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Analysis and Implementation of Robust Metaheuristic Algorithm to Extract Essential Parameters of Solar Cell

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ABSTRACT Optimization complications are solved using meta-heuristic methods, which transforms the complex data into simplest way and computational process is quite attractive because of their intensification, diversification, and accurate evaluating/computational behavior on the nonlinear data. Among different existing meta-heuristic algorithms, Tabu Search Optimization (TSO) algorithms have robust performance due to escaping strategy from local optimum and extensive extraction ability. Hence, this paper delineates the TSO searching technique for extracting the parasitic parameters of solar Photovoltaic (PV) modules under different climatic stipulations. Double diode design is developed and implemented in the operational aspect based on the extraction issue. The six parameters of the solar cell, i.e., I_{Ph}, I_{01}, I_{02}, R_S, R_P, a_1 are emulated and the obtained data is investigated using TSO approach, at the same time the extracted data is compared with the effective selected metaheuristic algorithms such as Gravitational Search Algorithm (GSA), Lightning Search Algorithm (LSA), Pattern Search (PS), Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Compared to the existing algorithms, TSO has very less computational time to extract all the six parameters.

INDEX TERMS Tabu search optimization (TSO), synthetic data (SD), genetic algorithm (GA), photovoltaic (PV) cell, tree growth algorithm (TGA).

NOMENCLATURE

I & V	Current (A) & Voltage (V).
η	Ideality Factor.
R_S	Parasitic Series Resistance (Ω).
R_P	Parasitic Shunt Resistance (Ω).
J_{Ph}	Photon Current Density (A/m^2).
J_O	Dark Current Density (A/m^2).
I_{SC}	Short Circuit Current (A).
V_{OC}	Open Circuit Voltage (V).
G	Irradiation (W/m^2).
V_{bi}	Built in Potential (V).
I_{Ph}	Photo Current (A).
I_{01}, I_{02}	Diode Currents (A).
I_S	Reverse Saturation Current (A).
K	Boltzmann Constant (m^2 kg s^{-2} K^{-1}).
T	Temperature in (K).
Q	Charge of an electron (C).
I_C	Output current of the cell (A).
$I_{Ph,C}$	Photo Current of single solar cell (A).
a_1	Diffusion & recombination current const.
V_C	Voltage of single solar cell.
R_{SC}	Parasitic Series Resistance of cell (Ω).
R_{PC}	Parasitic Shunt Resistance of cell (Ω).
V_{ThC}	Thermal voltage of single solar cell (V).
J	Fitness Function.
N_S	Number of solar cells connected in series.
N_P	Number of solar cells in Parallel.
V_{OC}	Output voltage of solar cell (V).
I_M	Optimal solar current (A).
V_M	Optimal solar Voltage (V).
Φ_M	Max. value of an extracted parameter.

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N	Number of I-V data set.
S^I	Old solution during the iteration.
N(S)	New solution obtained during the TS.
T(S)	Updated Tabu list.
A(S)	Aspiration Criteria.

I. INTRODUCTION

Renewable energy sources are contributing major share in electric power generation in many nations. These sources contribute energy from sun, wind, floating water and ocean waves, etc. [1]. Out of these sources, solar energy (sun radiated energy) plays an important role, due to simplicity involved in converting it to thermal or electrical energy [2]. The salient features of Photovoltaic (PV) systems are environmentally friendly, economical, and easily integrated with conventional electrical grid [3]. In order to avoid power mismatch, solar panels are not connected directly to the load [4]. To avoid this situation, a power tracking strategy between panel and load is proposed [5]. Apart from this, the extraction of parasitic parameters from the solar cell is also significant study to get optimum performance [6]. This paper mainly describes the extraction of solar parameters using TSO scheme. Villalva *et al.* [7], developed mathematical analysis to encounter the criteria of the one-diode modeled PV system. The proposed modeling is accessible, rapid, meticulous, and easy for emulation. The design approach includes about the necessity of series and shunt resistances and matches with the real-time operational array in terms of maximum power [8]. The proposed model adjusts the nonlinear equation based on I-V curve using trial and error method dependent on three points [9].

Ma *et al.* [10] introduced data-driven I–V technique, which is tested on the three parameters (I_{SC}, R_{Sh}, and V_{OC}) of single diode model solar cell. Saleem *et al.* [11], proposed a Four Point Extraction technique to identify design specifications, particularly ideality constant, R_S, R_P, current due to activation of photons and dark current. In [12] conducted three-terminal examination on GaAsP and SiGe based tandem structure to extract the sub-cell parameters. The proposed technique mainly concentrates on the potential difference between the two reference cells through analytical measurements and obtain individual voltage. In addition, I-V curves are adjusted by forecasting the passive losses of the sub-cell. Therefore, the performance of the multi-junction is obtained at various input bands by distinct identical circumstances [13]. Wei *et al.* [14], introduced Particle Swarm Optimization (PSO) algorithm to isolate the performance parameters of the organic solar cells, integrated with three diode lumped parameters. The proposed algorithm helps to conquer the deficiency to avoid the drifting of local optimum issues [15].

Diab *et al.* [16], introduced and investigated a fast and accurate method to extract unknown solar parameters using Tree Growth Algorithm (TGA) for many solar PV modules. In this technique, all the extracted parameters are computed at best conditions and the resultant outcome is to be optimum. As a future scope, this method is to be implemented under partial shading conditions of a PV system [17], [18]. Raba *et al.* [19], proposed the implementation of a Definite Markov Chain Monte Carlo technique to eliminate the uncontrollable phenomena of 2-D Organic Solar Cells, the test is conducted in both dark and bright conditions. Caracciolo *et al.* [20], [21], proposed a single-variable optimization technique at fixed climatic conditions. But, when tested under strident climatic conditions, resolved most of the parameters like R_S, R_{Sh}, I_O, and the range of panels. Hence the proposed method is powerful to all strident contributed conditions [22]. Cervellini *et al.* [23], [24], introduced a novel Genetic Algorithm (GA) to transform the conventional data into designed data, applies to various Kelvins and irradiation (G) zones [25], [26]. The proposed GA approach is very simple and eliminates the complexity of evaluation, i.e., describes I-V curve and other related equations in a transparent and uncomplicated way [27], [28].

Liao *et al.* [29], developed Difference Vector in Differential Evolution with Adaptive Mutation (DVADE) strategy for a single, double, and multi-diode design. The function of DVADE is to determine the extracted parameters of different PV models in a quick interval of time, it reuses the past individual vectors and these vectors using differential evolution process and applied these vectors to mutation strategy [30]. Toledo *et al.* [31], [32], proposed Two Step-Linear-Least Square (TSLLS) method. The main advantage of the proposed method is to fetch the data irrespective of choosing the same from I-V curve, i.e., it does not require any primary guesses and not mandatory to perceive any previous works or information regarding the parameters [33]. Manda *et al.* [34], Portrays that the extraction of built-in potential (Vbi) from the cells can be eliminated by using a physics-based model and an empirical technique based on J-V characteristics [35]. The suggested method has a continuity equation to solve the current-carrying transport. Experiments conducted on poly (3 hexyl thiophene): phenyl-C61- butyric acid methyl ester solar cells. Therefore, implementing the proposed computation strategies V_{bi} is easily extracted.

