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Enhanced leader particle swarm optimisation (ELPSO): An efficient algorithm for parameter estimation of photovoltaic (PV) cells and modules

A. Rezaee Jordehi

Department of Electrical Engineering, Lashtenesha-Zibakenar Branch, Islamic Azad University, Lashtenesha, Iran

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ABSTRACT

Today, photovoltaic (PV) systems are generating a significant share of electric power. Parameter estimation of photovoltaic cells and modules is a hot research topic and plays an important role in modelling PV systems. This problem is commonly converted into an optimisation problem and is solved by metaheuristic optimisation algorithms. Among metaheuristic optimisation algorithms, particle swarm optimisation (PSO) is a popular leader-based stochastic optimisation algorithm. However, premature convergence is the main drawback of PSO which does not let it to provide high-quality solutions in multimodal problems such as PV cells/modules parameter estimation. In PSO, all particles are pulled toward the leader, so the leader can significantly affect collective performance of the particles. A high-quality leader may pull all particles toward good regions of search space and vice versa. Therefore, in this research, an improved PSO variant, with enhanced leader, named as enhanced leader PSO (ELPSO) is used. In ELPSO, by enhancing the leader through a five-staged successive mutation strategy, the premature convergence problem is mitigated in a way that more accurate circuit model parameters are achieved in the PV cell/module parameter estimation problem. RTC France silicon solar cell, STM6-40/36 module with monocrystalline cells and PVM 752 GaAs thin film cell have been used as the case studies of this research. Parameter estimation results for various PV cells and modules of different technologies confirm that in most of the cases, ELPSO outperforms conventional PSO and a couple of other state of the art optimisation algorithms.

1. Introduction

Despite the intermittency of Photovoltaic (PV) power generation and the uncertainty that they add to electric power systems, they are deemed as popular sources for power generation. They are environmentally friendly power generation sources that are usually used as distributed generators near load centers. Photovoltaic systems play an important role in today's electric power systems and their penetration in electric power generation is increasing. For rapid and reliable design of PV systems, an accurate and fast simulator is very crucial (Chin et al., 2015). This simulator can be used for purposes such as design of maximum power point tracking systems and efficiency estimation of PV systems (Chin et al., 2015). PV cell model is the most important component of a PV simulator. It is envisaged to have a model that closely imitates the behavior of real PV cells, i.e. fits its measured I–V data under all operating conditions (Chin et al., 2015). The most commonly used modeling approach for PV cells is to use their electrical equivalent circuit (Chin et al., 2015; Jordehi, 2016a).

Single diode model is the most popular equivalent circuit model for PV cells. It has been illustrated as Fig. 1.

Single diode model has five parameters; photocurrent denoted by I_{Ph}, diode's ideality factor denoted by a, diode's reverse saturation current denoted by I_S, series resistance represented by R_S and shunt resistance denoted by R_P. For modeling a PV cell, these five parameters must be determined properly.

I-V characteristic of single diode model is given by Eq. (1).

$$I = I_{Ph} - I_S\left[exp\left(\frac{q(V+R_SI)}{aKT}\right)-1\right]-\frac{V+R_SI}{R_P} \tag{1}$$

where I and V respectively represent current and voltage of the cell and K stands for Boltzmann constant.

Double diode model, is the second most widely used circuit model for PV cells. It has been illustrated as Fig. 2 and its I-V characteristic is represented by Eq. (2) Gow and Manning, 1996; Chowdhury et al., 2007; Gupta et al., 2012. It has seven parameters; I_{Ph}, R_S, R_P, a and I_S of the first diode, a and I_S of the second diode. For modeling a certain PV cell/module as double diode model, these seven parameters must be found. Double diode model provides higher accuracy than single diode model, but it is more complex.

E-mail address: ahmadrezaeejordehi@gmail.com.

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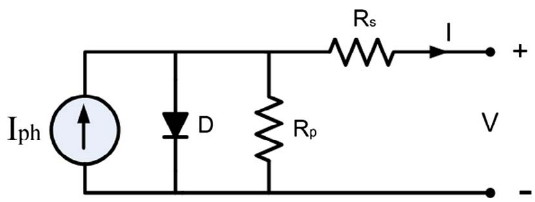

Fig. 1. Single diode model (Jordehi, 2016b).

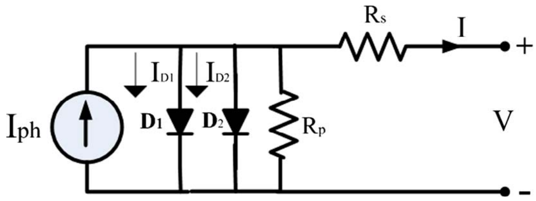

Fig. 2. Double diode model (Jordehi, 2016b).

$$I = I_{Ph} - I_{S_1}\left[exp\left(\frac{q(V+R_S I)}{a_1 KT}\right)-1\right] - I_{S_2}\left[exp\left(\frac{q(V+R_S I)}{a_2 KT}\right)-1\right] - \frac{V+R_S I}{R_P} \tag{2}$$

For modeling a PV cell/module, its circuit model parameters, i.e. the five parameters of single diode model and seven parameters of double diode model, must be determined in a way that the I-V characteristic of the resultant circuit closely emulates the experimental I-V data of the real PV cell. This problem is known as PV cell/module parameter estimation problem. In this problem, the circuit model parameters are typically determined in a way that root mean square error (RMSE) of model currents and experimentally measured currents are minimised. This represents a nonlinear, multimodal optimisation problem that is typically solved by population-based metaheuristic optimisation algorithms. Metaheuristics includes popular algorithms in solving challenging engineering optimisation problems. These algorithms do not require any preconditions such as differentiability or convexity of the problem and therefore can be employed for solving any optimisation problem. They are probabilistic algorithms that attempt to provide near-global solutions for the optimisation problem in hand.

Metaheuristics has been widely used for solving the PV cell/module parameter estimation problem (Jordehi, 2016b). In Hasanien (2015), shuffled frog leaping algorithm (SFLA), inspired from food foraging behavior of frogs, has been used for modeling PV modules as a single diode model. The absolute error between experimental currents and currents given by model parameters is the objective function. Datasheet information has been used for parameter estimation. The results show the superiority of the SFLA over the genetic algorithm (GA).

In Derick et al. (2017), the wind-driven optimisation (WDO) algorithm has been used for parameter estimation of the PV modules. It is inspired from the microscopic air parcels in a multi-dimensional space. RMSE has been chosen as objective of the optimisation problem. A Kyocera-KC215 module has been used as the case study. The simulation results for the parameter estimation of the used PV module illustrate the outperformance of the wind-driven optimisation algorithm over a diverse set of state-of-the-art algorithms, including pattern search, genetic algorithm, simulated annealing, opposition-based teaching learning-based optimisation, artificial bee swarm algorithm, harmony search and flower pollination algorithm. For a more detailed comparison, the relative error, given by different algorithms has been compared. In Louzazni et al. (2016), a leader-based metaheuristic optimisation algorithm, named as firefly algorithm, has been used for parameter estimation of the photovoltaic modules. A Photowatt-PWP201 module has been used as the case study and the simulation results with single-diode model illustrate the outperformance of the firefly algorithm with respect to the Newton-Raphson, pattern search, simulated annealing and genetic algorithm.

