

Parameters Estimation of Photovoltaic Cells Using Self-adaptive Multi-population Rao Optimization Algorithm

Abdelhady Ramadan, Salah Kamel, and Abdalla A. Ibrahim

Department of Electrical Engineering, Faculty of Engineering, Aswan University, Aswan 81542, Egypt
eng.abdalahady@gmail.com , skamel@aswu.edu.eg , abdalla.ibrahim@aswu.edu.eg

Abstract— the design of PV system is considered one of trendy industries in nowadays. Usually, the designers required a simulation models for testing the new designed PV systems. The parameters estimation for this model is one of big challenges. This paper proposes an application of adaptive Rao algorithm (SAMP-Rao) for solar cell parameters estimation more over PV panels. The advantages of SAMP-Rao are adaptation of the population size based on the improvement in the fitness value during the search process .SD and DD models is used as a simulation model. The SAMP-Rao is applied to estimate the parameters of SD and DD models for different types of solar cells and PV panels. The results are evaluated and compared with others recent optimization algorithms using different evaluation methods like comparing root mean square values, absolute error also the statistical analysis of the obtained results.

Keywords— PV system, Rao algorithm, Optimization, SAMP-Rao, SD, DD.

Nomenclature

Symbol	description	Symbol	description
$RMSE$	Root Mean Square Error	SD	Single Diode
$SAMP-RAO$	self-adaptive Multi-population Rao	DD	Double Diode
$TLBO$	Teaching Learning-Based Optimization	TD	Triple Diode
PSO	Particle Swarm Optimization	PV	Photo Voltaic
$IBSO$	improved brain storming optimization	I_{tm}	PV real current
n, n_1	Diffusion Diode Ideality	I_{ph}	Photo generated current source
n_2	Recombination Factor	R_{sh}	Shunt resistance
n_3	Leakage Factor	I_t	PV module output current
K	$=1.380 \times 10^{-23} (J/Ko)$ Boltzmann constant	I_{d1}, I_{sd}	First diode current
q	$1.602 \times 10^{-19} (C)$ Coulombs.	I_{d2}	Second diode current
$T (Ko)$	Photocell temperature (Kelvin)	I_{d3}	Third diode current
R_{sh}	Shunt resistance	V_t	Terminal voltage
R_s	Series resistance	V_{tm}	PV real voltage

I. INTRODUCTION

In the recent years the development of solar energy technology has a rapid change. This is due to the lack of energy developed by petroleum energy [1]. The optimization techniques take places for solving engineering problems, such as data classification, microgrid, unit commitment, optimal allocation of DGs in radial networks and many other problems [2- 21]. The photo-voltaic (PV) is one source of renewable energy resources that has growing interest in power market due to it expand rapidly. This rapid development search for designers to develop a flexible and reliable model for the PV system to accurately simulate PV arrays and predict the useful information for various sizes of PV arrays. The definition of solar cell is a semiconductor device that produces electricity from sunlight [22–24].

The relationship between current-voltage of semiconductor P-N junction is similar to the relationship between current-voltage of solar cell [25]. So Most of recent mathematical models for solar cells are developed based on number of diodes in the models .the single diode model is simplest model presented for solar cell in literature. The simplicity of the model is based on using single diode in the model more over it contains five variables. The second model is the DD model which developed to overcome the drawbacks of the SD by using two diodes in the model to present the recombination process in the cell. Although the DD model gives more accurate results than SD, its complexity increased as it has seven variable parameters [26-27].

Recalling that the selection of the best elements from some set of available alternatives (with regard to some criterion) is processed by optimization techniques. The optimization problem here is the apply an optimization algorithm to select the best model parameters to minimize the difference between the model output and the real solar cell output in case of different inputs at different conditions [28-30]. Different types of optimization techniques have been proposed in literature. It is a multiple ways in categorization of the main types of these techniques. One of popular ways to categorize these techniques based on the type of target function. This category divided to two main groups: Differentiable objective function that can be solved with algorithm based on the derivative information and non-Differentiable objective function that can be solved with algorithm not based on the derivative information. Examples of algorithms based on the derivative information (classical algorithms) are Bracketing Algorithms, Local Descent Algorithms, First-Order Algorithms and Second-Order Algorithms. Examples of algorithms not based on the derivative information are Direct Algorithms, Stochastic Algorithms and Population Algorithms [31-34].

