Indo-Iranian Journal of Scientific Research (IIJSR)
Volume 1, Issue 1, Pages 114-122, October-December 2017

Evaluation of the Performance of the State-of-the-art Meta-Heuristics Techniques for Varying Insolation

Puneet Joshi[1] and Sudha Arora[2]

[1]*Department of Electrical Engineering, COT, GBPUAT, Pantnagar, Uttarakhand, India. Email: puneet.joshi07 @gmail.com*
[2]*Department of Electrical Engineering, COT, GBPUAT, Pantnagar, Uttarakhand, India. Email: arora.sudha@gmail.com*

Article Received: 05 October 2017 *Article Accepted: 21 October 2017* *Article Published: 30 October 2017*

ABSTRACT

Development of efficient and effective converter for Maximum Power Point Tracking (MPPT) under varying insolation is a great challenge for researchers working on solar photovoltaic systems. Meta-heuristic techniques are claimed to be effective but still scope for improvement does exist. To this end, a comparative study of popular approaches may be helpful for selection of best approach. In this paper, an evaluation of the behavior of the state-of-the-art meta-heuristics based maximum power point tracking (MPPT) techniques has been presented. Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA) and a hybrid co-evolutionary scheme PSO-GSA have been compared for various insolation levels. Statistical indices and a test statistic (t-test) have been applied to compare and determine the scheme having superior performance. From the simulation results, it is evident that the hybrid PSO-GSA may outperform other algorithms for PV systems for changing environments. This work will also serve as a source to instigate with the application of modern optimization methodologies in the domain of MPPT of PV systems.

Keywords: Solar PV Systems, MPPT, Converter and Meta-Heuristics Techniques.

1. INTRODUCTION

Solar energy is a pollution free, unlimited, clean and inexhaustible source of Renewable energy. PV systems are designed for both stand-alone and hybrid applications. these include street lighting, water pumps, electric vehicles, solar-wind hybrid systems, Microgrids, etc. Nonetheless, one of the major problems associated with the PV systems is the efficiency of the solar panels which is very low ((17-21%) [1]. In addition, the performance of solar panels degrades exponentially under low irradiance levels. Major challenge in extracting power from the solar panels is due to the nonlinear behavior of a PV cell with varying irradiance and temperature, Fig.1 On the P-V curve, there lies a point, called the Maximum Power Point (MPP) at which the complete PV system operates with maximum efficiency, Fig. 1. But the trouble lies in the fact that this point is not known and the task is to track this point by applying the Maximum Power Point Tracking (MPPT) algorithms [2]. Many conventional MPPT algorithms have been proposed in literature; viz., Perturb and Observe (P&O), Incremental Conductance, Incremental Resistance, Temperature method. However, a more modern approach to this problem is to consider it as an optimization problem where the ask is to maximize power subject to constraints like duty ratio. Approaches like PSO, GSA, Ant Colony Optimization [2], Differential Evolution [3], Cuckoo Search [4] etc. fall under this category.

In this article, the more efficient and modernized MPPT algorithms have been scrutinized and compared under the categories: energy production and convergence rate. The three MPPT algorithms are PSO, GSA & PSO-GSA. These methods have been chosen due to the incapability of the classical approaches to trace the MPPT during rapidly changing environment and oscillations. Besides these are easier to carry out in hardware as compared to their peers. The MPPT techniques are investigated using the MATLAB/SIMULINK toolbox considering variety of insulations. Without the loss of generality stand-alone PV system is taken, in the analysis, by plugging into a boost converter as shown in Fig.2.

2. PV ARRAY/ SYSTEM OVERVIEW

Generally, PV systems consist of PV panels, a DC-DC converter, battery and controllers. PV panels convert the solar energy to the electrical energy which is then fed to the chopper circuitry controlled by the MPPT controllers. The controller, at all times, matches the load characteristics with those of the PV panels. Battery is an all-important component in case of grid interconnections, since, it bestows stabilized voltage levels corresponding to different loads at the inverter input terminals, in addition, it also delivers power during low irradiances.

