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To cite this article: O D Montoya *et al* 2020 *J. Phys.: Conf. Ser.* **1671** 012008

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Sine-cosine algorithm for parameters' estimation in solar cells using datasheet information

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Abstract. This paper explores the problem of optimal calculation of electrical parameters in solar cells using three well-known operative points provided by manufacturers considering a single-diode model. These are open circuit, short circuit, and maximum power point; with these points is formulated a nonlinear non-convex optimization problem that deals with the minimization of mean square errors associated with variables evaluated at these points, *i.e.*, open-circuit voltage, short circuit current, and current in the maximum power point, respectively. A sine-cosine algorithm is addressed in this research to solve the resulting optimization problem. Numerical results provided by the sine-cosine algorithm show objective functions lower than 1×10^{-12}, which confirms the efficiency and robustness of the proposed approach. All the numerical validations are conducted via MATLAB software.

1. Introduction

Solar generation is the most popular renewable generation globally [1]. The large-scale solar photovoltaic generation is promoted by clean energy policies that try to replace fossil fuels commonly used for electricity generation [2]. A photovoltaic system (PV) allows solar radiation to transform into electrical energy using PV cells connected in series and parallel [3]. In general terms, the PV arrays require power electronic converters for large scale integration into the power systems [4]. Notwithstanding, for low voltage applications, these can be directly connected to the loads [3]. To ensure the satisfactory operation of PV sources is required that these devices work in the maximum power point (MPP). However, before any implementation of PV arrays in real applications is needed to know the appropriate model of each PV cell, this model is the main input for a detailed study via computational simulations. These will allow identifying the best configuration of the PV system in the physical (real) implementation [3].

The configuration of a PV cell is represented by a $p - n$ junction, which can be defined with an equivalent electric circuit [5]. In the mathematical modeling of PV cells, there are two predominant models, which depend on the number of diodes considered, *i.e.*, models with one or two diodes. The single-diode model is the most common representation of a PV cell due to its simplicity and acceptable performance defined by the $I - V$ characteristic. If the study requires additional precision in the PV model, then models with two or three didoes can be employed [6]. However, it is worth mentioning that models with three or more diodes are highly complex to implement in real applications [7, 8].

This paper focuses on the single-diode model with a new metaheuristic approach to estimate its parameters. The parameters to be estimated are the ideality diode factor and the series and parallel resistances [3]. This problem has been widely studied in specialized literature with metaheuristics such

as particle swarm optimization [7], flower pollination algorithm [3], differential evolution algorithms [9], bacterial foraging algorithm [10] and imperialist competitive algorithms [11], among others.

Here, we propose an alternative metaheuristic optimizer to deal with this optimization problem. This optimizer is known as the sine-cosine algorithm (SCA) [12, 13]. The SCA's main advantage is that it works with a simplified optimization model formulated considering manufacturer information provided for solar cells. This information considers the open voltage, short circuit, and maximum power points. This is formulated a nonlinear non-convex optimization problem to minimize the mean square error by evaluating the general PV equation for a single-diode equation at these points [3]. Numerical results confirm the efficiency of the proposed approach to solve the optimization problem. The main advantage of using SCA is its simplicity, and it only requires five control parameters to know: three random numbers, population size, and the number of iterations, which is easily implemented at any programming language. Numerical results have been conducted in MATLAB software 2017*b* by considering the single-diode model for the PV cells with manufacturer data for the Kyocera KC200GT [3].

This paper is organized as follows: section 2 presents the general mathematical formulation for the single-diode model for the PV cells, considering the three main operative points; section 3 presents the main characteristics of the sine-cosine algorithm; section 4 shows the main features of the test systems based on the Kyocera KC200GT solar cells, and it presents all the computational validations for the single-diode model; section 5 presents the main concluding remarks derived from this research.