The selection of a suitable optimization technique has a kind of challenge due to hundreds of techniques that have been developed. Development of simple optimization techniques with good performance is very important due to it is useful to decrease the computation time. A lot developed algorithms on used due to its complexity [35-38]. Rao algorithm is one of recently proposed population based algorithm. The simplicity is one of main advantages of Rao algorithm [39-43]; moreover, it is parameter-less algorithm. The performance of various population-based advanced optimization.

Recalling that the search scheme of multi-population has significant improvement on the population based algo-rithms [36-38]. This improvement is achieved by dividing the total population into number of sub –population small groups to explore for the best solution in wide different areas. The range of the population area adapted by the algorithm based on the obtained best and worst solution. This strategy of search is proposed by SAMP-Rao algorithm [44].

In this paper SAMP-Rao algorithm is discussed to apply on parameter estimation of solar cell SD and DD models. The results of SAMP-Rao is proposed and compared with others recent algorithms. The paper

is presented as follow: section 2 presents PV models. The SAMP-Rao is discussed in section 3. Section 4 presents the comprehensive results. The conclusion is presented in section 5.

II. PV MODEL

The recent PV models is based on the semiconductor P-N junction (diode), due to the similarity between the electrical characteristics of solar cell and the electrical characteristics of P-N junction (diode). Every model distinct than others by the number of diodes in the model equivalent circuit [45]. In this section a brief discretion about the recent PV models has been discussed also the optimization problem for each model.

The I-V characteristic of photovoltaic cell have been describing by different models in the literature, the most prac-tice common models are those who depends on no of diodes connected to shunt and series resistances. SD and DD have been selected in this paper.

A. SD mathematical model.

The main components of SD model is presented in fig. 1. From the figure, the circuit consists of:

- 1.Photo generated current source (I_{ph}).
- 2.One diode rectifier current (I_{sd}).
- 3.Shunt & series resistance (R_{sh} & R_s).

The bulk regions, emitter resistance and contact resistances are represented by R_s . The current leakage across the P-N junction of the solar cell is represented by the shunt resistance (R_{sh}) current (I_{sh}) the terminal voltage is named (V_t) [45].

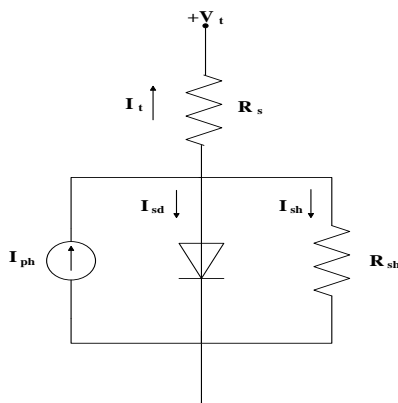


Fig. 1 Photovoltaic SD equivalent circuit.

$$I_t = I_{ph} - I_{sd} - I_{sh} \quad (1)$$

$$I_t = I_{ph} - I_{sd} \left[\exp\left(\frac{q(V_t + R_s I_t)}{n K T}\right) - 1 \right] - \frac{(V_t + R_s I_t)}{R_{sh}} \quad (2)$$

B. Double diode equivalent circuit.

The main difference between the DD and SD is in DD two diodes are used, as shown in the fig.2. One of them is used for rectifier, the other one is used for representing recombination current and some non-idealities of the solar cell [45]. The output current of the PV module (I_t) is calculated from (3) and (4):

$$I_t = I_{ph} - I_{d1} - I_{d2} - I_{sh} \quad (3)$$

$$I_t = I_{ph} - I_{d1} \left[\exp\left(\frac{q(V_t + R_s I_t)}{n_1 K T}\right) - 1 \right] - I_{d2} \left[\exp\left(\frac{q(V_t + R_s I_t)}{n_2 K T}\right) - 1 \right] - \frac{(V_t + R_s I_t)}{R_{sh}} \quad (4)$$

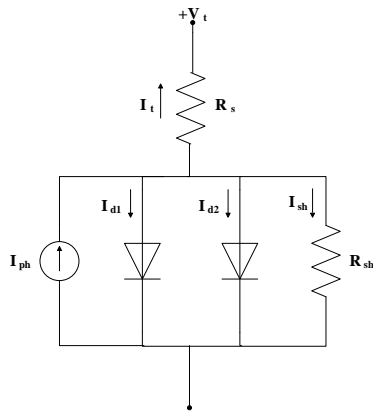


Fig. 2 Photovoltaic DD equivalent circuit.

