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Parameter Estimation of Solar Modules Operating Under Outdoor Operational Conditions Using Artificial Hummingbird Algorithm

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ABSTRACT In this article, an artificial algorithm called hummingbirds optimization method, named AHA algorithm, is settled to extract accurately the parameters of PV modules under outdoor operational conditions. AHA is the main contribution in this work, regarding its efficiency and good performance in terms of standard deviation (StD), root mean square error (RMSE), sum of squared error (SSE), maximum number of iterations (MaxIt), particularly, for extracting parameter from modules operating in real conditions, and under different temperature and irradiance levels. The AHA is applied on a Polycrystalline-solar panel module type 320W-72P at real operating conditions and on a PV array of three polycrystalline PV modules connected in series. PV cells of the same modules are assumed operating under the same conditions where they share the same electric current and voltage values. In this last pattern, eight different scenarios are chosen. In the first five scenarios, the temperatures are (46.97, 44.23, 42.87, 40.59 and 30.60°C), and the irradiance varies, such as (910, 800.57, 614.13, 415.1 and 200.87W/m²), respectively. In the other three testing scenarios, the solar irradiance is equal (803 W/ m²), and the temperature differs, such as T=47.93 °C, 53.38 °C and 36.62°C. Lower values of root mean square errors (RMSE) are achieved (9.8602×10^{-4} and 2.572533×10^{-2} for RTC France PV cell and the 320W-72P module respectively) with 6000 iterations. Moreover, all the eight scenarios are lower than 7.245916×10^{-2} for the last case study. Moreover, results show that we could recommend the AHA algorithm as an advanced and efficient method for dealing with real time parameter optimization of photovoltaic modules. In fact, a high closeness between the simulated and the experimental curves is achieved, which indicates the perfectness of this optimization method. Finally, the proposed AHA algorithm can be engaged as tools for the best designing of PV systems.

INDEX TERMS Artificial hummingbird algorithm, photovoltaic cells, physical parameters, PV extraction.

I. INTRODUCTION

Nowadays, energy has become an indispensable means for practically all our activities in life, e.g. for communication, for education, at work, at home, for travelling, etc. On the other hand, in the last two years, the global pandemic of COVID-19 has unbalanced the energy markets and highlighted the energy and climate issues, which oblige the scientific community to act and help to build a more strong society

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ready to face future crises. Business closures, stay-at-home orders and restrictions on movement have reduced electricity consumption and shifted daily demand patterns. Scientific researchers have shown during this crisis their agility and their ability to build adapted responses in various engineering fields.

COVID-19 pandemic has also had a major impact on the industry. Interest in renewable energies is increasing: an important factor on the reduction of CO₂ emissions. While the transition to renewable energy sources is a path towards the energy sovereignty of states. In our opinion, renewable

energies could protect us in the face of current and future crises thanks to its lower operating costs and preferential access to electricity networks. In fact, the photovoltaic source is the low-cost renewable energy technology. In 2021, solar PV capacity reached 139 GW; this brought the global to an estimated total of 760 GW, including both on-grid and off-grid capacity [1]. In fact, the share of solar photovoltaic energy (PV) is increasing in many power systems around the world and is projected to continue increasing in the future.

Actually, the important increase in energy demands and the environmental difficulties lead to a necessary requirement to produce electricity from renewable sources. Energy generation from solar PV technology is clean, simple and suitable for standalone applications. However, the primary price and the cost of kWh generated by PV system is still high compared to the conventional electric grid. In our opinion, PV power generation is still not reached the point that can substitute conventional nuclear-powered, gas-powered and coal-powered generating facilities. The power of the PV system mostly depends on incident irradiation and temperature. Many years ago, PV solar modules have been used in isolated locations to deliver electricity since in remote area there are no grids connected yet. Though, the quantity of the electricity generated depends largely on the efficiency of the PV cells and the environmental conditions. solar cell's efficiency depends on numerous factors such as photocurrent, ideality factor, series and shunt resistances, and saturation current [2]–[4]. Solar cells are generally used for their unpolluted and ecological benefits, pushing scientists to precisely model their electrical characteristics. Recently, based on the non-linearity of current-voltage (IV) curves of photovoltaic (PV) modules, meta-heuristic algorithms seem very efficient approach and became very popular in the PV energy field to estimate various parameters.

Hence, to get the parameters of PV module, many researchers have suggested different techniques from diverse perspectives. These methods can be classified into three classes, iterative-based techniques, analytical methods, and meta-heuristic-based algorithms. The main idea behind using meta-heuristic methods is its ability to overwhelm the limits of analytical and deterministic methods. Meta-heuristics methods have a great ability for dealing with many objective problems, which shows a vital role in PV system design. In the other hand, making IV measurements and analyzing the impact of PV parameters is an important issue in solar engineering development, from the characterization of PV materials and components needed for a design, to testing of models, to quality control during manufacture, to process and maintenance of the PV systems. In the present work, we have adopted an algorithm named Artificial Hummingbird Algorithm (AHA) [5] to find accurately the different factors of PV modules.

From previous reviews, various meta-heuristic algorithms are utilized to optimize internal electrical PV parameters of solar panels. To extract the PV parameters, an algorithm using chaotic generator via Rao-1 optimization

algorithm (LCROA) has been suggested [6]. The authors concluded that LCROA enhances the basic Rao-1 algorithm, related to its convergence speed, and demonstrated the advantage of using a chaotic map for process diversification. In [7] the authors have developed a variety of butterfly optimization algorithm (termed EABOA) to evaluate the unidentified parameters of three PV models. They concluded that EABOA provides good performance compared to selected meta-heuristic approaches in terms of reliability and accurateness. In [8] MTLBO algorithm is suggested to identify efficiently the PV parameters. It is applied on single and double models, and three PV modules: Photowatt-PWP201, STP6-120/36, and STM6-40/36 modules. A recent variant named Whippy Harris Hawks Optimization and termed WHHO has been proposed to improve the performance of the original HHO algorithm [9]. It is validated on three classes of marketable PV modules considering the influence of temperature and irradiance variations. The authors concluded that the photocurrent and the saturation current are slightly changed with the variation of the irradiance and temperature, respectively, and the other parameters linger quasi-constant under different operating conditions. To simulate the parameters of solar cells and modules, the authors [10] applied a gradient based optimizer (GBO). A great agreement between the simulated and experimental data of P-V and I-V curves is attained by GBO algorithm. In [11] the authors applied Runge-Kutta optimizer (RUN) algorithm to estimate PV parameters. They concluded that the closeness between the simulated I-V and P-V curves reached by the RUN algorithm compared with the experimental data is very high. In order to extract the parameters from PV model, an algorithm based on gaining-sharing knowledge (GSK) was presented [12]. It was applied to five PV models including the SDM, DDM, and three PV modules. Also, to solve the problem of the parameter identification in PV models, enhanced GBO combined with a random learning mechanism, called RLGBO, has been considered [13]. RLGBO was tested for three different PV models, which are ST40, SM55, and KC200GT, to resolve the SDM and DDM model's parameter identification problem under outdoors conditions. A comparison between an improved spherical evolution algorithm using a dynamic sine-cosine mechanism (DSCSE) and ten other optimization algorithms has been accomplished to identify the unknown variables of PV cell/module at a given light and temperature [14]. An improved algorithm called IMPA (Marine Predators Algorithm) for simulating PV variables of different models has been proposed [15]. The IV and PV curves prove that the simulated and measured data are in good agreement. However, the authors have concluded that IMPA doesn't attain the smallest CPU time compared to other optimization algorithms. In [16] an enhanced Harris Hawks optimization is suggested to simplify the modelling of a PV system and estimation of PV variables by combining vertical and horizontal crossover mechanism of the crisscross optimizer and Nelder-Mead algorithm, termed CCNMHHO. It was compared with IJAYA, MLBSA and GOTLBO algorithms and it has reached