In Oliva et al. (2017a), a chaotic artificial bee colony (ABC) algorithm has been proposed for parameter estimation of the PV panels. In the proposed chaotic ABC, the random number in the onlooker bee phase is replaced by a chaos-generated number. A diverse set of chaotic maps have been investigated and the best one, named as Tent map has been used in the proposed chaotic ABC algorithm. The simulation results with both single and double diode models illustrate the superiority of the proposed chaotic ABC over the conventional ABC, a chaotic variant of PSO, artificial bee swarm optimisation algorithm, simulated annealing, cat swarm optimisation algorithm, teaching learning-based optimisation algorithm and harmony search. An RTC-France PV cell, STM6-120/36 as a polycrystalline panel and STM6-40/36 as a mono-crystalline PV panel have been used as the case studies.

In Oliva et al. (2017b), a chaotic variant of whale optimisation algorithm (WOA) has been proposed for parameter estimation of the PV cells and panels. WOA takes inspiration from the behavior of whales. In WOA, at each iteration, in the process of updating the position of the whales, a random number in [0,1] is generated and determines the probability of choosing either spiral model or shrinking encircling mechanism. In the proposed chaotic WOA, this randomly generated number is replaced by a chaos-based generated number. Four different chaotic maps including Singer, Sinusoidal, Logistic and Tent maps have been tested and the best one has been chosen for the proposed chaos-based WOA. Singer map proved to be the best map for the parameter estimation problem. The simulation results with both single and double diode models illustrate the superiority of the proposed chaos-based WOA over some state-of-the-art optimisation algorithms such as the ABC, PSO, artificial bee swarm optimisation algorithm, simulated annealing, bird mating optimisation algorithm, differential evolution and harmony search.

In Mughal et al. (2017), the hybrid of PSO and SA has been proposed for estimating parameters of the PV cells. At each iteration of the proposed PSO-SA, in order to exploit the advantages of both algorithms, both the operators of PSO and the operators of SA are applied to the search agents. RMSE has been used as the objective of the optimisation algorithm. The simulation results on a RTC-France PV cell with both double diode and single diode models show that the proposed hybrid algorithm performs better than the PSO, SA, HS and pattern search. In Gong et al. (2017), PSO with changing acceleration coefficients and inertia weight has been used for estimating parameters of the PV modules. In Fathy and Rezk (2017), the imperialistic competitive algorithm (ICA), has been used for estimating the circuit model parameters of the PV modules. Both the single diode and the double diode models have been used and the simulations have been done for different technologies such as mono-crystalline, polycrystalline, thin film and amorphous. The findings show the outperformance of ICA over the pattern search, a chaos-based PSO, bird mating optimisation algorithm, an adaptive DE, artificial bee swarm optimisation, simulated annealing and harmony search.

In Xu and Wang (2017), a hybrid of flower pollination algorithm and Nelder-Mead algorithm has been used for the parameter estimation of PV modules in both the single and double-diode models. The PV's of mono-crystalline, polycrystalline, thin film technologies have been used in the simulations. The proposed algorithm has been validated by comparing with some state-of-the-art optimisation algorithms such as the ABC, PSO, PS, HS and artificial bee swarm optimisation algorithm. In Jordehi (2016c), the PSO with time-varying acceleration coefficients has been used for estimating the parameters of PV cells and modules. In order to develop a suitable trade-off between explorative and exploitative capabilities of the algorithm, the cognitive acceleration coefficient is linearly decreased during the course of the run, while the social acceleration coefficient is linearly increased. In Jordehi (2017), a gravitational search algorithm with linearly decreasing gravitation constant has been proposed for parameter estimation of PV cells and modules, where the simulation results of the proposed GSA outperformed GSA with a fixed gravitation constant and exponentiallychanging gravitation constant.

Other than the described research works, in Ram et al. (2017), an improved variant of the flower pollination algorithm, in Sudhakar and Babu (2016), the fireworks optimisation algorithm and in Rezk and Fathy (2017) the water cycle algorithm have been used for the parameter estimation of PV cells and modules. Although the advantages of metaheuristics with respect to other parameter estimation strategies cannot be denied, they may get stuck in local optima. This issue is called premature convergence and is more accurate in the PV cell parameter estimation problem as a multimodal problem. This is evidenced by relatively high RMSE values in existing applications of metaheuristics to the PV cell parameter estimation problem. A great deal of effort is being put to mitigate premature convergence problem of metaheuristic optimisation algorithms. In this research, an improved variant of particle swarm optimisation (PSO) with a strong explorative capability is used for solving the PV cell parameter estimation problem. At each iteration of the used PSO variant, five successive mutation operators are used to enhance the swarm leader (Jordehi, 2015a, 2014; Rezaee Jordehi and Jasni, 2015). The synergic effect of diverse employed mutation operators has resulted in an efficient PSO variant with a strong explorative capability that efficiently explores different regions of search space and locates promising regions containing the global optimum. In this way, premature convergence problem is alleviated and high quality solutions are achieved in PV cell/module parameter estimation problem.

The rest of the paper is structured as follows; in Section 2, PV cell/module parameter estimation problem is formulated. In Section 3, the proposed methodology is introduced. Results and analysis are provided in the fourth section. Finally, the concluding remarks are put in Section 5.

2. Formulation of the PV parameter estimation problem

In the PV cell parameter estimation problem, model parameters must be found in a way that the circuit provides an I-V characteristic very close to the experimentally measured I-V data of real PV cell (Jordehi, 2016b, 2016c, 2017).

In the single diode model, for every experimental I-V pair ($V_{m,j}$,$I_{m,j}$), using $V_{m,j}$, the PV cell current is calculated by solving (3) as a nonlinear equation.

$$I_{est,j} = I_{Ph} - I_S\left[exp\left(\frac{q(V_{m,j} + R_S I_{est,j})}{aKT}\right) - 1\right] - \frac{V_{m,j} + R_S I_{est,j}}{R_P} \tag{3}$$

Since in (3), current has not been explicitly expressed as a function of voltage, the equation is solved by Newton-Raphson (Jordehi, 2016c).

In (3), $I_{est,j}$ denotes the estimated current of PV cell, i.e. the PV cell current given by the circuit model.

Using (3), the estimated current is determined for all the experimentally measured voltages, then the root mean square error (RMSE) is used to quantify the proximity of the experimentally measured currents and the estimated currents. RMSE is defined by (4) and is used as the objective of the optimisation problem.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(I_{est,j} - I_{m,j})^2}{N}} \tag{4}$$

where N represents the number of the experimental I-V pairs (Jordehi, 2016b, 2016c, 2017).

In the single diode model, the decision vector of the optimisation problem is represented as (5).

$$X = [I_{Ph}, I_S, a, R_S, R_P] \tag{5}$$

In the double diode model, for every experimental I-V pair ($V_{m,j}$,$I_{m,j}$), using $V_{m,j}$, the PV cell current is calculated by solving (6) as a nonlinear equation.

$$I_{est,j} = I_{Ph} - I_{S_1}\left[exp\left(\frac{q(V_{m,j} + R_S I_{est,j})}{a_1 KT}\right) - 1\right] - I_{S_2}\left[exp\left(\frac{q(V_{m,j} + R_S I_{est,j})}{a_2 KT}\right) - 1\right] - \frac{V_{m,j} + R_S I_{est,j}}{R_P} \tag{6}$$

Then, Newton-Raphson is assisted to solve Eq. (6) (Jordehi, 2016c).

