Mostefai Mohamed [1], Miloudi Abdullah [1], Miloud Yahia [1]

Laboratoire Géométrie, Analyse, Contrôle Et Applications, University of Saida, Algeria (1)

doi:10.15199/48.2021.02.26

Parameters Estimation of Photovoltaic Module Using Grey Wolf Optimization Method

***Abstract**. Parameter prediction of a photovoltaic module is fundamental to simulate the photovoltaic generator for correctly reproduce the photovoltaic curves under natural environment. In this work, a new method for solar parameter estimation applying grey wolf algorithm is presented. This technic mimics the mechanism of the chase and the chain of command of wolves in wildlife. In the grey wolf optimizer algorithm four kinds of wolves are used for simulating the control hierarchy. This technique is tested on three different photovoltaic modules. The results showed the effectiveness and validity of the method to find with great precision the parameters of the three photovoltaic modules at various values of temperatures and illuminations.*

***Streszczenie**. Przedstawiono nową metodę określania parametrów ogniw fotowoltaicznych wykorzystującą algorytm Grey Wolf. Wykorzystano cter modele zaworów do symulacji. Algorytm przetestowano na różnych modułach. Modele potwierdziły swoją efektywność dla różnych temperatur i naświetleń. (**Określanie parametrów modułu fotowoltaicznego z wykorzystaniem algorytmu Grey Wolf**)*

Keywords: Solar cell; modelling; parameter estimation, grey wolf optimizer.
Słowa kluczowe: ognowo fotowoltaiczne, parametry ognwa, algorytm Grey Wolf

Introduction

Application of photovoltaic panels as clean energy resources in electricity production and distribution is growing dramatically every year. To exploit these resources in efficient way and to implement them successfully, it is so important to model solar cell and analyse its behaviour and dynamics in proper method.

In the previous works, various models have been presented to define the electrical equivalent model of the solar cell to reproduce the photovoltaic curves in real environment. Two models exist to reproduce the electrical characteristics of photovoltaic cell: single and double diode model [1], [2]. The model built on one diode is the more utilized because it's easy to implement and uses a small number of parameters. To model the solar cell using a single diode model, five parameters must be determined, such as the photo generated current, the series and parallel resistance, the saturation current of the diode and the ideality factor of the diode. These parameters depend on the climatic parameters such as temperature and sunlight [2].

In [3], an analytical technique is illustrated to calculate the parameters of the solar single diode model, from the datasheets for PV solar panels delivered by manufacturer. [4] Uses Newton Raphson method to find the solar model parameters. [5, 6] Uses differential evolution to determine the parameters of solar cells. [7]-[11] Describes other methods to predict photovoltaic parameters.

Biologically inspired algorithms have proved to be very effective for solving stochastic and non-linear problems without using complicated mathematical calculations [12,13].Recently, numerous optimization methods such as harmony seeking method [14], the model search[15], the birds reproducing optimizer[16], the swarm optimization bee[17],genetic algorithm[18].

In [19]-[23] particle swarm optimization are implemented to compute the precise values of the parameters and finally[24],presents a new proposal using a grey wolf optimization for maximum power point .

In this work, a new method for parameter extraction of photovoltaic module is presented. The operation is based on mechanism of the chase and the chain of command of wolves in wildlife. Four kinds of wolves are used for determination of unknown parameters like reverse saturation current, series and parallel resistance at fixed temperature and irradiation.

Mathematical model of photovoltaic panel

Different models of photovoltaic cells can be found, these pattern diverge in the quantity of parameters utilized in the computation of the voltage and current of a solar cell. These models rest on the number of diode utilized; the single diode model represents a best compromise between precision and simplicity [25].

As presented in Fig. 1, a solar cell is symbolized with a current source in parallel with a diode, in practice, a parallel and series resistances are added to the model to take into account for losses and leakage current.

