,QDOO FDVHV (2 REWDLQHG UHVXOWV KDYH EHHQ FRPSDUHG ZLWK WKH PRUH UHFHQW RSWLPL]
DOJRULWKPV VXFK DV 3DUWLFOH VZDUP RSWLPL]DWLRQ 362 7HDFKLQJ OHDUQLQJ EDVHG 2SWLPL]DWL
7/%2 DQG +DUULHV +DZN RSWLPL]DWLRQ +++2)URP WKH DOO REWDLQHG UHVXOWV (2 DOJRULWKP
JLYHVPRUHDFFXUDWH39PRGHOVLQFRPSDULVRQZLWKWKHURSWLPL]DWLRQDOJRULWKPV

.HZRUGVHTXLOLEULXPRSWLPL]DWLRQDOJRULWKPSKRWRYROWDLFVLQJOHGLRGHGRXEOHGLRGHWU
GLRGH39PRGHO

NOMENCLATURE

Symbol	description		description
SD	Single Diode	RMSE	Root Mean Square Error
DD	Double Diode	EO	Equilibrium optimization
TD	Triple Diode	TLBO **Symbol**	Teaching Learning-Based Optimization
PV	Photo Voltaic	PSO	Particle Swarm Optimization
I_{ph}	Photo generated current source	HHO	Harries Hawk optimization
R_s	Series resistance	η , η_1	Diffusion Diode Ideality
R_{sh}	Shunt resistance	η_2	Recombination Factor
I_t	PV module output current	η_3	Leakage Factor
I_{d1},I_{sd}	First diode current	*K*	=1.380X10-23(J/Ko) Boltzmann constant
I_{d2}	Second diode current	*q*	1.602 X 10-19 (C) Coulombs.
I_{d3}	Third diode current	*T (Ko)*	Photo cell temperature (Kelvin)
V_t	Terminal voltage	X(t)	Current position
PO	Political Optimizer	X(t+1)	Position in next iteration
		MRFO	Manta Ray Foraging Optimization

INTRODUCTION

Renewable energy has a great concern from the entire world in the recent days. The lake of nature fuel resources and the high cost of fuel production have the main issue in the renewable energy spreading. One of important renewable energy resources is the solar energy. Solar energy is converted to electricity through solar cells. Sun light has huge number of photons. Each photon has specific amount of energy. When a solar cell is exposed to the sun light, the solar cell has absorbed the photons and the photons energy is converted to electrical current through the cell. The current produced by the cell, can be measured through different ways (open circuit current and short circuit current). These types of currents determine the cell efficiency [1, 2]. The electrical energy produced from cells is directly used or stored in batteries for night use [3]. The amount of electricity produced from cells depends on deferent factors environmental and manufactural factors such as the sun light, ambient temperature, cell position to sun light and cell efficiency. So it became very important to develop a simulation model for the PV system specially for systems installed in variable climate. Developing an accurate model for the PV system is very important to discuss the characteristic and behavior for each PV system in case of variant environmental conditions. The challenge in the model development is the nonlinear characteristics for the solar cell [4-6].

The recent models in literature are the models depends in electrical diodes due to it have electrical characteristics similar to the solar cells.

Single diode model (SDM), double diode model (DDM) and triple diode model (TDM) are different models depends on the number of diodes in each model. SDM is considered the simplest one due to it has one diode as a main component and two resistances (series and shunt resistance). The total number of estimated parameters in SDM is five parameters which consider a simple number for estimation [7-9]. The DDM has two diodes as main components and two resistances (series and shunt resistance). The total number of estimated parameters in DDM is seven parameters. DDM is more accurate than SD [10-13]. The TDM has three diodes as main components and two resistances (series and shunt resistance). The total number of estimated parameters in TDM is nine parameters. TDM is more accurate than SD and DDM, despite of its complexity due to large number of estimated parameters [14-18].

There are a lot of optimization algorithms in literature, but the most popular techniques are deterministic and stochastic techniques. Deterministic techniques are more suitable for linear than nonlinear optimization problems [19]. Stochastic techniques have an advantage than deterministic techniques due to they generate and use random variables and then search the domain in global manner to find the best solution.

Meta-heuristic algorithms are considered the most popular stochastic techniques [20]. Meta-heuristic algorithms are inspired from different nature resources such as: human behavior (TLBO) [21-23]. human body (Genetic algorithm (GA)) [24]. Animals, birds and other insects hunting behavior and food way demand (Grey Wolf Optimization (GWO) [25 and 26], Harries Hawk optimization (HHO) [27], PSO [28 - 30] and chaotic whale optimization [31 and 32]). Physical theory such as equilibrium Optimization. Meta-heuristic algorithms distinct than others in simplicity and general applicability.

Equilibrium optimization algorithm is considered one of meta-heuristic algorithms inspired from natural physical theory. EO inspired from controlling mass balance through specific volume until reaching equilibrium state [33]. In this paper, three PV models (SD, DD and TD) are discussed, EO algorithm also presented. EO algorithm is applied to estimate the parameter of PV systems for different PV model. The behavior of EO in parameter estimation is tested by applying it to different real system.

The main contribution of this paper can be summarized as follows:

- EO is presented to be applied for PV model parameter estimation.

-SD, DD and TD models are presented as an example for PV models and their parameter estimation is considered as the optimization problem.

-The performance of EO is tested through different applications,

- application one, EO has been use to estimate the parameters of SD and DD model considering the real data measured from 57 mm diameter commercial silicon R.T.C France solar cell (under 1000 W=m2 at 33 °C).

-The applicability of EO with complex model Has been tested by estimating TD model parameters through real PV panel application.

-The real data of polycrystalline PV panel STM6-120/36 have been considered for the real PV panel application.

-By comparing obtained results, EO results is more accurate than other recent compared optimization algorisms.

The rest this paper is arranged as follow:

Section 2 presents the PV model and the optimization problem. Section 3 describes the EO algorithm. The results and application have been discussed in section 4. Section 5 presents the conclusion.

MATHEMATICAL PV MODELS AND THE OPTIMIZATION PROBLEM

The solar cell electrical characteristics is similar to P-N junction (diode) electrical characteristics as shown in Fig. 1 and 2. Therefore, the main element in the equivalent circuit of each model is the diode. Every model distinct than others by the number of diodes in the model equivalent circuit. In this section a brief discretion about the most popular PV model has been presented also the optimization problem for Each model. In each model the advantages and drawbacks have been discussed [34]. These models are arranged from simple to complex as SD, DD and TD.

