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EL-PSO based MPPT for Solar PV under Partial Shaded Condition

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Abstract

Photovoltaic Electrical Power Generation System (PV-EPGS) is gaining more importance due to its benefits like no fuel cost, eco-friendliness and less maintenance. However, harnessing the maximum power from large PV-EPGS has become difficult due to the occurrence of a number of peaks in P-V characteristics under partial shaded conditions. This paper presents simulation study of MPPT under partially shaded conditions using the modified version of Particle Swarm Optimization method known as Enhanced Leader Particle Swarm Optimization (EL-PSO). Proposed ELPSO method has advantages over PSO like fast convergence, better dynamic performance, easy implementation and high efficiency. To evaluate the proposed method simulation result of PV panel, Siemens S75 is provided for three different shaded conditions.

Keywords: Photovoltaic Electrical Power Generation System (PV-EPGS), Partial Shaded Condition (PSC), Enhanced Leader Particle Swarm Optimisation (ELPSO).

1. Introduction

The never ending call for energy and less availability of fossil fuels has led the mankind to search for sustainable alternatives. On the other hand, green energy harvestment from renewable energy resources has raised the hopes for

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pollution free power generation. Particularly, solar energy is the current emerging trend with huge potential to solve surmount energy demand [1,2].

Photovoltaic Electrical Power Generation System (PV-EPGS) converts solar energy into electrical energy. In general, PV system consists of PV modules connected in series and parallel [2]. Under such conditions, PV panels may receive non-homogeneous irradiation due to passage of cloud or tree and chimney shadow. This effect in PV is renowned as partial shading effect. This effect in turn reduces the PV panel output significantly and multiple peaks in P-V characteristics are created as a consequence. Hence there is always a necessity to operate PV at Global maximum power point to utilize the maximum available power. For this reason, the maximum power point controllers are adapted.

To achieve MPP, various MPPT algorithmic techniques like Perturb and Observe (P&O), Incremental Conductance (INC) and Hill Climbing methods are used. The basic principle behind all the methods are voltage/duty of the converter is changed stepwise and correspondingly the operating point of the PV varies [1]. However the common drawbacks found on these methods are (i) repeated perturbations, (ii) higher steady state oscillations and (iii) Less conversion efficiency. Earlier methods that fall under the category of conventional MPPT fail to detect the global point and get trapped within one of the local MPP hence result in poor usage of the entire PV array power. As an alternative to earlier methods as well as to overcome the drawback in above methods, another category called as bio-inspired is introduced. These methods are designed based on the biological behavior of swarm movement such as ants and other insects. Metaheuristic techniques like Particle Swarm Optimization (PSO) [3], Improved PSO (IPSO) [4] and Modified Swarm optimization (MPSO) [5,6] are applied for MPPT. In PSO, iteration wise strategy is followed to trace operating point where the maximum power point is located [7,8]. Although PSO methods introduced higher possibilities to reach global peak under shade conditions, their convergence to the optimal operating region is not always guaranteed.

In addition to the earlier methods, recently bio and nature inspired algorithms like Firefly, Artificial Bee Swarm optimization (ABSO), Cuckoo Search and Flower Pollination Algorithm (FPA) [7,8] is also proposed for maximum power point tracking. However the methods have common drawback that the exploitation in control variables is not created once after the algorithm reaches steady state position. Thus the possibility to extract the same power at MPP becomes crucial. Therefore there is always a necessity to introduce randomness in the control variable even after convergence to MPP. Further it is also important to have less complexity method with fewer parameters since; it imparts higher influence to the convergence rate [9,10].

Thus from the above literature it is found that all the methods follow swarm optimized methods where it has all the possibilities to reach Global convergence but due to the improper initialization and velocity updation constraints the PSO method have found to be less appealing [1,2]. Hence in this paper, the authors have proposed a new Enhanced Leader PSO [11] by doing modifications in basic PSO. The common problem found in PSO method is that the particles are misguided due to lack of randomness. So, the modifications are made in PSO to introduce mutations on global best (*Gbest*) particle to strengthen the search ability. These mutations add high value to the particle updation and thus global convergence is always ensured. The remainder of the paper is organized as follows.