2. Mathematical modeling

The mathematical formulation for parametric estimation in PV modules with N_c number of cells connected in series is developed based on the ideal formulation of photovoltaic cells considering single-diode representation, as presented in Figure 1. The general current-voltage $I - V$ relation for single-diode circuit equivalent is given in Equation (1).
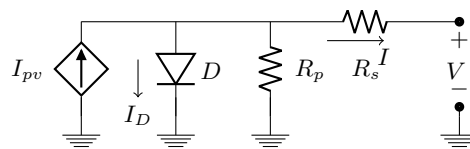

Figure 1. PV equivalent circuit.

$$ I = I_{pv} - I_0 \left[\exp\left(q \frac{V + R_s I}{a k N_c T} \right) - 1 \right] - \frac{V + R_s I}{R_p}, \tag{1} $$

where I_{pv} represents the photo-current, I_0 corresponds to the reverse saturation current of the PV module; R_s and R_p represent the equivalent series and parallel resistances, respectively. q corresponds the charge of an electron, *i.e.*, $1.60217646 \times 10^{-19}$ Coulomb. Note that that k is the Boltzmann constant $1.38064852 \times 10^{-23}$ Joules/Kelvin; T defines the absolute temperature of the diode junction in Kelvin, here, we assume this constant as $275 + 25$; a represents the ideality factor of the diode. Observe that $\exp(y)$ calculates the exponential function of the y variable.

Here, three operative points in the PV module are considered, which define the behavior in all the voltage domain with high precision. First, we consider the open circuit point, where $V = V_{oc}$ and $I = 0$, which allows reaching the Equation (2) for calculating I_{pv}.

$$ I_{pv} = I_0 \left[\exp\left(q \frac{V_{oc}}{a k N_c T} \right) - 1 \right] - \frac{V_{oc}}{R_p}. \tag{2} $$

The second point for analysis is the short circuit case, where $I = I_{sc}$ and $V = 0$; now if we substitute this point in Equation (1), then, the short circuit current is reached as defined in Equation (3).

$$I_{sc} = I_{pv} - I_0 \left[\exp\left(q\frac{R_s I_{sc}}{akN_cT} \right) - 1 \right] - \frac{R_s I_{sc}}{R_p}. \tag{3}$$

Now, if Equation (2) is substituted into Equation (3), and some algebraic manipulations are made, then, we find a general expression for I_0 presented in Equation (4).

$$I_0 = \frac{I_{sc} + \frac{R_s I_{sc}}{R_p} + \frac{V}{R_p}}{\exp\left(q\frac{V_{oc}}{akN_cT} \right) - \exp\left(q\frac{R_s I_{sc}}{akN_cT} \right)}, \tag{4}$$

in addition, if we use Equation (4) in Equation (2), we obtain Equation (5).

$$I_{pv} = \frac{\left(I_{sc} + \frac{R_s I_{sc}}{R_p} + \frac{V}{R_p} \right) \left[\exp\left(q\frac{V_{oc}}{akN_cT} \right) - 1 \right]}{\exp\left(q\frac{V_{oc}}{akN_cT} \right) - \exp\left(q\frac{R_s I_{sc}}{akN_cT} \right)} - \frac{V}{R_p}. \tag{5}$$

In third case, the maximum power point is (I_{mpp}, V_{mpp}) in Equation (1), which produces the result reported in Equation (6).

$$I_{mpp} = \left(\begin{array}{c} I_{pv} - I_0 \left[\exp\left(q\frac{V_{mpp}+R_s I}{akN_cT} \right) - 1 \right] \\ - \frac{V_{mpp}+R_s I_{mpp}}{R_p} \end{array} \right). \tag{6}$$

Now, to formulate the optimization problem for estimating parameters in PV cells using the information provided by the manufacturer, *i.e.*, the open circuit, short circuit and maximum power points, respectively, we select a single objective function based on the minimization of the mean square error in these points as defined in Equation (7).

$$\min z = E_{oc}^2 + E_{sc}^2 + E_{mpp}^2, \tag{7}$$

where each one of its components is defined in Equation (8), Equation (9), and Equation (10).

$$E_{oc} = I_0 \left[\exp\left(q\frac{V_{oc}}{akN_cT} \right) - 1 \right] - \frac{V}{R_p} - I_{pv}, \tag{8}$$

$$E_{sc} = I_{pv} - I_0 \left[\exp\left(q\frac{R_s I_{sc}}{akN_cT} \right) - 1 \right] - \frac{R_s I_{sc}}{R_p} - I_{sc}, \tag{9}$$

$$E_{mpp} = \left(\begin{array}{c} I_{pv} - I_0 \left[\exp\left(q\frac{V_{mpp}+R_s I}{akN_cT} \right) - 1 \right] \\ - \frac{V_{mpp}+R_s I_{mpp}}{R_p} \end{array} \right) - I_{mpp}. \tag{10}$$