higher performance based on the convergence speed and the reliability of the simulation results with the measurement results. Another algorithm called CPMPPO which is an optimization algorithm using particle swarm is suggested to solve the problem of PV parameter [17]. The experimental results have confirmed the effectiveness of CPMPPO algorithm in terms of rapidity, stability, and accuracy. In [18] the authors have proposed an enhanced HHO, which combines HHO with two mechanisms of GOBL and OL. It was applied to extract the unknown PV parameters. In [19] an enhanced adaptive differential evolution algorithm, named EJADE, has been settled to estimate the parameters of different PV models. The authors concluded that EJADE cannot resolve constrained multi-objective problem. In [20] an enhanced Lévy flight bat algorithm (ELBA) has been proposed. It has been confirmed that ELBA accomplishes its objective of competently estimating PV parameters for different PV models from measured data. In [21] the authors have proposed an orthogonal moth flame optimization (MFO) using a local search to identify PV parameters of cell models, which is termed NMSOLMFO. The statistical results indicated that NMSOLMFO outperform IGWO, OBLGWO, ALCPSO, CGPSO, RCBA, CBA, OBSCA and SCADE approaches regarding accurateness and convergence speed. Self-adaptive ensemble-based DE (SEDE) optimizer has been suggested in [22] for identifying PV parameters of different models. The results obtained have proved that SEDE has gotten better results concerning accuracy and stability than related algorithms. WLCSODGM is an improved variant of CSO that was proposed in [23] to estimate parameters for PV models. It was compared with twelve other algorithms using four different PV models. In [24] a combined use of the similarity-guided evolutionary multi-task optimization framework and the DE, named SGDE, has been proposed to identify the parameters of different PV models. The performance of SGDE was assessed on SDM, DDM and PVMM and compared with single task DE and other algorithms. The results verified that SGDE successfully enhanced the accuracy and stability of DE. In [25] the authors proposed another algorithm called SDO (Supply-Demand-Based Optimization) to extract PV parameters from PV models. They have concluded that the SDO provided minor absolute errors of the experimental points for the simulated currents and powers. In [26] the authors developed new approach of meta-heuristic optimization named IEO (Improved Equilibrium Optimizer) algorithm for PV parameters estimation. The algorithm showed high robustness and optimization quality under fast fluctuations of climate conditions and partial shading testing conditions. The optimization of the PV models [27] (SDM, DDM, and PV module) shows that the convergence accuracy and robustness of the hybrid PSO-based on random reselection mechanisms are superior to those obtained by the original PSO and CS algorithms. In [28] Forensic-Based Investigation Algorithm (FBIA) is suggested to accurately extract the electrical parameters of diverse PV models. The numerical results are compared with other optimization algorithms for the commercial

Photowatt-PWP 201 polycrystalline and Kyocera KC200GT modules. In [29] the authors introduced a Stochastic Fractal Search (SFS) optimization algorithm to extract values of solar PV variables for its accurate modelling. They have concluded that the obtained PV parameters by SFS were closely matched with real data. Marine Predators Algorithm [30] was tested to extract the variables of the well-known models (SDM, DDM and TDM) of PV cells. The proposed algorithm has robust statistical analysis and good convergence for different levels of irradiance. In [31] the authors have proposed an improvement of differential evolution (DE) technique to estimate electrical parameters of solar photovoltaic modules. The selection of the best parameter and crossover factors for each specific I-V curve is based on the Lambert W function and meta-heuristic step. In [32] hybrid use of Grey Wolf Optimizer and Cuckoo Search Algorithm (GWOCSA) has been compared with some selected algorithms which are PSO, MVO, SCA, CSA, and GWO. The performance analysis is approved using TDM model to demonstrate the effectiveness of GWOCSA. The authors in [33] have presented an investigation of the meta-heuristic methods applied in numerous researches on the optimization of PV parameters. They settled that there was limited research available for the three-diode model in literature due to its complexity and higher computational strength. Chaotic LSHADE algorithm is proposed in [34] to solve the 7-parameter DDM model and 9-parameter TDM model estimation problem of the PV equivalent circuits based on the minimization of the RMSE values calculated. Manta Ray Foraging Optimization (MRFO) algorithm has been proposed in [35] for parameter extraction of TDM model. The authors have compared it with six other algorithms; a good balance between the simulated and experimental I-V characteristic was proven. The Fractional Chaotic-Ensemble Particle Swarm Optimizer (FC-EPSO) method has been developed [36] for modelling the solar cell using experimental data in outdoors conditions. The authors have concluded that the obtained variables of the tested models using different variants of FC-EPSO showed that the best model presents minimal deviation at MPP (Maximum Power Point) with high convergence rate and low execution time once compared it with other algorithms. In [37] Wild Horse Optimizer (WHO) is suggested to estimate the parameters of a DDM model, TDM model, and their modified models (MDDM and MTDM). The performance of the algorithm using the RMSE and robustness is based on statistical analysis. Different models have been used [38] such as villalva's iterative model, genetic algorithm, Lambert W function, multi-objective GA, particle swarm optimization, pattern and pareto search, Nelder-mead method and simulated annealing, to identify series and shunt resistances of commercially PV modules. The highest performance was reached by Particle swarm optimization and Nelder-mead method. The iterative method had the lowest performance. An improved algorithm using adaptive differential evolution algorithm [39] has been established to find the unidentified variables of various PV models. In [40] statistical-based

results were used to analyze various meta-heuristic techniques. They have concluded that fractional chaotic ensemble PSO (FC-EPFO) can offer the best RMSE values. While memetic adaptive MADE takes the shortest CPU calculation time. In [41] to deal with PV parameter estimation of various types of solar PV models, directional permutation differential evolution (DPDE) algorithm was proposed. It was compared to other fifteen representative algorithms. RMO (Radial Movement Optimization) algorithm is suggested for estimating solar cell variables [42]. The RMO-based current-voltage and power-voltage curves were compared with those obtained by the DET and PSO methods. In [43] an algorithm named opposition-based equilibrium optimization (OBEO) has been proposed for identifying the parameters of different PV models, based on three distinct points: open-circuit voltage, short-circuit current, the maximum power point provided by the datasheet. A combination method between the Newton Raphson method and a self-adaptive algorithm named the Drone Squadron Optimization has been compared within heuristics algorithms in the field of PV estimation [44]. In another work, the authors have proposed an I-AVO algorithm (Improved-African Vultures Optimization) with the orthogonal learning and the general Opposition-Based Learning approaches and to determine the variables of the PV modules with good accuracy [45]. They have concluded that the proposed algorithm is the best one compared to other algorithms for two case studies. In [46], to generate solar cells and PV modules parameters, the authors have suggested a genetic algorithm based on non-uniform mutation (GAMNU). The performance of the method is approved using diverse PV models and modules. The authors concluded that suggested method is designed to be adequate for solving real optimization problems in the energy area. Since the No-free lunch theory [47] states that no algorithm offers perfect performance on all optimization problems. Hence, several attempts are still required to achieve the best algorithm. Taking into account the mentioned reason, this paper applied a newly proposed meta-heuristic algorithm called AHA to cope with the problem of parameter optimization of PV models operating in outdoor conditions, and raise new, more efficient optimizers from different aspects to deal with this field of research. The main objective is to reduce the error between the experimental data and the suggested approaches by optimizing the variables of PV modules.

The content of this manuscript is structured by: Section II presents the single diode equivalent circuit model (SDM) and module based SDM model. The problem definition and AHA algorithm main principles are offered in section III. The validation of the proposed method using three experimental cases is shown in section IV. At the end, the manuscript is closed by the conclusion of section V.

II. PV CELLS MODELS

PV cells models have been principally categorized into three types that are single-diode model (SDM), double diode model (DDM), and three-diode model (TDM). SDM represent a simple configuration for representing a solar PV cell without

considering the recombination losses occurring in the depletion region. Its structure is simple and involves fewer parameters (five unknown parameters to be determined). DDM has been presented by adding an extra diode to SDM. It is considered during the recombination loss of carriers in the depletion region. Thus, DDM is more appropriate for low irradiance level operation of the PV cell. DDM has seven unknown parameters to be determined. The third model TDM is used for industrial applications. TDM has been presented by adding an additional diode in parallel with the two other diodes to DDM. TDM has nine unknown parameters to be determined. In this article we have limited the problem of optimization to the five parameters model to ensure the robustness of the algorithm with less numerical calculation, and show the effectiveness of the AHA algorithm in a very simple way. The parameter meanings are given in Table 1, and the equivalent circuits and the mathematical equations of the SDM and PV module based on the SDM are represented in Table 2.

