International Journal of Power Electronics and Drive Systems (IJPEDS)
Vol. 13, No. 3, September 2022, pp. 1645~1653
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v13.i3.pp1645-1653 ❒ 1645

Ensemble of constraint handling techniques for PV parameter extraction using differential evolutionary algorithms

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Article Info

Article history:

Received May 31, 2022
Revised Jun 7, 2022
Accepted Jun 28, 2022

Keywords:

Double diode model
Ensemble of constraint
Handling techniques
Objective function
Parameter estimation
Root mean square error

ABSTRACT

The depletion of fossil fuels and rising environmental concerns have paved the way for the development of clean renewable energy sources. Photovoltaic (PV) cells are represented by electrical equivalent circuits. Finding the right circuit model parameters for PV cells is critical task. Estimating accurate parameters helps in better performance assessment, control, efficiency calculation and maximum power point tracking. This manuscript describes a new approach for obtaining PV system parameters using ensemble of constraint handling techniques (ECHT) with evolutionary algorithms (EA). Four distinguished technologies of solar PV cells are considered to estimate the parameters with best accuracy. Experiments reveal that ECHT outperforms each individual constraint handling approach by competing with state-of-the-art algorithms. The experimental data for these Kyocera cells is compared with estimated values obtained from the proposed algorithm using MATLAB 2021B for different irradiation. The performance plots show excellent match between the real and simulated values. The root mean square error (RMSE) values for research tax credit RTC France were found to be $7.325513 * 10^{-4}$ and Kyocera processing the normalize RMSE of 0.414%. On comparison with recent algorithms the proposed method achieves the lowest root mean square error (RMSE) meeting the main objective of proposed work.

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1. INTRODUCTION

Most industrial energy businesses are presently investing millions of dollars in renewable energy projects, and every increase in efficiency has tremendous economic and societal benefits right away. According to approved worldwide targets various sorts of renewable energy sources have increased considerably in the last five years and numerous extremely successful solutions have been offered in this respect [1]. It's worth emphasizing that water, biomass, wind, sun, and earth energy are the primary sources of renewable energy. Sustainable energy sources (SES) produce green energy with low environmental impact [2]. In addition to meeting power demand, switching to solar energy, especially photovoltaic (PV), offers many benefits such as modularity, minimal maintenance, environmental friendliness and quietness. However, its cell modeling is important for the design, simulation analysis, evaluation, and control of PV systems [3]. However, accurate modeling of PV cells is complicated by the non-linearity of PV, the presence of large unknown model parameters and the lack of proprietary methods. Determining their values has high priority since the number of related model parameters are directly related to the accuracy and efficiency of the model [4]. Solar energy is abundant and at the forefront, but its growth is hampered by factors such as partial shading, intermittent properties, high initial costs, and expensive storage requirements [5], [6]. Therefore, accurate modeling is essential and unavoidable to predict PV system performance prior to implementation [7]. The characteristics of PV modules are essential for the design, simulation analysis, evaluation, and control of PV systems. In addition, modeling helps to understand the operating principles and characteristics of photovoltaic systems under different atmospheric conditions [8]. However, limited by inherent lack of data availability, PV cell modeling approaches to date have applied analytical, iteration and metaheuristic methods to model PV module properties [9]. In this case, all methods aim to reconstruct the PV properties by identifying the missing unknown parameters as the mathematical procedure for "n" iterations is executed until the desired output is reached. It is important to know the arithmetic model of the PV module coupled to the power converter of the PV system [10]. Unfortunately, not all model parameters are available in the manufacturer's datasheet. The manufacturer's data sheet includes several parameters such as open circuit voltage (V_{oc}), ideality factor (n), short circuit current (I_{sc}), voltage and current at maximum power point (V_{mpp}), current at maximum (I_{mpp}), temperature coefficient of voltage (K_V). Current (K_I) at standardized test conditions (STC). STC refers to an irradiation of 1000 W/m^2 and a temperature of 25°C. Therefore, it is important to estimate unknown parameters in order to accurately model the PV system [11]. However, the selected procedure remains un-suitable for changing irradiation conditions. Besides, it's obvious that incorrect parameter identification can lead to incorrect results [12], [13].

