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Parameters extraction of photovoltaic cells using swarm intelligence-based optimization technique: research on single diode model and double diode model

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K E Y W O R D S

Particle Swarm Optimization

Solar Energy

Renewable Energy

Photovoltaic Modules

Diode Models

A B S T R A C T

Solar-energy is a clean source of energy and photovoltaic (PV) panels are constructed from solar cells (SC) which convert energy of light into electricity without any environmental effect. The researchers and policy makers focus on the huge scale adoption of solar panels due to their cleaner production. However, there is non-linear behavior in current-voltage characteristics of solar panels and shortage of data in manufacturer's datasheet. To enhance the efficiency of solar panels it is mandatory to develop the PV panels scheme accurately by extracting the basic parameters. In this research study a mathematical model of two different solar cell models is used such as Single Diode Model (SDM) and Double Diode Model (DDM). The Particle Swarm Optimization (PSO) is used to extract the five and seven unknown parameters of SDM and DDM. The algorithm runs with one thousand iterations to minimize the Root Mean Square Error (RMSE) where the RMSE is the vector of five unknown parameters for SDM($I_{ph}, I_{s1}, a_1, R_s, and\ R_{sh}$) and seven ($I_{ph}, I_{s1}, I_{s2}, a_1, a_2, R_s, and\ R_{sh}$) for DDM. The superiority of the proposed PSO algorithm is proved by the optimized results of unrevealed parameters with minimized RMSE of up to 10^{-3}. Optimum parameter values for the solar cell models are applied on the real time data of a 55 mm diameter commercial RTC-France SC. Finally, the results reveal that P-V and I-V curves exhibit the smallest deviation between estimated and real time values. The results reveal that the proposed PSO converges to optimal solution with least number of iterations compared to the existing metaheuristic algorithms.