Section 2 discusses the mathematical modelling of Solar PV. Section 3 details the effect of partial shading to the PV generation; Section 4 outlines the basic PSO and gives the idea on implementation of EL-PSO method and simulation and results are discussed in section 5 where the conclusion derived are presented at last.

2. MODELING OF SOLAR PV

To model the solar cell characteristics authors in this paper have used one diode model due to its simple structure [12-15]. Schematic of single diode model is given in Fig.1.

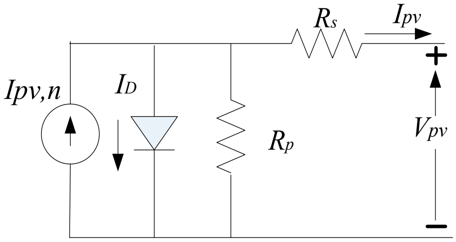


Fig.1. Schematic of One diode model.

The output current of a solar PV cell is given by

$$I_{PV} = I_{PV,n} - I_D - \frac{V + IRs}{Rp} \tag{1}$$

The diode current equation in equation (1) is given below,

$$I_D = I_O(e^{V_D/\alpha V_T} - 1) \tag{2}$$

Where 'I_o' is the reverse saturation current, 'a' is the diode ideality factor and V_T is the thermal voltage. The thermal voltage subjected to any temperature is given by,

$$V_T = \frac{N_S KT}{q} \tag{3}$$

Where 'Ns' is the number of cells connected in series, 'K' is the Boltzman constant $1.3805*10^{-23}$, T is the temperature at STC and 'q' is the charge of the electron $1.9*10^{-19}$C. To improve the accuracy of modeling solar PV module the values of 'Rs' and 'Rp' were selected by guidelines provided in [3].
The output current equation for a PV module is obtained and it given below:

$$I_{PV} = N_{pp}\left\{I_{PV,n} - I_O\left[\exp\left(\frac{V + IR_S}{V_t N_{ss}}\right) - 1\right]\right\} - \left(\frac{V + IR_S}{R_P}\right) \tag{4}$$

Where 'N_{ss}' and 'N_{pp}' are the number of cells connected in series and parallel [14,15].