C. PV module and array.

A PV module consists on a number of solar cells in series connection and the PV array is consists on number of modules are in series and parallel connection. Fig. 3, 4 presents the structure of PV module and PV array respectively.

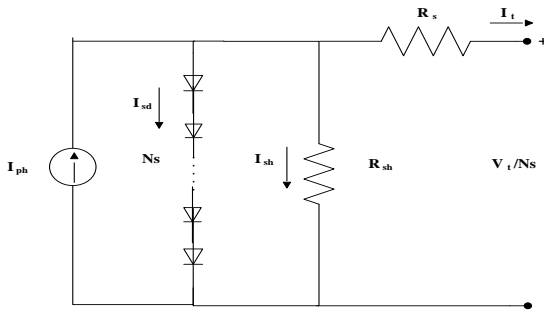


Fig. 3 Photovoltaic module.

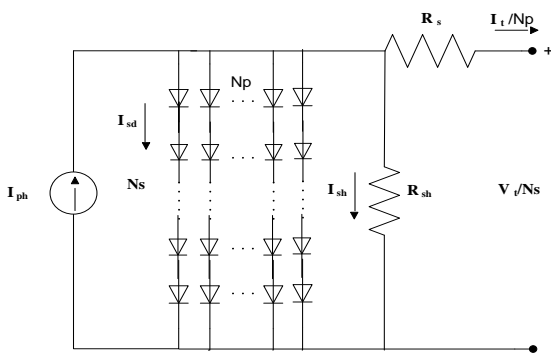


Fig. 4 Photovoltaic array.

D. Optimization problem.

From sec 2.A, in SD model there are five parameter for estimation, these parameters are $[R_s, R_{sh}, I_{ph}, I_{sd}, n]$ and the represented by a vector $x=[x_1, x_2, x_3, x_4, x_5]$, as follow:

$$f_{SD}(V_t, I_t, X) = I_t - X_3 + X_4 [\exp(q(V_t + X_1 I_t) / (X_5 K T)) - 1] + ((V_t + X_1 I_t) / X_2) \quad (5)$$

From sec 2.B, in the DD model there are seven estimated parameter $[R_s, R_{sh}, I_{ph}, I_{d1}, I_{d1}, n_1, n_2]$ and represented by a vector $x=[x_1, x_2, x_3, x_4, x_5, x_6, x_7]$, as follows:

$$f_{DD}(V_t, I_t, X) = I_t - X_3 + X_4 [\exp(q(V_t + X_1 I_t) / (X_6 * K * T)) - 1] + X_5 [\exp(q(V_t + X_1 I_t) / (X_7 * K * T)) - 1] + ((V_t + X_1 I_t) / X_2) \quad (6)$$

The parameter constrains are shown in table 1.

TABLE I. Parameter lower and upper constrains

Parameter	Solar Cell		PV module	
	Lower Value	Upper Value	Lower Value	Upper Value
Rs	0	0.5	0	2
Rsh	0	100	0	1000
Iph	0	1	0	2
Id1	0	1	0	1
Id2	0	1	0	1
n1	1	2	1	50
n2	1	2	1	50

III. SELF-ADAPTIVE MULTI-POPULATION RAO ALGORITHM

Rao is a simple optimization algorithm with no specific parameters. The main idea behind Rao algorithm is the updated solutions in each iteration depend on the best and worst solutions [39]. Equation 7 presents this concept. SAP-Rao is based on Rao algorithm. In SAP-Rao algorithm the population size is adapted in each iteration based on the obtained objective function. The population size increased in case of the distance between the old and new objective function increased. And vis versa The population size decreased in case of the distance between the old and new objective function decreased. Fig 5. Presents the flowchart of SAP-Rao.

$$X_{new} = X_{old} + r1(X_{best} - X_{worst}) \quad (7)$$

where

(X_{new}) is the new solutions.

