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Extraction of solar cell parameters from a single current–voltage characteristic using teaching learning based optimization algorithm

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HIGHLIGHTS

- Teaching learning based optimization (TLBO) algorithm is investigated to extract solar cell parameters.
- The TLBO is implemented using LabVIEW.
- All five solar cell parameters are extracted from single illuminated *I–V* characteristic.
- The results are found to be highly reliable and reproducible.

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ABSTRACT

The determination of values of solar cell parameters is of great interest for the evaluation of solar cell performance. This paper proposes a simple, efficient and reliable method to extract all five parameters of a solar cell from a single illuminated current–voltage (*I–V*) characteristic using teaching learning based optimization (TLBO) algorithm. The TLBO is implemented by developing an interactive numerical simulation using LabVIEW as a programming tool. The effectiveness of the algorithm has been validated by applying it to the reported *I–V* characteristics of different types of solar cells such as silicon, plastic and dye-sensitized solar cells as well as silicon solar module. The obtained values of parameters by the TLBO algorithm are found to be in very good agreement with reported values of parameters. The algorithm is also applied to the experimentally measured *I–V* characteristics of a silicon solar cell and a silicon solar module for the extraction of parameters. It is observed that the TLBO algorithm repeatedly converges to give consistent values of solar cell parameters. It is demonstrated that our program based on TLBO algorithm can be successfully applied to a wide variety of solar cells and modules for the extraction of parameters from a single illuminated *I–V* curve with minimal control variables of the algorithm.

1. Introduction

Solar energy is one of the most important renewable energy sources as it is clean, safe and plentiful in nature. The solar cell converts the energy of photons coming from the sunlight directly into electrical energy on the basis of photovoltaic effect. The overall performance and the conversion efficiency of a cell rely upon various physical parameters such as series resistance (R_s), shunt resistance (R_{sh}), ideality factor (n), photocurrent (I_{ph}) and saturation current (I_o). Therefore, the knowledge of these parameters is always desirable not only to evaluate the performance of a cell but also to improve the design, fabrication process and quality control of the cell [1]. These parameters can be determined by considering the solar cell in terms of its equivalent circuit described by various models such as single-diode model [2–5], double-diode model [6], or three-diode model [7]. Although, the double-diode and three diode models are more accurate as they take into account the space charge recombination current as well as leakage current, the single diode model has been extensively used for solar cell parameters extraction problems owing to its simplicity and adequate reliability for a wide variety of solar cells [2–5]. The current (I) – voltage (V) relation of a solar cell for a single diode model is given by,

$$I = I_{ph} - I_o\left[e^{\frac{q(V+IR_S)}{nk_BT}} - 1\right] - \frac{V + IR_s}{R_{sh}} \tag{1}$$

From Eq. (1), it is clearly seen that the direct parameter extraction from experimental *I–V* characteristic data is limited by the non-linear and transcendental nature of the *I–V* relation of a solar cell.

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Over the years, several methods have been reported for the extraction of solar cell parameters. Some of these methods employ analytical [8–10,2] or numerical [1,11–14] techniques to determine the parameters from experimental *I–V* characteristic. Analytical techniques require the knowledge of some selected values of *I–V* characteristic such as short-circuit current, open-circuit voltage, current and voltage at the maximum power, and slopes of the *I–V* characteristic at the axis intersections. This approach is generally based on simple formulae and may be affected by the correctness of the selected points on the *I–V* curve. On the other hand, the *I–V* characteristic exhibits highly non-linear behavior and the correctness of the selected points may introduce a significant error in the extracted parameters.

Numerical techniques involve certain mathematical algorithms like curve fitting algorithm to fit all the point on the *I–V* characteristic in order to extract the solar cell parameters. Using such algorithm, we can get an accurate result because all the points on the *I–V* curve are utilized. In addition, the deviation of several data points may not severely affect the accuracy of the parameters as in the case of the analytical method. However, the accuracy of these techniques depends on the types of fitting algorithm, the fitting criterion, objective function and the starting values of the parameters [11]. Moreover, this method cannot guarantee the global convergence because it depends strongly on the initial values of the parameters such as number of iterations and tolerance criteria.

In recent years, techniques based on evolutionary algorithms (EAs) have gained significant attention in the field of the solar cell parameters extraction because of their effectiveness and flexibilities [15,16]. Among the evolutionary algorithms, genetic algorithm (GA) has been extensively used for the solar cell parameters extraction [17–20]. GA also outperforms the quasi-Newton methods, curve fitting methods and other optimization algorithms. However, there are deficiencies related to GA performance [21]. Here, in particular, the degradation of the efficiency is mainly observed when highly hypostasis objective functions are used, i.e. when the parameters being optimized are highly correlated. In addition, the crossover and mutation operators do not always guarantee better fitness of offspring because individuals in the population have similar structure and their average fitness is high towards the end of evolutionary process. Moreover, in the case of multivariable optimization problem, the GA has the tendency to get trapped in local minima instead of global optimum, which can be attributed to the inappropriate selection of crossover and mutation rate probability. On the other hand, optimization of the proper rate of such operators is very tedious and it varies from problem to problem.

Recently, particle swarm optimization (PSO) has been investigated for the extraction of solar cell parameters [22–24]. Although PSO offers several advantages over GA, one must also take into the consideration the limitations associated with the PSO, viz. (1) it cannot guarantee the consistency of extracted parameters and (2) it requires a large number of iterations to converge the solution to the global optimum [24]. Moreover, the inappropriate selection of key parameters such as acceleration constants (c_1 and c_2) and inertia weight may also lead to trap the search process in local optimum instead of global one [25]. In general, all nature-inspired population based algorithms such as evolutionary algorithm and PSO are highly sensitive to the control parameters. Moreover, the selection of these control parameters, for example crossover and mutation operators in GA or inertia weight in PSO are highly problem specific.