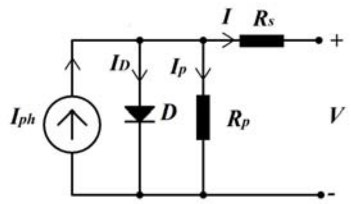

Fig.1. Electrical equivalent model of the solar cell

The equation 1 and 2 describes the current–voltage relationship of solar cell:

$$I = I_{ph} - I_D - I_p \tag{1}$$

$$I = I_{ph} - I_0(\exp(q(\frac{V+IR_s}{AKT})-1) - \frac{V+IR_s}{R_P} \tag{2}$$

$$I = I_{ph} - I_0(\exp((\frac{V+IR_s}{AV_T})-1) - \frac{V+IR_s}{R_p} \tag{3}$$

Where: V- photovoltaic cell voltage; I - photovoltaic cell current; A - diode ideality factor; I_{ph} - photo generated current proportional to the sunlight; I_D - diode current; I_P - parallel resistance current; I_o - dark saturation current; R_s - series resistance; R_p - parallel resistance; V_T : ($V_T=KT/q$) the thermal voltage; K - Boltzmann's constant; q - electron charge; T- cell temperature.

This model of a solar cell can be used to model the photovoltaic module which composed of parallel and series connected solar cells. The equation of a photovoltaic module is given by:

(4) $$I = N_P I_{ph} - N_P I_0 (\exp((\frac{V+IR_s}{AV_T N_S}) - 1) - \frac{1}{N_P}\frac{V+IR_s}{R_{sh}}$$

where *Ns* refers the number of cells placed in series and *Np* indicates the number of branches.

The grey wolf optimizer algorithm (GWO)

The grey wolf optimization algorithm presented by Mirjalili [26] imitates the chasing mechanism and the control pyramid of wolves in wildlife.

This pack is classified into four groups, alpha, beta, delta, and omega for the simulation of guidance hierarchy. Alpha is the first level and is the leader of the pack. Beta is the second level on the hierarchy of wolves and help alpha wolves to make a decision .Delta is the third level in the pack, delta wolves have to succumb alpha and beta, but they dominate omega. Omega wolves have the lowest position in the pack. They always have to succumb to all other dominant wolves. Fig 2 shows the gray wolf social hierarchy [26].

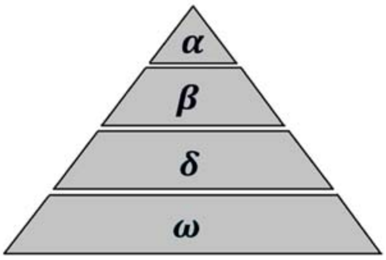

Fig.2. Gray wolf social pyramid

Hunting is also an interesting activity of wolves, as given in Fig 3, the three important phases of chasing are:
Step one: Tracking and approaching the prey.
Step two: Following, encircling, and disrupt the target until it stops moving.
Step three: Attacking the goal (prey).

Fig.3. Hunting conduct of grey wolves: (A) approaching, and pursuing target (B–D) Following, encircling, and disturb the target (E) Attacking the target [27]

Wolves encircle the target during the chase and the encircling is modeled by the equation 5 and 6 [27]:

(5) $$\vec{D} = \left|\vec{C}.\vec{Xp}(t) - \vec{Xp}(t)\right|$$

(6) $$\vec{Xp}(t+1) = \vec{Xp}(t) - \vec{A}.\vec{D}$$

with *t* represents the current iteration, *(A,D,C)* represent coefficient vectors, ***Xp*** is the position vector of the victim and ***X*** represents the position vector of wolf. *A* and *C* are computed with these two equations:

(7) $$\vec{A} = 2\vec{k}.\vec{p} - \vec{k}$$

(8) $$\vec{C} = 2\vec{r}$$

k linearly reduces from 2 to 0 through the iterations and (*p,w*)are random vectors in [0, 1]. The pursuit is habitually directed by the leader alpha (α) followed by beta (β) and delta (δ) which can sometimes contribute in chasing. *δ* and *ω* look after the injured wolves in the group. Alpha (α) is considered the best result attributed to it the best information of the place of the target, beta *(β*) and delta (*δ*) are the second and the third best solutions respectively in designing GWO. Omega is the last best. At what time the prey stops moving, the wolves terminate the chase by attacking it.