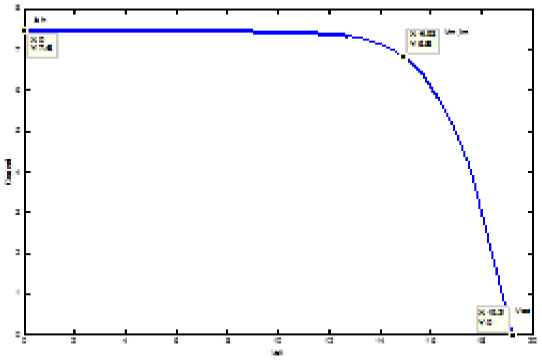

Figure 1 Current Vs voltage characteristics for polycrystalline PV panel

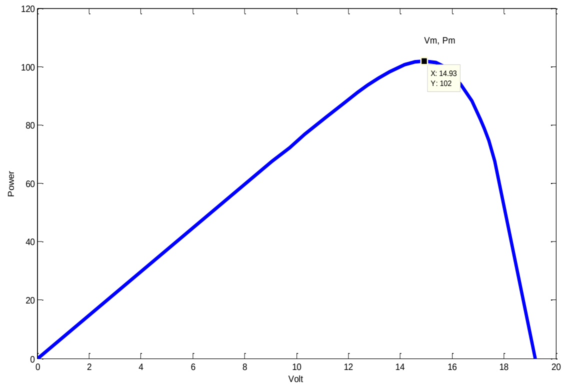

Figure 2 Power Vs voltage characteristics for polycrystalline PV panel

A. SD model

The SD model is considered the simplest model as shown in the model equivalent circuit of this model Fig. 3. The model has five parameters listed below:

-Solar cell photo generation current (I_{ph}) represents by one current source.

-Diode current (I_{sd}) for representing the P-N junction characteristics.

-Equivalent series resistance represented by R_s.

- Equivalent shunt resistance represented R_{sh}.

- Diode ideality factor (η)

The output current (It) is calculated through the following equations:

$$I_t = I_{ph} - I_{sd} - I_{sh} \tag{1}$$

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

The SD model estimated parameters are [R_s, R_{sh}, I_{ph}, I_{sd}, η]. The five parameters can be represented in one vector x= [x_1, x_2, x_3, x_4, x_5], hence the optimization problem is described by (3).

$$f_{SD}(V_t, I_t, X) = I_t - X_3 + X_4\left[\exp(\frac{q(V_t + R_s * I_t)}{X_5 * K * T}) - 1\right] + \frac{(V_t + X_1 * I_t)}{X_2} \quad (3)$$

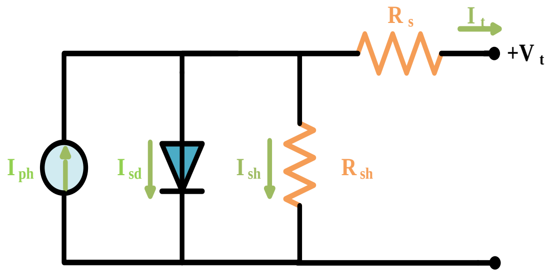

Figure 3 SD model

B. DD model

The DD model is differentiated from SD model by 2 diodes as shown in Fig. 4. This model is represented by (4) and (5).

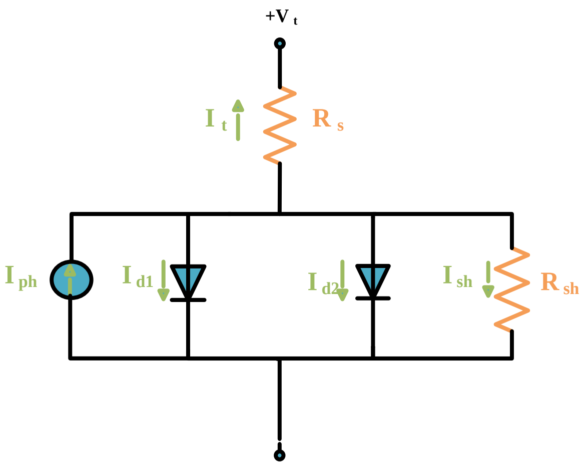

Figure 2 DD model

$$I_t = I_{ph} - I_{d1} - I_{d2} - I_{sh} \quad (4)$$

$$I_t = I_{ph} - I_{d1}\left[\exp(\frac{q(V_t + R_s * I_t)}{\eta_1 * K * T}) - 1\right] - I_{d2}\left[\exp(\frac{q(V_t + R_s * I_t)}{\eta_2 * K * T}) - 1\right] - \frac{(V_t + R_s * I_t)}{R_{sh}} \quad (5)$$

In DD model, seven estimated parameters are considered [R_s, R_{sh}, I_{ph}, I_{d1}, I_{d2}, η_1, η_2] and they can be represented in one vector x= [x_1, x_2, x_3, x_4, x_5, x_6, x_7], hence the optimization problem is described by (6).

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

C. TD model

The TD equivalent circuit is the same as DD taking in consideration the leakage current which represented by a third diode as shown in Fig. 5.

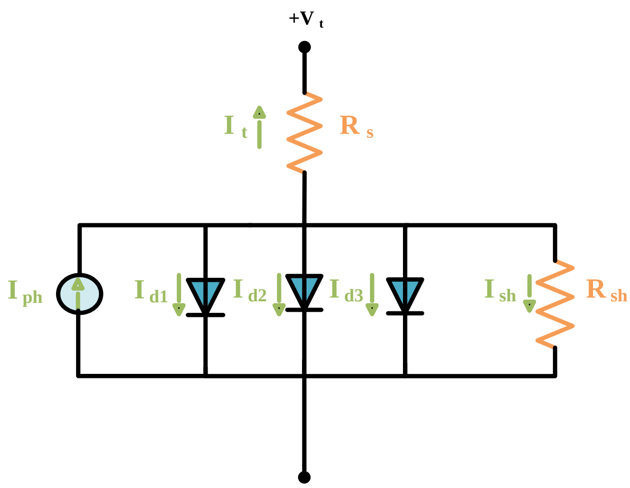

FIGURE 5. TD model mathematical model

Equation (7) and (8) describe the mathematical model of TD model

$$I_t = I_{ph} - I_{d1} - I_{d2} - I_{d3} - I_{sh} \quad (7)$$

$$I_t = I_{ph} - I_{d1}\left[\exp(\frac{q(V_t + R_s * I_t)}{\eta_1 * K * T}) - 1\right]$$
$$- I_{d2}\left[\exp(\frac{q(V_t + R_s * I_t)}{\eta_2 * K * T}) - 1\right]$$
$$- I_{d3}\left[\exp(\frac{q(V_t + R_s * I_t)}{\eta_3 * K * T}) - 1\right] - \frac{(V_t + R_s * I_t)}{R_{sh}} \quad (8)$$

In TD model, nine estimated parameters are considered [R_s, R_{sh}, I_{ph}, I_{d1}, I_{d2}, I_{d3}, η_1,η_2, η_3] and they can be represented in one vector x= [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9], hence the optimization problem is described by (9).

$$f_{TD}(V_t, I_t, X) = I_t - X_3 + X_4\left[\exp(\frac{q(V_t + R_s * I_t)}{X_7 * K * T}) - 1\right]$$
$$+ X_5\left[\exp(\frac{q(V_t + R_s * I_t)}{X_8 * K * T}) - 1\right] + X_6\left[\exp(\frac{q(V_t + R_s * I_t)}{X_9 * K * T}) - 1\right]$$
$$+ \frac{(V_t + X_1 * I_t)}{X_2} \quad (9)$$

EO ALGORITHM

A new metaheuristic algorithm based on physics laws is proposed in [24], namely equilibrium optimizer (EO). Firstly, the purpose of EO is to solve optimization problems. Secondly, other applications are realized as thresholding image segmentation [25]. The mathematical formulation of the EO algorithm is given as following:

Step 1: Initialization

In this step, EO uses a group of search agents representing the concentration vectors that are candidate solutions. These initial concentration vectors are randomly generated as:

$$\vec{v}_i = Lb_i + rand * \left(Ub_i - Lb_i\right);\ i = 1, 2, \ldots, N$$

where denotes the concentration vector of the ith solution, the upper and lower bound for the problem domain, respectively, rand the random number generator in the range of [0 ;1], and N the number of search agents.