In (6), $I_{est,j}$ denotes the estimated current of PV cell, i.e. the PV cell current given by the circuit model.

Using (6), the estimated currents are determined for all the experimentally measured voltages, then RMSE as the objective function of the optimisation problem, is calculated by (4) (Jordehi, 2016c, 2017).

For the double diode model, the decision vector of the optimisation problem is represented as (7).

$$X = [I_{Ph}, I_{S_1}, a_1, I_{S_2}, a_2, R_S, R_P] \tag{7}$$

3. Enhanced leader PSO

The particle swarm optimisation (PSO) is a well-known swarm-intelligence-based metaheuristic optimisation algorithm. The number of publications on engineering applications of PSO is very huge (Alfi, 2011; Jordehi, 2015b; Zhao et al., 2012; Yucekaya et al., 2009; Yu and Zhang, 2014). Even some other metaheuristic algorithms such as the firefly optimisation algorithm can be considered as variants of PSO. It is a probabilistic, population-based algorithm wherein each search agent is called a particle. The particles collectively attempt to find the position with the least value of objective function to be minimised. In PSO, during the run, each particle memorises its own best experience, i.e. the position with the least objective value among its visited positions. The best position of a particle is called its personal best. Moreover, the best position found by the whole swarm is memorised and referred to as the global best, swarm leader or leader (Shi and Eberhart, 1998). Let's assume that the swarm includes N_P particles, and denote the position and velocity of i th particle as X_i and V_i respectively.

At the beginning, the particles are randomly dispersed in the search space and their initial velocities are set as zero. The objective function is calculated for all particles. Since, this is the first experience of the particles, the position of each particle will also be its personal best. The particle having the least objective value, the global best or swarm leader.

At each iteration, the velocities of particles are updated by Eq. (8).

$$V_i(t+1) = \omega V_i(t) + C_1 r_1 (P_i - X_i) + C_2 r_2 (P_g - X_i) \tag{8}$$

where t denotes iteration number, V_i denotes the velocity of i th particle, P_i and P_g respectively represent the position of personal best and global best, C_1 and C_2 are respectively named personal acceleration coefficient and social acceleration coefficient, ω representss inertia weight. Eventually, r_1 and r_2 are two uniformly generated random numbers in [0,1] (Shi and Eberhart, 1998).

Eq. (8) explicitly shows that the new velocity of each particle is attracted toward its current velocity, its personal best as well as its global best. The contribution of these three vectors in new velocity can be respectively adjusted by ω, C_1 and C_2.

After updating velocities, the positions of particles are updated by Eq. (9).

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{9}$$

Then, the all particles are re-evaluated and their personal bests and global best are updated.

The process of updating the velocities, positions, personal bests and global best are continued iteration by iteration until stopping criterion is met.

In PSO, due to the following two factors, the premature convergence is likely to happen in multimodal optimisation problems (Jordehi, 2015a, 2014; Rezaee Jordehi and Jasni, 2015). Premature convergence is defined as the convergence of particles to the local optima in lieu of

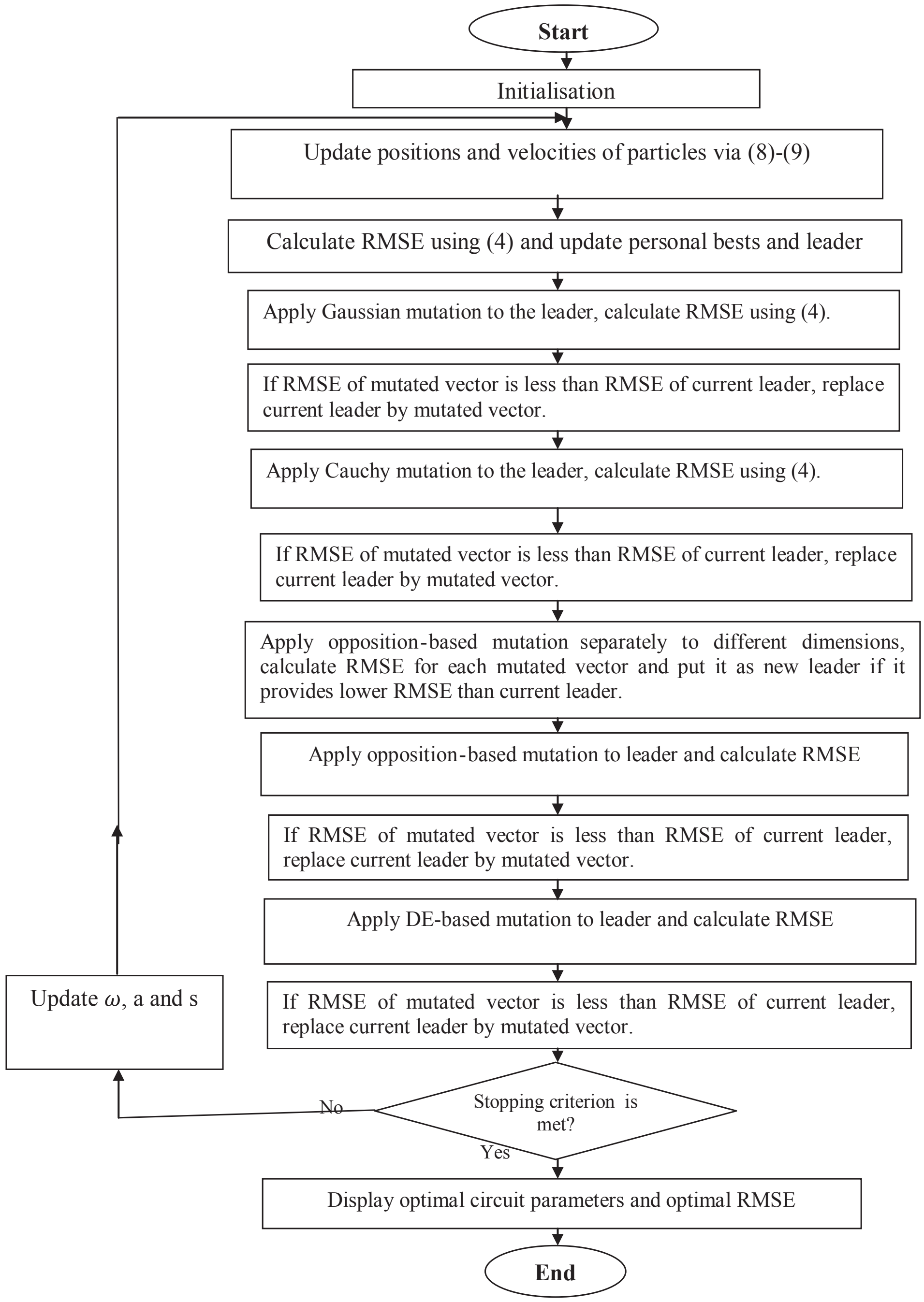

Fig. 3. The flowchart of the application of the ELPSO in the PV cell/module parameter estimation.

the global one.