Observe that the variables of this objective function are: a, R_s and R_p, in addition are required the calculation of the variables I_0 and I_{pv} as defined by Equation (4) and Equation (5), respectively. The optimization mathematical model is complete, by adding box-type constraints to the optimization variables as presented in Equation (11).

$$a^{\min} \le a \le a^{\max}, \ R_p^{\min} \le R_p \le R_p^{\max}, \ R_s^{\min} \le R_s \le R_s^{\max}, \tag{11}$$

where $a^{\min}$ and $a^{\max}$ as the lower and upper bounds of the ideality factor of the diode, $R_p^{\min}$ and $R_p^{\max}$ are the minimum and maximum admissible values for the parallel resistance, and $R_s^{\min}$ and $R_s^{\max}$ are the lower and upper bounds in the case of the series resistance.

The optimization model defined by the objective function Equation (7) with constraints Equation (4) and Equation (5) added to the constraints Equation (8) to Equation (11) is nonlinear and non-convex, which implies that there may be multiple combinations of variables with the same numerical performance. A simple metaheuristic algorithm for continuous optimization problems is used to deal with the nonlinear and non-convexities of this optimization problem. It works with trigonometric functions known as sine and cosine [12], which explores and exploits the solution space based on an evolution criterion. This algorithm is known in specialized literature as a sine-cosine algorithm [14, 15].

3. Optimization approach

This section discusses the main aspects of implementing the sine-cosine algorithm for nonlinear optimization in the continuous domain. This optimization methodology was initially proposed for solving optimal power flow problems in alternating current networks by [12]. This optimization algorithm works with trigonometric functions such as sine and cosine to control the solution space exploration by making evolving the initial population through a random controlled process [16]. The main aspects of implementing the SCA for solving optimization problems in the continuous domain are discussed below.

3.1. Initial population

As the most of the optimization approaches, the SCA works with populations that evolve to refining the current best solution. The initial population in the case of the parameters' optimization in solar cells has the following dimensions: $n_v \times n_i$, being n_v the number of variables, (note that in the optimization case analyzed in this paper, where the variables are: a, R_p and R_s, respectively, $n_v = 3$.) and n_i the number of individuals in the population. In Equation (12) is presented the general structure of the population for the problem analyzed in this paper, considering that $x_i = [a_i \ R_{pi} \ R_{si}]$ as presented in Equation (12).

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_{n_i} \end{bmatrix} = \begin{bmatrix} x_{11} & \dots & x_{13} \\ \vdots & \ddots & \vdots \\ x_{n_i 1} & \dots & x_{n_i 3} \end{bmatrix}. \tag{12}$$

Note that to generate, the ith in the population, *i.e.*, x_i, we guarantee the feasibility on it as presented in Equation (13).

$$x_i = x_i^{\min} + r \cdot \left(x_i^{\max} - x_i^{\min} \right), \tag{13}$$

being r a vector with n_v values generated randomly between 0 and 1; $x_i^{\min} = [a^{\min} \ R_p^{\min} \ R_s^{\min}]$ and $x_i^{\max} = [a^{\max} \ R_p^{\max} \ R_s^{\max}]$. Note that $r \cdot x$ implies the inner product between vectors r and x.

3.2. Fitness function

Typically in mataheuristic optimization to guide the population through the solution space a fitness function is used instead of the original objective function. This strategy is preferred where in the optimization problem has inequalities different from type-box ones. Nevertheless, in the case of the

parameters' estimation in solar cells using manufacturer information, the fitness function is equivalent to the objective function, *i.e.*, as defined in Equation (14).

$$\min z = \min f_f = E_{oc}^2 + E_{sc}^2 + E_{mpp}^2, \tag{14}$$

where f_f means fitness function value.