Step 2: Equilibrium pool and candidates

$$\vec{C}_{eq.pool}$$

In an optimization algorithm, there is an objective function and the best solution. For instance, EO, we call it searches for the equilibrium state of the system. When reaching the equilibrium state, EO reaches to the near-optimal solution. In the optimization process, EO is unsware of the level of concentrations to achieve the equilibrium state. Hence, it allocates the best four solutions found so far, as well as one more solution containing the average of the best four solutions. These five candidate solutions help EO in the process of exploration and exploitation. Here, the first four candidate solutions assist EO to have diversification, and the average solution works for exploitation. These five candidate solutions are stored in an equilibrium pool:

$$\vec{C}_{eq.pool} = \left[\vec{C}_{eq.(1)}; \vec{C}_{eq.(2)}; \vec{C}_{eq.(3)}; \vec{C}_{eq.(4)}; \vec{C}_{eq.(avg)}\right] \quad (10)$$

A. Step 3: updating the concentration

To balance between exploration and exploitation, EO uses following term. Because the turnover rate varies over time, is a random vector between 0 and 1.

$$\vec{F} = e^{-\vec{\lambda}(t-t_0)} \quad (11)$$

where t decreases with the iteration (it) increment as:

$$t = \left(1 - \frac{it}{t_{\max}}\right)^{\left(a_2 * \frac{it}{t_{\max}}\right)} \quad (12)$$

where it and tmax are the present and the maximum number of iterations, respectively. a2 is a constant used to control the exploitation. a1 is supposed to enhance the exploitation as follows:

$$\vec{t_0} = \frac{1}{\vec{\lambda}} \ln\left(-a_1 sign\left(\vec{r} - 0.5\right)\left(1 - e^{-\vec{\lambda} t}\right)\right) + t \quad (13)$$

where a1 is a constant used to manage the exploration when it is higher, the exploration is better, and the exploitation is lower. Opposite to a1, a2 is a constant used to control the exploitation. When a2 is higher, the exploitation is enhanced and the exploration is lowered. Generation rate (R) is another term used to improve the intensification operator and is formulated as follows:

$$\vec{R} = \vec{R}_0 * e^{-\vec{\lambda}(t-t_0)} \quad (14)$$

where is a random generator [0, 1] and is the initial value:

$$\vec{R}_0 = \overrightarrow{RCP} * \left(\overrightarrow{c_{eq}} - \vec{\lambda} * \vec{C}\right) \quad (15)$$

$$\overrightarrow{RCP} = \begin{cases} 0.5 r_1 & r_2 \succ 0.5 \\ 0 & else \end{cases} \quad (16)$$

where r1 and r2 are the random generator [0, 1]. Here, represents the generation rate control parameter that decides the generation rate to be applied to the updating process based on a probability RP. The updating equation of EO is as follows:

$$\vec{C} = \overrightarrow{c_{eq}} + \left(\vec{C} - \overrightarrow{c_{eq}}\right) * \vec{F} + \frac{\vec{R}}{\vec{\lambda} * V} * \left(1 - \vec{F}\right) \quad (17)$$

where V is equal to 1. The main steps of EO are explained by the framework depicted in Fig.6

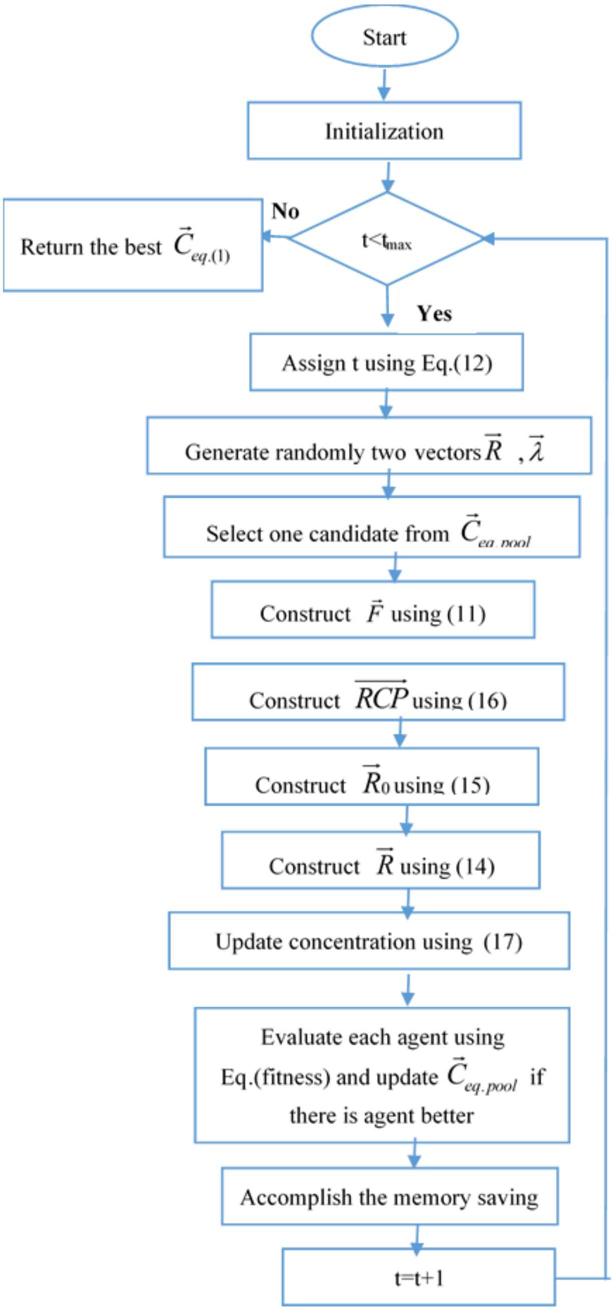

FIGURE 6. EO flowchart

SIMULATION RESULTS

The simulation results are presented through two applications. To evaluate the performance of the EO algorithm, it has been used to estimate the parameters of PV model through different real application. The results of EO have been compared with other algorithms.

A. APPLICATION 1

In this application, the EO is applied for estimating the parameters of SD and DD PV model. The real data considered in this application is the measured data from 57 mm diameter commercial silicon R.T.C France solar cell (under 1000 W=m2 at 33 °C) table. 2 [34]. A comparison between EO and seven algorithms (TLBO, HHO, PSO, PO, MRFO and JAYA) are implemented for SD and DD models. The parameters of each algorithm have been presented in table1.