The rest of the paper is articulated as follows, Section III, presents the mathematical analysis and modeling of the solar cell parameters, Section IV, presents the evolution of the proposed TSO algorithm to extract solar cell parameters, Section V, presents comparison between the proposed and existing algorithms, and finally Section VI, presents the summary of solar parameter extraction using TSO approach.

II. PV CELL PARAMETERS

A. MODELING OF PV MODULE

The study and analysis of the tracking algorithms, dynamic behavior of the converters and other components mainly depends on the mathematical modeling of the PV system [36]. Various environmental factors are influencing the efficiency

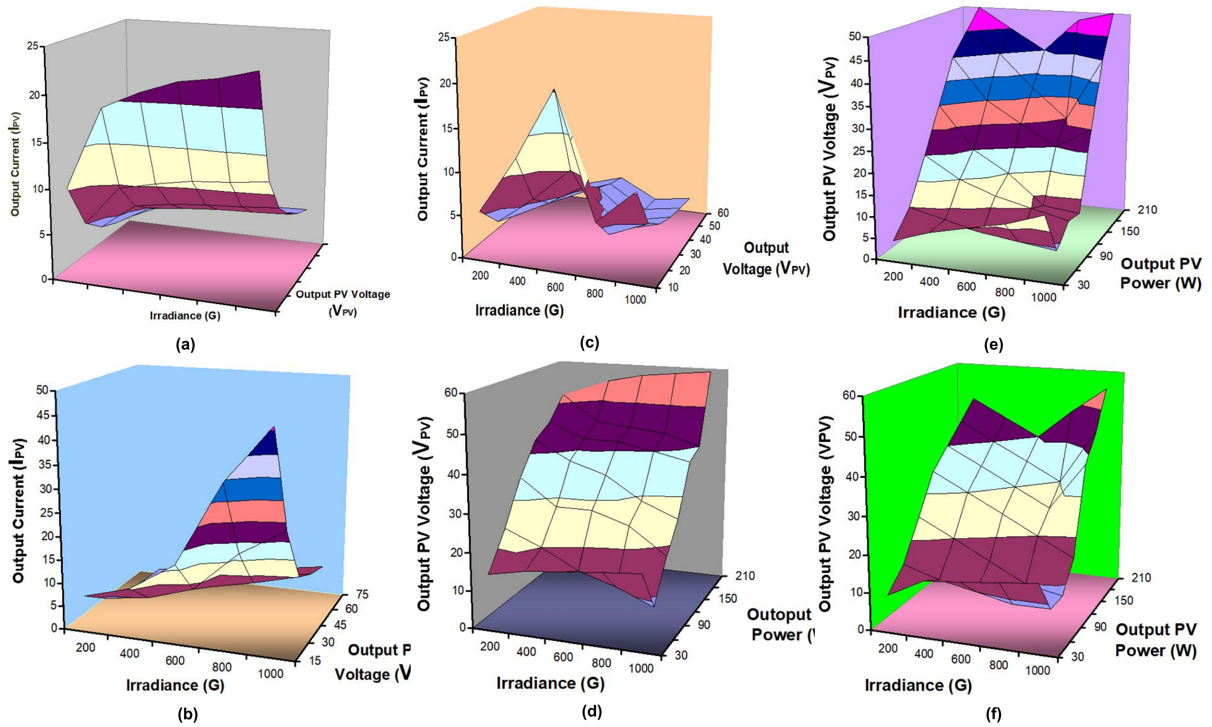


FIGURE 1. Three dimensional (3D) view of I-V and P-V plots of 200W PV array, (a) PSC with minimum number of power peaks. (b) Uniform irradiation. (c) Maximum number of power peaks, (d) Uniform irradiation. (e) Maximum number of power peaks and (f) PSC with minimum power peaks.

of the PV system, partial shading is one among them. In broad sense affects the PV system with multiple peaks in the output power curve [37]. Therefore, proper extensive mathematical analysis is necessary to compensate this particular issue [38]. The PV current obtained from the solar panel is given as

$$I_{PV} = I_{Ph} - I_d \tag{1}$$

The above parameters are influenced by G and T, which is calculated further by the formulae in Eq. (2).

$$I_{Ph}(G) = (I_{PV} + K_i T_{diff}) \frac{G}{G_r} \tag{2}$$

The reverse saturation current (I_{rs}) at certain base temperature is as follows

$$I_{rs} = \frac{I_{SC}}{\exp\left(\frac{qE_{OC}}{K_b \eta T_k} - 1\right)} \tag{3}$$

Diode current is obtained by the Shockley equation is

$$I_d = I_S \left[\exp\left(\frac{q(V_{PV} + I_{PV} R_S)}{\eta K_b T_k}\right) - 1\right] \tag{4}$$

Diode saturation current (I_S) is fluctuating according to the environmental changes, and determined by the following mathematical equation

$$I_S = I_{rs} \left[\frac{T_k}{T_r}\right]^3 \exp\left[\frac{qE_{qo}}{\eta K_b}\left(\frac{T_{dif}f}{T_k T_r}\right)\right] \tag{5}$$

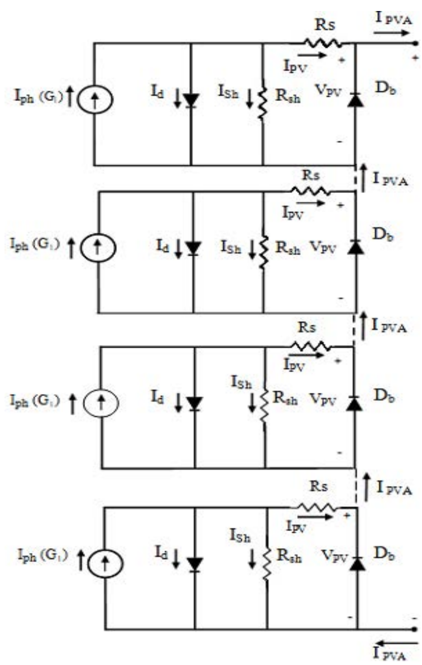


FIGURE 2. PV array with bypass diode.

On substituting Eq. (5) into Eq. (1), then the output current of PV cell is as follows

$$I_{PV} = I_{Ph} - I_S \left[\exp\left(\frac{q(V_{PV} + I_{PV} R_S)}{\eta K_b T_k}\right) - 1\right] - \frac{V_{PV} + I_{PV} R_S}{R_P} \tag{6}$$

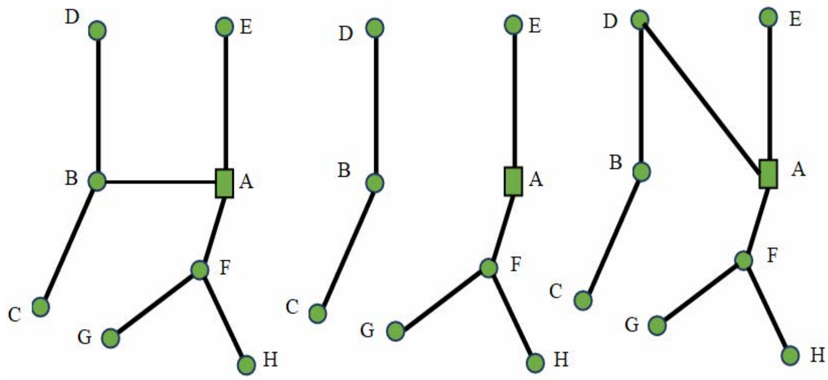


FIGURE 3. Strategic moves involved in non-linear solution of TSO algorithm.