In recent year, teaching–learning-based optimization (TLBO) algorithm proposed by Rao et al. [26] has emerged as new promising global optimization algorithms capable of solving wide range of optimization problems. There are some features of the TLBO algorithm that make it a very effective algorithm. For example, the algorithm is very simple and easy to implement. It requires a very few control variables like population size and number of iterations in order to achieve the global optimum solution. Moreover, these control operators are not very problem specific. Apart from these, the convergence to the final solution is almost independent from the initial population. So far, to the best of our knowledge, the TLBO algorithm has not been investigated for the solar cell parameters extraction problem. Hence, here we report a study on the effectiveness of the TLBO algorithm for the extraction of solar cell parameters. We applied the algorithm to extract all the five parameters of the solar cell from a single *I–V* characteristic data measured under illumination, which is feasible only with a very few methods. The algorithm is implemented through an interactive program prepared using LabVIEW (laboratory virtual instrument engineering workbench, version-10) as a programming tool.

In this work, the validity, consistency and the robustness of the TLBO algorithm are verified by applying the algorithm to the *I–V* characteristics of a silicon solar cell [27], a plastic solar cell [2], a dye-sensitized solar cell (DSSC) [3] and a silicon solar module [27]. The *I–V* characteristics were synthesized from the reported values of parameters using Newton–Raphson method. The parameters were extracted from these synthesized *I–V* curves using the TLBO algorithm and compared with the reported values that extracted by other methods for the respective solar cell in the literatures. After validation, the TLBO algorithm is applied to the experimental *I–V* characteristics of a monocrystalline silicon solar cell as well as a polycrystalline silicon solar module, measured at our lab in order to extract the desired parameters.

2. Description of TLBO algorithm

The TLBO algorithm employs the concept of teaching–learning process in a classroom. It is a simple population based optimization algorithm that uses a population of solutions to proceed to the global optimum based on the real numbers. A group of learners in the classroom are considered as population. The algorithm is inspired by passing on knowledge within a classroom environment, where learners (i.e. individuals) first obtain their knowledge from a teacher and then they also interact with each other to propagate the knowledge. The design variables to be optimized are analogous to different subjects offered to learners. The learners are evaluated by means of a problem specific objective function called 'fitness function'. Thus, how good or bad a learner 'X' is can be represented by the value of the fitness function $F(X)$, also called the fitness of the learner. Thus, the fitness of a population is improved by the propagation of knowledge though two phase: (1) Teacher Phase (2) Learner Phase.

2.1. Teacher Phase

This is the first stage of the TLBO algorithm where initially learners learn from the teacher. The teacher is considered as a highly learned person in the population who shares his or her knowledge with other learners in the classroom. The quality of the teacher directly affects on the outcome of the learners. It is obvious that a good teacher trains learners in such way that they can have better fitness in terms of their results. During this phase, algorithm tries to improve the fitness of other individuals (X_i) by moving their positions towards the position of the teacher ($X_{teacher}$) by using the mean value of individuals (X_{mean}). Generally, the mean value of individuals decides the quality of individuals in the population. The teacher modifies the learners in the classroom according to the following Eq. (2).

$$X_{new} = X_i + r \cdot (X_{teacher} - (T_F \cdot X_{mean})) \tag{2}$$

where, $i = 1, 2, 3\ldots, N$. Here N is the number of learners in the classroom. The X_{new} is the modified learner and if it is found to be better than X_i, it replaces X_i otherwise it is rejected. Here, r is the random number which is generated between 0 and 1. It represents the fraction of knowledge being shared during the interaction. The extreme values 0 and 1 for 'r' represents two extreme considerations where a learner learns either nothing or everything that teacher has to offer. Low values of 'r' represents less knowledge transfer and hence slower convergence but at the same time ensures better exploration of the search space. T_F is the teaching factor which decides the value of mean to be changed. Rao and Patel [28] have suggested that the algorithm is found to perform better for the value of T_F between 1 and 2. However, the best results were obtained when the value of T_F is kept either 1 or 2 and therefore to simplify the algorithm in the present study, the value of T_F is settled randomly to either 1 or 2 with equal probability using Eq. (3).

$$T_F = round[1 + rand(0,1)] \tag{3}$$

Where, *rand* is the random number in the range [0,1]. Both, T_F and 'r' are stochastic parameters for the algorithm and are not fed as an input to the programme.

2.2. Learner Phase

During the learner phase, learners increase their knowledge through interactions among themselves. Every learner (X_i, $i = 1, 2, 3\ldots, N$) interacts with other randomly selected learner (X_j, $j = 1, 2, 3\ldots, N$) in the population, where $i \neq j$. If X_i is better than X_j, X_j is moved towards X_i according to Eq. (4). Otherwise, X_i is moved towards X_j according to Eq. (5). A mathematical representation of the learner phase for the modification of fitness can be given as follow:

$$X_{new} = X_i + r(X_i - X_j); \quad \text{If} f(X_i) > f(X_j), \quad i \neq j \tag{4}$$

$$X_{new} = X_i + r(X_j - X_i); \quad \text{If} f(X_i) < f(X_j), \quad i \neq j \tag{5}$$

Again X_i is replaced by X_{new} only if X_{new} is better than X_i.

3. Implementation of TLBO algorithm for parameters extraction

The extraction of the solar cell parameters are generally carried out using the set of experimental I–V data. The performance of the extracted parameters is evaluated using the fitness function at every iteration of the TLBO process. Therefore, the selection of fitness function is very important and it directly affects the performance of the algorithm. In our program, the fitness function is defined as,

$$F(X) = \frac{\left\{\sum_{k=1}^{p}\left[I^{exp}(V_k) - I^{cal}(V_k, X)\right]^2\right\}}{p} \tag{6}$$

where $I^{exp}(V_k)$ is the experimental value of current (I) at voltage V_k, $I^{cal}(V_k, X)$ is the calculated values of current, which can be obtained by Eq. (1), for given set of parameters (*i.e.* $X_i = I_{Oi}$, I_{phi}, n_i, R_{si} and R_{shi}) at voltage V_k, and p is the total number of voltage steps in the I–V characteristic. Theoretically, the value of fitness function should become zero when the exact value is achieved for each solar cell parameter. However, in reality, we expect a very small but finite difference between the experimental and calculated values. Thus, lower value of the fitness function represents better agreement of the fitted I–V characteristic with the experimental I–V characteristic.