TABLE 1 PARAMETER SETTING FOR EACH COMPARED ALGORITHM

Algorithm	Parameter setting			
EO	V=1	a_1=2	a_2=1	GP=0.5
TLBO	NP=1000	TF = randi([1 2]		
HHO	NP=1000	beta=1.5		
PSO	NP=1000	wdamp=0.99	c1=1.5	c_2=2.0
PO	lambda = 1.0			
MRFO	NP=1000	S=2		
JAYA	gen=1			

1. SD RESULTS

Based on the optimization problem of SD model equation 3, EO has been applied to estimate five parameters. Table 2 presents the SD model estimated five parameters for EO and others compared algorithms. The Root Mean Square Error

value (RMSE) (Equation 18) for each algorithm has been presented also in Table 1, Table 3 presents the real measurements for voltage and output current also the calculated output currents from the estimated parameters by each algorithm. Fig. 7 presents the absolute error between real output current and the output current calculated from the parameter estimated from each algorithm (Equation 19), from Fig. 7 the values presented by EO algorithm are more close to zero. Fig. 8 presents the convergence curves for EO and other algorithms. Table 4 represents the minimum, average, maximum and standard deviation (STD) values for 30 run statistical results. The RMSE values calculated in each run are figured in boxplot for each algorithm as shown in Fig. 9, (+) represents the outliers. From Fig. 7 ,8 and 9, EO algorithm results are more accurate than others. For more comparison Current Vs volt and Power Vs volt characteristics curves for real system, EO and others algorithms have been discussed in Fig. 10 and 11 respectively. The accuracy of the SD model by developed by EO algorithm is tested through the Current Vs volt and Power Vs volt characteristics curves at different temperatures, Fig. 12 and 13 respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{K=1}^{N} f^{2}(V_{tm}, I_{tm}, X)} \qquad (18)$$

$$Absolute\_error = \left| I_{real} - I_{Calculated} \right| \qquad (19)$$

TABLE 2 ESTIMATED PARAMETER IN CASE OF SD OBTAINED BY DIFFERENT OPTIMIZATION ALGORITHMS

	EO	TLBO	HHO	PSO	PO	MRFO	JAYA
Rs (Ω)	0.0363	0.0364	0.0364	0.0364	0.030327933	0.036311401	0.026510622
Rsh(Ω)	53.7191	53.7191	32.0200	53.776	120.2672245	54.48125626	2000
Iph(A)	0.7608	0.7608	0.7631	0.76077	0.760418556	0.7608	0.756265697
Isd(A)	3.23E-07	3.23E-07	2.74E-07	3.24e-07	1.15E-06	3.29E-07	2.26E-06
η	1.4769	1.4769	1.4610	1.4771	1.616998759	1.4786	1.703056187
RMS	0.000986022	0.000986022	0.0020053	0.00098603	0.002780458	0.0009867	0.005115

TABLE 3 THE REAL AND OUTPUT CURRENT FOR EACH ALGORITHM

V real	I real	EO	TLBO	HHO	PSO	PO	MRFO	JAYA
-0.2057	0.764	0.7641	0.7641	0.7687	0.7641	0.7619	0.7641	0.7564
-0.1291	0.762	0.7627	0.7627	0.7663	0.7627	0.7613	0.7627	0.7563
-0.0588	0.7605	0.7614	0.7614	0.7641	0.7613	0.7607	0.7614	0.7563
0.0057	0.7605	0.7602	0.7602	0.7621	0.7601	0.7602	0.7602	0.7563
0.0646	0.76	0.7591	0.7591	0.7602	0.7591	0.7597	0.7591	0.7562
0.1185	0.759	0.7580	0.7580	0.7585	0.7580	0.7592	0.7581	0.7561
0.1678	0.757	0.7571	0.7571	0.7570	0.7571	0.7587	0.7572	0.7560
0.2132	0.757	0.7561	0.7561	0.7554	0.7562	0.7582	0.7562	0.7558
0.2545	0.7555	0.7551	0.7551	0.7539	0.7552	0.7574	0.7552	0.7551
0.2924	0.754	0.7537	0.7537	0.7520	0.7541	0.7560	0.7538	0.7538
0.3269	0.7505	0.7514	0.7514	0.7494	0.7524	0.7534	0.7515	0.7511
0.3585	0.7465	0.7474	0.7474	0.7452	0.7499	0.7487	0.7474	0.7461
0.3873	0.7385	0.7401	0.7401	0.7378	0.7456	0.7404	0.7402	0.7372
0.4137	0.728	0.7274	0.7274	0.7252	0.7386	0.7263	0.7274	0.7224
0.4373	0.7065	0.7070	0.7070	0.7050	0.7278	0.7045	0.7070	0.6999
0.4590	0.6755	0.6753	0.6753	0.6737	0.7117	0.6717	0.6752	0.6668
0.4784	0.632	0.6308	0.6308	0.6297	0.6898	0.6270	0.6306	0.6222
0.4960	0.573	0.5719	0.5719	0.5713	0.6614	0.5691	0.5717	0.5650
0.5119	0.499	0.4996	0.4996	0.4994	0.6273	0.4986	0.4993	0.4958
0.5265	0.413	0.4136	0.4136	0.4137	0.5875	0.4153	0.4133	0.4140
0.5398	0.3165	0.3175	0.3175	0.3176	0.5436	0.3217	0.3170	0.3219
0.5521	0.212	0.2122	0.2122	0.2120	0.4962	0.2184	0.2115	0.2197
0.5633	0.1035	0.1023	0.1023	0.1017	0.4472	0.1092	0.1015	0.1108
0.5736	-0.01	-0.0087	-0.0087	-0.0098	0.3982	-0.0033	-0.0096	-0.0025

0.5833	-0.123	-0.1255	-0.1255	-0.1274	0.3470	-0.1232	-0.1266	-0.1241
0.5900	-0.21	-0.2085	-0.2085	-0.2110	0.3109	-0.2108	-0.2097	-0.2143

