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# Enhanced solar PV cell parameter identification via particle swarm optimization (PSO) with weighted objective function

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**Abstract**

This work aims to identify the parameters of solar photovoltaic (PV) cells, which can then be used for modeling PV systems and designing controllers. The dynamic equation governing correlation among current and voltage at the output terminals of a solar cell is predominantly dependent on different parameters of the single diode model (SDM) or double diode model (DDM) representation of that solar PV cell. Without easy access to this information, accurately modeling PV systems for further studies becomes difficult. So, to identify those parameters with greater accuracy and less complexity, particle swarm optimization (PSO) in conjunction with the weighted objective function (WOF) has been proposed in this paper. This proposition of multi-objective optimization with a metaheuristic algorithm is found to give very satisfactory results while reducing any further modification in conventional PSO and with faster convergence.

Keywords: parameter identification; solar PV cell; PSO; weighted objective function.

## I. Introduction

A common way to deal with climate change due to the overuse of fossil fuels is by using renewable energy sources [1]. Of these renewable sources, the longevity and abundance of solar energy have made us fascinated to use solar photovoltaic (PV) cells for the generation of electrical power on large scales [2]. Given the pivotal role that solar PV cells play as the cornerstone of any photovoltaic power generation system, the modeling of these cells, predominantly carried out through the single diode model (SDM) and double diode model (DDM), has assumed critical importance. This modeling process is indispensable for the precise characterization of PV cells as it extracts model parameters with a high degree of accuracy. Its significance reverberates throughout the entire spectrum of PV system activities, including design, simulation, analysis, control, and comprehensive optimization. Based on the intrinsic physical behavior within the solar cell, SDM and DDM have been derived to give us an equivalent circuit [1][3].

Parameter identification [4] is the process of deducing unknown parameters in the relationship between the input (cause) and output (effect) of a system (process) based on observed (measured) data, with some constraints in hand to be satisfied through some complex optimization technique. With this, the

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model parameters can be identified, which helps to replicate any real system behavior [3]. Over the past few years, a multitude of endeavors have been undertaken to unearth the enigmatic parameters inherent to different photovoltaic (PV) cells, harnessing the formidable prowess of various metaheuristics where particle swarm optimization (PSO) [5] is the most prominent contender among different swarm intelligence based techniques such as simplified particle swarm optimization (SPSO) [6], genetic algorithm (GA) [7], dynamic self-adaptive and mutual-comparison teaching-learning-based optimization (DSA-MCTLBO) [8], enhanced particle swarm optimization (EPSO) [9], multi-strategy success-history-based adaptive differential evolution with linear population size reduction (MLSHADE) [10], lightning search algorithm (LSA) [11], etc. These are the kinds of algorithms that are generally used for finding solutions to transcendental equations, which include nonlinear optimization functions with several unknowns. Within this literature, the work is confined within the identification of PV cell model parameters.

A thorough application of PSO-based parameter extraction of solar PV system is presented in [12]. Literatures [1][6][9], again deal with different solar cell models for parameter extraction using PSO-based algorithm and having root mean square error (RMSE) as optimization criterion, other than [6]. Employing the lightning search algorithm under various weather conditions, literature [11] has extracted the unidentified solar cell parameters. An alternative approach for evaluating specific models tailored to various photovoltaic technologies is considered in [3] by modifying the dynamic equation describing the PV cell model. In literature [13], an iterative algorithm proposed considering some modified PV cell dynamic equations is able to estimate the SDM parameters from the PV panel's datasheet. Literature [14] uses a hybrid optimization method to find the PV cell parameters derived from Levenberg-Marquardt along with PSO. A chaotic optimization approach is the core of estimating SDM and DDM solar cell parameters in [15]. The grasshopper optimization algorithm is used by the researchers in [16] to identify unknowns of a three-diode photovoltaic model. The same issue is being addressed through dynamic self-adaptive and mutual-comparison teaching-learning-based optimization in [8]. Other than previously mentioned metaheuristic algorithms followings have also been applied for photovoltaic (PV) parameter identification, including hybrid Nelder-Mead and modified PSO [17], artificial bee colony (ABC) [18], cat swarm optimization (CSO) [19], and improved artificial bee colony (ABC) [20]. Additionally, modified particle swarm optimization (PSO) [21], arithmetic optimization algorithm (AOA) with newton-raphson [22], and various other metaheuristic techniques [23] have been explored for enhanced accuracy and convergence. The researchers have given an intriguing idea in [24] to find unknown parameters of an intricate solar photovoltaic (PV) cell model. Their approach combines the strengths of the artificial bee colony (ABC) algorithm and the PSO algorithm, resulting in a potent hybrid optimization strategy. A useful broad review of the application of metaheuristics for parameter extraction in the context of solar photovoltaic systems can be read in [25]. Now, all these techniques are very complex and resource-hungry with increased algorithm complexity.

This research has used particle swarm optimization (PSO) [5] to minimize the proposed weighted objective function (WOF) and find the desired parameters of the PV cell models. This method operates solely on the I-V data of a solar cell, aiming to discern the model parameters by solving the transcendental equation that encapsulates the relationship between terminal voltage and output current of any solar PV system. The PSO is thought to be one of the best optimization methods for such equations [12]. Obtained results are then compared with other techniques from several standard literatures for the validation of the applied methodology. Consequently, this approach is straightforward to implement and comprehend. Both the SDM-based and DDM-based representations have been addressed with different computational complexities in MATLAB due to the incorporation of a higher number of unknown model parameters for DDM than for SDM.

## II. Materials and Methods

### A. Modeling of solar cell

*1) Single diode model*

The predominant equivalent circuit, employed for solar cells across various applications, is exemplified in Figure 1, commonly referred to as the single diode model (SDM). The principal objective when formulating the mathematical model lies in elucidating the intricate interplay between the terminal voltage, $V_t$

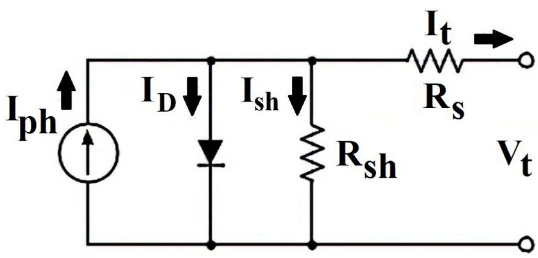


Figure 1. Equivalent circuit model of solar cell (SDM).