In this work, the set of solar cell parameters is defined as a learner X_i. An individual parameter is considered as a subject. Thus, a learner X_i learns five subjects, viz. I_{Oi}, I_{phi}, n_i, R_{si} and R_{shi}. Here, $i = 1, 2, 3\ldots N$, where N represents the classroom strength. The overall performance of X_i can be evaluated by determining the value of fitness function $F(X_i)$, which depends on these five subjects as evident from the Eq. (6). The values of these parameters and consequently the fitness of X_i are modified via teacher and learner phases through continuous evolution by the TLBO algorithm. The values of parameters are adjusted in such a way that the value of fitness function in Eq. (6) is minimized. The execution of the TLBO algorithm requires primarily three control variables viz. population size (i.e. classroom strength), number of iterations and the search space, i.e. range of random numbers for individual parameter. These control variables are fed as input parameters in the program. The detailed flow chart of the TLBO algorithm for the extraction of parameters is shown in Fig. 1. The TLBO algorithm terminology in the context of solar cell parameters extraction problem is shown in Table 1.

4. Results and discussion

To verify the accuracy, reliability and robustness of the TLBO algorithm, it is applied on I–V characteristics synthesized from the data of a wide variety of solar cells reported in the literature such as silicon solar cell, plastic solar cell, DSSC and a silicon solar module to extract the values of solar cell parameters viz. I_o, I_{ph}, n, R_s and R_{sh}. The synthetic I–V characteristics were obtained by considering a single diode model using the reported values of parameters in the literature. The consistency of the program is checked in terms of obtained values of parameters as well as the shape of I–V characteristic by repeating the program for a large number of times for each solar cell and solar module. After the validation of the program, it is applied to the experimentally measured I–V characteristics of a silicon solar cell and a silicon solar module in our lab in order to extract the parameters. The control variables of the algorithm such as classroom strength, number of iterations and search ranges for each solar cell parameters were optimized and generalized to cover the wide variety of solar cells used. In this work, both, the classroom strength (i.e. number of sets of solar cell parameters) and the number of iterations were fixed to 1000 for all cells and modules. The whole extraction process was repeated for 100 times for each type of solar cell.

4.1. Silicon solar cell

First, TLBO algorithm is applied to extract the parameters of a 57 mm-diameter commercial silicon solar cell from R.T.C. France [27]. The synthetic I–V characteristic is generated using the parameters values as reported in the literature [27]. Fig. 2 shows the synthetic (dotted circles) and TLBO fitted I–V characteristics (solid line). It is clearly observed that the synthetic I–V curve exactly overrides on the fitted curve. The values of parameters obtained by our program are compared with the reported values in Table 2. Here, it can be seen that the values obtained by TLBO algorithm match with the reported values up to 5 significant digits.

Fig. 3 shows the variation of the fitness functions as well as that of individual solar cell parameters as the iteration progresses. Here, it can be seen that the fitness value decreases steadily and consistently as program proceeds. The fitness function is the measure of matching between the synthetic (in principle experimental) I–V curve and the I–V curve generated by TLBO algorithm. Thus, the reducing fitness function indicates that this matching is gradually improving iteration by iteration. After 100 iterations, the value of fitness function becomes very small and the change is not visible in the graph. However, the values from the data reveal consistent improvement in the fitness until it saturates at about 500 iterations.

The R_s, R_{sh}, and I_o fluctuate significantly during initial iterations. The values become stable after about 400 iterations and then the

