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Study Comparison Between Enhanced Firefly and Differential Evolution to Solve the Maximum Power Point Tracking Problem

Issa Ahmed Abed[1*], May Mohammed Ali[1], Ali Ahmed Abed[2]

[1] Basrah Engineering Technical College, Southern Technical University, Basrah 61001, Iraq
[2] College of Engineering, University of Basrah, Basrah 61001, Iraq

Corresponding Author Email: issaahmedabed@stu.edu.iq

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ABSTRACT

The penetration of photovoltaic (PV) in electric power generation is continually increasing. On the other side, the load will receive the actual power, which is a part of power supplied by the photovoltaic. Therefore, it is necessary to extract maximum power from PV. One of a defy problem, is the tracking maximum power point (MPPT) in photovoltaic frameworks and it is a significant task. It can be a reproducer of maximum power from a photovoltaic system, which it depends on the adjusting of duty cycle of DC-DC converter. In order to produce a maximum power transfer, the impedance between the source and the load should be coincide by using of a buck boost converter. In this work, the proposed methods; Firefly algorithm (FA), Enhanced Firefly (EFA), Differential Evolution Scheme1, Differential Evolution Scheme2, and Differential Evolution Scheme 3 were tested for their performances in different conditions. Finally, the simulation results confirm that the second scheme of DE outperforms the others. Visual Basic. Net has been used to simulate the results and proceed with algorithms.

1. INTRODUCTION

The energy prerequisite of the world is always expanding. The expanding energy requests put a great deal of weight on the classical energy sources (oil, gas and coal). Be that as it may, the fossil fuel-based energy sources are restricted in amount and furthermore cause ecological contamination. The negative impacts of the traditional energy sources can be overcome by making utilization of sun's vitality. This source will never harm the earth [1]. In photovoltaic (PV) source generators, the electrical energy straightway produces by changing over the energy of sunlight based radiation [2]. With a flow in the utilization of non-traditional energy sources, PV compositions are by and large progressively utilized in several applications [3]. Notwithstanding, a noteworthy test in utilizing a PV source is to handle the circumstances like unstable atmospheric conditions [4]. The characteristic of a photovoltaic system emphatically relies on upon the operating ecological conditions, for example, temperature and solar insolation [5]. The PV systems ought to work at the maximum power point, so as to accomplish maximum efficiency. Then and in order to obtain maximum power, the MPP tracking (MPPT) is inserted between the photovoltaic frameworks and the load [6]. Babu et al. [7] do an endeavor for maximum power point tracking by providing amendments to particle swarm optimization method, taking in the consideration the selection of the initial value. The basic combination of this technique adds strengthen in order to follow global peak power precisely with the influence of change in ecological situation together with steady state oscillations of very nearly to zero, quicker dynamic reaction, and easy enforcement. Accurate estimation is executed for various situations of partial shading and lastly the outcomes acquired are contrasted with other techniques. MPPT using genetic algorithm (GA) for PV system is displayed by Kumar et al. [8]. It is incorporated with a unit of battery storage as power source unit in standalone mode. Photovoltaic supply relies on upon solar irradiance, site position and ecological factors such as temperature, and wind. In this way photovoltaic output is fluctuating in quality and the insertion of non linear load leads to make the circumstance more ticklish. In order to get wanted evaluated voltage, DC-DC converter is utilized. Where, battery storage unit goes about as secondary supply to guarantee continuous power source. In present work, different artificial intelligence methods have been suggested to solve the problem of Maximum power point tracking with the use of buck-boost converter. In this paper, in order to draw all the power supplied from the PV system different optimization methods are proposed to control the duty cycle. The remnant of the paper is arranged as follows: section one gives some introduction about the paper, a brief explanation of buck-boost converter is given in section two. Section three discussed the proposed optimization algorithms. The results and their simulations are given in section four. The last section presented the conclusion.

2. THE CONVERTER OF BUCK-BOOST

The DC-DC converters have different applications in our life [9]. The case study in this work is suggested a buck-boost converter. Buck converter and boost converter are incorporated to produce this type. Because of the duty cycle, the resultant voltage can be increased or decreased [10]. However, the suggested converter is moreover manufactured using similar fragments used as a piece of alternate converters [11]. The circuit diagram shown in Figure 1 [12], where V_{INP}

is the input voltage to the circuit, SW1 and SW2 are the switches, L1 represents the inductor, C1 illustrates the capacitor, the output resistor is R_{OUT}, and V_{OUT} is the voltage across this resistor.