The PV cell output characteristics is minimized by using the following implicit form

$$F(I_{PV}, V_{PV}, T_K, G) = I_{Ph} - I_{PV} - I_S\,[\alpha_1] - \beta_1 \tag{7}$$

where

$$\left.\begin{aligned}\alpha_1 &= \exp\left(\frac{q(V_{PV} + I_{PV}R_S)}{\eta K_b T_k}\right) - 1\\ \beta_1 &= \frac{V_{PV} + I_{PV}R_S}{R_P}\end{aligned}\right\} \tag{8}$$

PV module is obtained by connecting PV cells either in parallel (N_P) or series (N_S). The output power of single cell is least efficient compared to PV module, hence the output implicit form of PV module is re arranged as

$$F(I_{PV}, V_{PV}, T_K, G) = I_{Ph} - I_{PV} - I_S\,[\alpha_2] - \beta_2 \tag{9}$$

where

$$\left.\begin{aligned}\alpha_2 &= \exp\left(\frac{q(V_{PV} + I_{PV}R_S)}{N_S\eta K_b T_k}\right) - 1\\ \beta_2 &= \frac{V_{PV} + I_{PV}R_S N_S}{N_S R_P}\end{aligned}\right\} \tag{10}$$

B. FITNESS FUNCTION

An objective function (J) is used for the evaluation of the extraction parameters. J is nothing but the root mean square of the synthetic and current data. For N numbers of I-V data set, it is represented as follows

$$J = \sqrt{\frac{1}{N}\sum_{m=1}^{N} f(I_M, V_M, \varphi)^2} \tag{11}$$

where,

$$F(I_M, V_M, \varphi) = I_{Ph} - I_{01}\left\{\exp\left(\frac{V + IR_S}{a_1 V_{th}}\right) - 1\right\} - \frac{V + IR_S}{R_P} - I \tag{12}$$

In continuation $\phi = [I_{Ph}, I_{01}, R_S, R_P, a_1]$ are the extracted parameters from the PV module, where the extraction system is to be reduced based on ϕ. A zero value of J is acceptable, satisfying the condition of J as nonlinear.

C. PV SYSTEM UNDER PSC

The non-uniform insolation conditions occurred due to the whole or some portion of the PV module is shaded by high buildings, passing clouds, and trees, etc. During partial shading, some of the PV cells receive uniform irradiance, i.e., unshaded and the remaining portion of the PV cells are shaded and required to maintain the same amount of current similar to unshaded cells. [39], and the point of occurrence is when shaded cells are operating with reverse bias voltage, the uniform current is maintained in the PV module [40]. But, the reverse polarity causes more power consumption and maximum output power is drastically reduced in the partial shaded module. Moreover, reverse bias voltage causes ''hotspots'' phenomena and leads to open circuit condition in the whole PV module [41]. This issue occurrence is resolved by inserting bypass diode. It is worthwhile to discuss the effect of bypass diode in the PV module. The working of PV array with and without bypass diodes is quite different. The I-V and P-V three dimensional (3D) view of 200W PV panel is shown in Fig. 1. During partial shaded situation bypass diode provides an alternate path to the flow of current as shown in Fig. 2.

III. EVOLUTION OF TSO ALGORITHM

The meta-heuristic algorithm is used to solve the state of problem of multiple optimizations. The strategic movement of non linear solutions is depicted in Fig.3, from the figure it is clear that the methodology involved perform iterations based on memory. During optimization, the smallest value will be selected first and further search follows. The memory functional mechanism named on Tabu List (TL) not only records the data but also stores the previous solution, while performing the next move. To avoid local optima unnecessary data will be restricted and optimized data will be segregated at Aspiration Criteria (AC). The TSO algorithm is based on offering a formative memory organization with imperative constraints and aspiration levels to exploit search spaces and counseling local heuristic research proceedings to scrutinize the outcome space ahead of local optimum with the help of TL. The investigating process based on dynamic properties

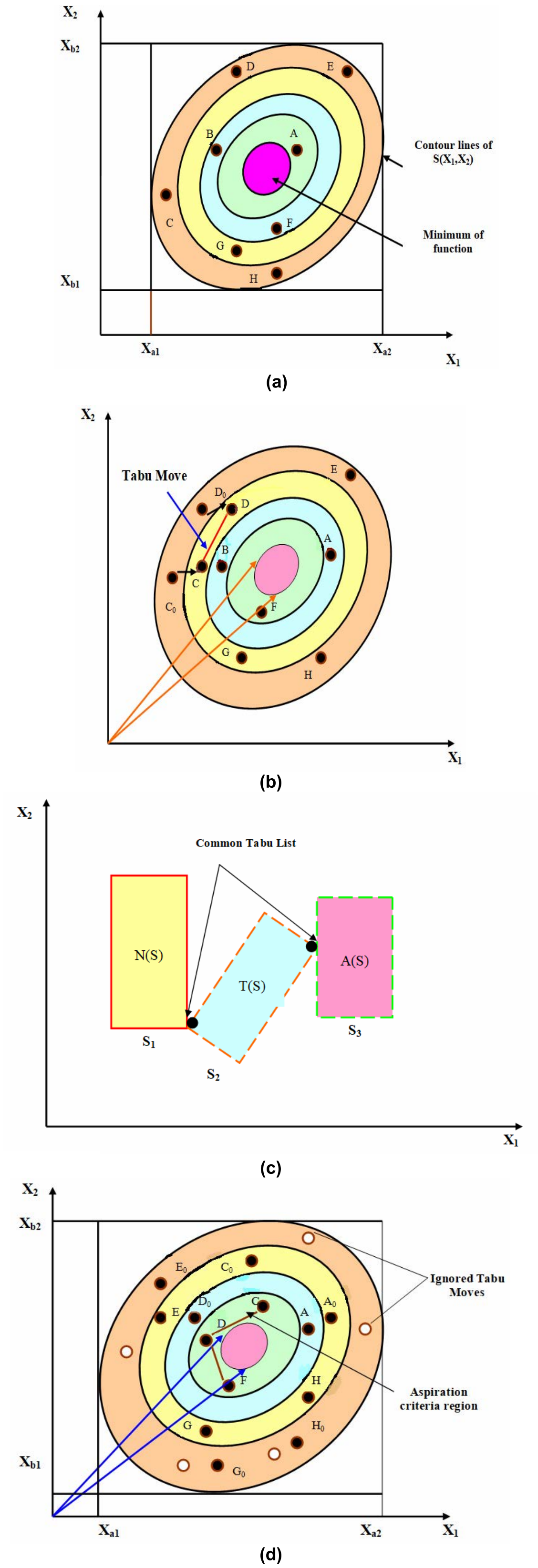


FIGURE 4. (a) Initialization of tabu search operation, (b) Tabu movement phenomena, (c) dynamic sectionalising, (d) effect of ignoring the repeated data.