TABLE 1. The meaning of electrical parameters of PV model.

Parameters	Description
I_{ph}	Photo-generated current
I_o	Reverse saturation current
n	Ideality factor
R_s	Series resistance
R_{sh}	Shunt resistance
V	Output voltage
I	PV current

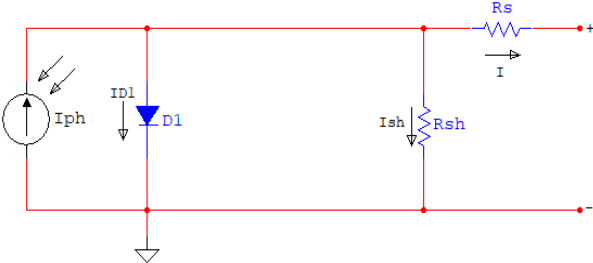
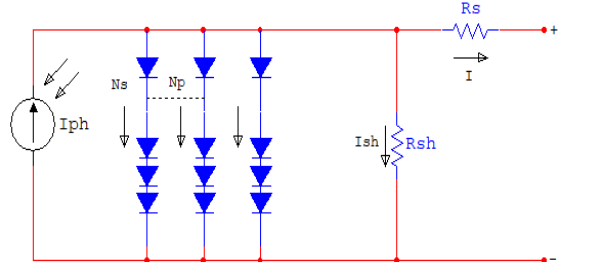
III. PROBLEM DEFINITION AND AHA ALGORITHM

A. PROBLEM DEFINITION

Accurate extraction of the PV models' parameters is still a very challenging task due to the different characteristic's types (non-linear, multi-variable, and multi-modal), in addition to the insufficient information data provided by manufacturers. Accordingly, with regards to this non-linearity, multi-variability and multi-modality problems of IV curves of PV cells/modules, meta-heuristic algorithms seem very efficient approach to exceed the limitations of analytical and deterministic methods. Recently, meta-heuristic algorithms became very popular in the PV energy field to estimate various parameters. However, applying the optimization algorithms for this kind of problems have need of defining the parameters to be extracted, and the goal function that should be reduced. Figure 1 summarizes the overall process for using meta-heuristic methods to improve the performance of a given function (system to be optimized).

The parameters to be optimized are obviously the five parameters of the simplest model (SDM). So, the optimized

TABLE 2. SDM model and PV module based on the SDM.

Model	Electrical equivalent circuit	Mathematical model
SDM		$I = I_{ph} - I_o \left[\exp\left(\frac{V + IR_s}{nV_t}\right) - 1 \right] - \frac{V + IR_s}{R_{sh}}$ <p>05 parameters to be extracted: I_{ph}, I_o, n, R_s and R_{sh}</p>
PV module model based on the SDM		<p>The modules considered are connected in series, N_p is equal to 1.</p> $I = I_{ph} - I_o \left[\exp\left(\frac{V + IN_s R_s}{nN_s V_t}\right) - 1 \right] - \frac{V + IN_s R_s}{N_s R_{sh}}$ <p>05 parameters to be extracted: I_{ph}, I_o, n, R_s and R_{sh}</p>

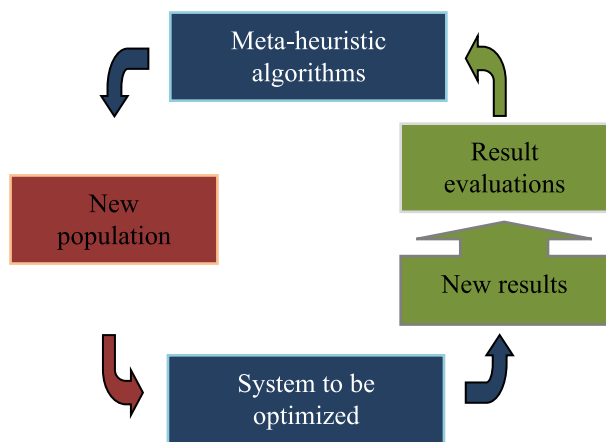


FIGURE 1. Interaction process between meta-heuristic algorithms and system to be optimized.

parameter (knowledge base) set may be such that:

$$\tilde{K} = [R_s \ R_{sh} \ I_{pv} \ I_o \ n]^T \quad (1)$$

The design approach presented in this paper allows for constraints to be involved in the optimization process either in the constraint equations or with the upper and lower bounds on the design vector. The objective function must be explicitly or implicitly dependent upon a set of design parameters.

The general multi-objective optimization problem can be stated as follows:

$$\begin{aligned} &\text{Minimizes } F(\tilde{K}) \\ &\text{Subject to } G_j(\tilde{K}) \leq 0 \quad j = 1, \dots, m_c \text{ and } k_{Loweri} \\ &\leq k_i \leq k_{Upperi} \quad i = 1, \dots, n_c \end{aligned} \quad (2)$$

where $F(\tilde{K})$ is an objective function, when minimized, will result in best performance of the system. The vector \tilde{K} contains n_b systems parameters which are varied through the iterative optimization process. $G_j(\tilde{K})$ is the j^{th} constraint on the design parameters. There are m_c constraints. Each design parameter k_i is bounded by upper and lower limits k_{Loweri} and k_{Upperi} , respectively. A constraint is violated if $G_j(\tilde{K}) > 0$. The design procedure involves:

- Defining the knowledge base to be optimized.
- Determining an optimization objective to be evaluated.
- Defining the constraint equations.
- Defining the bounds for the parameters of the design vector.
- Specifying the type of optimization algorithm to be applied.

Table 3 summarizes various performances criteria (objective function) that could be used in the context of function optimization.

In this work, we have used the RMSE between estimated (I_{simu}) and measured (I_{meas}) currents using the identified model parameters. N is the number of measured points. Next, the AHA Algorithm is used as an optimization procedure to find the optimal variables employed in PV modules for electricity generation.

B. AHA DESIGN PROCESS

The best performance of a PV system is obtained by choosing an appropriate optimization technique such as meta-heuristic techniques which have been tested in recent years. In this present work, AHA Algorithm is suggested as a learning

TABLE 3. Typical performances criteria.

Performance index	Expression	Characteristics
<ul style="list-style-type: none"> Integration of Absolute magnitude of the Error (IAE) Integration of Time multiplied by Absolute Error (ITAE) Integration Square Error (ISE). Integration of Time multiplied Squared Error (ITSE). Integration of Squared of Time multiplied Error (ISTE). Integral of Squared of Time multiplied Error Squared (ISTES). 	<ul style="list-style-type: none"> $I_{IAE} = \int_0^T e(t) dt$ $I_{ITAE} = \int_0^T t \cdot e(t) dt$ $I_{ISE} = \int_0^T e^2(t) dt$ $I_{ITSE} = \int_0^T t \cdot e^2(t) dt$ $I_{ISTE} = \int_0^T (t \cdot e(t))^2 dt$ $I_{ISTES} = \int_0^T (t^2 \cdot e(t))^2 dt$ $I_{ISTES} = \int_0^T (t^2 \cdot e(t))^2 dt$ 	<ul style="list-style-type: none"> IAE to obtain the absolute value of the error. ITAE represents error with time. ISE is used to remove negative error components.
<ul style="list-style-type: none"> Mean Square Error (MSE) Root Mean Squared Error (RMSE) 	<ul style="list-style-type: none"> $I_{MSE} = \frac{1}{N} \sum_{i=1}^n (e(t))^2$ $I_{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^n (e(t))^2}$ 	<ul style="list-style-type: none"> MSE shows variations from the target value.
<ul style="list-style-type: none"> QPI (Quadratic Performance Index) 	$I_{QPI} = \frac{1}{2} \int_{t_i}^{t_f} [e^T(t) Q e(t)] dt$	<ul style="list-style-type: none"> QPI is used for designing linear optimal control system., $Q(t) = Q^T(t) \geq 0$

method that gives optimal solution for structure and variables of the PV system, which are represented as an primordial problem of optimization index. Figure 2 illustrates the optimization process of AHA Algorithm related to this present work.