(expressed in volts) and the current output, $I_t$ (measured in amperes) of the photovoltaic cell, delineated in terms of several essential circuit parameters.

Now, the mathematical expression representing the relation between $I_t$ and $V_t$ can be written as equation (1) [23].

$$I_t = I_{ph} - I_D - I_{sh} = I_{ph} - I_D - \frac{V_t + I_t R_s}{R_{sh}} \quad (1)$$

where, $I_{ph}$ is current generated by light in the cell, $I_D$ is diode current, $R_s$ is series resistance, $I_{sh}$ is current flowing through the parallel resistance and $R_{sh}$ is parallel resistance of the SDM-based equivalent circuit of the solar cell.

The diode current ($I_D$), as per the *Shockley equation*, is given by equation (2).

$$I_D = I_0 \left[ e^{\left(\frac{V_t + I_t R_s}{a V_T}\right)} - 1 \right] \quad (2)$$

where, $I_0$ is reverse saturation current of diode, $a$ is ideality factor of diode (range: 1 – 2) and $V_T$ is thermal voltage is $\frac{kT_c}{q}$ (where, Boltzmann's constant is given by '$k$'= $1.381\times10^{-23}$ joule/kelvin, $q$ = charge of an electron = $1.602\times10^{-19}$ coulomb and $T_c$ = p-n junction temperature in kelvin).

Thus, the current $I_t$ is given by equation (3).

$$I_t = I_{ph} - I_0 \left[ e^{\left(\frac{V_t + I_t R_s}{a V_T}\right)} - 1 \right] - \frac{V_t + I_t R_s}{R_{sh}} \quad (3)$$

Here, the system identification is to work with the above equation (3) for extracting the following five indefinite parameters, i.e. $X_{SDM} = [I_{ph}, I_0, a, R_s \text{ and } R_{sh}]$.

*2) Double diode model*

It's a bit complicated one, where, two diodes are used instead of one as in case of SDM; to represent the solar cell. In this case, the mathematical expression representing the relation of current output, $I_t$ and terminal voltage, $V_t$ of the solar cell is represented by equation (4)[19].

$$I_t = I_{ph} - I_{D_1} - I_{D_2} - I_{sh} = I_{ph} - I_{D_1} - I_{D_2} - \frac{V_t + I_t R_s}{R_{sh}} \quad (4)$$

where, $I_{D_1}$ and $I_{D_2}$ are diode currents of the diodes present in the equivalent circuit of Figure 2, and other terms have the same meaning as previously discussed.

The current $I_t$ becomes equation (5) (using *Shockley equation*).

$$I_t = I_{ph} - I_{0_1} \left[ e^{\left(\frac{V_t + I_t R_s}{a_1 V_T}\right)} - 1 \right] - I_{0_2} \left[ e^{\left(\frac{V_t + I_t R_s}{a_2 V_T}\right)} - 1 \right] - \frac{V_t + I_t R_s}{R_{sh}} \quad (5)$$

where, $I_{0_1}$ and $I_{0_2}$ are diode reverse saturation currents and $a_1$ and $a_2$ respectively, are diode ideality factors present in the equivalent circuit of Figure 2 with other terms having the same meaning as discussed for SDM.

Applying the system identification method, these seven unknowns, i.e. $X_{DDM} = [I_{ph}, I_{0_1}, I_{0_2}, a_1, a_2, R_s \text{ and } R_{sh}]$ can be determined with the help of equation (5).

## B. Formulation of the problem

Parameter identification deals with the extraction or calculation of unknown quantities that are required in defining the exact dynamic model replicating the original system's behavior from some known information or available data of prospective system variables. In this case, with the help of available I-V data for a solar cell at certain ambient temperature and solar irradiance, its parameters of equivalent circuit have been determined. With the estimated parameters for different terminal voltages, corresponding output currents of that PV cell can be obtained from equations (3) and equation (5). Thus, it's basically a curve-fitting problem and can also be categorized as an optimization issue to be handled. This optimization is done by estimating the SDM or DDM parameters and comparing all the estimated values of output cell currents with experimental results, considering the same operating conditions.

Various performance indices, such as mean square error (MSE), root mean square error (RMSE), absolute error (AE), mean absolute error (MAE), and others [4], have been employed to quantify the disparities between estimated and experimental data. The aim is to minimize the objective function to arrive at solutions for unknown variables successfully. In this investigation, a composite objective function comprising of MAE expressed by equation (6) and RMSE expressed by equation (7), is utilized to ascertain the most favorable values for the unidentified parameters. Now, this combination of two performance indexes is named as weighted objective function (WOF), as represented by equation (8). In this context, MAE and RMSE are expressed in the following manner:

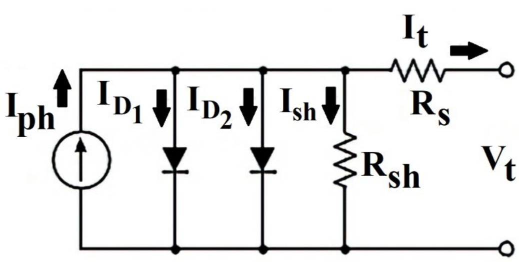


Figure 2. Equivalent circuit model of solar cell (DDM).

$$\text{MAE} = \frac{1}{N}\sum_{j=1}^{N}\left|(I_{t\_measured} - I_{t\_estimated})\right| \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \times \sum_{j=1}^{N}(I_{t\_measured} - I_{t\_estimated})^2} \quad (7)$$

$$\text{WOF} = w_1 \times \text{MAE} + w_2 \times \text{RMSE} \quad (8)$$

where, $w_1$ and $w_2$ are provided weightages to MAE and RMSE and for any $(w_1, w_2)$ such that $w_1 + w_2 = 1$ with $w_1 \geq 0$ and $w_2 \geq 0$.

The empirically acquired solar cell $I - V$ dataset is readily available from [1], and the estimated current ( $I_{t\_measured}$ ) values are calculated using the equation (3) for SDM and using equation (5) for DDM. Now, using equation (9) to frame the problem as an optimization challenge, the precise objective function can be depicted as follows:

$$\text{WOF(X)} = w_1 \times \frac{1}{N}\sum_{j=1}^{N} f\left(V_{t\_measured}, I_{t\_estimated}, X\right) + w_2 \times \sqrt{\frac{1}{N} \times \sum_{j=1}^{N}\{f\left(V_{t\_measured}, I_{t\_estimated}, X\right)\}^2} \quad (9)$$

where, $f(V_t, I_t, X_{SDM}) = I_t - I_{ph} + I_D + I_{sh}$ for SDM and $f(V_t, I_t, X_{DDM}) = I_t - I_{ph} + I_{D_1} + I_{D_2} + I_{sh}$ for SDM with $N$ indicating the overall count of experimentally obtained $(V_t, I_t)$ data points, the vector $X$ contains the unknown parameters that are to be extracted. As seen in equation (8), it becomes clear that a smaller WOF value results in a more precise identification of parameters.