- Due to the fact that all particles are attracted toward leader, the particles become similar to each other and different regions of search space are not explored efficiently. Weak exploration induces premature convergence.
- After some iterations, as the particles get close to each other, the second and third terms of right hand side of Eq. (8) tend to be zero and particles will have low velocities and will get nearly motionless. In this situation, if they stuck in a region with the local optimum, they do not have the capability to jump out from that region. This inherent property of PSO increases premature convergence probability.

In a multimodal optimisation problem, such as the problem considered in this paper, due to existence of multiple optima, premature convergence is a serious threat that may lead to low-quality solutions. This is evidenced by relatively high values of RMSE in existing research works on the PV cell parameter estimation.

Considering the above-mentioned intrinsic drawbacks of PSO, in Jordehi (2015a), an improved PSO variant, named as enhanced leader PSO (ELPSO) has been developed. In ELPSO, at each iteration, five successive mutation operators are applied to the swarm leader. After applying each mutation, if the mutated P_g has better objective value than the current P_g, it takes the position of current P_g. In this way, the leader is enhanced and pulls all other particles toward better regions in the search space (Jordehi, 2015a).

At the first stage of the mentioned five-staged mutation strategy, a Gaussian mutation is applied to the leader as (10).

$$P_{g1}(d) = P_g(d) + (X_{max}(d) - X_{min}(d)).\ Gaussian(o,a) ford = 1,2,\ldots,n \quad (10)$$

where $X_{max}(d)$ and $X_{min}(d)$ respectively stand for the upper and lower

Table 1
Used ranges of the PV cell parameters in the single diode model (Jordehi, 2016b, 2016c).

Parameter	Lower bound	Upper bound
I_{Ph} (A)	0	1
I_S (A)	0	10^{-6}
a	1	2
R_S (Ω)	0	0.5
R_P (Ω)	0	100

bounds of dth decision variable, and a is standard deviation of Gaussian distribution. If the objective value of P_{g1} is better than that of P_g, then takes the position of P_g. In order to have a decreasing exploration capability during the run, the standard deviation of the Gaussian distribution is linearly decreased during the run.

At the second stage, a Cauchy mutation is used as (11).

$$P_{g2}(d) = P_g(d) + (X_{max}(d) - X_{min}(d)).\ \text{Cauchy}(o,s) \text{for} d = 1,2,...,n \tag{11}$$

where s is a scale parameter of Cauchy distribution which is linearly reduced during the run to have a decreasing explorative capability.

If the mutated vector leads to better objective value than current leader, it takes the position of current leader.

At the third stage, opposition-based mutation is separately applied to all dimensions of P_g as (12).

$$P_{g3}(d) = X_{min}(d) + X_{max}(d) - P_g(d) \tag{12}$$

After using (12) for each dimension, the resultant vector is evaluated and if its objective value is less than the objective value of the current leader, it will be the new leader. This means that in this stage, n points are searched in the hope of finding a better leader.

At the fourth stage, opposition-based mutation is applied to the whole P_g as (13).

$$P_{g4} = X_{min} + X_{max} - P_g \tag{13}$$

If the mutated vector leads to better objective value, it takes the position of current leader.

At the last stage, DE-based mutation operator is used as (14).

$$P_{g5} = P_g + F(X_e - X_q) \tag{14}$$

where e and q are two random unequal particles in swarm and F is a control parameter called scale factor. Again, if the mutated vector leads to better objective value, it takes the position of current leader (Jordehi, 2015a).

The flowchart of the application of the ELPSO to the PV cell parameter estimation problem has been depicted in Fig. 3.

4. Results and analysis

In this section, the results of the application of ELPSO for parameter estimation of three various PV cells/modules PV of different technologies will be presented and analysed. The superior performance of ELPSO is validated by comparing with a couple of state of the art algorithms including conventional PSO (CPSO), artificial bee colony (ABC), genetic algorithm (GA), pattern search (PS), backtracking search algorithm (BSA) and Newton algorithm. RTC France silicon solar cell, STM6-40/36 module with 36 monocrystalline cells and PVM 752 GaAs thin film cell have been used as the case studies of this research. The parameter estimation is done both for single diode and double diode models. The compared algorithms have been run for 30 times. For CPSO and ELPSO, $C_1 = C_2 = 2$ and ω is linearly decreased from 0.9 to 0.4. For ELPSO, the control parameters have been directly taken from Jordehi (2015a). To make a fair comparison, all the compared algorithms are allocated the same number of function evaluations.

4.1. Case study #1: RTC France silicon solar cell at 33 °C and full irradiation

In this subsection, the experimentally measured I-V pairs of RTC France silicon solar cell at 33 °C and full sun (irradiation of 1000 W/m^2) have been used for estimating the circuit model parameters. The results for single and double diode models are presented below.

4.1.1. Results for case study #1with the single diode model

The results and the analysis of the application of ELPSO and other compared algorithms for the parameter estimation of RTC France PV cell with the single diode model are provided in this subsection. As stated in the problem formulation section, in the single diode model, the number of decision variables (the problem dimension in optimisation problem) is five. In the single diode model, the number of function evaluations (NFE's) allocated for each algorithm is 101,000. The maximum number of iterations is set as 100. The number of individuals for the GA, CPSO and BSA is set as 1000. In the ELPSO, due to the incorporated mutation strategy, the number of function evaluations per iteration is higher than other algorithms. Therefore, to make a fair comparison, in the ELPSO, the number of individuals (particles) must be set lower than other algorithms. To this end, the number of particles in the ELPSO is set as 991. In this way, the number of allocated function evaluations is the same for all used algorithms. Used ranges for the PV cell parameters in single diode model have been tabulated as Table 1. It must be noted here that the above-mentioned ranges of decision variables, number of individuals and maximum number of iterations will be also used for finding the single diode circuit model parameters of the next two case studies.

Table 2 contains the statistics of RMSE values achieved by different algorithms, in 30 runs. This table indicates that in terms of the average of the achieved RMSE values, the ELPSO performs better than the conventional PSO, ABC and other algorithms. In terms of the worst RMSE and standard deviation of achieved RMSE values, ELPSO outperforms all other used algorithms. From the viewpoint of the best achieved RMSE, ELPSO and CPSO outperform all other optimisation algorithms. The best (the most accurate) circuit model parameters achieved by used algorithms have been tabulated as Table 3. Convergence curve of the best run of ELPSO has been plotted as Fig. 4.

In Table 4, for each experimentally measured I-V pair ($V_{m,j}$,$I_{m,j}$), the absolute error and relative error of the experimental and estimated currents have been tabulated. The forth column of the table represents the currents calculated by the circuit model parameters of ELPSO. In this table, for jth pair of I-V data, the absolute error and the relative error are respectively calculated by (15) and (16). The error metrics indicate that the estimated currents are in good agreement with the measured currents of the real PV cell.

$$AE = |I_{m,j} - I_{est,j}| \tag{15}$$

Table 2
Statistics of the RMSE values, achieved by different optimisation algorithms for the single diode model.