1. Introduction

Utilization of Renewable energy sources can fulfil the gap of demand and supply without any environmental pollution. Among the renewable energy sources, Solar energy is one of the mature technologies. In contrast, non-renewable energy sources are environmental pollutants, costly and limited in amount Due to great dependence on renewable sources especially solar energy whose efficiency is directly dependent on the environmental conditions (temperature and irradiation) the analysis for such characteristics is importance for optimized energy production from the solar devices. Therefore, electricity usage of solar energy source is increased in few decades because it is clean energy which convert light energy directly into the electricity. Now a day the usage of solar energy has been increased globally because of easy and free energy. The main advantages of SCs are that they are stationary and have not noise in there working, there are various applications of energy from solar PV technology i.e., satellites, heating, cooling and water treatment [7-9]. the PV is clean source of generating power, but PV models are non-linear. Due to incomplete data on designer's datasheet, there are some unknown parameters. Different methods are proposed to increase the precision of PV systems by explaining the parameters of the Solar Cells. However, the literature reveals that the existing methods suffer from inherit deficiencies in search mechanism. Two models of solar cells with different number of unknown parameters are presented. Single diode models (SDMs) have five unknown parameters and seven parameters in double diode models (DDMs). Therefore, various methods are used for accuracy in simulation and modelling of PV cell parameters identification i.e. numerical simulation and adaptive control [10-12]. The cleaning and maintenance of PV panels is point for required accuracy [13]. The authors in [14] used semiconductor material with P-N junction in construction of solar cells which has space-charge region and quasi-neutral region. The power drops in these regions is described by diffusion of the charge carriers and recombination. The serious consideration is required in the construction of the solar cell model. The defined current in ideal model of PV is named as photo-generated current. The magnitude of generated current in real PV model varies from the magnitude of experiment current. This magnitude difference is because of dropping of current in the depletion layer of semiconductor and this contribute to PV model in single diode models (SDMs). New simple technique for five loss parameters is introduced, the number five variables were reduced to two by excluding the series resistance and diode current in simple equation of SDM [16]. Non-linearity in V-I characteristics of PV cells is main object of optimization. two methods have been used to extract the parameters, one is metaheuristic optimization algorithms which has ability to solve highly non-linear optimization problems in large scale [16], and other is iterative mathematical methods, various methods have been used for estimation of these parameters i.e. iterative mathematical technique which consider the value of ideality factor for extraction of parameters. The nature-inspired algorithm is iterative method and used in the field of optimization which proved to be very efficient for solving complex problems with different abilities like improving accuracy, efficiency, and convergence speed [17]. The Lambert W-Function and analytical formulation method is also applied to datasheet of PV cells for estimation of these parameters, this method is straight forward, non-iterative and does not require initial values for parameters extraction. It works on data provided by manufacturer's datasheet and realistic model of solar cells can be constructed from this method [18]. Bond Graph technique is used for identification of parameters, in this developed model only five parameters of single diode model was identified without iterative process.in this method data form manufacturer's datasheet is applied along with ambient temperature and solar irradiation, this method is also applicable to single diode model only. The model with bond graph methodology allows identifying five unknown parameters without any process of iterations and all the parameters of PV in this method are used as a function of recoded solar irradiation and ambient temperatures [19]. Iterative method is also used for the extraction of parameters i.e., Gauss-seidel method and the least square method [20]. For demonstrating effects of temperature and irradiance a new analytical based method is used, in this method the physical parameters of SDM on standard operating conditions are used. This method contains four mathematical equations which link output current to output voltage in three different conditions ie short-circuit, open circuit and maximum power. In this method initial conditions are considered as numerical values of physical parameters [21]. Tow-step linear last-square method is introduced in which five unrevealed variables are extracted by using coordinates of I-V curves, with different curve fitting points parameters are calculated like other methods it does not require any kind of initial guess values. There are two steps in this method, the I-V curve is divided into two parts in which one is linear and other is exponential [22]. Varying maximum power with respect to two different conditions is presented the consideration of results are taken under STC and environmental conditions to compare the results [23]. The non-linearity and complexity of optimization problems adopted for extraction of parameters was resolved with metaheuristic algorithms. It becomes only possible with fast advancement in swarm intelligence and meta-heuristic algorithms [24]. With introduction of metaheuristic algorithms, it becomes possible to get values with a smaller number of iterations while maintaining accuracy. Two problems of PV models are considerable first is climacteric characteristics of current-voltage data and second is growing number of variables to be estimated. The multiple learning back tracking search algorithm (MLBSA) is proposed to get improved results of parameters in the world of metaheuristic algorithms [25]. Cuckoo search algorithm (CSA) and Grey wolf optimizer (GWO) Two methods in combination are called GWOCS, the purpose of combining the both methods was to get similar values of simulation and practical results. alpha, beta and gamma theses three decision variables are used in this method to increase diversity of GWO. At initial ten complex functions are tested then algorithm is applied to extract variables under different operating conditions. This study proved that GWO is poor at global exploration, and this is first time used two metaheuristic algorithms together for optimization purpose [26]. [27-34]. sine cosine approach based on opposition is applied to evaluate the optimum values of variables, the scheme of opposition-based learning (OBL) and Nelder-Mead simplex (NMs) were used. ISCA used Nelder-Mead to explore the best position of curve which indicates the maximum power output [35]. The literature reveals that a lot of work is carried out to minimize error between real time data and simulated data. However, the techniques suffer two methodological limitations. Firstly, the existing algorithms stuck into local or global optima, resulting in huge errors. Secondly, even if the algorithms achieve minimum error but are slow in response. Therefore, the proposed study develops PSO based mechanism for parameter optimization of SDM and DDM. The PSO based mechanism attains higher accuracy with least number of iterations.

2. System Description

SDM and DDM are the electrical circuits with different number of diodes. The electrical circuit single diode model is shown in Fig. 1.

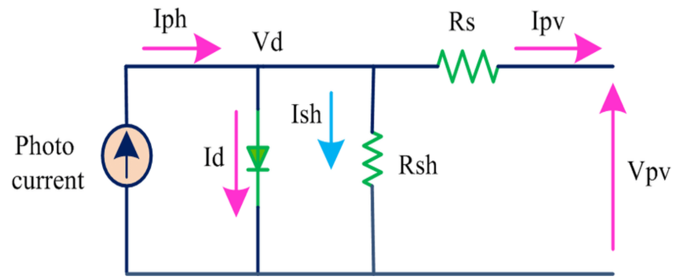


Fig. 1. Single diode model

2.1. Single Diode Model

The equation of total current is

$I = I_{ph} - I_{d1} - I_{sh}$ eq (1)

where I indicate total current, I_{ph} indicates photo generated current and I_{sh} is shunt resistance current.

Appling Shockley diode equation

$$I = I_{ph} - I_{s1}\left(\frac{q(V+IR_s)}{e^{a_1 KT_c}} - 1\right) - \left(\frac{V+IR_s}{R_{sh}}\right) \quad (2)$$

The efficiency of SDM directly depends on the output values of unknown parameters (I_{ph}, I_{s1}, a_1, R_s, and R_{sh}) and current voltage , The total voltage is shown by V, Is_1 is diode reverse saturation current, series resistance and shunt resistances are written as R_s and R_{sh} respectively. a_1 non-physical idealist factor, k = $1.3806503 \times 10^{-23}$ (J/K) is the Boltzmann's constant, the variable q = $1.60217646 \times 10^{-19}$ C is the charge of the electron, and in last T_c is the temperature in Kelvin. The outputs V and I are responsible for the efficiency of the models. These unknown parameters are to be estimated very carefully to enhance the efficiency of the model.