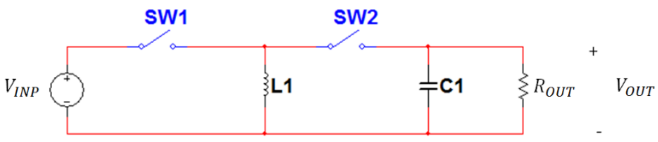

Figure 1. The circuit of the proposed converter

where the ratio of conversion can be calculated as follows [10]:

$$\frac{V_{OUT}}{V_{INP}} = \frac{I_{INP}}{I_{OUT}} = \frac{D_U}{1-D_U} \tag{1}$$

where, D_U is the duty cycle of converter, I_{INP} and I_{OUT}, respectively.

$$V_{INP} = \frac{V_{OUT}(1-D_U)}{D_U} \tag{2}$$

$$I_{INP} = \frac{I_{OUT} D_U}{1-D_U} \tag{3}$$

After the calculation of V_{INP} and I_{INP}, the converter input resistance is obtained as follows [10].

$$R_{INP} = \frac{V_{INP}}{I_{INP}} = \frac{(1-D_U)V_{OUT}/D_U}{D_U\, I_{OUT}/(1-D_U)} = \frac{V_{OUT}(1-D_U)^2}{I_{OUT} {D_U}^2} = R_{OUT}\left(\frac{1-D_U}{D_U}\right)^2 \tag{4}$$

here, R_{INP} varies from ∞ to 0 when D_U varies from 0 to 1.

According to the mentioned equations, the resistance of the input of the converter is subject to the resistance of the load and the converter duty cycle. In this manner, one of the subsystems is the DC-DC converter. The power maximum can be moved to the DC-DC converter and thus to the load, on the off chance that the R_{INP} of the converter be on the V_{MPP}, I_{MPP} point. Henceforth the maximum power point tracking is DC-DC converter which is utilized to match the PV with load, for example, batteries, DC motor and DC pump [10].

3. THE CONTROL ALGORITHMS OF MAXIMUM POWER POINT TRACKING

The use of artificial intelligent is increased rapidly nowadays. Where different concepts have been used to find or modified many optimization algorithms [13].

3.1 Differential evolution

Nowadays, among the real-parameter and the most capable stochastic optimization techniques, differential evolution (DE) is utilized [14]. The main features that are promoted this algorithm; first, the capability to find the global optimum solution paying little respect to the values of initial parameters. Second, fast rate of convergence. Finally, little usage of parameters [15]. Genetic algorithm is like DE in terms of the principle of work. Be that as it may, as opposed to GA— which depends basically on the operation of the crossover to produce the variation in the population, differential evolution uses the mechanism of the mutation to search the possible regions in the search space. Using the generations of mutation, crossover and selection, DE can enhance the population of solutions [16]. DE has turned out to be a hopeful technique for optimization of multimodal objective functions. It is exceptionally easy to comprehend and to execute. DE is likewise especially simple to work with [17]. The algorithm begins with members which are produced randomly by using the uniform distribution. A trial solution is resulted by using mutation and crossover producers at every iteration. Then the operation of selection is used to find the best solutions into the next generation. The population advances iteration by iteration till the algorithm reach the maximum generation [18].

3.1.1 Initialization

An initial population of *N* candidate solutions or individuals is first generated and is used as the parent population of the first iteration or generation. The premier individuals ought to spread to the all search space in so far as possible using the population which is randomized uniformly in the space bounded by minimum and maximum limits [18].

Thus, real encoding can be used for each member (*mem*) as follows [17]:

$$mem_{jk} = LL_{jk} + rand * (LH_{jk} - LL_{jk}) \tag{5}$$

where, LH_{jk} and LL_{jk} denote the upper and lower bounds of each chromosome, rand is a random number chosen from the range [0, 1], k=1, .., N, and j=1, …, d.