	ELPSO	CPSO (Jordehi, 2016c)	BSA	ABC	GA (Jordehi, 2017)	PS (Jordehi, 2016c)	Newton (Easwarakhanthan et al., 1986)
Mean	**7.7314E−4**	7.7847E−4	2.7798E−3	0.001089	9.8771E−3	2.0502E−3	9.7000E−3
Min	**7.7301E−4**	7.7301E−4	1.4436E−3	8.8636E−4	4.1020E−3	2.0502E−3	9.7000E−3
Max	**7.7455E−4**	9.2832E−4	5.8117E−3	0.0013	0.01516	2.0502E−3	9.7000E−3
Std	3.4508E−7	2.8344E−5	9.7202E−4	1.0314E−4	2.7197E−3	0	0

Table 3
Circuit model parameters for the single diode model, achieved by different optimisation algorithms.

	ELPSO	CPSO (Jordehi, 2016c)	BSA	ABC	GA (Jordehi, 2017)	PS (Jordehi, 2016c)	Newton (Easwarakhanthan et al., 1986)
I_{Ph}	0.760788	0.760788	0.761051	0.761012	0.766535	0.760574	0.7608
I_s	3.106775E−7	3.106975E−7	4.787662E−7	3.348957E−7	7.456099E−7	9.809079E−7	3.223E−7
a	1.475256	1.475262	1.519642	1.483057	1.570175	1.600097	0.0364
R_S	0.036547	0.036547	0.034695	0.035994	0.031438	0.031171	53.7634
R_p	52.889336	52.892521	79.569251	48.784551	29.482993	100.00	1.4837
RMSE	**7.7301E−4**	**7.7301E−4**	1.4436E−3	8.8636E−4	4.1020E−3	2.0502E−3	9.7000E−3

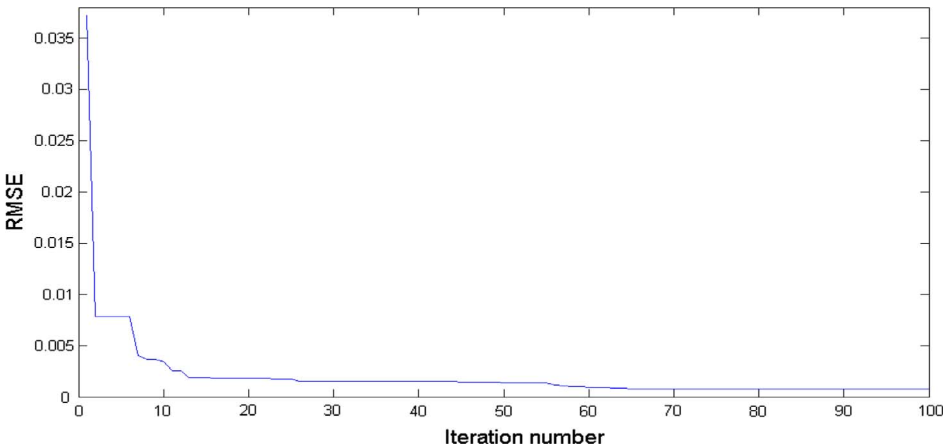

Fig. 4. The convergence curve of ELPSO for the single diode model at its best run (RMSE = 7.7301E−4).

Table 4
Error metrics for each measurement in the single diode model obtained by ELPSO.

Number	Voltage	Measured current	Calculated current	Absolute error (AE)	Relative error (RE)
1	−0.2057	0.7640	0.7641	0.0001	−0.0002
2	−0.1291	0.7620	0.7627	0.0007	−0.0009
3	−0.0588	0.7605	0.7614	0.0009	−0.0011
4	0.0057	0.7605	0.7602	0.0003	0.0005
5	0.0646	0.7600	0.7590	0.0010	0.0013
6	0.1185	0.7590	0.7580	0.0010	0.0013
7	0.1678	0.7570	0.7570	0.0000	−0.0001
8	0.2132	0.7570	0.7561	0.0009	0.0012
9	0.2545	0.7555	0.7550	0.0005	0.0006
10	0.2924	0.7540	0.7536	0.0004	0.0005
11	0.3269	0.7505	0.7513	0.0008	−0.0011
12	0.3585	0.7465	0.7473	0.0008	−0.0011
13	0.3873	0.7385	0.7401	0.0016	−0.0021
14	0.4137	0.7280	0.7274	0.0006	0.0008
15	0.4373	0.7065	0.7070	0.0005	−0.0007
16	0.4590	0.6755	0.6754	0.0001	0.0001
17	0.4784	0.6320	0.6310	0.0010	0.0016
18	0.4960	0.5730	0.5722	0.0008	0.0014
19	0.5119	0.4990	0.4995	0.0005	−0.0011
20	0.5265	0.4130	0.4135	0.0005	−0.0012
21	0.5398	0.3165	0.3172	0.0007	−0.0021
22	0.5521	0.2120	0.2120	0.0000	−0.0001
23	0.5633	0.1035	0.1026	0.0009	0.0083
24	0.5736	−0.0100	−0.0093	0.0007	0.0702
25	0.5833	−0.1230	−0.1244	0.0014	−0.0111
26	0.5900	−0.2100	−0.2091	0.0009	0.0043

$$RE = \frac{I_{m,j} - I_{est,j}}{I_{m,j}} \tag{16}$$

4.1.2. Results for case study #1 with double diode model

The results and analysis of the application of ELPSO and the other compared algorithms for the parameter estimation of RTC France the PV cell with the double diode model are presented in this subsection. In the double diode model, the number of decision variables or the problem dimension in the optimisation problem is seven. Therefore, in this case, the number of function evaluations (NFE's) allocated for each algorithm is set higher than that for single diode model. The number of function evaluations for each algorithm is set as 151,500. Maximum number of iterations is set as 100. The number of individuals for CPSO, GA and BSA is set as 1500. As stated in the presentation of the results for the single diode model, to make a fair judgment, in ELPSO, the number of search agents must be set lower than other algorithms. To this end, the number of search agents in ELPSO is set as 1489. The ranges used for different PV cell parameters in the double diode model have been tabulated as Table 5. It must be noted here that the above-mentioned ranges of the decision variables, number of individuals and maximum number of iterations will be also used for finding the double diode circuit model parameters of the next two case studies.

Table 5
The ranges of the PV cell parameters in the double diode model (Jordehi, 2016b, 2016c).

Parameter	Lower bound	Upper bound
I_{Ph} (A)	0	1
I_{S_1} (A)	10^{-12}	10^{-6}
a_1	1	2
I_{S_2} (A)	10^{-12}	10^{-6}
a_2	1	2
R_S (Ω)	0	0.5
R_P (Ω)	0	100

Table 6 contains statistics of the RMSE values achieved by the used algorithms, in 30 runs. Table 6 clearly shows that in all terms of the average, best, worst and standard deviation of the obtained RMSE values, ELPSO performs better than conventional PSO, ABC and the other algorithms. Such a reduction in the RMSE value(s) is practically significant and this improvement influences practical applications. The best circuit model parameters provided by the used algorithms have been tabulated in Table 7.

In Table 8, based on the best estimated parameters given by ELPSO, for each experimentally measured I-V, the absolute error and relative error of experimental and the estimated currents have been tabulated.

Table 6
Statistics of the RMSE values, achieved by different optimisation algorithms for the double diode model.

