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Parameter Extraction of PV Solar Cell: A Comparative Assessment Using Newton Raphson, Simulated Annealing and Particle Swarm Optimization

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Abstract
Proper modelling of PV cell is important to calculate its unknown parameters close to the accurate values, to attain the *I-V* characteristic curve close to the hardware model. This can help for simulation, computing efficiency, maximum power point tracing design, optimization and regulation of PV system. This paper estimates single diode PV model parameters such as photocurrent, the saturation current, the series resistance, the shunt resistance and the ideality factor. The estimation is done by three different optimization methods for single-diode model in an attempt to judge which method is surpassing in terms of convergence time and relative error. The first method Newton-Raphson is a numerical method based on gradient descent approach, while the second and third methods are evolutionary methods, simulated annealing and particle swarm optimization respectively. It was observed that particle swarm optimization algorithm is best among the methods and simulated annealing showed the worse performance.

Keywords- PV Cell, Simulated Annealing, Newton Raphson, Particle Swarm Optimization, Single-Diode Model.

1. Introduction

Rising pollution due to conventional sources of energy has alarmed the need for fast contribution of environmental friendly sources of energy. Due to the booming prices of oil and fossil fuels, and their non-abundance characteristics governments of all the countries are focusing on the renewable sources to produce energy. Among different renewable sources the most potential renewable source that is presently being used around the globe for meeting increasing necessity of electric energy is solar photovoltaic (PV) system (El-Naggar et al., 2012). In 2017 America's community solar market will exceed 400MW and by 2019 it is expected that 500 megawatts of community solar projects will be installed each year in the states across the country (Hunt, 2015). With Tamil Nadu at the top of the list leading the output potential, followed by Rajasthan and Gujarat, India has generated 9GW solar power as on December 31, 2016. Solar power depends upon the availability of land, cost of financing, irradiance, thus it differs from state to state and country to country. Solar panel installation can be done on the roofs, therefore building with large area of roof can be installed with PV panel, also the PV panel can be installed in a fashion (inclined) that in minimum place maximum panels can be installed. Modeling of solar cell requires its electrical equivalent circuit. There are other ways also by with modeling of solar cell can be done but they are complex and the best way until now is to have the equivalent circuit of the PV cell (Awadallah and Venkatesh, 2015). The thing to be considered while choosing the model is its simplicity and accuracy.

The estimation of the unknown parameters of a PV model is associated as "PV cell parameter assessment challenge". The characteristic equation of PV cell is non-linear and it becomes challenging to calculate the unknown variables from the non-linear equation. For long time researchers are estimating the parameters using different analytical, numerical, evolutionary based approaches. PV cell parameter can be determined on the bases of analysis of its *I-V* characteristic, taking some assumptions this approach comes under analytical approach. Tivanov et al. (2005) proposed a simple analytical method. In this method an algorithm is proposed to calculate the four unknown parameters (i.e. diode coefficient, reverse current density, series and parallel resistance) from its current–voltage characteristics. It is assumed that photocurrent and short-circuit current are equal to each other, following which four equations are derived from *I-V* characteristic equations. Furthermore, these four equations are deducted to equations which directly determine the unknown parameters. Ortiz Conde et al. (2016) proposed the Co-content function CC, using the Lambert W function and the Co-content function CC, the *I-V* characteristic equation of single-diode was obtained and CC function was used to determine the five unknown parameters of single-diode model. Chan et al. (1986) proposed analytical five-point method. Analytical method is quick, simple, needs a single iteration and provides convincingly results, however, these methods are by some means found unsuitable because the PV models are located in the continuously changing climate, the calculation for different irradiance and temperature becomes hectic.