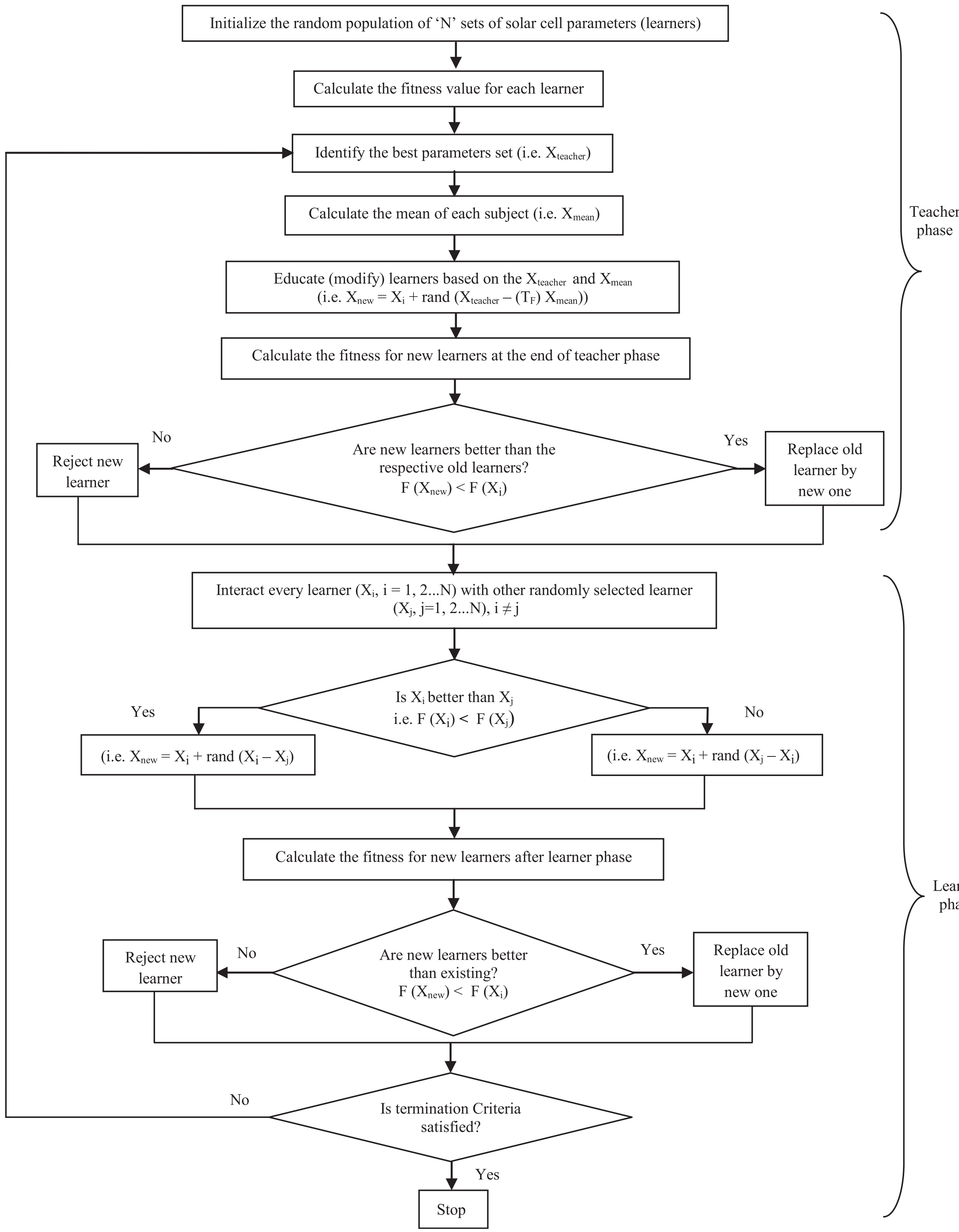

Fig. 1. Flow chart of TLBO algorithm for the extraction of solar cell parameters.

change in the values are slow and smooth as appeared from Fig. 3. The value of n decreases sharply and immediately becomes stable. The change in I_{ph} values is rather smooth and steady before it becomes constant at about 100 iterations. Overall, it takes about 500 iterations for the algorithm to converge to the stable solution.

Since the synthesized I–V curve is an ideal curve, it is important to see how the algorithm responds to the noise or errors encountered during the experimental measurements. To address this issue, we added random noise in the form of % error from ±1% up to ±5% in the synthetic I–V data of Si solar cell [27]. The random errors in the current values of synthesized I–V data were added using the following equation [4].

$$I_{with\_noise} = I_{without\_noise}\{1 + (percent\_error \times rand(-1, 1)\} \quad (7)$$

Table 1
TLBO terminology in the context of solar cell parameters extraction problem.

TLBO terms	Equivalent Solar cell parameters
Classroom strength (i.e. population)	Number of sets of solar cell parameters
Learner (i.e. individual)	A set of five solar cell parameters
Subject	An individual parameter of the solar cell
Teacher ($X_{teacher}$)	Best parameters set in the population with minimum value of fitness function
Mean of individuals for particular subject (X_{mean})	Mean value for particular solar cell parameter in the classroom
Search space	Range of minimum and maximum possible value of parameters to be extracted

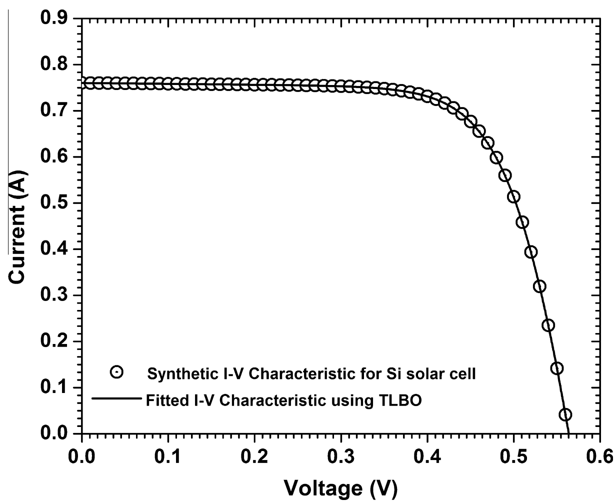

Fig. 2. Synthetic and TLBO fitted I–V characteristics for Si solar cell.

The data thus obtained with added noise were then subjected to the TLBO for the parameters extractions. The effect of this random noise on the values of extracted parameters is evaluated by means of relative errors in the values of extracted parameters in reference to the respective values without the noise. Fig. 4 shows the effect of various level of random noise on the percentage of relative error in the extracted parameters. As seen from the figure, the relative errors increases in all parameters as the random noise intensity increases. The relative errors in R_s and n is less than 2% even at noise level of ±5%, which shows good immunity of TLBO to the noise for extraction of these parameters. The relative error in I_{ph} is also found to be less than 4% throughout the noise levels up to ±5%. However, the relative errors in I_o and R_{sh} are comparatively large. This is because the current I is exponential function of R_s and n as evident from Eq. (1). Hence very small deviation in these values lead to significant change in the fitness function. Thus to minimize the fitness function during the evaluation, the program requires strong control over these parameters, which results in less deviation and consequently more precise extraction of their values. However, the dependence of I on other three parameters is not so strong, which allows relatively more deviation in those parameters without significantly affecting the fitness function.

The values of parameters extracted using random noise up to ±4% are shown in Table 2. As seen from the table, the values obtained with added noise up to ±4% are still reasonably acceptable, confirming the usefulness of the TLBO approach.

4.2. Dye-sensitized solar cell (DSSC) and plastic solar cell

To further check the effectiveness of the TLBO algorithm over a diverse world of the solar cell technologies, it is used for extraction of the parameters values of a DSSC [3] and a plastic solar cell [2,29]. The synthetic I–V characteristics, as obtained from the reported values of parameters in the literature for respective cells, and the fitted I–V characteristics (solid lines) obtained by the TLBO algorithm for both these cells are shown in Fig. 5. In both these cases, the TLBO algorithm successfully converges to stable solutions, which is clearly indicated by excellent matching between the synthetic and the fitted curves. The parameters values obtained by the algorithm and reported values for DSSC and plastic cell are summarized in Table 2. It is clearly observed that the parameters extracted by the TLBO algorithm are in excellent agreement with reported values for the respective cell in both these cases establishing the validity of the algorithm.

Table 2
Comparison of solar cell parameters obtained by the TLBO algorithm with reported values.

Cell or module	I_o (μA)	I_{ph} (A)	R_S (Ω)	R_{Sh} (Ω)	n
Silicon solar cell (33 °C)					
Reported values [27]	0.3223	0.7608	0.0364	53.76	1.4837
TLBO method	0.3223	0.7608	0.0364	53.76027	1.4837
TLBO method (with noise)[a]	0.3374	0.7777	0.0354	55.76183	1.4857
Required loop iterations	452	431	435	480	452
Plastic solar cell (27.3 °C)					
Reported values [2]	0.0136	0.00794	8.59	197.24	2.31
TLBO method	0.013596	0.00794	8.590942	197.2418	2.30994
Required loop iterations	860	725	845	836	830
DSSC (20 °C)					
Reported values [3]	0.035	0.00206	43.8	3736	2.5
TLBO method	0.03488	0.00206	43.79241	3732.832	2.49927
Required loop iterations	610	525	650	692	635
Silicon solar module (45 °C)					
Reported values [27]	3.2876	1.0318	1.2057	549	48.45
TLBO method	3.280945	1.031805	1.206	548.666	48.44228
Required loop iterations	420	410	390	418	415

[a] Random noise with 4% relative intensity.