2.2. Two Diode Model

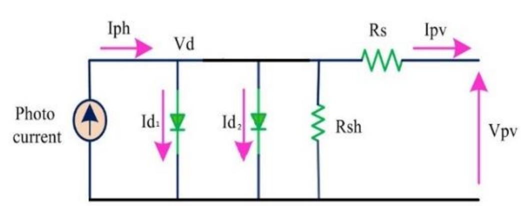


Fig. 2. Two diode model

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

Applying Kirchhoff's current law in the circuit as shown in Fig. 2, however, the equation of total current is Eq. 4 where I, I_{ph} and I_{sh} show total current, photogenerated current and shunt resistance current respectively. Appling Shockley diode equation to Eq. 1 we get.

$$I = I_{ph} - I_{s1}\left(\frac{q(V+IR_s)}{e^{a_1 KT_c}} - 1\right) - I_{s2}\left(\frac{q(V+IR_s)}{e^{a_2 KT_c}} - 1\right) - \left(\frac{V+IR_s}{R_{sh}}\right) \quad (4)$$

The efficiency of DDM depends on the outputs I and V and the seven unknowns ($I_{ph}, I_{s1}, I_{s2}, a_1, a_2, R_s, and\ R_{sh}$) which are essential to be calculated.

where I_{ph} *is photo generated current*, I_{s2} is reverse saturation current for second diode, a_2 is non-physical ideality factor for second diode.

3. The Objective Function for Parameters Extraction

The objective function is to minimize the RMSE value. There are some boundary conditions for such problems and these boundary spaces are defined in Table 1.

Table 1

The boundary limits of parameters [1].

Parameters	Lower bound	Upper bound
I_{ph} (A)	0	1
I_{s1}, I_{s2}, (μA)	0	1
R_s(Ω)	0	0.5
R_{sh}(Ω)	0	100
a_1, a_2	1	2

The mathematical formula for calculation of RMSE is written as under:

$$J\ (V, I, Y) = I - I_{exp} \quad (5)$$

The vector contains decision variables for the SDM is Y=($I_{ph}, I_{s1}, a_1, R_s, R_{sh}$). And the same for DDM is $Y = (I_{ph}, I_{s1}, I_{s2}, a_1, a_2, R_s, R_{sh})$

$$RMSE = \sqrt{{}^{1}/_{N} \sum_{i=1}^{N} (J\ (V, I, Y))^2} \quad (6)$$

Where I_{exp} shows the experimental value of current, and N shows the reading data number.

3.1 Particle Swarm Optimizer

PSO is metaheuristic and population-based algorithm, originally it was inspired by social behaviour of living organisms. In simple it was related to the flocking birds in nature for food searching purpose in particular area. The behaviour of search was related optimization search for solutions to non-linear equation in real world problems [36, 38-39]. It comprises of two vectors position and velocity. The position vector consists of the values for each of the variables in problem, if the problem has three parameters the particles will have position vectors in three dimensions. To update the position of the particles the second velocity vector is considered.

3.2 Initialization Stage

Like other particle-based techniques, the PSO initialize the process of optimization with an initial independently generated population from random distribution.

3.3 Original PSO

Original PSO is very simple and easy in implementation as defined before the PSO consists of two vectors which are defined below equations.

$$\overrightarrow{X_i(t+1)} = \overrightarrow{X_i(t)} + \overrightarrow{V_i(t+1)} \quad (7)$$

In this equation the vector $X_i(t)$ represents the position of $i\ th$ particle at $t\ th$ iteration. $V_i(t)$ shows the velocity of $i\ th$ particle at $t\ th$ iteration.

$$\overrightarrow{V_i(t+1)} = w\overrightarrow{V_i(t)} + c_1 r_1\left(\overrightarrow{P_i(t)} - \overrightarrow{X_i(t)}\right) + c_2 r_2\left(\overrightarrow{G_i(t)} - \overrightarrow{X_i(t)}\right) \quad (8)$$

Where w is the weight of inertia, individual co-efficient, $r_1 r_2$ are random numbers in [0,1], P_i(t) is best solution of individual swarm particles and $G_i(t)$ is the best solution in all swarms which is also called global best [37].