Another popular approach is numerical approach. These are basically iterative techniques. Silva et al. (2016) proposed two methods MAEP and RMSD and compared the result with Xiao et al. (2004) Method, Comprehensive approach (Villalva et al., 2009). Nonlinear Least Square (NLS) Method (Nayak et al. 2013), parameterization approach (Mahmoud et al., 2013). Lun et al. (2013), used pade's approximants method to linearize the nonlinear *I-V* characteristic. Ghani and Duke (2011), proposed Lambert W-function to calculate series and shunt resistance assuming that the diode constant value is known. It was experimentally examined that by assuming diode constant to unity, a difference in the experimental value and the model output is coming. To solve this issue the diode constant was also calculated by Ghani et al. (2013), in later study. The most common numerical approach used to solve non-linear equation in most of the literature (Quaschning & Hanitsch, 1996; Enebish et al., 1993) was Newton-Raphson approach. Appelbaum and Peled (2014), compared three parameter estimation methods Newton-Raphson method, Levenberg–Marquardt algorithm, and Genetic-Algorithm. It remains questionable which technique is best in terms of accuracy however the error obtained by the NRM was less compared to the other two. Thus it was concluded in this paper that NRM is favorable over other two methods in term of low error although it is less convenient in terms of convergence.

Emerging approach for parameter extraction inspired by biological activity known as evolutionary technique were used to overcome the difficulty and complexity of analytical and numerical method. There are many reviews on these methods i.e. genetic algorithm (GA) (Dizqah et al., 2014), simulated annealing (SA) (El-Naggar et al., 2012), particle swarm optimization (Soon and Low, 2012), chaos particle swarm algorithm (Wei et al., 2011). Ishaque et al. (2011) estimated the parameter of two-diode model using three evolutionary algorithms, Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE). DE was concluded the best among all other methods, PSO also give better result when number of iteration is increased in comparison of GA. Ishaque and Salam (2011) proposed differential evolution algorithm, which was found superior in case of continuous irradiance and temperature variations. Askarzadeh and Dos Santos Coelho (2015), proposed the bird mating optimizer approach. This technique was compared with chaos particle swarm optimization (CPSO), genetic algorithm (GA), pattern search (PS), simulated annealing (SA), artificial bee swarm optimization algorithm (ABSO), harmony search-based algorithms (HS), grouping-based global harmony search (GGHS) and innovative global harmony search (IGHS). Siddiqui and Abido (2013), has compared different evolutionary algorithms. First they did a comparison between the standard EA, such as, genetic algorithm, differential evolution and particle swarm optimization. The best result in this case was also differential evolution and the worst was by genetic algorithm as discussed by Ishaque and Salam (2011). Secondly they compared three hybrid evolutionary algorithms, but there results were poorer then standard evolutionary algorithm. PSO can give better results by increasing its iteration. Ma et al. (2013) compared cuckoo search with CPSO, GA, PS for single-diode model. Cuckoo search algorithm has the lowest RMSE value compared to other algorithms but it successfully extracted the parameter of single-diode model and Improved Single Diode Model under various operating condition (De Soto et al., 2006).

2. Single Diode Model

To calculate the unknown parameters of a PV cell it is required to have an equivalent circuit or model of a PV cell. There are many models of PV cell available in literature (Almonacid et al, 2009; Almonacid et al, 2010). Although there are many equivalent circuits for PV cell, to keep it accurate and simple we have chosen to work on single-diode model having series and parallel resistance. The single diode model with series and shunt resistance is given in figure 1.

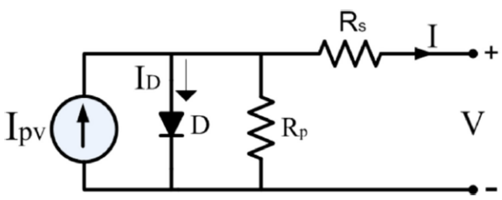

Figure 1. Single diode model (with series and shunt resistance) of a PV cell.

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The *I-V* characteristic equation of the model is given by equation (1).

$$I = I_{Ph} - I_o \left[\exp\left(\frac{(V + R_S I)}{V_T} \right) - 1 \right] - \frac{V - R_S I}{R_P} \tag{1}$$

The above model has five unknowns I_{PV}, I_0, V_T, R_S and R_{sh} which have to be estimated. Where I_{PV} is the photovoltaic current, flowing in the circuit due to irradiance, therefore, PV cell is a current source because it does not depend upon the load attached to the PV cell. I_0 is the saturation current, V_T is thermal voltage, R_S and R_{sh} are the series and shunt resistance respectively. To estimate the five unknowns of single-diode model, five equations are derived from the circuit in figure 1. The equations are given below.