3.1.2 Mutation

The enforcement of mutation step is the fundamental distinction between differential evolution and other evolutionary methods. In differential evolution, the operation of mutation does the vector differences between the current individuals of population in order to find the value and the orientation of perturbation which is utilized to the member subject of the operation of the mutation. This operator is basically in charge of protecting a population powerful as well as for seeking new regions. DE is considered as self-adjusting algorithm where it derives the perturbations from the differences between the individuals, rather than utilizing a predefined probability in order to apply the mutation. In DE, the "self-adjusting" means: while the individuals reach to the optimal solution, any randomly selection distinction vector will reduce in size. Ultimately the distinction vector approximates to zero then this operator will be debilitated, in case the individuals reach to a solitary result. Then the vectors which are recently perturbed are created by append the weighted distinction to different vector. Based on the kind of the problem, different schemes where suggested for a number of options [17]. Three methods of mutation actualized here were DE/rand/1, DE/current-to-best/1, and DE/rand/1/either/or, which encase the accompanying strides: DE scheme 1/rand/1 [19]:

$$V_{T_{k,g}}^{j} = x_{r1,g}^{j} + F(x_{r2,g}^{j} - x_{r3,g}^{j}) \tag{6}$$

where, $V_{T_{k,g}}^{j}$ is the trial vector, $r1$, $r2$, $r3$∈{1, 2, …., N}, $r1 \neq r2 \neq r3 \neq k$. F is a scale factor greater than zero. In order to control the increasing in the differential variation, real number F is used. F represents the mutation factor, g is the number of generation.

DE scheme 2/current-to-best/1 [17]:

In order to provide a means to enhance the greed of the scheme, an additional control variable λ is introduced. Thus, a perturbed vector is generated according to Eq. (7).

$$V_{T}{}^{j}_{k,g} = x^{j}_{k,g} + \lambda\left(x^{j}_{best,g} - x^{j}_{k,g}\right) + F(x^{j}_{r2,g} - x^{j}_{r3,g}) \quad (7)$$

DE scheme 2/rand/1/either/or [20]:

$$V_{T}{}^{j}_{k,g} = x^{j}_{r1,g} + 0.5(F+1) * (x^{j}_{r2,g} + x^{j}_{r3,g} - 2\, x^{j}_{r1,g}) \quad (8)$$

3.1.3 Crossover (recombination)

From the mutation operation the perturbed vector will produce. Then go through the operation of the crossover to raise the variety of the members and in order to not trap in a local minimum. As per to the *kth* vector and its associated vector, this operator results a new trial vector as follows:

$$u^{j}_{k,g} = \begin{Bmatrix} V_{T}{}^{i}_{k,g} & if\ (rand^{j}(0,1) \leq C_r\ or\ j = j_{rand} \\ x^{j}_{k,g} & if\ (rand^{j}(0,1) > C_r\ or\ j = j_{rand} \end{Bmatrix} \quad (9)$$

where, C_r is a crossover factor in the range [0,1].

3.1.4 Selection

Actually, the step of selection in differential evolution is straightforward, because it checks the situations where the trial vector can go through the members. Comparison between the two fitness functions will perform due to the trial vector that result will just exchange with the original member if and only if has better fitness.

$$x_{k,g+1} = \begin{Bmatrix} u_{k,g} & if\ f\left(u_{k,g}\right) \leq f(x_{k,g}) \\ x_{k,g} & else \end{Bmatrix} \quad (10)$$

Finally, the DE can be summarizing as follows [21]:

1: Generate an initial population=(x_1, x_2, x_3, …., x_N)
2: Repeat
3: for k=1 to N do
4: Generate a new trial vector y
5: if $f(y)<f(x_k)$ then insert y into new generation Q
6: else insert x_k into new generation Q
7: end if
8: end for
9: P=Q
10: Until stop criteria is met

In design the DE, the user must choose the key parameters that control DE, i.e., population size (N), boundary constraints of optimization variables, mutation factor (F), crossover rate (C_r) and the stopping criterion [18].