Considering that equations (3) and equation (5) are transcendental in nature, the quest for their solutions is best suited for a *metaheuristic* optimization approach. Consequently, in this particular scenario, for minimizing the WOF, particle swarm optimization (PSO) [5][12] has been chosen as the method of choice.

## C. Identification of solar cell model parameters

The central concern revolves around the strategic utilization of PSO to optimize the objective function and deduce the obscure parameters. The approach we utilize, as outlined in reference [5], can be concisely described using the subsequent procedural summary with the following steps:

- Step 1: Define the model structure as outlined by equation (3) or equation (5) and the unknown model parameter *X*. Here, the 'particle' is nothing but the unknown model parameter.
- Step 2: In the first iteration of PSO, initialize multiple sets of *X* as particles. Specify PSO parameters, including population size, maximum and minimum velocities, and momentum, among others.
- Step 3: Create the initial swarm randomly in the first iteration. Calculate the fitness of each particle using the cost function described in equation (8).
- Step 4: The velocity of particles, inertia weight, and each particle's position are then updated using equations (10), equation (11) and equation (12), respectively.
- Step 5: If the ongoing iteration number is lower in value than the maximum number of iterations, the procedure needs be repeated from step 4. If the maximum number of iterations is completed or for certain previous iterations the value of the cost function is not changed, then the simulation is to be stopped. The particle with maximum fitness is the solution to this optimization.

The mathematical representation of altering the particle's velocity and position is elucidated by the following equation (10).

$$V_i^{k+1} = wV_i^k + c_1 rand_1(\dots) \times \left(pBest_i - s_i^k\right) + c_2 rand_2(\dots) \times \left(gBest - s_i^k\right) \quad (10)$$

where, velocity of $i^{th}$ agent at $k^{th}$ iteration is $V_i^k$, $w$ is the weighting function, $c$ is weighting factor, random number $rand$ is distributed uniformly within the range of 0 to 1, at $k^{th}$ iteration $s_i^k$ is the current position of $i^{th}$ agent, $pBest_i$ is pbest of $i^{th}$ agent, $gBest$ is gbest of the group.

Weighting function of equation (10) is generally expressed by equation (11).

$$w = w_{Max} - [(w_{Max} - w_{Min}) \times iter]/maxIter \quad (11)$$

where, $w_{Max}$ is initial weight, $w_{Min}$ is final weight, $maxIter$ is maximum number of iterations, $iter$ is current iteration number.

The equation for updating position is equation (12).

$$s_i^{k+1} = s_i^k + V_i^{k+1} \quad (12)$$

where, $s_i^{k+1}$ is modified position and $V_i^{k+1}$ is modified velocity of $i^{th}$ agent, respectively.

Now, with the help of a flowchart Figure 3, the approach for extracting solar cell parameters using a particle swarm optimization algorithm is basically described. Here, the goal is to determine the undisclosed PV cell parameters, either five unknowns for SDM or seven unknowns for DDM, through some number of particles or search agents, which are under consideration. Now, the specialty of this approach is the objective function or the criterion function, which is a combination of the weighted sum of two different errors. Also, for comparison purposes, the best scores obtained in objective space have been used to obtain the closeness of identified parameters with the actual values, as the parameter values of different simulations with different optimization algorithms are unable to directly

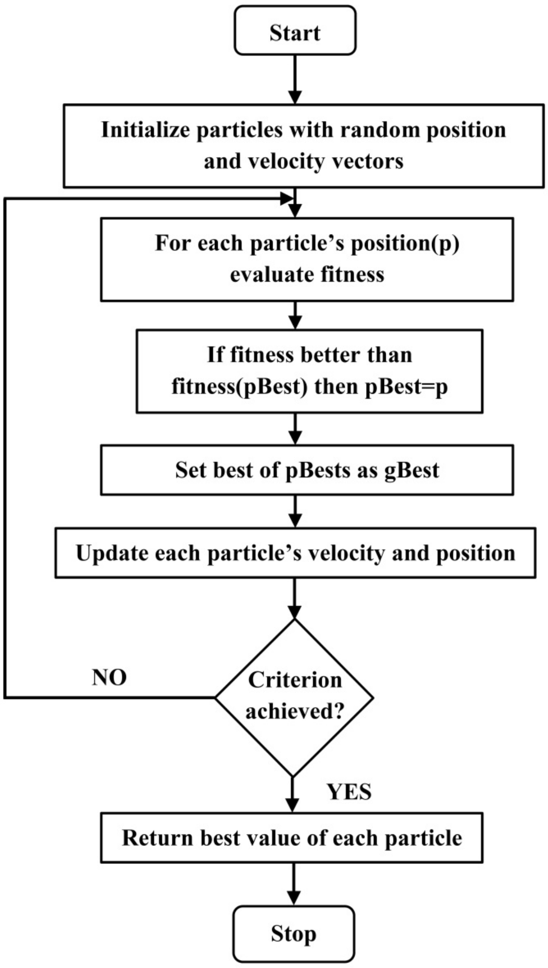


Figure 3. Flowchart of the used PSO algorithm for PV cell parameter estimation.

quantify the accuracy of the results. So, this value can be treated as a measure of the accuracy of the applied technique for finding unknown PV cell parameters under consideration.

For all the simulation purposes, the following values of different algorithm parameters, as listed in Table 1, are considered.

## III. Results and Discussions

Now, after applying the stated technique, results obtained are discussed and compared with the results of some standard literature. The I-V datasets of [8] have served as a standard in evaluating algorithms' performance with the newly proposed objective function. The datasets comprise 26 data points pertaining to an RTC France PV cell (in solar irradiance of 1000 W/m$^2$ and at 33 °C temperature). With these data in hand, a consideration of a total of ten cases is made, five for each SDM and DDM, with different values of WOFs and RMSE only as objective functions. It's a well-known fact that most metaheuristics are profoundly implemented using MATLAB. The search range for the PV cell parameters considered is listed in Table 2 and is commonly used in the literature; they are considered for fair comparisons among different literature and this research work.