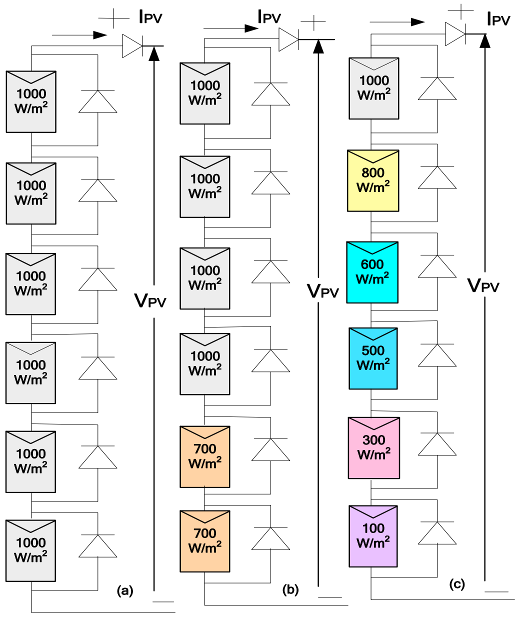


Fig.2. PV shade patterns

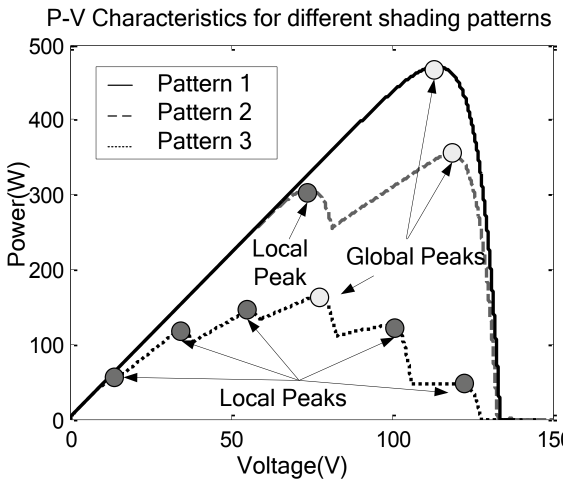


Fig.3. P-V characteristics for shade patterns

3. Effect of Partial Shaded Condition (PSC) On Photo Voltaic Electric Power Generation Systems (PV-EPGS)

In order to scale up the PV power according to demand requirement, PV modules are connected in series and parallel fashion to form a PV array. Under such condition, the panels receive non-uniform irradiation will introduce shading effect to the panels [8,9]. Specifically, in a cloudy day the panels may witness faster and dynamic insolation change. Under such circumstances, the nature of P-V curve distorting to produce multiple peaks is shown in Fig.3. During this period, the panels receiving less irradiation introduce hotspots and act as a load to the panel. Further the shade condition increases the probability of damaging the panels and hence reduces the efficiency of power delivered by the panel. Hence to avoid the severity, each panel connected in PV array is connected with a bypass diode and it gets forward biased when any irradiation changes occur [5]. The occurrence of multiple peaks under partial shading condition is shown in Fig.3. From Fig.3, P-V characteristics with local and global peaks under partial shaded conditions are clearly mentioned where the significant power reduction is also clearly seen. It is also important to note that depending on the shade pattern, the GMPP is varying. Thus the importance of tracking GMPP under shade conditions is mandatory to improve the efficiency of power generation.

3.1. Outline of PSO

Particle swam optimization (PSO) is simple bio-inspired technique applied for non linear optimization problems. Inspired from bird flocking, fish schooling or bee interaction in search for food, the PSO method is devised and is widely implemented in various fields of engineering and science for optimization and design applications. PSO in general works on two basic principles; one is learning by previous data and communication of present information among the swarm agent [3].

Two important rules are applied on these swarm agents. Let us call these agents as particles. First rule is that all particles should follow that particle whose performance is best. Second rule is that all particles should move towards that particle having best condition. Until the termination criterion is met, the particles tend to move towards optimal result. It is noteworthy to mention that velocity and position of best particle is taken as reference and all the remaining will move to reach the global particle fitness. The velocity and position updation used in conventional PSO can be mathematically represented as,

$$V_i(k+1) = wV_i(k) + x_i(k) + C_1 r_1 (P_{best} - x_i(k)) + C_2 r_2 (G_{best} - x_i(k)) \tag{5}$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \tag{6}$$

Where 'w' is inertia weight; 'r_1' and 'r_2' are random variables uniformly distributed within the interval 0 to 1; and 'C_1', 'C_2' are the cognitive and social coefficient, respectively. The steps followed in conventional PSO are given as follows

Step 1: *Initialization of PSO*: Initialize the particles randomly in the search space where early velocities for the particles are chosen arbitrarily.

Step 2: Assessment of fitness: Fitness of each particle is evaluated by contributing single particle elucidation to objective function.

Step 3:Updating the personal G_{best} and P_{best}: The computed fitness values are compared against the previous values for updating the individual personal and global best. Their corresponding positions are also updated accordingly.

Step 4: Velocity and position Updation: Using equations (5) and (6) velocity along with the position of every particle is modernized.

Step 5: Determination of convergence: Check for the convergence criterion and stop the procedure if it satisfied. Else, increment iteration count and repeat the process from step 2.

3.2. Enhanced Leader PSO:

EL-PSO is a modified version of PSO that enhances the global leader for every iteration in a procedure to locate GMPP. Considering the initial count of particles/swarm as five, corresponding five consecutive mutation procedure is applied to the swarm leader. If any of the mutated particle attains better fitness than the global best particle (i.e) power generated is more than the from present best particle G_{best} particle (P_g), then it replaces the position P_g. In the similar way, the leader is enhanced at each iteration resulting in improved efficiency of the search process [11]. The mutations followed in EL-PSO are described in the following.

