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Research paper

Parameterization of Solar Cell Model Using Multiculture & Hybrid Mutation Based Evolutionary Programming

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Abstract

In this paper, parameterization of the single diode model for solar cell has presented. The problem of obtaining the optimal parameter has transformed as an optimization problem where individual absolute error has minimized by hybrid mutation strategy in the Evolutionary programming. Hybridization has given between Gaussian mutation strategy and Cauchy mutation strategy to obtain the better offspring. To increase the reliability of the solution, two stages based a multiculture architecture has proposed. On the first stage, a multi-population strategy has applied to form a multiculture environment, where each population evolved independently to explore the solution domain.This stage will prevent the solution to trap in the local minima. In the second stage, evolved population from first stage combine and members having high fitness are selected to form a new population of the same size as the individual population in the first stage. This second stage population evolved further to meet the final objective. The performance of the proposed method has evaluated over a 57mm diameter commercial solar cell. The obtained performance has compared with results available in current literature where various other approaches like, Levenberg–Marquardt with Simulated annealing, Global Grouping-based Harmony Search, Artificial Bee Swarm Optimization, Chaotic Particle Swarm Optimization, Differential Evolution, etc. have considered. The proposed solution has delivered the minimum error in comparison to other methods and very closer to the experimental data.

Keywords: *Solar cell, Single diode model; Evolutionary programming, Gaussian distribution; Cauchy distribution.*

1. Introduction

In the simulation of solar array, there is need to involve the model of solar cell which include the effect of exposed condition like, illumination and temperature. The performance of photovoltaic generator is sensitive towards the various factors, among them aging, weather conditions are dominant one. Hence, it is necessary to have the information of degradation in advance to reduce its effect over PV based power development. There were number of equivalent electric models have been presented in the past to capture the behavior of solar cells under illumination. The electric circuit containing single diode model and double diode model is most frequently used in the practice. In this paper, the single diode model has considered which used five intrinsic electric parameters to define the non-linear relationship between PV current and PV voltage. These five electric parameters are: series resistance, shunt resistance, photocurrent, saturation current and diode ideality factor. To have a better model of solar cell, it is required that these parameters should be more accurate as much as possible so that the model could be closer to practical experimental validation.

In this paper, we proposed for the parameter identification of the solar cell single diode model, using a variation of evolutionary programming which has used a multi-population strategy to maintain the diversity and hybrid mutation strategy for better exploration.The small jump in Gaussian distribution helps to explore local region in more details while longer tail in the Cauchy distribution includes the possibility of exploring the outer region of the landscape from the point of exploration. Among the two explorations the better one has selected as offspring and this process has delivered optimized and faster convergence.

In the past, there were number of researchers have given effort in the identification of single diode model parameters. Different types of methods like Genetic algorithm [1], Simulated annealing [2], Pattern search [3], Newton–Raphson based Nonlinear Minimization[4], Differential evolution[5], Chaos based particle swarm optimization [6], Artificial Bee optimization [7], Harmony search algorithm[8] and integration of Levenberg–Marquardt with Simulated annealing [9] etc. have shown the remarkable progress with time. In [11-12] behavior of single and double diode model has analyzed. Firefly algorithm has applied in [12] to predict the parameters. A Shockley's equation based solar cell I-V curve fitting has presented in [13].

The proposed method, which has a multiculture hybrid mutation in evolutionary programming (MHMEP) explored the real value landscapes in better manner, has shown the high accuracy to parameterize the single diode model of a commercial solar cell. The obtained value of parameters has shown lesser error from experimental data in compare to previously reported values in literature.

The rest of the paper is mainly organized as follows: Section 2 describes the solar cell modeling and introduced the minimized objective function. The section 3 presents the details ofEvolutionary programming while section 4 contains the proposed solution methodology MHMEP. The Section 5 presents the obtained re-

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sults and the related discussions, while the Section 6 gives a conclusion of the paper.

2. Problem Formulation

In order to illustrate the procedure of parameter estimation, the mathematical model of the solar cell/module and the objective function of the optimization process for parameter estimation are introduced in this section.

