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Parameterization of photovoltaic solar cell double-diode model based on improved arithmetic optimization algorithm

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ABSTRACT

After avoiding the Standard Test Condition (STC) related to the manufacturer of PV cells, accurate solar system modeling is considered the most important task to study this system. Several mathematical developments based-approaches or algorithms were considered valuable tools to parameterize the electrical circuit of the photovoltaic models. Thus, these parameters are well determined using optimization algorithms. To achieve this goal, an experimental database or manufacturer's datasheet is requested. This paper proposes a novel Improved Arithmetic Optimization Algorithm (IAOA) to extract the solar cell/panel parameters. Also, practical tests are presented for obtaining the measured illustration of the I-V and P-V characteristics. Thus, the Double Diode Model (DDM) of the electrical circuit of PV panel is studied considering various statistical analyzes, to know the Minimum ($Min_{Fobj,DDM}$), the Maximum ($Max_{Fobj,DDM}$), the Average ($Ave_{Fobj,DDM}$), and the Standard Deviation ($SD_{Fobj,DDM}$). The estimated I-V and P-V curves using IAOA is compared with eight other recently published algorithms. In addition, the evaluation of the proposed IAOA proves that this proposal has a satisfactory performance than all tested algorithms. The obtained results show that the IAOA is considered first in terms of effectiveness and accuracy by $9.537e^{-06}$ of standard deviation. Moreover, considering the variability of operating conditions, the proposed IAOA shows its high superiority to optimize the electrical parameters of the solar cell TDM Where it has the lowest errors by $3.623e^{-05}$ of RMSE, $4.183e^{-06}$ of MAE, and $1.397e^{-05}$ of RMSD.

1. Introduction

To minimize the climatic changes provided by the high exploitation of fossil energies, the main reason for environmental pollution, the (Green Renewable Energy) GRE sources must be more exploited and used. Considering its availability, cleanliness, and ease of use, the solar resource is mandatory for supporting some existing power systems based on Diesel Generator (D.G.) or Natural Gas Turbines (NGT). On the other hand, this potential can also be exploited for the remote area as a principal energy source. Recently, this topic has

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Nomenclature

I_{ph}	Photo-current (A)
I_{01}, I_{02}	Saturation currents of the diodes (A)
a_1,a_2	Ideality factors of the diodes
V_t	Thermal voltages (V)
N_s	Number of PV cells connected in series
K	Boltzmann constant (J/K)
q	Electron charge (C)
T	Cell temperature (K)
R_{sh}	Shunt resistance (Ω)
R_s	Series resistance (Ω)
I_{sc}	Short circuit current (A)
V_{0c}	Open circuit voltage (V)
I_{mp}	PV current at maximum power point (A)
V_{mp}	PV voltage at maximum power point (V)
I	Output current of the PV panel (A)
V	Output voltage of the PV panel (V)
P	Power provided by the PV cell/panel (W)
P_{mp}	Maximum Power (W)
K_i (α)	Temperature coefficient of I_{sc} (%/°C)
I_{sc_STC}	Short circuit current at STC (A)
V_{oc_STC}	Open-circuit voltage at STC (V)
K_v (β)	Temperature coefficient of V_{oc} (%/°C)
γ	Temperature coefficient of maximum power (%/°C)
G	Solar irradiation (W/m^2)
G_{STC}	Solar irradiation at STC (W/m^2)
T_{STC}	Cell temperature at STC (K)
I_{mp_STC}	PV current at maximum power point at STC (A)
V_{mp_STC}	PV voltage at maximum power point at STC (V)
d	Solutions size
N	Number of used solutions
MOA(C_Iter)	Values of Math Optimizer Accelerated at the current iteration
M_Iter	Maximum number of iterations of the IAOA algorithm
Min	Accelerated function's minimum value
Max	Accelerated function's maximum value
$x_i(C\_Iter+1)$	The i_{th} new solution at the next iteration
$x_{i,j}(C\_Iter)$	The j_{th} position of the i_{th} solution
$best(x_j)$	The j_{th} position in the best solution
μ	Tuning parameter specified to adapt the search progress
MOP(C_Iter)	Value of the Math Optimizer Probability at the t_{th} iteration
C_Iter	Used iteration at the current process
M_Iter	Maximum determined number of iterations
α	is a tuning parameter employed to surveillance the exploitation performance throughout the evolution process
$QF(C\_Iter)$	Quality function at the current iteration
G_1, G_2	Parameters
$Levy(D)$	Levy flight
s	Fixed value
u, ν	Random numbers
β	Constant value
σ	Calculated value
$F_{obj,DDM}$	Objective function of the Double Diode Model
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
NRMSD	Normalized Root Mean Square Deviation
N	Number of points in each current or voltage vector
I_{calc}, I_i, $\widehat{I_j}$	Calculated currents
I_{actual}, $I(V_i)$, I_j	Measured currents
N_{sa}	Number of search agents

T_{iter}	Maximum number of iterations
Dim	Dimensions of decision variables
Tr	Number of runs
$SDF_{obj,DDM}$	Standard Deviation of the objective function
$MinF_{obj,DDM}$	Minimum of the objective function
$MaxF_{obj,DDM}$	Maximum of the objective function
$AveF_{obj,DDM}$	Average of the objective function

gained the attention of several researchers around the world.

The modeling of PV cells involves the parameterization of each electrical circuit based on I-V and P-V curves provided by the datasheet manufacturer. To achieve this exciting subject, a more representative manner for identifying and simulating the electrical circuit of such PV model is requested. In addition, the construction of reliable vision depends on a multitude of factors according to the complexity of the studied model as primary constraint [1,2]. Related to [3–5], a variety of algorithms were used for extracting the parameters of the equivalent electrical circuit of PV cells. Industrially, the PV technologies were classified into many families based on the semi-conductor nature, the number of cells, and other manufacturers' terms. To move forward, it is vital to study the photovoltaic conversion system considering their precision, accuracy, effectiveness, and performance to describe some real-time variations [6]. Thanks to the literature overview, the models that describe the equivalent electrical circuit of PV generation are different concerning the number of diodes. Moreover, the parameterization of these models can be considered more complicated from one to another, and it can be the cause of the choice of the particular model. In this context, the One Diode Model (ODM) is the most studied, composed of five parameters to be estimated [7,8].