Fig.3 shows the equivalent circuit of a PV cell. A solar panel comprises of several series parallel combinations of such cells. With reference to fig.3, (1) describes the I-V characteristics of a solar panel:

$$I = I_{ph} - I_o\left(\exp\left(\frac{V+IR_s}{n_s v_T}\right)-1\right) - \frac{V+IR_s}{R_p} \quad (1)$$

Rp is very large, in modern PV cells typically, it is >100kΩ. Thus, current through it has been overlooked for the sake of restraint in the computation. Mathematically, current at MPP is given by:

$$I_{mpp} = I_{ph} - I_o\left(\exp\left(\frac{V_{mpp}+I_{mpp}R_s}{n_s v_T}\right)-1\right) - \frac{V_{mpp}+I_{mpp}R_s}{R_p} \quad (2)$$

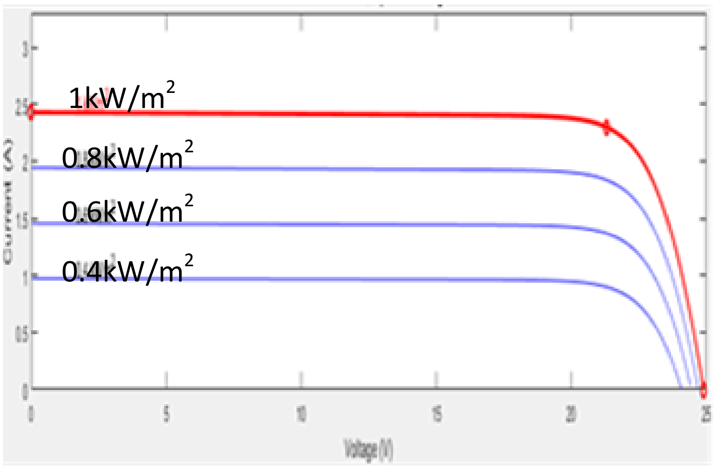

Fig.1(a) current vs voltage with varying irradiance

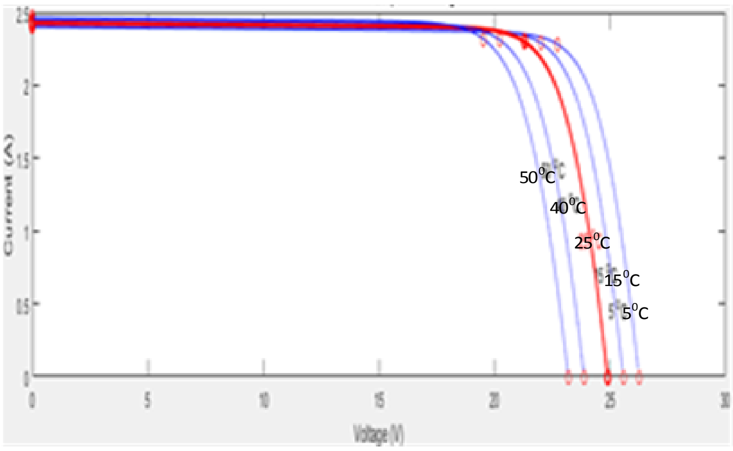

Fig.1 (c) Current vs voltage with varying temperature

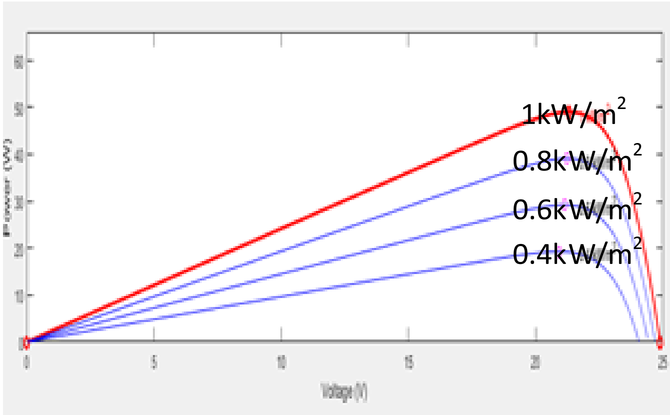

Fig.1 (b) Power vs voltage with varying irradiance

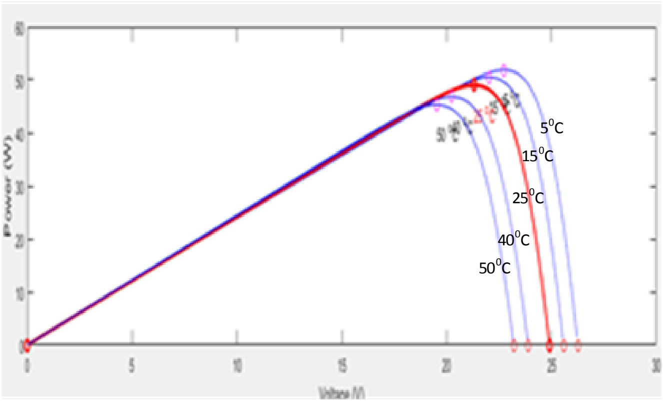

Fig.1(d) Power vs voltage with varying temperature

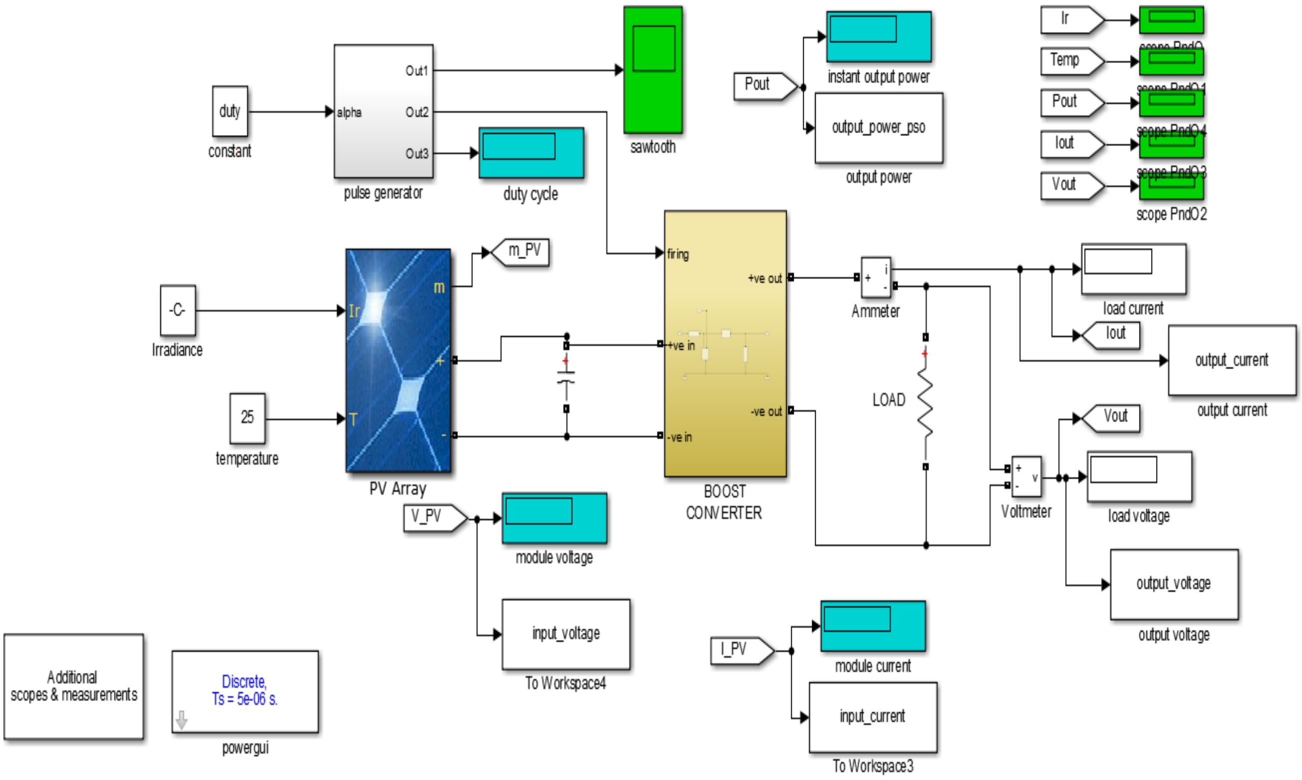

Fig.2 MATLAB/SIMULINK based modelling of stand-alone PV system

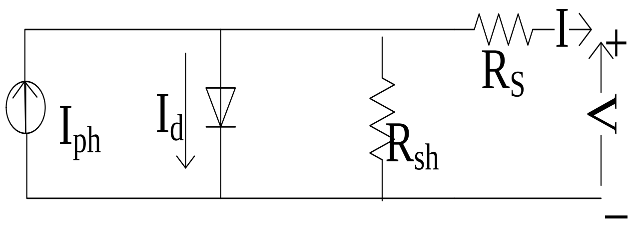

Fig.3 Equivalent circuit of a PV cell

However analytical solution of (2) is Table I indicates the parameters of the PV panel used for the simulation purposes.