	ELPSO	CPSO (Jordehi, 2016c)	BSA	ABC	GA (Jordehi, 2017)	PS (Jordehi, 2016c)
Mean	**7.5904E−4**	7.902041E−4	2.8606E−3	0.00118	8.6115E−3	8.1646E−3
Min	**7.4240E−4**	7. 4444E−4	0.00110851	8.0824E−4	5.91958E−3	8.1646E−3
Max	**7.9208E−4**	0.001220	4.6684E−3	0.0016	0.014432	8.1646E−3
Std	9.4291E−6	1.0145E−4	8.3519E−4	1.9721E−4	0.001818	0

Table 7
Circuit model parameters for the double diode model, achieved by different optimisation algorithms.

	ELPSO	CPSO (Jordehi, 2016c)	BSA	ABC	GA (Jordehi, 2017)	PS (Jordehi, 2016c)
I_{Ph}	0.760808	0.760805	0.761617	0.760717	0.768864	0.763353
I_{s1}	1E−006	9.575723E−7	4.163866E−7	2.866992E−7	6.606207E−7	2.86013E−10
a_1	1.835767	1.881069	1.505369	1.469147	1.608739	1.000120
I_{s2}	9.916824E−8	1.334501E−7	1E−12	2.474846E−7	4.551497E−7	1E−12
a_2	1.386091	1.407490	2	1.968374	1.628899	1.000908
R_S	0.037551	0.037353	0.035392	0.036659	0.029144	0.058611
R_p	55.920471	55.441518	54.455178	58.299556	51.116	18.210627
RMSE	**7.4240E−4**	7.4444E−4	0.00110851	8.0824E−4	5.91958E−3	8.1646E−3

Table 8
Error metrics for each measurement in double diode model obtained by ELPSO.

Number	Voltage	Measured current	Calculated current	Absolute error	Relative error
1	−0.2057	0.7640	0.7640	0.0000	0.0000
2	−0.1291	0.7620	0.7626	0.0006	−0.0008
3	−0.0588	0.7605	0.7613	0.0008	−0.0011
4	0.0057	0.7605	0.7602	0.0003	0.0004
5	0.0646	0.7600	0.7591	0.0009	0.0011
6	0.1185	0.7590	0.7582	0.0008	0.0011
7	0.1678	0.7570	0.7572	0.0002	−0.0003
8	0.2132	0.7570	0.7563	0.0007	0.0010
9	0.2545	0.7555	0.7552	0.0003	0.0004
10	0.2924	0.7540	0.7537	0.0003	0.0004
11	0.3269	0.7505	0.7513	0.0008	−0.0011
12	0.3585	0.7465	0.7472	0.0007	−0.0009
13	0.3873	0.7385	0.7399	0.0014	−0.0019
14	0.4137	0.7280	0.7272	0.0008	0.0011
15	0.4373	0.7065	0.7068	0.0003	−0.0004
16	0.4590	0.6755	0.6753	0.0002	0.0003
17	0.4784	0.6320	0.6311	0.0009	0.0015
18	0.4960	0.5730	0.5724	0.0006	0.0011
19	0.5119	0.4990	0.4997	0.0007	−0.0015
20	0.5265	0.4130	0.4136	0.0006	−0.0015
21	0.5398	0.3165	0.3172	0.0007	−0.0021
22	0.5521	0.2120	0.2119	0.0001	0.0005
23	0.5633	0.1035	0.1025	0.0010	0.0100
24	0.5736	−0.0100	−0.0094	0.0006	0.0559
25	0.5833	−0.1230	−0.1244	0.0014	−0.0111
26	0.5900	−0.2100	−0.2089	0.0011	0.0051

Table 9
Statistics of RMSE values, achieved by different optimisation algorithms for STM6-40/36 (monocrystalline) at 51 °C and full irradiation with single diode model.

	ELPSO	CPSO	BSA	ABC
Mean	2.2503E−3	**2.1803E−3**	6.0155E−3	3.5460E−3
Min	**2.1803E−3**	**2.1803E−3**	3.6289E−3	2.3977E−3
Max	3.7160E−3	**2.1803e−3**	9.4360E−3	5.6195E−3
Std	2.9211E−4	**6.3747E−9**	1.4603E−3	7.7909e−4

Table 10
Circuit model parameters STM6-40/36 at 51 °C and full irradiation, for single diode model, achieved by different optimisation algorithms.

	ELPSO	CPSO	BSA	ABC
I_{Ph}	1.666268	1.666268	1.659404	1.667181
I_s	4.596141E−7	4.596154E−7	6.335228e−7	4.656705E−7
A	50.458643	50.458652	51.762752	50.475178
R_S	0.5	0.5	0.527342	0.5
R_p	497.747315	497.748669	723.391770	495.520578
RMSE	**2.1803E−3**	2.1803E−3	3.6289E−3	2.3977E−3

Table 11
Error metrics for each measurement in single diode model obtained by ELPSO for STM6-40/36 module at 51 °C and irradiation of 1000 W/m^2.

Number	Voltage (V) (Oliva et al., 2017b)	Current (A) (Oliva et al., 2017b)	Calculated current (A)	Absolute error (AE)	Relative error (RE)
1	0.1180	1.6630	1.6644	0.0014	−0.0008
2	2.2370	1.6610	1.6601	0.0009	0.0005
3	5.4340	1.6530	1.6537	0.0007	−0.0004
4	7.2600	1.6500	1.6499	0.0001	0.0001
5	9.6800	1.6450	1.6444	0.0006	0.0004
6	11.5900	1.6400	1.6383	0.0017	0.0010
7	12.6000	1.6360	1.6331	0.0029	0.0018
8	13.3700	1.6290	1.6271	0.0019	0.0011
9	14.0900	1.6190	1.6187	0.0003	0.0002
10	14.8800	1.5970	1.6040	0.0070	−0.0044
11	15.5900	1.5810	1.5829	0.0019	−0.0012
12	16.4000	1.5420	1.5434	0.0014	−0.0009
13	16.7100	1.5240	1.5219	0.0021	0.0014
14	16.9800	1.5000	1.4994	0.0006	0.0004
15	17.1300	1.4850	1.4852	0.0002	−0.0001
16	17.3200	1.4650	1.4651	0.0001	−0.0000
17	17.9100	1.3880	1.3854	0.0026	0.0019
18	19.0800	1.1180	1.1191	0.0011	−0.0010

Table 12
Statistics of RMSE values, achieved by different optimisation algorithms for STM6-40/36 (monocrystalline) at 51 °C and full irradiation with double diode model.

	ELPSO	CPSO	BSA	ABC
Mean	**2.0351E−3**	2.0536E−3	6.6880E−3	3.4274E−3
Min	**1.8307E−3**	1.8343E−3	4.0335E−3	2.0538E−3
Max	**2.1178E−3**	2.4820E−3	9.1132E−3	5.3626E−3
Std	**8.4271E−5**	1.3007E−004	1.46600E−3	8.1672E−4

Table 13
Circuit model parameters STM6-40/36 at 51 °C and full irradiation, for double diode model, achieved by different optimisation algorithms.

