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Mating-based Sine Cosine Algorithm for Modelling a Solar Photovoltaic Cell

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Abstract: This paper presents a mating-based sine-cosine algorithm (MSCA) for solving global optimization problems with an application to optimize the static model of a solar photovoltaic (PV) cell. It is an improved variant of the sine-cosine algorithm (SCA). The original SCA relies heavily on its sine-cosine position update equation formulated based on elitism and random techniques. Euclidean distance between an agent to the elite agent provides a good searching strategy as it keeps track of the current best solution. However, solely relying on the equation has led to a premature stagnation among the search agents and thus yielding a local optimum solution. A mating-based technique is introduced to enhance the exploration of the searching agents and their motion on the feasible region. Some good features of the elite agent are shared with other agents thereby improving their traits. With the new characteristics, the search agents explore more diversely thereby producing a more promising path. The algorithm is tested on several real-parameter benchmark functions. It is also applied to optimize the static model of a solar PV cell based on a single Current-Voltage (I-V) curve approach, a pair of electrical signals captured from real system. The result on benchmark function test shows that the proposed MSCA has gained greater accuracy. Wilcoxon signed-rank test shows that the two-tailed p-value is less than 0.05 implying the improvement is significant. On the other hand, the result on the static modeling of solar PV cell shows both algorithms have satisfactorily acquired a good model. The MSCA attained a better accuracy than the SCA algorithm and state-of-the-art spiral dynamic algorithm (SDA).

Keywords: Global optimization; Photovoltaic cell; Renewable energy; Sine-cosine algorithm; Static modeling.

1. INTRODUCTION

In the current world, solar photovoltaic (PV) systems are considered as an important renewable energy technology. It has faced a growing demand from various domestic and industrial users from all over the world. Some industry players employ hybrid type systems such as integrating solar PV with wind energy technologies while many domestic and households adopted solely the solar PV technology [1]. Unlike the conventional energy generation such as fossil fuel, solar PV technology offers a range of great advantages. The renewable solar resource is abundant, provides clean energy leading to less carbon emission and is environmentally friendly which is an important factor to keep the world sustainable. Unlike other renewable technologies such as wind energy, solar PV technology is also economically less expensive and does not produce significant noise [2]. All these benefits attract strong interest from people across a wide range of groups regardless of their financial and educational background. To meet these demands, a reliable and efficient solar PV technology capable of generating optimal energy is required and thus presents an ongoing challenge for engineers and researchers worldwide. One way to achieve the goal is to study characteristics and behavior of a solar PV cell which can be done by simulating its mathematical model.

However, the PV solar cell is complex and it exhibits non-linear behavior since it reacts differently under varying environment conditions such as temperature and irradiance changes. Due to this factor, developing an accurate physical model for the solar PV cell is challenging. Internal parameters are one of the crucial factors when simulating a PV solar cell and it affects the system performance very much. A good physical model requires an accurate value of physical parameters and it gives a valuable insight about behavior of the solar PV cell. In many real-world practices, it is commonly used for monitoring, detection and diagnosing faults as well as designing a nonlinear compensator including neural network and intelligent control [3]. Modeling of a solar PV cell can be categorized into analytical and via optimization algorithm approaches. The analytical approach is a conventional method and often suffers from singularity issues or mathematical approximations when fitting a fixed condition such as load, irradiance and temperature [4]. Optimizing the internal parameters even for a single constant (Current-Voltage**)** I-V curve remains a highly non-linear optimization challenge. The mathematical representation of a solar

PV cell is commonly structured as highly non-linear one-diode or two-diode models. The internal parameters of these models are crucial factors that dictate simulation accuracy and system performance. However, determining these physical parameters is challenging because they cannot be directly measured. To isolate and accurately estimate these unknown internal parameters, a modeling approach conducted under constant temperature and constant irradiance conditions is frequently utilized. Aligned with the Standard Test Conditions (STC) of 1000 W/m^2 and 25ºC, this static environmental profile establishes a well-defined engineering control, ensuring that parameter extraction is evaluated independently of transient thermal and solar dynamics. By freezing the environmental variables, the complex electro-thermal coupling of the PV cell is decoupled, reducing the system's behavior to a single, stable Current-Voltage (I-V) characteristic curve.

An optimization algorithm approach offers a more flexible situation. It can cope with the non-linear characteristics of the solar PV cell. Metaheuristic optimization algorithm is the most common optimization algorithm for handling such non-linear problems. Unlike the conventional type of optimization algorithms, metaheuristic employs stochastic optimization strategy and a non-gradient based algorithm. Its formulation is commonly inspired from natural phenomena such as spiral phenomena on earth [5] and bacterial foraging strategy [6]. Moreover, it offers few great features such as adaptive, self-learning and self-organization [7]. It has been employed to optimize parameters of a physical model of many real-world physical systems which include twin rotor system [8-11], flexible manipulator system [12-14], electromechanical system [15], proton exchange membrane fuel cells [16] and water heater system [17]. Metaheuristic algorithms have also been used to optimize parameters of a solar PV cell. Some of them are categorized into animal-based inspired which include snake [18], particle swarm [19], artificial rabbit [20], moth flame [21] and grey wolf [22], genetic-based inspired which include genetic algorithm [23], and plant-based inspired such as invasive weed [24]. Other metaheuristic algorithms also formulated based on physics-based inspiration such as Archimedes [25] and stochastic fractal search [26] while bare-boned imperialist competition is a social-political based inspired algorithm [27]. These algorithms have successfully optimized parameters of the solar PV cell with considerable good accuracy. Nevertheless, their performance varies to one another depending on the problem landscape. Some of them show a good convergence rate but compromise the accuracy of the final solution and vice versa. Literature study [28] stated that the final parameter accuracy is considered significantly more critical than a rapid convergence rate. Premature convergence to an inaccurate local optimum lead to severe errors in estimating physical characteristics like internal ohmic losses. While in literature [29] indicated that there is no single algorithm that can perform the best for all problems. This fundamental trade-off is governed by the No Free Lunch theorem, which establishes that no single optimization mechanism can maintain an ideal balance between convergence velocity and final tracking precision across all problem topographies. Modern optimization literatures utilized standard benchmark functions to verify a newly developed algorithm or any structural modifications of optimization algorithms can deliver statistically meaningful advantages over predecessor algorithms [30, 31].