Considering various weather conditions, a Marine Predators Algorithm (MPA) for estimating the parameters of the photovoltaic module is proposed in [9,10]. These works considered the technical data sheet of the manufacturer of three photovoltaic module technologies as a reference and did not obtain the characteristics via experimental tests. Identification of parameters based on the dynamic equivalent circuit for one diode model of a photovoltaic panel is suggested [11]. This work was in need of a comparative study with algorithms which showed its performance in the extraction of the parameters of electrical circuit. Based on the diversification-enriched Harris Hawks Optimization (HHO) algorithm, identification of parameters of photovoltaic cells and modules approach is presented in [12]. Despite the satisfactory results obtained by this algorithm, it is necessary to validate the models developed by a real experimental study and it is not to use the manufacturer's data. In the same context, a Flexible Particle Swarm Optimization (FPSO) algorithm is proposed to estimate PV cells and modules parameters [13]. This work is considered complete; it only lacked the practical validation to really show the accuracy of the proposal. The authors in [14] proposed a modified JAYA algorithm for identifying the parameters of solar cells but they did not take into account a thorough statistical analysis of the results obtained in addition to the lack of a real validation. An improved Lozi map-based optimization algorithm for extracting the parameters of photovoltaic cells is developed in [15]. In this study, a detailed statistical analysis has been presented but the experimental data are addressed by other works and not made by the authors. In [16], a teaching-learning optimization approach has been elaborated for estimating the parameters of photovoltaic models but the weak point is the use of undeveloped data. Another approach based on opposition sine cosine with local search for estimating the parameters of photovoltaic models is proposed [17]. Despite it is considered a good work; it just lacks these researchers to develop its own test bench in order to validate its models. In [18], the authors suggested a hybrid flower pollination algorithm for extracting the main parameters of photovoltaic modules. In the same context, a hybrid pollinator flower pollination-based approach to estimate the solar PV parameter is developed in [19]. Based on hybridized optimizer, the authors in [20] introduced a novel approach to estimate the parameters of photovoltaic systems. In addition, new metaphor-less algorithms for estimating the photovoltaic parameters have been proposed in [21]. The four references presented above are well studied in terms of the statistical analyzes of the results compared to the data obtained by the manufacturer. But frankly in experimentation everything is different and the irradiance and temperature values measured by the sensors may be different from the standard values used. Thus, in terms of scientific contribution, the experimental test bench developed presents a very important part of the results. Furthermore, the extraction of uncertain parameters of both single and double diode models of the photovoltaic panel using the Salp Swarm Algorithm (SSA) is proposed [22]. This work lacked more analyzes in terms of the results and the SSA algorithm is already used in the resolution of the same problem previously. Also, [23] developed a combination between Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) for extracting the uncertain parameters of the single diode model. A new combination between two algorithms is presented, but the authors forgot to compare the performance of their proposal algorithm with other valid algorithms. Based on Differential Evolution (DE) algorithm, the unknown parameters of the double diode model are extracted [24]. This study was mainly based on the datasheet information provided by the manufacturer for the PV module and the comparison was applied only on numerical and older methods. An Adaptive Chaotic Grey Wolf Optimizer (ACGWO) is used to identify the parameters describing the equivalent electrical circuit of the photovoltaic cells [25]. The authors introduced the GWO as a new proposal, but this algorithm has been used previously. In [26], a simplified approach to extract the solar cells and modules parameters is presented, but this method is not comparable with the algorithms proposed in other works. The lightning attachment procedure is proposed to extract the parameters of the single diode model of the photovoltaic panel [27]. [28] Proposed an enhanced Levy Flight Based Grasshopper Optimization Algorithm (LGOA) to determine the parameters of solar photovoltaic models. [27] and [28] presented the same weak point as most of the other work which is the use of the same manufacturer data of the same technology. For an adequate validation, it is necessary to have a real experimental study. A least square estimator and IEC-60891 procedure have been developed to estimate the parameters of the single diode model of photovoltaic generator [29]. As it is a numerical method, its weak point is the calculation time and the accuracy at the level of the identified parameters. Thus, an Improved Equilibrium Optimizer Algorithm (IEOP) is suggested to extract the solar cell parameters [30]. The R.T.C. France solar cell technology under a single weather condition (G = 1000 W/m^2 and T = 33 °C) has been used, but it is not sufficient to conclude the validity of a model which has tested for a single value. A critical analysis of the limitations of the analytical approach used to determine the electrical parameters of photovoltaic cells is discussed in [31]. The equivalent electrical parameters of different photovoltaic models are identified using an Opposition-based Equilibrium Optimizer Algorithm (OEOA) [32]. The different electrical circuits of photovoltaic model have been studied but equilibrium optimizer has been used a lot previously. The authors in [33] proposed a hybrid modeling technique based on a general radial basis function neural network to estimate the parameters of PV cells. An explicit mathematical formulation was presented but this work failed to make a comparative study with other recently published methods. A review of PV systems' modeling and parameters extraction based on experimental validations is suggested in [34]. In [35], the enhanced adaptive butterfly optimization algorithm is proposed to optimize the parameters of the photovoltaic models. This is a good work, only the use of experimental data is missing. State of the art on the variety of algorithms used to estimate the solar cell models is performed [36]. A Hybrid Algorithm (HA) is developed to identify the parameters of the triple diode model of photovoltaic cells [37]. In [38], a boosting Slim Mould Algorithm (SMA) is proposed for estimating the parameters of the photovoltaic models considering different irradiance and temperature levels. The previously two works are focused their studies on the commercial PV module models, which are the ST40, SM55, and KC200GT and therefore they did not take into account the impact of measured data. A comprehensive overview of various available methods used to extract the parameters of different technologies of the PV solar cells is elaborated in [39]. Although more than 100 existing approaches for identifying unknown parameters of the solar cell have been discussed, but the authors have avoided devoting a large part to evolutionary algorithms which have shown their superiority over other methods. Based on the Lambert W function, a comparative study of parameters identification of photovoltaic module is presented in [40]. The authors avoided comparing the proposed numerical method with certain evolutionary algorithms. A new efficient optimization approach based on the Salp Swarm-inspired Algorithm (SSA) for identifying the requested parameters related to the double diode model of photovoltaic cell is proposed and presented in [41]. Furthermore, an improved version of the previously mentioned paper is developed [42], using an enhanced exploratory Salp chains-based approach called OLMSSA for parameters extraction of PV cell double diode model. The authors of the two previously mentioned papers have developed two new algorithms but the experimental validation was defined on a single type of solar panels which is the only one available in their research laboratory. The authors in [43] proposed a winner-leading competitive swarm optimization approach, with an enhanced exploration phase based on dynamic Gaussian mutation, to extract the parameters of PV models. Nevertheless, the authors did not use actual experimental data, his study was based on manufacturer data. Considering different operating conditions and modeling a PV generator, a comparative study of improved single diode model parameters estimation is performed in [44]. Despite the comparison between three different approaches for extracting the parameters of the equivalent electrical circuit of solar panel, the genetic algorithm was not considered new and it was accessible to everyone. The fruit of a combination of numerical and analytical approaches to extract the single diode model parameters is presented in [45]. The latter study is considered classic and is not of the same value as the recently developed approaches. A comprehensive overview of meta-heuristic algorithm used to extract the parameters of the PV cell is proposed in [46]. The most recent twenty eight algorithms suggested in this research axis were presented and discussed. The effectiveness of any selective renewable energy source like solar PV may begin a new stage for improving the yield and reducing the cost of investment. Different statistical analyses and techniques can prove the appropriate model for solar PV modeling and simulation. In addition, the determination of parameters that composed the equivalent electrical circuit of the photovoltaic cell/panel is demonstrated according to a variety of algorithms and approaches. Many methods were proposed and investigated depending on the chosen model, number of parameters, accuracy, and effectiveness. Moreover, the evolutionary algorithms are counted first to search for the best solution for the decision variables. Following convergence, stability, simulation time, a competitive works have been elaborated and performed. In this context, this study aims to identify the parameters composed of the equivalent electrical circuits of the Double Diode Model (DDM) of photovoltaic solar cell/panel. Excited by the motivations as mentioned above, the main contributions and novelty of this paper are:

- A new design of optimized models of photovoltaic cell/panel is suggested.
- A novel IAOA algorithm has been proposed to estimate the parameters of DDM PV models.
- An investigation of the highlighting of real experimental data of I-V and P-V curves.
- Extensive modeling of the DDM of photovoltaic cell/panel taking into account various operating conditions.
- For the first time, considering some statistical analysis of obtained results, IAOA can reach the fitness function's minimum of the DDM with the best convergence time compared with eight recently published algorithms.
- An investigation of the performance of the proposed IAOA, based on the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE), and the Normalized Root Mean Square Deviation (NRMSD) is employed.
- Compared with eight other algorithms, the proposed IAOA is tested statistically by the Standard Deviation (SD), the Minimum (Min), the Maximum (Max), and the Average (Ave) of the objective functions and it achieves a high level of reliability, accuracy, and effectiveness.
- Compared with the original version of AOA, the IAOA has shown its superiority for all presented weather conditions.

The main parts of the paper are presented as follows; Section 2 handles the modeling of the equivalent electrical circuit of the photovoltaic DDM. Section 3 closely tackles the proposed IAOA. The problem formulation is revealed and investigated in Section 4. Then, Section 5 presents and discusses the experimental and simulation results. Finally, the main conclusions of the obtained results are drawn in Section 6.

2. PV cell double-diode model (DDM)

From an electrical point of view, and for simplifying the simulation and analysis of the correspondence framework, the solar cell/panel can be modeled by one or two diodes, and it depends on the number of parameters that can be expressed [39, 41, and 42]. Fig. 1 shows the most used electrical circuits, (a, b) one or (c) double diode models.

According to the I-V and P-V curves, the parameters depicted in the equivalent electrical circuits can be identified. For the modeling of the PV cells, it is not necessary to use the datasheet of such technologies. The following part discusses the mathematical development of the presented DDM in the reference and real operating conditions in detail.

According to Fig. 1(c), the output current of a DDM of solar cell/panel is expressed by the following relation [39, 41, and 42]:

$$\mathrm{I} = \mathrm{I_{ph}} - \mathrm{I_{D1}} - \mathrm{I_{D2}} - \mathrm{I_{sh}} = \mathrm{I_{ph}} - \mathrm{I_{01}}\left(\exp^{\left(\frac{V+R_sI}{a_1V_t}\right)} - 1\right) - \mathrm{I_{02}}\left(\exp^{\left(\frac{V+R_sI}{a_2V_t}\right)} - 1\right) - \frac{V+R_sI}{R_{sh}} \tag{1}$$

where I_{ph} is the photo-current, I_{01} and I_{02} are the saturation currents due to diffusion mechanism and space charge region. a_1 and a_2 are the ideality factors due to diffusion current and generation recombination current. V_t is the thermal voltages, which can be defined by:

$$V_t = \frac{N_s kT}{q} \tag{2}$$

With N_s describes the number of series-connected PV cells and K reflects the Boltzmann's constant (1.38064852 $\times 10^{-23}$ J K^{-1}). The first presented equation of the DDM is composed by seven unknown parameters. The manufacturer provides three characteristics points are the open-circuit voltage (V_{oc}, 0), the short-circuit current (0, I_{sc}), and the current-voltage at MPP (V_{mp}, I_{mp}). The basis current-voltage relation can be evaluated at three characteristics points as follows [39]:

$$0 = I_{ph} - I_{01}\left(\exp^{\left(\frac{V_{oc}}{a_1V_t}\right)} - 1\right) - I_{02}\left(\exp^{\left(\frac{V_{oc}}{a_2V_t}\right)} - 1\right) - \frac{V_{oc}}{R_{sh}} \tag{3}$$

$$I_{sc} = I_{ph} - I_{01}\left(\exp^{\left(\frac{R_sI_{sc}}{a_1V_t}\right)} - 1\right) - I_{02}\left(\exp^{\left(\frac{R_sI_{sc}}{a_2V_t}\right)} - 1\right) - \frac{R_sI_{sc}}{R_{sh}} \tag{4}$$

$$I_{mp} = I_{ph} - I_{01}\left(\exp^{\left(\frac{V_{mp}+R_sI_{mp}}{a_1V_t}\right)} - 1\right) - I_{02}\left(\exp^{\left(\frac{V_{mp}+R_sI_{mp}}{a_2V_t}\right)} - 1\right) - \frac{V_{mp}+R_sI_{mp}}{R_{sh}} \tag{5}$$

So, the power provided by the PV cell/panel can be expressed by the following equation:

$$P = I \times V \tag{6}$$

Furthermore, the derivative of the fundamental equation concerning the voltage can give the following form:

$$\frac{dI}{dV} = -\frac{I_{01}}{a_1V_{t1}}\left(1 + R_s\frac{dI}{dV}\right)\exp^{\left(\frac{V+R_sI}{a_1V_t}\right)} - \frac{I_{02}}{a_1V_{t1}}\left(1 + R_s\frac{dI}{dV}\right)\exp^{\left(\frac{V+R_sI}{a_2V_t}\right)} - \frac{1}{R_{sh}}\left(1 + R_s\frac{dI}{dV}\right) \tag{7}$$

By substituting the previously equations, we have obtained the following relation between maximum current and voltage:

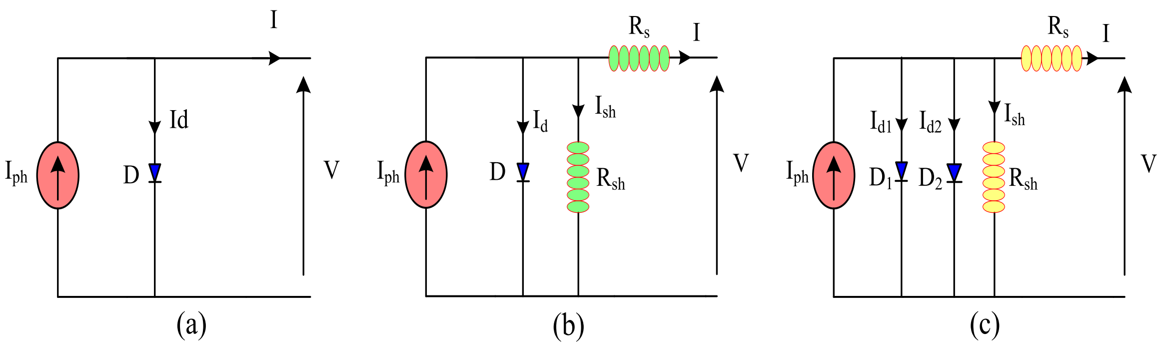

Fig. 1. Equivalent electrical circuits of solar cell models.