(X_{old}) is the old solutions.

(X_{best}) the best obtained results.

(X_{worst}) the w obtained results.

r1 random value

The steps of the SAMP_Rao are as follow:

Step1: Initialize the population size and no. of iteration and no. of variables and their upper and lower limits

Step2: generate random solutions based on the lower and high limit of all variables

Step3: evaluate the random solutions by objective functions equation 5, or 6.

Step 4: Split the population size to n number of sub population groups based on the evaluated solutions

Step4: calculate the best and worst results for each sub-population group

Step5: update the new solutions for each sub-population group by equation 7.

Step6: compare the result of new and old solutions in each sub-population group and accept the best one.

Step7: check the termination factor if it reached, stop .if no repeat the last process.

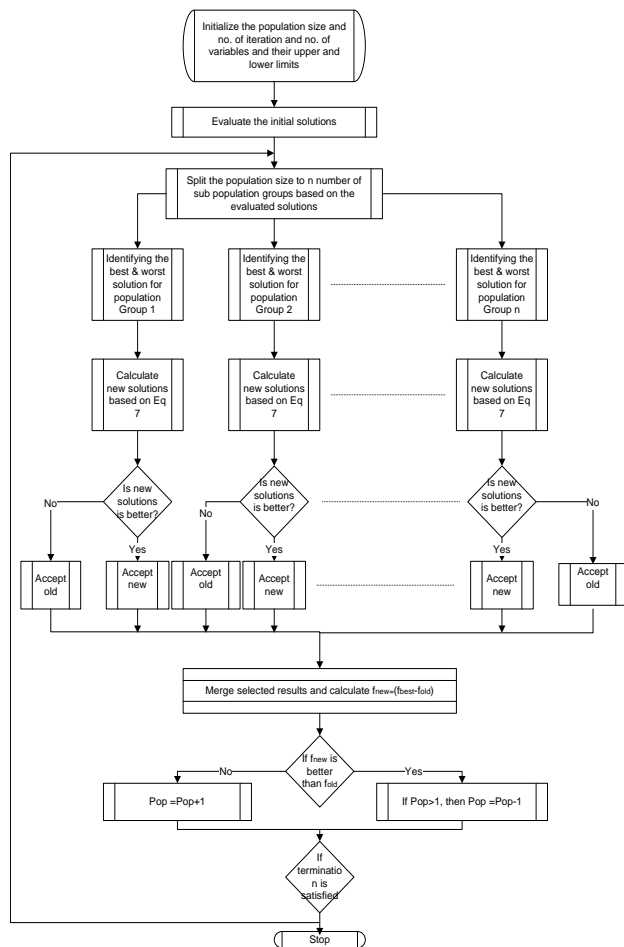


Fig. 5 SAMP_Rao Flowchart

IV. SIMULATION RESULTS

In this section, the application of SAMP-Rao to optimize the parameters of SD and DD models is discussed. Part 1 discuss a comparative study between optimized parameters SD and DD models, obtained by SAMP-Rao and other recent algorithms for commercial silicon R.T.C France solar cell. Part 2 discuss a comparative study between optimized parameters SD and DD models, obtained by SAMP-Rao and other recent algorithms for a polycrystalline PV panel STM6-120/36.

A. Part 1 results

This part discuss the application of SAMP-Rao for estimating the parameters of SD and DD PV model. The real data of 57 mm diameter commercial silicon R.T.C France solar cell (under 1000 W/m^2 at 33°C) is considered in this application and presented in table II. For comprehensive study a comparison between the results of SAMP-Rao and different recent algorithm is presented.