4. Simulation and Results

The results are extracted with Particle Swarm Optimization (PSO) algorithm by simulating and implementing the mathematical model of single diode model (SDM) and double diode models (DDM). At the first step simulation of mathematical model on MATLAB software is performed to find out five and seven parameters of SDM and DDM which define the losses of solar cell in different regions of diodes. After that the value of objective function is found, both measured and simulated results are compared in the I-V and P-V curves. The results of the proposed PSO are benchmarked against widely used recent algorithms like Harris Hawk Optimization (HHO) algorithm, Grey Wolf Optimization (GWO), Artificial Bee colony (ABC), Slime Mould Optimization (SMO) algorithms.

The performance of PSO is validate by the comparison of its outcomes with HHO, AEO, ABC, SMO algorithms and previous works. In this section, we have shown particulars of extracted results and the best values of RMSE by above discussed techniques one by one. The results are separated into three main parts firstly, the extracted optimized results of each optimization algorithm are presented in terms of RMSE Secondly current and power are optimized and in lastly, the simulated current and power and the real current and power data, the absolute error for current and power data are measured.

4.1. Results Using SDM

The results of the SDM are presented in Table 2 , and the comparison for the single diode model (SDM) is also presented. best RMSE values of the parameters extracted with present work of different algorithms and past work for comparison the results. the RMSE value attained by GWO algorithm in previous work is 1.388476989167E-03 reference and the best value of RMSE 9.860218778916E-04 is gained by PSO algorithm. The RMSE value actually shows the accuracy of parameters extracted. Value of Iph photo generated current calculated by GWO algorithm is 0.769969 and the best value of Iph calculated by algorithm HHO is 0.7787793. the value of total current I depends on the five unknown parameters Iph, Is1, a1, Rs, Rsh. The smaller the Is1 value larger the Iph value and hence greater the value of total current I, and in same case the Rsh if greater the Rsh value smaller the value of shunt resistance current Ish and hence greater the Iph value the superiority of results in terms of the absolute error (AE) for twenty-six different curve fitting points are presented, on each point of curve the simulated and real time current and power values are estimated which validate the smallest deviation between real time and simulated results and further the largest AE for power as estimated is 0.000504057 and the largest AE value for current is 0.000854334 these smallest values of errors show the accuracy of parameters extracted by PSO algorithm, the detailed Table 2 is given as under.

Table 2

Estimated parameters for single diode model at the best root mean square error (RMSE).

Algorithm	I_{ph}(A)	I_{s1}(μA)	R_{sh}(Ω)	R_s(Ω)	a_1	RMSE
PSO	0.76077553	0.323020767	53.71852296	0.036377093	1.481185486	9.8602E-04
AEO	0.76059345	0.3302958	61.35381387	0.036457701	1.483194727	1.09E-03
ABC	0.76074675	0.454301305	61.39769802	0.034896486	1.516409376	1.20E-03
HHO	0.77877939	0.728961052	10.5169849	0.029504413	1.573134678	1.32E-02
GBO [1]	0.76077553	0.32302	53.71852549	0.036377092	1.481183596	9.86E-04
MLBSA [25]	0.7808	0.323	53.7185	0.0364	1.596658	9.8602E-04
GWO [26]	0.769969	0.91215	18.103	0.02928	1.522764245	1.39E-03
GWOCS [26]	0.760773	0.32192	53.632	0.034639	1.4808	9.8607E-04
LCJAYA [27]	0.7608	0.323	53.7185	0.0364	1.4819	4.7628 E-03

Table 3

Absolute Error (AE) of Single Diode Model at the best Root Mean Square Error using PSO.

Items	Real time data		Current simulated data		Power simulated data	
	V(V)	Iexp(A)	Isim(A)	AEI(A)	Psim(W)	AEP(W)
1	-0.2057	0.764	0.763198174	0.000801826	-0.1571548	0.000164936
2	-0.1291	0.762	0.762031192	3.11923E-05	-0.0983742	4.02693E-06
3	-0.0588	0.7605	0.760959897	0.000459897	-0.0447174	2.70419E-05
4	0.0057	0.7605	0.759975703	0.000524297	0.00433485	2.98849E-06
5	0.0646	0.76	0.759075068	0.000924932	0.049096	5.97506E-05
6	0.1185	0.759	0.758243257	0.000756743	0.0899415	8.96741E-05
7	0.1678	0.757	0.757457432	0.000457432	0.1270246	7.67572E-05
8	0.2132	0.757	0.756657619	0.000342381	0.1613924	7.29957E-05
9	0.2545	0.7555	0.755736222	0.000236222	0.19227475	6.01185E-05
10	0.2924	0.754	0.754427778	0.000427778	0.2204696	0.000125082
11	0.3269	0.7505	0.752244642	0.001744642	0.24533845	0.000570324
12	0.3585	0.7465	0.748264917	0.001764917	0.26762025	0.000632723
13	0.3873	0.7385	0.74104133	0.00254133	0.28602105	0.000984257
14	0.4137	0.728	0.728261266	0.000261266	0.3011736	0.000108086
15	0.4373	0.7065	0.707740616	0.001240616	0.30895245	0.000542521