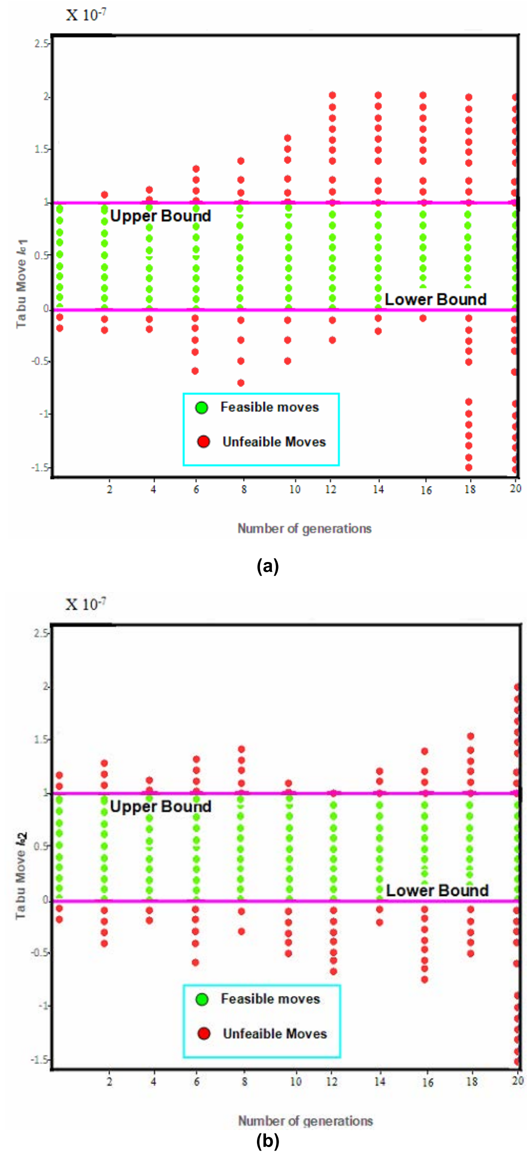


FIGURE 5. Resulting tabu move (a) I_{01} and (b) I_{02}.

is mainly preferred to solve finite solution set optimization problems due to flexible memory uses in the tabu moves so that the repeated solutions cannot be included in the operation.

TSO can be categorized as Forbidding Strategy (FS), Freeing Strategy System (FSS), and Short Term Strategy (STS). FS restricts that which type of data is coming into the operating region where as FSS manages that what exists from the optimization process and STS controls interrelation between FS and FSS by performing estimated solutions. Fig. 4 (a), described about the initiation of tabu moves from upper bound level to lower bound level, such that the tabu move decides the sequence of operation and improves the extraction ability. The multiple iterations are shown in Figure 4(b) and

TABLE 1. Data comparison between GA, LSA, GSA, PS, PSO and proposed TSO algorithms for 20 WATT PV panel.

S.NO	Parameter	Synthetic data	GA	LSA	GSA	PS	PSO	TSO
1	*Iph*	0.912A	1.893A	1.302A	1.346A	1.189A	0.935A	0.920A
2	I_{01}	2.543×10^{-9}A	5.54×10^{-9}A	3.26×10^{-9}A	2.91×10^{-9}A	2.65×10^{-9}A	2.799×10^{-9}A	2.61×10^{-9}A
3	I_{02}	2.834×10^{-5}A	8.543×10^{-5}A	6.28×10^{-5}A	5.59×10^{-5}A	4.765×10^{-5}A	3.75×10^{-5}A	2.90×10^{-5}A
4	*Rs*	0.032 Ω	0.087 Ω	0.067 Ω	0.056 Ω	0.0765 Ω	0.0315 Ω	0.03 Ω
5	*Rp*	109.95 Ω	115.72 Ω	113.53 Ω	112.45 Ω	111.76 Ω	109.887 Ω	110.23 Ω
6	a_1	1.9	2.16	2.12	2.25	2.17	1.89	1.9
7	*Time (s/min)*	...	475	357	264	248	142	94

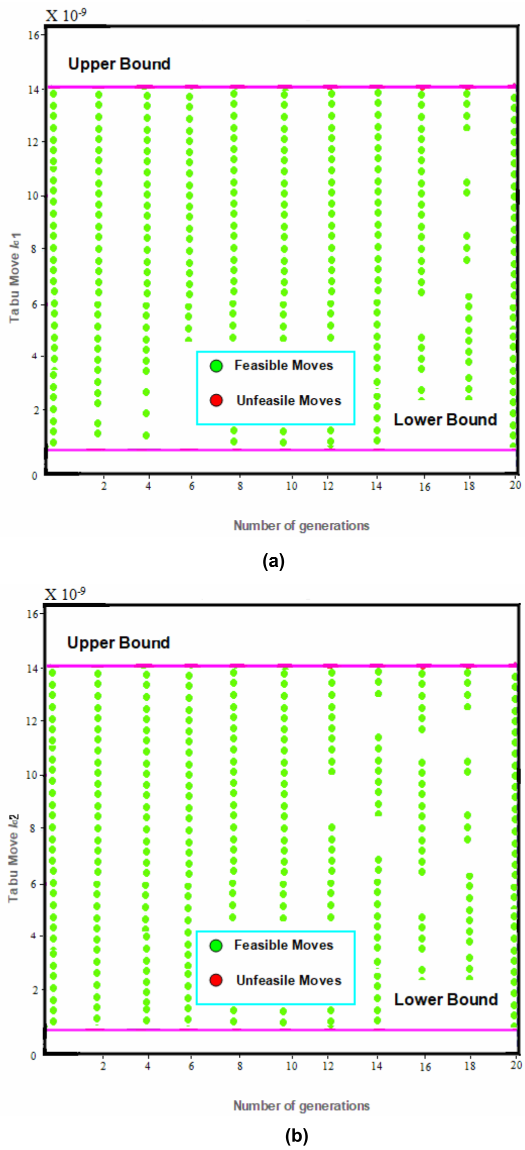


FIGURE 6. Resulting tabu move after applying the penalty (a) I_{01} and (b) I_{02}.

the transformation of every Tabu Solution is inter linked with the tabu list as shown in Figure 4 (a), and described about the initiation of tabu moves from upper bound level to lower bound level, such that the tabu move decides the sequence of operation and improves the extraction ability. Multiple iterations are shown in Figure 4(b) and the transformation of every Tabu Solution is inter linked with the tabu list as shown in Figure. 4(c). The repeated data is ignored in TL, because the count of number of iterations are very high. The aspiration and ignored tabu region is described in Figure. 4(d).

A. BASIC INGREDIENTS OF TSO ALGORITHM

The tabu movement is based on memory and neighborhood solutions, considering non improved and non linear solutions. Moreover, these solutions should not include in the TL. The tabu classification can be overridden by introducing the new Tabu moves. The new set of TS solution can be obtained as

$$S' \in N(S) = \{(N(S)T(S)\} + A(S) \tag{13}$$

The feasible and unfeasible parameters describe about the tabu moves in upperband and lower band regions. Fig. 5 (a) and (b), describes about the feasible parameters present in between upper and lower band regions. The feasibility is less because of the lesser number of generations during the execution. The perfect feasible parameters are obtained after implementing the proposed strategy on each generation as depicted in Fig. 6 (a) and (b).