In order to construct an algorithm of optimization based on the AHA, we must use the following stages:

- Determine the initial configuration of the AHA.
- How to generate of the initial population.
- Define the fitness function.
- Specify the AHA operators, i.e. Guided, Territorial and Migration foraging.

In the following, the mathematical model of the optimization algorithm used in this work will be given.

C. AHA MATHEMATICAL MODEL

AHA is a new bio-inspired optimization algorithm [5], which has three main components: Food sources, Hummingbirds

and Visit table. Mathematically, AHA algorithm has been presented as follows:

1) INITIALIZATION

The randomly initialization of a population of *n* hummingbirds that are placed on *n* food sources, is given by:

$$x_i = L + r(U - L) \quad i = 1, 2, \dots, n \quad (3)$$

where *L* and *U* are the lower and upper boundaries respectively for a given *d*-dimensional problem. *r* represents a random vector in [0, 1], and *x_i* is the position of the *i*th food source which is the solution of the considered problem.

The initialization of the visit table of food sources is given by:

$$VT_{i,j} = \begin{cases} 0 & \text{if } i \neq j \\ null & \text{if } i = j \end{cases} \quad i, j = 1, 2, \dots, n \quad (4)$$

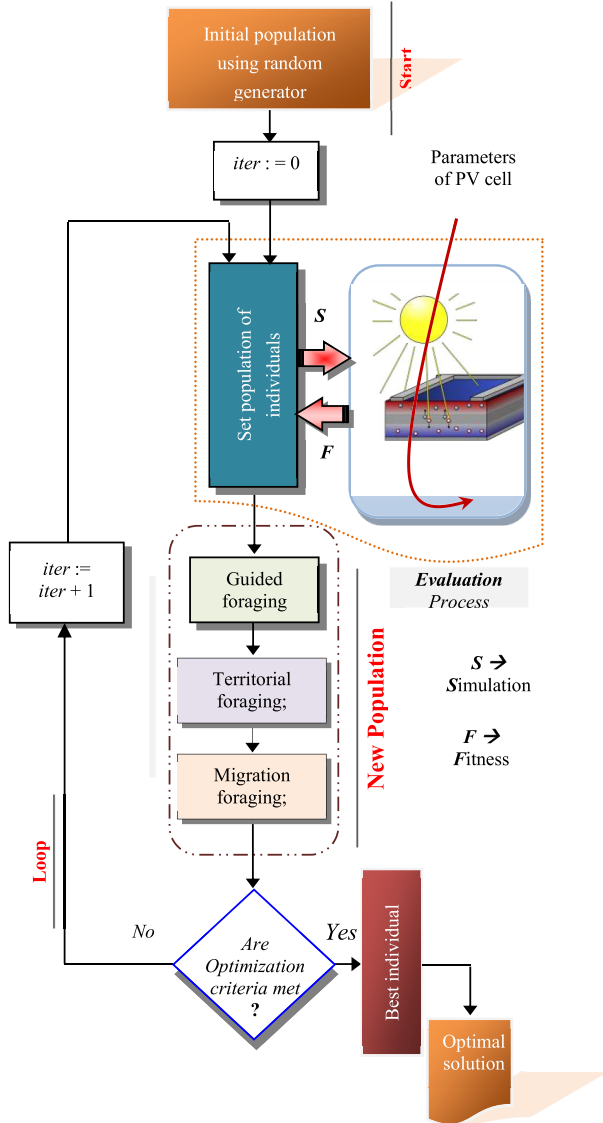


FIGURE 2. Optimization process using AHA Algorithm.

where the j^{th} represents the food source which is visited by the i^{th} hummingbird in the present iteration if $i \neq j$. The food is taking by hummingbird at its particular food source when $i = j$,

2) GUIDED FORAGING

In the AHA algorithm,

Three flight skills are used and modeled, including omnidirectional, diagonal, and axial flights. A direction switch vector is introduced to control one or more directions in d-dimensional space. The simulation model of guided foraging behavior and a candidate food source is given by:

$$v_i(t+1) = x_{i,tar}(t) + aD(x_i(t) - x_{i,tar}(t)), a \sim N(0, 1) \quad (5)$$

$x_i(t)$ represents the position of the i^{th} food source at time t .

$x_{i,tar}(t)$ represents the target location food source where the i^{th} hummingbird intends to visit and a represents a guided factor which is the normal distribution $N(0, 1)$ with standard deviation (σ) = 1 and mean = 0.

The new position of the i^{th} food source is given by:

$$x_i(t+1) = \begin{cases} x_i(t) & f(x_i(t)) \leq f(v_i(t+1)) \\ v_i(t+1) & f(x_i(t)) > f(v_i(t+1)) \end{cases} \quad (6)$$

where $f(\cdot)$ indicates the function fitness value.

3) TERRITORIAL FORAGING

The local search of hummingbirds in the territorial foraging corresponding to the specific food source which is simulated by:

$$v_i(t+1) = x_i(t) + bD(x_i(t)), b \sim N(0, 1) \quad (7)$$

b represents the territorial factor corresponding to the normal distribution $N(0,1)$ with $\sigma = 1$ and mean = 0.

4) MIGRATION FORAGING

The migration foraging of a hummingbird from the source corresponding to the worst nectar refilling rate to a randomly produced new one can be expressed by:

$$x_{wor}(t+1) = L + r(U - L) \quad (8)$$

where x_{wor} represents the food source corresponding to the worst nectar-refilling rate.

IV. NUMERICAL RESULTS, DISCUSSION AND EXPERIMENTAL VALIDATION

In the section, the results will be compared in terms of accuracy of the best solutions found. The proposed AHA is applied to the variable identification of SDM model and PV modules to evaluate their effectiveness. The recent meta-heuristics techniques to be considered for comparison include EABOA [7], MTLBO [8], WHHO [9], GBO [10], RUN [11], GSK [12], RLGB [13], DSCSE [14], IMPA [15], CCNMHHO [16], CPMP [17], EHHO [18], EJADE [19], ELBA [20], NMSOLMFO [21], SEDE [22], WLCSDGM [23], SGDE [24]. Root mean square error (RMSE), standard deviation (StD) and squared statistical error (SSE) are used as a performance indicators of each meta-heuristic technique. These optimization techniques are utilized to tackle the parameters extraction problem, first of RTC France PC cell (The cell is a commercial silicon cell with 57 mm of diameter, operating at $1000 \text{ W.m}^{-2} / 33 \text{ }^\circ\text{C}$), second of a Poly-solar panel module type 320W-72P at real operating conditions (photovoltaic laboratory, physics department, Islamic university, KSA, Fig. 3), third of a PV array of three polycrystalline PV modules (CLS-220P by CHINALIGHT Solar Co, Fig. 4) in series (placed on the terrace of DIEEI laboratory edifice, Catania University Italy). The electrical characteristics of these devices are reported in Table 4, where the values of parameters are shown in Table 5. PV cells of the same modules are assumed operating under the same conditions where they share the same electric current and voltage values.



FIGURE 3. Photograph of Poly-solar panel module type 320W-72P.



FIGURE 4. Photograph of polycrystalline PV modules (CLS-220P by CHINALIGHT Solar Co).

TABLE 4. Electrical characteristics of the used PV cells/modules.