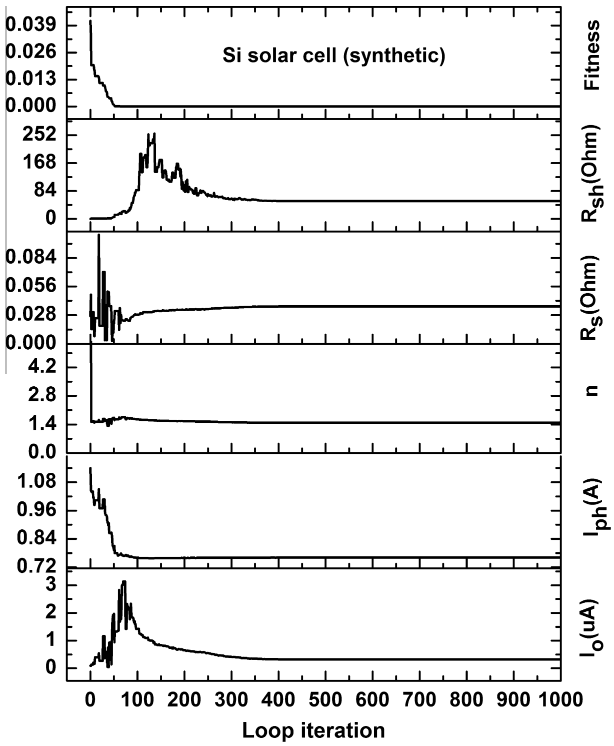

Fig. 3. Fitness function and parameters values as a function of loop iteration for synthetic *I–V* characteristic of Si solar cell.

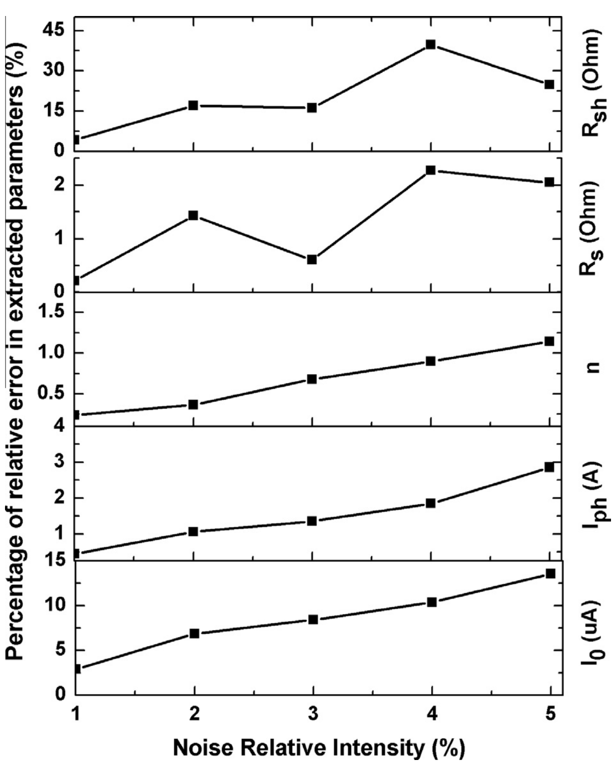

Fig. 4. Relative errors in extracted parameters as a function of random noise.

Fig. 6 depicts the solar cell parameters and fitness function variation in case of DSSC as a function of loop iterations. As shown in the figure, the fitness function value reduces rapidly showing quick convergence. The values of n, I_{ph}, and I_o also become stable quickly. Although, these variations in the values of n, I_{ph}, and I_o are fast in

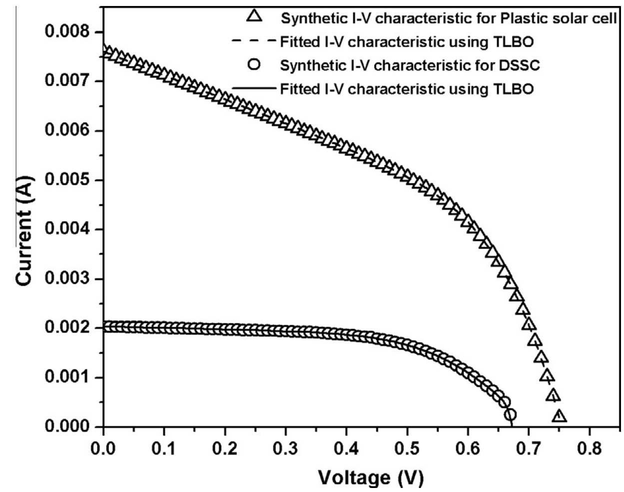

Fig. 5. Synthetic and TLBO fitted *I–V* characteristics for DSSC and plastic solar cell.

terms of number of iterations, it must also be noted that the algorithm scans a good amount of search ranges before reaching to a stable solution. Thus, the probability for the program to get trapped in local minima of solution is very less in the case of TLBO algorithm. This fact can further be validated by looking at the changes in the value of R_s and R_{sh} with the number of iterations. The scanning for the correct values of R_{sh} ranges from 0 to almost 132 kΩ as evident from the graph within first 400 iterations. R_s is also scanned in the range from 0 to almost 120 Ω. The step accuracy, i.e. the minimum possible change in the value of a parameter that can occur in an iteration, for R_s is 0.000001 Ω, which reveals the efficiency of scanning the values of the program. Also, it can be seen from Fig. 6 that a sudden turbulence is observed in the steady value of R_{sh} between 200 and 300 iterations. These types