IV. RESULTS ANALYSIS

Using MATLAB/Simulink, the proposed method is simulated along with other existing algorithms such as LSA, GSA, PS, GA and PSO. There is a close comparison between the obtained numerical values and Synthetic Data (SD). The performance of the proposed TSO algorithm is studied for different ranges of solar panel i.e., 20W, 40W, 80W and 200W respectively. It is worth full to benchmark that the all the algorithms are simulated in a common platform with unique basic data using 1.2 GHz Mobile Intel processor,

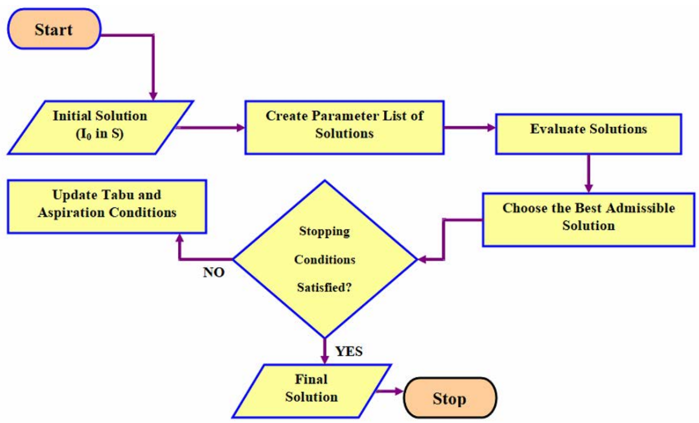


FIGURE 7. Flow chart of the proposed tabu search optimization (TSO) algorithm.

TABLE 2. Data comparison between GA, LSA, GSA, PS, PSO and proposed TSO algorithms for 40 Watt PV panel.

S.NO	Parameter	Synthetic data	GA	LSA	GSA	PS	PSO	TSO
1	*Iph*	1.987A	2.79A	2.75A	2.162A	2.189A	2.01A	1.95A
2	I_{01}	6.43×10^{-9}A	9.81×10^{-9}A	8.6×10^{-9}A	8.6×10^{-9}A	7.65×10^{-9}A	5.65×10^{-9}A	6.55×10^{-9}A
3	I_{02}	22.9×10^{-7}A	33.6×10^{-7}A	29.9×10^{-7}A	26.28×10^{-7}A	26.76×10^{-7}A	23.32×10^{-7}A	11.82×10^{-7}A
4	*Rs*	0.0875 Ω	0.0994 Ω	0.0975 Ω	0.097 Ω	0.0969 Ω	0.0954 Ω	0.0882Ω
5	*Rp*	732.65 Ω	888.95 Ω	932.65 Ω	878.53 Ω	816.76 Ω	782.65 Ω	742.68 Ω
6	a_1	1.25	1.38	1.29	1.32	1.47	1.38	1.29
7	*Time (s/min)*	…	779	682	395	362	237	112

TABLE 3. Data comparison between GA, LSA, GSA, PS, PSO and proposed TSO algorithms for 80 Watt PV panel.

S.NO	Parameter	Synthetic data	GA	LSA	GSA	PS	PSO	TSO
1	*Iph*	4.85A	6.95A	6.942A	5.92A	5.79A	5.27A	4.89A
2	I_{01}	8.87×10^{-9}A	10.92×10^{-9}A	9.26×10^{-9}A	9.8×10^{-9}A	9.5×10^{-9}A	9.22×10^{-9}A	8.99×10^{-8}A
3	I_{02}	8.54×10^{-7}A	9.65×10^{-7}A	9.28×10^{-7}A	8.68×10^{-7}A	8.76×10^{-5}A	8.65×10^{-7}A	8.95×10^{-7}A
4	*Rs*	0.196 Ω	2.155 Ω	2.1867 Ω	2.273 Ω	2.169 Ω	2.07 Ω	0.194 Ω
5	*Rp*	1055.76 Ω	1523.54 Ω	1357.53 Ω	1395.93 Ω	1366.76 Ω	1245.76 Ω	1075.32 Ω
6	a_1	1.21	1.45	1.36	1.38	1.27	1.32	1.23
7	*Time (s/min)*	…	875	717	669	402	328	173

under Windows XP. Effectiveness of the parameter extraction process is assessed in terms of convergence, I-V data curve, and computational performance.

The extracted parameters of 20W PV module are depicted in Table 1. The synthetic data for the parameters I_{Ph}, I_{01}, I_{02}, R_S, R_P, and a_1 are 0.912A, 2.543×10^{-9}A, 2.834×10^{-5}A, 0.032Ω, 109.95 Ω and 1.9 respectively. From the table, it is clear observed that the GA algorithm has taken 475Sec to extract the essential parameters and the time consumed by the rest of the algorithms i.e., LSA, GSA, PS and PSO are 357Sec, 264Sec, 248Sec, and 142Sec respectively. Therefore, it is significant to quote that

TABLE 4. Data comparison between GA, LSA, GSA, PS, PSO and proposed TSO algorithms for 200 Watt PV panel.

S.NO	Parameter	Synthetic data	GA	LSA	GSA	PS	PSO	TSO
1	*Iph*	5.300A	7.65A	7.31A	6.95A	6.45A	6.06A	5.41A
2	I_{01}	8.97×10^{-9}A	9.68×10^{-9}A	9.47×10^{-9}A	9.27×10^{-9}A	9.027×10^{-9}A	9.17×10^{-9}A	8.9×10^{-9}A
3	I_{02}	9.29×10^{-7}A	10.98×10^{-7}A	10.49×10^{-7}A	9.87×10^{-7}A	10.22×10^{-7}A	10.98×10^{-7}A	9.49×10^{-7}A
4	*Rs*	0.896 Ω	1.32 Ω	1.176 Ω	1.0968 Ω	1.796 Ω	1.016 Ω	0.912 Ω
5	*Rp*	1298.18 Ω	1698.58 Ω	1645.08 Ω	1534.78 Ω	1428.18 Ω	1388.08 Ω	1319.98 Ω
6	*a1*	1	1.98	1.76	1.63	1.43	1.19	1.01
7	*Time (s/min)*	…	898	731	676	487	341	228

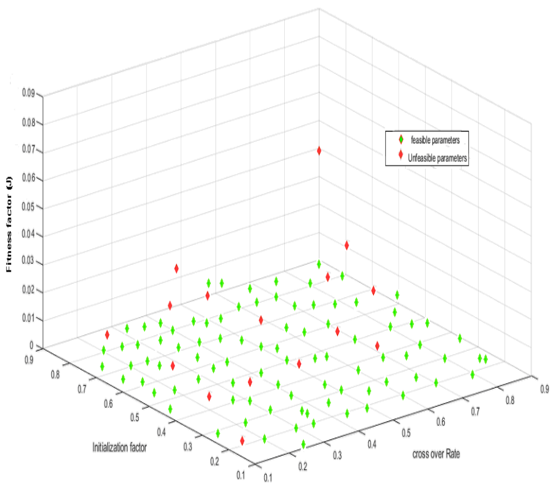


FIGURE 8. Effect of control parameters on TSO performance based on crossover rate and initialization factor.

the time taken by the TSO algorithm to extract the same essential parameters is 94Sec. The rest of the parameters obtained by the proposed TSO algorithm are 0.920A (I_{Ph}), 2.617 × 10^{-9}A (I_{01}), 2.9 × 10^{-5}A (I_{02}), 0.03Ω (R_S), 110.23Ω (R_P), and 1.9 (a_1). Similarly, Table 2 depicts the data comparison of 40W PV panel. The data obtained from the GA algorithm for the parameters I_{Ph}, $I_{01,}$ $I_{02,}R_{S,}$ $R_{P,}$ and a_1 are 2.79A, 9.81 × 10^{-9}A, 33.6 × 10^{-7}A, 0.0994Ω, 888.95Ω and 1.38 respectively. In continuation the data extracted by the proposed TSO algorithm are 1.95A (I_{Ph}), 6.55 × 10^{-9}A (I_{01}), 11.82 × 10^{-7}A (I_{02}), 0.0882Ω (R_S), 742.68Ω (R_P), and 1.29(a_1). From observation, it is evident that there is a huge difference between the numerical values obtained by GA, LSA, GSA, PS, PSO and proposed TSO in comparison with the pre-existing synthetic data.

