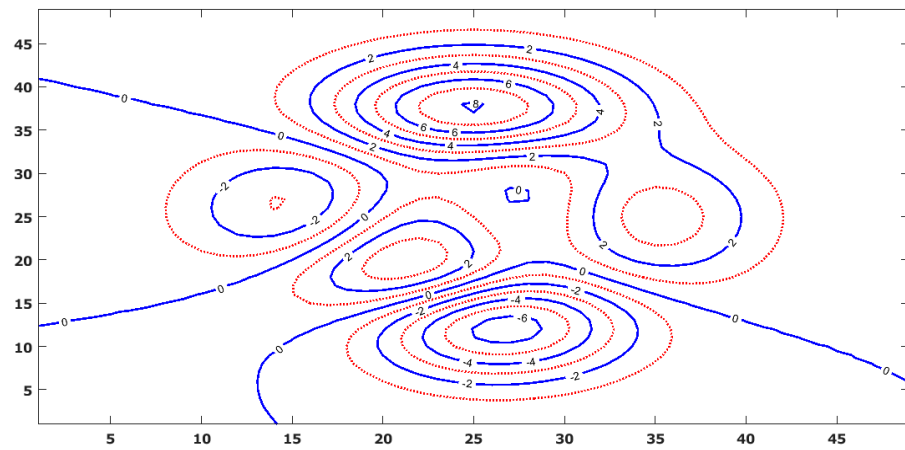


Figure 10. Temperature gradient for different objective functions.

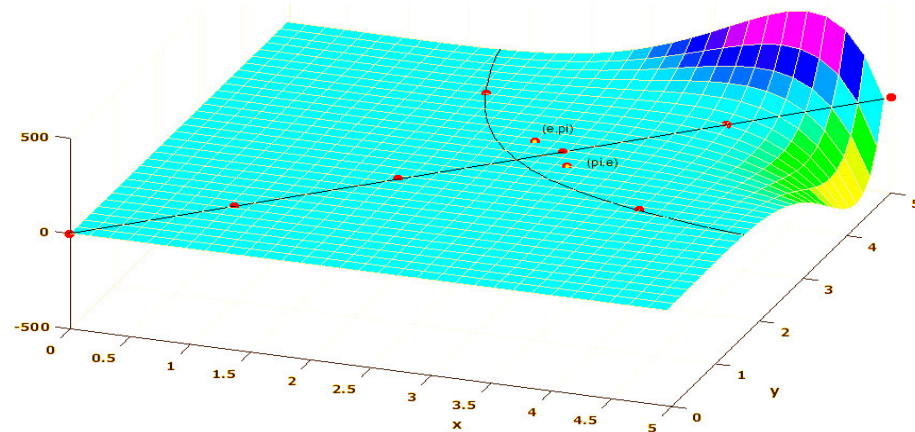


Figure 11. 3D view of the PIV characteristics of the solar PV source.

Table 1. Processing time of MPPT and DA—MPPT.

Objective Function Iteration	Temperature Range of the Objective Function	Processing Time (Sec)		Power Drawn from Solar (Watts)	
		MPPT	DA with MPPT—FR	MPPT	DA with MPPT—FR
f_1	25 °C	18.056	15.334	563.12	776.32
f_2	45 °C	17.998	14.987	605.20	805.43
f_3	65 °C	17.056	14.003	645.15	890.33
f_4	85 °C	16.580	13.564	698.98	901.11
f_5	105 °C	15.016	12.976	705.64	934.67
f_6	125 °C	14.118	12.731	780.77	987.35
f_7	145 °C	16.119	11.564	801.24	1045.76

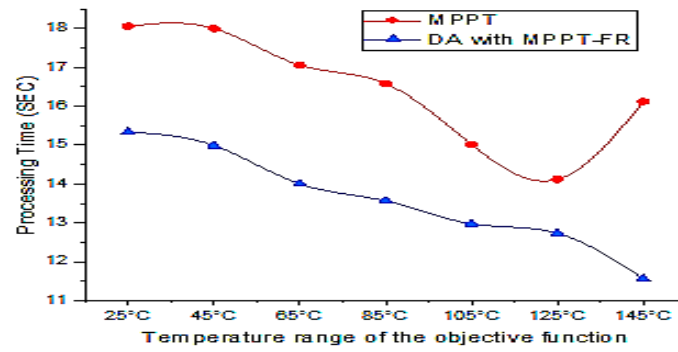


Figure 12. Temperature vs. processing time of MPPT and DA with the MPPT-FR algorithm.

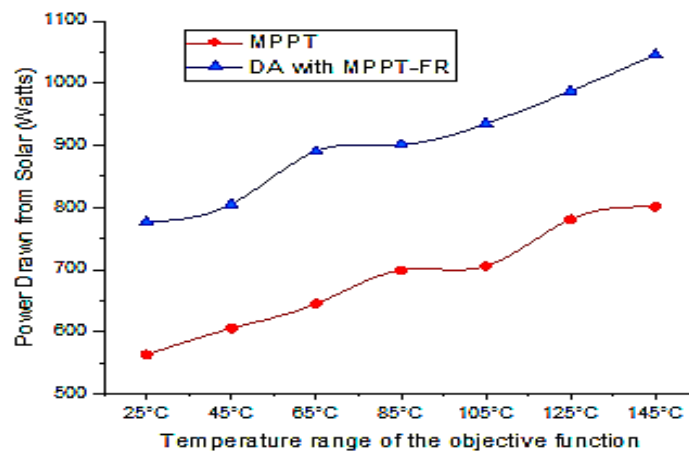


Figure 13. Power drawn from PV system as a function of temperature of MPPT and DA with MPPT-FR algorithm.