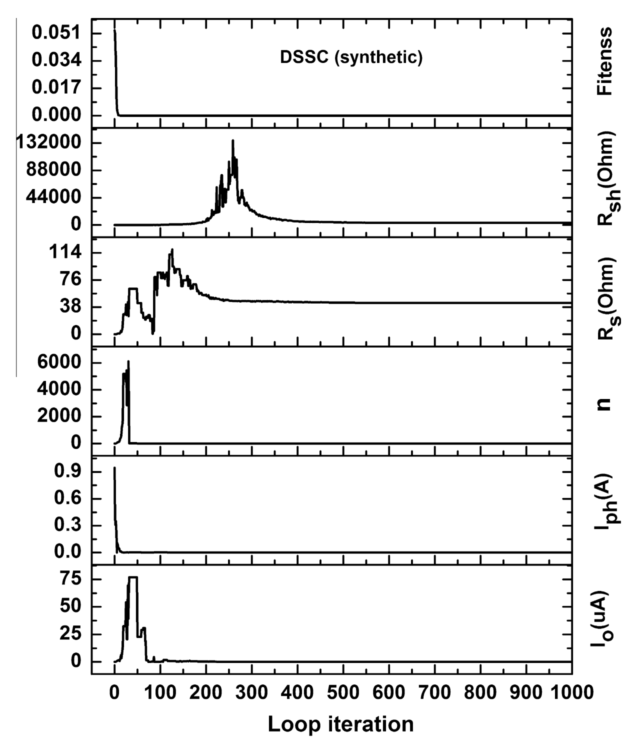

Fig. 6. Fitness function and parameters values as a function of loop iteration for synthetic *I–V* characteristic of DSSC.

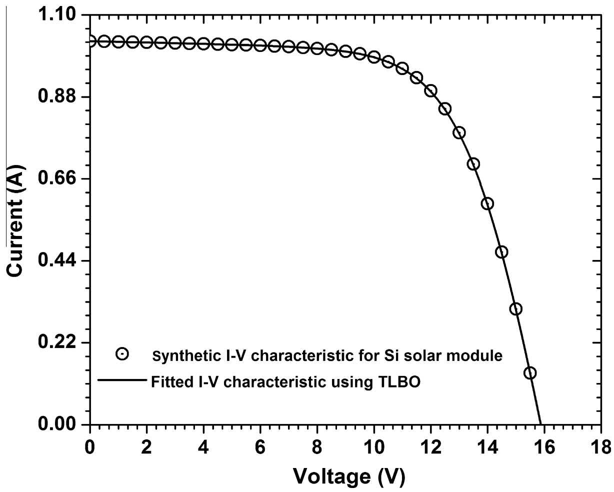

Fig. 7. Synthetic and TLBO fitted *I–V* characteristic for Si solar module.

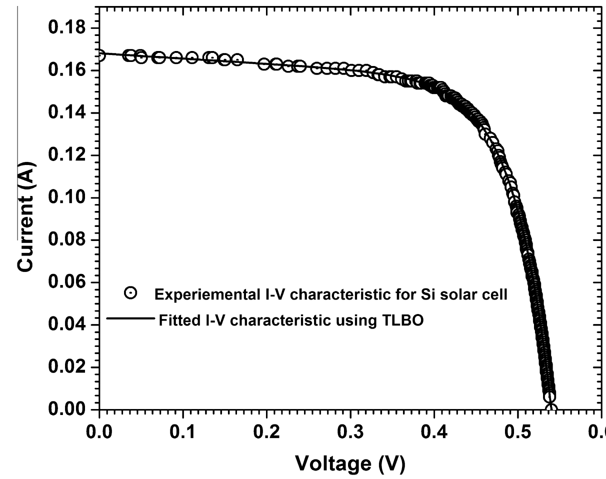

Fig. 9. Experimental and TLBO fitted *I–V* characteristics for Si solar cell.

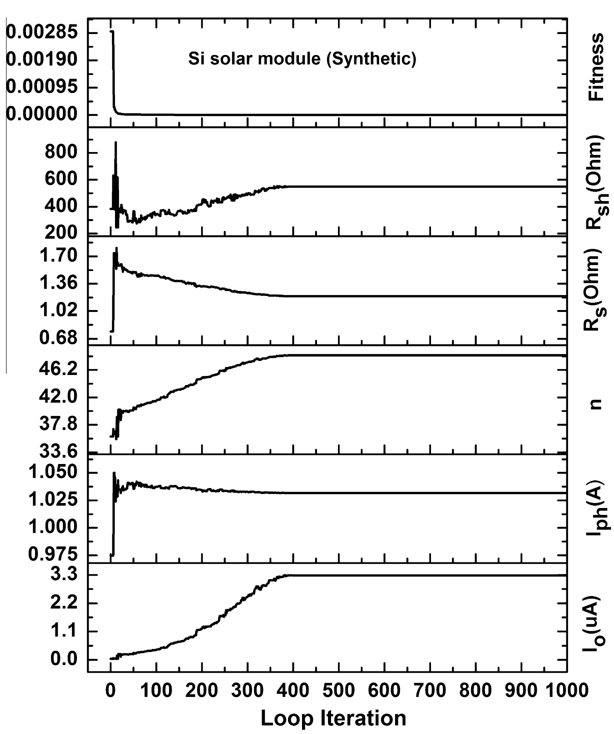

Fig. 8. Fitness function and parameters values as a function of loop iteration for synthetic *I–V* characteristic of Si solar module.