$$f_1 = I_{SC} - I_{Ph} + I_o \left(e^{\frac{I_{SC} R_S}{V_T}} - 1 \right) + \frac{I_{SC} R_S}{R_P} \tag{2}$$

$$f_2 = I_{Ph} - I_o \left(e^{\frac{V_{OC}}{V_T}} - 1 \right) - \frac{V_{OC}}{R_P} \tag{3}$$

$$f_3 = I_{mp} - I_{Ph} + I_o \left(e^{\frac{(V_{mp} + I_{mp} R_S)}{V_T}} - 1 \right) + \frac{(V_{mp} + I_{mp} R_S)}{R_P} \tag{4}$$

$$f_4 = I_{mp} - (V_{mp} - I_{mp} R_S) \left(\frac{I_o}{V_T} \left(e^{\frac{(V_{mp} + I_{mp} R_S)}{V_T}} \right) + \frac{1}{R_P} \right) \tag{5}$$

$$f_5 = \frac{R_S}{R_P} - \frac{I_o}{V_T} \left(e^{\frac{I_{SC} R_S}{V_T}} \right) (R_P - R_S) \tag{6}$$

Where I_{SC} is the short circuit current, V_{oc} is the open circuit voltage, V_{MP} is voltage at maximum power, I_{MP} is current at maximum power. These details are provided with the PV cell during purchase. In the next section the different methods to estimate five unknown parameters have been discussed. All the methods use the equation (2), (3), (4), (5), (6).

3. Parameter Estimation Techniques

This section is divided into three sub-sections where each subsection explains the existing technique. First subsection is based on numerical approach while the last two subsections use evolutionary approach.

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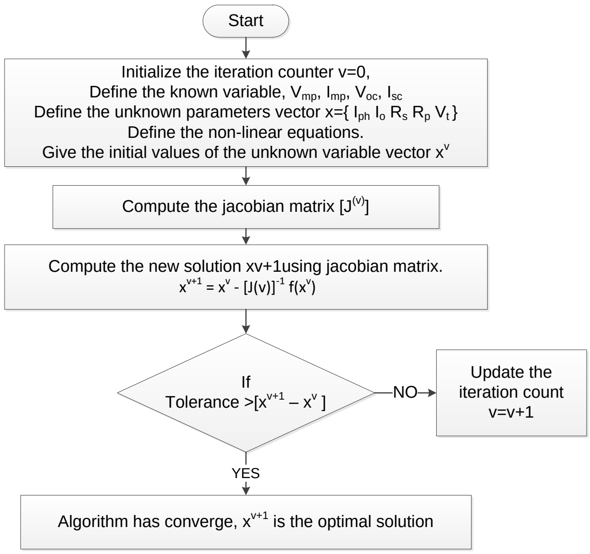

Figure 2. Flow chart of newton-raphson method

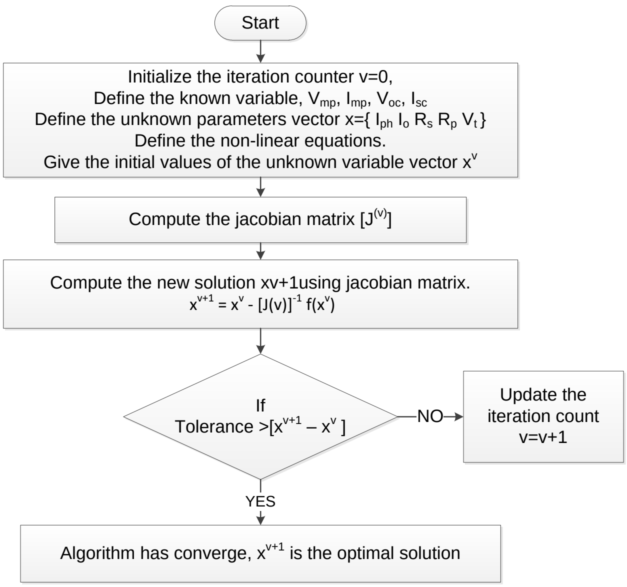

Figure 3. Flow chart ff pso algorithm

3.1 Newton-Raphson Method

Newton-Raphson is a classic gradient-based, optimization method. The flow chart of Newton-Raphson method is given in figure 2.

3.2 Particle Swarm Optimization

Particle swarm optimization is an intelligent optimization algorithm. It belongs to a class of optimization algorithm called metaheuristic optimization algorithm. In 1995, Eberhart and Kennedy, (1995) developed an optimization technique PSO, which is based on the social behavior of swarms such as school of fish, birds etc. The flow chart of PSO is given in figure 3.