Similarly, Table 3 and 4 depict data comparison between the proposed TSO and existing algorithms for 80W and 200W PV module. The synthetic data values for the parameters I_{Ph}, $I_{01,}$ $I_{02,}R_{S,}R_{P,}$ and a_1 of 80W and 200W PV panels are (4.85A, 8.87 x 10^{-9}A, 8.54 x 10^{-7} A, 0.196Ω, 1055.76Ω, and 1.21), (5.300A, 8.87 x 10^{-9}A, 9.29 x 10^{-7}A, 0.896Ω, 1298.18Ω, and 1). From Table 3, it is observed that the proposed TSO algorithm has least number of iterative operations and takes minimum time i.e., 173 sec. The GA algorithm has more execution time, due to huge number of internal iterations i.e., 875Sec. In all the algorithms synthetic data is included for the initial execution process. The parameters obtained from the GA algorithm are (6.95A, 10.92 × 10^{-9}A, 9.65 × 10^{-7}A, 2.155Ω, 1523.54Ω and 1.45). PSO algorithm occupies the second best position in the extraction of the parameters and the obtained numerical values are (5.27A, 9.22 × 10^{-9}A, 8.65 × 10^{-7}A, 2.07Ω, 1245.76Ω and 1.32). Finally, the proposed TSO algorithm has at most performance and the extracted numerical values are 4.89A (I_{Ph}), 8.99 × 10^{-9}A (I_{01}), 8.95 × 10^{-5}A (I_{02}), 0.194Ω (R_S), 1075.32Ω (R_P), and 1.23 (a_1). From Table 4, it is observed that the proposed TSO algorithm has obtained numerical values resembling the synthetic data i.e., 5.41A (I_{Ph}), 8.9× 10^{-9}A (I_{01}), 9.49× 10^{-5}A (I_{02}), 0.912Ω (R_S), 1319.98Ω (R_P), and 1.01 (a_1). TSO algorithm consumes less computational time i.e., 228Sec compared to the existing algorithms. Therefore, it is observed that the performance of the proposed TSO algorithm is superior to the existing metaheuristic algorithms.

In addition to the above analysis, the performance of the proposed TSO algorithm is examined using Multi-Crystalline (S75, S115), Mono- Crystalline (SM55, SQ150PC) and thin-film (ST36, ST40) PV modules under different irradiance levels such as 1000W/m^2, 600W/m^2 and 200W/m^2. The data extracted under the above conditions are depicted in Table 5. At G = 1000W/m^2, the ST40 thin film PV panel has taken minimum computational time (0.37Sec) to obtain the parameters, but the I_{Ph} numerical value lie very less (i.e.,3.657A). Whereas 0.5Sec is the time consumed by the S75 Multi crystalline panel to extract the parameters. The other parameters of the S75 PV module is I_{Ph}, $I_{01,}$ $I_{02,}R_{S,}$ $R_{P,}$ and a_1 are 5.420A, 9.97 × 10^{-9}A, 6.29 × 10^{-7}A, 0.696Ω, 416.18Ω, and 1.15. Similarly, at G = 600W/m2 and 200W/m2 the

TABLE 5. Data extracted from multi-crystalline, mono-crystalline and thin-film panels under various irradiance levels.

S.NO	Parameter	Multi – Crystalline		Mono - Crystalline		Thin-film	
$G=1000W/m^2$		S75	S115	SM55	SQ150PC	ST36	ST40
1	I_{Ph} (A)	5.420A	5.457A	3.876A	4.046A	3.243A	3.657A
2	I_{01} (A)	9.97×10^{-9}A	10.87×10^{-9}A	1.68×10^{-9}A	2.47×10^{-9}A	3.27×10^{-9}A	3.47×10^{-9}A
3	I_{02} (A)	6.29×10^{-7}A	6.37×10^{-7}A	2.98×10^{-7}A	3.049×10^{-7}A	3.22×10^{-7}A	3.78×10^{-7}A
4	Rs (Ω)	0.696 Ω	0.968 Ω	0.32 Ω	0.876 Ω	1.296 Ω	1.316 Ω
5	Rp (KΩ)	416.18 Ω	434.78 Ω	598.58 Ω	345.08 Ω	328.18 Ω	308.08 Ω
6	a_1	1.15	1.23	1.08	1.76	1.43	1.19
7	*Time (s)*	0.5	0.43	0.41	0.39	0.37	0.37
$G=600W/m^2$							
1	I_{Ph} (A)	3.420A	3.457A	3.876A	2.546A	2.243A	2.657A
2	I_{01} (A)	10.09×10^{-9}A	8.87×10^{-9}A	3.68×10^{-9}A	8.47×10^{-9}A	4.27×10^{-9}A	4.17×10^{-9}A
3	I_{02} (A)	8.29×10^{-7}A	6.37×10^{-7}A	2.98×10^{-7}A	3.029×10^{-7}A	2.22×10^{-7}A	4.08×10^{-7}A
4	Rs (Ω)	0.596 Ω	0.698 Ω	0.52 Ω	0.976 Ω	2.26 Ω	2.96 Ω
5	Rp (KΩ)	426.18 Ω	464.38 Ω	698.58 Ω	1345.08 Ω	828.18 Ω	1408.08 Ω
6	a_1	1.15	1.13	1.28	1.36	1.93	1.90
7	*Time (s)*	0.41	0.36	0.36	0.39	0.37	0.37
$G=200W/m^2$							
1	I_{Ph} (A)	1.420A	1.457A	1.876A	1.546A	1.243A	1.657A
2	I_{01} (A)	6.97×10^{-9}A	8.87×10^{-9}A	1.28×10^{-9}A	8.47×10^{-9}A	4.17×10^{-9}A	4.07×10^{-9}A
3	I_{02} (A)	8.29×10^{-7}A	6.17×10^{-7}A	1.98×10^{-7}A	4.049×10^{-7}A	2.12×10^{-7}A	5.98×10^{-7}A
4	Rs (Ω)	0.196 Ω	0.068 Ω	0.62 Ω	0.776 Ω	0.996 Ω	1.116 Ω
5	Rp (KΩ)	316.18 Ω	834.78 Ω	828.58 Ω	1545.08 Ω	987.18 Ω	1608.08 Ω
6	a_1	1.25	1.03	1.06	1.36	1.53	1.19
7	*Time (s)*	0.36	0.32	0.36	0.36	0.30	0.36

S75 modules consume much computational time and ST40 has the least one. But, the overall numerical values of the S75 Multi crystalline module are appreciable under any irradiance conditions.