Application of GWO for parameter extraction

GWO is an optimization method able of finding optimum points by applying social communication of simple agents. Four kinds of wolves are used for determination of unknown parameters like reverse saturation current, series resistance and parallel resistance at fixed temperature and irradiation. GWO algorithm requires the definition of fitness (*f*) to evaluate each particle. The target is matching model parameters to a number of sampled points. Therefore, the fitness is the relative error between measurement and model prediction. The error compares the variance between the measured and the estimated photovoltaic current. The fitness function of one set of parameters is:

(9) $$f = \frac{1}{N}\sqrt{\sum_{1}^{N}(I_{real} - I_{estimated})^2}$$

(10) $$I_{estimated} = I^*_{ph} - I^*_0 (\exp((\frac{V+IR^*_s}{(AV_T)^*}) - 1) - \frac{V+IR^*_s}{R^*_p}$$

$I_{estimated}$ is predicted load current, I_{real} is measured load current, the index * means the computed value ,N indicates the number of measured data points, *Iph,Io,Rs,Rsh,VT* are the photovoltaic parameters to be fixed. Table 1 illustrates the parameters to be computed for photovoltaic cell.

Table 1 Parameters to be computed for photovoltaic cell

Model	Parameters
Single diode	*Iph Io Rs Rp AVT*

The parameters of GWO are presented in Table 2.

Table 2 Parameter of GWO algorithm

Parameter	iterations	wolves number	r1, r2
Value	200	30	random (0-1)

The flowchart of the grey wolf optimization approach is given in Fig 4.

Sahara solar breeder project (ssb)

In the context of the Sahara Solar Breeder (SSB) project a Sahara Solar Energy Research Center (SSERC) was created in the University of Saida in Algeria [28]. This research center is equipped with photovoltaic measurement system. The system measures current-voltage curve and module back-side temperature continually to appraise the effectiveness of each module under weather conditions and the natural sun light.

The photovoltaic modules installed in the university of Saida are composed of five different varieties of technologies: mono-crystalline (m−Si),CIS, poly-crystalline back contact, mono-crystalline with intrinsic thin layer (HIT) and thin film(a-Si μc−Si).Fig 5 shows the image of photovoltaic modules mounted in the university of Saida in Algeria.