Sine-cosine algorithm is another promising stochastic algorithm that was successfully employed to solve problems in various disciplines such as in modeling [32]. Its formulation was inspired from the mathematical sine-cosine terms. Stochastic, random and elitism strategies are mainly the important mechanisms it has employed. The elitism ensures agents are guided to the best solution while the random ensures that the agents are well-distributed in a search space. The algorithm has a simple structure and hence it produces a considerable convergence rate. However, there is a chance to improve accuracy performance of the algorithm especially for solving a nonlinear and complex problem. The SCA algorithm suffers from premature convergence at a considerable convergence rate. Its convergence becomes stagnant from the early phase until the end of search operations and thus leading to inaccurate solutions. It originated from insufficient exploration and exploitation phases throughout the operation. Agents became trapped at various local optima points and it prevented them from reaching global optimum. The dynamic motion of the agents, governed by the sine and cosine dynamic model and iteration-based step-sizes, is still not sufficient to overcome the local optima. Therefore, this paper proposes a mating-based sine-cosine optimization algorithm (MSCA) for global optimization and to optimize the real-parameter of a solar PV cell. It is a further enhancement of the original SCA optimization algorithm [33] as a result from incorporating a mating process into its original structure. The algorithm is tested on several real-parameter benchmark functions that have been widely used and also is applied to optimize internal parameters of one-diode and two-diode models of a solar PV cell.

The paper makes two primary contributions as follows.

(a) It proposes the novel variant of Hybrid MSCA. The novel idea lies in the incorporation of mating strategy into the original SCA structure in which it counteracts the limitations of the original SCA. The simple structure of the original SCA leads to insufficient exploration and exploitation phases throughout the searching process. While the mating strategy is an enhancement of the existing exploration and exploitation phases involving parent agents, random agents and the global best agent. It offers higher dynamic motion and varying step size to an individual search agent. The proposed MSCA has improved the accuracy attainment in solving optimization problems which include various global benchmark functions.

(b) The paper demonstrates the effectiveness of the proposed MSCA algorithm in obtaining a set of optimal real-parameters for one-diode and two-diode models of a solar photovoltaic system conducted under constant temperature and constant irradiance conditions which is aligned with the Standard Test Conditions (STC) of 1000 W/m^2 and 25ºC. Considering the real-parameters are unknown and difficult to determine using a conventional modeling approach, a single I-V curve response collected from a real PV system is utilized.

The remainder of this paper is organized as follows. Section 2 presents the flowchart and detailed information about the proposed MSCA. Methodology about performance tests on the benchmark functions and parameter estimation under fixed environmental conditions are explained. Section 3 presents results of the proposed MSCA tested on the benchmark functions and applied on the solar PV cell in comparison to the predecessor SCA and state-of-the-art spiral dynamic algorithm (SDA). Section 4 presents the conclusion of the paper and future work.

2. METHODOLOGY

The methodology section consists of three parts. The first part presents the proposed Mating-based Sine Cosine Algorithm (MSCA). The step-by-step procedure and the mathematical equations used in the algorithm are presented and explained. The second part explains the experimental setup for performance test of the MSCA in comparison to SCA on real-parameter optimization problems. The third part presents application of the MSCA algorithm to optimize static model for solar PV cell. An I-V curve data-driven modeling technique is applied to optimize physical parameters of the system. The experiments were conducted using Matlab R2019a running on a desktop computer equipped with 31.9 GB of RAM, AMD Ryzen 7 3700X 8-core processor, and a 11 GB graphics processing unit.

2.1 Mating-based Sine Cosine Algorithm (MSCA)

MSCA is a new formulation and enhanced variant of SCA algorithm. Table 1 shows symbols and parameters used in the algorithm while Figure 1 shows flowchart of the proposed MSCA. It starts with defining number of agents in a population, N, mating rate, w and initialization of agents' position, x_i^t, on a feasible search space. The algorithm evaluates fitness cost of the agents and determining the current best agent, P^t. Next step is performing mating process for all agents. The mating rate, w, decided the mating weightage between 2 agents based on percentage of the agents' size. A threshold value of 0.2 is used to decide the pairing agent involved in the mating process. It is chosen to force all individual agents to perform exploration process and thus avoiding local optima problem. The i^{th} agent, x_i^t will be mated with P^t if a generated random value is less than the threshold value. If the random value is greater than the threshold value, then the i^{th} agent, x_i^t will be mated with a randomly picked agent from the population. The next step is to apply sine-based or cosine-based position update equation. The sine-based and cosine-based is applied if a newly generated random value is less or greater than a threshold value of 0.5. A 50% trade-off option is considered between sine or cosine terms. Once the agents have updated their position, the algorithm calculate their corresponding fitness cost and determining a new current best agent in the population. The agents also are ascendingly sorted based on the evaluated fitness cost. Agent with the lowest fitness cost implies the best agent in the population. The algorithm is continuously repeated until the stopping criterion is fully met or the running iteration is equal to maximum iteration.