At first step of mutation strategy Gaussian distributions based mutation is applied to the first particle (*D(1)*) as:

$$D(1) = P_g + (upband1 - lwband1).Gaussian(o, h) \quad (7)$$

Where *'h'* is standard deviation of Gaussian distribution and *'upbnd1'* and *'lwbnd1'* represent the upper and lower bounds of decision vectors. For example, consider five duty cycle in the population, where '*D(1)*' is the mutated first particle position. If the power of '*D(1)*' is better than the 'G_{best}', then '*D(1)*' out places '*Pg*'.For enhanced exploitation lessening of standard deviation of the Gaussian distribution is carried out linearly after every iteration.

$$h(iter + 1) = h(iter) - \left(\frac{1}{\max iter}\right) \quad (8)$$

Cauchy mutation is applied to the position of the current best fitness/ duty as *D(2)*',using the equation (9):

$$D(2) = P_g + (upband1 - lwband1).Cauchy(0, s) \quad (9)$$

'*D(2)*' is the mutated second particle position. If the power of '*D(2)*' is better than the 'G_{best}', then '*D(2)*' takes the position of Pg. Where's' is scale parameter of Cauchy that is lessened linearly after every iteration. . This is done to have more exploitation capability.

$$s(iter + 1) = s(iter) - \left(\frac{1}{\max iter}\right) \quad (10)$$

Third mutation is opposition-based particle position (*D (3)*), that is mathematically represented as:

$$D(3) = (upband1 + lwband1) - P_g \quad (11)$$

'*D (3)*' is the third mutated particle position. If the power of *D (3)* is better than the G_{best}, then *D(3)* takes the place of Pg.

Fourth mutation is yet another opposition-based particle position updated fourth time to find global best leade (*D(4)*), where it can be represented as,

$$D(4) = (upband1 + lwband1) - P_g \quad (12)$$

'D(4)' is the mutated third particle position. If the power of *D(4)* is better than the 'G_{best}', then *D(4)* takes the place of P_g.

Fifth mutation is DE-based operator and that can be mathematically represented as,

$$D(5) = P_g + F(dt_r - dt_s) \quad (13)$$

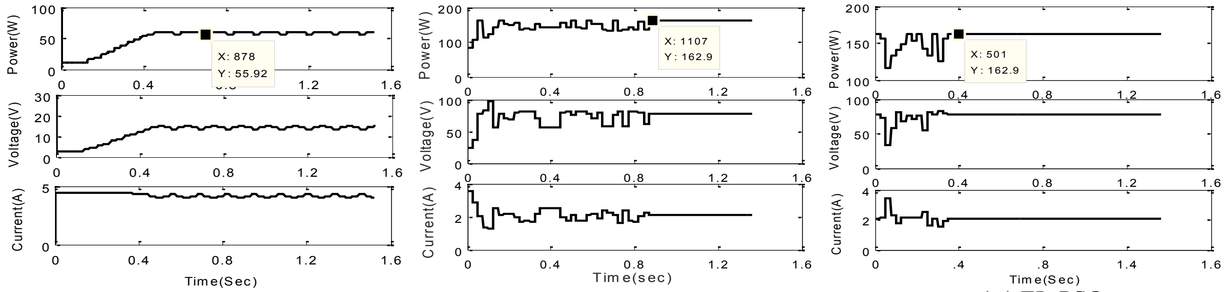
F -Control parameter called scale factor and r and s are two random unequal particles in swarm. If the power of *D(5)* is better than the G_{best}, then *D(5)* takes the place of P_g.

From all the mutations applied to the global leader, it is expected that premature convergence in non linear optimization function is reduced and results of good leader of swarm/ duty with better fitness. In this case, global MPP regions are achieved faster and hasty convergence is obtained.