Parameters	Pmax (W)	Vmp (V)	Imp (A)	Voc (V)	Isc (A)	Ns
R.T.C solarcell	0.31	0.4590	0.6755	0.5727	0.7605	1
Poly-solar 320W-72P	320	36.03	8.88	42.31	9.50	72
CLS-220P	220	28.9	7.61	36.8	8.24	60

A. FIRST CASE STUDY # RTC FRANCE SILICON SOLAR CELL

The reason behind this first case study is to validate the effectiveness of the applied AHA algorithm. AHA is compared with 18 other algorithms selected from literature. The algorithms have been used for simulating the data of the five parameters of SDM model of RTC France silicon solar cell. The estimated five unknown variables for SDM at the best RMSE are reported in table 4. These variables reveal the accuracy and the consistency of the AHA. The results are much closed to these obtained from others compared algorithms. In addition, I-V curve is shown in Fig. 5 using the parameters achieved at the best RMSE. From this figure, it is observable that the values of the estimated parameters

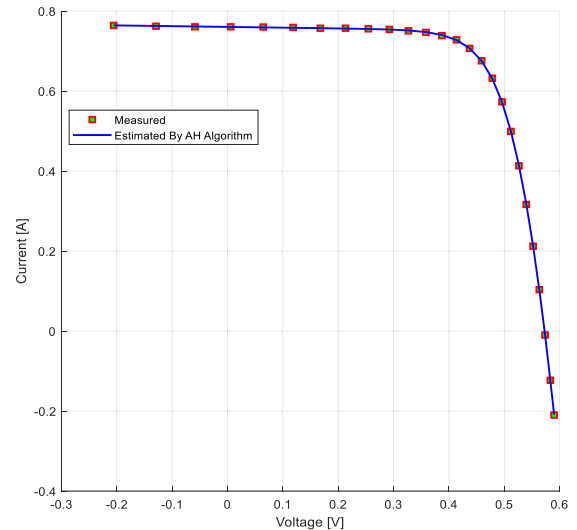


FIGURE 5. Measured and estimated IV data in SDM model.

obtained through AHA ensure a perfect reproduction of the experimental curves.

Hence, to expose the efficiency of the present algorithm over these recently reported algorithms in the literature, Table 7 shows statistical results including the minimum, the average, the worst values respectively, and the standard deviation (Std) of RMSE over 30 runs, in order to make the comparison more robust. Additionally, the number of iterations of each model is reported for each involved variant. It shows that AHA can get its performance simulation in terms of median, mean, maximum, and StD of RMSE among all the algorithms in a smaller number of iterations. However, MTLBO, SEDE, GSK, IMPA, CPMP SO, EJADE, NMSOLMFO and SEDE have certain competitiveness when identifying PV parameters of SDM model, but with higher number of iterations. Regarding the correlation between the lower values of RMSE, MaxIt and StD, we could say that the proposed method becomes prominent among the others.

Fig. 6 illustrates the convergence characteristic of AHA algorithm for all independent runs. Evidently, best RMSE is obtained is achieved within a short number of iterations, and all these values have small variations in 30 independent runs which, proves that AHA performs well in terms of accuracy. Fig. 7 and Fig. 8 show the IAEI values (absolute error values for the current) and the relative error (RE) for each measurement, respectively. The IAE for every set of voltage is small. The maximum of IAEI is 2.5074E-03, the minimum is 8.7704E-05, and all (RE) values are within the range $[-7.2746 \times 10^{-3}; 1.2065 \times 10^{-2}]$ which designates that AHA algorithm has good stability.

B. SECOND CASE STUDY # POLY-SOLAR PANEL MODULE TYPE 320W-72P

The performance of the AHA algorithm is validated using real IV curve measured at photovoltaic laboratory, Islamic University, KSA, for a Poly-solar panel

TABLE 5. Unknown PV parameter ranges.

Parameters	RTC France cell		Module 320W-72P		03 CLS-220P modules	
	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
$I_{ph} (A)$	0	1	0	10	0	10
$I_0 (\mu A)$	0	1	0	1	0	100
N	1	2	1	2	1	2
Series resistance (Ω)	0	0.1	0	0.1	0	0.1
Shunt resistance (Ω)	0	100	0	50000	0	50000

TABLE 6. The parameters of solar module estimated with best RMSE using single diode model.

Item	$I_{ph} [A]$	$I_0 [\mu A]$	N	$R_s [\Omega]$	$R_{sh} [\Omega]$	RMSE
AHA	0.76078	0.32302	1.48118	0.03638	53.71852	9.8602E-04
EABOA [7]	0.76077	0.32293	1.48115	0.03638	53.76600	9.8602E-04
MTLBO [8]	0.76078	0.32300	1.48118	0.03638	53.71853	9.8602E-04
WHHO [9]	0.76078	0.32302	1.48111	0.03638	53.71867	9.8602E-04
GBO [10]	0.76070	0.32300	1.48110	0.03630	53.71850	9.8602E-04
RUN [11]	0.76076	0.32000	1.48025	0.03642	53.67071	9.8624E-04
GSK [12]	0.76080	0.32310	1.48120	0.03640	53.72270	9.8602E-04
RLGBO [13]	0.76078	0.32302	1.48118	0.03638	53.71870	9.8602E-04
DSCSE [14]	0.76078	0.32302	1.48118	0.03638	53.71850	9.8602E-04
IMPA [15]	0.76078	0.32302	1.48118	0.03638	53.71852	9.8602E-04
CCNMHHO [16]	0.76078	3.23020	1.48118	0.03638	53.71810	9.8602E-04
CPMPSO [17]	0.76078	0.32302	1.48118	0.03638	53.71852	9.8602E-04
EHHO [18]	0.76078	0.32300	1.48124	0.03638	53.74282	9.8602E-04
EJADE [19]	0.76080	0.32300	1.48120	0.03640	53.71850	9.8602E-04
ELBA [20]	0.76078	0.32302	1.48119	0.03638	53.71852	9.8602E-04
NMSOLMFO [21]	0.76078	0.32302	1.48118	0.03638	53.71853	9.8602E-04
SEDE [22]	0.76078	0.32302	1.48118	0.03638	53.71852	9.8602E-04
WLCSODGM [23]	0.76078	0.32302	1.48118	0.03638	53.71852	9.8602E-04
SGDE [24]	0.76078	0.32302	1.48118	0.03638	53.71853	9.8602E-04

(module type 320W-72P) positioned on the terrace of the laboratory building in outdoor conditions. This module is operating at $G = 1028W/m^2$ and $T = 46.8817\text{ }^\circ C$.

In Table 8, RMSE is introduced to measure the fitting accuracy between the calculated current value and the actual current value of five parameters. The AHA algorithm finds RMSE of $2.572533E-02$, which is the lowest value presented in this table. The GBO and SEDE algorithm identify the same results as the AHA algorithm, when this latest has the best StD, the Rao1 and RUN algorithms also have good results, which are very reasonable. The Rao1 and RUN algorithms have lower results in terms of StD. Fig. 9 represents the I-V characteristic showing the good agreement of the suggested algorithm.

For a good illustration of the SSE and the RMSE values given in table 8 the bar charts representation is used (Fig. 11) for different algorithms. Graphically all algorithms have closed results with slight improvement for AHA, GBO, and SEDE algorithms.

Fig. 10 illustrates the convergence curves; AHA algorithm converges well than compared algorithms and more precisely than the Rao1, GBO and RUN algorithms. The AHA algorithm converges fastest in the early stage to achieve the best accuracy solution corresponding to the number of iterations about 6,000. The performance of GBO algorithm in term of convergence is better than that of the Rao1 and RUN algorithms. RUN algorithm has the poorest convergence performance.

TABLE 7. RMSE results obtained by various algorithms in single diode mode.

Algorithm	Year	RMSE				MaxIt	Pop
		Min ($\times 10^{-4}$)	Mean ($\times 10^{-4}$)	Max ($\times 10^{-4}$)	StD		
AHA	Present	9.8602	9.8602	9.8602	4.0444E-15	6000	30
EABOA [6]	2021	9.8602	9.8678	9.8784	9.3036E-07	50000	30
MTLBO [7]	2021	9.8602	9.8602	9.8602	1.9293E-17	50000	50
WHHO [8]	2021	9.8602	9.8602	9.8602	NA	5000	30
GBO [9]	2021	9.8602	9.8602	9.8602	1.7530E-10	-	-
RUN [10]	2021	9.8624	1.4799	2.4446	4.3070E-04	1000	30
GSK [12]	2021	9.8602	9.8602	9.8602	2.1800E-17	30000	30
RLGBO [13]	2021	9.8602	9.8607	9.8647	1.3894E-07	20000	30
DSCSE [14]	2021	9.8602	9.8602	9.8603	1.1321E-09	20000	30
IMPA [15]	2021	9.8602	9.8602	9.8602	1.7186E-17	20000	20
CCNMHHO [16]	2020	9.8602	NA	NA	NA	20000	30
CPMPSO [17]	2020	9.8602	9.8602	9.8602	2.1756E-17	50000	50
EHHO [18]	2020	9.8602	NA	NA	NA	2000	30
EJADE [19]	2020	9.8602	9.8602	9.8602	5.1300E-17	10000	50
ELBA [20]	2020	9.8602	9.8602	9.8602	1.9711E-17	50000	20
NMSOLMFO [21]	2020	9.8602	9.8602	9.8602	2.4856E-16	10000	40
SEDE [22]	2020	9.8602	9.8602	9.8602	4.2000E-17	50000	30
WLCSDGM [23]	2020	9.8602	9.8602	9.8602	2.6371E-17	50000	50
SGDE [24]	2020	9.8602	9.8602	9.8604	2.4747E-09	150000	150