Alternatively, numerical extraction techniques are used in accurate reproduction of a single point on the actual IV curve and thus all changes in irradiance and temperature conditions. During its popularity, the calculation is complicated because it consumes all the data points of the IV curve [14]. Therefore, many new optimization algorithms have been developed to generate better solutions for PV. Over the years there is an extensive intelligent optimization approach applied to extract the parameters of the PV model. Crow search algorithm [15], behavior search algorithm (BSA) [16], particle swarm optimization (PSO) [17], nonlinear search algorithm nonlinear least squares (NLS) [18], JAYA (JAYA) [19], cuckoo search (CS) [20], differential evolution (DE) [21], whale optimization algorithm (WOA) [22]. This paper offers a novel optimization technique based on this cutting-edge version to predict the electrical parameters of the PV module using the doubles-diode model representation. The suggested approach corresponds to the ensemble of constraint handling techniques ECHT, which has not been applied to this issue utilizing the PV data sheet before, with the key benefit that all the seven parameters of the double diode are computed with convergence time and accurate results in comparison with the recent algorithms. Furthermore, numerical findings show objective function values lower than others algorithms considering the same PV technology which are clearly better than the results published in [23]-[28]. The suggested technique also has the benefit of reaching the best solution in less than 2 seconds by assuring optimal solution. The rest of this paper is structured as follows. Section 2 explains the formulation of the parametric estimate issue in PV modules using the manufacturer's data sheet information. Section 3 provides a broad overview of the proposed ECHT. Section 4 illustrates the results of the test system along with computational validation elements.

2. ELECTRICAL EQUVIVALENT CIRCUIT MODEL OF PV CELL

In this manuscript, all the three diode models namely 1-diode and 2-diode are selected to model the PV cell. The most commonly used model is single and double diode model with five parameters, as shown in Figures 1(a) and 1(b). It has five and seven unknown parameters such as photogenic current (I_{ph}), saturation current (I_o), diode quality factor (a), series resistance (R_s) and shunt. Resistance (R_{sh}). Figure 1 shows their equivalent diagram. The double diode model accounts for two more parameters due to diffusion and recombination in the emitter and bulk regions of the PN junction namely (I_{o1} and I_{o2}) and ideality factor (a_1 and a_2) respectively. The load current of a PV cell is given by (1) [29]. This equation can be extended for all the models with variation in ‘i’ values ranging from 1 to 2 respectively.

$$I = I_{ph} - I_{d1} - I_{d2} - \left(\frac{V_{pv}+I_{pv}R_s}{R_{sh}}\right) \tag{1}$$

$$I_{pv} = I_{ph} - \sum_{i=1}^{2} I_{01}\left[exp\left(\frac{V_{pv}+I_{pv}R_s}{a_1V_t}\right) - 1\right] - \left(\frac{V_{pv}+I_{pv}R_s}{R_{sh}}\right) \tag{2}$$

The load current of a PV cell is given by in (1). This equation can be extended for other models with variation in ‘i’ values ranging from 1 to 2 respectively.

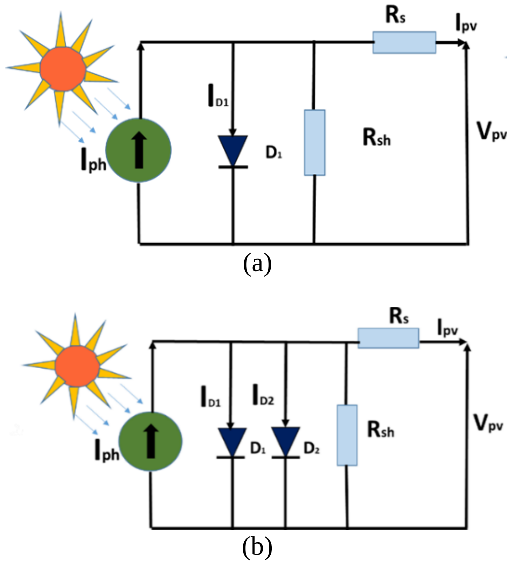

Figure 1. Equivalent circuit diagram of (a) single-diode model and (b) double-diode model