The innovative idea of the proposed MSCA stems from the mating process. The current search agent, x_i^t is mated either with the current best agent, P^t i.e elite, or with other agents depending on the random number generated. Mating with the elite can guide the agent towards the near-best solution while mating with other agents can relocate the agent at a diverged location. Prior to the mating process, the algorithm defines weightage of the mating process and randomly decided which part of the agent features is inherited from the best agent. It increases the random scheme present in the algorithm. Noted that, both exploration and exploitation process are well-covered in the technique. It offers few extra mechanisms to further fined-tune the acquired solution. Another novel idea lies in the cosine-based update position. Instead of using the current best agent generated from standard SCA method, the update position used the elite agent generated from mating process. Thus, a modified mechanism was applied in the formula and hence enhancing the agents' distribution on search space.

2.2 Test on Real-Parameter Benchmark Functions Optimization Problems

Table 2 shows 5 benchmark functions of real-parameter optimization problems. Their corresponding names and mathematical models are presented. All functions have rotated and non-separable characteristics. Functions 1-3 have unimodal feature while functions 4 and 5 have the multimodal feature. In general, due to the presence of multi-location of local optima solution, functions 4 and 5 pose higher challenges in finding the global optima solution. The symbol x represents vector of decision variables or a solution vector. More details information about the functions such as 2D contour map and 3D plot can be referred to [34].

Table 1. Symbol and parameter.

Symbol	Parameter
N	Number of agents
x_i^t	Position of the i^{th} agent at iteration t
T	Maximum iteration
w	Mating rate
P^t	Destination location at iteration t
$xmat_i^t$	Position of the mated i^{th} agent at iteration t

Table 2. Benchmark functions.

Benchmarks function's name	Benchmarks function's equation
1. High conditioned elliptic	$f_1(x) = \sum_{i=1}^{D} (10^6)^{\frac{i-1}{D-1}} x_i^2$
2. Bent cigar	$f_2(x) = x_1^2 + 10^6 \sum_{i=2}^{D} x_i^2$
3. Discus	$f_3(x) = 10^6 x_1^2 \sum_{i=2}^{D} x_i^2$
4. Rosenbrock	$f_4(x) = \sum_{i=1}^{D-1} (100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2)$
5. Griewank	$f_5(x) = \sum_{i=1}^{D-1} \frac{x_i^2}{4000} - \prod_{i=1}^{D} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$

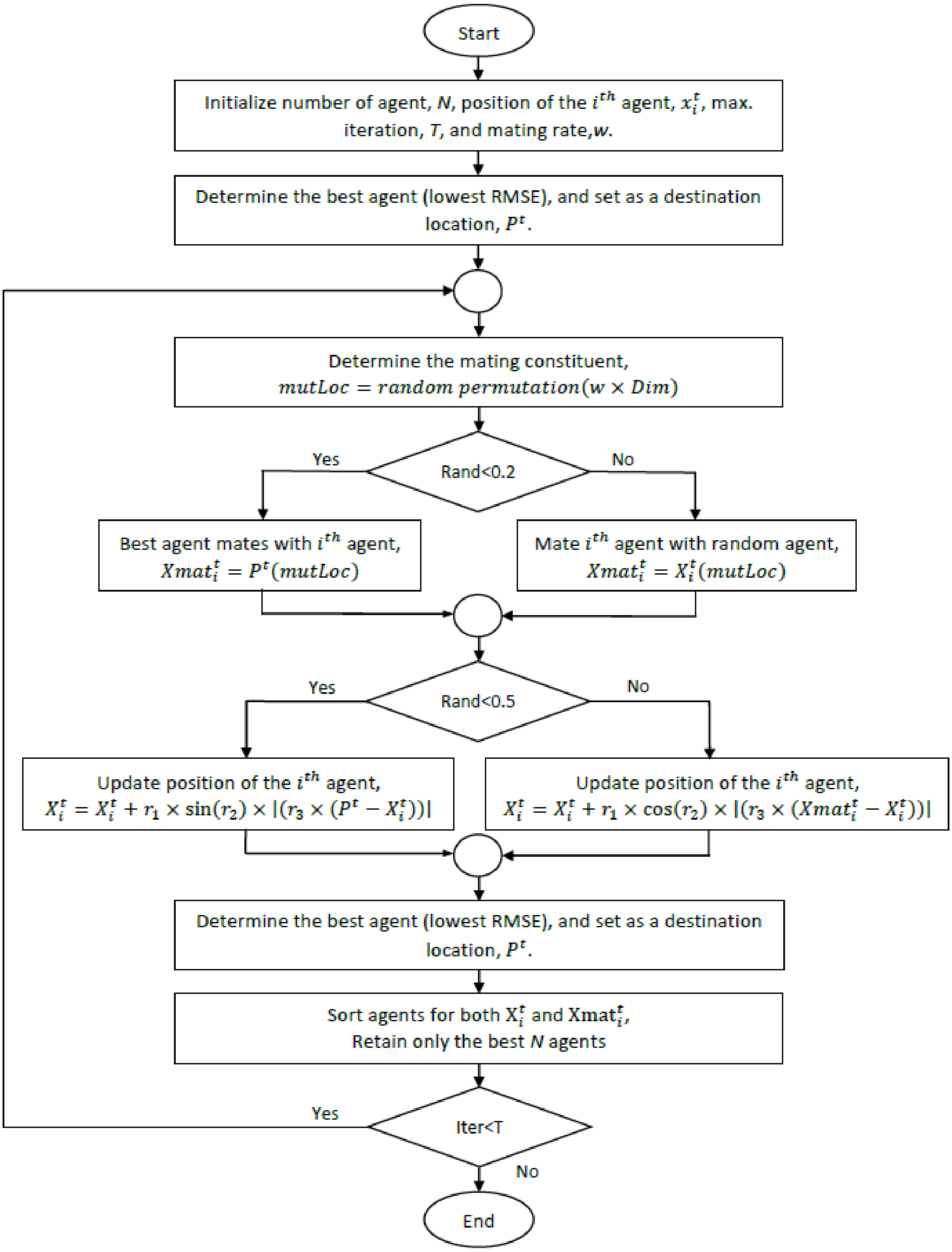


Figure 1. Flowchart of the MSCA. t represents the current iteration loop index, T_{max} is the maximum allowable number of iterations, P_m is the user-defined mating threshold probability, r_1 through r_4 represent the randomized control parameters inherited from the baseline SCA framework for governing trajectory and balance between exploration and exploitation.