2.1. Solar Cell/Module Model

The mathematical expression between the current passing to the photovoltaic cell and the applied voltage can describe through the Schottky diffusion model in PN junction and defined by Eq.1. The appeared corresponding equivalent electric circuit has shown in Fig.1 as discussed in [10]. At a given temperature and illumination, absorbed photons from light converted in to photocurrent I_{ph} and a leakage current appeared at the PN junction. Because of defect in material and contacts, shunt resistance R_{sh} and series resistance R_s have appeared in the model. There are two intrinsic parameters available with the diode that is saturation current I_s and ideality factor n.

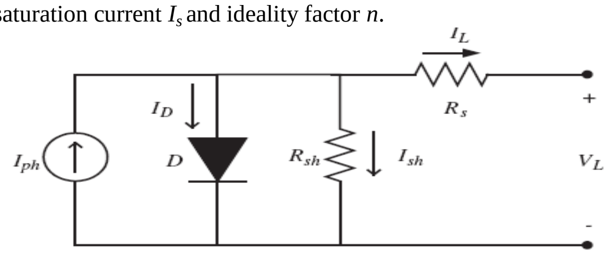

Fig.1: The single diode equivalent electrical model of solar cell.

$$I = I_{ph} - I_s\left[\exp\left(\frac{V_{PV} + R_S I_{PV}}{nV_{th}}\right) - 1\right] - \left(\frac{V_{PV} + R_S I_{PV}}{R_{sh}}\right) \quad (1)$$
$$= f\left(I_{PV}, V_{PV}, \theta\right)$$

Where

$$V_{th} = \frac{AT}{q} \quad (2)$$

Where, V_{th}: Thermal voltage, A: Boltzmann constant (1.3806503 x 10^{-23} J/K), q: Charge of the electron (1.6021764x 10^{-19} C), T: Temperature of the cell in Kelvin.

2.2. Parameter Identification Process as Optimization Model

In order to identify the intrinsic parameters $R_s, R_{sh}, I_{ph}, I_s, n$ from the $I_{PV}(V_{PV})$ characteristic, we have estimated the parameters value through the multipopulation based hybrid strategy in the evolutionary programming. The fitness criteria has considered as the sum of the individual absolute error (SIAE) which has given in Eq.3.

$$F = \sum_{i=1}^{N}\left|I_{PVmes\ i} - f\left(I_{PV}, P_{PV}, \theta\right)_i\right| \quad (3)$$

Where $I_{PVmes\ i}$ is the i^{th} measures value of *Ipv*, N: Number of the measurement points, $\theta = [R_s, R_{sh}, I_{ph}, I_s, n]$. The objective is to minimize the SIAE with having the optimal value of $R_s, R_{sh}, I_{ph}, I_s, n$.

3. Evolutionary programming

Evolutionary computation is a heuristic method to search thecontinuous space in a very efficient manner. The primaryoperators in the EP are mutation and selection. Mutation operator creates an offspring from a parent through the random perturbation by use of some kind of distribution function. In practice, mostly Gaussian distribution has applied and shown very efficient also. But the probability of generating a high value is vey less which may cause of slow exploration. To overcome this issue a wider distribution function, Cauchy distribution can be considered, but it may lose the fine exploration of local region as shown in Fig.2. In this paper a self adaptive strategy of the EP has applied to adjust the parameters of mutation strategy. There are two populations exist, one is solution population which contains the parameter's value and other population carries the analogous mutation strategy parameters which control the spreadness of considered distribution function. In another word each solution can be represented as a set pair of two vectors (x_i, σ_i) and $i \in \{1,2,\ldots n\}$ where x_i denotes the solution vector while σ_i denotes the strategy parameter vector and i define the problem dimension. Initial value of solution population has defined through uniform random distribution in the solution range while strategy parameter has taken as the same small constant value. The offspring generation through Gaussian mutation strategy and Cauchy mutation strategy has defined through the Eq.3 and Eq.4 correspondingly.