3.3. Evolution criterion

To explore and exploit the solution space, the SCA works with a roulette selection methodology, that uses a controlled random process to select the possible next individual to be included in the offspring population. The roulette rule has the structure presented in Equation (15).

$$y_j^t = \left\{ x_j^t + r_1 \sin{(r_2)} \left| r_3 x_{\text{best}}^t - x_j^t \right| \quad \text{if} \quad r_4 \geq \tfrac{1}{2}; \; x_j^t + r_1 \cos{(r_2)} \left| r_3 x_{\text{best}}^t - x_j^t \right| \quad \text{if} \quad r_4 < \tfrac{1}{2} \right. \tag{15}$$

where y_j^t is the potential individual that will replace the current one x_j^t. Note that x_{best}^t is the best solution in the current population, *i.e.*, the solution that produces the minimum value in the fitness function, being t is the iterative counter. In addition, r_1 is a number that control the exploration in the solution space, this is defined as $r_1 = 1 - \frac{t}{t_{\max}}$ where $t_{\max}$ represents the maximum number of iterations; r_2 is a random number contained between 0 and 2π; and r_3 and r_4 are another random numbers between 0 and 1, respectively. To guarantee feasibility in all the variables, the lower and upper bounds of y_j^t are verified as can be seen in Equation (16).

$$y_j^t = \left\{ y_j^t \quad \text{if} \quad x_j^{\min} \leq y_j^t \leq x_j^{\min}; \; x_j^{\min} + r \cdot \left(x_j^{\max} - x_j^{\min} \right) \quad \text{if} \quad \text{otherwise}, \right. \tag{16}$$

in addition, to replace the current individual in the population, the questions presented in Equation (17) must be satisfied.

$$x_j^{t+1} = \left\{ y_j^t \quad \text{if} \quad f_f\left(y_j^t\right) < f_f\left(y_j^t\right); \; x_j^t \quad \text{if} \quad \text{otherwise}. \right. \tag{17}$$

3.4. Stopping criteria

The SCA algorithm stops its searching process in the solution space when each one the following conditions is reached: *(i)* if all the iterations have been made, *i.e.*, $t = t_{\max}$, and *(ii)* if during k consecutive iterations the best best fitness function has not been modified, being $k_{\max}$ the maximum consecutive iterations without improvement, *i.e.*, $k = k_{\max}$.

4. Test system and computational validation

We consider the Kyocera KC200GT solar cell with is polycrystalline type as the test system. The relevant information of this solar cell is reported in Table 1. Furthermore, it is built with the information provided by [3]. In addition, the minimum and maximum bounds of the optimization variables, *i.e.*, a, R_p, and R_s are the following: $0.5 \leq a \leq 2$, $0.001 \leq R_p \leq 1$, and $50 \leq R_s \leq 200$.

The software and computer characteristics for solving the parameters' estimation problem in solar cell considering manufacturer information with the SCA. These computational validations are carried–out in MATLAB 2017a. In the parametrization of the SCA we consider a population about 20 individuals and 10000 iterations, as non-consecutive improvements we employ $k_{\max} = 1000$.

Table 1. Manufacturer information for the Kyocera KC200GT. Information taken from [3].

Parameter	Symbol	Value
Open circuit voltage	V_{oc}	32.900 V
Short circuit current	I_{sc}	8.210 A
Voltage at maximum power	V_{mpp}	26.300 V
Current at maximum power	I_{mpp}	7.610 A
Temperature coefficient of V_{oc}	$K_{V_{oc}}$	-0.123 V/^{o}C
Temperature coefficient of I_{sc}	$K_{I_{sc}}$	3.180$\times 10^{-3}$ A/^{o}C
Number of cells connected in series	N_c	54

Table 2 reports as the best-founded solutions 10 solutions reached by the proposed SCA. The interpretation of the columns in this table is from left-to-right as follows: the number of the solution, ideality factor of the diode, series and parallel resistances, inverse current in the panel, photocurrent, and the fitness function, *i.e.*, objective function.

Table 2. Best results reached by the SCA.

N_o	a	R_s (Ω)	R_p (Ω)	I_0 (A)	I_{pv} (A)	f_f
1	1.217507226	0.1639332466	97.6612757	$2.74242520\times 10^{-08}$	8.22378128	$1.58031406\times 10^{-15}$
2	1.200645650	0.0280413540	60.5398205	$2.02885521\times 10^{-08}$	8.21380280	$5.65303651\times 10^{-15}$
3	1.377142520	0.0343013740	82.9656779	$2.59885349\times 10^{-07}$	8.21339464	$5.37726984\times 10^{-13}$
4	0.837598121	0.2132050588	52.8891611	$3.86011529\times 10^{-12}$	8.24309588	$7.25698362\times 10^{-13}$
5	1.367469326	0.1091774730	118.999639	$2.33737962\times 10^{-07}$	8.21753272	$1.60093596\times 10^{-12}$
6	1.180105995	0.0456435467	60.8860103	$1.43968408\times 10^{-08}$	8.21615469	$3.29287225\times 10^{-12}$
7	0.677305245	0.5045796888	148.503516	$4.99685957\times 10^{-15}$	8.23789563	$5.40114994\times 10^{-12}$
8	1.439594035	0.0520078676	106.744074	$5.54768598\times 10^{-07}$	8.21400076	$1.12024967\times 10^{-11}$
9	1.217986706	0.1322651804	83.4669330	$2.74318924\times 10^{-08}$	8.22300996	$1.74468956\times 10^{-11}$
10	1.213320080	0.0031589052	58.9520275	$2.48789806\times 10^{-08}$	8.21043995	$2.04825629\times 10^{-11}$