$$\frac{I_{mp}}{V_{mp}} = \frac{I_{01}}{\mathrm{a_1 V_{t1}}}\left(1 + \mathrm{R_s}\frac{dI}{dV}\right)\exp^{\left(\frac{\mathrm{V+R_sI}}{\mathrm{a_1V_t}}\right)} + \frac{I_{02}}{\mathrm{a_1 V_{t1}}}\left(1 + \mathrm{R_s}\frac{dI}{dV}\right)\exp^{\left(\frac{\mathrm{V+R_sI}}{\mathrm{a_2V_t}}\right)} + \frac{1}{\mathrm{R_{sh}}}\left(1 + \mathrm{R_s}\frac{dI}{dV}\right) \tag{8}$$

Now, after substitution of some developed equations, the photo-current, the short-circuit current, and the current at MPP, which can be considered as the start of research of other unknown parameters, which are the saturation currents and the resistances related to the electrical circuit, are expressed by the following equations, respectively:

$$\mathrm{I_{ph}} = \mathrm{I_{01}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_1V_t}}\right)} - 1\right) + \mathrm{I_{02}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_2V_t}}\right)} - 1\right) + \frac{\mathrm{V_{oc}}}{\mathrm{R_{sh}}} \tag{9}$$

$$\mathrm{I_{sc}} = \mathrm{I_{01}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_1V_t}}\right)} - \exp^{\left(\frac{\mathrm{R_sI_{sc}}}{\mathrm{a_1V_t}}\right)}\right) + \mathrm{I_{02}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_2V_t}}\right)} - \exp^{\left(\frac{\mathrm{R_sI_{sc}}}{\mathrm{a_2V_t}}\right)}\right) + \frac{\mathrm{V_{oc}} - \mathrm{R_sI_{sc}}}{\mathrm{R_{sh}}} \tag{10}$$

$$\mathrm{I_{mp}} = \mathrm{I_{01}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_1V_t}}\right)} - \exp^{\left(\frac{\mathrm{Vmp+R_sImp}}{\mathrm{a_1V_t}}\right)}\right) + \mathrm{I_{02}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_1V_t}}\right)} - \exp^{\left(\frac{\mathrm{Vmp+R_sImp}}{\mathrm{a_2V_t}}\right)}\right) + \frac{\mathrm{V_{oc}} - \mathrm{V_{mp}}}{\mathrm{R_{sh}}} - \frac{\mathrm{R_sI_{mp}}}{\mathrm{R_{sh}}} \tag{11}$$

$$\mathrm{I_{mp}}(1 + \frac{\mathrm{R_s}}{\mathrm{R_{sh}}}) = \mathrm{I_{01}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_1V_t}}\right)} - \exp^{\left(\frac{\mathrm{Vmp+R_sImp}}{\mathrm{a_1V_t}}\right)}\right) + \mathrm{I_{02}}\left(\exp^{\left(\frac{\mathrm{V_{oc}}}{\mathrm{a_1V_t}}\right)} - \exp^{\left(\frac{\mathrm{Vmp+R_sImp}}{\mathrm{a_2V_t}}\right)}\right) + \frac{\mathrm{V_{oc}} - \mathrm{V_{mp}}}{\mathrm{R_{sh}}} \tag{12}$$

The seven unknown parameters need to be solved from the non-linearity behavior described by the basic equation. Under real-time conditions, the photo-current can be obtained by:

$$\mathrm{I_{ph}} = (\mathrm{I_{ph-STC}} + \mathrm{K_i}(\mathrm{T} - \mathrm{T_{STC}}))\frac{\mathrm{G}}{\mathrm{G_{STC}}} \tag{13}$$

$$\mathrm{I_{ph-STC}} = \mathrm{I_{sc-STC}}\frac{\mathrm{R_{sh}} + \mathrm{R_s}}{\mathrm{R_{sh}}} \tag{14}$$

With $\mathrm{K_i}$ is the temperature coefficient of $\mathrm{I_{sc}}$ and $\mathrm{I_{sc\_STC}}$ is the short circuit current at STC. The saturation currents of the two diodes $\mathrm{D_1}$ and $\mathrm{D_2}$ are equal and can be formulated by the following form:

$$\mathrm{I_0} = \mathrm{I_{01}} = \mathrm{I_{02}} = \frac{\mathrm{I_{sc-STC}} + \mathrm{K_i}(\mathrm{T} - \mathrm{T_{STC}})}{\exp\left(\frac{\mathrm{V_{oc-STC}} + \mathrm{K_v}(\mathrm{T} - \mathrm{T_{STC}})}{\mathrm{aV_t}}\right) - 1} \tag{15}$$

with $\mathrm{V_{oc\_STC}}$ is the open-circuit voltage at STC and $\mathrm{K_v}$ reflects the temperature coefficient of $\mathrm{V_{oc}}$. By introducing the solar irradiance as a variable, the saturation currents $\mathrm{I_{01}}$ and $\mathrm{I_{02}}$ can be rewritten so by the following equation:

$$\mathrm{I_0} = \mathrm{I_{01}} = \mathrm{I_{02}} = \frac{\mathrm{I_{sc-STC}} + \mathrm{K_i}(\mathrm{T} - \mathrm{T_{STC}})}{\exp\left(\frac{(\mathrm{V_{oc-STC}} + \mathrm{K_v}(\mathrm{T} - \mathrm{T_{STC}})) + \mathrm{aV_t}\ln(\frac{\mathrm{G}}{\mathrm{G_{STC}}})}{\mathrm{aV_t}}\right) - 1} \tag{16}$$

Also, in terms of uncertain variability of solar radiation or temperature, the short-circuit current, the open-circuit voltage, the current, and voltage at MPP can be established and given by the following four equations, respectively:

$$\mathrm{I_{sc}}(\mathrm{G}, \mathrm{T}) = \mathrm{I_{sc\_STC}}\frac{\mathrm{G}}{\mathrm{G_{STC}}} + \mathrm{K_i}(\mathrm{T} - \mathrm{T_{STC}}) \tag{17}$$

$$\mathrm{V_{oc}}(\mathrm{G}, \mathrm{T}) = \mathrm{V_{oc\_STC}} - \mathrm{K_v}(\mathrm{T} - \mathrm{T_{STC}})\frac{\mathrm{G}}{\mathrm{G_{STC}}} + \mathrm{aV_t}\ln(\frac{\mathrm{G}}{\mathrm{G_{STC}}}) \tag{18}$$

$$\mathrm{I_{mp}}(\mathrm{G}, \mathrm{T}) = \mathrm{I_{mp\_STC}}\frac{\mathrm{G}}{\mathrm{G_{STC}}} \tag{19}$$

$$\mathrm{V_{mp}}(\mathrm{G}, \mathrm{T}) = \mathrm{V_{mp\_STC}}\frac{\mathrm{G}}{\mathrm{G_{STC}}} - \mathrm{K_v}(\mathrm{T} - \mathrm{T_{STC}}) \tag{20}$$

3. Improved arithmetic optimization algorithm

3.1. Overview

Typically, population-based search methods start their evolutionary steps with a set of random candidate solutions [47]. Then, the optimization rules incrementally enhance the given solutions throughout a number of iterations. Finally, the optimization rules are evaluated at each iteration according to the generated solutions using a pre-specified objective function. As population-based search methods try to determine the best solution for the given problem stochastically, obtaining a single-run solution is not guaranteed.