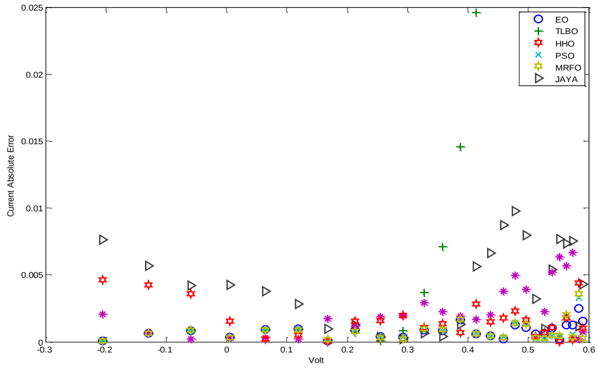

Figure 7. PV Output Current Absolute Error for EO and other algorithms

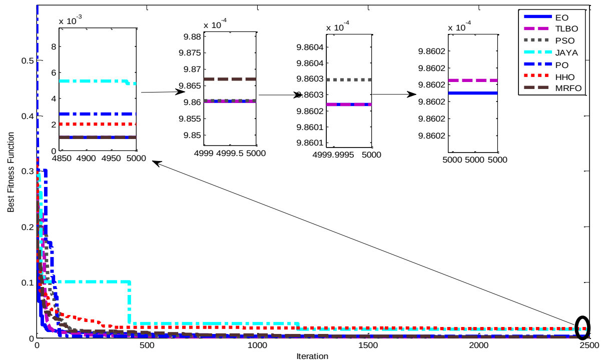

Figure 8. Fitness function for SD model

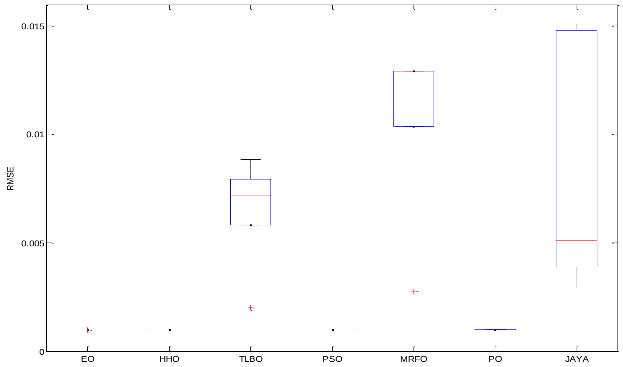

Figure 9 . Boxplot for RMSE values of different algorithms for SD model

TABLE 4 THE STATISTICAL RESULTS OF ALL ALGORITHMS

	Minimum	**Average**	**Maximum**	**STD**
EO	0.000986022	0.000986141	0.000986546	2.27567E-07
TLBO	0.00098602	0.00098602	0.00098602	3.89754E-12
HHO	0.0020053	0.006543327	0.0088269	0.002629385
PSO	0.00098602	0.00098603	0.00098604	5.99571E-09
PO	0.002780458	0.010876092	0.0129	0.004525597
MRFO	0.0009867	0.000996299	0.0010199	1.35517E-05
JAYA	0.0029177	0.0084053	0.015089	0.005976283

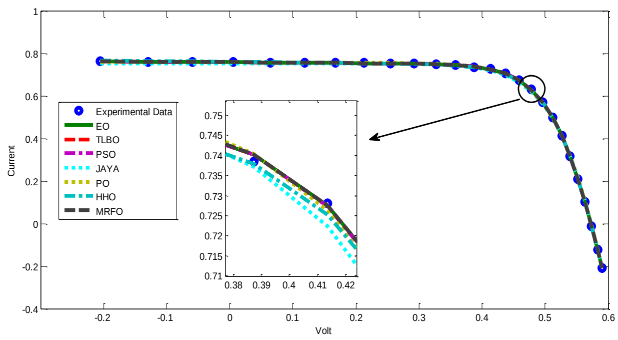

Figure 10 Current Vs volt characteristics for real system, EO and other algorithms

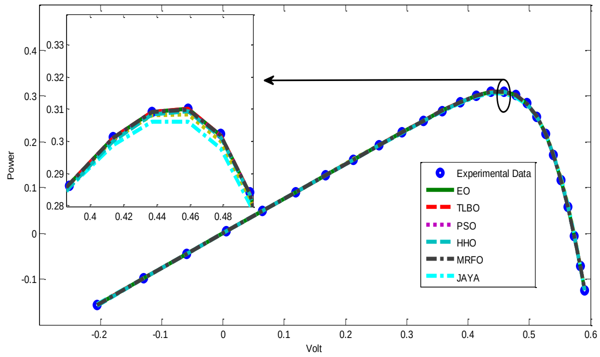

Figure 11 Power Vs volt characteristics for real system, EO and other algorithms

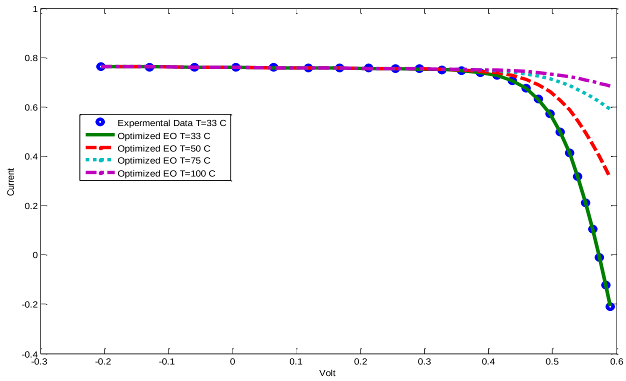

Figure 12. Current Vs Volt characteristics for real system and EO algorithm at different temperatures

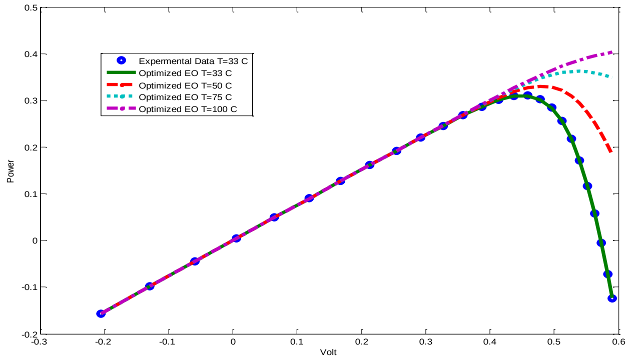

Figure 13. Power Vs volt characteristics for real system and EO algorithm at different temperatures

1. DD RESULTS

Based on the optimization problem of DD model equation 6, EO has been applied to estimate seven parameters of DD model. Table 5 presents the DD model estimated seven parameters for all compared algorithms. RMSE for each algorithm has been presented also in Table 5. Table 6 presents the real measurements for voltage and output current and the calculated output currents from the estimated parameters by each algorithm. Fig. 14 presents the convergence curves for EO and others algorithms. Table 7 represents the minimum, average, maximum and standard deviation (STD) values for 30 run statistical results. The RMSE values calculated in each run are figured in boxplot for each algorithm as shown in Fig. 15. (+) represents the outliers. Fig. 16 presents the absolute error between real output current and the output current calculated from the parameter estimated from each algorithm. From Fig. 14 ,15 and 16, EO algorithm results are more accurate than others. For more comparison Current Vs volt and Power Vs volt characteristics curves for real system for EO and other algorithms have been discussed in Fig. 17 and 18 respectively. The accuracy of the SD model developed by EO algorithm has been tested through the Current Vs volt and Power Vs volt characteristics curves at different temperatures, Fig. 19 and 20 respectively.

TABLE 5 ESTIMATED PARAMETER IN CASE OF DD OBTAINED BY DIFFERENT OPTIMIZATION ALGORITHMS

	EO	**TLBO**	**HHO**	**PSO**	**PO**	**MRFO**	**JAYA**
R_s (Ω)	0.036476624	0.036377169	0.039305	0.036377	0.039055293	0.036371149	0.033811339
R_{sh}(Ω)	54.2828582	53.71752132	64.21864	53.71978	67.64321612	54.25275385	25000
I_{ph}(A)	0.760783425	0.760775574	0.760812	0.760774	0.760780079	0.760752044	0.757922525
Id_1(A)	2.88E-07	3.23E-07	1.88E-06	3.23E-07	3.63E-06	3.28E-07	6.80E-07
Id_2(A)	2.64E-07	2.10E-14	9.31E-09	4.71E-13	2.79E-08	1.00E-10	0
η_1	1.467337453	1.476892351	1.809901	1.476893	1.99893977	1.479130558	1.554919177
η_2	1.99996513	1.558689891	1.222267	1.679222	1.286171318	1.223207247	1
RMS	0.000984107	0.00098602	0.001109	0.00098602	0.001100709	0.000986441	0.002459632