$$X_k' = X_k + \eta_k N_k(0,1) \quad (3)$$

$$X_k' = X_k + \eta_k \delta_k \quad (4)$$

Where, $N_k(0,1)$ is the random number generated for the k_{th} dimension for a solution through the Gaussian distribution having mean equal to 0 and standard deviation equal to 1. Similarly δ_k is a random number generated through the Cauchy distribution and defined through Eq.5.

$$\delta_k = \tan\left[\pi\left(U(0,1) - 0.5\right)\right] \quad (5)$$

Where, U(0,1) is the random number generated through uniform distribution in the range of [0 1]. The change for k^{th} dimension in strategy parameter is defined through Eq.6.

$$\sigma_k' = \sigma_k \exp(\tau' N(0,1) + \tau N_k(0,1)) \quad (6)$$

Where $\tau = [\sqrt{2\sqrt{n}}]^{-1}$ and $\tau' = [\sqrt{2n}]^{-1}$

The tournament selection operation has considered in this paper to extract the members from a previous generation parent population and offspring population. First a pool has created where parent population and offspring population placed and shuffling has done to make their position order random. For each member, *p*opponents have selected randomly through uniform distribution and fitness oriented comparison has made to decide the total tournament score. This has repeated for every member in the pool and at the end better scored members are selected for the next generation. Such process of tournament selection maintains the balance between pressure and opportunity.

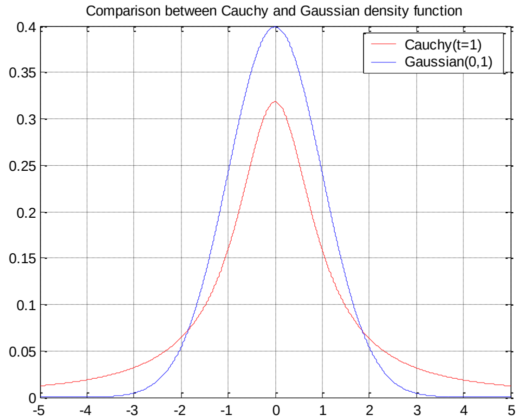

Fig.2: Cauchy and Gaussian density function

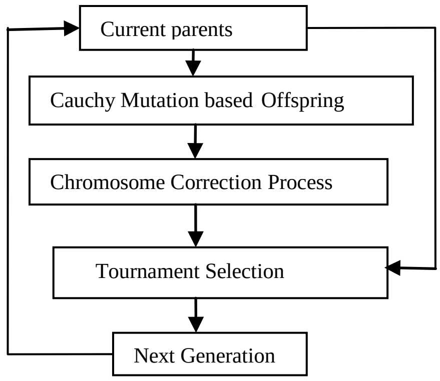

Fig.4: Cauchy mutation strategy based EP

4. Proposed Solution

We have applied the genotype representation of parameter values as a chromosome. The fitness function is a very important part of the evolutionary computation because evolution of solutions takes place with respect to the fitness judgment by the fitness function. Essentially description of fitness function is problem dependent and defined the objectives. In this paper total sum of individual absolute error (SIAE) has taken to define the fitness value. We have applied three variations of evolutionary programming to minimize the SIAE. (1) Evolutionary programming with Gaussian mutation (GsEP) (2) Evolutionary programming with Cauchy mutation (ChEP) (3) Multipoulation based Evolutionary programming with hybrid mutation (MHMEP). Functional block diagram for GsEP, ChEP and MHMEP algorithm have shown in Fig.3 to Fig .5. The detail flow of HMEP in evolving the population has shown in Fig.6

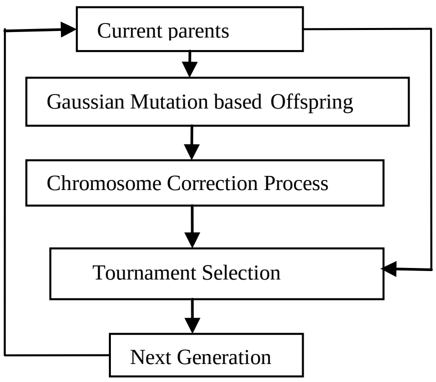

Fig.3: Gaussian mutation strategy based EP

5. Experimental Results

Experimental measurement reported in [4] at temperature of 33^0C and illumination of 1000 W/m^2 corresponding to a commercial solar cell (R.T.C.France), having silicon material and size of 57mm in diameter has considered in this paper to estimate the parameter's value. The parameter estimation process carried out by the EP algorithm has implemented and executed in Matlab environment. The EP process has executed with following process parameters: population size:100, solution range: [0 5], initialization of σ: [0.01], allowed no. of iterations:500, number of opponents in the selection process:10.