Figure 4 and Figure 5 imply that the results of the SDM model in terms of current (I) and power (P) estimations are almost resembling all the 26 (twenty-six) measured data points of RTC France cell w. r. t. the developed voltage (V) at terminals of the PV cell. Table 3 shows the estimated PV cell parameters of SDM, for which the estimated curves have a perfect match with the measured one. Also, the same table can reveal the power of the chosen objective function, which has mostly given values in the objective space lower than the case when RMSE is used for optimization using the PSO algorithm. Not only that, but Figure 6 also shows us the variation of errors corresponding to the estimated currents at different data points for different objective functions.

The displayed convergence plots of Figure 7 show that the results obtained with $w_1$ = 0.7 and $w_2$ = 0.3 have

Table 1.
PSO Parameters.

| PSO parameters | $w_{Max}$ | $w_{Min}$ | $c_1$ | $c_2$ | maxIter | No. of search agents | Problem dimension or number of unknown parameters |
|---|---|---|---|---|---|---|---|
| **Values** | 0.9 | 0.2 | 2 | 2 | 1000 | 50 | 5 (for SDM)/7 (for DDM) |

Table 2.
Parameter boundary values for SDM and DDM parameters of PV cell.

| Parameters | Lower boundary | Upper boundary |
|---|---|---|
| $I_{ph}$ (A) | 0 | 1 |
| $I_0$ / $I_{0_1}$ / $I_{0_2}$ (μA) | 0 | 1 |
| $a$ / $a_1$ / $a_2$ | 1 | 2 |
| $R_s$ (Ω) | 0 | 0.5 |
| $R_{sh}$ (Ω) | 1 | 100 |

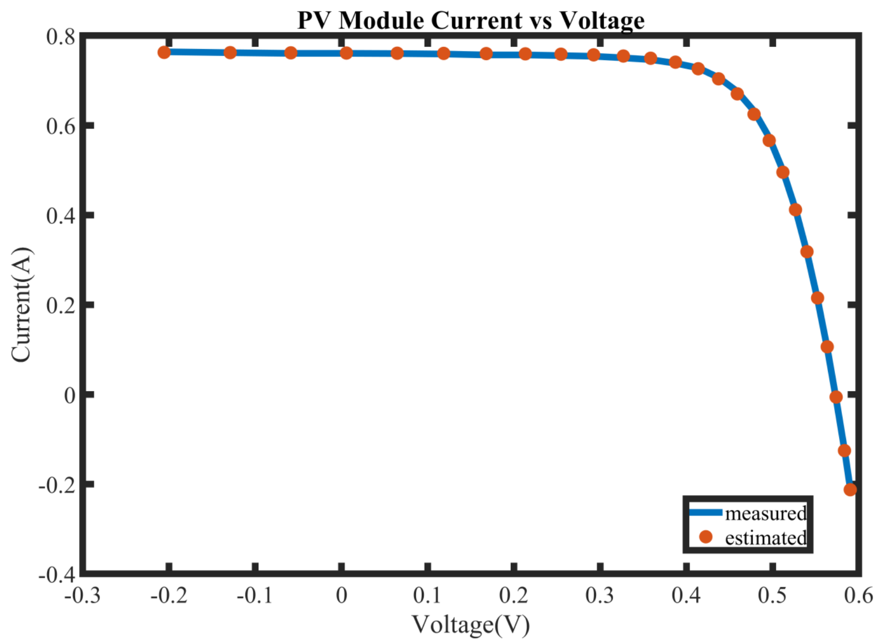


Figure 4. Output current (I) vs terminal voltage (V) of solar cell with estimated and measured output currents (SDM).

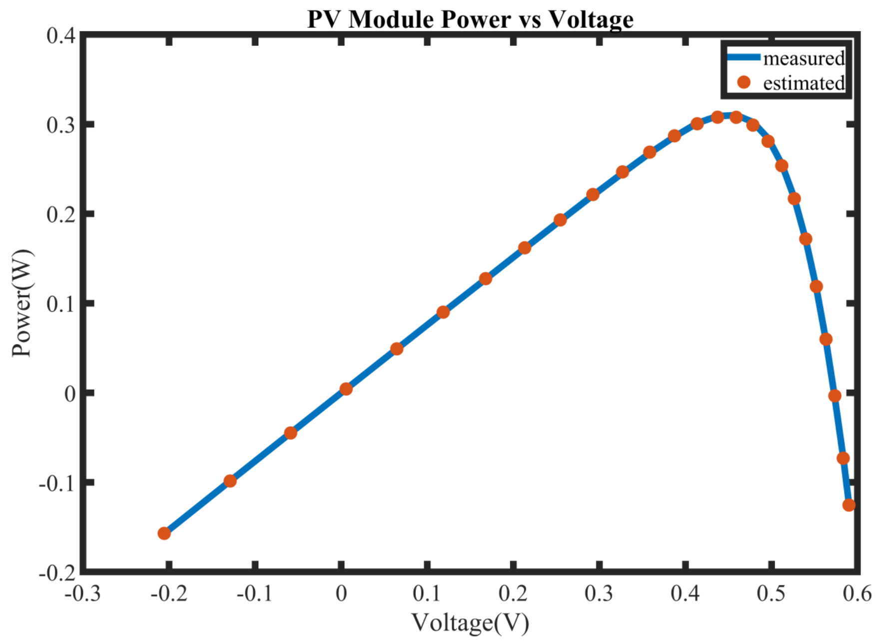


Figure 5. Output power (P) vs terminal voltage (V) of solar cell with estimated and measured output powers (SDM).