3.2 Enhanced firefly algorithm

The bioluminescence operations are in charge of the fireflies flashing light. During the life time of fireflies, many contradictions about the concepts behind the cause and significance of flashing light, hence a big part of those thoughts being associated with the intermarriage stage [22, 23]. The basic job of flashing light is to build the intermarriage copartner, and in this stage the operations of bioluminescence is recognized as luminescent emanation. The one of a kind symbol of the flashing floodlight is the sign for their preparedness on intermarriage and outcomes of like correct shining emission operation is to fetch both the fireflies of similar class for sex. One class firefly is the photinus, then amongst them the masculine firefly uses compendious signal manner and female firefly interacts to it in a limit time period. Various kinds of firefly introduce special intermarriage practices on different situations [24]. They, have a place with group of Lampyridae, are little winged insects equipped for delivering a cool light so that to pull the mates [25]. It is supposed to have a capacitor-like mechanism, which gradually fills with the charge till the specific limit is come to, at which fireflies discharge the energy as light, after which the cycle does again [26]. Yang, created this algorithm which is inspired by the light attenuation with the separation and fireflies' mutual attraction, instead of by phenomenon of the fireflies' light flashing. In order to modify the FA, the search locally is performed to raise the exploration and abilities of the search of the algorithm, then guarantee that the convergence will be rapid. FA is allowed to search for the global optima for a given objective function [25]. Thus, FA can avoid the falling in local optima.

4. SIMULATION RESULTS

Intel Core 2 Due CPU 2.1 GHz laptop computer has been used to find the results with Visual Basic. Net software. Two values of load are suggested (R_{OUT}=25 and R_{OUT}=50). Each is tested for different conditions of irradiance (I) and temperature (T) as well as the duty cycles are recorded as shown in Tables 1 and 2.

Table 1. Duty cycle and output values when R_{OUT}=25Ω

$I\left(\frac{W}{m^2}\right) - T(K)$	D_U	$V_{OUT}(V)$	I_{OUT} (V)	R_{OUT} (Ω)
118.28-318.32	0.531557542	13.97926829	0.72	25
148-321.25	0.535395	14.3078	0.76	25
306-327.7	0.635007	13.8759	1.68	25
711-324.21	0.727455	13.6156	3.88	25
780-329.1	0.730481	14.5661	4.28	25
840-331.42	0.754206	13.17	4.96	25
978-328.56	0.760327	13.9113	5.6	25

Table 2. Duty cycle and output values when R_{OUT}=50Ω

$I\left(\frac{W}{m^2}\right) - T(K)$	D_U	$V_{OUT}(V)$	$I_{OUT}(A)$	$R_{OUT}(\Omega)$
118.28-318.32	0.616087	13.97926829	0.72	50
148-321.25	0.619727	14.3078	0.76	50
306-327.7	0.711018	13.8759	1.68	50
711-324.21	0.790563	13.6156	3.88	50
780-329.1	0.793088	14.5661	4.28	50
840-331.42	0.812714	13.17	4.96	50
978-328.56	0.81773	13.9113	5.6	50

Comparison study has been done between the proposed methods in term of cost function, in order to clearly demonstrate the best technique. From all figures, FA and EFA can be comparable; however, EFA is better than FA in terms of precision and the speed. Differential evolution of scheme 1 and of scheme 3 near each other and gradually reach to the same value of error. Yet, they do good and better than EFA and FA. On the other hand, Scheme 2 of DE did excellent speed and approaching to the optimum error faster than the others. Figures 2-8 show the comparison with the load resister of 25 Ω.