TABLE 6 THE REAL AND OUTPUT CURRENT FOR PROPOSED AND ORIGINAL ALGORISM

V real	I real	EO	TLBO	HHO	PSO	PO	MRFO	JAYA
-0.2057	0.764	0.7641	0.7641	0.7635	0.7641	0.7612	0.7613	0.7579
-0.1291	0.762	0.7627	0.7627	0.7624	0.7627	0.7603	0.7601	0.7579
-0.0588	0.7605	0.7614	0.7614	0.7613	0.7614	0.7594	0.7590	0.7579
0.0057	0.7605	0.7602	0.7602	0.7603	0.7602	0.7585	0.7580	0.7579
0.0646	0.76	0.7591	0.7591	0.7593	0.7591	0.7577	0.7571	0.7579
0.1185	0.759	0.7581	0.7580	0.7585	0.7580	0.7568	0.7562	0.7579
0.1678	0.757	0.7571	0.7571	0.7576	0.7571	0.7557	0.7551	0.7578
0.2132	0.757	0.7562	0.7561	0.7567	0.7561	0.7541	0.7537	0.7577
0.2545	0.7555	0.7551	0.7551	0.7556	0.7551	0.7515	0.7514	0.7573
0.2924	0.754	0.7537	0.7537	0.7540	0.7537	0.7470	0.7474	0.7564
0.3269	0.7505	0.7514	0.7514	0.7515	0.7514	0.7394	0.7401	0.7544
0.3585	0.7465	0.7473	0.7474	0.7471	0.7474	0.7265	0.7274	0.7503
0.3873	0.7385	0.7401	0.7401	0.7395	0.7401	0.7062	0.7070	0.7426
0.4137	0.728	0.7274	0.7274	0.7265	0.7274	0.6748	0.6753	0.7291
0.4373	0.7065	0.7070	0.7070	0.7061	0.7070	0.6308	0.6308	0.7077
0.4590	0.6755	0.6754	0.6753	0.6748	0.6753	0.5725	0.5720	0.6749
0.4784	0.632	0.6309	0.6308	0.6308	0.6308	0.5004	0.4997	0.6296
0.4960	0.573	0.5722	0.5719	0.5724	0.5721	0.4143	0.4138	0.5704
0.5119	0.499	0.5000	0.4996	0.5004	0.4998	0.3178	0.3177	0.4983
0.5265	0.413	0.4142	0.4137	0.4143	0.4139	0.2120	0.2124	0.4129
0.5398	0.3165	0.3182	0.3175	0.3179	0.3179	0.1017	0.1026	0.3176
0.5521	0.212	0.2130	0.2122	0.2120	0.2127	-0.0091	-0.0084	0.2130
0.5633	0.1035	0.1033	0.1023	0.1017	0.1029	-0.1256	-0.1251	0.1036
0.5736	-0.01	-0.0075	-0.0087	-0.0092	-0.0079	-0.2074	-0.2080	-0.0077
0.5833	-0.123	-0.1241	-0.1255	-0.1257	-0.1244	0.7612	0.7613	-0.1253
0.5900	-0.21	-0.2069	-0.2084	-0.2075	-0.2073	0.7603	0.7601	-0.2098

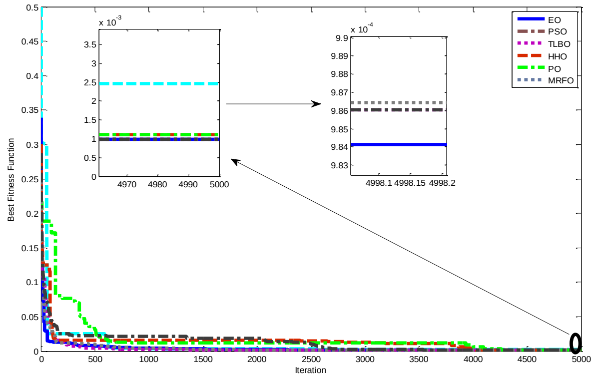

Figure 14. Fitness function for DD model for different optimization algorisms

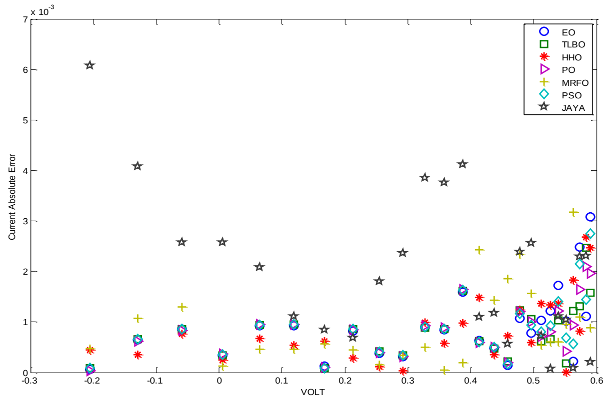

Figure 15. PV Output Current Absolute Error for EO and other algorithms

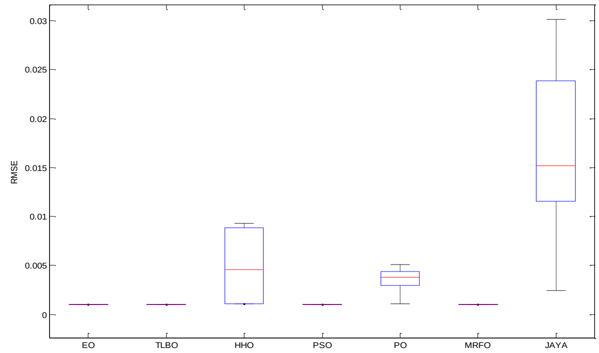

Figure 16. Boxplot for RMSE values of different algorithms for DD model

TABLE 7 THE STATISTICAL RESULTS OF ALL ALGORITHMS

	Minimum	**Average**	**Maximum**	**STD**
EO	0.0009841	0.00097494	0.00098602	1.30096E-06
TLBO	0.00098602	0.00099791	0.00102173	1.45777E-05
HHO	0.001109	0.0049636	0.0093	0.003956423
PSO	0.00098602	0.00099079	0.00099905	5.6331E-06
PO	0.00110071	0.00354014	0.0051	0.001480586
MRFO	0.00098644	0.00099014	0.00099735	4.50056E-06
JAYA	0.00245963	0.01683193	0.0301	0.010184928

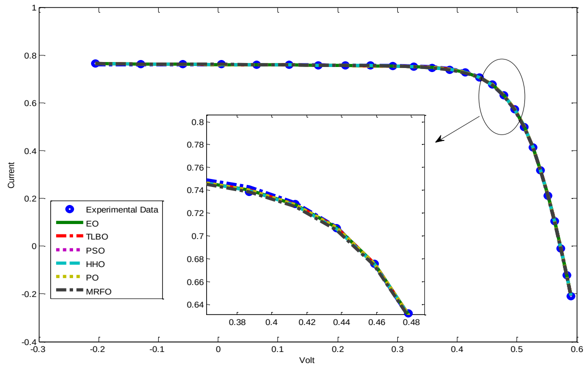

Figure 17. Current Vs volt characteristics for real system, EO and other algorithms