3.3 Simulated Annealing

Simulated annealing is motivated by the physical procedure of annealing of metal involving heating and cooling to reduce the defects in its structure using minimum energy. The application was first introduced in optimization problem by Kirkpatrick et al. (1983). The major drawback of Newton Raphson and other gradient based methods is that they get trapped into local minima. Simulated annealing overcomes this problem. The flow chart for simulated annealing is shown in figure 4.

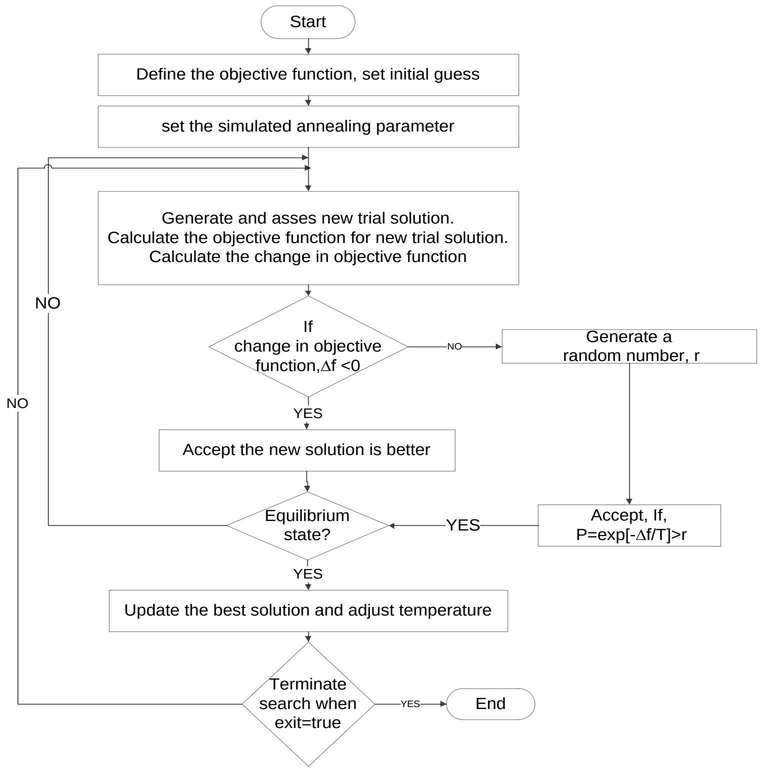

Figure 4. Flow chart of simulated annealing.

4. Results and Discussion

Parameter of PV module KC200GT is estimated using NR, PSO and SA. The information of the module in the datasheet is given in the Table 1. Table 2 shows the value of extracted parameters using Newton Raphson, while table 3 gives the value of unknown parameters obtained using PSO, SA. The lower and upper limit is the same in the case of PSO and SA. While for NR the initial guess is different. The *I-V* graph obtained from the different technique for the same module is shown in figure 5. The *P-V* graph obtained from the different technique for the same module is shown in figure 6.

Table 1. PV module KC200GT manufacturer's data sheet

At STC :Irradiance 100W/m^2, module temperature 25˚C	
Maximum power	200(+10% / -5%)W
V_{mpp}	26.3 V
I_{MPP}	7.61A
I_{SC}	8.21A
V_{OC}	32.9V
Number of cells in series	54

Table 2. Extracted parameters using NR

Parameters	Initial guess	Estimated value
I_{PV} (A)	8	8.2119
I_0 (A)	1E-7	1.7017E-7
R_S (Ω)	0.2	0.2172
R_{sh} (Ω)	1000	951.927
V_T	1.5	1.8606