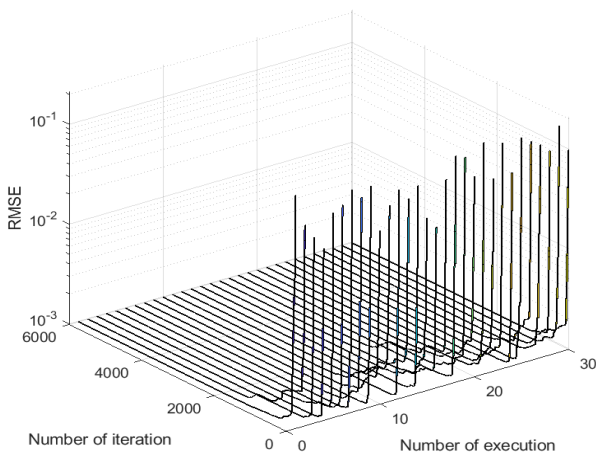


FIGURE 6. Number of iterations vs. number of runs in SDM model.

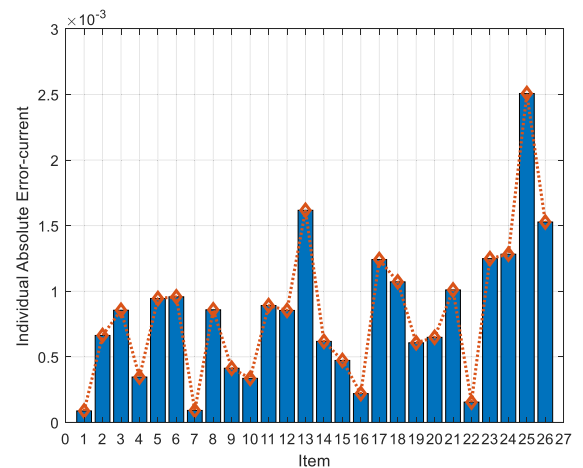


FIGURE 7. The IAE for the current in SDM on the RTC France cell dataset.

C. THIRD CASE STUDY # CLS-220P BY CHINALIGHT SOLAR CO

The experimental validation of AHA algorithm has been done using measured data at DIEEI lab, Catania University Italy for a PV array of three polycrystalline PV modules (CLS-220P by CHINALIGHT Solar Co) connected in series and has been located on the terrace of the laboratory building in outdoor conditions. These modules are operating at

different values of solar irradiation and temperature of (910.01, 800.57, 614.13, $G = 415.1$ and 200.87W/m^2) with (46.97, 44.23, 42.87, 40.59 and 30.60°C) respectively.

We have used eight different tests in this application. In the first five testing scenarios, the temperatures are (46.97, 44.23, 42.87, 40.59 and 30.60°C), and the solar irradiance varies, such as (910.01, 800.57, 614.13, $G = 415.07$ and 200.87W/m^2), respectively. In the other three testing phase,

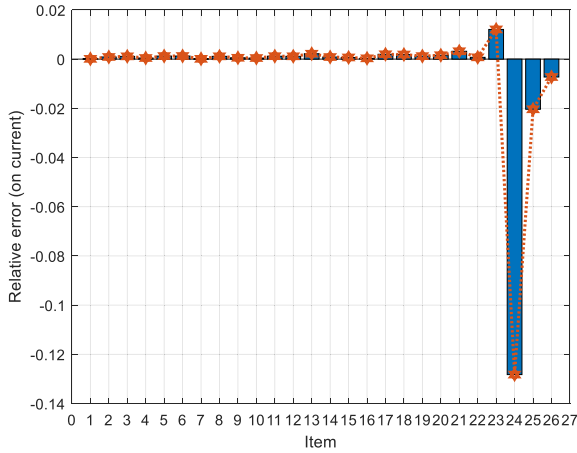


FIGURE 8. The RE for the current in SDM model (RTC France cell data-set).

TABLE 8. Estimated parameters of Poly-solar panel (module type 320W-72P) at the best RMSE.

Parameter	AHA	Rao1	GBO	RUN	SEDE
s					
I_{ph} [A]	9.6052	9.6080	9.6052	9.6050	9.6052
I_0 [A]	1.8622E-07	2.3454E-07	1.8622E-07	1.8541E-07	1.8622E-07
N	1.1860	1.2015	1.1860	1.1857	1.1860
R_s [Ω]	4.5588E-03	4.4872E-03	4.5588E-03	4.5603E-03	4.5588E-03
R_{sh} [Ω]	50000.0	48031.6	50000.0	48489.5	50000.0
RMSE [10^{-2}]	2.57253	2.61040	2.57253	2.57259	2.57253
StD	1.2207E-14	5.6733E-03	2.3934E-14	3.8018E-05	4.5571E-16
SSE [10^{-2}]	2.44863	2.52125	2.44863	2.44875	2.44863
	2	5	2	3	2

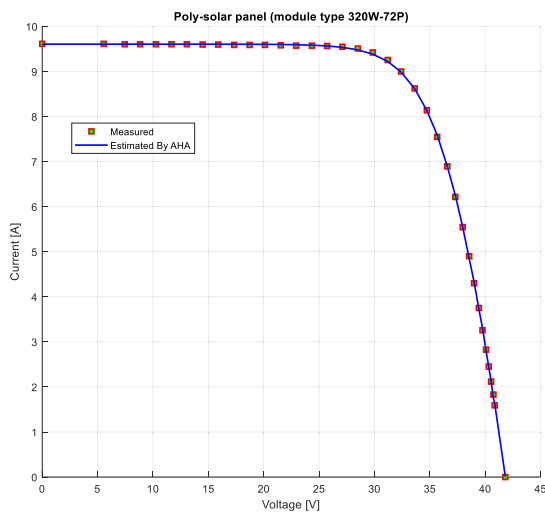


FIGURE 9. I-V curves of measured and estimated data of the Poly-solar panel module type 320W-72P.

the solar irradiation is 803 W/m^2 (the same), and the temperature varies, such as $47.93 \text{ }^\circ\text{C}$, $53.38 \text{ }^\circ\text{C}$ and $36.62 \text{ }^\circ\text{C}$. The obtained results by the proposed algorithm as well as

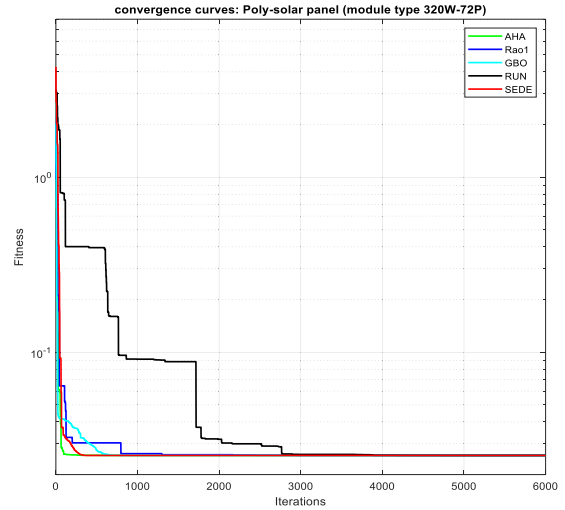


FIGURE 10. Convergence curves of the compared algorithms for Poly-solar panel module type 320W-72P.