The original Arithmetic Optimization Algorithm (AOA) proposed in [48] by Abualigah et al. stimulated the principal operators in computational science (i.e., Multiplication, Division, Subtraction, and Addition). AOA is a gradient-free population-based search method for addressing various complicated problems with a particular objective function. The procedure of the original AOA is depicted in Fig. 2 and described as follows.

Arithmetic is a fundamental frame of the numerical system. Along with geometry, mathematics, and analysis, it is a primary phase of functional mathematics. The standard arithmetic operators employed to evolution the solutions are multiplication, division, subtraction, and addition. In addition, these operators are applied as a component of a mathematical optimization procedure to determine the best solution provided with specific constraints. The main procedure of the AOA is given as follows.

3.1.1. Initialization phase

As stated in Matrix (21), the optimization practices in the AOA start with different generated random solutions (X). Then, the best solution is defended in each iteration as an approximate solution to the optimal value so far.

$$X_i = \begin{bmatrix} x_1^1 & x_1^1 \cdots & x_{1,d}^1 \\ x_1^2 & x_2^2 \ldots & x_d^2 \\ \vdots & \ddots \ddots & \vdots \\ x_1^N & x_d^N \ldots & x_d^N \end{bmatrix} \tag{21}$$

Where, d is the solutions size and N is the number of used solutions. The search process, either exploration or exploitation, should be determined in each iteration based on the primary function, called Math Optimizer Accelerated (MOA), defined using Eq. (22).

$$MOA(C\_Iter) = Min + C\_Iter \times \left(\frac{Max - Min}{M\_Iter}\right) \tag{22}$$

where MOA(C_Iter) presents the values of MOA at the current iteration (C_Iter), M_Iter is the maximum number of iterations. The Min and Max are the accelerated function's minimum and maximum values, respectively.

3.1.2. Exploration phase

The exploratory development of AOA is described in this part [49]. The phase's optimization process employed either the Division (D) course or the Multiplication (M) course to obtain high-distributed choices subject to the Arithmetic operators. Nevertheless, unlike

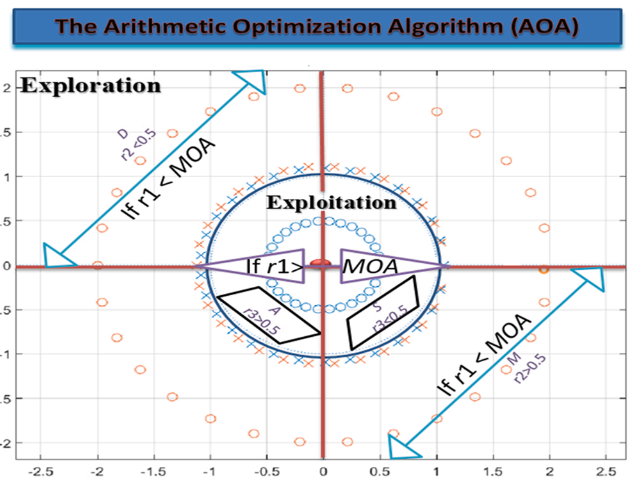

Fig. 2. : The optimization processes of the AOA [48].

other commands, these courses (i.e., D and M) cannot quickly raise the goal area due to their extensive distribution (i.e., S and A). As a result, the discovery search explores a near-optimal solution that can be explored after many iteration.

AOA's exploration stage explores the search area in several places stochastically. It operates two search systems (D and M) represented in Eq. (23) to reach a better solution. If $r1 > MOA$, where r1 is a random value and MOA is defined by Eq. (22), this step is permitted. The D operator is adapted by $r2 < 0.5$ in this condition; otherwise, the other operator (M) would complete the current development, with r2 is a random value. To produce more diversification, a stochastic coefficient is employed.

$$x_{i,j}(C\_Iter+1) = \left\{ \begin{array}{l} best(x_j) \div (MOP+\epsilon) \quad \times \left(\left(UB_j - LB_j \right) \times \mu \quad + \quad LB_j \right), \&r2 < 0.5 \\ best(x_j) \times \quad MOP \quad \times \left(\left(UB_j - LB_j \right) \times \mu + LB_j \right), \&otherwise \end{array} \right\} \tag{23}$$

where $x_i(C\_Iter+1)$ is the i_{th} new solution at the next iteration, $x_{i,j}(C\_Iter)$ is the j_{th} position of the i_{th} solution, and $best(x_j)$ is the j_{th} position in the best solution. μ is a tuning parameter specified to adapt the search progress, which is 0.5 according to [48].

$$MOP(C\_Iter) = 1 - \frac{C\_Iter^{\left(\frac{1}{\alpha}\right)}}{M\_Iter^{\left(\frac{1}{\alpha}\right)}} \tag{24}$$

where Math Optimizer Probability (MOP) is a stochastic coefficient function, MOP(C_Iter) is the function value of the MOP determined at the t_{th} iteration, and C_Iter is the used iteration at the current process, and M_Iter is the maximum determined number of iterations. α is a tuning parameter employed to surveillance the exploitation performance throughout the evolution process, which is 5 according to [48].

3.1.3. Exploitation phase

The AOA exploitation rules are represented in this part. To acquire high-dense results using the invented Arithmetic operators, mathematical equations based on these operators (i.e., S or A) are applied. Associated with other operators, they can precisely recognize the target region due to their minimal distribution. Consequently, the exploitation method defines the near-optimal solution that can be distinguished over different iterations. Besides, by increasing the coordination among the search processes, the exploitation mechanisms expedite the exploitation process.

This step is conditioned by $r1 \leq MOA(C\ Iter)$. The manipulation directors of AOA (i.e., S and A) investigate the search area widely on many deep regions and produce a better solution represented in Eq. (25). Thus, this rule manages the search space by offering an in-depth exploration. If $r3 < 0.5$, the S operator will be employed in Eq. (25); otherwise, the A operator will perform the current task. Exploitation mechanisms (i.e., S and A) usually seek to stay apart from the local area (local optima). This phase explores the search space to find the top best solution while keeping various candidate solutions. Thus, this phase assists in preventing local optima trapped, especially in the final number of iterations.

$$x_{i,j}(C\_Iter+1) = \left\{ \begin{array}{l} best(x_j) - MOP \quad \times \left(\left(UB_j - LB_j \right) \times \mu \quad + \quad LB_j \right), \&r3 < 0.5 \\ best(x_j) + \quad MOP \quad \times \left(\left(UB_j - LB_j \right) \times mu + LB_j \right), \&otherwise \end{array} \right\} \tag{25}$$

Fig. 3 shows how a search solution renews its positions in a 2-Dimensional search space using math operators and the updating process in AOA. Thus, the final-obtained region can be in a random location within an area defined by the positions of math operators

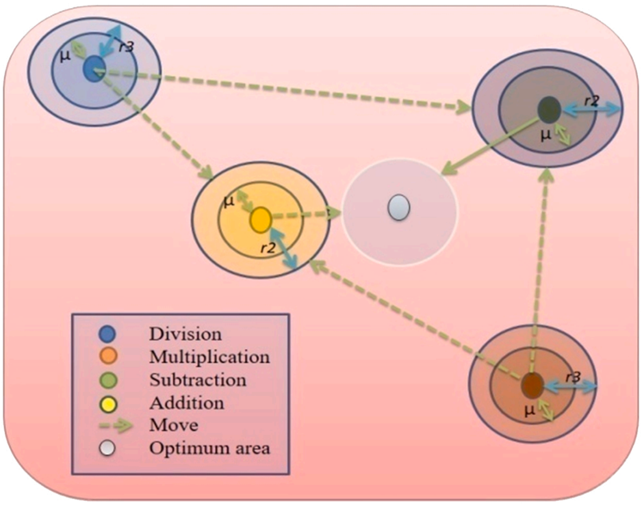

Fig. 3. Shows updating process using in AOA.

as the search range, which can be identified.