16	0.459	0.6755	0.67586382	0.00036382	0.3100545	0.000166994
17	0.4784	0.632	0.63109784	0.00090216	0.3023488	0.000431593
18	0.496	0.573	0.571984087	0.001015913	0.284208	0.000503893
19	0.5119	0.499	0.499371812	0.000371812	0.2554381	0.00019033
20	0.5265	0.413	0.413140024	0.000140024	0.2174445	7.37227E-05
21	0.5398	0.3165	0.316779091	0.000279091	0.1708467	0.000150653
22	0.5521	0.212	0.21127014	0.00072986	0.1170452	0.000402956
23	0.5633	0.1035	0.101297971	0.002202029	0.05830155	0.001240403
24	0.5736	-0.01	-0.009644533	0.000355467	-0.005736	0.000203896
25	0.5833	-0.123	-0.126325618	0.003325618	-0.0717459	0.001939833
26	0.59	-0.21	-0.209145666	0.000854334	-0.1239	0.000504057

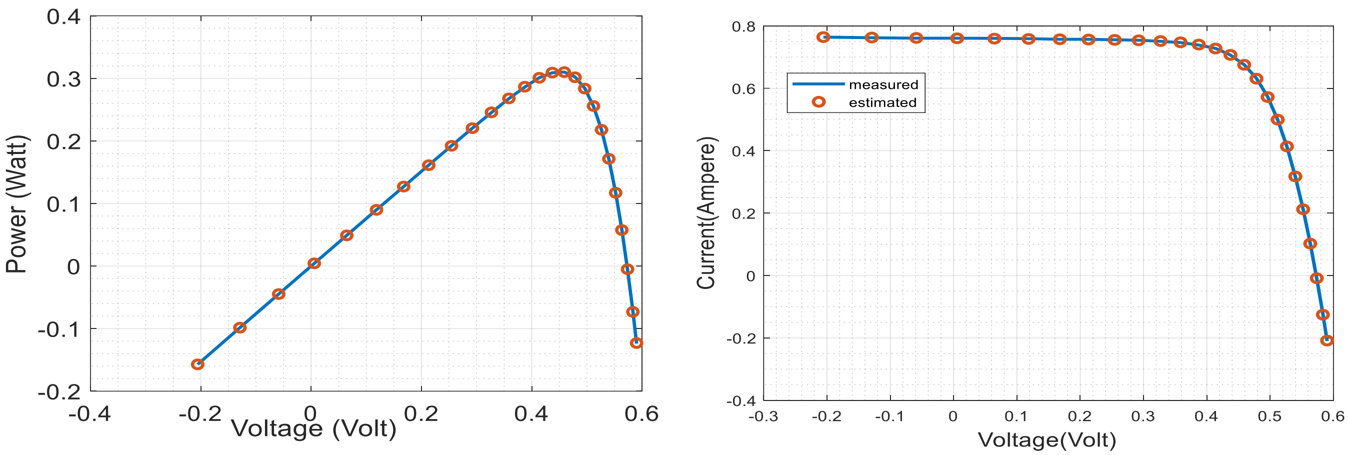


Fig. 3. P-V and I-V curves for Single Diode Model based on parameters estimated from PSO

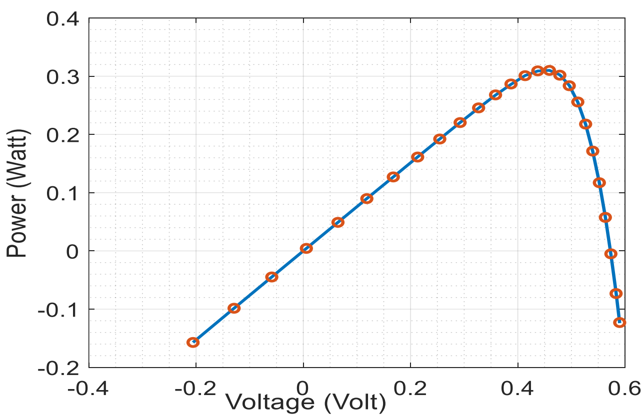
4.2. Results Using DDM

The comparative analysis of results for the DDM as shown in Table 3. It contains the calculated parameters by each algorithm at the best RMSE. The minimized RMSE value (9.8249E-4) by MLBSA and second-best value is obtained by (9.8258E-4) by GBO to ensure the accuracy of results, the absolute error (AE) for twenty-six different curve fitting points for current and power is calculated same as for SDM which are shown in Table 4. The smallest value of AE for power is 1.4428E-06 and the minimized value for AE is 8.1542E-06. The minimum AE value is2.78871E-05 and second minimum value for current AE is 4.55844E-05. These smallest values for the errors show the accuracy of PSO algorithm for extracted result.