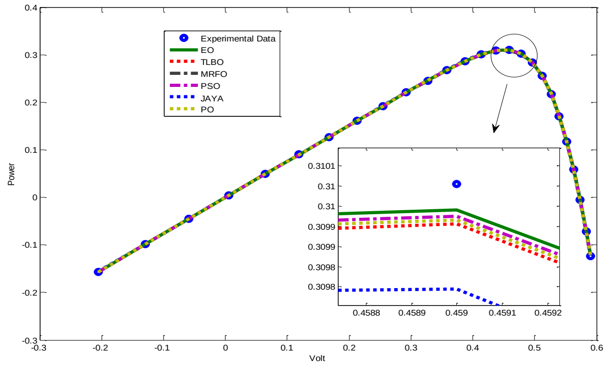

Figure 18. Power Vs volt characteristics for real system, EO and other algorithms

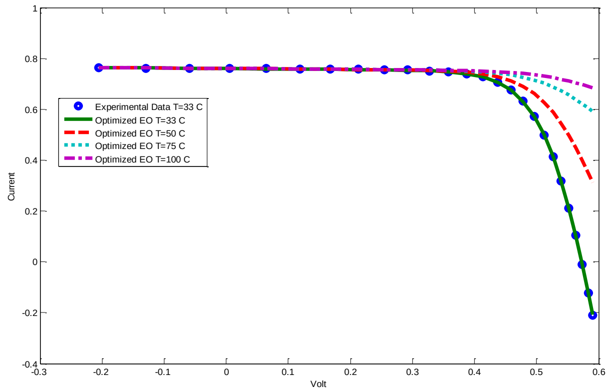

Figure 19. Current Vs Volt characteristics for real system and EO algorithm at different temperatures

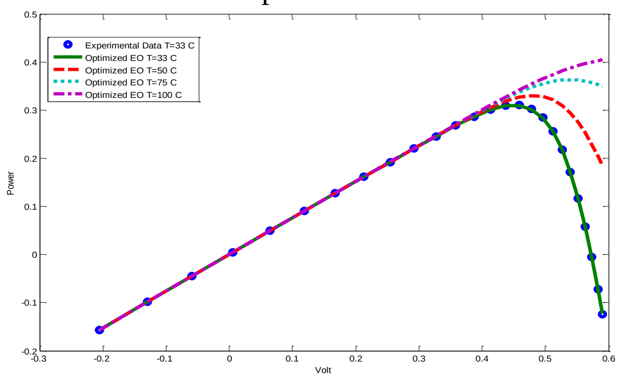

Figure 20. Power Vs volt characteristics for real system and EO algorithm at different temperatures

B. Application 2

In this application, according to the optimization problem for TD model described in equation 9, EO is applied to estimate nine parameters for TD PV model. The real data considered in this application are the data measured from a polycrystalline PV panel STM6-120/36 [34]. The panel has open circuit voltage V_{oc}=19.21, and Short circuit current I_{sc}=7.48A. The measured data from the panel at temperature 55C are listed in Table 8. Also the calculated output current from the estimated parameter for TD model by EO are presented in Table 8. The estimated parameters and RMSE for EO and other compared algorithms are listed in Table 9. Fig. 21 presents the convergence curves for all algorithms. The RMSE values calculated in each run in the statistical results are figured in boxplot for each algorithm as shown in Fig. 22, (+) represents the outliers. The statistical results for 30 run are presented in table 10. Fig. 23 presents the absolute error between real output current and the output current calculated from the parameter estimated from each algorithm. From Fig. 21 ,22 and 23, EO algorithm results are more accurate than others. For more comparison Current Vs volt and Power Vs volt characteristics curves for real system, EO and others algorithms have been discussed in Fig. 24 and 25 respectively. The accuracy of the DD model developed by EO algorithm is tested through the Current Vs volt and Power Vs volt characteristics curves at different temperatures, Fig. 26 and 27 respectively.

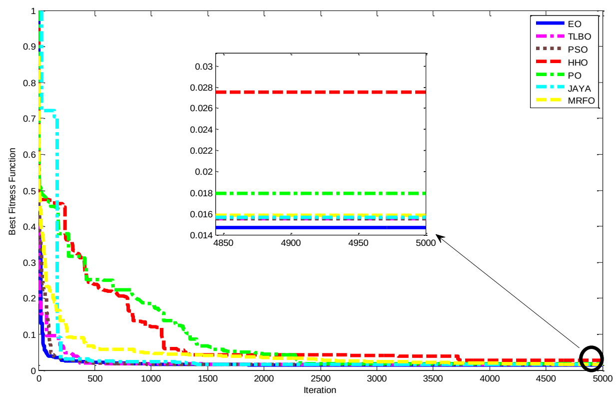

Figure 21. Fitness function of TD model for different optimization algorisms

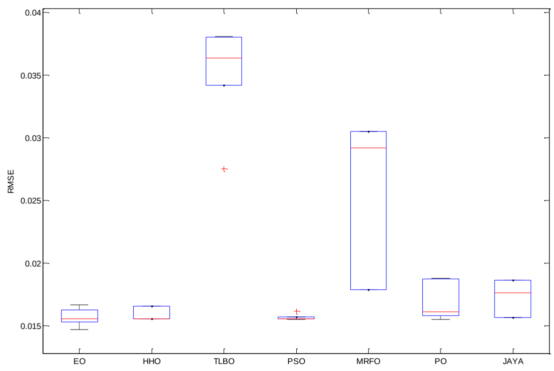

Figure 22 Boxplot for RMSE values of different algorithms for TD model

TABLE 8 THE REAL AND OUTPUT CURRENT FOR THE PROPOSED AND ORIGINAL ALGORISM

V_{real}	I_{real}	*EO*	*TLBO*	*HHO*	*PSO*	*PO*	*MRFO*	*JAYA*
17.65	3.83	3.8467	3.8455	3.7908	3.8553	3.8610	3.8371	3.8588
17.41	4.29	4.2695	4.2615	4.2615	4.2715	4.2634	4.2600	4.2725
17.25	4.56	4.5395	4.5290	4.5487	4.5386	4.5313	4.5301	4.5387
17.10	4.79	4.7807	4.7692	4.7988	4.7783	4.7745	4.7718	4.7780
16.90	5.07	5.0799	5.0691	5.1036	5.0775	5.0781	5.0727	5.0769
16.76	5.27	5.2650	5.2575	5.2953	5.2653	5.2625	5.2616	5.2646
16.34	5.75	5.7729	5.7701	5.7961	5.7760	5.7776	5.7733	5.7757
16.08	6.00	6.0369	6.0361	6.0510	6.0408	6.0445	6.0380	6.0409
15.71	6.36	6.3401	6.3427	6.3479	6.3463	6.3455	6.3434	6.3466
15.39	6.58	6.5647	6.5665	6.5597	6.5691	6.5711	6.5657	6.5698
14.93	6.83	6.8181	6.8180	6.7993	6.8195	6.8237	6.8156	6.8205
14.58	6.97	6.9655	6.9639	6.9402	6.9649	6.9694	6.9608	6.9658
14.17	7.10	7.0971	7.0943	7.0692	7.0949	7.0978	7.0909	7.0957
13.59	7.23	7.2263	7.2231	7.2013	7.2234	7.2225	7.2199	7.2237
13.16	7.29	7.2911	7.2881	7.2711	7.2884	7.2846	7.2854	7.2883
12.74	7.34	7.3361	7.3336	7.3223	7.3339	7.3278	7.3316	7.3334
12.36	7.37	7.3656	7.3638	7.3578	7.3640	7.3568	7.3623	7.3633
11.81	7.38	7.3951	7.3943	7.3957	7.3946	7.3871	7.3937	7.3934
11.17	7.41	7.4160	7.4162	7.4254	7.4165	7.4109	7.4167	7.4151
10.32	7.44	7.4312	7.4325	7.4501	7.4328	7.4325	7.4342	7.4311
9.74	7.42	7.4369	7.4389	7.4611	7.4391	7.4440	7.4413	7.4374
9.06	7.45	7.4409	7.4434	7.4701	7.4436	7.4554	7.4465	7.4418