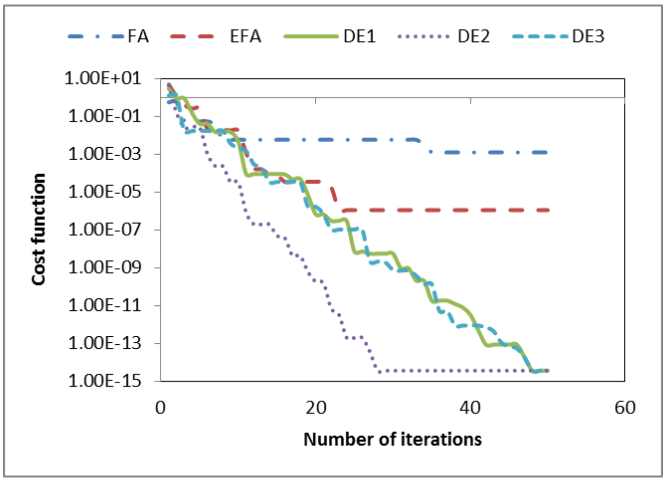

Figure 2. The comparison between the methods at 118.28 W/m^2-318.32 K

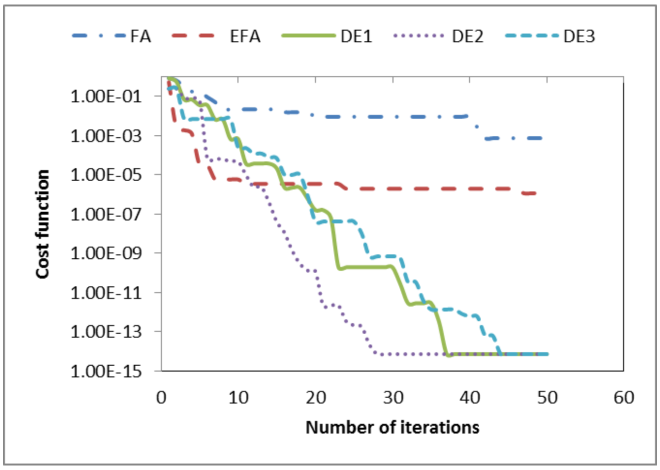

Figure 3. The comparison between the methods at 148 W/m^2-321.25 *K*

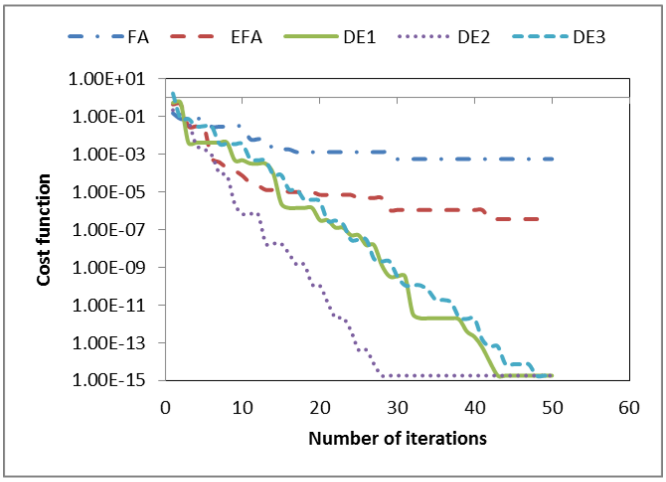

Figure 4. The comparison between the methods at 306 W/m^2-327.7 *K*

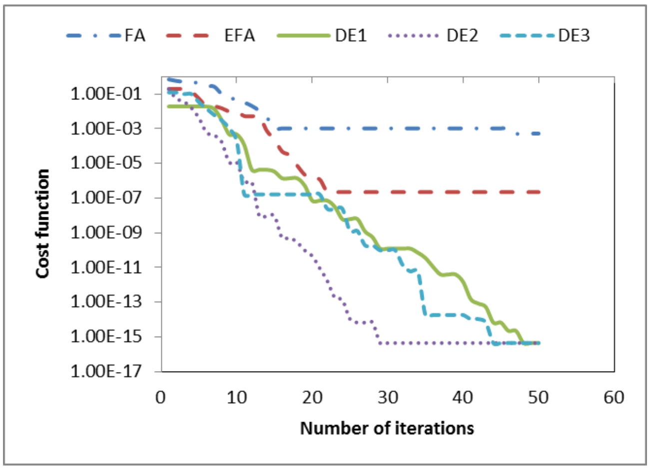

Figure 5. The comparison between the methods at 711 W/m^2-324.21 *K*

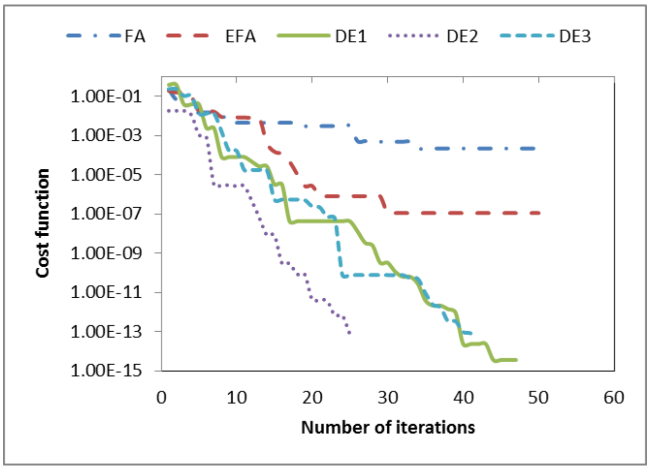

Figure 6. The comparison between the methods at 780 W/m^2-329.1 K