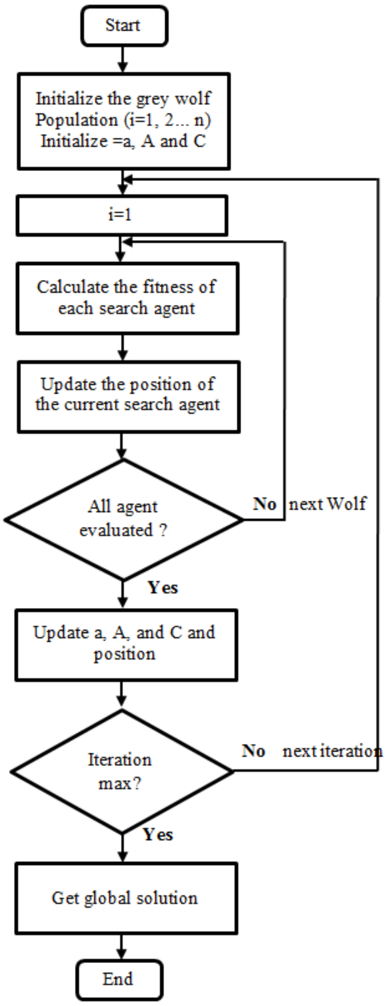

Fig.4. The GWO algorithm flowchart

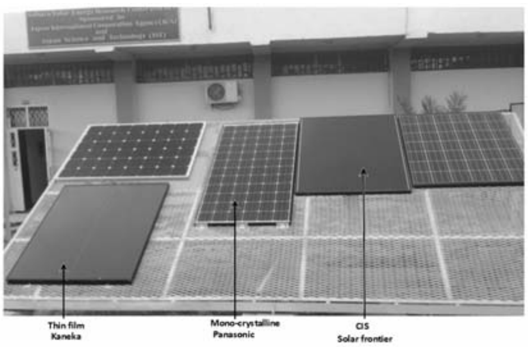

Fig.5. Photovoltaic modules mounted in the University of Saida

Table 3 Parameters of photovoltaic modules under standard testing conditions (STC)

Type	*Pmax* (W)	*Isc* (A)	*Voc* (V)	*Impp* (A)	*Vmpp* (V)
Mono-crystalline	233	5,84	51,6	5.47	42.7
Thin film	110	2.5	71	2.04	54
CIS	150	2.2	108	1.85	81.5

where P_{max} signifies power at maximum power point (MPP), I_{SC} (short circuit current), V_{pm} (voltage at MPP), I_{mpp} (current at MPP), V_{OC} (Open circuit voltage).

The proposed technique will be applied and tested on three kinds of photovoltaic solar panels (Mono-crystalline from Panasonic model VBHNV 233Sj01A [29], thin film from Kaneka model U-VB110 [30] and CIS from Solar frontier model SF-150-S [31]) whose datasheet information is given in Table 3. The simulated and experimental results will be compared under different climatic conditions.

Results and discussion

The estimated photovoltaic cell parameters using GWO are represented in Table 4. These parameters are used to find photovoltaic electrical parameters. Table 5 shows the computed and experimental electrical parameters

Table 4 Computed parameters of three photovoltaic modules (pv cell) at irradiance=960w/m2 and temperature=67 °

Parameter	*RSH* (Ω)	*RS* (Ω)	*Io* (A)	*Iph* (A)	*AVT* (V)
Panasonic PV module	3.2868	0.0021	7.063e-09	5.5203	0.0276
Solar frontier PV module	3.3101	0.0570	2.225e-11	1.9899	0.0347
Kaneka PV module	1.5290	0.0255	9.747e-10	2.4614	0.0252

Referring to Table 5, the parameters I_{SC}, I_{mpp}, V_{mpp}, V_{oc} and P_{max} are computed with precision.

Table 5 Computed electric parameters of three photovoltaic modules at irradiance=960w/m2 and temperature=67 °c

Model of PV	Parameter	Pmax (W)	Isc (A)	Voc (V)	Impp (A)	Vmpp (V)
Panasonic	Experimental	200.60	5.487	48,03	5.12	39.18
	GWO	200.14	5.513	48.100	5.078	39.41
	Error (%)	0,22	0.47	0.14	0.8	0.58
Kaneka	Experimental	97.566	2.330	62.38	2.012	48.49
	GWO	99.228	2.398	62.40	2.037	48.67
	Error (%)	1.71	2.94	0.03	1.32	0.37
Solar frontier	Experimental	128.13	1.896	100.41	1.648	77.75
	GWO	130.25	1.953	100.40	1.664	78.27
	Error (%)	1.65	3.1	0.01	0.97	0.66

The power-voltage and current-voltage curves are shown in Fig 6a and Fig 6b respectively.