Table 3.
Identified values of unknown PV cell (SDM) parameters with different objective functions.

| **Identified parameters** | **Objective functions** | | | | |
|---|---|---|---|---|---|
| | **RMSE** | **WOF = $w_1 \times$ MAE + $w_2 \times$ RMSE** | | | |
| | | $w_1 = 0.5$, $w_2 = 0.5$ | $w_1 = 0.2$, $w_2 = 0.8$ | $w_1 = 0.8$, $w_2 = 0.2$ | $w_1 = 0.7$, $w_2 = 0.3$ |
| Best score in objective space | 0.0018 | 0.0013 | 0.0019 | 0.0009 | 0.0008 |
| $I_{ph}$ (A) | 0.7603 | 0.7606 | 0.7761 | 0.7609 | 0.7606 |
| $I_0$ (μA) | 0.7370 | 0.5636 | 0.7303 | 0.4193 | 0.3066 |
| $a$ | 1.5691 | 1.5393 | 1.5750 | 1.5079 | 1.4758 |
| $R_s$ (Ω) | 0.0329 | 0.0341 | 0.0326 | 0.0352 | 0.0365 |
| $R_{sh}$ (Ω) | 99.6853 | 78.0507 | 96.5800 | 59.1347 | 53.7273 |

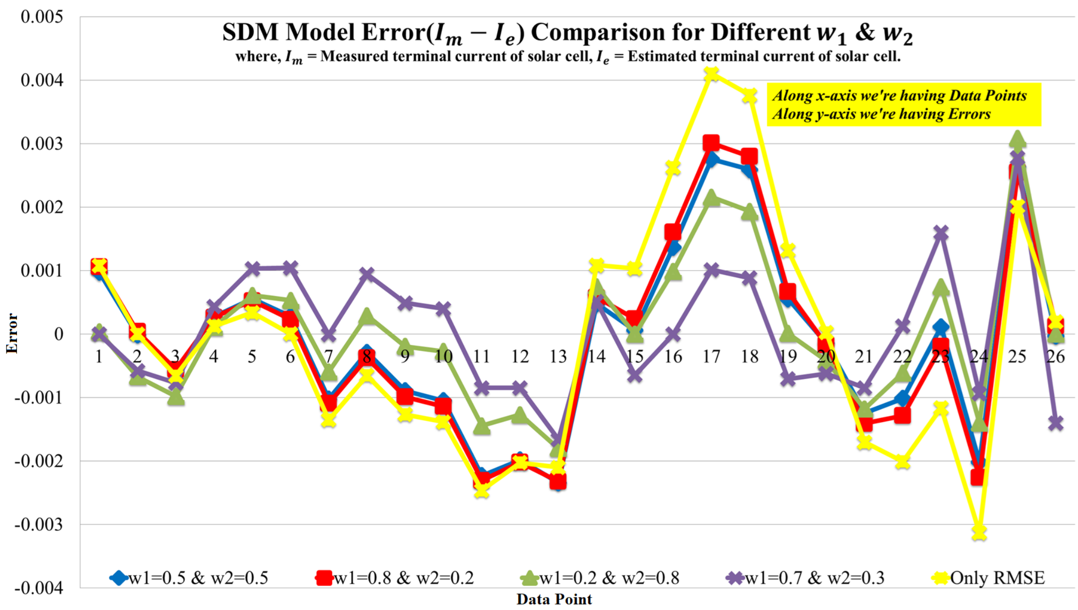


Figure 6. Error comparison for different WOFs and RMSE as optimization functions in case of SDM's parameter estimation.

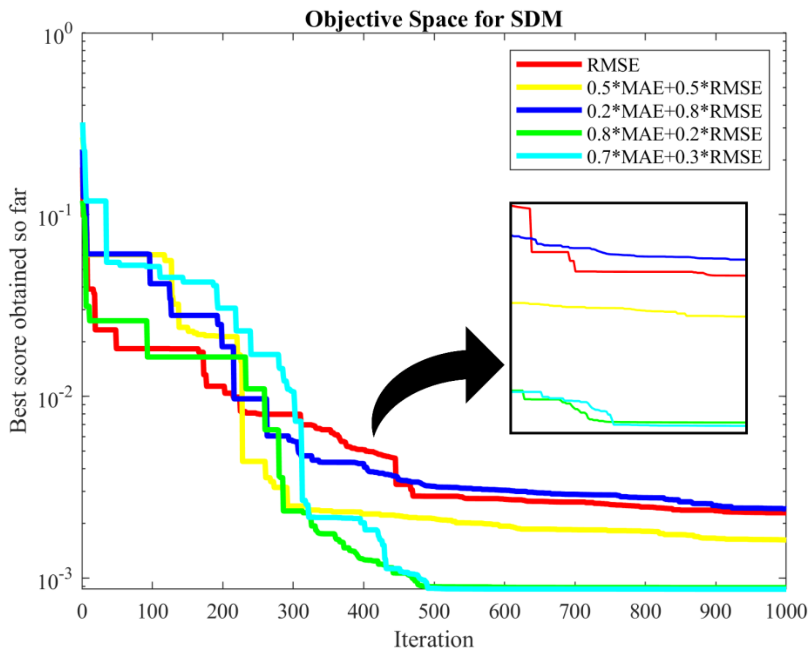


Figure 7. Convergence comparison of simulations to find unknown PV cell parameters with different WOFs and RMSE for SDM-based representation.

converged very rapidly in contrast to other selected weightages. It indicates the improved algorithm efficacy with WOF considering the proper selection of weightages. In this paper, this selection is totally based on a thumb rule with the qualifying factor that can be given by $w_1 + w_2 = 1$. It assures the impact of both the errors with a total 100 % presence of the error factor as a termination criterion.

Now, if DDM is considered, the corresponding parameter boundaries can be found from Table 2. Similar results are obtained here as in the case of SDM but with greater accuracy. In terms of best objective space value and convergence of the optimization algorithm, the appropriate WOF has also given better results and faster convergence, as can be seen from Table 4, Figure 8 and Figure 9. Mean absolute error (MAE) for the estimated currents in case of DDM with $w_1 = 0.7$ and $w_2 = 0.3$ is $7.9 \times 10^{-4}$ as compared to $8.12 \times 10^{-4}$, as in case of SDM. This directly quantifies the better results obtained for identified parameters of DDM with the proposed technique, using weighted objective function. All these claims can be better verified from the comparison represented in Table 5.

Table 5 essentially shows all the values of estimated currents for both SDM and DDM and compares them to the measured 26 data sets of RTC France solar cell.