3. PROBLEM FORMULATION

3.1. ECHT Algorithm

Differential evolution (DE)-based constraint optimization issues have grabbed the interest of researchers due to the randomization of the starting population through asexual reproduction to create offspring. This strategy is more reliant on phenotypic behavioral evolution than genetic change. To investigate and use the whole search area, many kinds of DE are applied [30]. It is extremely difficult for a single constraint handling method to perform optimally for a particular task. This strategy is favored when each population has a distinct constraint management methodology for solving constrained based optimization issues. The generic formulation of objective function for DDM is given by of the optimization problem with constraints is provided in (3):

$$f\,(V_{pv}, I_{pv}, \phi) = I_{ph} - I_{01}\left[exp\left(\frac{V_{pv}+I_{pv}R_S}{a_1V_t}\right) - 1\right] - I_{02}\left[exp\left(\frac{V_{pv}+I_{pv}R_S}{a_2V_t}\right) - 1\right] - \left(\frac{V_{pv}+I_{pv}R_S}{R_{sh}}\right) \quad (3)$$

$$\emptyset = \{I_{ph}, I_{01}, I_{02}, R_{sh}, a_1, a_2, R_s\} \quad (4)$$

The general formulation of the optimization problem subjected to constraints are given in (5) and (6)

$$\text{Min/Max: } f(x),\ X = (x_1, x_2 \ldots\ldots x_n) \quad (5)$$

Constraints: $G_i\,(x) \leq 0$ i=1 m

$$Hi(x) = 0 \ j = m+1 \ldots\ldots, n \quad (6)$$

$$P_x = \frac{\sum_{1=1}^{W} K_i(G_i(\text{x}))}{\sum_{1=1}^{W} K_i} \quad (7)$$

Where 'V' is entire search space, m being the inequality constraint, (n-m) is the equality constraint and X ∈V. Here f should be bounded else it may not be continuous. Inequality constraints which satisfy $G_i(x) = 0$ is referred as active constraints because it achieves global optimum, converting equality to inequality and assembling with other inequality constraints.

4. FLOW CHART

The detailed flowchart of ECHT algorithm is depicted in Figure 2. This algorithm includes six steps as followed:

– Step 1: The population and parameters of various CHT are specified with n dimensions and people. The total number of generations is set to k=1 and the learning rate is set to P=10 for both the one and two diode

models, with upper and lower bounds (ub) and (lb) is a set of parameters chosen at random for each person in each population.
- Step 2: optimize the fitness function: Check the fitness function and constraints that violates the limits in every population using equation given in (5), (6) and (7).
- Step 3: Updation: Updating the population based on objective function evaluation is done and every offspring's generated in every iteration are saved. The mean of the values are calculated and η parameter for next generation is updated.
- Step 4: Select best Species: Offspring produced by each parent population are accessed and best parent produced offspring are chosen by mutation and crossover. These rates are chosen to be 0.9 and 0.7 respectively from literature.
- Step 5: Re-evaluation: Evaluate the objective function.
- Step 6: All the four different CH group population parents and their offspring are combined with their own offspring's and also with other population offspring's. Each individual that belongs to population1 randomly selects the new generated offspring' and competes to complete the process.