The benchmark function performance test for both SCA and MSCA was setup as follows. Adopting the standard setup for testing the benchmark function as outlined in the literature [34], the dimension, D, number of independent runs, maximum number of function evaluation, *maxfes*, search range, number of search agent, m, were defined as 10, 51, $1000 \times D$, [-100, 100] and 50 respectively. As for MSCA, additional parameter as such mating rate was defined as 0.1. The 51 independent runs generated 51 independent data comprising of solely the fitness cost value of the algorithms in locating the theoretical global optima solution. The generated set of data was used for conducting a statistical analysis to determine accuracy of the algorithm in generating the solution. The Wilcoxon sign rank test was applied to statistically analyze the significant difference between data provided by the SCA and MSCA algorithms. Setting the significance level of 0.05, the two-tailed, ρ-value should be less than 0.05 to imply that the MSCA algorithm improvement is significantly better than SCA algorithm.

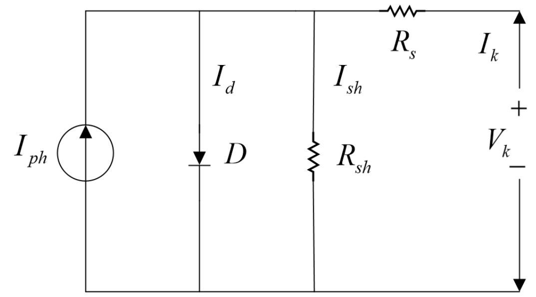


Figure 2. One-diode schematic of solar PV cell.

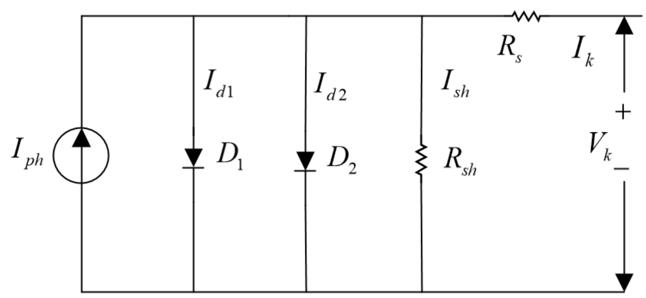


Figure 3. Two-diode schematic of solar PV cell.

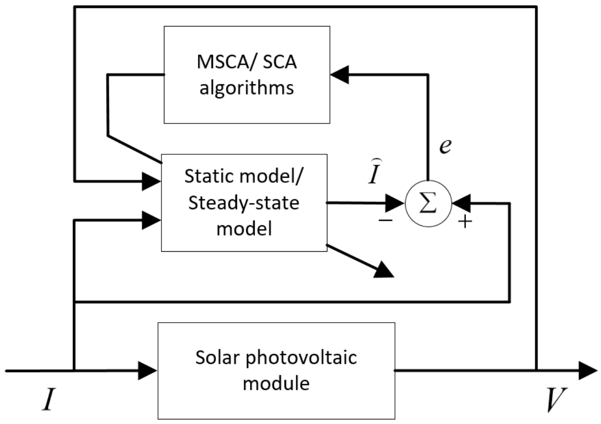


Figure 4. MSCA-based steady-state modelling of a solar PV cell.

2.3 Modelling of Solar Photovoltaic System

Modelling for one-diode and two-diode cells are presented in the section. Figure 2 shows the schematic diagram of the one-diode cell. It comprises of 3 basic components which includes of a diode, D, a series resistor, R_s and a shunt resistor, R_{sh}. The presence of current source as a result of photocurrent solar cell is considered as the main source of the circuit. The construction of the PV system is based on the semiconductor principle. Therefore, the diode mimics the p-n junction behavior and thus creating a diode current, I_d. The shunt resistor allows the flow of leaking current while the series resistor limits the output voltage at a high current. The I_k and V_k are the output current and output voltage respectively which are then used by a load. The solar PV cell exhibits a highly non-linear characteristic of current-voltage relationship.

The output current equation of the one-diode cell for the *k*-th data point is shown as Equation (1).

$$I_k = I_{ph} - I_{sd}\left[e^{\frac{q(V_k+I_kR_s)}{mk_BT}} - 1\right] - \frac{V_k + I_kR_s}{R_{sh}} \tag{1}$$

where I_{ph} is the photocurrent, I_{sd} is the diode saturation current, q is the electron charge, 1.602×10^{-19} C, m is the diode ideality factor, k_B is the Boltzmann constant, $1.381 \times 10^{-23}\, J/K$ and T is the constant cell operating temperature in Kelvin (T at 298.15 K, corresponding to 25 °C). Under constant environmental conditions, there are 5 unknown parameters i.e, I_{ph}, I_{sd}, R_s, R_{sh} and m that should be optimized to optimally match the real solar PV system.

Figure 3 shows the schematic diagram of the two-diode cell. It comprises of 3 basic components which includes of 2 diodes, D_1 and D_2, a series resistor, R_s and a shunt resistor, R_{sh}. It is the enhanced version of the one-diode cell. The only difference is the additional of a diode component into the schematic. The first diode accounts for p-n junction diffusion current while the second diode accounts for charge recombination in the depletion region of the semiconductor component.