Initialization factor of the TSO algorithm, increases the computation level and the crossover, termed as recombination levels are generated. The accurate Tabu List (TL) is generated based on the best fitness factor associate with the corresponding Tabu Moves(TM). The feasible parameters are preferable for further process, where as unfeasible parameters are entered into the TL, the nature of TM is depicted in Fig. 8. I-V plots of the S75, S115, SM55, SQ150PC, ST 36, and ST40 PV modules using TSO algorithm and experimental data is shown in Fig. 9.

Meta heuristic algorithms finds a wide scope in different applications due to the accurate optimization achieving

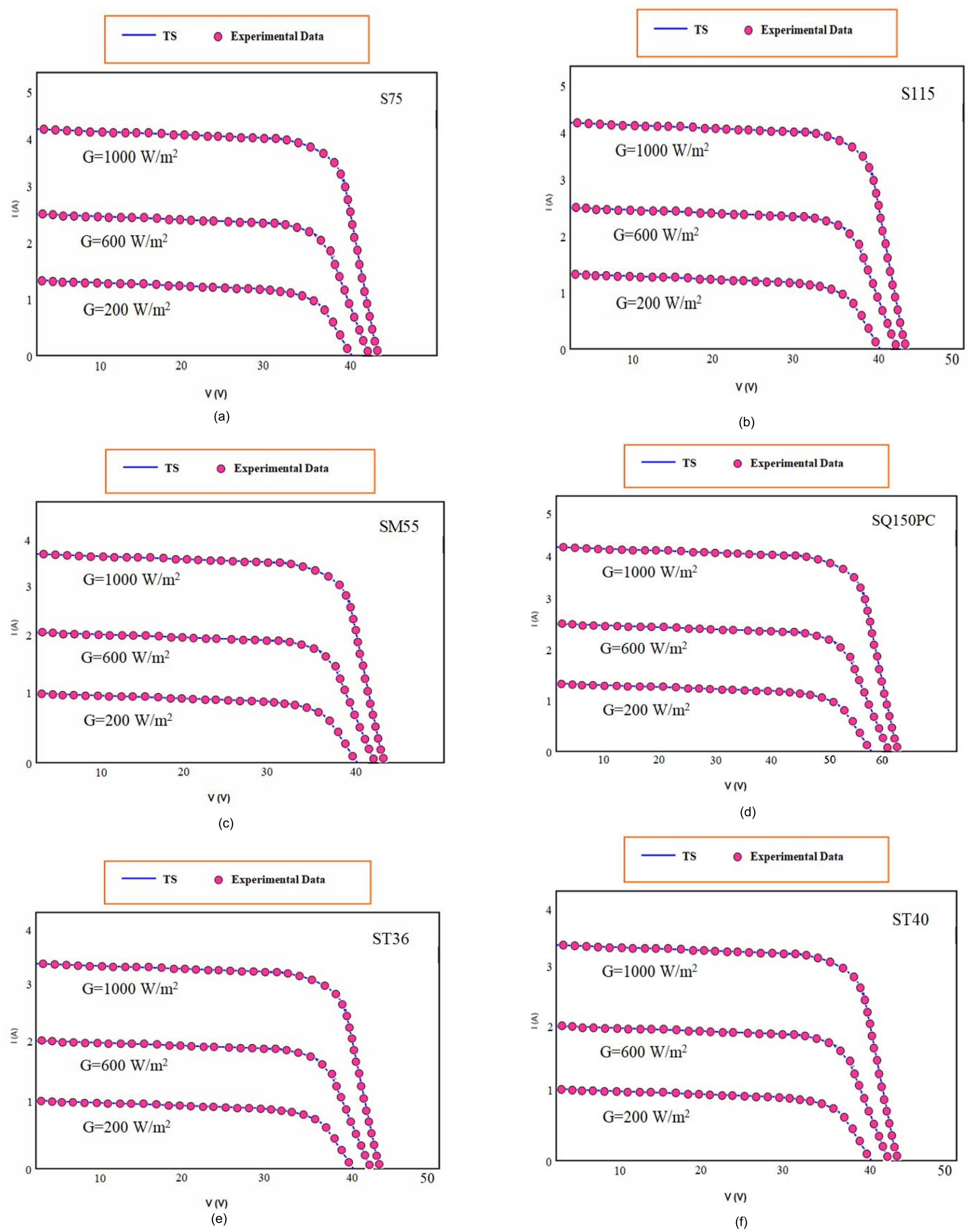


FIGURE 9. I–V characteristics obtained using TSO algorithm and experimental data (a) S75, (b) S115, (c) SM55, (d) SQ150PC, (e) ST36 and (d) ST40.

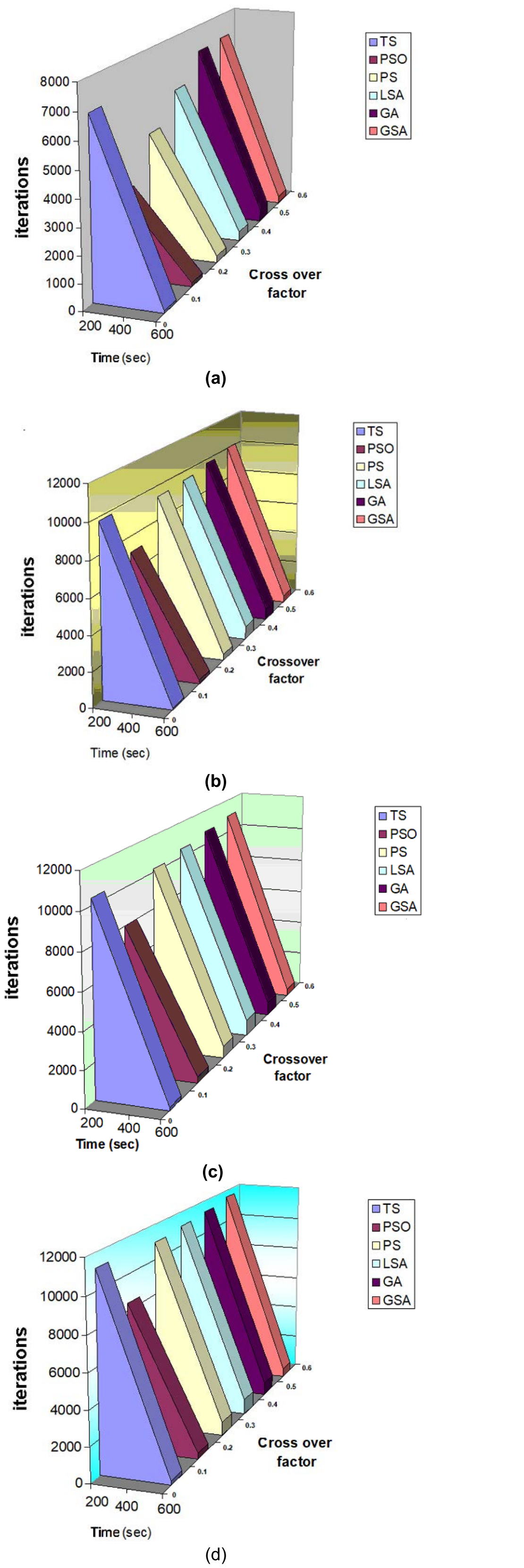


FIGURE 10. Convergence characteristics of (a) 20W, (b) 40W, (c) 80W, and (d) 200W PV module.