From Table 2, we can observe the following facts: *(i)* all the solutions in terms of the objective function (see the last column in Table 2) are lower than 1×10^{-10}, which implies that satisfy the numerical requirements in metaheuristic optimization, since, in analytical terms, the global solution must be equal to zero; *(ii)* all the solutions reported in the first three columns fulfill the box-type bound imposed by Equation (11), which implies that all of them are feasible; *(iii)* the inverse current I_0 is strongly related to the ideality factor of the diode a since the minimum value of a (see solution seven, the second column in Table 2) produces the minimum value in the inverse current (see answer seven, column five in Table 2). This behavior is also the same for the maximum value of the ideality factor, which also produces the maximum value in the inverse current (see solution eight, columns two and five in Table 2); *(iv)* the behavior of the photocurrent (see column six in Table 2) presents a quasi-constant demeanor, since its mean value for all the solutions is 8.2212 A, with maximum and minimum values about 8.2431 A and 8.2104 A, respectively, which produce and standard deviation about 10.8 mA.

In general terms, all the solutions reported in Table 2 can be selected to parametrized the equivalent circuit of a photovoltaic array since this is an electrical representation in terms of circuit elements of the energy transformation process occurred inside of the panels; and due to their nonlinear non-convex formulation, it is not possible to ensure uniqueness in the mathematical equivalent. In this sense, to verify that all the solutions are suitable for modeling the solar cells, we present the general solution of Equation (1) considering discretized values for V from 0 to the V_{oc} with a resolution about 0.10 V. We use the "fsolve" function in MATLAB for reaching the solution of I, considering all the parameters reported in Table 2 as depicted in Figure 2.
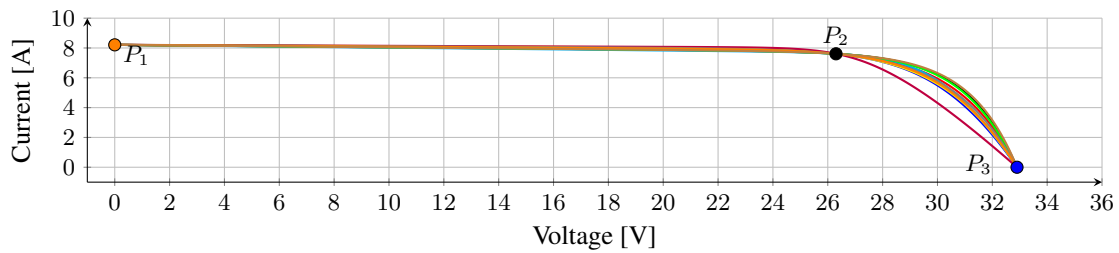
Figure 2. Solution of general Equation (1) for results reported in Table 2.

Observe that $P_1 (0, 8.210)$ represents the short circuit operative condition, $P_2 (26.300, 7.610)$ corresponds to the maximum power point, an $P_3 (32.900, 0)$ is the open circuit operative condition. These points imply that the minimization of the mean square error using these three points provided by the solar cells manufacturer guarantees to reach the equivalent circuit parameters with minimum errors by solving the resulting nonlinear non-convex optimization problem with heuristics.

It is important to mention that authors of [3] have reached similar results with an adaptive differential evolution algorithm, by reporting errors lower than 1×10^{-12} in the fitness function. These results imply that the proposed SCA is an attractive alternative optimization approach to deal with continuous optimization problems by presenting efficient results compared to the specialized literature. Furthermore, the proposed SCA algorithm's important fact is that after 100 consecutive iterations, the mean processing time to resolve the parameters' estimation problem in a solar cell is about 8 s. This confirms its efficiency; since it can be used repetitively to refine the solution's quality with low computational effort.