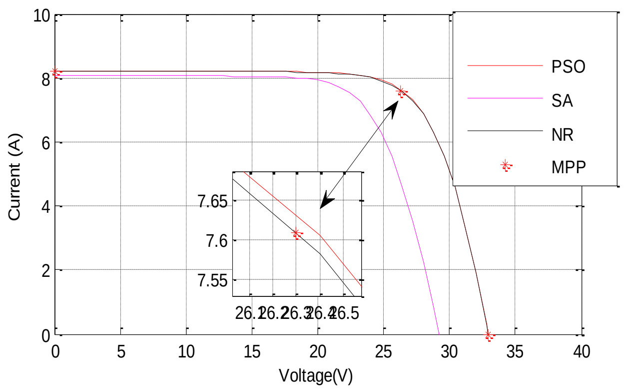

Figure 5. I-V Curve of PV module KC200GT

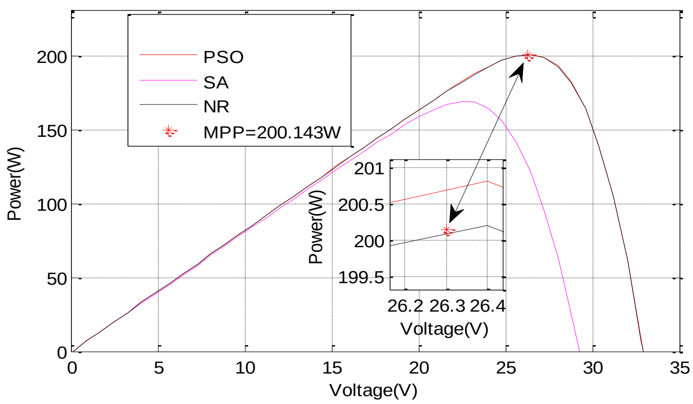

Figure 6. P-V Curve of PV module KC200GT

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Table 3. Extracted parameter using PSO and SA.

Parameters	Lower limit	Upper limit	Estimated Value(PSO)	Estimated Value(SA)
I_{PV} (A)	8	9	8.2123	8.0982
I_0 (A)	1e-6	10e-10	9.9003e-8	5.3907e-8
R_S (Ω)	0.1	0.5	0.2304	0.3322
R_{sh} (Ω)	50	2000	1159.8	371.85
V_T	0.1	2	1.8062	1.555

Table 4. Error in the power of hardware and experimental

parameter Estimation technique	MAXIMUM POWER		$\alpha = \left\lvert \frac{P_{MAX} - P_{obtained}}{P_{MAX}} \right\rvert \times 100$ Relative power error
	P_{MAX} (w)	$P_{OBTAINED}$ (w)	
Newton-Raphson	200.143	199.93	**0.0415**
PSO		200.06	0.2683
SA		168.8	

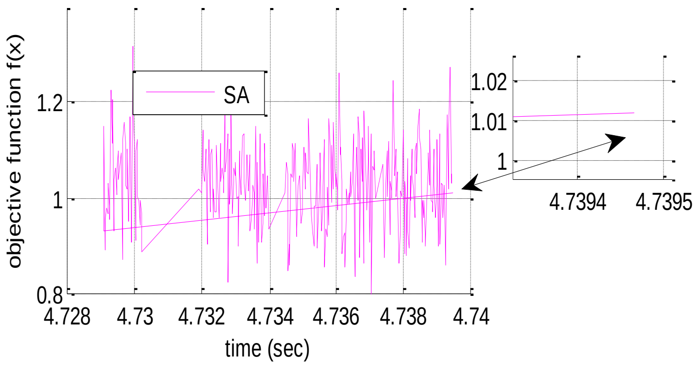

Figure 7(a). Simulated annealing convergence graph

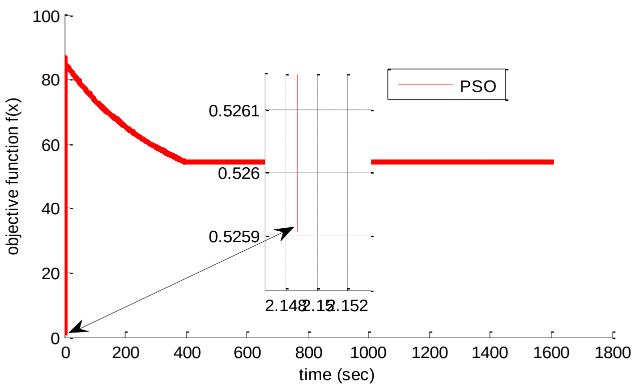

Figure 7(b). PSO convergence graph

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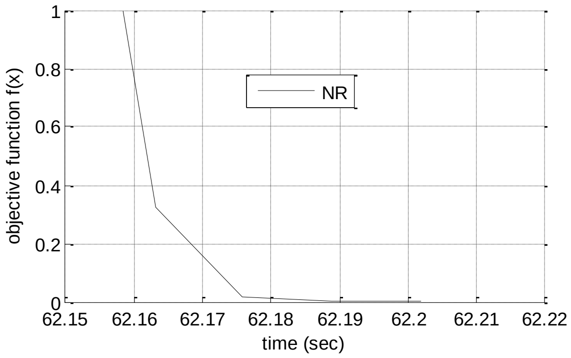