TABLE 9 ESTIMATED PARAMETER IN CASE OF TD MODEL OBTAINED BY DIFFERENT OPTIMIZATION ALGORITHMS

	EO	**TLBO**	**HHO**	**PSO**	**PO**	**MRFO**	**JAYA**
Rs (Ω)	0.235737	0.19554965	0.098412	0.193106485	0.293852	0.18606	0.197331188
Rsh(Ω)	3000	1876.408397	294.5907	2999.999993	73.75618	1636.513	2000
Iph(A)	7.449466	7.454717079	7.514373	7.452881983	7.610416	7.463605	7.452639898
Id1(A)	5.22E-07	3.01E-12	2.01E-06	5.05E-08	1.01E-30	0.001967	1.00E-20
Id2(A)	1.23E-30	1.04E-06	4.56E-06	9.14E-07	6.01E-08	0.000291	9.72E-07
Id3(A)	1.00E-30	1.24E-12	4.43E-06	1.57E-07	1.04E-30	1.29E-06	1.00E-20
η 1	41.67721	49.9300779	50	43.41977256	42.93381	321.0831	50
η 2	50	43.09655968	50	43.24146306	37.23775	389.7796	42.9314594
η 3	9.730666	50	50	43.61075117	9.752726	43.63422	42.06287338
RMS	0.01470872643	0.015550871	0.027533	0.015519846	0.017895	0.015883	0.015626857

TABLE 10 THE STATISTICAL RESULTS OF ALL ALGORITHMS

	Minimum	Average	Maximum	STD
EO	0.01470873	0.01571738	0.01667917	0.000740527
TLBO	0.01555087	0.01595619	0.01656268	0.000553647
HHO	0.027533	0.0352866	0.0381	0.004412352
PSO	0.01551985	0.01565567	0.01614341	0.000272778
PO	0.017895	0.025198	0.0305	0.006687788
MRFO	0.015508	0.0170016	0.0188	0.001610594
JAYA	0.01562686	0.01722686	0.01862686	0.001516575

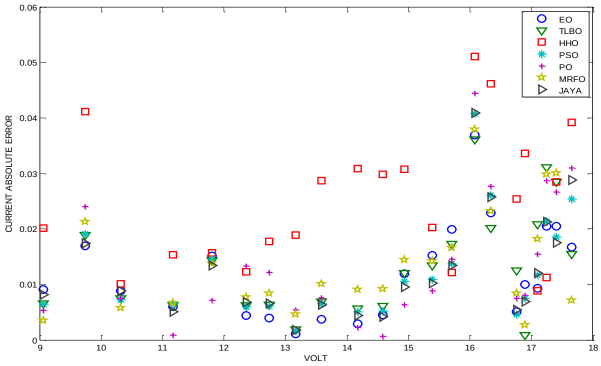

Figure 23. PV Output Current Absolute Error for EO and other algorithms

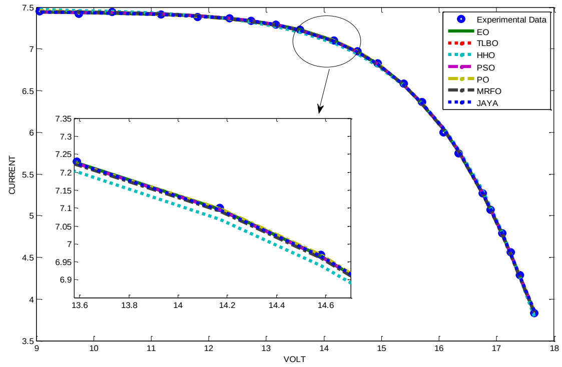

Figure 24 Current Vs volt characteristics for real system, EO and other algorithms

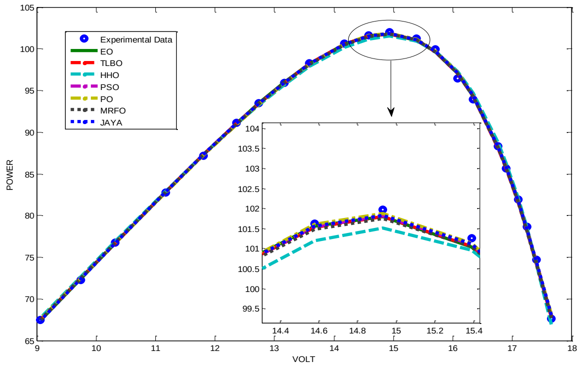

Figure 25 Power Vs volt characteristics for real system, EO and other algorithms

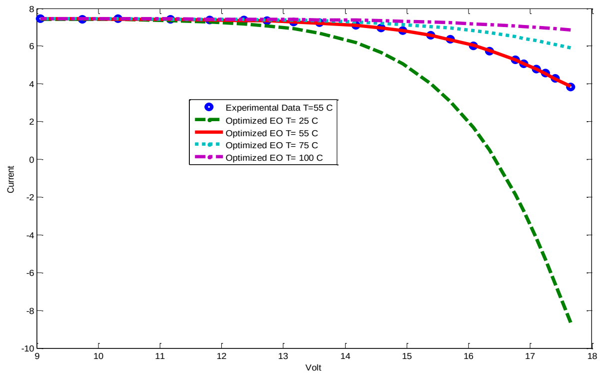

Figure 26 Current Vs Volt characteristics for real system and EO algorithm at different temperatures

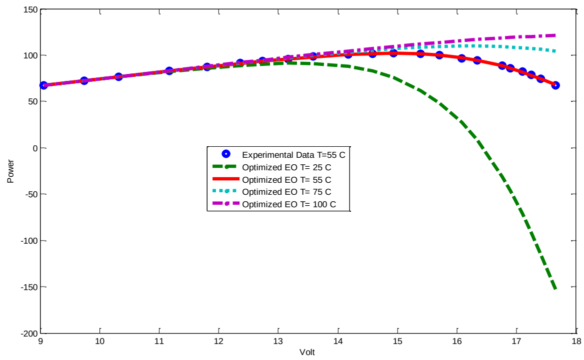

Figure 27 Power Vs volt characteristics for real system and EO algorithm at different temperatures

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CONCLUSION

In this paper, the most recent three PV models have been discussed (SD, DD and TD models), also an EO algorithm has been discussed and applied for solving the optimal parameter estimation of different PV models. The EO has been tested though parameter estimation of SD and DD PV models through real PV system. In addition, it has been applied for estimating the parameters for polycrystalline PV panels through TD PV model. The comparison between EO and other algorithms has been covered by comparing different evaluation parameters for example RMSE and absolute error. In all cases, the results obtained by EO are more accurate than those obtained by the other optimization algorithms.

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