The output current equation of the two-diode cell for the *k*-th data point is shown as Equation (2).

$$I_k = I_{ph} - I_{sd1}\left[e^{\frac{q(V_k+I_kR_s)}{m_1k_BT}} - 1\right] - I_{sd2}\left[e^{\frac{q(V_k+I_kR_s)}{m_2k_BT}} - 1\right] - \frac{V_k + I_kR_s}{R_{sh}} \tag{2}$$

where I_{sd1} and I_{sd2} represent diffusion current and saturation current respectively, while m_1 and m_2 represent ideality factor for the first and second diodes respectively. Under constant environmental conditions, there are 7 unknown parameters i.e, I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, m_1 and m_2 that should be optimized to optimally represent the real solar PV system.

Figure 4 shows the MSCA-based and SCA-based steady-state modelling or static parameter estimation for the solar PV cell. The I_k and V_k represent the measured current and measured voltage respectively. The input-output pair (I_k, V_k), which represents discrete data points sampled along a single, stable I-V characteristic curve is experimentally measured from input and output terminals of the real solar PV cell with STC of 1000 W/m^2 irradiance and 25ºC temperature [35]. PV parametric model is the mathematic equation of the one-diode and two-diode cells as shown in Equations (1) and (2). The input-output pair, (I_k, V_k) from real system is applied into the mathematical parametric model. Estimated output from the model is compared with the input current measured from the real system. The difference between the two currents is defined as the error and is applied to the MSCA and SCA for minimization. The error, e is applied into the objective function of the MSCA shown in Equation (3) which is formulated as the root-mean-square-error (RMSE) with respect to the cell current.

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(I_k - \hat{I}(V_k, \theta)\right)^2} \tag{3}$$

N represents the total number of measured data points on the I-V curve, V_k is the k-th measured voltage and I_k is the k-th measured current, while the $\hat{I}(V_k, \theta)$ is the estimated output response of the one-diode and two-diode cells based on voltage-current relationship shown in Equations (1) and (2). The symbol θ represents the vector of unknown model parameters for the PV cells.

The setup for both SCA and MSCA to optimize real-parameter of solar PV cell as follows. The maximum number of function evaluation, *maxfes*, search range, number of search agent, *m*, were defined as $100{,}000 \times D$, [-100, 100] and 50 respectively. The dimension, D was defined as 5 and 7 for one-diode and two-diode models respectively. As for MSCA, additional parameter as such mating rate was defined as 0.1.

3. RESULT AND DISCUSSION

This section is divided into 2 sections. The first section presents the algorithms' performance on real parameters benchmark functions. The accuracy attainment result based on the 51 independent trials and analysis via the Wilcoxon sign rank test are provided. Convergence plots for various benchmark functions are also shown. The second part presents the algorithms' performance for optimizing real parameters of solar PV cells. The proposed MSCA performance is compared with its predecessor algorithm (SCA) and another metaheuristic algorithm known as spiral dynamic algorithm (SDA) [36].

3.1 Performance on Real-Parameters Benchmark Function

Table 3 presents the generated average cost value of the MSCA, SCA and SDA algorithms tested on 5 real-parameter benchmark functions. It is an average value calculated from the 51 independent runs on each function. The cost represents an error of the acquired solution compared to theoretical optima solution. Lower value indicates that the error is low as well as the solution is more accurate and is highlighted in bold font. The table shows that the average costs attained by the proposed MSCA have the smallest values implying that the solutions are better than its counterparts. The solutions presented by the SDA have the largest cost values among all algorithms implying that the SDA has the worst performance. Table 4 shows statistical analysis result of the Wilcoxon sign rank test. It shows that the two-tailed, *p* value for all functions are less than 0.05 and the z-value has a positive sign. It implies that the attained solutions of the MSCA are significantly improved. The higher value of z- ranks than the z+ ranks for all functions has confirmed the performance analysis. Functions 1 and 5 have the least two-tailed, *p* value followed by Functions 2 and 4. Although Function 3 has the largest two-tailed, *p* value among all, the result also implies that the improvement is significant. The result has proved that the proposed MSCA outperformed the original SCA in finding the theoretical optima solution for the global optimization problems. Table 5 shows statistical Wilcoxon sign rank test result comparing MSCA and SDA. It shows that all the two-tail, *p* values are less than 0.05 indicating that the performance of the proposed MSCA is significantly better than the SCA for all 5 benchmark functions. Function 3 has the most significant result while function 2 has the least significant result among the 5 functions. The results presented in Tables 4 and 5 are consistent and closely align with Table 3.

Table 3. Average cost value of the MSCA and SCA.

Func. no	Average Cost		
	MSCA	SCA	SDA
1	**1.1974E7**	4.3217E7	7.9375E07
2	**1.9587E8**	8.0831E8	3.3614E09
3	**1.0097E4**	1.1997E4	5.7278E05
4	**462.9502**	594.5464	934.8928
5	**704.5662**	714.3613	782.5994

Table 4. Wilcoxon sign rank test result with MSCA-SCA.

Func. no	Statistical analysis result (MSCA-SCA)			
	p value	Z value	z+	z-
1	**5.9718E-8**	4.5274	180	1146
2	**2.0704E-7**	5.1929	109	1217
3	**2.5074E-2**	2.2403	424	902
4	**8.2043E-7**	4.9304	137	1189
5	**5.7967E-10**	6.1959	2	1324

Table 5. Wilcoxon sign rank test result with MSCA-SDA.