4. Simulation and Experimental Results

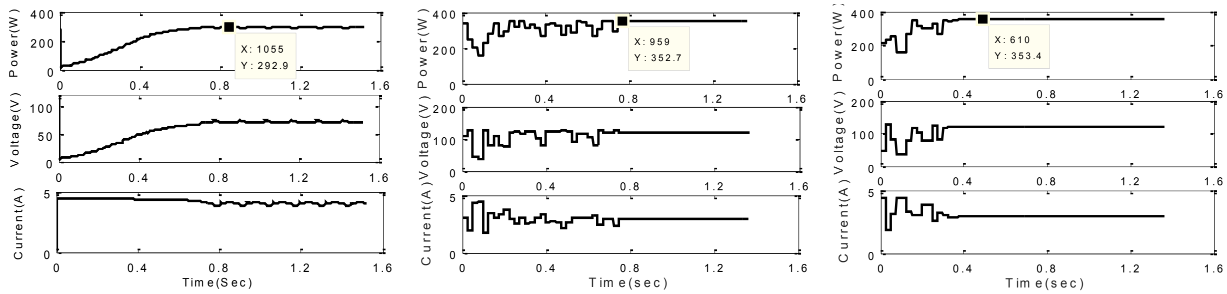
To demonstrate the effectiveness of ELPSO, simulations are carried out in 2 different shade conditions (1) Uniform irradiation (2) Partial shading conditions. Further the results of El-PSO methods are compared with conventional PSO and P&O method as performance evaluation. Dedicated MATLAB code is developed and tested for simulating ELPSO along with other two methods P&O and PSO. For performing extermination, DC-DC boost converter is used in order to obtain an output which has practical applications. The PV model used in this experiment has a PV array system linked to a DC to DC boost converter. The input to this converter is provided from sensors of voltage and current. The codes for all the methods are implemented using digital MPPT controller.

The converter operated in continuous conduction mode where their design specifications (DC-DC boost converter) are switching frequency-10 kHz, capacitor C-100uF and inductor L of 2000mH respectively. Enough caution is taken during simulation to ensure that same operating conditions are considered for comparing all the three methods. This comparison plays a vital role in proving that the projected technique has good efficiency than other methods.



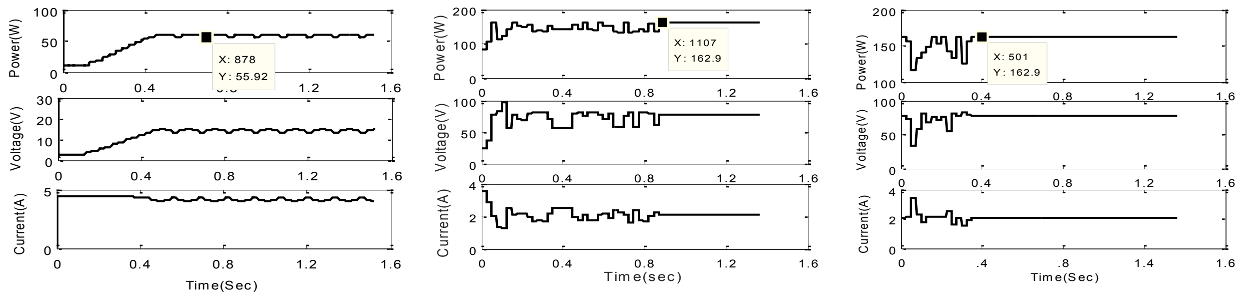
(a) P&O (b) PSO (c) EL-PSO

Fig. 4(a). Simulated Results of Power, Voltage and Current waveform for Pattern I.



(a) P&O (b) PSO (c) EL-PSO

Fig. 4(b). Simulated Results of Power, Voltage and Current waveform for Pattern II.



(a) P&O (b) PSO (c) EL-PSO

Fig. 4(c). Simulated Results of Power, Voltage and Current waveform for Pattern III.

Simulated results for all the three patterns under uniform and partial shaded conditions are shown in Fig.4(a), (b) and (c) respectively. From the above results, we infer that ELPSO is faster than P&O and PSO. Furthermore, PSO takes around 10 iterations, whereas ELPSO takes just 4 iterations to reach global point.

Here important to notify that P&O method has got trapped in pattern 2 and 3 where the both PSO and EL-PSO methods have managed to reach Global power point. However the steady state oscillation and convergence time taken by PSO method is comparatively high.