Table I. Solar Array Specifications (25 0C, 1000 W/m¬2)

Parameters	**Definitions**
Maximum Power	48.99
Voltage at Maximum Power Point, V_{MPP}	21.30
Current at Maximum Power Point, I_{MPP}	2.30
Short Circuit Current, I_{SC}	2.43
Open Circuit Voltage, V_{OC}	24.9

Nomenclature:

I_{ph}	Photoelectric current (A)
I_o	Diode reverse saturation current (A)
q	Charge of an electron, 1.6021×10^{-19} C
K	Boltzmann constant, 1.3865×10^{-23} J/K
T	Standard Operating Temperature (Kelvin)
n	Diode factor ($1 \le n \le 2$)
G	Insolation (W/m^2)
R_s	Series resistance (Ω)
R_p	Shunt resistance (Ω)
n_s	Number of cells in series
V_{oc}	Open Circuit Voltage
I_{sc}	Short Circuit Current
V_{mpp}	Voltage at Maximum Power Point
I_{mpp}	Current at Maximum Power Point
I_d	Diode current
I	PV module Current (A)
V	PV module Voltage (V)
E_g	Silicon gap energy of semiconductor
v_T	Thermal voltage equivalent (V)
STC	Standard Temperature Condition

3. META-HEURISTICS BASED MPPT APPROACHES

Over the years, several meta-heuristics approaches have been proposed, but some have reached enormous popularity and credit. Broadly any optimization method starts with a set number of practicable solutions, known as, population. Grounded along the problem in hand and the technique applied these solutions are adopted, iteratively, to achieve the destination. Once the desired output is obtained, the procedure is stopped by some stopping criteria. Thus, initialization and stopping criteria are an important issue. More often than not, in case of the MPPT method, initialization consists of distributing population uniformly between the multiples of the VOC. Possibly, a variety of convergence criteria can be adopted. It may be set as threshold for velocity of the particles. Limiting the number of iterations can also act as a complementary convergence criterion. For re-initialization of the process, usually, a relative change in power can be employed as a measure. Some other way to reboot, is to set up a set time point. After this time, the technique is automatically initialized with new, random positions of the particles. Hereafter, three such popular approaches have been discussed.

3.1 Particle Swarm Optimization

PSO starts with independent random selection of the agents. In between iterations, the agents share the acquired knowledge in its respective endeavour. Each agent, referred to as a particle, tries to improve its own accomplishment against the best particle in the swarm. In this manner, each particle ultimately attains an optimal or a nearly optimal solution.