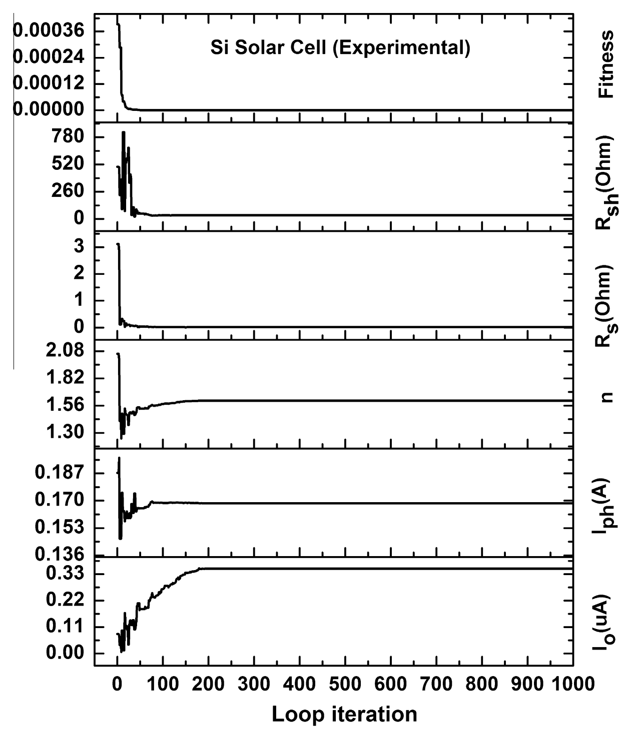

Fig. 10. Fitness function and parameters values as a function of loop iteration for experimentally measured *I–V* characteristic of Si solar cell.

of sudden fluctuations after constant values for some iterations are the results of quick transition of solution from one local minimum to the other. This behavior is equivalent to the effects of mutation in the GA based approach. Overall, a global optimum of the solution is achieved within about 650 iterations and the fitness function becomes constant as shown in Fig. 6. Similar trends are observed in the variation of parameters and fitness function for plastic solar cell (not shown here) as the loop iteration progresses and the steady state solution is reached after about 850 iterations.

4.3. Silicon solar module

Solar cells are generally used in the form of modules consisting of a large number of cells which are connected in series or parallel. Hence, it is often required to analyze such modules. Moreover, since the module contains a large number of solar cells in series or parallel, the values of parameters are also quite different from the values of individual cells. For example, the values of open circuit voltage and the ideality factor are very large in case of modules. The ideality factor of a diode is a measure of how closely the diode follows the ideal diode equation. The large value of the ideality factor mainly results from the tunneling junctions connecting the sub-cells of the module. Although the one diode model losses its relevance up to certain extent under such circumstances, the performance evaluation of module is still convenient and reasonably reliable by single diode model approach [4,5].

To check the relevance and applicability of the TLBO approach on the module, a silicon solar module (Photowatt-PWP-201) in which 36 polycrystalline silicon cells are connected in series [27]

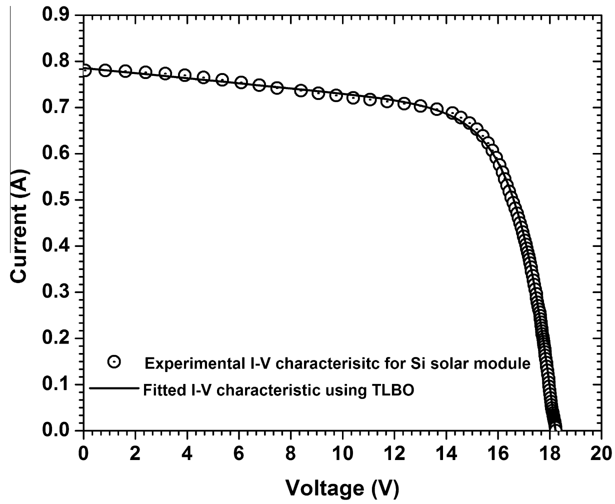

Fig. 11. Experimental and TLBO fitted *I–V* characteristic for Si solar module.

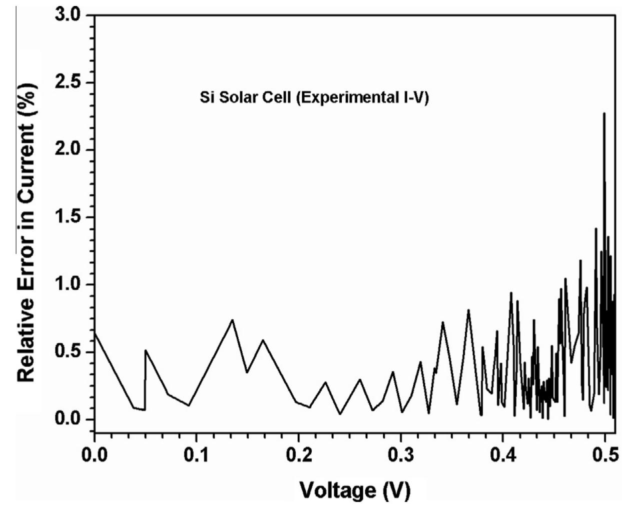

Fig. 13a. Relative error in current versus voltage plot of Si solar cell.

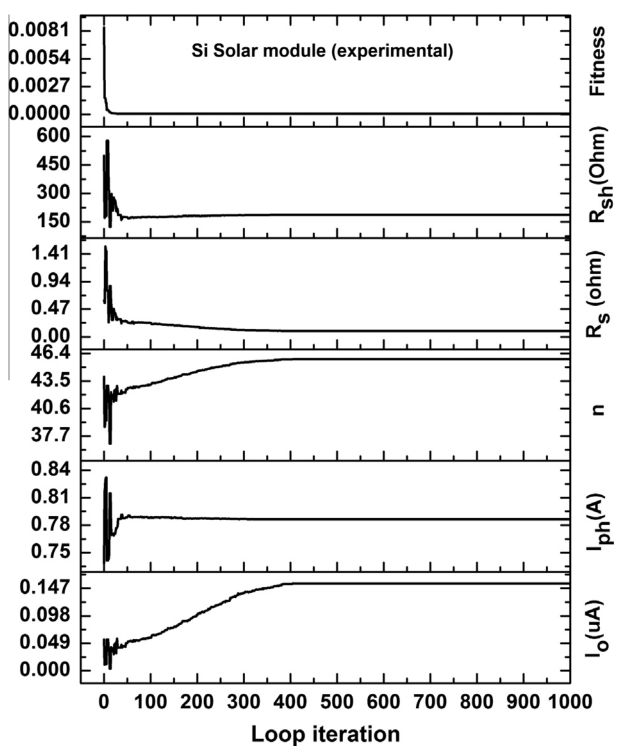

Fig. 12. Fitness function and parameters values as a function of loop iteration for experimentally measured *I–V* characteristic of Si solar module.