• SD model results

The SD model has a five estimated parameters as discussed in section 2. Equation 5 present the optimization objective function of SD model. The target of the optimization algorithm is to minimize the objective function by comparing the Root Mean Square Error value (RMSE) (Equation 9) in each iteration. And considering the best solutions which has the minimum RMSE. Table II presents the five estimated parameters of SD model for SAMP-Rao and TLBO, PSO and MRFO. The convergence curve of SAMP-

Rao is presented in fig.6. The comparison between SAMP-Rao results and optimization algorithms developed by other references is presented through the statistical results in table III. From the statistical results the accuracy of most of compared algorithm are the same but The SAMP-Rao has the best reliability as it has the best slandered deviation. The boxplot for the statistical results is presented in fig. 7. The current and power curve for different temperature of the estimated SD model are presented in fig. 8, 9.

$$RMSE = \sqrt{\frac{1}{N} \sum_{K=1}^N f^2(V_{tm}, I_{tm}, X)} \quad (9)$$

TABLE II. ESTIMATED PARAMETER IN CASE OF SD OBTAINED BY DIFFERENT OPTIMIZATION ALGORITHMS

	SAMP-RAO	TLBO	PSO	MRFO
Rs (Ω)	0.036377	0.0364	0.0364	0.036311401
Rsh(Ω)	53.72208	53.7191	53.7760	54.48125626
Iph(A)	0.760775	0.7608	0.7608	0.7608
Isd(A)	3.23E-07	3.23E-07	3.24E-07	3.29E-07
n	1.4769	1.4769	1.4771	1.4786
RMS	0.000986021	0.000986022	0.00098603	0.0009867

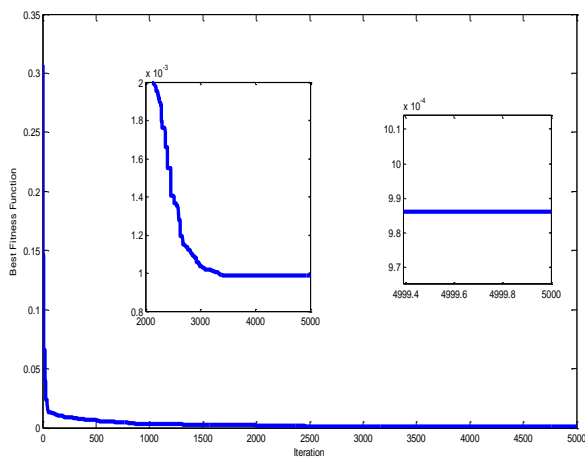


Fig. 6 Convergence curve of SAMP-Rao for SD model

TABLE III. THE STATISTICAL RESULTS OF ALL ALGORITHMS

	Minimum	Average	Maximum	STD
SAMP-RAO	0.00098602	0.00098602	0.00098602	5.74267E-12
TLBO	0.00098602	0.00098602	0.00098602	7.03322E-12
PSO	0.00098602	0.00098603	0.00098603	3.49975E-09
MRFO	0.00098603	0.0009874	0.00099058	1.55593E-06
IBSO [26]	0.00098602	0.00098602	0.00098602	1.0442E-11
IJAYA[26]	0.00098640	1.0117E-03	1.0680E-03	2.2707E-05
ABC[26]	0.0010075	0.0012187	0.0010680	1.5917E-04