3.1.4. Structure of the arithmetic optimization algorithm (AOA)

The optimization course in the original AOA is based on conducting a random collection of solutions (population). The arithmetic operators discover the feasible regions of the near-optimal solution utilizing a course of iterations. Each solution replaces its positions according to the underlying rules (exploration or exploitation) from the obtained best solution. The MOA function value is grown linearly from 0.2 to 0.9 to support the search processes. Candidate solutions seek to update their positions based on the given near-optimal solution as r1 > MOA and vice versa. Finally, until the end termination condition is satisfied, the AOA optimizer is finished.

3.2. Narrowed exploitation of aquila optimizer

This method is recognized as "walk and grab prey" [50], which is one of the best search operators used in Aquila Optimizer (AO). This search method updates the solutions based on stochastic movements to narrow the search area. Eq. (26) describes its mathematical procedure.

$$x_{i,j}(C\_Iter+1) = QF(C\_Iter)^* \quad best(x_j) - (G_1{}^*x_{i,j}{}^*rand) - G_2{}^*Levy(D) + rand^*G_1 \tag{26}$$

where quality function (Q.F.) is applied to equilibrium the search procedures determined by Eq. (27). G1 and G1 are calculated using Eqs. (28) and (29), respectively.

$$QF(C\_Iter) = \quad C\_Iter^{\left(\frac{2^*rand-1}{(1-M\_Iter)^2}\right)} \tag{27}$$

$$G_{1=2^*rand-1} \tag{28}$$

$$G_2 = 2^*(1-\frac{C\_Iter}{M\_Iter}) \tag{29}$$

The levy flight (Levy) is computed by Eq. (30).

$$Levy(D) = s^*\frac{u^*\sigma}{|\nu|^{\frac{1}{\beta}}} \tag{30}$$

where s is a fixed value of 0.01, u, and ν are random numbers [0 1], β is a constant value fixed to 1.5, and σ is a value determined by Eq. (31).

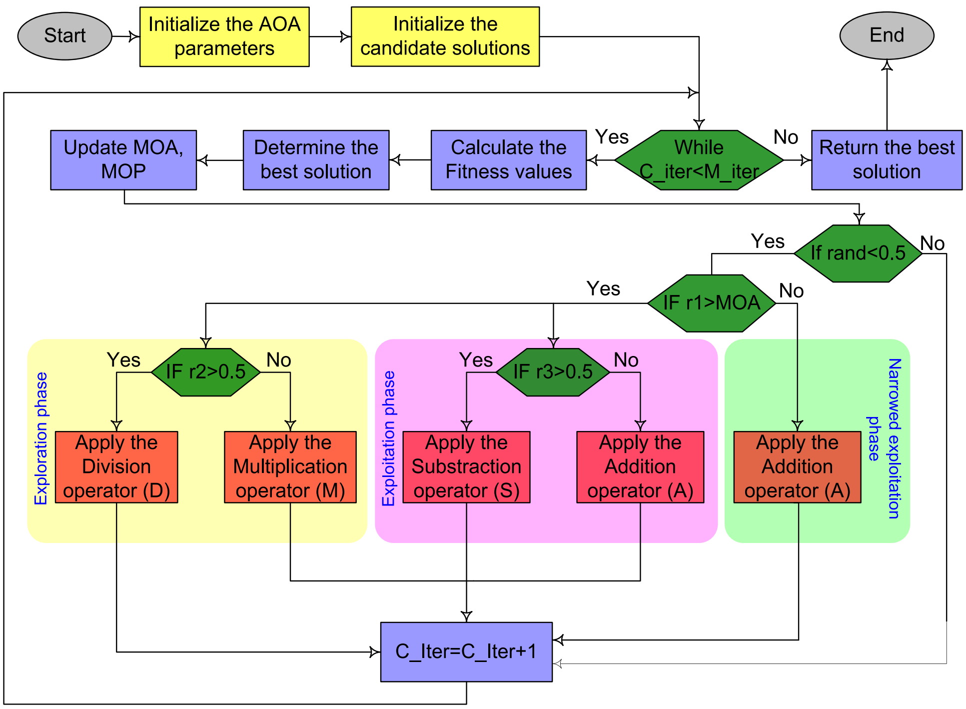

Fig. 4. Flowchart of the proposed IAOA.

$$\sigma = \left(\frac{\Gamma(1+\beta)*sine(\frac{\pi\beta}{2})}{\Gamma\left(\frac{1+\beta}{2}\right)*\beta*2^{(\frac{\beta-1}{2})}}\right) \tag{31}$$

3.3. The proposed improved arithmetic optimization algorithm

In this section, the conventional AOA is improved by using one external operator from AO to enhance the local search ability. Typically, the AOA lost control of focusing on the most prominent search area. Thus, it is necessary to tackle this weakness by using an external operator. The new operator is called narrowed exploitation (N.E.), which narrows the search area and focuses on the most attractive search area to find the optimal solution. Fig. 4 illustrates the new IAOA rule in detail.

The proposed method is called IAOA, which starts the search process of each iteration by a condition to either execute the AOA operators or NE. This procedure can keep the equilibrium between the search methods and improve the local search process. The main procedure of the proposed IAOA is given in Algorithm 1.

Algorithm 1: Improved Arithmetic Optimization Algorithm (IAOA)
Initialize the Arithmetic Optimization Algorithm parameters N, α, μ, etc.
Initialize the solutions' positions randomly. (Solutions: $i = 1. N$).
WHILE (C_Iter<M_Iter)
Calculate the Fitness Function for the given solutions.
Find the best solution so far.
Update the MOA parameter usingEq. (22).
Update the MOP parameter usingEq. (24).
FOR (i = 1 to N)
FOR (j = 1 to d)
If (rand <0.5)
Generate random values between [0,1] (r1, r2, and r3)
IF (r1 > MOA)
IF (r2 > 0.5) **Exploration phase**
Update the i_{th} solutions' positions using the first part inEq. (23).
ELSE
Update the i_{th} solutions' positions using the second part inEq. (23).
ENDIF
ELSE
IF (r3 > 0.5) **Exploitation phase**
Update the i_{th} solutions' positions using the first part inEq. (25).
ELSE
Update the i_{th} solutions' positions using the second part inEq. (25).
ENDIF
ENDIF
ELSE **Narrowed exploitation phase**
Update the i_{th} solutions' positions using the second part inEq. (26).
END
ENDFOR
ENDFOR
C_Iter=C_Iter+ 1
ENDWHILE
Return the best solution (best_x).