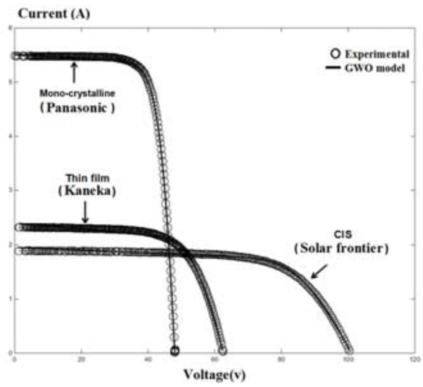

Fig. 6a. Estimated and experimental current-voltage curves of photovoltaic module at irradiance=960W/m2 and temperature=67°C

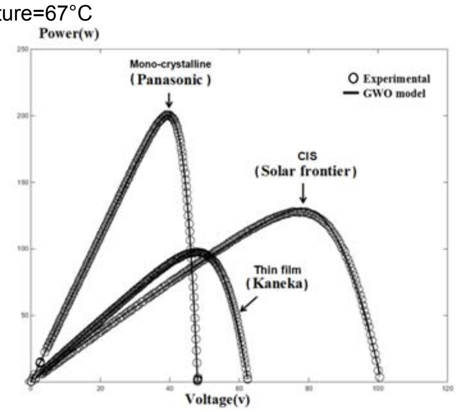

Fig.6b. Estimated and experimental power-voltage curves of photovoltaic module at irradiance=960W/m2 and temperature=67°C

GWO data corresponds exactly to the measured values (open circuit, short circuit and maximum power) as presented in these figures.

Furthermore, in order to evaluate the suggested extraction technique, a comparative between calculated and experimental data has been evaluated at various values of temperature and brightness of the sun. The results are showed in Table 6.

Table 6. Computed and experimental electric parameters of photovoltaic modules at irradiance=480w/m2 and temperature=25°c

Model of PV	Parameter	Pmax (W)	Isc (A)	Voc (V)	Impp (A)	Vmpp (A)
Panasonic	Experimental	130.9	3.229	51.13	3.0279	43.23
	GWO	131.28	3.235	51.20	3.0283	43.35
	Error (%)	0.23	0.18	0.13	0.013	0.27
Kaneka	Experimental	45.648	1.023	67.15	0.8760	52.11
	GWO	46.786	1.049	67.18	0.8930	52.39
	Error (%)	2.49	2.54	0.044	1.94	0.3
Solar frontier	Experimental	66.227	0.894	105.42	0.7940	83.41
	GWO	67.848	0.893	105.44	0.795	85.34
	Error (%)	2.44	0.1	0.018	0.12	2.22

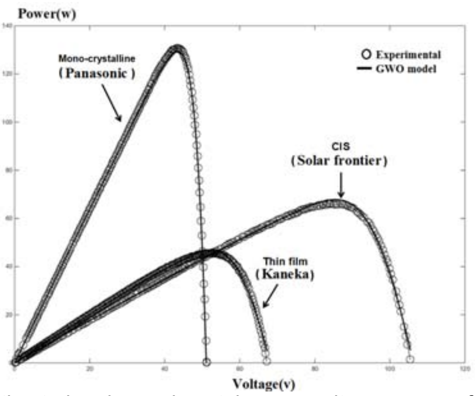

Fig.7. Estimated and experimental power-voltage curves of photovoltaic module at irradiance=480W/m2 and temperature=25°C

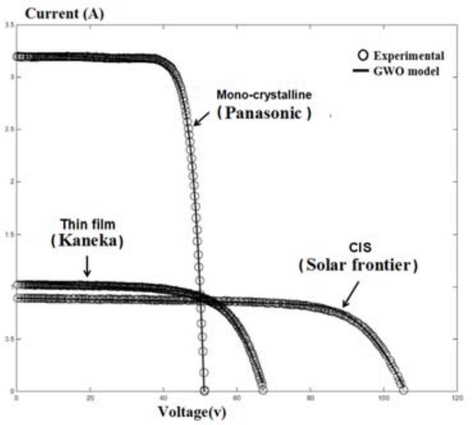

Fig.8. Estimated and experimental current-voltage curves of photovoltaic module at irradiance=480W/m2 and temperature=25°C

From the Fig. 7 and Fig. 8 it can be noted that the simulated results approve the experimental data accurately. Each point in the simulated power-voltage and current-voltage curves are in agreement with experimental values. This validates the precision of the identification method at various temperature and solar radiation.