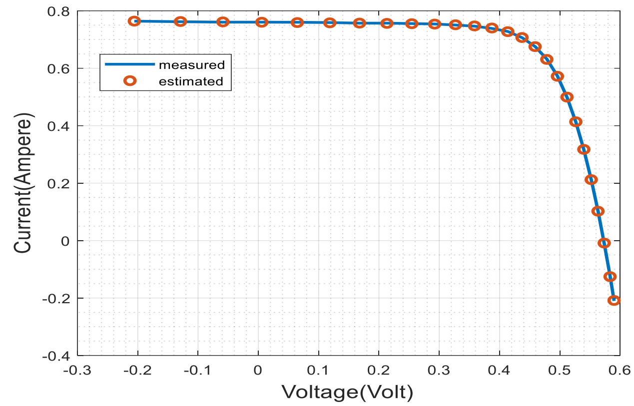
Table 4

Extracted parameters for double diode model at the best root mean square error (RMSE).

Algorithm	Iph(A)	Is1(μA)	Is2(μA)	Rsh(Ω)	Rs(Ω)	a_1	a_2	RMSE
PSO	0.7607731611	0.298321385	0.172667035	57.35973139	0.036116699	1.47722376	1.799232478	0.00098143
AEO	0.760859378	0.008748085	0.551406997	72.5281128	0.03463192	1.86941153	1.537152756	0.001674193
ABC	0.760684155	0.229455399	0.160260596	57.64554259	0.036439724	1.579822862	1.444925337	0.001004579
HHO	0.768470051	0.608476671	0.280653777	20.09564372	0.031314634	1.552784036	1.965411091	0.006165252
GBO [1]	0.60780326	0.85705	0.2138	55.77677015	0.036793056	1.999776183	1.446432096	0.00098258
MLBSA [25]	0.7608	0.2273	0.7384	55.4612	0.0367	1.4515	2	0.00098249
GWO [27]	0.761668	0.40302	0.45338	72.52775	0.03265	1.646	1.5527	0.0022124
GWOCS [27]	0.76076	0.53772	0.24855	54.7331	0.03666	2	1.4588	0.00098334
LCJAYA [28]	0.7608	0.22596	0.7464	55.4815	0.0367	1.4518	2	0.00503457



(a)



(b)

Fig. 4. (a) P-V and **(b)** I-V curves for Double Diode Model based on parameters estimated from PSO

Table 5

Absolute Error (AE) of Double Diode Model at the best Root Mean Square Error using PSO

Items	Real time data		Current simulated data		Power simulated data	
	V(V)	Iexp(A)	Isim(A)	AEI(A)	Psim(W)	AEP(W)
1	-0.2057	0.764	0.76392008	7.992E-05	-0.1571548	1.64395E-05
2	-0.1291	0.762	0.762589859	0.000589859	-0.0983742	7.61508E-05
3	-0.0588	0.7605	0.761368712	0.000868712	-0.0447174	5.10803E-05
4	0.0057	0.7605	0.760246878	0.000253122	0.00433485	1.4428E-06
5	0.0646	0.76	0.759220353	0.000779647	0.049096	5.03652E-05
6	0.1185	0.759	0.758272656	0.000727344	0.0899415	8.61903E-05
7	0.1678	0.757	0.757378978	0.000378978	0.1270246	6.35925E-05
8	0.2132	0.757	0.756475097	0.000524903	0.1613924	0.000111909
9	0.2545	0.7555	0.755449536	5.04635E-05	0.19227475	1.2843E-05
10	0.2924	0.754	0.754027887	2.78871E-05	0.2204696	8.1542E-06
11	0.3269	0.7505	0.751713988	0.001213988	0.24533845	0.000396853
12	0.3585	0.7465	0.747577036	0.001077036	0.26762025	0.000386117
13	0.3873	0.7385	0.740171073	0.001671073	0.28602105	0.000647207
14	0.4137	0.728	0.727200946	0.000799054	0.3011736	0.000330569
15	0.4373	0.7065	0.706528136	2.81358E-05	0.30895245	1.23038E-05
16	0.459	0.6755	0.674596759	0.000903241	0.3100545	0.000414588
17	0.4784	0.632	0.629937375	0.002062625	0.3023488	0.00098676
18	0.496	0.573	0.571116767	0.001883233	0.284208	0.000934084
19	0.5119	0.499	0.498954416	4.55844E-05	0.2554381	2.33347E-05
20	0.5265	0.413	0.413283433	0.000283433	0.2174445	0.000149227
21	0.5398	0.3165	0.317475765	0.000975765	0.1708467	0.000526718
22	0.5521	0.212	0.212423308	0.000423308	0.1170452	0.000233708
23	0.5633	0.1035	0.102700778	0.000799222	0.05830155	0.000450202
24	0.5736	-0.01	-0.008329945	0.001670055	-0.005736	0.000957943
25	0.5833	-0.123	-0.125347273	0.002347273	-0.0717459	0.001369164
26	0.59	-0.21	-0.208752558	0.001247442	-0.1239	0.000735991