Figure 7(c). SA convergence graph

The three load points are indicated in the graph by red dots; the first red dot indicates the short circuit point at which voltage is zero (0, I_{SC}), the second dot indicates the open circuit voltage where current is zero, and it lies on (V_{OC}, 0) axis, the third point is MPP where the value of voltage and current obtained is maximum, and it lies on the axis (V_{max}, I_{max}). The three dots are the hardware data. The *I-V* and *P-V* graph should cross these points because we want to estimate parameters such that the *I-V* and *P-V* graphs are accurately fitting on the hardware data.

The result obtained from the simulated annealing shows the poor *I-V* and *P-V* graph. The NR and PSO gives head to head result but on analyzing the graph closely NR seems to be best. To further compare the techniques the error between the maximum power and the power obtained by the techniques is calculated. Table 4 shows the relative power error. The error for Newton-Raphson is less compare to PSO and SA. The comparison on the bases of convergence time is also given. The convergence graph for each method is given in figure 7.
Table 5 contains all the detail of convergence time, number of iteration and the objective function obtained by all the three methods. Here the objective function is the summation of all the five equations and the objective is to minimize it. It is observed that PSO takes longer time compared to other methods to converge to the solution but the solution obtained by PSO is better than SA.

Table 5. Different parameter respective to technique

Parameters	NR	PSO	SA
Objective function f(x)	≈0	0.5259	1.0135
Convergence time (sec)	62.18	1400	4.7
Number of iteration	100	50,000	300

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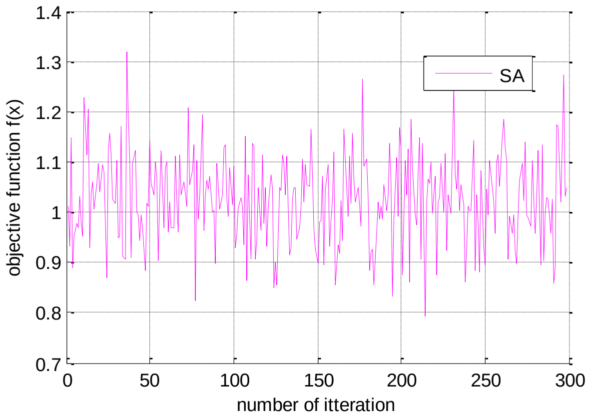