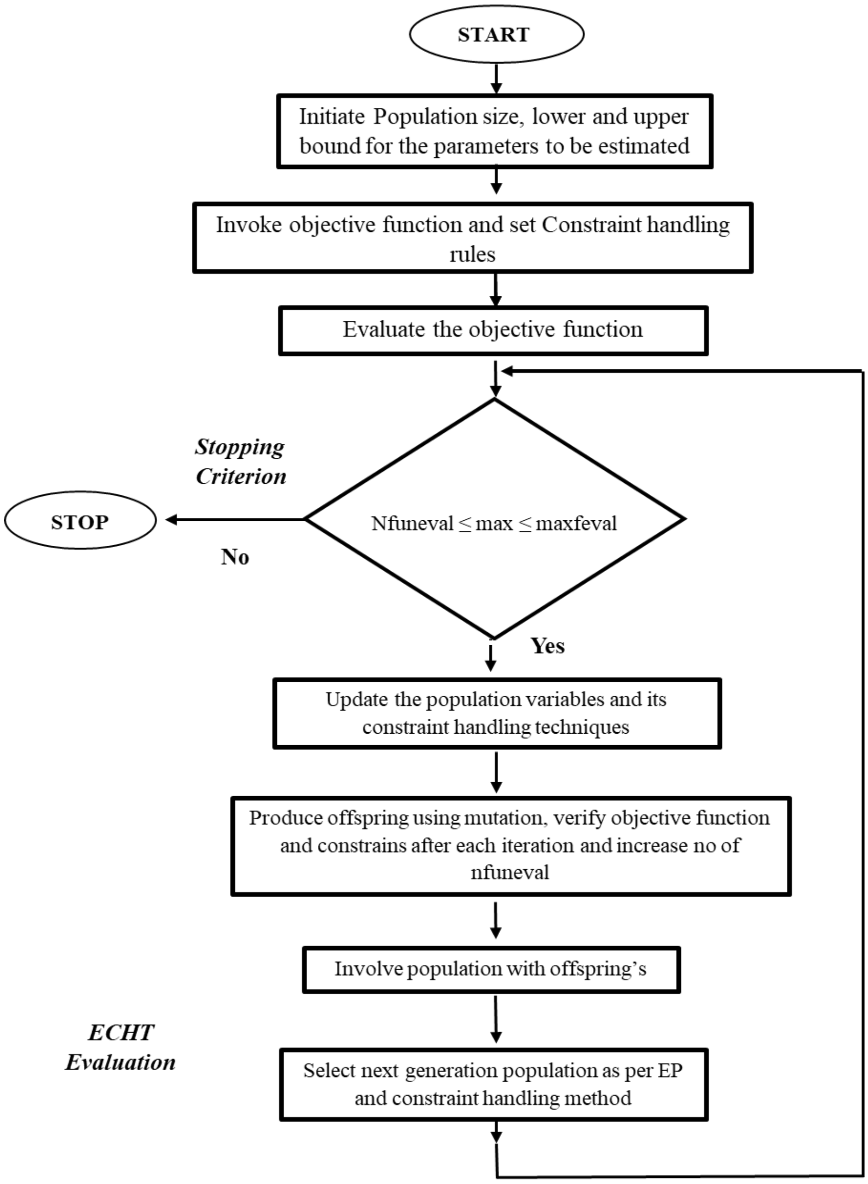

Figure 2. Flowchart representing ECHT algorithm

5. EXPERIMENTAL RESULTS

To test the reliability of estimated parameters real time data obtained from datasheet of RTC France model are considered at 1000 W/m^2 irradiance and 33°C temperature [31], [32]. The estimated and real values obtained from the data sheet are compared and the error is presented in Table 1. This table clearly depicts the comparison performance of proposed method with EVPS. The root mean square error RMSE value obtained by ECHTE is 7.325513*10^{-4} which is comparatively low. The plots obtained p-v and i-v cell are presented in Figure 3. Table 2 presents the data of estimated values of 2-diode model for three commercial PV cells. The RMSE for all the three cells are also considered to prove upper hand in estimated efficiency.

Table 1. The performance of ECHT in accurate estimation of model parameter

Parameter	*ECHT	EVPS
I_{ph} (A)	0.760813	0.7608118
R_{sh}(Ω)	58.37134	58.36465
I_{o1}(μA)	0.760	1.96
I_{o2}(μA)	0.086952	0.0776
a_1	1.37	1.36
a_2	1.99	1.95
R_s(Ω)	0.038	0.038
RMSE*10^{-4}	**7.325513**	7.340683

Table 2. Parameter estimated for three different PV cells using ECHT algorithm

Parameters	Shell SP140-PC	Kyocera, KS20T	Sun module, SW245
I_{ph} (A)	1.232	1.263	8.4901
I_{o1}(μA)	1.3858	4.252	0.035459
I_{o2}(μA)	1.3334	0.01	0.92614
R_S (mΩ)	440	90	5.8
R_P (Ω)	1148.6	1329.1	799.7526
a_1	1.9618	2.0264	4.171
a_2	1.3609	1.1656	1.518
NRMSE (%)	0.1264	0.414	0.040765