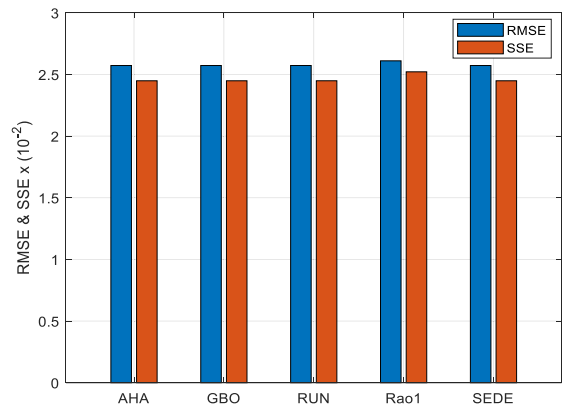


FIGURE 11. The bar charts of RMSE and SSE of different algorithms on Poly-solar panel (module type 320W-72P) (operating at $G = 1028 \text{ W/m}^2$ and $T = 46.8817 \text{ }^\circ\text{C}$).

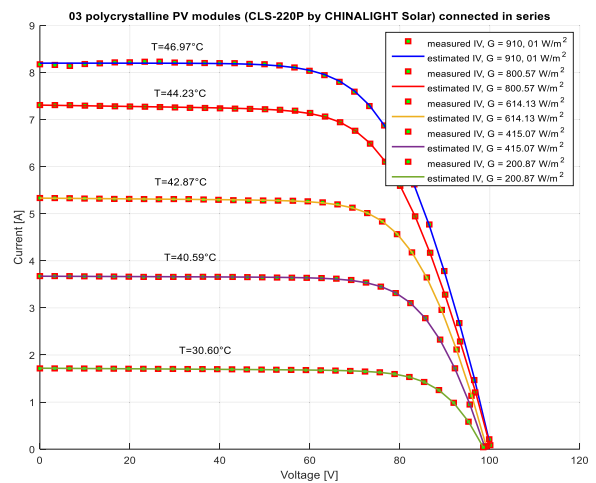


FIGURE 12. Measured and estimated I-V dataset by AHA for three polycrystalline PV modules (CLS-220P) connected in series under different irradiances.

given by other algorithms, such as Rao1, GBO, RUN and SEDE, are presented in Table 9 and Table 10.

TABLE 9. Results of five parameters of three polycrystalline PV modules connected in series (CLS-220P) operating in outdoor condition.

Parameters	AHA	Rao1	GBO	RUN	SEDE
G=910.01W/m ² -- 46.97°C					
<i>I_{ph} (A)</i>	8.1987	8.1986	8.1987	8.1992	8.1987
<i>I_o (A)</i>	2.9760E-06	2.9628E-06	2.9760E-06	3.1143E-06	2.9760E-06
<i>N</i>	1.3629	1.3625	1.3629	1.3670	1.3629
<i>R_s (Ω)</i>	9.2499E-03	9.2516E-03	9.2499E-03	9.2269E-03	9.2499E-03
<i>R_{sh} (Ω)</i>	50000.00	50000.00	50000.00	50000.00	50000.00
<i>RMSE (10⁻²)</i>	2.230291	2.230325	2.230291	2.231836	2.230291
<i>StD</i>	7.2835E-14	3.9536E-05	1.0212E-14	8.2696E-03	3.7646E-16
G=800.57W/m ² -- 44.23°C					
<i>I_{ph} (A)</i>	7.3287	7.2773	7.3287	7.3114	7.3287
<i>I_o(A)</i>	3.4762E-07	1.0178E-06	3.4762E-07	1.1663E-06	3.4762E-07
<i>N</i>	1.2096	1.2911	1.2096	1.3024	1.2096
<i>R_s (Ω)</i>	1.1225E-02	1.0872E-02	1.1225E-02	1.0684E-02	1.1225E-02
<i>R_{sh} (Ω)</i>	3.9011	26.5266	3.9011	6.3541	3.9011
<i>RMSE (10⁻²)</i>	1.025619	1.901616	1.025619	1.698920	1.025619
<i>StD</i>	5.503E-05	4.6481E-04	2.1699E-03	9.5903E-03	4.7163E-16
G=614.13W/m ² -- 42.87°C					
<i>I_{ph} (A)</i>	5.3394	5.3119	5.3394	5.3286	5.3394
<i>I_o (A)</i>	2.1525E-07	6.7818E-07	2.1525E-07	5.6921E-07	2.1525E-07
<i>N</i>	1.1920	1.2774	1.1920	1.2637	1.1920
<i>R_s (Ω)</i>	9.9675E-03	9.3706E-03	9.9675E-03	9.4213E-03	9.9675E-03
<i>R_{sh} (Ω)</i>	7.0218	87.3276	7.0218	12.4795	7.0218
<i>RMSE (10⁻²)</i>	7.245916	13.03209	7.245916	10.45935	7.245916
<i>StD</i>	1.3778E-11	1.1828E-04	1.0097E-12	5.4771E-03	2.8854E-16
G=415.07W/m ² -- 40.57°C					
<i>I_{ph} (A)</i>	3.6761	3.6681	3.6761	3.6688	3.6761
<i>I_o (A)</i>	1.0888E-07	2.1487E-07	1.0888E-07	2.8072E-07	1.0888E-07
<i>N</i>	1.1747	1.2221	1.1747	1.2422	1.1747
<i>R_s (Ω)</i>	1.0245E-02	9.7448E-03	1.0245E-02	9.5601E-03	1.0245E-02
<i>R_{sh} (Ω)</i>	14.5376	43.9348	14.5376	39.9590	14.5376
<i>RMSE (10⁻²)</i>	4.584494	6.353163	4.584494	6.872365	4.584494
<i>StD</i>	3.5871E-13	2.9415E-04	5.2281E-04	1.2999E-02	1.9016E-16
G=200.87W/m ² -- 30.60°C					
<i>I_{ph} (A)</i>	1.7215	1.7234	1.7215	1.7171	1.7215
<i>I_o (A)</i>	2.4748E-08	2.2454E-08	2.4748E-08	1.5272E-07	2.4748E-08
<i>N</i>	1.1630	1.1567	1.1630	1.2928	1.1630
<i>R_s (Ω)</i>	1.0717E-02	1.0855E-02	1.0717E-02	7.5638E-03	1.0717E-02
<i>R_{sh} (Ω)</i>	9.1458	8.7195	9.1458	12.0935	9.1458
<i>RMSE (10⁻²)</i>	2.178953	2.402372	2.178953	4.551546	2.178953
<i>StD</i>	2.1563E-14	2.7984E-03	1.8314E-14	1.3858E-01	3.7199E-17

From the estimated results shown in Figs. 12 and 13, we can see that the AHA algorithm is suitable for the measured data of PV modules connected in series at different levels of temperatures and irradiance. Furthermore, from Table 9, we can see that the RMSE values of the fitting results are all around 2.23E-2 when the irradiance is G=910.01 W/m² and the temperature is 46.97 °C, the RMSE values of fitting results are around 1.21E-2 for AHA, GBO and SEDE, 1.962607 for Rao1, and 1.932287 for RUN when the irradiance is 614.13 W/m² and the temperature is 42.87°C, and so on. Fig. 14 shows the bar charts of RMSE of different algorithms, the RMSE values of fitting results

increase with the increase of the irradiance level, which demonstrates that meta-heuristic algorithms could estimate the IV characteristic of PV modules under low irradiance level.

From Table 10, we can see that the RMSE values of the fitting results are all around 0.02 when the temperature is 36.62°C and 0.9685199E-2 for AHA, GBO and SEDE when the temperature is 47.93 °C. However, the RMSE values of fitting results are between 1.213373E-2 and 1.962607E-2 when the temperature is 53.38 °C. Hence, Fig. 15 shows that the RMSE values of fitting results are not temperature dependency.

TABLE 10. The best solution of three polycrystalline PV modules connected in series (CLS-220P) operating at different levels temperature and the same level of irradiance.