Figure 8(a). Number of iteration vs. objective function for SA

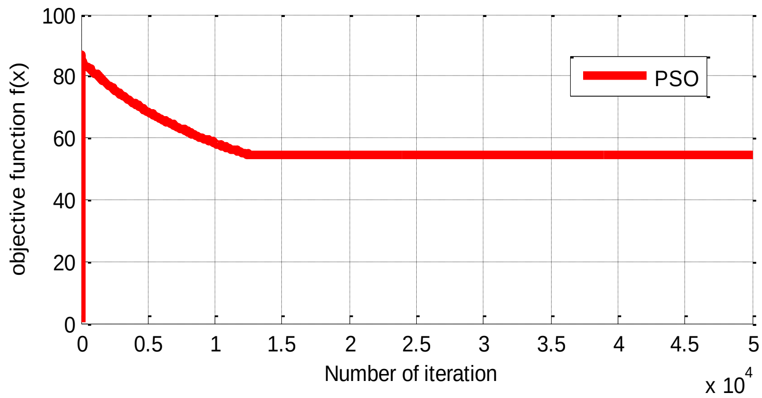

Figure 8(b). Number of iteration vs. objective function for PSO

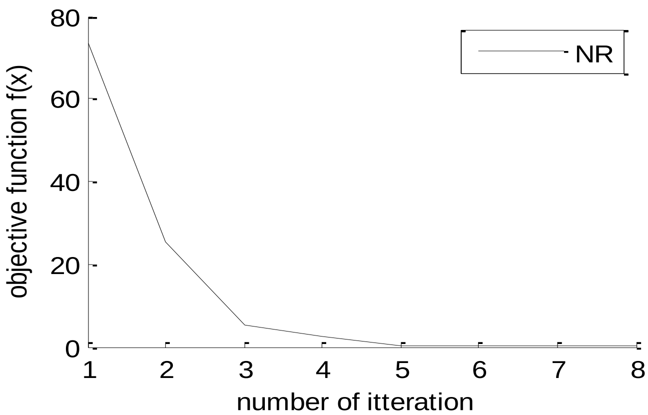

Figure 8(c). Number of iteration vs. objective function for NR

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The graph for number of iteration vs. objective function for the three methods is shown in figure 8. Figure 8 shows that minimum objective function is achieved by NR with less number of iteration, where as PSO also minimizes the objective function close to NR, but the number of iteration is greater in number.

Although NR has shown a better performance compared to the other two but there is a major drawback with NR. In Newton-Raphson method the solution will not converge till the initial guess is very close to the solution and it is very difficult to guess all the five unknown values very closely. Table 3 shows that the upper limit and the lower limit for all the unknowns in PSO is widely spaced, so even though PSO take much time the guess work needed is minimal.

5. Conclusion

Estimate PV model parameters such as photocurrent, the saturation current, the series resistance, the shunt resistance and the ideality factor is carried out by three different optimization methods for a PV module KC200GT using single-diode equivalent circuit. The three methods are compared in terms of characteristic curve, their convergence speed and relative power error. The first method Newton-Raphson is a numerical method based on gradient descent approach, while the second and the third methods are evolutionary method, simulated annealing and particle swarm optimization respectively. NR has shown better results, but it is not appropriate in this case because the number of unknown variables is greater in number. Overall PSO gives satisfactory result and over perform Newton-Raphson as its upper and lower limit is of wide range. SA performed the worst among the three methods.

References

Almonacid, F. J. M. F., Rus, C., Hontoria, L., & Muñoz, F. J. (2010). Characterisation of PV CIS module by artificial neural networks. A comparative study with other methods. Renewable Energy, 35(5), 973-980.

Almonacid, F., Rus, C., Hontoria, L., Fuentes, M., & Nofuentes, G. (2009). Characterisation of Si-crystalline PV modules by artificial neural networks. Renewable Energy, 34(4), 941-949.

Appelbaum, J., & Peled, A. (2014). Parameters extraction of solar cells–A comparative examination of three methods. Solar Energy Materials and Solar Cells, 122, 164-173.

Askarzadeh, A., & dos Santos Coelho, L. (2015). Determination of photovoltaic modules parameters at different operating conditions using a novel bird mating optimizer approach. Energy Conversion and Management, 89, 608-614.

Awadallah, M. A., & Venkatesh, B. (2015, March). Estimation of PV module parameters from datasheet information using optimization techniques. In Industrial Technology (ICIT), 2015 IEEE International Conference on (pp. 2777-2782). IEEE.

Chan, D. S. H., Phillips, J. R., & Phang, J. C. H. (1986). A comparative study of extraction methods for solar cell model parameters. Solid-State Electronics, 29(3), 329-337.

De Soto, W., Klein, S. A., & Beckman, W. A. (2006). Improvement and validation of a model for photovoltaic array performance. Solar Energy, 80(1), 78-88.

Dizqah, A. M., Maheri, A., & Busawon, K. (2014). An accurate method for the PV model identification based on a genetic algorithm and the interior-point method. Renewable Energy, 72, 212-222.

Eberhart, R., & Kennedy, J. (1995, October). A new optimizer using particle swarm theory. In Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on (pp. 39-43). IEEE.

El-Naggar, K. M., AlRashidi, M. R., AlHajri, M. F., & Al-Othman, A. K. (2012). Simulated annealing algorithm for photovoltaic parameters identification. Solar Energy, 86(1), 266-274.

Enebish, N., Agchbayar, D., Dorjkhand, S., Baatar, D., & Ylemj, I. (1993). Numerical analysis of solar cell current-voltage characteristics. Solar Energy Materials and Solar Cells, 29(3), 201-208.