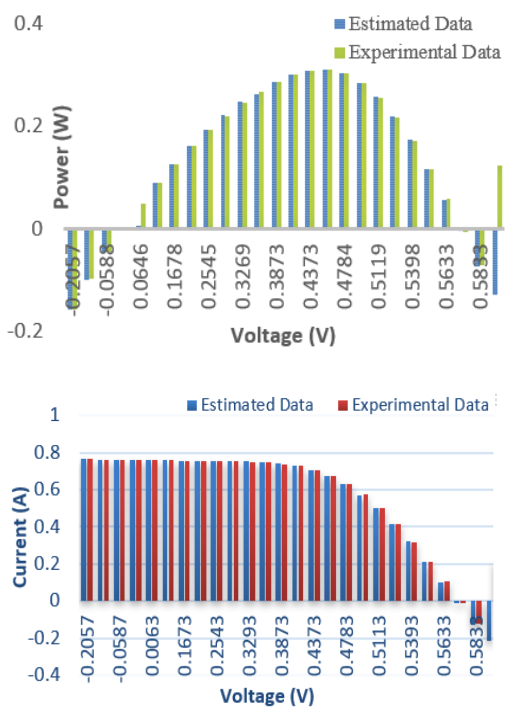

Figure 3. P-V and I-V plots for estimated and experimental values obtained using ECHT for RTC France cell at 1000 W/m^2 irradiance and 33 °C

Figure 4. Shows the variation of RMSE of RTC France cell with respect to various data points using EVPS algorithm. It is clearly evident from the plot that ECHT outperforms to yield better accuracy in comparison with EVPS. The detailed comparison with reference to the work done in the literature is tabulated in Table 3. The results obtained by ECHT shows greater precision in terms of extracted parameters which accounts for minimized error. RMSE analysis with various methods is presented in Figure 5. From the plot it is very clear that ECHT shows the best and HFAPS the least performance in terms of estimated error which is least 7.3255*10^{-4} among the different methods existing in the literature. The proposed optimum values are kept in bold.

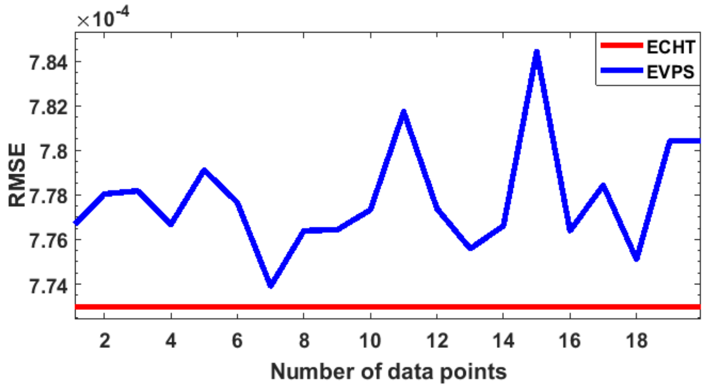

Figure 4. RMSE depicting the error in comparison with ECHT

Table 3. The performance comparison of ECHT with recent literature

Algorithm	I_{ph} (A)	I_{o1}(μA)	I_{o2}(μA)	a_1	a_2	R_s(Ω)	R_{sh}(Ω)	RMSE* 10^{-4}
ECHT	0.7608131	0.7608131	0.0869527	1.371206	1.999	0.0380	58.3713	7.3255
EVPS [23]	0.7607	0.29749	0.2504	0.0363	55.88	1.4749	1.9726	9.851
ImCSA [24]	0.760781	0.225966	0.747309	1.451543	2	0.0367	55.4826	9.8249
BHCS [25]	0.76078	0.74935	0.22597	2	1.451	0.0367	55.4854	9.8248
ITLBO [26]	0.7608	0.226	0.7493	1.451	2	0.0367	55.4854	9.8248
EO [27]	0.76792	0.39999	0.26605	0.03659	54.17	2	1.46451	9.8353
HFAPS [28]	0.760781	0.225974	0.749358	1.45101	2	0.0367	55.4855	9.8248