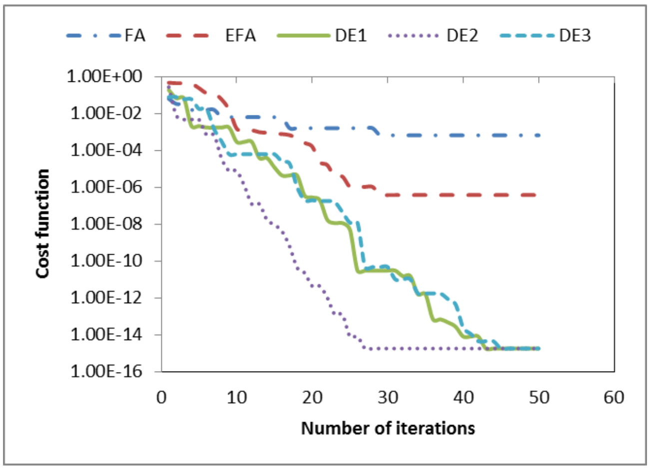

Figure 7. The comparison between the methods at 840 W/m^2-331.42 K

Another case has been taken here to examine the methods when the load is switched to 50 Ω. Two scheme of DE are comparable but they are better than the schemes of firefly algorithm where they are fast in response with acceptable accuracy as shown in Figures 9-15. Table 3 compares the objective function values for all methods at different irradiance and temperature for 25Ω and 50Ω loads.