4.3 Covergence Curves

All the algorithms run in MATLAB software with one thousand iterations for same objective function different algorithms converge at different number of iterations as shown in Fig. 5 and 6. The very first convergence point is of PSO algorithm which converge between one hundred iterations with objective function minimization of 10^{-3}. Other curves shown in Fig. 5 and 6 are converging greater than one hundred iterations with objective functions. The PSO convergence curve is shown in the last for the case of comparison, the last curve converged at about fifty iterations for the same objective function with maximum value of minimization which is 10^{-3} and shown clearly in Fig. 5 and Fig 6. This reveals the convergence and accuracy of the PSO as compared to other algorithms shown in Fig. 5 and 6.

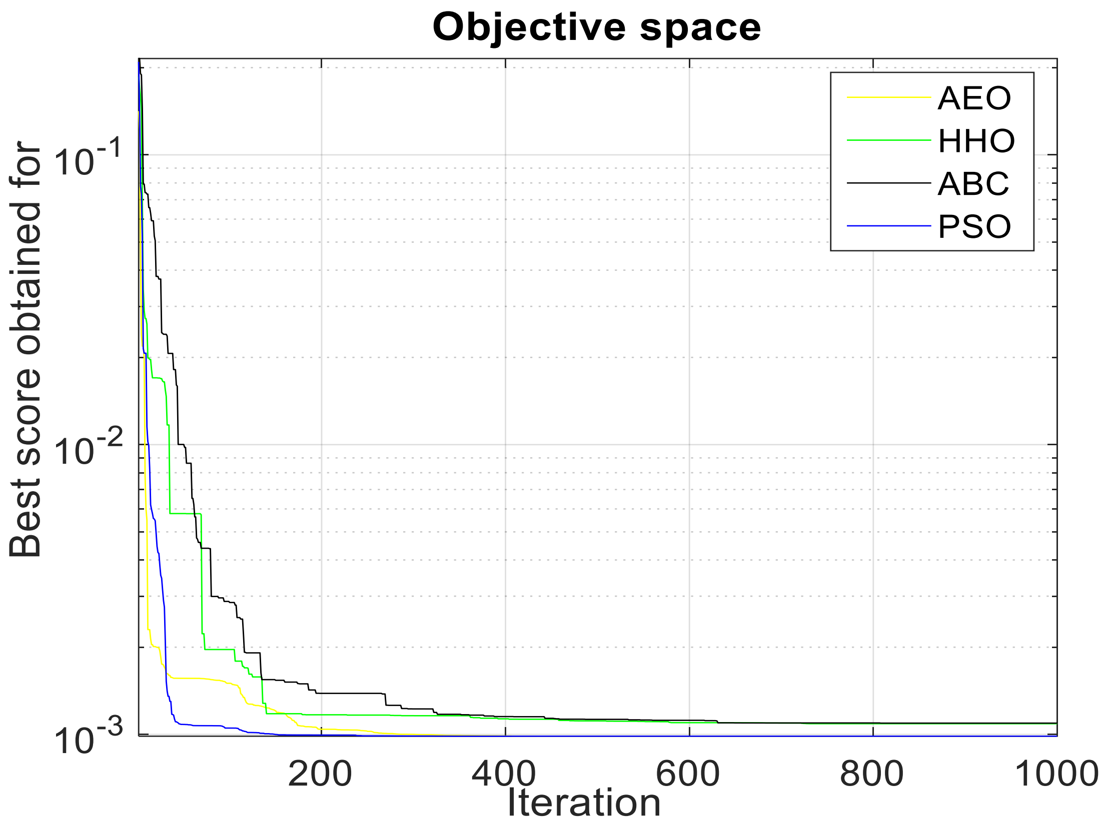


Fig. 5. Convergence curves of SDM with different algorithms and PSO

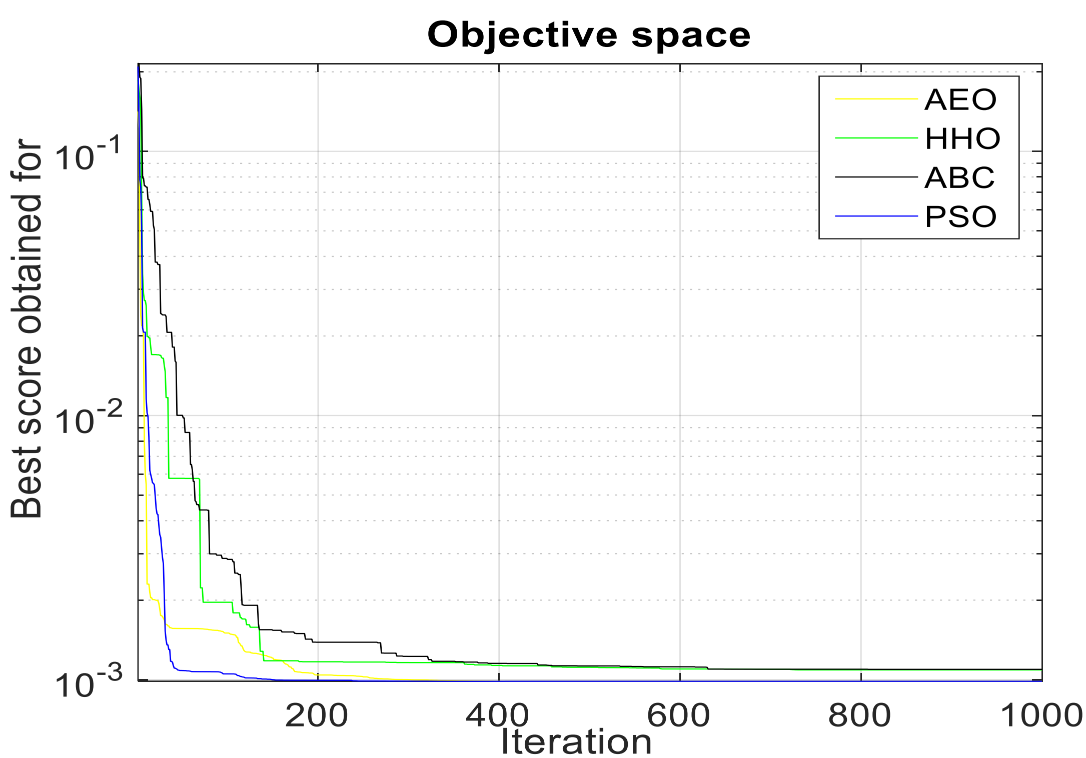


Fig. 6. Convergence curves of DDM with different algorithms and PSO

5. Discussions

The purpose of this research is to propose a search mechanism and show its efficiency of optimization for PV models. The efficiency of PSO is proved in name section number by discussing the and comparative study with other optimization algorithms. The PSO algorithm has following advantages:

- The PSO is good as optimizer algorithm, the optimization solution generated with PSO has best fitness values give value direct solution.
- In consideration of (AE), the PSO attained the least AE for each value current and power between measured and simulated data which defines the superiority of results as presented in Table 3 and in Table 5.