Ghani, F., & Duke, M. (2011). Numerical determination of parasitic resistances of a solar cell using the Lambert W-function. Solar Energy, 85(9), 2386-2394.

Ghani, F., Duke, M., & Carson, J. (2013). Numerical calculation of series and shunt resistances and diode quality factor of a photovoltaic cell using the Lambert W-function. Solar Energy, 91, 422-431.

Hunt, T. (2015). The solar singularity is nigh. Greentech Media. Retrieved, 29.

Ishaque, K., & Salam, Z. (2011). An improved modeling method to determine the model parameters of photovoltaic (PV) modules using differential evolution (DE). Solar Energy, 85(9), 2349-2359.

Ishaque, K., Salam, Z., Taheri, H., & Shamsudin, A. (2011). A critical evaluation of EA computational methods for Photovoltaic cell parameter extraction based on two diode model. Solar Energy, 85(9), 1768-1779.

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. Science, 220(4598), 671-680.

Lun, S. X., Du, C. J., Yang, G. H., Wang, S., Guo, T. T., Sang, J. S., & Li, J. P. (2013). An explicit approximate I–V characteristic model of a solar cell based on padé approximants. Solar Energy, 92, 147-159.

Ma, J., Ting, T. O., Man, K. L., Zhang, N., Guan, S. U., & Wong, P. W. (2013). Parameter estimation of photovoltaic models via cuckoo search. Journal of Applied Mathematics, 2013.

Mahmoud, Y. A., Xiao, W., & Zeineldin, H. H. (2013). A parameterization approach for enhancing PV model accuracy. IEEE Transactions on Industrial Electronics, 60(12), 5708-5716.

Nayak, B. K., Mohapatra, A., & Mohanty, K. B. (2013, December). Parameters estimation of photovoltaic module using nonlinear least square algorithm: A comparative study. In India Conference (INDICON), 2013 Annual IEEE (pp. 1-6). IEEE.

Ortiz-Conde, A., Sánchez, F. J. G., & Muci, J. (2006). New method to extract the model parameters of solar cells from the explicit analytic solutions of their illuminated I–V characteristics. Solar Energy Materials and Solar Cells, 90(3), 352-361.

Quaschning, V., & Hanitsch, R. (1996). Numerical simulation of current-voltage characteristics of photovoltaic systems with shaded solar cells. Solar Energy, 56(6), 513-520.

Siddiqui, M. U., & Abido, M. (2013). Parameter estimation for five-and seven-parameter photovoltaic electrical models using evolutionary algorithms. Applied Soft Computing, 13(12), 4608-4621.

Silva, E. A., Bradaschia, F., Cavalcanti, M. C., & Nascimento, A. J. (2016). Parameter estimation method to improve the accuracy of photovoltaic electrical model. IEEE Journal of Photovoltaics, 6(1), 278-285.

Soon, J. J., & Low, K. S. (2012). Photovoltaic model identification using particle swarm optimization with inverse barrier constraint. IEEE Transactions on Power Electronics, 27(9), 3975-3983.

Tivanov, M., Patryn, A., Drozdov, N., Fedotov, A., & Mazanik, A. (2005). Determination of solar cell parameters from its current–voltage and spectral characteristics. Solar Energy Materials and Solar Cells, 87(1-4), 457-465.

Villalva, M. G., Gazoli, J. R., & Ruppert Filho, E. (2009). Comprehensive approach to modeling and simulation of photovoltaic arrays. IEEE Transactions on Power Electronics, 24(5), 1198-1208.

Wei, H., Cong, J., Lingyun, X., & Deyun, S. (2011, April). Extracting solar cell model parameters based on chaos particle swarm algorithm. In Electric Information and Control Engineering (ICEICE), 2011 International Conference on (pp. 398-402). IEEE.

Xiao, W., Dunford, W. G., & Capel, A. (2004, June). A novel modeling method for photovoltaic cells. In Power Electronics Specialists Conference, 2004. PESC 04. 2004 IEEE 35th Annual (Vol. 3, pp. 1950-1956). IEEE.

Ye, M., Wang, X., & Xu, Y. (2009). Parameter extraction of solar cells using particle swarm optimization. Journal of Applied Physics, 105(9), 094502.