Table 4.
Identified values of unknown PV cell (DDM) parameters with different objective functions.

| **Identified parameters** | **Objective functions** | | | | |
|---|---|---|---|---|---|
| | **RMSE** | **WOF = $w_1 \times$ MAE + $w_2 \times$ RMSE** | | | |
| | | $w_1 = 0.5, w_2 = 0.5$ | $w_1 = 0.2, w_2 = 0.8$ | $w_1 = 0.8, w_2 = 0.2$ | $w_1 = 0.7, w_2 = 0.3$ |
| Best score in objective space | 0.0009 | 0.0010 | 0.0012 | 0.0011 | 0.0008 |
| $I_{ph}$ (A) | 0.7607 | 0.7606 | 0.7603 | 0.7608 | 0.7609 |
| $I_{0_1}$(μA) | 0.1878 | -1.3117 | 0.9009 | 0.0842 | 0.1388 |
| $I_{0_2}$ (μA) | 0.9766 | 1.0827 | -1.5325 | 0.0050 | 0.1533 |
| $a_1$ | 1.4360 | 1.8009 | 1.5794 | 1.7688 | 1.9903 |
| $a_2$ | 1.9721 | 1.5833 | 1.9785 | 1.3365 | 1.4192 |
| $R_s$ (Ω) | 0.0369 | 0.0344 | 0.0339 | 0.0389 | 0.0371 |

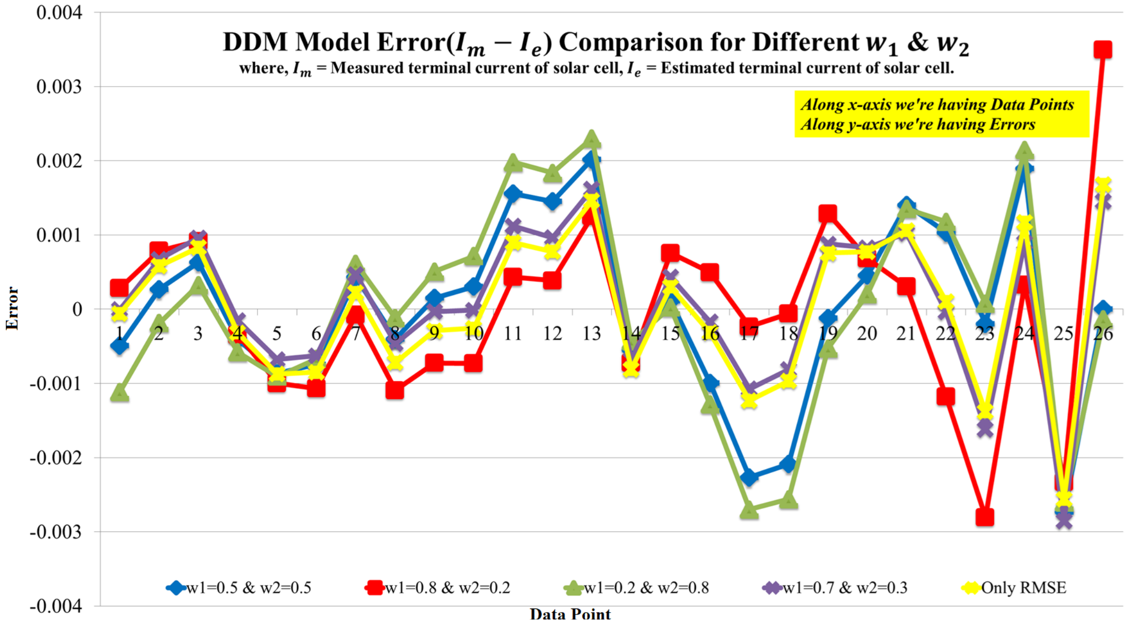


Figure 8. Error comparison for different WOFs and RMSE as optimization functions in case of DDM's parameter estimation.

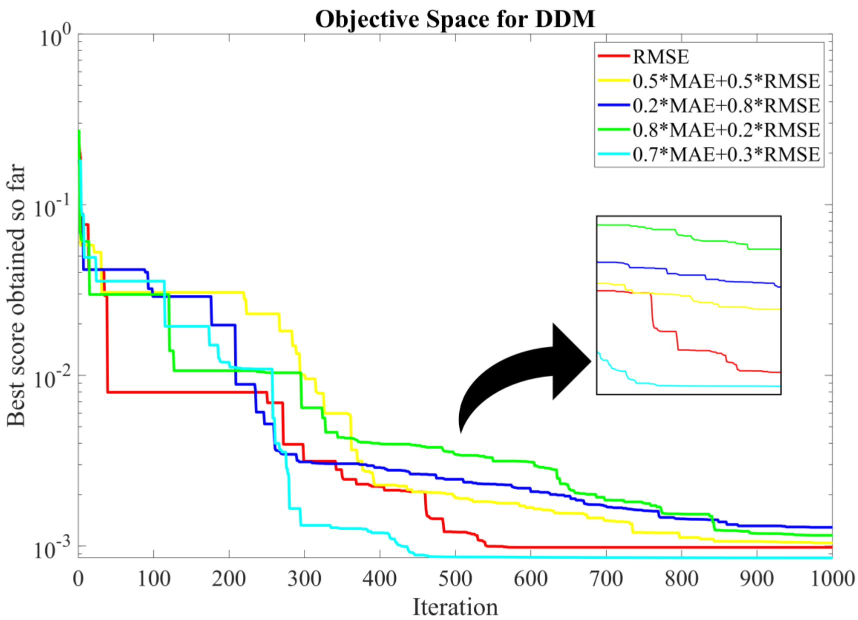


Figure 9. Convergence comparison of simulations to find unknown PV cell parameters with different WOFs and RMSE for DDM-based representation.

Table 5.
Comparison of measured and estimated currents of RTC France PV cell.