Func. no	Statistical analysis result (MSCA-SDA)			
	p value	Z value	z+	z-
1	**4.1704E-8**	5.4835	78	1248
2	**1.6894E-5**	4.3024	204	1122
3	**5.1453E-10**	6.2146	0	1326
4	**7.4333E-7**	5.3804	89	1237
5	**5.7967E-10**	6.1959	2	1324

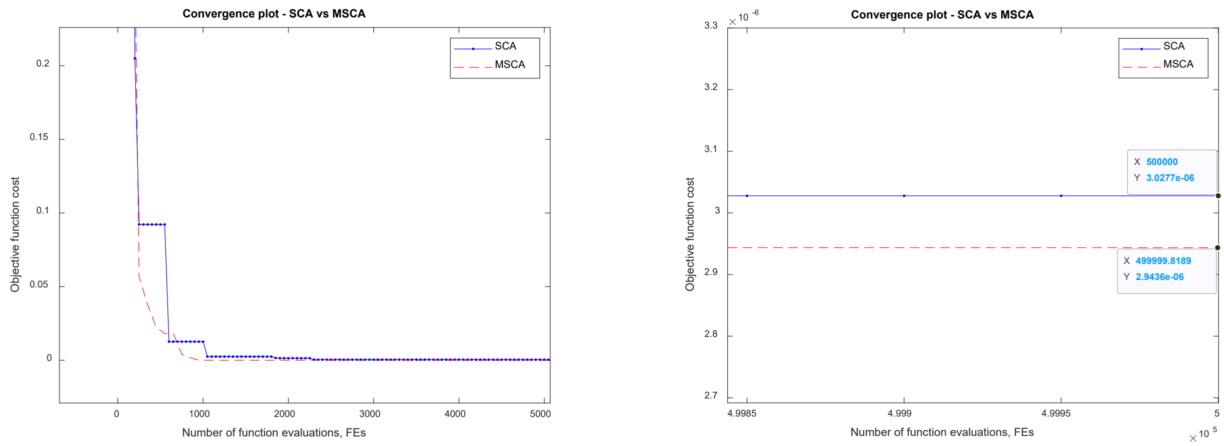
3.2 Modelling of Solar Photovoltaic Cell

Result of the modelling part comprises of the convergence plot of the algorithms to minimize objective function, I-V and Power-Voltage (P-V) graphs representing the solar PV model. Error plot of the actual and estimated I-V graphs is also included.

3.2.1 One-diode Model

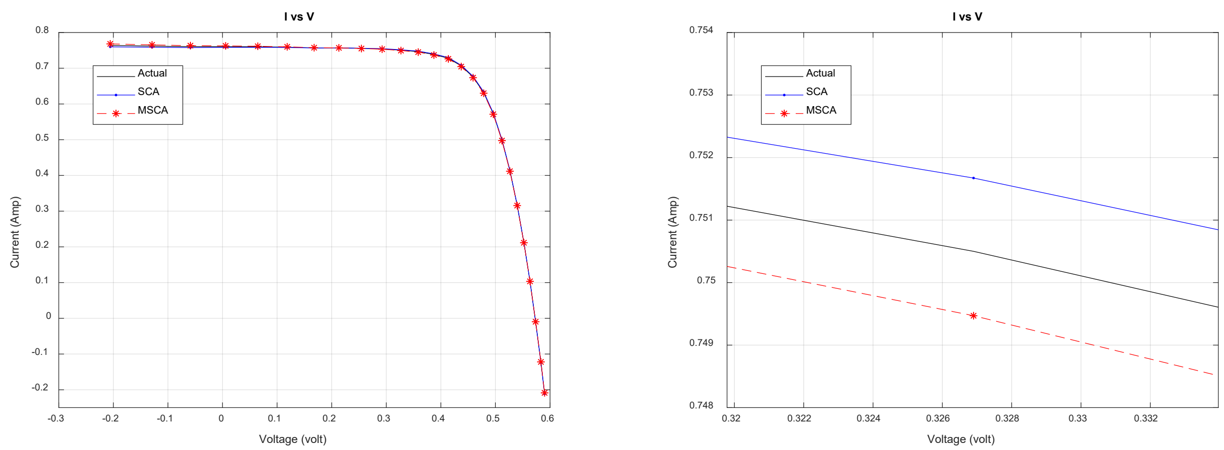
Figure 5 shows convergence plot of the MSCA and SCA algorithms for optimizing real parameters of the one-diode PV model. The convergence pattern for both MSCA and SCA is shown in Figure 5(a). Noted from the figure, the MSCA graph has the smoother convergence. The SCA has faced problem to converge between number of function evaluations (FEs) [242, 547] and [548, 1001]. Figure 5(b) shows MSCA has converged to a lower cost at 2.94E-6 and is better than the SCA which settled at the cost 3.02E-6 thus implying that the MSCA has attained the higher accuracy performance.

Figures 6(a) and 6(b) show the I-V graph and zoomed-in I-V graph of the one-diode model respectively. Figures 7(a) and 7(b) show the P-V graph and zoomed-in P-V graph of the one-diode model respectively. Noted from the graph, both MSCA and SCA have successfully imitated the I-V and P-V behavior of the solar PV system. However, the MSCA graph has acquired a closer and better model as compared to the SCA graph. The difference is obviously seen from the zoomed-in graphs.



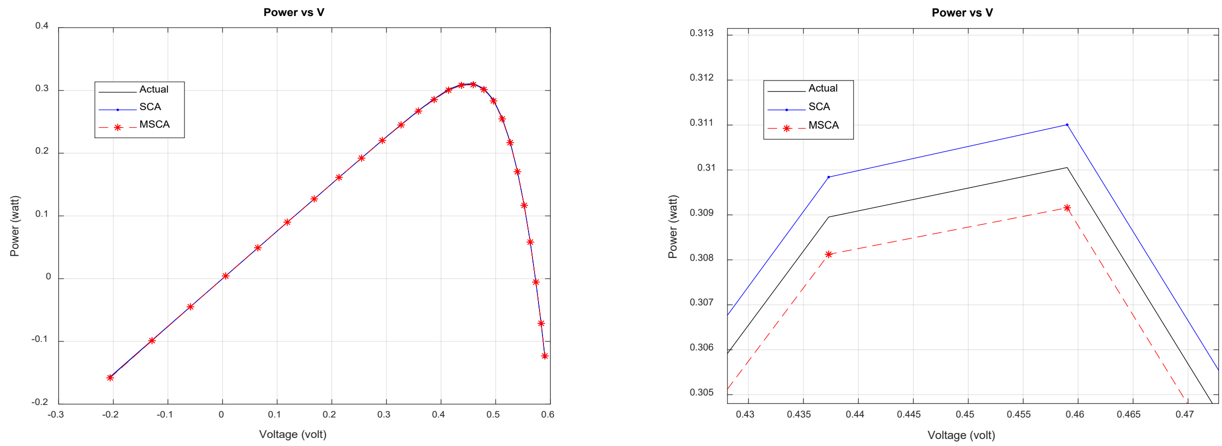
(a) (b)

Figure 5. Convergence graph of the MSCA and SCA for one-diode model: (a) Cost vs FEs; (b) Cost vs FEs zoomed-in.