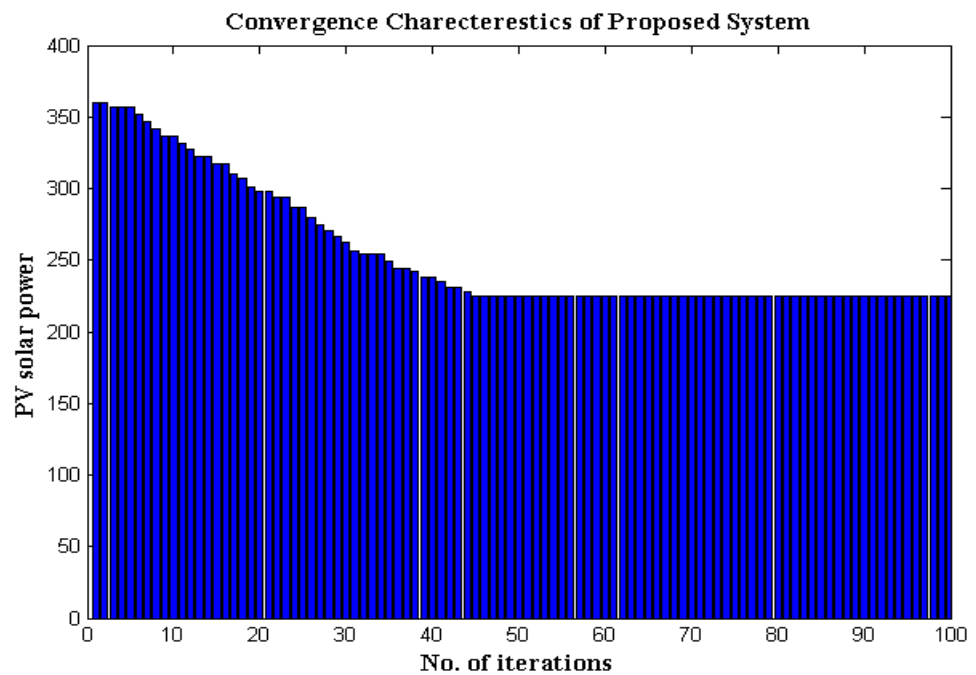


Figure 14. Convergence characteristics.

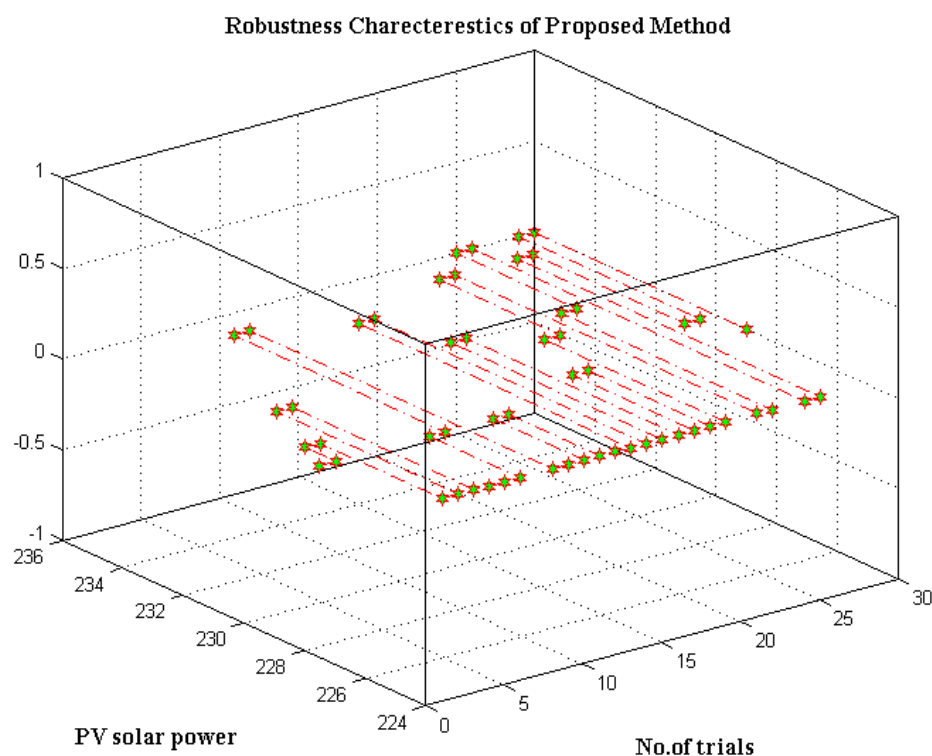


Figure 15. Robustness characteristics.

5. Conclusions

This manuscript is proposed with novel MPPT-forward and reverse flow technique with the dragonfly concept. By using this algorithm the maximum amount of energy is drawn from solar with a minimum of processing time. The multi-objective problem is focused in the analysis. The analysis is focused and simulated to trace maximum temperature with less processing time. Randomization based on SI played an important role in exploration and exploitation. The randomization of DA in MPPT-forward and reverse flow is effectively utilized in PV source to track maximum power. The different objective function $f_1, f_2, f_3, \dots, f_7$ is calculated using Equation (2). The objective function calculated the temperature as membership population and for each range of temperature level, processing time, and power tracking from solar PV system is tabulated.

The proposed algorithm is tested solar PV system to track maximum power. The tracking time of DA based MPPT-FR algorithm is less than conventional MPPT technique as tabulated in Table 1. Additionally, the power drawn using the DA-based MPPT-FR algorithm is more than a conventional tracking system. The implementation of a new controlling variable R makes the complete PV system track the maximum amount of power even under partial shading conditions. Additionally, the use of DA-based MPPT has the sharp edges in tracking the maximum power at all times during the day as it is based on memory-based techniques. With the implementation of DA based MPPT-FR algorithm the tracking power is maximum at all times with less tracking and processing time.

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