| Measurement (data) | Measured voltage (V) | Measured current (A) | Estimated current (A) | | Error in estimated current | | %-age error in estimated current | |
|---|---|---|---|---|---|---|---|---|
| | | | SDM | DDM | SDM | DDM | SDM | DDM |
| 1 | -0.2057 | 0.7640 | 0.764000479 | 0.76400360 | -4.79E-07 | -3.60E-06 | 0.0001 | 0.0004 |
| 2 | -0.1291 | 0.7620 | 0.762576104 | 0.76132448 | -5.76E-04 | 6.76E-04 | 0.0756 | 0.0676 |
| 3 | -0.0588 | 0.7605 | 0.761268550 | 0.75953742 | -7.69E-04 | 9.63E-04 | 0.1011 | 0.0963 |
| 4 | 0.0057 | 0.7605 | 0.760067457 | 0.76065277 | 4.33E-04 | -1.53E-04 | 0.0569 | 0.0153 |
| 5 | 0.0646 | 0.7600 | 0.758968955 | 0.76067591 | 1.03E-03 | -6.76E-04 | 0.1357 | 0.0676 |
| 6 | 0.1185 | 0.7590 | 0.757956587 | 0.75962595 | 1.04E-03 | -6.26E-04 | 0.1375 | 0.0626 |
| 7 | 0.1678 | 0.7570 | 0.757007006 | 0.75653178 | -7.01E-06 | 4.68E-04 | 0.0009 | 0.0468 |
| 8 | 0.2132 | 0.7570 | 0.756059338 | 0.75746282 | 9.41E-04 | -4.63E-04 | 0.1243 | 0.0463 |
| 9 | 0.2545 | 0.7555 | 0.755010657 | 0.75553290 | 4.89E-04 | -3.29E-05 | 0.0648 | 0.0033 |
| 10 | 0.2924 | 0.7540 | 0.753599501 | 0.75401271 | 4.00E-04 | -1.27E-05 | 0.0531 | 0.0013 |
| 11 | 0.3269 | 0.7505 | 0.751348137 | 0.74938073 | -8.48E-04 | 1.12E-03 | 0.1130 | 0.1119 |
| 12 | 0.3585 | 0.7465 | 0.747346353 | 0.74553573 | -8.46E-04 | 9.64E-04 | 0.1134 | 0.0964 |
| 13 | 0.3873 | 0.7385 | 0.740160687 | 0.73688030 | -1.66E-03 | 1.62E-03 | 0.2249 | 0.1620 |
| 14 | 0.4137 | 0.7280 | 0.727489573 | 0.72867613 | 5.10E-04 | -6.76E-04 | 0.0701 | 0.0676 |
| 15 | 0.4373 | 0.7065 | 0.707144456 | 0.70606791 | -6.44E-04 | 4.32E-04 | 0.0912 | 0.0432 |
| 16 | 0.4590 | 0.6755 | 0.675499953 | 0.67567028 | 4.66E-08 | -1.70E-04 | 0.0000 | 0.0170 |
| 17 | 0.4784 | 0.6320 | 0.630987513 | 0.63307341 | 1.01E-03 | -1.07E-03 | 0.1602 | 0.1073 |
| 18 | 0.4960 | 0.5730 | 0.572116597 | 0.57381371 | 8.83E-04 | -8.14E-04 | 0.1542 | 0.0814 |
| 19 | 0.5119 | 0.4990 | 0.499706595 | 0.49812042 | -7.07E-04 | 8.80E-04 | 0.1416 | 0.0880 |
| 20 | 0.5265 | 0.4130 | 0.413621355 | 0.41217056 | -6.21E-04 | 8.29E-04 | 0.1504 | 0.0829 |
| 21 | 0.5398 | 0.3165 | 0.317347362 | 0.31547627 | -8.47E-04 | 1.02E-03 | 0.2677 | 0.1024 |
| 22 | 0.5521 | 0.2120 | 0.211872789 | 0.21203835 | 1.27E-04 | -3.83E-05 | 0.0600 | 0.0038 |
| 23 | 0.5633 | 0.1035 | 0.101896610 | 0.10511774 | 1.60E-03 | -1.62E-03 | 1.5492 | 0.1618 |
| 24 | 0.5736 | -0.0100 | -0.009059459 | -0.01089595 | -9.41E-04 | 8.96E-04 | 9.4054 | 0.0896 |
| 25 | 0.5833 | -0.1230 | -0.125776671 | -0.12014668 | 2.78E-03 | -2.85E-03 | 2.2575 | 0.2853 |
| 26 | 0.5900 | -0.2100 | -0.208596993 | -0.21145236 | -1.40E-03 | 1.45E-03 | 0.6681 | 0.1452 |
| MAE | | | | | 8.12E-04 | 7.90E-04 | | |

Table 6.
Comparison of SDM-based estimated model parameters of RTC France PV cell, obtained by various optimizations.

| Sl. No. | Technique | $I_{ph}$ (A) | $I_0$ (μA) | a | $R_s$ (Ω) | $R_{sh}$ (Ω) | Best score in objective space |
|---|---|---|---|---|---|---|---|
| 01. | PSO with WOF (proposed) | 0.7606 | 0.3066 | 1.4758 | 0.0365 | 53.7273 | 8.0000E-04 |
| 02. | PSO [1] | 0.7383 | 0.319 | 1.4799 | 0.0364 | 53.409 | 1.43E-03 |
| 03. | MSSA [1] | 0.7683 | 0.3262 | 1.4958 | 0.0367 | 54.2557 | 9.86E-04 |
| 04. | NM-MPSO [17] | 0.76078 | 0.32306 | 1.48120 | 0.03638 | 53.7222 | 9.8602E-04 |
| 05. | CSO [19] | 0.76078 | 0.3230 | 1.48118 | 0.03638 | 53.7185 | 9.8602E-4 |
| 06. | ABSO [19] | 0.76080 | 0.30623 | 1.47583 | 0.03659 | 52.2903 | 9.9124E-04 |
| 07. | MPSO [21] | 0.760776 | 0.32302 | 1.481184 | 0.036377 | 53.71852 | 9.8602E-04 |
| 08. | BLPSO [21] | 0.760805 | 0.34839 | 1.488862 | 0.036115 | 53.41719 | 10.3122E-04 |
| 09. | CLPSO [21] | 0.760699 | 0.31726 | 1.479384 | 0.036434 | 54.04802 | 9.92075E-04 |

Percentage errors are so low that the estimation is in conformity with the actual I-V and P-V curves as can be found through Figure 4, Figure 5, Figure 10 and Figure 11.

At the end, a comparison of the obtained result is very much necessary with other appropriate literature based on swarm intelligence related metaheuristic optimizations, to establish its supremacy over others. Thus, Table 6 and Table 7 serve the required purpose of giving us a better view of the novelty of the proposed technique, which has much lesser complexity than others.