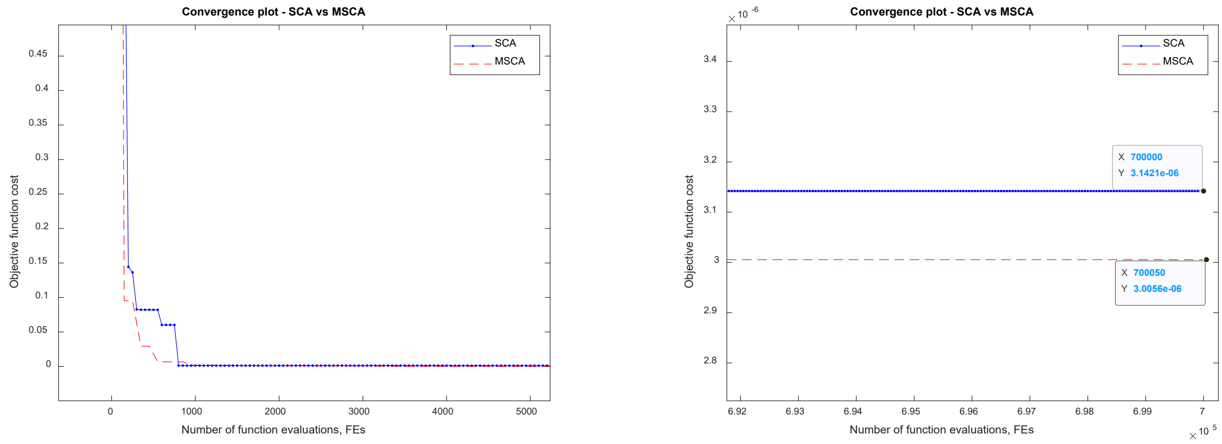
(a) (b)

Figure 6. One-diode model: (a) I-V graph; (b) I-V graph zoomed-in.



(a) (b)

Figure 7. One-diode model: (a) P-V graph; (b) P-V graph zoomed-in.



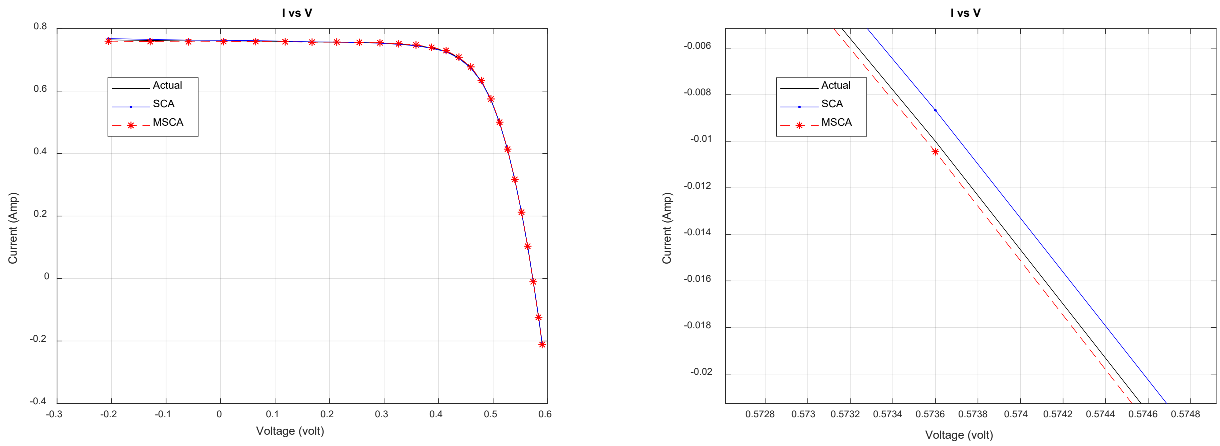
(a) (b)

Figure 8. Convergence graph of the MSCA and SCA for two-diode model: (a) Cost vs FEs; (b) Cost vs FEs zoomed in.