Parameters	AHA	Rao1	GBO	RUN	SEDE
T=47.93 °C -- G=803 W/m ²					
<i>I_{ph}</i> (A)	7.3005	7.2631	7.3005	7.3182	7.3005
<i>I₀</i> (A)	1.3811E-06	2.8855E-06	1.3811E-06	5.5572E-07	1.3811E-06
<i>N</i>	1.2828	1.3460	1.2828	1.2120	1.2828
<i>R_s</i> (Ω)	9.5506E-03	9.2225E-03	9.5506E-03	9.9474E-03	9.5506E-03
<i>R_{sh}</i> (Ω)	5.2876	47.6409	5.2876	3.5145	5.2876
<i>RMSE</i> (10 ⁻²)	0.9685199	1.526454	0.9685199	1.386439	0.9685199
<i>StD</i>	3.0148E-14	3.1849E-04	6.5449E-04	7.2497E-03	3.6852E-16
T=53.38 °C -- G=803 W/m ²					
<i>I_{ph}</i> (A)	7.2545	7.2169	7.2545	7.2296	7.2545
<i>I₀</i> (A)	1.4774E-06	4.8746E-06	1.4774E-06	5.4022E-06	1.4774E-06
<i>N</i>	1.2374	1.3402	1.2374	1.3502	1.2374
<i>R_s</i> (Ω)	9.9134E-03	9.3688E-03	9.9134E-03	9.2680E-03	9.9134E-03
<i>R_{sh}</i> (Ω)	3.2184	10.0086	3.2184	6.1003	3.2184
<i>RMSE</i> (10 ⁻²)	1.213373	1.962607	1.213373	1.932287	1.213373
<i>StD</i>	9.8807E-14	1.0145E-03	2.4480E-13	4.5734E-03	3.9127E-16
T=36.62°C -- G=803 W/m ²					
<i>I_{ph}</i> (A)	7.2565	7.2562	7.2565	7.2574	7.2565
<i>I₀</i> (A)	8.5583E-08	8.7406E-08	8.5583E-08	9.8291E-08	8.5583E-08
<i>N</i>	1.1776	1.1789	1.1776	1.1865	1.1776
<i>R_s</i> (Ω)	9.9411E-03	9.9341E-03	9.9411E-03	9.8849E-03	9.9411E-03
<i>R_{sh}</i> (Ω)	50000.00	50000.00	50000.00	49974.52	50000.00
<i>RMSE</i> (10 ⁻²)	2.043508	2.044222	2.043508	2.051820	2.043508
<i>StD</i>	2.7629E-14	5.9819E-04	1.2520E-11	9.6214E-03	3.2878E-16

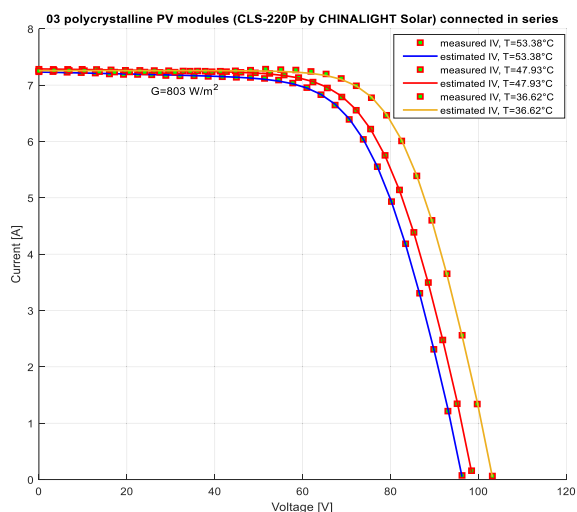


FIGURE 13. Measured and estimated I-V dataset by AHA for three polycrystalline PV modules (CLS-220P) connected in series under different temperature.

It is noticeable, since the temperature sensitivity of a solar cell depends on the open-circuit voltage; the shape of the experimental IV characteristic shows the most its variation at the vicinity of the open-circuit voltage. This effect simultaneously slightly increases the short-circuit current. The fitting errors to estimate PV parameters by an optimization algorithm depend typically on the shape itself and the

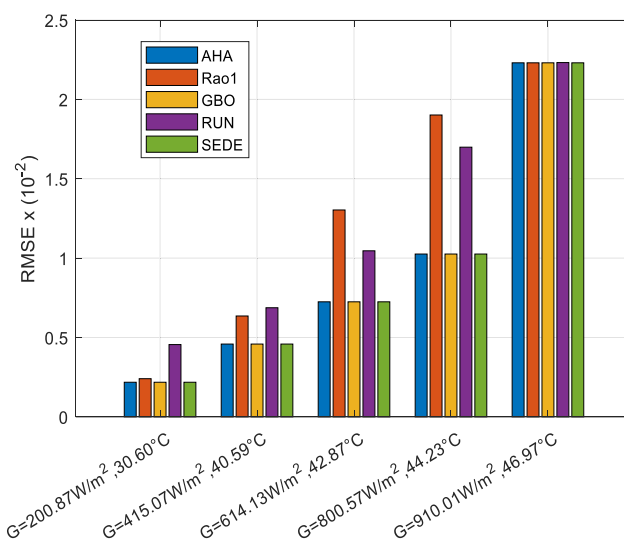


FIGURE 14. The bar charts of RMSE of different algorithms on three polycrystalline PV modules connected in series (CLS-220P) operating at different temperature and different irradiance.

implicit mathematical model to be fitted, and will not show an apparent dependency on the temperature in normal operating conditions, e.g. we could not say that the error of fitting increases or decreases with the increase or the decrease of the temperature as demonstrated by the shown results.

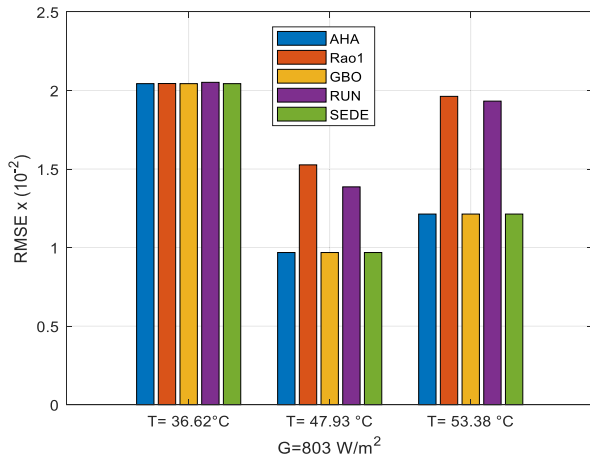


FIGURE 15. The bar charts of RMSE of different algorithms on three polycrystalline PV modules connected in series (CLS-220P) operating at different T and the same irradiance.

Table 9, Table 10 and Figs. 14–15, prove the effectiveness and validate AHA method and its applicability at a wide range of environmental conditions and different PV models (single cell, single module and modules connected in series).

Finally, AHA algorithm can be applied to extract the five-parameter of single cell, single PV module or modules connected in series under different temperature and irradiance conditions.

V. CONCLUSION

AHA is a meta-heuristic optimization algorithm, proposed in this work using MATLAB script on the PV parameter extraction problem. The only required information is the measured I–V characteristic curves of the PV modules under outdoor operational conditions. Limiting the search space of the five parameters and assuming that all cells are identical ensure the robustness of the algorithm by overcoming the complexity of the numerical solution. This work was validated using three cases from different sites at different ranges of solar irradiance conditions and temperatures: RTC France cell based SDM model, Poly-solar panel module type 320W-72P, and three polycrystalline PV modules (CLS-220P) connected in series. Results based on real data demonstrated that AHA algorithm gives best performance in point of view accuracy, reliability and convergence speed compared with others algorithms. The optimal parameters using AHA algorithm are coherent compared to the other diverse algorithms. The obtained parameters were closely matched with the experimental data-set, which shows the perfectness of these optimization algorithms. Also, the best RMSE is obtained by AHA within a short number of iterations compared to the other algorithms, and hence, proves that AHA performs well regarding both accuracy and computation time. In our opinion, AHA could be recommended as a high valued optimization technique for the estimation of internal PV parameters.

AUTHOR CONTRIBUTIONS

The authors contributed to this manuscript by participating in the proposed methodology and by preparing the content of the manuscript. Data analysis, software development and validation were performed by Dr. Sofiane Haddad and Dr. Badis Lekouaghet. The review, correction, and editing have been elaborated by Prof. Mohamed Benghanem, Dr. Ammar Soukkou, and Dr. Abdelhamid Rabhi. They agreed to send this version of the manuscript for possible publication. They also want to thank Prof. Tina from Catania University, Italy, for making availability of data.

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CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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