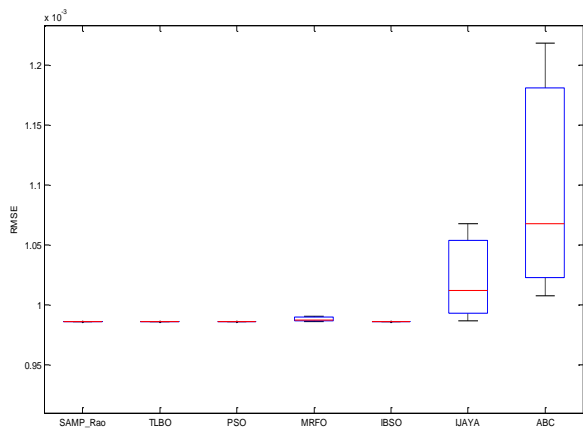


Fig. 7 Boxplot for statistical results of different algorithms

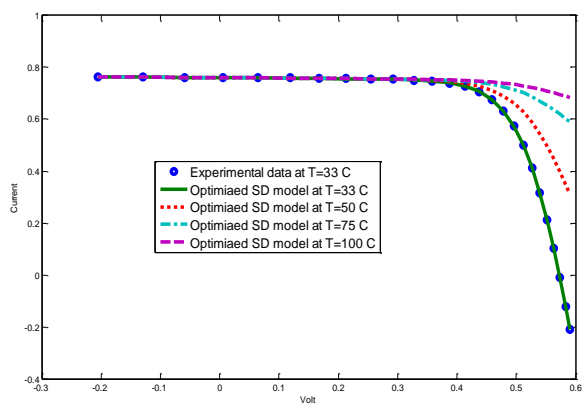


Fig. 8 Current at different temperature for optimized SD model

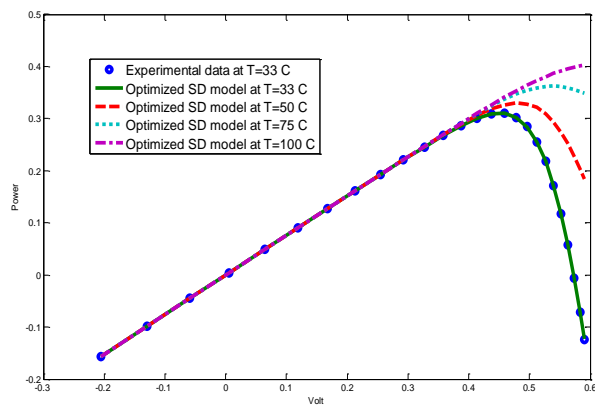


Fig. 9 Power at different temperature for optimized SD model

• DD model results

The DD model has seven estimated parameters as discussed in section 2. Equation 6 present the optimization objective function of DD model. Table IV presents the seven estimated parameters of DD model for SAMP-Rao and TLBO, PSO and MRFO. The convergence curve of SAMP-Rao is presented in

fig.10. The comparison between SAMP-Rao results and optimization algorithms developed by other references is presented through the statistical results in table V. From the statistical results have the best minimum RMSE value and the best accuracy due to best average value. The boxplot for the statistical results is presented in fig. 11. The current and power curve for different temperature of the estimated DD model are presented in fig. 12, 13.

TABLE IV. ESTIMATED PARAMETER IN CASE OF DD OBTAINED BY DIFFERENT OPTIMIZATION ALGORITHMS

	SAMP-RAO	TLBO	PSO	MRFO
Rs (Ω)	0.036377	0.0364	0.0364	0.036311401
Rsh(Ω)	53.72208	53.7191	53.7760	54.48125626
Iph(A)	0.760775	0.7608	0.7608	0.7608
Isd(A)	3.23E-07	3.23E-07	3.24E-07	3.29E-07
n	1.4769	1.4769	1.4771	1.4786
RMS	0.000986021	0.000986022	0.00098603	0.0009867

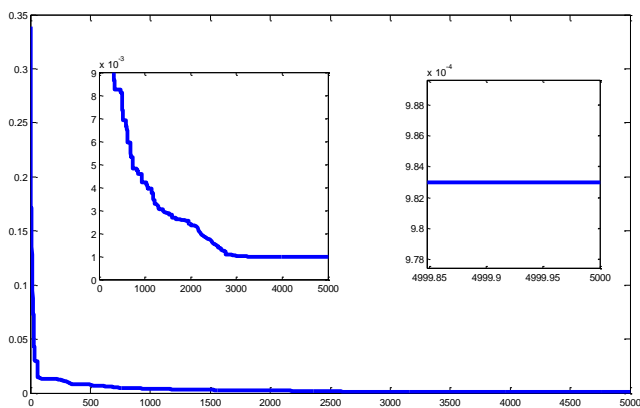


Fig. 10 Convergence curve of SAMP-Rao for DD model

TABLE V. THE STATISTICAL RESULTS OF ALL ALGORITHMS

	Minimum	Average	Maximum	STD
SAMP-RAO	0.000982961	0.00098472	0.000987222	9.03467E-07
TLBO	0.00098602	0.00099539	0.00103245	2.0719E-05
PSO	0.00098602	0.00099539	0.00103245	2.0719E-05
MRFO	0.00098591	0.00100681	0.00106299	3.35579E-05
IBSO [26]	0.0009835	0.0009106	0.0011161	2.3748E-05
IJAYA[26]	0.0009830	0.001042	0.001400	9.9580E-05
ABC[26]	0.00099550	0.001093	0.0014988	1.0136E-4