3.2.2 Two-diode Model

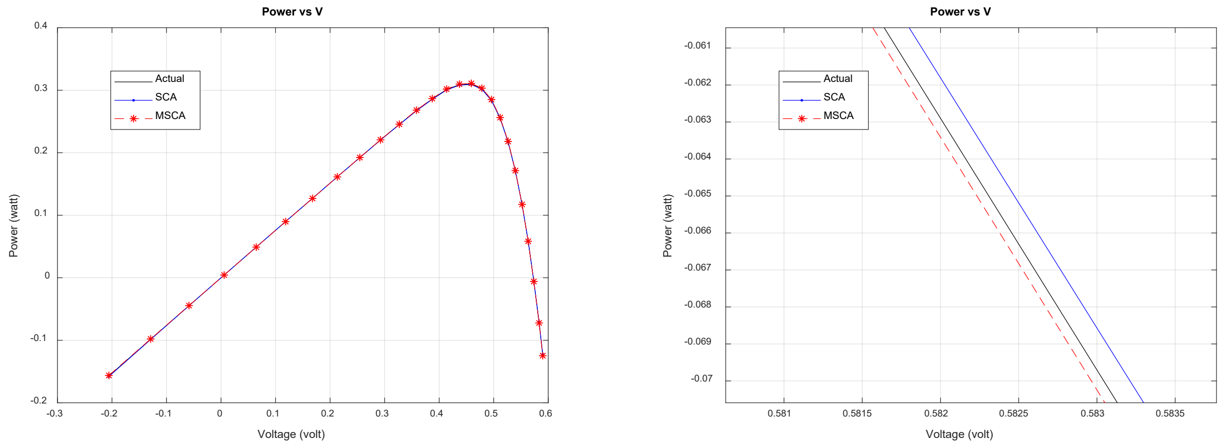
Figure 8 shows convergence plot of the MSCA and SCA algorithm for optimizing real-parameters of the two-diode solar PV model. The MSCA algorithm has attained a smoother convergence compared to SCA as shown in Figure 8(a). The SCA unable to converge smoothly in the range between [304, 550] and [551, 750] of the FEs. Figure 8(b) shows that MSCA has successfully settled at 3.01E-6, a slightly lower cost than the SCA which reached at the cost 3.14E-6. Figures 9(a) and 9(b) show the I-V graph and zoomed-in I-V graph while Figures 10(a) and 10(b) show the P-V graph and zoomed-in P-V graph of the two-diode model. Noted from the graph, both MSCA and SCA have satisfactorily imitated the I-V and P-V behavior of the PV system. The zoomed-in plot in shows that the MSCA graph has acquired a closer graph as compared to the SCA graph implying that it has acquired a better model.

Table 6 presents cost value of the objective function and error range of the I-V graph for one-diode model. Performance comparison is made between the proposed MSCA, its predecessor algorithm, SCA and another state-of-the-art algorithm, SDA. Result with better performance is highlighted in bold font. Noted from the table, the SDA has a smallest error range in the first half while the MSCA attained smallest error range in the second half. However, the MSCA has acquired a smallest total error and thus outperformed both SCA and SDA. Different error trend applies to the two-diode model as shown in Table 7. The SCA has a smallest error range in the first half while the MSCA attained smallest error range in the second half. However, the MSCA has acquired a smallest total error and thus outperformed both SCA and SDA. It also observed that, the cost value of the two-diode model for both MSCA and SCA is slightly greater than the one-diode model. The two-diode model has posed greater challenges since it comprises of extra 2 unknown parameters as compared to one-diode model. The zoomed-in figures show that the distance between the graph of SCA-based PV model and the graph of actual PV cell is slightly far than the distance between the graph of MSCA-based PV model and the graph of actual PV cell. The result has proved the superiority performance of the proposed MSCA followed by the SCA and SDA in solving solar PV model for one-diode and two-diode models.



(a) (b)

Figure 9. Two-diode model: (a) I-V graph; (b) I-V graph zoomed-in.



(a) (b)

Figure 10. Two-diode model: (a) P-V graph; (b) P-V graph zoomed-in.

Table 6. One-diode model.

Algorithm	Model optimization	
	Cost value	3-point error range
MSCA	**2.9436E-6**	[-4.198E-3, 1.953E-3, -1.361E-3]
SCA	3.0277E-6	[4.107E-3, -2.076E-3, 1.628E-3]
SDA	6.9064E-5	[9.945E-4, -7.326E-3, 2.198E-2]

Table 7. Two-diode model.

Algorithm	Model optimization	
	Cost value	3-point error range
MSCA	**3.0056E-6**	[4.256E-3, -1.965E-3, 1.327E-3]
SCA	3.1421E-6	[-4.142E-3, 1.935E-3, 2.457E-3]
SDA	1.6063E-5	[9.859E-3, -4.5299E-3, 2.9965E-3]

4. CONCLUSION

An improved variant of sine-cosine algorithm (SCA) known as the mating-based sine-cosine algorithm (MSCA) has been proposed in the paper. A mating strategy has been incorporated into the original SCA enhancing the exploration and exploitation of searching agents in the feasible search space. Some good features of the current best agent are transferred into other agents and hence improving the features of the targeted agents. With the new features, the agents have higher capability to escape local optima trap. Accuracy performance of the proposed MSCA has been tested on various real parameters global optimization problems and compared with the original SCA and spiral dynamic algorithm (SDA). The problem has posed various challenges imitating wide range of the real-world problems. The Wilcoxon Sign rank test has been applied to statistically analyze the algorithms performance. The analysis has shown that the MSCA has outperformed the SCA and SDA for all benchmark functions. It also evident from the analysis that two-tailed *p*-value is less than 0.05 implying that the improvement made are significant. The algorithm also has been applied to optimize static models of one-diode and two-diode solar PV cells for steady-state electrical performance modeling. Graphical results of I-V and P-V have been presented showing both algorithms have successfully modelled the solar PV cells. The error plot has shown that MSCA achieved the smallest range implying that it has acquired better static model. It also evident from convergence plot of the optimization the static model that the proposed MSCA achieved better accuracy than its predecessor SCA and SDA. A significant challenge of the algorithm that users may encounter includes determining a correct user-defined parameter such as the weighting factor of mating process. Lower and higher values tend to force all individual agents to perform exploration and exploitation respectively. Depending on the types of optimization problem intended to solve, the user-defined parameter is heuristically selected. Setting this threshold value to 0.5 under the assumption that it automatically balances exploration and exploitation processes is often not the best strategy as the mating process is complementing the original SCA structure. As to overcome the limitation, an adaptive mating approach can be incorporated into the model. Nevertheless, the proposed algorithm offers a promising strategy and it will be applied to solve other complex models such as neural network and artificial fuzzy logic in the future.

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DECLARATION OF CONFLICTING INTERESTS

The authors declare no potential conflicts of interest with respect to the research and publication of this article.

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