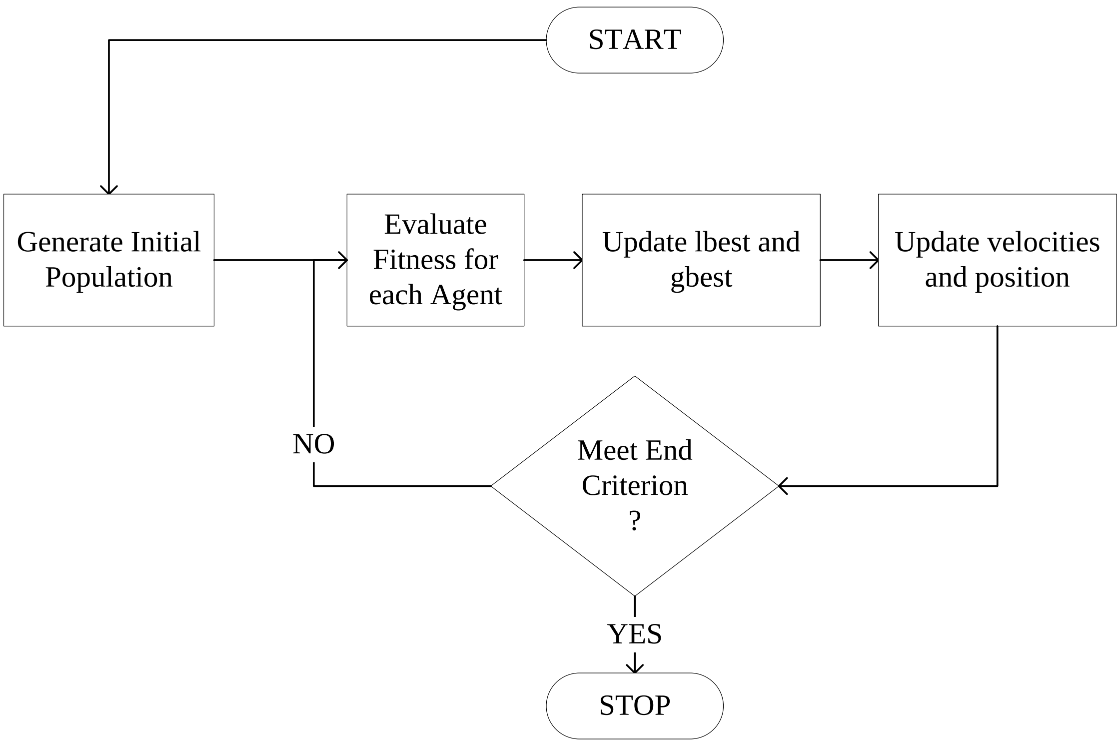

Fig.4 Flowchart for PSO

The standard PSO is formally interpreted by:

$$x_i^{t+1} = x_i^{t} + v_i^{t+1} \quad (3)$$

Where

$$v_i^{t+1} = wv_i^{t} + c_1 r_1 (localbest^{t+1} - x_i^{t}) + c_2 r_2 (globalbest^{t+1} - x_i^{t}) \quad (4)$$

Where, xi is the particle position, vi is the velocity of ith particle; w is an inertial weight; t is the iteration number; and r2 are random selected values between [0,1]. c1 is the cognitive coefficient and c2 is the social factor. The localbest variable stores the best value that an individual has achieved till the ith iteration, and globalbest stores the best solution obtained by all the particles collectively [5]-[8]. The flowchart of a basic PSO algorithm is exemplified in fig. 4. The algorithm of a basic PSO method is identified as follows:

3.2 Gravitational Search Algorithm

GSA is based along the principle of Newtonian gravitation. As mentioned by the authors in [9], the population in each step updates through cooperation, competition and self-adaptation. The performance of any agent is indicated by its mass. All agents engage each other by the gravity force given by:

$$F_{ij}^{d}(t)=G^{t}\frac{M_{pi}^{t}\times M_{aj}^{t}}{R_{ij}^{t}+\varepsilon}(X_{j}^{d}(t)-X_{i}^{d}(t)) \qquad (5)$$

Where

$$G(t)=G_{0}\times e^{(-\alpha\times iter/max\_iter)} \qquad (6)$$

α and G0 are descending coefficient, iter is the current iteration, and max_iter is upper limit of iterations. Rij(t) is the Euclidean distance between agents i and j, ε is a constant, x represents the position in the search space, M are the active gravitational masses given by:

$$m_{i}^{t}=\frac{fit_{i}^{t}-worst^{t}}{best^{t}-worst^{t}} \qquad (7)$$

$$M_{i}^{t}=\frac{m_{i}^{t}}{\sum m} \qquad (8)$$

$$a_{i}^{d}(t)=\frac{F_{i}^{d}(t)}{M_{ii}^{t}} \qquad (9)$$

$$v_{i}^{d}(t+1)=rand_{i}\times v_{i}^{d}(t)+a_{i}^{d}(t) \qquad (10)$$

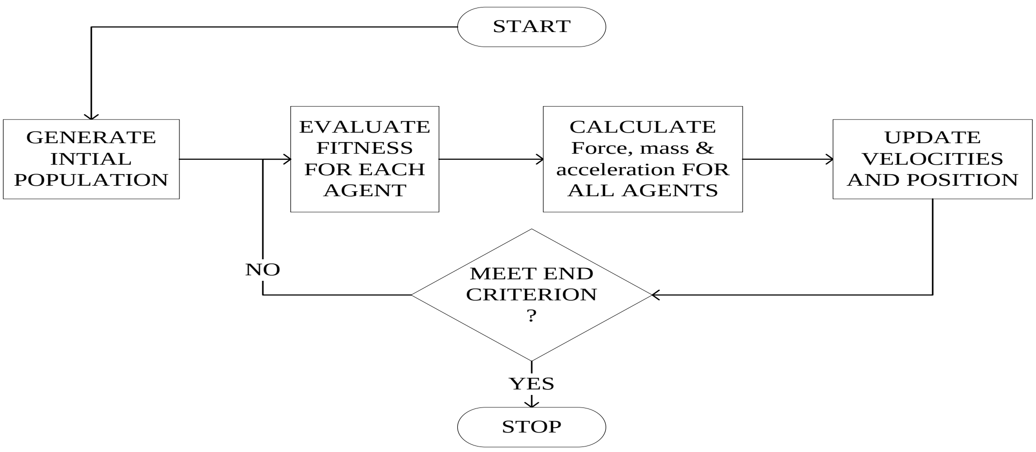

Fig.5 Flowchart for GSA

Henceforth, next position is calculated by using (3). The flowchart for the method is shown in Fig.5 [10-11].

3.3 PSO-GSA

PSO-GSA integrates the capability of social thinking (exploitation) in PSO with the local exploration potential of GSA. It uses a hybrid approach which is low-leveled, co-evolutionary and inhibits heterogeneity. The hybrid is low-level because the functionality of both algorithms is blended. It is co-evolutionary because the two approaches run in incognito and concurrence. It is heterogeneous because there are two different algorithms that are required to get a solution. [12]

Resultant forces among agents is given by (5). Henceforth, the acceleration of particles is calculated by (9) and the best solution(globalbest) so far is updated. Through the globalbest, the velocities of all agents can be computed as follows:

$$v_i^{t+1} = w \times v_i^t + c_1 \times rand \times a_i^t + c_2 \times rand \times (globalbest - x_i^t) \quad (11)$$

The agents new position is again calculated by (3).

4. RESULTS AND DISCUSSION

A Simulink model shown in fig.2 was used to simulate the system as specified in Table I. From the simulations results Table II was summarized and following conclusions were inferred:

- All methods are able to achieve Global MPP at all irradiances with fewer particles required (~3).
- All methods have very fast convergence rate (3-5 iterations max.).
- PSO and PSO-GSA have no oscillations, whereas, GSA suffers from minute oscillations in output power.
- PSO requires least computations and is thus, easier to program in hardware.
- PSO and PSO-GSA produce almost same output at all irradiances.

Table II. Comparison of Different MPPT Methods at Various Irradiance Levels

Irradiance	Method	Optimum Duty	Max. Power
1000	*PSO*	0.49	46.29
	GSA	0.43	46.29
	PSO-GSA	0.41	46.29
800	*PSO*	0.51	38.86
	GSA	0.57	38.86
	PSO-GSA	0.56	38.86
600	*PSO*	0.61	28.47
	GSA	0.64	28.47
	PSO-GSA	0.69	28.47
400	*PSO*	0.76	19.23