4. Problem formulation

Based on the above description, our problem can be reformulated as three different objective functions which can be minimized.

$$F(V, I, z) = I - I_{ph} - I_{01}\left(\exp^{\left(\frac{V+R_sI}{a_1V_t}\right)} - 1\right) - I_{02}\left(\exp^{\left(\frac{V+R_sI}{a_2V_t}\right)} - 1\right) - \frac{V + R_sI}{R_{sh}} \tag{32}$$

$$F_{obj,DDM} = \text{Min RMSE} = \sqrt{\frac{1}{N}\sum_{1}^{N}(F(V, I, z))^2} \tag{33}$$

where N number of points in each current or voltage vector, $z = [R_s\ R_{sh}\ I_{ph}\ I_{01}\ I_{02}\ a_1\ a_2]$ are the parameters set to extract. With respect to some operational constraints which are:

$$I_{phmin} \le I_{ph} \le I_{phmax} \tag{34}$$

$$\mathrm{I_{01min}},\quad \mathrm{I_{02min}} \leq \mathrm{I_{01}},\quad \mathrm{I_{02}} \leq \mathrm{I_{01max}},\quad \mathrm{I_{02max}} \tag{35}$$

$$\mathrm{a_{1min}},\quad \mathrm{a_{2min}} \leq \mathrm{a_1},\quad \mathrm{a_2} \leq \mathrm{a_{1max}},\quad \mathrm{a_{2max}} \tag{36}$$

$$\mathrm{R_{smin}} \leq \mathrm{R_s} \leq \mathrm{R_{smax}} \tag{37}$$

$$\mathrm{R_{shmin}} \leq \mathrm{R_{sh}} \leq \mathrm{R_{shmax}} \tag{38}$$

$$\mathrm{I_{scmin}} \leq \mathrm{I_{sc}} \leq \mathrm{I_{scmax}} \tag{39}$$

$$\mathrm{V_{ocmin}} \leq \mathrm{V_{oc}} \leq \mathrm{V_{ocmax}} \tag{40}$$

$$\mathrm{I_{mmin}} \leq \mathrm{I_m} \leq \mathrm{I_{mmax}} \tag{41}$$

$$\mathrm{V_{mmin}} \leq \mathrm{V_m} \leq \mathrm{V_{mmax}} \tag{42}$$

As mentioned above, the optimization process will be made in this study for the DDM. The operating of this process is presented in Fig. 5. Based on the number of runs, search agents, dimension, and the number of iterations, the IAOA will look for the best and optimal solutions of the objective function $F_{obj,DDM}$. Therefore, the best fitness function will be illustrated, and all the equivalent electrical circuit parameters will be estimated. Based on those parameters, the I-V and P-V characteristics of the photovoltaic model can be shown.

For demonstrating the effectiveness and the performance of the proposed IAOA, some other statistical analyses will be done. Thus, regarding the accuracy of the proposed IAOA-based method, the Root Mean Square Error (RMSE) (Eq. 42), the Mean Absolute Error (MAE) (Eq. 43), and the Normalized Root Mean Square Deviation (NRMSD) (Eq. 45) are employed. The following equations, respectively express those statistical errors:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{actual} - I_{calc}\right)^2} \tag{43}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|I_i - I(V_i)\right| \tag{44}$$

$$RMSD = \sqrt{\frac{\sum_{j=1}^{N}\left(\widehat{I}_j - I_j\right)^2}{N}} \tag{45}$$

$$NRMSD = \frac{RMSD}{I_{sc}} \tag{46}$$

where I_{calc}, I_i, and $\widehat{I}_j$ are the calculated currents and I_{actual}, $I(V_i)$ and I_j are the measured currents. Table 1 presents the details of the main program used to simulate all algorithms.

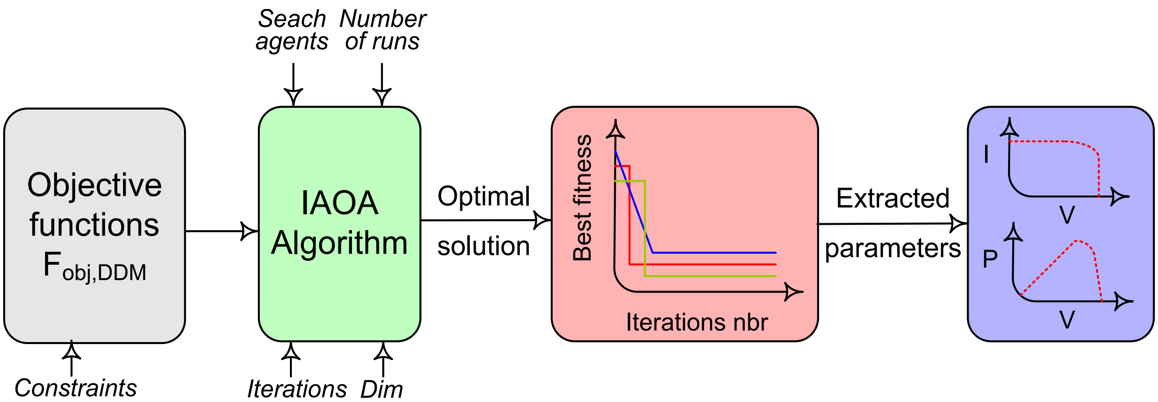

Fig. 5. : Detailed explication of the problem formulation.

5. Results and discussion

The experimental test bench is employed for implementing the current-voltage characteristic curves of the TITAN-12–50 technology of the used photovoltaic cell/panel. The key specifications of the used PV module are depicted in Table 2. In order to achieve this goal, we have to start by measuring the electrical quantities which describe the electrical circuit of the solar cell. Current and voltage sensors (LA25-NP, LV25-P) are used to visualize these two quantities in this context. To do this, and according to the variation of the solar irradiance and the temperature throughout the day, we have considered the value of this meteorological data every one hour. The solar and temperature sensors used in this experimental facility were based on TLO82, and LM335, respectively. Variable resistance is also exploited to show a variation in terms of current and voltage. This variation is shown based on digital storage oscilloscope scopiX, II (OX 7104). The complete test-bench developed in this study is illustrated in Fig. 6.

In order to validate and simulate the DDM depicted in this work, we carried out different experimental tests to obtain the I-V and P-V characteristics under various operating conditions. The variations of the fitness function $F_{obj,DDM}$ is evaluated as minimization in relation with the number of iterations. For proving the Improved Arithmetic Optimization Algorithm (IAOA) performance, several well-established algorithms and approaches used previously and showed a very satisfactory performance were selected for the comparison. For this aim, the IAOA is tested by their accuracy, fastness and furthermore, to improve the PV cells/panel performance. As conventional and reliable meta-heuristic and evolutionary approaches, the comparison includes the Salp Swarm Algorithm (SSA) [41], the Gravitational Search Algorithm (GSA) [51], the Whale Optimization Algorithm (WOA) [52], the Sine Cosine Algorithm (SCA) [47,53], the Virus Colony Search (VCS) algorithm [54], the Multi-Verse Optimizer (MVO) algorithm [55], the Aquila Optimizer (AO) [50], and the original Arithmetic Optimization Algorithm (AOA) [48,49]. 30 runs are conducted for each method to find the mean values for the comparisons purpose.