In MHMEP, for 1st stage 10 different populations of the same size have evolved independently till 100 iterations while in 2nd stage the newly formed population has evolved up to 100 iterations. The comparative SIAE minimization performance with generation between Gaussian mutation and Cauchy mutation based evolutionary programming has shown in Fig7. The obtained value of SIAE was 0.0451 and 0.0459 for Cauchy and Gaussian based mutation strategy correspondingly.The parameter's evolution using GsEP with generation has also shown in Fig8. Minimization of SIAE using MHMEP on the first stage has shown in Fig.9, while for 2nd stage performance curve has shown in Fig10. It is clear from the Fig.9 that for all the 10 different population there is a nearly similar convergence characteristic. The obtained final value of parameters has shown in Table1.The obtained value of IAE for all the 26 data samples has shown in Table 2. In Table 3, obtained values of parameters from different methods proposed in literature along with obtaining the value of SIAE have shown. It is clear that in compare to all the MHMEP has delivered the much lower value of SIAE. The details comparative obtained value for different sample data has shown in Table 4.

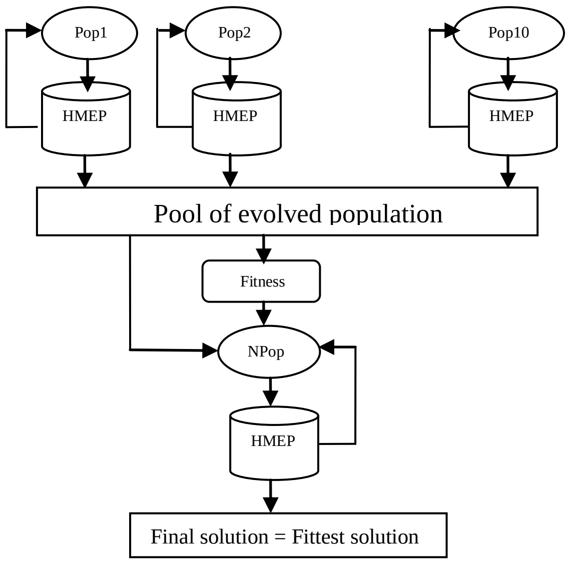

Fig.5: Multipopulation strategy in MHMEP

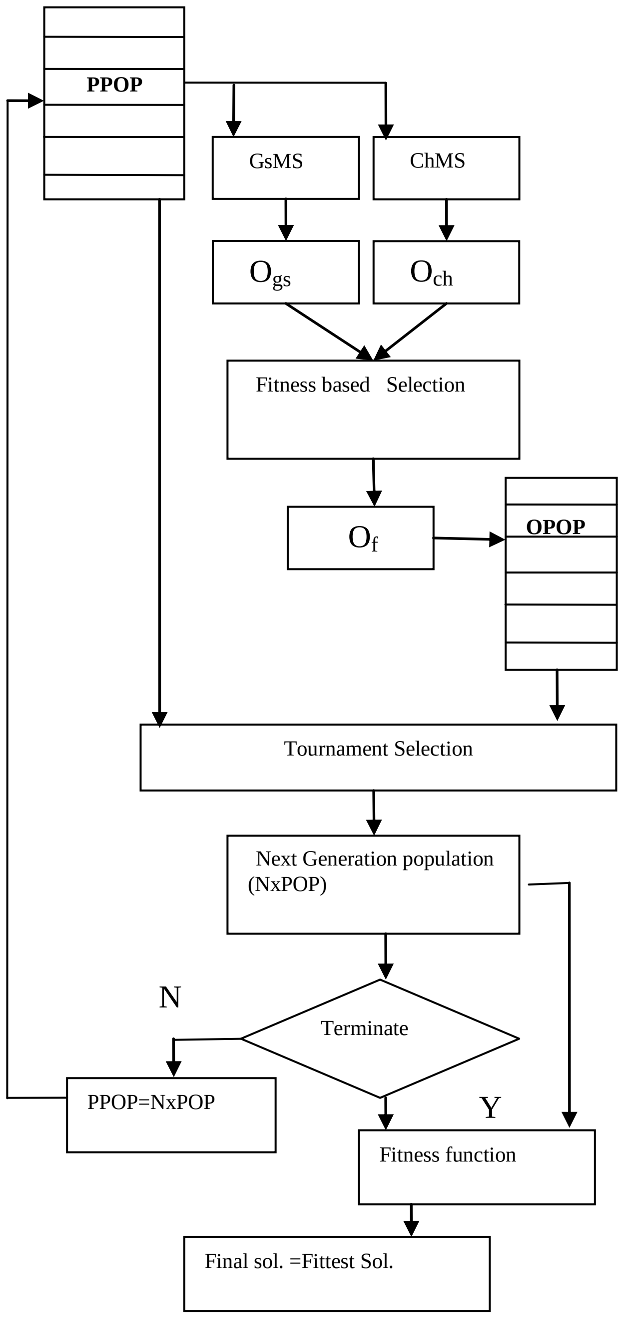

Fig.6: Functional block diagram of HMEP

Table1: Obtained parameter value using MHMEP

	Parameter	Estimated value
1	I_{ph}	0.76086982136046
2	I_s	0.38020037902964
3	R_s	0.03571507984118
4	R_p	57.31817612328356
5	n	1.49840920900993

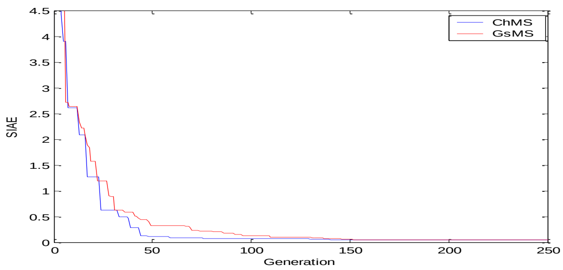

Fig.7: Comparative convergence between Cauchy mutation based EP and Gaussian mutation based EP