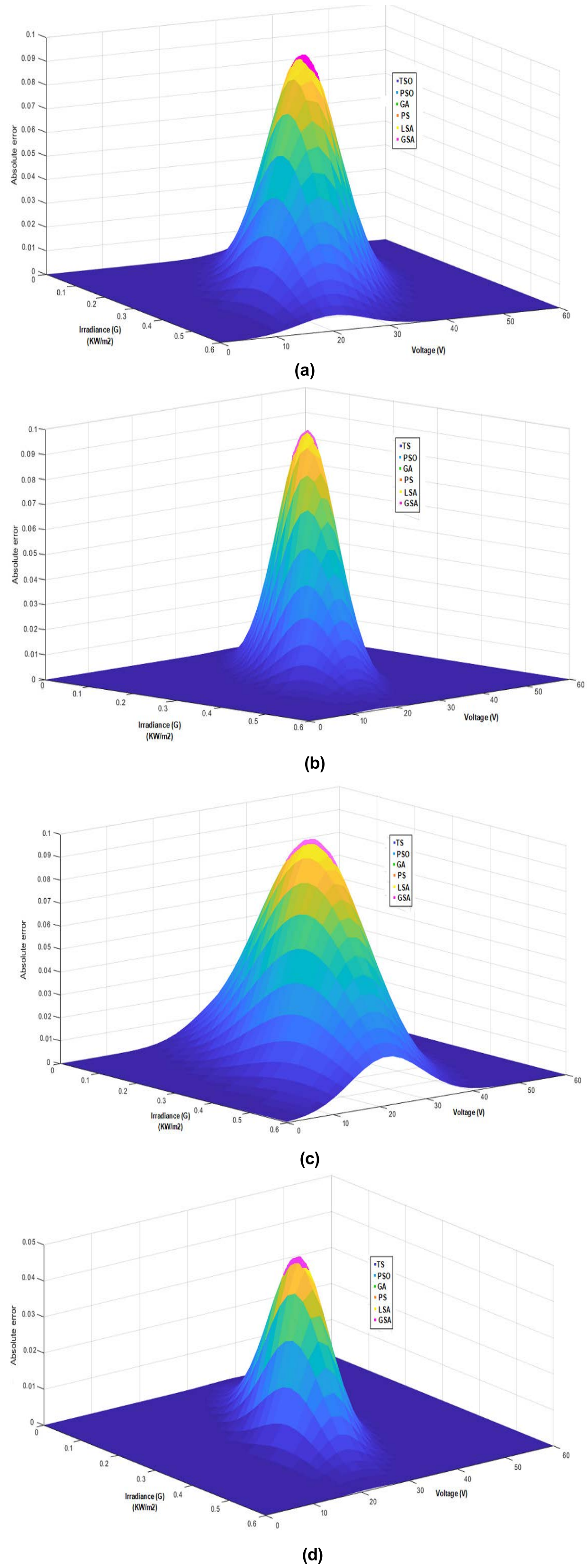
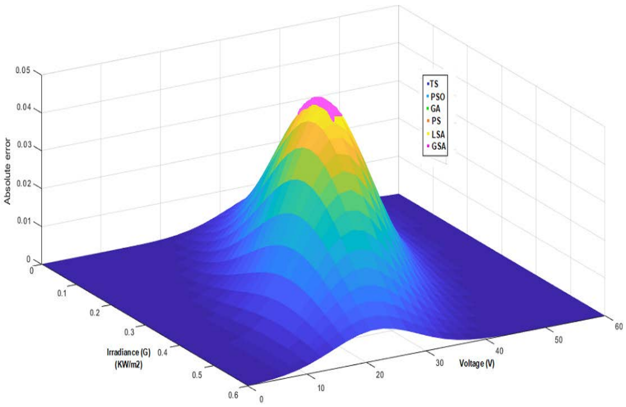
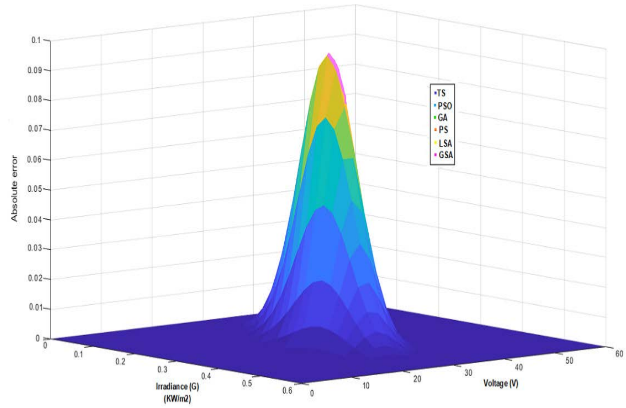


FIGURE 11. Absolute errors for (a) S75 (multi-crystalline), (b) S115 (multi-crystalline), (c) SM55 (mono-crystalline), (d) SQ150PC (mono-crystalline), (e) S75 (thin film), and (f) S115 (thin film).



(e)



(f)

FIGURE 11. ***(Continued.)*** **Absolute errors for (a) S75 (multi-crystalline), (b) S115 (multi-crystalline), (c) SM55 (mono-crystalline), (d) SQ150PC (mono-crystalline), (e) S75 (thin film), and (f) S115 (thin film).**

capability, perfect computational approach with less number of iterations and the best run is available in a quick instant of time. Initially, the diversification of the algorithms should maintain uniform convergence if not leads to incomplete convergence. The convergence time depends on the number of iterations performed in the TSO algorithm. Moreover, increase in iterations lead to increase in the time duration of execution as well as the crossover rate. The Convergence response of PV modules with rating 20W, 40W, 80W and 200W are shown in Fig.10 (a)-(d).

Output voltage of PV module depends on the amount solar energy concentrated on the panel. The percentage of absolute error decides that the system can be represented with equivalent one, two or three diode. The proposed TSO algorithm and the existing methods are effectively influenced by change of absolute errors under various irradiance patterns. The percentage absolute error on Mono-Crystalline, Multi-Crystalline, and thin film PV panel is shown in Fig. 11 (a)-(f).

V. CONCLUSION

This paper proposes a robust algorithm based on Tabu Search Optimization (TSO) to extract the parasitic parameters of PV module under different climatic stipulations. The performance of the proposed TSO algorithm is benchmarked in comparison with existing algorithms such as Genetic Algorithm (GA), Lighting Search Algorithm (LSA), Gravitational Search Algorithm (GSA), Pattern Search (PS) and Particle Swarm Optimization (PSO) using different range of PV modules i.e., 20W, 40W, 80W, 200W, Multi crystalline, Mono crystalline and thin film modules. The convergence speed of GSA and GA algorithm is very slow as a result consumes much time to complete the computation process. LSA algorithm has higher accuracy but the evaluation process is very complex and the operational data is in the form of computational projectile data. Therefore, accurate evolution is a time taking process. PS is an excellent tool for the extraction of data but the forecasting sequence for the searching is very huge, hence affects the convergence speed. Due to poor initial assumption in the operating parameters of the PSO algorithm, PSO traps at local minimum. Therefore, in terms of convergence speed and performance analysis the TSO algorithm has better features with less complexity compared to the existing algorithms. From the numerical values tabulated from Table 1-5 and in comparison with experimental data and obtained values in Fig. 9, it is observed that the proposed TSO algorithm has better performance under any condition.

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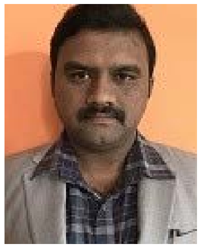

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