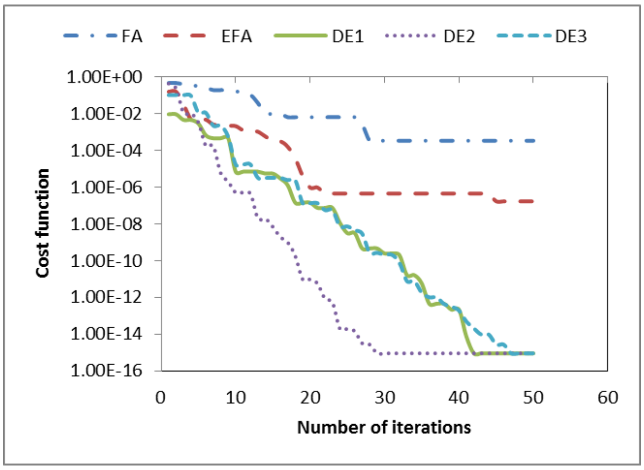

Figure 8. The comparison between the methods at 978 W/m^2-328.56 K

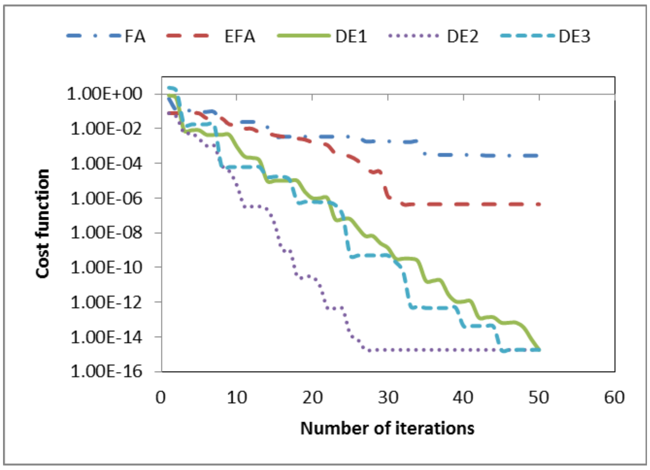

Figure 11. The comparison between the methods at 306 W/m^2-327.7 K

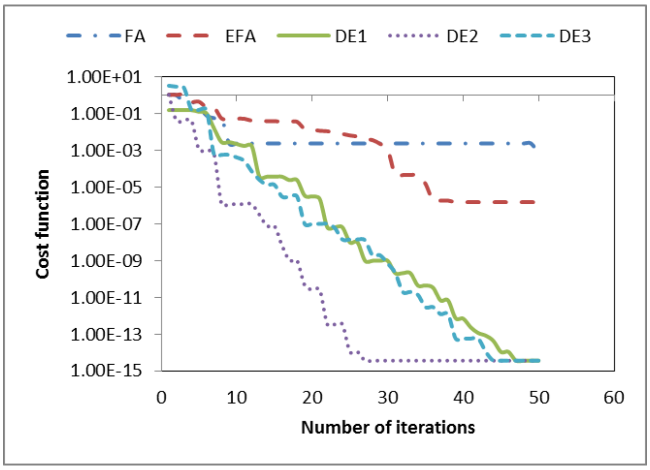

Figure 9. The comparison between the methods at 118.28 W/m^2-318.32 K

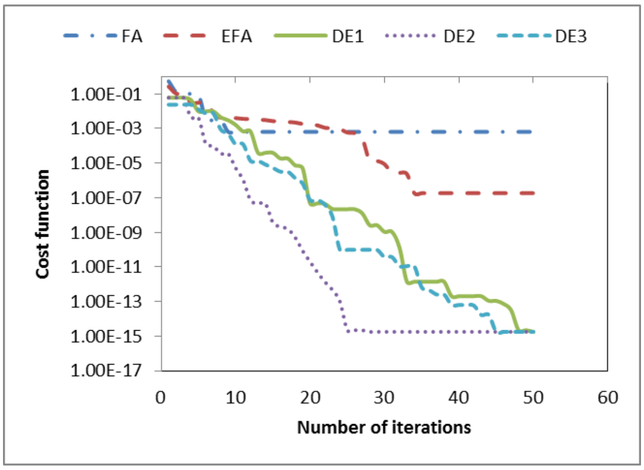

Figure 12. The comparison between the methods at 711 W/m^2-324.21 K

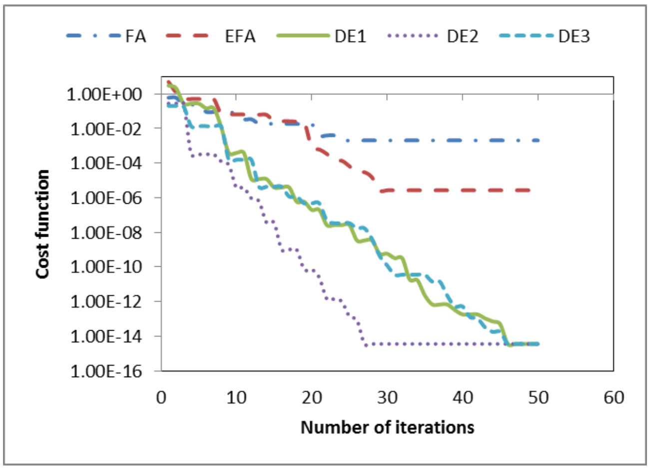

Figure 10. The comparison between the methods at 148 W/m^2-321.25 K

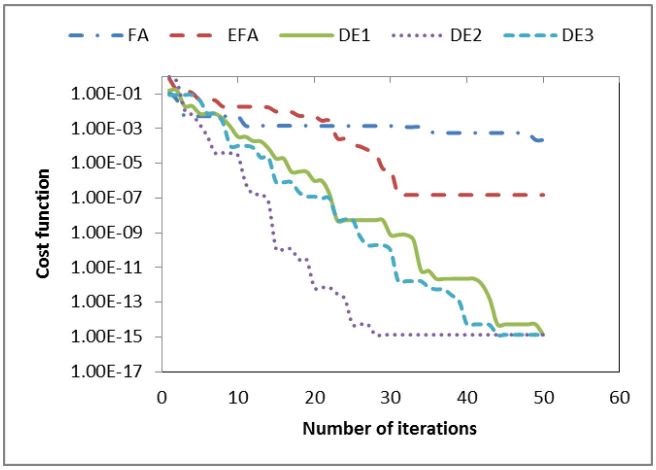

Figure 13. The comparison between the methods at 780 W/m^2-329.1 K

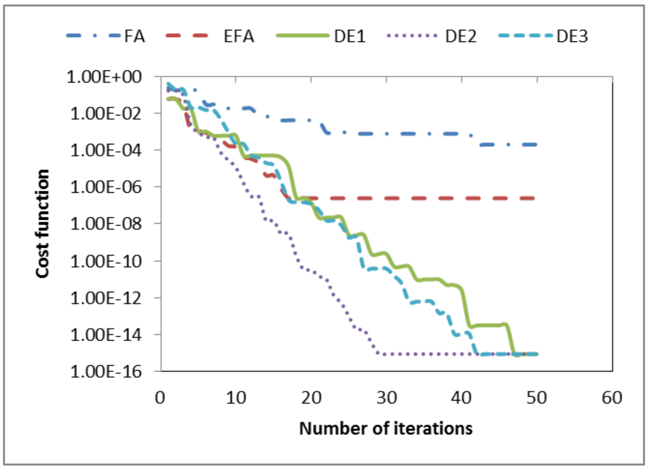

Figure 14. The comparison between the methods at 840 W/m^2-331.42 K

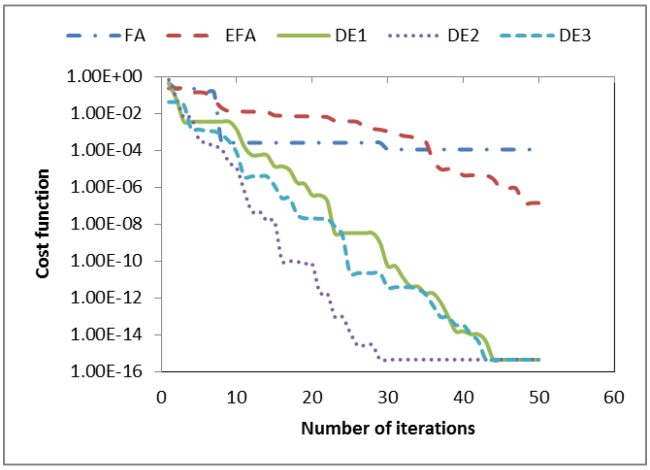

Figure 15. The comparison between the methods at 978 W/m^2-328.56 K

Table 3. The values of cost function

$I(\frac{W}{m^2})$-T(k)	$R_{OUT} = 25\ \Omega$				
	DE1	**DE2**	**DE3**	**FA**	**EFA**
118.28-318.32	3.55 E-15	3.55 E-15	3.55 E-15	0.001248	1.11 E-06
148-321.25	7.11 E-15	7.11 E-15	7.11 E-15	0.000725	1.13 E-06
306-327.7	1.78 E-15	1.78 E-15	1.78 E-15	0.000535	3.50 E-07
711-324.21	4.44 E-16	4.44 E-16	4.44 E-16	0.000531	2.24 E-07
780-329.1	0	0	0	0.000216	1.10 E-07
840-331.42	1.78 E-15	1.78 E-15	1.78 E-15	0.000663	3.80 E-07