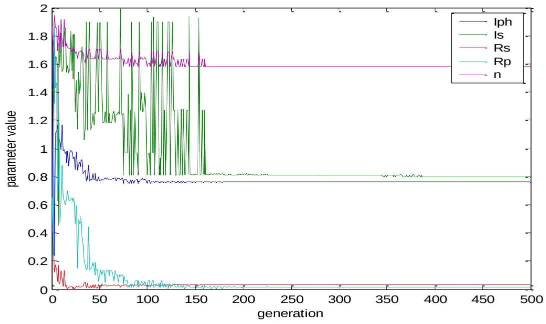

Fig.8: Parameter convergence in GsMS

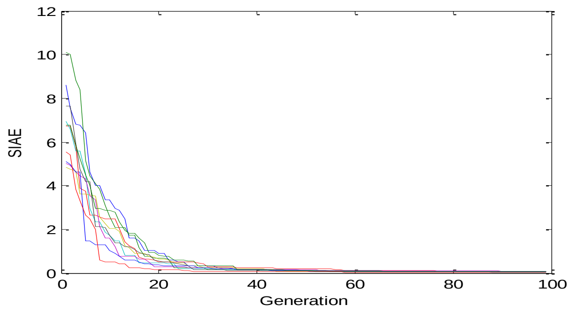

Fig.9: Convergence in 1st stage of MHMEP

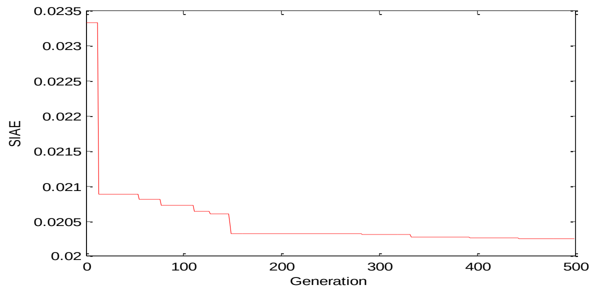

Fig.10: Convergence in 2nd stage of MHMEP

Table2: Computed parameters and IAE using MHMEP

Data	V_{PV} (V)	I_{PV} Measure	I_{PV} Estimated	IAE
1	-0.2057	0.7640	0.76398288679775	0.00001711320225
2	-0.1291	0.7620	0.76264770849592	0.00064770849592
3	-0.0588	0.7605	0.76142201425342	0.00092201425342
4	0.0057	0.7605	0.76029601407417	0.00020398592583
5	0.0646	0.7600	0.75926572548535	0.00073427451465
6	0.1185	0.7590	0.75831470806089	0.00068529193911
7	0.1678	0.7570	0.75741832471296	0.00041832471296
8	0.2132	0.7570	0.75651274362245	0.00048725637755
9	0.2545	0.7555	0.75548731700620	0.00001268299380
10	0.2924	0.7540	0.75406894554730	0.00006894554730
11	0.3269	0.7505	0.75176321083070	0.00126321083070
12	0.3585	0.7465	0.74764120298587	0.00114120298587
13	0.3873	0.7385	0.74025779677223	0.00175779677223
14	0.4137	0.7280	0.72731654391000	0.00068345609000
15	0.4373	0.7065	0.70667252894648	0.00017252894648
16	0.4590	0.6755	0.67476071125007	0.00073928874993
17	0.4784	0.6320	0.63009836156984	0.00190163843016
18	0.4960	0.5730	0.57124108924946	0.00175891075054
19	0.5119	0.4990	0.49900216971234	0.00000216971234
20	0.5265	0.4130	0.41321090572129	0.00021090572129
21	0.5398	0.3165	0.31724525628842	0.00074525628842
22	0.5521	0.2120	0.21200133512578	0.00000133512578
23	0.5633	0.1035	0.10206701872193	0.00143298127807
24	0.5736	-0.0100	-0.00918086505581	0.00081913494419
25	0.5833	-0.1230	-0.12643343256892	0.00343343256892
26	0.5900	-0.2100	-0.20999902690555	0.00000097309445
			SIAE	0.02026182025217

Table3: Results obtained by MHMEP and other methods for single diode mode