5. Conclusion

The problem of parameters' estimation in the solar cell was addressed via metaheuristic optimization in this paper. To solve the resulting nonlinear non-convex optimization problem was employed the sine-cosine algorithm. The formulation of the mathematical model was considered the information provided by the manufacturer in the datasheet. This model considered three main points in the photovoltaic array's operation curve: the open circuit, short circuit, and maximum power points. The SCA showed that the objective function was located between 1×10^{-1} and 1×10^{-15}, can be considered zero in any practical application. The optimization model's nonlinear structure showed that there were multiple solutions for the ideality factor, series and parallel resistance, the inverse current through the diode, and the photocurrent since all of the solutions reported in Table 2 that produce results in Figure 2, which are numerically valid, due to all of them pass through the three points considered in the optimization model.

References

[1] Timilsina G R, Kurdgelashvili L, Narbel L 2011 A review of solar energy markets, economics and policies *Policy Research Working Paper, WPS 5845* (Washington: World Bank Group)

[2] Imdadullah M, Ashraf I 2006 Estimation of CO2 mitigation potential through renewable energy generation *IEEE International Power and Energy Conference* (Putra Jaya: IEEE)

[3] Biswas P P, Suganthan P, Wu G, Amaratunga G A 2019 Parameter estimation of solar cells using datasheet information with the application of an adaptive differential evolution algorithm *Renewable Energy* **132** 425-438

[4] Zapata J W, Kouro S, Carrasco G, Renaudineau H, Meynard T A 2019 Analysis of partial power DC–DC converters for two-stage photovoltaic systems *IEEE Journal of Emerging and Selected Topics in Power Electronics* **7(1)** 591-603

[5] Deshmukh M, Deshmukh S 2008 Modeling of hybrid renewable energy systems *Renewable Sustainable Energy Reviews* **12(1)** 235-249

[6] Ishaque K, Salam Z, Taheri H 2011 Simple, fast and accurate two-diode model for photovoltaic modules *Sol. Energy Mater. Sol. Cells.* **95(2)** 586-594

[7] Khanna V, Das B, Bisht D, Singh P 2015 A three diode model for industrial solar cells and estimation of solar cell parameters using pso algorithm *Renewable Energy* **78** 105-113

[8] Allam D, Yousri D, Eteiba M 2016 Parameters extraction of the three diode model for the multi-crystalline solar cell/module using moth-flame optimization algorithm *Energy Convers. Manage.* **123** 535-548

[9] Jiang L L, Maskell D L, Bisht D, Patra J C 2013 Parameter estimation of solar cells and modules using an improved adaptive differential evolution algorithm *Appl. Energy* **112** 185-193

[10] Subudhi B, Pradhan R 2018 Bacterial foraging optimization approach to parameter extraction of a photovoltaic module *IEEE Trans. Sustain. Energy* **9(1)** 381-389

[11] Fathy A, Rezk H 2017 Parameter estimation of photovoltaic system using imperialist competitive algorithm *Renewable Energy* **111** 307-320

[12] Attia A F, Sehiemy R A E, Hasanien H M 2018 Optimal power flow solution in power systems using a novel sine-cosine algorithm *Int. J. Electr. Power Energy Syst.* **99** 331-343

[13] Giraldo J A, Montoya O D, Grisales-Noreña L F, Gil-González W, Holguín M 2019 Optimal power flow solution in direct current grids using sine-cosine algorithm *J. Phys. Conf. Ser.* **1403** 012009:1-6

[14] Li C, Luo Z, Yang F, Fan J, Liu P X 2019 An enhanced brain storm sine cosine algorithm for global optimization problems *IEEE Access* **7(28)** 211-229

[15] Rizk-Allah R M, Mageed H M A, El-Sehiemy R A, Aleem E A, Shahat A E 2017 A new sine cosine optimization algorithm for solving combined non-convex economic and emission power dispatch problems *Int. J. on Energy Conver.* **5(6)** 180-188

[16] Rizk-Allah R M 2018 Hybridizing sine cosine algorithm with multi-orthogonal search strategy for engineering design problems *J. Comput. Des. Eng.* **5(2)** 249-273