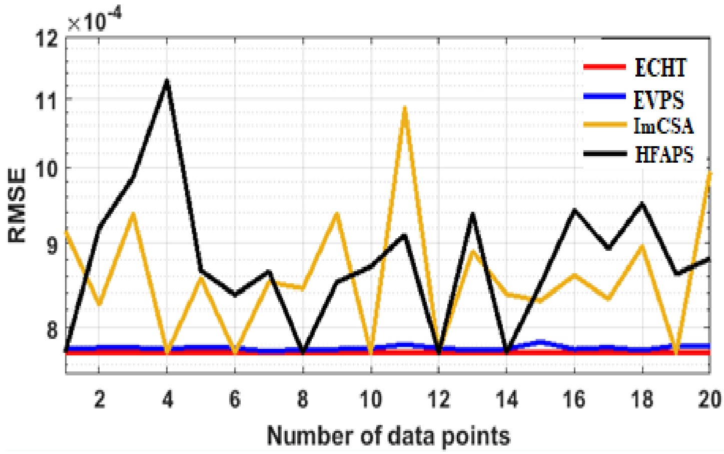

Figure 5. RMSE analysis of various methods in comparison with ECHT

To examine and validate the performance characteristics, seven variables (I_{ph}, I_{01}, I_{02}, R_s, R_{sh}, a_1 and a_2) of double-diode multi-crystalline Kyocera KS20T are computed and plotted as shown in Figure 5 and 6. The upper and lower bounds of the seven variables are defined as a_1 [0.5, 3], a_2 [0.5, 3], R_s [0.01, 3] **Ω**, I_{ph} [0, 10] A, I_{o1} [e^{-5}, $1e^{-15}$], I_{o2} [$1e^{-5}$, $1e^{-15]}$ A and R_{sh} [100, 3000] **Ω**. The parameters are extracted for four different irradiation condition and the plot of estimated and experimental values are obtained from MATLAB simulation. From the plot depicted in Figures 6 and 7. Represents effect of change in irradiation for Kyocera PV model. It is evident from the plots that the estimated and experimental values coincide at four different irradiations assuring the minimal deviation meeting the main objective of the proposed work.

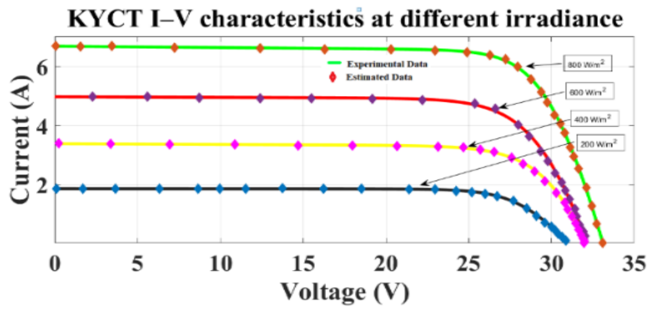

Figure 6. Effects of irradiation on i-v characteristics of Kyocera model

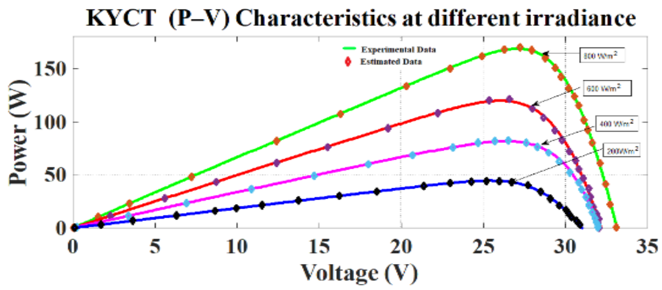

Figure 7. Effects of irradiation on p-v characteristics of Kyocera model

6. CONCLUSION

This paper aims in estimating the seven variables of double diode model adopting ECHT using differential evolutionary algorithm. Four commercial PV models shell SP140-PC, Kyocera (KS20T), SW245 and RTC France are tested on simulation and experimental values to evaluate the accuracy of the estimated parameters. The obtained results are compared with existing literature with different algorithms to prove the reliability in extracting results with good precision. The result shows the least RMSE, full filling the set objective functions with minimum iterations. Special case with change in irradiation is also performed on Kyocera model to obtain PV and IV performance plots to depict the closeness between experimental and estimated values. This work can be extended to analyze the impact of soiling and partial shading with the proposed algorithm. This work can eventually help the researchers to crate the virtual simulator tool which can predict the behavior and estimate the parameter with best accuracy.

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