	ELPSO	CPSO	BSA	ABC
I_{Ph}	1.664843	1.664746	1.661112	1.663472
I_{s1}	1.670160E − 8	2.529140E − 8	1.198529E − 6	8.937775E − 6
a_1	41.993481	42.816947	100	71.464981
I_{s2}	6.210924E − 6	8.779822E − 6	8.916770E − 7	1E − 12
a_2	67.344124	70.734863	52.874278	27.790714
R_S	0.500000	0.500000	0.500000	1.236435
R_p	606.888301	611.747136	924.813027	938.209991
RMSE	**1.8307E − 3**	1.8343E − 3	4.0335E − 3	2.0538E − 3

Table 14
Error metrics for each measurement in double diode model obtained by ELPSO for STM6-40/36 module at 51 °C and irradiation of 1000 W/m^2 (Oliva et al., 2017b).

Number	Voltage (V)	Current (A)	Calculated current (A)	Absolute error (AE)	Relative error (RE)
1	0.1180	1.6630	1.6633	0.0003	− 0.0002
2	2.2370	1.6610	1.6598	0.0012	0.0007
3	5.4340	1.6530	1.6544	0.0014	− 0.0008
4	7.2600	1.6500	1.6511	0.0011	− 0.0006
5	9.6800	1.6450	1.6458	0.0008	− 0.0005
6	11.5900	1.6400	1.6392	0.0008	0.0005
7	12.6000	1.6360	1.6335	0.0025	0.0015
8	13.3700	1.6290	1.6270	0.0020	0.0012
9	14.0900	1.6190	1.6180	0.0010	0.0006
10	14.8800	1.5970	1.6029	0.0059	− 0.0037
11	15.5900	1.5810	1.5817	0.0007	− 0.0004
12	16.4000	1.5420	1.5428	0.0008	− 0.0005
13	16.7100	1.5240	1.5217	0.0023	0.0015
14	16.9800	1.5000	1.4996	0.0004	0.0002
15	17.1300	1.4850	1.4856	0.0006	− 0.0004
16	17.3200	1.4650	1.4659	0.0009	− 0.0006
17	17.9100	1.3880	1.3871	0.0009	0.0006
18	19.0800	1.1180	1.1182	0.0002	− 0.0002

Table 15
Statistics of RMSE values, achieved by different optimisation algorithms for PVM 752 GaAs thin film cell at 25 °C and full irradiation with single diode model.

	ELPSO	CPSO	BSA	ABC
Mean	2.5400E − 2	2.5400E − 2	3.5990E − 3	**2.1113E − 3**
Min	2.5400E − 2	2.5400E − 2	2.1469E − 3	**2.0412E − 3**
Max	2.5400E − 2	2.5400E − 2	1.0997E − 2	**2.2427E − 3**
Std	0	0	2.2240E − 3	**5.3438E − 5**

Table 16
Circuit model parameters PVM 752 GaAs thin film cell at 25 °C and full irradiation, for single diode model, achieved by different optimisation algorithms.

	ELPSO	CPSO	BSA	ABC
I_{Ph}	0.115016	0.116530	0.103903	0.103312
I_s	0	0	8.490000E − 11	3.200000E − 11
A	1.768590	1.617093	1.858574	1.774159
R_S	0.159052	0.346578	0.5	0.5
R_p	14.429507	14.241982	100	100
RMSE	2.5400E − 2	2.5400E − 2	2.1469E − 3	**2.0412E − 3**

The error metrics signify that the estimated currents are in good agreement with the measured currents of real PV cell.

4.2. Results for case study #2: STM6-40/36 module at 51° C and full irradiation

STM6-40/36, manufactured by Schutten Solar, with 36 mono-crystalline cells (of size 38 mm × 128 mm) aligned in series, has been used as the second case study of this research. The experimental data has been extracted at T = 51 °C and full irradiation (Oliva et al., 2017b). The findings of parameter estimation for this module can be found as Tables 9–14. For the single diode model, from the perspective of the best achieved RMSE in 30 runs, the ELPSO and CPSO surpass the other used algorithms, while from the perspective of the mean of the achieved RMSE values in 30 runs, the CPSO surpasses all other algorithms. Table 11 includes the error metrics, resulted by parameter estimation for single diode model with the ELPSO and Table 14 includes the error metrics, resulted for double diode model with ELPSO. Tables 12 and 13 testify that in the case of double diode model, the ELPSO surpasses all other algorithms, either in the terms of the best achieved

Table 17
Error metrics for each measurement in single diode model obtained by ELPSO for PVM 752 GaAs thin film cell at 25 °C and irradiation of 1000 W/m^2.

Number	Voltage (V)	Measured current (A)	Calculated current (A)	Absolute error (AE)	Relative error (RE)
1	− 0.1659	0.1001	0.1251	0.0250	− 0.2501
2	− 0.1281	0.1000	0.1225	0.0225	− 0.2254
3	− 0.0888	0.0999	0.1198	0.0199	− 0.1997
4	− 0.0490	0.0999	0.1171	0.0172	− 0.1724
5	− 0.0102	0.0999	0.1145	0.0146	− 0.1458
6	0.0275	0.0998	0.1119	0.0121	− 0.1210
7	0.0695	0.0999	0.1090	0.0091	− 0.0911
8	0.1061	0.0998	0.1065	0.0067	− 0.0670
9	0.1460	0.0998	0.1038	0.0040	− 0.0396
10	0.1828	0.0997	0.1012	0.0015	− 0.0154
11	0.2230	0.0997	0.0985	0.0012	0.0123
12	0.2600	0.0996	0.0959	0.0037	0.0367
13	0.3001	0.0997	0.0932	0.0065	0.0653
14	0.3406	0.0996	0.0904	0.0092	0.0922
15	0.3789	0.0995	0.0878	0.0117	0.1177
16	0.4168	0.0994	0.0852	0.0142	0.1429
17	0.4583	0.0994	0.0823	0.0171	0.1716
18	0.4949	0.0993	0.0798	0.0195	0.1960
19	0.5370	0.0993	0.0770	0.0223	0.2251
20	0.5753	0.0992	0.0743	0.0249	0.2507
21	0.6123	0.0990	0.0718	0.0272	0.2748
22	0.6546	0.0988	0.0689	0.0299	0.3027
23	0.6918	0.0983	0.0663	0.0320	0.3251
24	0.7318	0.0977	0.0636	0.0341	0.3490
25	0.7702	0.0963	0.0610	0.0353	0.3669
26	0.8053	0.0937	0.0586	0.0351	0.3750
27	0.8329	0.0900	0.0567	0.0333	0.3703
28	0.8550	0.0855	0.0552	0.0303	0.3549
29	0.8738	0.0799	0.0539	0.0260	0.3258
30	0.8887	0.0743	0.0528	0.0215	0.2888
31	0.9016	0.0683	0.0520	0.0163	0.2392
32	0.9141	0.0618	0.0511	0.0107	0.1731
33	0.9248	0.0555	0.0504	0.0051	0.0924
34	0.9344	0.0493	0.0497	0.0004	− 0.0084
35	0.9445	0.0422	0.0490	0.0068	− 0.1616
36	0.9533	0.0357	0.0484	0.0127	− 0.3562
37	0.9618	0.0291	0.0478	0.0187	− 0.6438
38	0.9702	0.0222	0.0473	0.0251	− 1.1287
39	0.9778	0.0157	0.0467	0.0310	− 1.9769
40	0.9852	0.0092	0.0462	0.0370	− 4.0250
41	0.9926	0.0026	0.0457	0.0431	− 16.5855
42	0.9999	− 0.0040	0.0452	0.0492	12.3055
43	1.0046	− 0.0085	0.0449	0.0534	6.2823
44	1.0089	− 0.0124	0.0446	0.0570	4.5972

Table 18
Statistics of RMSE values, achieved by different optimisation algorithms for PVM 752 GaAs thin film cell at 25 °C and full irradiation with double diode model.