Conclusion

A new and precise method for solar parameter estimation applying grey wolf algorithm is presented in this paper. The results demonstrate the efficiency and validity of the presented method at different climatic conditions with excellent agreement between computed and the experimental values.

The GWO algorithm has demonstrated has capability to reproduce the curves of the photovoltaic module with a low relative error and identify the solar cell parameters with a high precision.

Authors

Mostefai Mohamed: assist Prof.faculty of Technology University of Moulay Tahar, Saida. Algeria Email:mostefaimed@yahoo.fr.
Miloudi Abdullah : Prof.Electrical Engineering Institute of The Prof.Faculty of Technology University of Moulay Tahar, Saida. Algeria, Email: amiloudidz@yahoo.fr.
Miloud Yahia: Prof.Electrical Engineering Institute of The Prof.Faculty of Technology University of Moulay Tahar, Saida. Algeria, Email: miloudyahiadz@yahoo.fr.

REFERENCES

1. M. G. Villalva, J. R. Gazoli, " Comprehensive approach to modeling and simulation of photovoltaic ", IEEE Transactions on Power Electronics Vol. 24 No.5 2009, pp. 1198–1208
2. S. Chih-Tang, R. N. Noyce, " Carrier generation and recombination in P–N junctions and P–N junction characteristics ", Proceedings of the IRE Vol. 45, No. 9, 1957, pp.1228–1243.
3. D. Sera, R. Teodorescu and P. Rodriguez, "PV panel model based on datasheet values ", IEEE International Symposium on Industrial Electronics, Jun. 2007, pp. 2392-2396.
4. T. T. Yetayew, T. R. Jyothsna, " Parameter Extraction of Photovoltaic Modules using Newton Raphson and Simulated Annealing Techniques ", 15 IEEE Power, Communication and Information Technology Conference (PCITC) Siksha 'O' Anusandhan University, Bhubaneswar, India.
5. Partha P. Biswas, P.N. Suganthan, Guohua Wu, Gehan A.J. Amaratunga, "Parameter estimation of solar cells using datasheet information with the application of an adaptive differential evolution algorithm", Renewable Energy, Volume 132, 2019, pp.425-438.
6. K. Sredenšek, S. Seme, "Parameter determination of a solar cell model using differential evolution algorithm" ,Przegląd Elektrotechniczny, 2019, pp. 165-168.
7. D. S. H. Chan and J. C. H. Phang, " Analytical methods for the extraction of solar-cell single and double diode model parameters from I–V characteristics ", IEEE Trans. Electron Devices, vol. 34, no. 2, pp. 286–293, Feb. 1987.
8. A.H.ALQahtani, M. S.Abuhamdeh, and Y. M.Alsmadi, " A Simplified and Comprehensive Approach to Characterize Photovoltaic System Performance ", Energytech, IEEE Conference Publications, 2012, pp.1-6.
9. M. Hejri, H. Mokhtari, M. R. Azizian, M. Ghandhari, and L. Soder, " On the Parameter Extraction of a Five-Parameter Double-Diode Model of Photovoltaic Cells and Modules ", IEEE J. of Photovoltaics,vol. 4, no. 3, 2014, pp. 915- 923.
10. Bonanno, F., Capizzi, G., Graditi, G., Napoli, C. and Tina, "A Radial Basis Function Neural Network Based Approach for the Electrical Characteristics Estimation of Aphotovoltaic Module ", Applied Energy, 97, pp.956-961.
11. A. Ortiz-Conde, F.J. Garcia Sanchez, J. Muci, " 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),2006, 352–36.
12. M. Tivanov, A. Patryn, N. Drozdov, A. Fedotov, A. Mazanik, " Determination of solar cell parameters from its current–voltage and spectral characteristics ", Solar Energy Materials and Solar Cells, 87 (1–4), 457-465 .
13. Kennedy, J. The particle swarm, " social adaptation of knowledge ", Proc. Intl. Conf. on Evolutionary Computation, Indianapolis,1997. pp.303-3088.
14. R. C. Eberhart, J. Kennedy, " A new optimizer using particle swarm theory ", Proceedings of the Sixth International