978-328.56	8.88 E-16	8.88 E-16	8.88 E-16	0.000324	1.64 E-07

$I(\frac{W}{m^2})$-T(k)	$R_{OUT} = 50\ \Omega$				
	DE1	**DE2**	**DE3**	**FA**	**EFA**
118.28-318.32	3.55 E-15	3.55 E-15	3.55 E-15	0.000626	1.47 E-06
148-321.25	3.55 E-15	3.55 E-15	3.55 E-15	0.002049	2.67 E-06
306-327.7	1.78 E-15	1.78 E-15	1.78 E-15	0.000283	4.42 E-07
711-324.21	1.78 E-15	1.78 E-15	1.78 E-15	0.000642	1.83 E-07
780-329.1	1.33 E-15	1.33 E-15	1.33 E-15	0.000223	1.51 E-07
840-331.42	8.88 E-16	8.88 E-16	8.88 E-16	0.000203	2.47 E-07
978-328.56	4.44 E-16	4.44 E-16	4.44 E-16	0.000113	1.39 E-07

5. CONCLUSIONS

With a specific end goal to accomplish optimum efficiency, a photovoltaic ought to work at their peak power point. Consequently, a MPPT structure is actualized between the photovoltaic framework and the load to get optimum power. Different algorithms have been suggested here to solve this problem. However, the results show that the DE algorithms which were proposed in different schemes superior the firefly and the enhanced firefly. The values of irradiance and temperature have been changed according to the variation of the climate. These values are because of cloud, dust, and the hours day. As a future work it can be used additional algorithms or can be test another module.

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