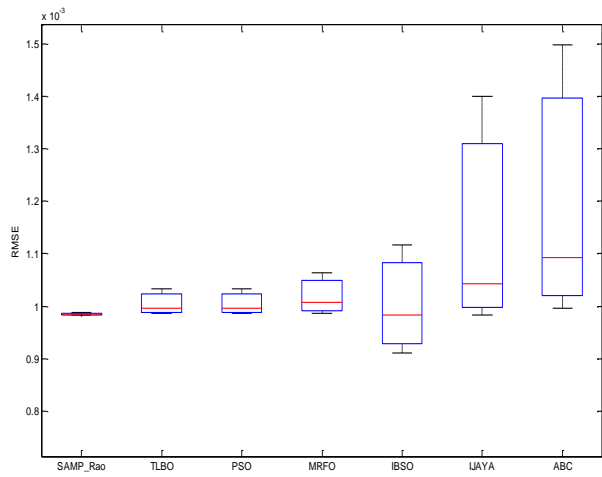


Fig. 11 Boxplot for statistical results of different algorithms

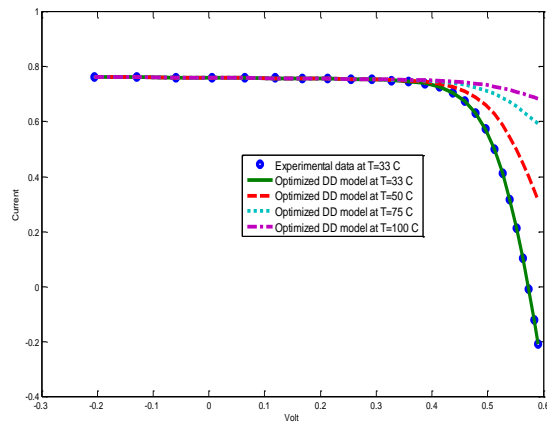


Fig. 12 Current at different temperature for optimized SD model

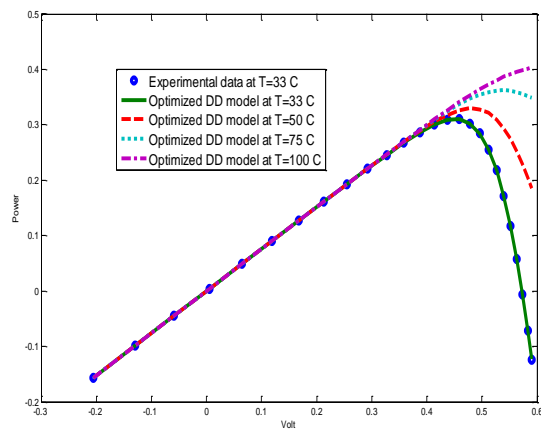


Fig. 13 Power at different temperature for optimized SD model

B. Part 2 (PV module results)

In this part the SAMP- Rao is applied to estimate the parameters of SD model for the real PV module Photowatt-PWP201. This module contains 36 polycrystalline silicon cells connected in series and operating at an irradiance of 1000 W/m² and temperature of 45C [26]. The convergence curve of SAMP-Rao when applied to the module is presented in fig.14. The comparison between SAMP-Rao results and optimization algorithms developed by other references is presented through the statistical results in table

VI. From the statistical results the accuracy of SAMP-Rao is the same IBSO which considered the best accuracy. The boxplot for the statistical results is presented in fig. 15. The current and power curve for different temperature of the estimated SD model are presented in fig. 16, 17.

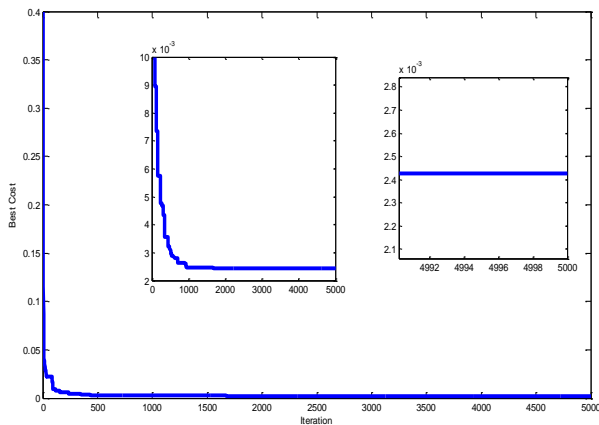


Fig. 14 Convergence curve of SAMP-Rao for SD model (PV module)