Table III. Various statistical indices for the three methods

Method		Mean	Median	Best	**Worst**
PSO	Power	45.85	46.29	46.29	33.20
	Duty	0.47	0.46	0.49	0.69
GSA	Power	38.12	43.44	46.29	22.74
	Duty	0.54	0.52	0.41	0.80
PSO-GSA	Power	46.12	46.29	46.29	**43.44**
	Duty	0.46	0.45	0.45	0.59

All methods produce almost same results, thus, the choice for any method depends on the ease in hardware implementation. However, another method to determine the superiority of a particular method is to form a hypothesis and then apply some test statistic to check it. 30 samples for each method were obtained for 1000 W/m2 and 250C. Table III summarizes the results for 30 samples. It is shown that PSO-GSA was able to perform better than the other two approaches. In addition, two sampled t-test was also applied for which the level of significance for the test was set to 95%. Through the test it was deduced that PSO and PSO-GSA have almost same performance and they prove to be a better choice over GSA. However, as stated earlier due to ease in hardware implementation PSO may be preferred over PSO-GSA.

5. CONCLUSION

In this paper, PSO, GSA and PSO-GSA methods were compared for tracking MPP of a PV system. The three approaches are very efficient compared to the classical approaches. As they require fewer steps and population size to converge to the GMPP. Oscillations existing in the conventional methods, were removed by means of social thinking and local search capability. Despite the mathematical and programming complexity, the proposed methods offer remarkable accuracy and speed. Furthermore, the methods can be easily implemented in real time using a microcontroller. In future, newer meta-heuristics based algorithms may be developed for MPPT or hardware based performance analysis of the existing schemes may be carried out.

REFERENCES

[1] D. P. Hohm, M. E. Ropp, “Comparative study of maximum power point tracking algorithms using an experimental, programmable, maximum power point tracking test bed,” Photovolt. Spec. Conf. 2000. Conf. Rec. Twenty-Eighth IEEE, pp. 1699–1702, 2000.

[2] L. L. Jiang, D. L. Maskell, and J. C. Patra, “A novel ant colony optimization-based maximum power point tracking for photovoltaic systems under partially shaded conditions,” Energy Build., vol. 58, pp. 227–236, 2013.

[3] M. F. N. Tajuddin, S. M. Ayob, Z. Salam, and M. S. Saad, “Evolutionary based maximum power point tracking technique using differential evolution algorithm,” Energy Build., vol. 67, pp. 245–252, 2013.

[4] J. Ahmed, Z. Salam, “A Maximum Power Point Tracking (MPPT) for PV system using Cuckoo Search with partial shading capability,” Appl. Energy, vol. 119, pp. 118–130, 2014.

[5] N. Khaehintung, A. Kunakorn, and P. Sirisuk, “A novel fuzzy logic control technique tuned by particle swarm optimization for maximum power point tracking for a photovoltaic system using a current-mode boost converter with bifurcation control,” Int. J. Control. Autom. Syst., vol. 8, no. 2, pp. 289–300, 2010.

[6] M. Miyatake, F. Toriumi, T. Endo, and N. Fujii, "A Novel maximum power point tracker controlling several converters connected to photovoltaic arrays with particle swarm optimization technique," 2007 Eur. Conf. Power Electron. Appl., pp. 1–10, 2007.

[7] P. Selvapriyanka, G. Vijayakumar, "Particle Swarm Optimization Based MPPT for PV System under Partial Shading Conditions," vol. 3, no. 1, 2014.

[8] C. Liu, "A PSO-based MPPT Algorithm for Photovoltaic Systems Subject to Inhomogeneous Insolation," no. 1, pp. 721–726, 2012.

[9] I. Sciences, "GSA : a Gravitational Search Algorithm," no. JUNE, 2009.

[10] E. Rashedi, H. Nezamabadi-pour, and S. Saryazdi, "GSA : A Gravitational Search Algorithm," Inf. Sci. (Ny)., vol. 179, no. 13, pp. 2232–2248, 2009.

[11] D. Saha, "A GSA Based Improved MPPT System for PV Generation," pp. 131–136.

[12] B. G. S. Dhas,S. N. Deepa, "A Hybrid PSO and GSA -Based Maximum Power Point Tracking Algorithm for PV Systems," no. 1, pp.2–5, 2013.