5. Conclusion

In this paper a new approach for MPPT via Enhanced Leader PSO is proposed. Based on successive mutations, ELPSO is found to be efficiently locating the global optimized regions. Obtaining the best swarm leader accomplish the identification of GMPP faster than the conventional PSO. Particularly, peaks with lesser power difference are also recognized by ELPSO. Furthermore, the performance comparison with PSO and P&O methods validates the supreme potential in ELPSO.

References

[1]. Ram, J. Prasanth, T. SudhakarBabu, and N. Rajasekar. "A comprehensive review on solar PV maximum power point tracking techniques." Renewable and Sustainable Energy Reviews 67 (2017): 826-847.

[2]. Ram, J. Prasanth, N. Rajasekar and Masafumi Miyatke. " Design and overview of maximum power point tracking techniques in wind and solar photovoltaic systems: A review" Renewable and Sustainable Energy Reviews 73 (2017): 1138-1159.

[3]. MasafumiMiyatake, M. Veerachary, Fuhito .T.N.Fujii, HidyoshiKo, Maximum Power Point Tracking of Multiple Photovoltaic Arrays: A PSO Approach, IEEE Transactions on Aerospace And Electronic Systems Vol. 47, NO. 1, 2011, 0018-9251.

[4]. Babu, T. Sudhakar, K. Sangeetha, and N. Rajasekar. "Voltage band based improved particle swarm optimization technique for maximum power point tracking in solar photovoltaic system." Journal of Renewable and Sustainable Energy 8.1 (2016): 013106.

[5]. Rajasekar, N., et al. "Application of modified particle swarm optimization for maximum power point tracking under partial shading condition." Energy Procedia 61 (2014): 2633-2639.

[6]. T.SudhakarBabu, N.Rajasekar, K.Sangeetha, Modified Particle Swarm Optimization technique based Maximum Power Point Tracking for uniform and under partial shading condition, Applied Soft Computing 34(2015)613-624.

[7]. Ram, J. Prasanth, and N. Rajasekar. "A novel Flower Pollination based Global Maximum Power Point method for Solar Maximum Power Point Tracking." IEEE Transactions on Power Electronics (2016).

[8]. Ram, J. Prasanth, and N. Rajasekar. "A new global maximum power point tracking technique for solar photovoltaic (PV) system under partial shading conditions (PSC)." Energy (2016).

[9]. S.R.Chowdhury, HiranmaySaha, Maximum power point tracking of partially shaded solar photovoltaic arrays, Solar Energy Materials &Solar Cells 94(2010) 1441-1447.

[10]. ChakkarpaniManickam, Guru Raghav Raman, Guru Praanesh Raman, SaravanaIllangoGanesan, Member, IEEE and Chilakapati Nagamani, Senior Member, IEEE . A Hybrid Algorithm for Tracking of GMPP Based on P&O and PSO with reduced Power Oscillations in String Invertors. IEEE Transactions on Industrial Electronics DOI 10.1.109/TIE.2016.2590382.

[11]. RezaeeJordehi, Enhanced leader PSO(ELPSO): A new PSO variant for solving global optimisation problems, Applied Soft Computing 26(2015)401-417.

[12]. Ram, J. Prasanth, et al. "A new hybrid bee pollinator flower pollination algorithm for solar PV parameter estimation." Energy Conversion and Management 135 (2017): 463-476.

[13]. Rajasekar, N., Neeraja Krishna Kumar, and Rini Venugopalan. "Bacterial foraging algorithm based solar PV parameter estimation." Solar Energy 97 (2013): 255-265.

[14]. M.G. Villalva, J.R. Gazoli, E.R. Filho, Comprehensive approach to modelling and simulation of PV arrays, IEEE Transactions On Power Electronics, VOL. 24, NO.5, 2009, 0885-8993.

[15]. Babu, T. Sudhakar, et al. "Parameter extraction of two diode solar PV model using Fireworks algorithm." Solar Energy 140 (2016): 265-276.