	ELPSO	CPSO	BSA	ABC
Mean	0.002304	0.002320	0.002447	0.002197
Min	0.002075	0.002303	0.002178	0.002044
Max	0.0024309	0.0024309	0.0027557	0.0023260
Std	5.4011E − 5	4.4174E − 5	1.2436E − 4	7.0060E − 5

Table 19
Circuit model parameters PVM 752 GaAs thin film cell at 25° C and full irradiation, for double diode model, achieved by different optimisation algorithms.

	ELPSO	CPSO	BSA	ABC
I_{Ph}	0.103192	0.102688	0.102497	0.103252
I_{s1}	1.775000e − 10	1.000000E − 12	1.000000E − 12	4.000000E − 11
a_1	2.000000	1.572718	1.635590	1.792987
I_{s2}	1.000000E − 12	1.000000E − 12	8.060000E − 11	1.000000E − 12
a_2	1.571052	1.572718	1.874265	2.000000
R_S	0.500000	0.500000	0.500000	0.500000
R_p	100.000000	100.000000	100.000000	100.000000
RMSE	0.002075	0.002303	0.002178	0.002044

Table 20
Error metrics for each measurement in double diode model obtained by ELPSO for PVM 752 GaAs thin film cell at 25 °C and irradiation of 1000 W/m^2.

Number	Voltage (V)	Measured current (A)	Calculated current (A)	Absolute error (AE)	Relative error (RE)
1	−0.1659	0.1001	0.1043	0.0042	−0.0422
2	−0.1281	0.1000	0.1040	0.0040	−0.0395
3	−0.0888	0.0999	0.1036	0.0037	−0.0367
4	−0.0490	0.0999	0.1032	0.0033	−0.0327
5	−0.0102	0.0999	0.1028	0.0029	−0.0288
6	0.0275	0.0998	0.1024	0.0026	−0.0261
7	0.0695	0.0999	0.1020	0.0021	−0.0209
8	0.1061	0.0998	0.1016	0.0018	−0.0183
9	0.1460	0.0998	0.1012	0.0014	−0.0143
10	0.1828	0.0997	0.1009	0.0012	−0.0116
11	0.2230	0.0997	0.1005	0.0008	−0.0076
12	0.2600	0.0996	0.1001	0.0005	−0.0049
13	0.3001	0.0997	0.0997	0.0000	0.0001
14	0.3406	0.0996	0.0993	0.0003	0.0031
15	0.3789	0.0995	0.0989	0.0006	0.0060
16	0.4168	0.0994	0.0985	0.0009	0.0088
17	0.4583	0.0994	0.0981	0.0013	0.0129
18	0.4949	0.0993	0.0977	0.0016	0.0156
19	0.5370	0.0993	0.0973	0.0020	0.0200
20	0.5753	0.0992	0.0969	0.0023	0.0230
21	0.6123	0.0990	0.0965	0.0025	0.0252
22	0.6546	0.0988	0.0960	0.0028	0.0285
23	0.6918	0.0983	0.0954	0.0029	0.0295
24	0.7318	0.0977	0.0945	0.0032	0.0328
25	0.7702	0.0963	0.0930	0.0033	0.0339
26	0.8053	0.0937	0.0906	0.0031	0.0328
27	0.8329	0.0900	0.0874	0.0026	0.0293
28	0.8550	0.0855	0.0833	0.0022	0.0252
29	0.8738	0.0799	0.0786	0.0013	0.0168
30	0.8887	0.0743	0.0736	0.0007	0.0089
31	0.9016	0.0683	0.0684	0.0001	−0.0019
32	0.9141	0.0618	0.0625	0.0007	−0.0108
33	0.9248	0.0555	0.0566	0.0011	−0.0197
34	0.9344	0.0493	0.0507	0.0014	−0.0284
35	0.9445	0.0422	0.0438	0.0016	−0.0391
36	0.9533	0.0357	0.0373	0.0016	−0.0458
37	0.9618	0.0291	0.0306	0.0015	−0.0506
38	0.9702	0.0222	0.0234	0.0012	−0.0557
39	0.9778	0.0157	0.0166	0.0009	−0.0576
40	0.9852	0.0092	0.0096	0.0004	−0.0457
41	0.9926	0.0026	0.0023	0.0003	0.1077
42	0.9999	−0.0040	−0.0052	0.0012	−0.2951
43	1.0046	−0.0085	−0.0102	0.0017	−0.1954
44	1.0089	−0.0124	−0.0148	0.0024	−0.1949

RMSE or in the terms of the mean of achieved RMSE values. As expected, the RMSE values, given by the double-diode model are lower than those, given by single diode model.

4.3. Results for case study #2: PVM 752 GaAs cell at 25 °C and full irradiation

PVM 752 GaAs thin film cell, has been used as the third case study of this research. The experimental data, including 44 pairs of I-V points has been extracted at T = 25 °C and full irradiation and was kindly provided by the national renewable energy laboratory (NREL). The findings of parameter estimation for this cell can be viewed as Tables 15–20. As per Tables 15 and 16, for the single diode model, the ABC surpasses the other used algorithms. Table 17 includes the error metrics, resulted by parameter estimation for the single diode model with ELPSO and Table 20 includes the error metrics, resulted for the double diode model with ELPSO. Tables 18 and 19 prove that in the case of the double diode model, the ABC and ELPSO surpass other algorithms, both in the terms of the best achieved RMSE and the mean of the achieved RMSE values. Comparing Tables 15–20 with results of RTC France cell and STM6-40/36 module indicate that due to the huge number of I-V pairs, estimating parameters of PVM 752 GaAs cell is more challenging for optimisation algorithms. For instance, the best RMSE, achieved by the ELPSO, in single diode model is as high as 0.0254. Comparing the results of the single diode model and double diode model indicates that, the RMSE values, given by the double-diode model are lower than those, given by the single diode model.

5. Conclusions

The PV cell/module parameter estimation is considered as a multimodal optimisation problem with multiple local optima. In such multimodal problems, metaheuristic algorithms, due to their premature convergence problem, are likely to converge into local optima in lieu of the global one. PSO is a popular metaheuristic optimisation algorithm. In this research, in an attempt to mitigate premature convergence, an improved PSO variant, named as enhanced leader PSO (ELPSO), has been used for solving the PV cell/module parameter estimation problem. At each iteration of the ELPSO, the leader is enhanced by five successive mutation operators. The enhanced leader may attract other particles toward better regions of search space and thereby the premature convergence problem is mitigated. An RTC France silicon solar cell, STM6-40/36 module with 36 monocrystalline cells and PVM 752 GaAs thin film cell have been used as the case studies of this research. The findings show that in RTC France silicon solar cell and STM6-40/36 module, the ELPSO surpasses all the other compared algorithms including the CPSO, GA, ABC, BSA, PS and Newton. In the PVM 752 GaAs cell, the ELPSO surpasses the conventional PSO, although the ABC outperforms all the compared algorithms.

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