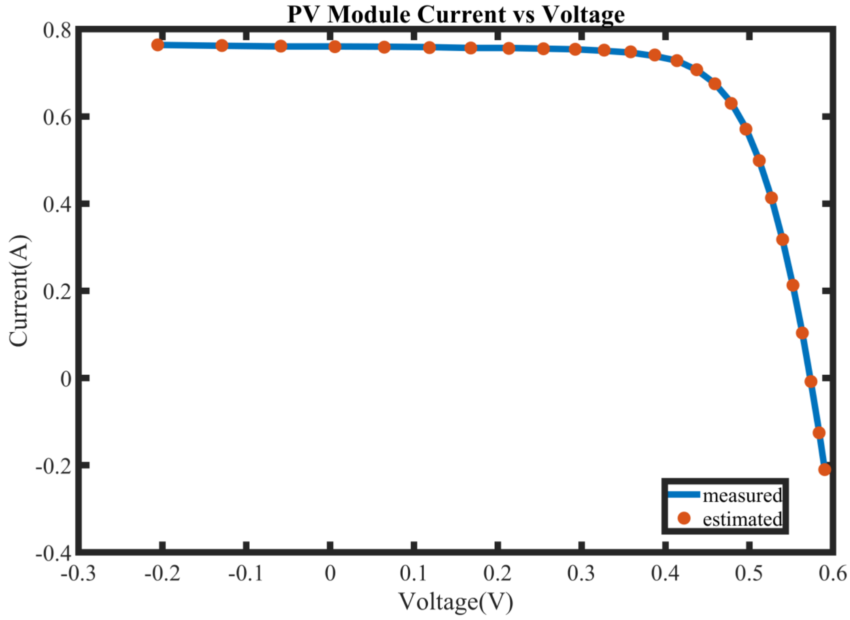


Figure 10. Output current (I) vs terminal voltage (V) of solar cell with estimated and measured output currents (DDM).

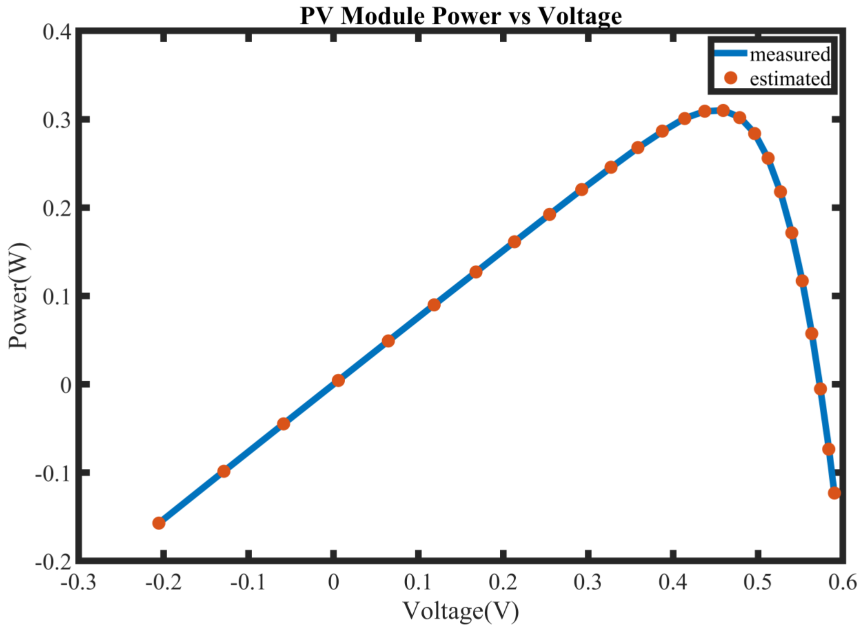


Figure 11. Output power (P) vs terminal voltage (V) of solar cell with estimated and measured output powers (DDM).

Table 7.
Comparison of DDM-based estimated model parameters of RTC France PV cell, obtained by various optimizations.

| Sl. No. | Technique | $I_{ph}$ (A) | $I_{0_1}$ (μA) | $I_{0_2}$ (μA) | $a_1$ | $a_2$ | $R_s$ (Ω) | $R_{sh}$ (Ω) | Best score in objective space |
|---|---|---|---|---|---|---|---|---|---|
| 01. | PSO with WOF (proposed) | 0.7609 | 0.1388 | 0.1533 | 1.9903 | 1.4192 | 0.0371 | 57.9426 | 8.0000E-04 |
| 02. | MSSA [1] | 0.7608 | 0.9731 | 0.1679 | 1.9213 | 1.4281 | 0.0369 | 53.8368 | 9.8300E-04 |
| 03. | CSO [19] | 0.76078 | 0.22732 | 0.72785 | 1.45151 | 1.99769 | 0.036737 | 55.3813 | 9.8252E-4 |
| 04. | ABSO [19] | 0.76078 | 0.26713 | 0.38191 | 1.46512 | 1.98152 | 0.03657 | 54.6219 | 9.8344E-4 |
| 05. | PSO [21] | 0.76078 | 0.74935 | 0.22597 | 2 | 1.45102 | 0.03674 | 55.4854 | 9.8248E-04 |
| 06. | MPSO [21] | 0.76078 | 0.22597 | 0.74935 | 1.45102 | 2 | 0.03674 | 55.4854 | 9.8345E-04 |
| 07. | BLPSO [21] | 0.76017 | 0.14880 | 0.32561 | 1.806683 | 1.48523 | 0.03596 | 63.4574 | 1.0822E-03 |
| 08. | CLPSO [21] | 0.76075 | 0.40103 | 0.24494 | 1.87635 | 1.45943 | 0.03642 | 55.0103 | 9.9432E-04 |

# IV. Conclusion

This paper has proposed a reliable technique for PV cell parameters estimation with a very well-known PSO-algorithm with a twist in the selection of objective criterion. This has bolstered the convergence capabilities of the basic PSO algorithm by ensuring a well-balanced optimization load for the intricate parameter identification of the comprehensive solar PV cell model, encompassing both the single diode and double diode equivalent circuits. Both sets of unknown solar cell parameters, consisting of five and seven elements, have been estimated with the use of WOF-constrained simple PSO and compared with other versions of swarm intelligence-based optimization algorithms. The comparisons have led to the fact that, in many cases, a suitable combination of different objective functions with PSO can be used to achieve the best results in parameter estimation through optimization in transcendental equations with unknowns. Not only that, but also the convergence values have always been under $9 \times 10^{-4}$ in objective space and speed of this methodology has always been better (under one sec. for SDM and 1 – 1.5 sec. for DDM parameters finding) or at the least at a comparable level than the other observed techniques mentioned herein with respect to the computational work load on computers during simulations.

# Declarations

## Author contribution

**B. Ghosh**: Writing - Original Draft, Writing - Review and Editing, Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization. **S. Mandal**: Writing - Review and Editing, Formal analysis, Investigation, Supervision, Project administration, Resources, Validation.

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## Competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Additional information

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