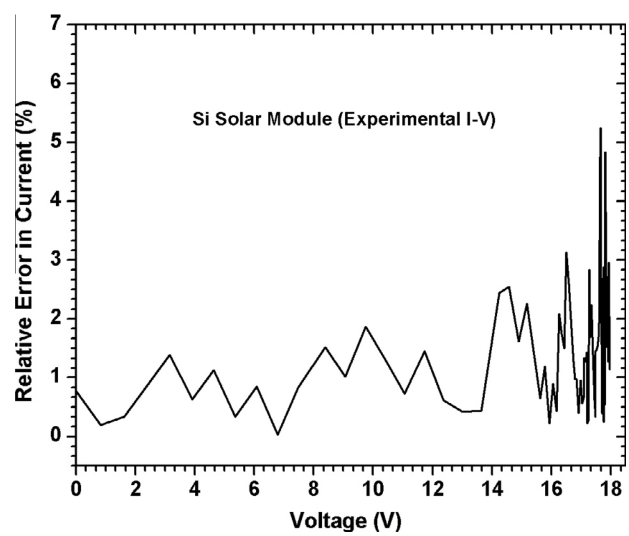

Fig. 13b. Relative error in current versus voltage plot of Si solar module.

is analyzed using the TLBO algorithm. The synthetic (dotted circles) and TLBO fitted *I–V* characteristic (solid line) obtained using the extracted parameters by this work is shown in Fig. 7. Even for the module, the match between the synthetic and TLBO fitted *I–V* curve is quite convincing, which proves the robustness of the algorithm. Fig. 8 shows the variation of fitness function and solar cell parameters with the number of iterations for silicon solar module. As seen from the Fig. 8, the values of all the parameters vary gradually and become stable after about 400 iterations. The final extracted values of the parameters by our work match considerably with those of the reported values as shown in Table 2.

As shown in Table 2, the TLBO algorithm successfully converges to the stable solution and extracts the values of solar cell parameters with very high accuracy for a very diverse class of solar cells. It is also noticed that the results obtained are very consistent and the extracted values are repeated for more than 90% of attempts in each case of solar cell. This shows that the algorithm achieves the global optimum with very good consistency.

After validation of the reliability of our program based on TLBO, we employed it to extract the five solar cell parameters from experimentally measured *I–V* characteristics of a monocryalline Si solar cell and a polycrystalline Si module in our laboratory. The *I–V* characteristic of monocrystalline Si solar cell with the active area of $4 \times 4\,cm^2$ (make: Bharat Electronic Limited, India) was measured using a solar simulator (make: NCPRE, IIT, Bombay, India) under the irradiance of 900 W/m^2 at the temperature 45 °C in our laboratory. The comparison between experimental *I–V* and TLBO fitted *I–V* characteristics for the cell is shown in Fig. 9. It is clearly seen that the *I–V* curve generated using the TLBO extracted parameters passes through all the experimental data points. This shows the stability of our approach. Fig. 10 shows the variation of the fitness function and individual solar cell parameters as a function of loop iterations. Here, we found that all solar cell parameters become stable within 120 iterations except the I_o, which gradually increases with small fluctuations up to about 200 iterations before being stable. The value of the fitness function

Table 3
Extracted solar cell parameters for experimentally measured I–V characteristics of Si solar cell and solar module.

Cell or module	I_o (μA)	I_{ph} (A)	R_S (Ω)	R_{Sh} (Ω)	n
Monocrystalline Si solar cell (45 °C)	0.365051	0.168470	0.0190	37.521	1.611516
Polycrystalline Si solar module (50 °C)	0.135551	0.785896	0.093	182.046	45.40178

decreases speedily during the initial iterations and takes about 200 iterations to achieve the global minimum.

The I–V characteristic of a Si solar module with the active area of ~960 cm^2 (make: Titan Energy System Limited, India and module no: TITAN-06-8665) was measured at 50 °C temperature under the irradiance of intensity AM 1 in our laboratory. The fitted I–V obtained using the TLBO extracted parameters is in excellent agreement with experimental one as shown in Fig. 11. Fig. 12 depicts the variation of the fitness function as well as that of individual solar parameters as loop iteration progresses. As evident from the figure, the convergence of the solution is slower in the case of solar module as compared to the single cell. It takes about 400 iterations to achieve the global minimum for the fitness function in case of Si solar module.

Further, to understand the closeness of the fitted curve with the experimental data we determined the relative error in the current value at every voltage step for experimentally measured I–V characteristic in case of both Si solar cell and Si solar module, which is shown in Figs. 13a and 13b respectively. As shown in the Fig. 13a, the relative errors in the currents for Si solar cell over the entire range of voltage is found to be below 2.5%, which suggests a very close matching between the experimental data and the fitted curve. However, in the case of solar module, the relative error is a bit higher as compared to the single cell especially near open circuit voltages. This is owing to a little fluctuation in the measurement of extremely low current near the open circuit voltage. Still the relative errors do not go beyond 5% for the entire range of voltages, indicating good reliability of the TLBO approach. The extracted values of parameters by TLBO algorithm from the experimentally measured I–V characteristics for both cell and module are listed in Table 3.

In case of both, Si solar cell and solar module, the experimental data were fitted through the TLBO algorithm for 100 times and it is observed that more than 90 times the exact matching is obtained with very consistent values of all five parameters. It is also found in both the cases that the TLBO fitted I–V curves comprehensively cover all the experimental data points to give an excellent match.

5. Conclusion

We have employed the TLBO algorithm to extract all the solar cell parameters from a single illuminated I–V characteristic of different types of solar cells as well as solar modules by considering a single-diode model. Initially, the effectiveness and the validity of the algorithm are confirmed by applying it to the synthetic I–V characteristics with known values of parameters. It is observed that the values of parameters extracted using TLBO algorithm match exactly with the reported data. The rate of repeatability to attain the global optimum solution is shown to be very high in case of the TLBO algorithm. After the validation of the algorithm, we used the program to extract the unknown values of solar cell parameters from the experimentally measured I–V characteristics of a monocrystalline Si solar cell and a polycrystalline Si solar module. It is demonstrated that the TLBO algorithm can be a very effective and useful tool to extract the information about all the five important solar cell parameters from a single I–V characteristic measured under illumination. The limitation of numerical methods and conventional optimization algorithms in solar cell parameters extraction problem can be significantly overcome with the help of the TLBO approach.

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