	I_{ph}	I_s	R_s	R_p	n	SIAE
MHMEP	0.7609	0.3802	0.0357	57.3182	1.4984	**0.0206**
GA[1]	0.7619	0.8087	0.0299	42.3729	1.5751	0.3135
SA[2]	0.7620	0.4798	0.0345	43.1034	1.5172	0.3343
PS[3]	0.7617	0.9980	0.0313	64.1026	1.6000	0.2798
Newt[4]	0.7608	0.3223	0.0364	53.7634	1.4837	0.1102
DE[5]	0.7608	0.3230	0.0364	53.7185	1.4806	0.0767
CPSO[6]	0.7607	0.4000	0.0354	59.012	1.5033	0.0281
ABSO[7]	0.7608	0.3062	0.0366	52.2903	1.4758	0.0223
GGHS[8]	0.7609	0.3262	0.0363	53.0647	1.4822	0.0221
LMSA[9]	0.7607	0.3184	0.0364	53.3264	1.4797	0.0215

6. Conclusion

The parameter estimation for modeling the solar cell using single diode model has done in this paper. To obtain the optimum parameters value, Evolutionary programming which contain the hybrid model of mutation strategy between Gaussian mutation and Cauchy mutation strategy has presented. The Gaussian model helps to explore through the small change while Cauchy mutation strategy provided the longer change exploration. Among the two explored the better has selected as offspring. Multipopulation concept provides the facility of reliability and helps in maintaining the diversity. The observed value of total individual absolute error was 0.0206 which is lesser in comparison to other reported values in literature. In the future, better parameters for single as well as a double diode model can achieve by exploring the possibilities under natural computing domain. Focus needed over maintaining the balance between exploration and exploitation. The application, like space craft, where the variation in operating condition occurs up to extreme range, needs a very efficient automated tool to update the solar cell parameters according to the change in the environment conditions.

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