Symposium on Micro Machine and Human Science, Nagoya, Japan, IEEE Press, Piscataway, NJ (1995),pp.39–43.
15. Askarzadeh, Alireza., Rezazadeh, Alireza, “ Parameter identification for solar cell models using harmony search-based algorithms”, Energy 86 2012,PP. 3241–3249.
16. 13M.F. AlHajri et al, “ Optimal extraction of solar cell parameters using pattern search”, Re A. 11Askarzadeh et al ”, Extraction of maximum power point in solar cells using bird mating optimizer-based parameters identification approach”, newable Energy 44 (2012),pp. 238-245.
17. 14A. Askarzadeh et al, “Artificial bee swarm optimization algorithm for parameters identification of solar cell models ”,Applied Energy 102(2013) ,PP.943–949.
18. J A. Jervase, et al, “ Solar cell parameter extraction using genetic algorithms”, Measurement.
19. W. Huang, C. Jiang, L. Xue, and D. Song, “ Extracting solar cell model parameters based on chaos particle swarm algorithm” ,Proceedings of the International Conference on Electric Information and Control Engineering (ICEICE '11), pp. 398–402, April 2011.
20. Azab, Mohamed, “ Identification of one-diode model parameters of PV devices from nameplate information using particle swarm and least square methods ”, 2015 First Workshop on Smart Grid and Renewable Energy (SGRE), 2015.
21. Dali, Ali, Abderrezzak Bouharchouche, and Said Diaf. “ Parameter identification of photovoltaic cell/module using genetic algorithm (GA) and particle swarm optimization (PSO) ”, 2015 3rd International Conference on Control Engineering & Information Technology (CEIT), 2015.
22. S. J. Jun and L. Kay-Soon, “ Photovoltaic model identification using particle swarm optimization with inverse barrier constraint”, IEEE Transactions on Power Electronics, vol. 27, 2012, pp. 3975–3983,.
23. M. Ye, X. Wang, and Y. Xu, “ Parameter extraction of solar cells using particle swarm optimization,Journal of Applied Physics”, may. 2009 vol. 105 no. 9, pp. 094502 –094502–8.
24. Satyajit Mohanty, Bidyadhar Subudhi, “A New MPPT Design Using Grey Wolf Optimization”, IEEE Transactions on Energy conversion,vol. 26, no. 3, september 2015
25. C. Carrero, J. Amador, S. Arnaltes, “A single procedure for helping PV designers to select silicon PV modules and evaluate the loss resistances”, Renewable Energy, vol. 32, 2007,pp. 2579-2589
26. S. Mirjalili, S. M. Mirjalili, and A. Lewis, “Grey wolf optimizer,” Adv. Eng. Software, vol. 69 , 2014, pp. 46–61
27. C.Muro, R. Escobedo, L. Spector, “Wolf-pack (Canis lupus) hunting strategies emerge from simple rules in computational simulations”, Behavioural processes 2011, vol. 88, pp. 192-197.
28. http://www.ssb-foundation.com/
29. Panasonic(VBHNV233S)datasheet:
30. ftp://ftp.panasonic.com/solar/specsheet/n325330-spec-sheet.pdf
31. kaneka(U-VB110)datasheet:
32. http://www.kaneka-solar.com/product/thin-film/pdf/U-EA.pdf
33. Solar-frontier(SF-150-S)datasheet: https://www.solarfrontier.eu/fileadmin/content/downloads/modules/en/20141030/product-overview-s-series-english.pdf