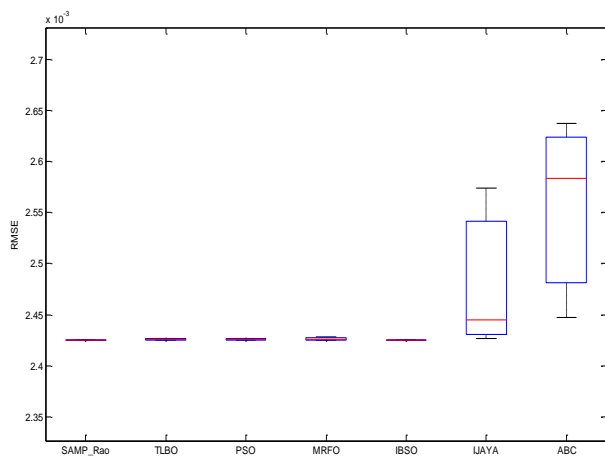


Fig. 15 Boxplot for statistical results of different algorithms

TABLE VI. THE STATISTICAL RESULTS OF ALL ALGORITHMS

	Minimum	Average	Maximum	STD
SAMP-RAO	0.0024250	0.0024251	0.0024253	9.03467E-07
TLBO	0.00242500	0.0024256	0.00242670	9.29157E-07
PSO	0.0024251	0.0024257	0.0024267	8.32666E-07
MRFO	0.0024251	0.0024262	0.0024283	1.81934E-06
IBSO [26]	2.4250E-03	2.4251E-03	2.4251E-03	6.5323E-12
IJAYA[26]	2.4263E-03	2.4452E-03	2.5739E-03	3.3065E-05
ABC[26]	2.4469E-03	2.5835E-03	2.6372E-03	5.4862E-05

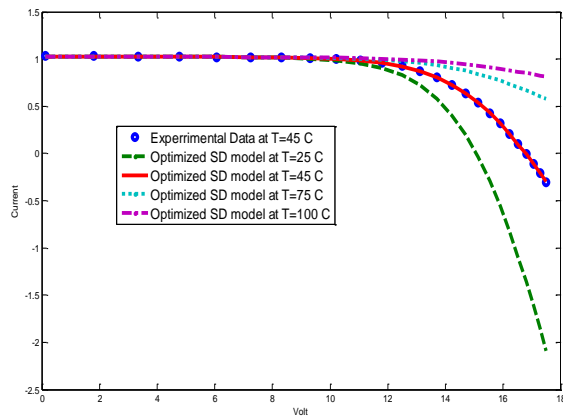


Fig. 16 Current at different temperature for optimized SD model

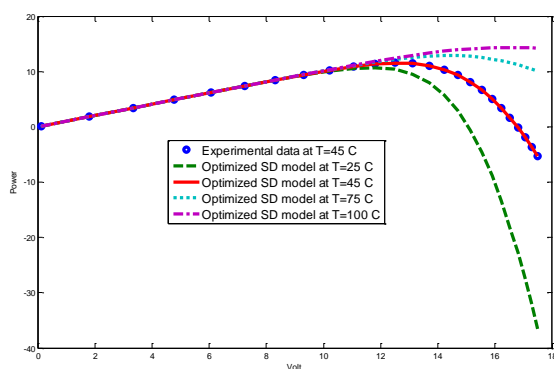


Fig. 17 Power at different temperature for optimized SD model

V. CONCLUSION

In this paper, a self-adaptive multi-population Rao optimization algorithm is discussed and applied to estimate the parameters of different PV models. Two main different PV models is discussed, SD and DD models .the difference be-tween the two models and the advantages and disadvantages of the two models are also discussed. The obtained results of SAMP-Rao is compared with recent optimization algorithms and also with other references. For deep check The SAMP-Rao is applied to estimate the parameters of PV module Photowatt-PWP201 contained 36 polycrystalline silicon cells. In all cases, the results obtained by SAMP-Rao are more accurate than those obtained by other optimization algorithms. The obtained results for DD model are more accurate than SD models.

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