- The mathematical model of PSO is simple and consists of only two equations. Therefore, it is very easy to implement the algorithm for further steps.
- The selected values of PSO may vary in each run, because PSO optimization technique is based on random values. Therefore, the values generated in one run may not guaranteed in another run.

6. Conclusion

In this research work a new application of PSO algorithm presented for parameters estimation of two PV models.

- The main idea of this research was to design the two PV models efficiently for proper extraction of their parameters.
- The mathematical model of SDM was formulated as a non-linear equation of I and V, due to shortage of manufacturer's datasheet it is including five unrevealed parameters.
- The DDM is also treated like SDM except the number of unknowns in DDM was seven.
- The main objective function of the two models was minimizing the root mean square error between measured and simulated values of current, power and extracted parameters.
- The R.T.C France solar cell was used for checking the efficiency of parameters and minimization of objective functions as well.
- The PSO technique for optimization problems was used earlier but at this time it is new technique implemented to minimize the objective function of the loss parameters extraction of PV cells by using two different models SDM and DDM.
- However, PSO algorithm have various advantages such as it has good accuracy in solution, balance, and better convergence speed.

The outcomes achieved by the PSO are very accurate than other competitor algorithms. For solving the optimization problems of solar cells, the PSO is, thus, a good candidate. In the future work it can be used for multidimensional diodes and models for PV parameters extraction.

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