The DDM related objective function $F_{obj,DDM}$ is demonstrated as minimization, and its variation is shown in Fig. 7. This figure shows that the proposed IAOA is considered first in terms of convergence and minimization of the objective function compared to AO and AOA algorithms. The excellent performance of this algorithm is illustrated by 0.31455 of the fitness function, and the fast response to found this minimization is also demonstrated. Then, from the best-founded solutions of requested parameters composed of the electrical circuit of the DDM, this algorithm also presents a good agreement between the measured and estimated I-V and P-V characteristics. As one of the critical issues of this formulation, all parameters describing the equivalent electrical circuit and define the adjustment of the I-V and P-V curves, IAOA show its ideality to found the three key points, which are the open-circuit voltage, the short-circuit current, and the maximum power point (voltage and current). Considering the results obtained from the experimental validation, four different cases are considered to show the I-V and P-V characteristics concerning the irradiance variation in one hand (G=366 W/m^2, G=566.7 W/m^2, G=745.2 W/m^2, and G=902 W/m^2,) and the temperature in another hand (T = 18 °C, T = 20.43 °C, T = 22.10 °C, and T = 23.87 °C).

All presented I-V, and P-V curves show good accuracy and agreement between the experimental database and estimated. Figs. 8, 9, 10, and 11, and considering the variation at the irradiance level and temperature, show that these curves present a high level of agreement even in the three characteristic points (V_{oc}, I_{sc}, and MPP). Regarding the reliability, the accuracy and the effectiveness, and compared to VCS, GSA, WOA, SCA, MVO, SSA, AO, and AOA algorithms, the proposed IAOA algorithm is tested statistically by the Standard Deviation ($SDF_{obj,DDM}$), the Minimum ($MinF_{obj,DDM}$), the Maximum ($MaxF_{obj,DDM}$), and the Average ($AveF_{obj,DDM}$) of the objective function. Table 3 illustrates a statistical analysis of the obtained results of the DDM. Also for the DDM, The results prove that the IAOA has the more satisfactory performance and accuracy compared with all presented eight algorithms by the less value of $SDF_{obj,DDM}$ (9.537e^{-06}).

Figs. 8 and 9 represent the comparison between the measured and estimated I-V and P-V characteristics at G= 366 W/m^2, T = 18 °C, G= 566.7 W/m^2, T = 20.43 °C, respectively. In this case, the I-V and P-V curves show an excellent accuracy between the experimental database and the estimated one.

From these Figures, and according to the three characteristic points (V_{oc}, I_{sc}, and MPP), it can be showed that the IAOA can introduce a high level of agreement. Regarding the parameters that can be extracted for the DDM, all the I-V characteristics presented in this section introduce a high level of correspondence, and therefore, the exact parameters can be estimated with a very low error value. In this context, this study can improve the PV cell/panel modeling according to a high level of confidence, which increases by itself the industrialization of photovoltaic cells and, consequently, the exploitation of this type of green renewable energy in the long term.

In this case, three parameters from the equivalent electrical circuit of the DDM are extracted and introduced by the reference condition to define the real operating condition that contains various meteorological data. Table 4 illustrates the estimated parameters of the DDM at G= 366 W/m^2, T = 18 °C, and G= 556.7 W/m^2, T = 20.43 °C, respectively.

Figs. 10 and 11 represent the comparison between the measured and simulated I-V and P-V characteristics at G= 745.2 W/m^2,

Table 1
Parameters of the main simulation program.

Parameter	Value
Number of search agents N_{sa}	30
Maximum number of iterations T_{iter}	300
Dimensions *Dim*	7
Number of runs *Tr*	30

Table 2
The key specifications of the TITAN-12–50 PV module.

Parameter	Value
Short circuit current I_{sc} (A)	3.2
Open circuit voltage V_{oc} (V)	21
Maximum Power P_{mp} (W)	50
Current at maximum power point I_{mp} (A)	2.9
Voltage at maximum power point V_{mp} (V)	17.2
Temperature coefficient of short circuit current (α)	+ 0.1%/°C
Temperature coefficient of open circuit voltage (β)	-0.38%/°C
Temperature coefficient of maximum power (γ)	-0.47%/°C
NOCT	45$\pm$0.2
Number of PV cells connected in series (N_s)	36

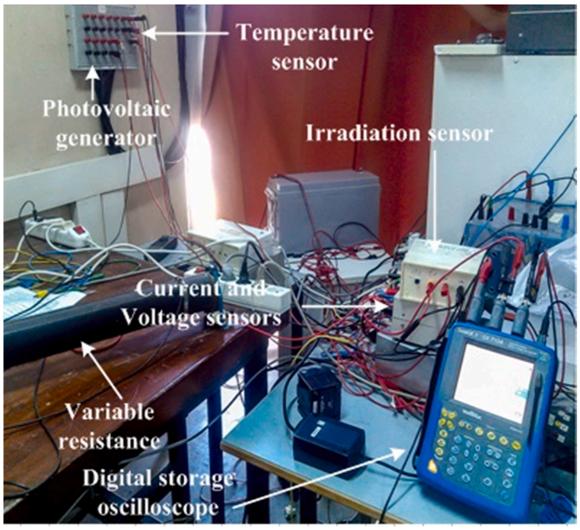

Fig. 6. Experimental test-bench.

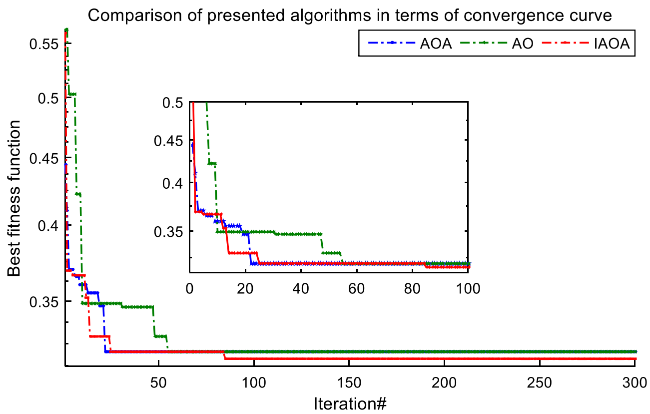

Fig. 7. Evolution of the convergence curve of $F_{obj,DDM}$.

T = 22.10 °C, G= 902 W/m^2, T = 23.87 °C, respectively. I-V and P-V curves present an excellent agreement between the experimental database and the estimated one from these Figures. Concerning the three characteristic points (V_{oc}, I_{sc}, and MPP), it can be showed that the IAOA can introduce a high level of agreement. Thus, the seven parameters describing the electrical circuit of the DDM, which can be estimated, can be obtained with a very low error value.

Regarding the parameters that can be extracted for the DDM, all the I-V and P-V characteristics presented in this section introduce a high level of correspondence, and therefore, the exact parameters can be estimated. Thus, the PV cell/panel/module modeling manner

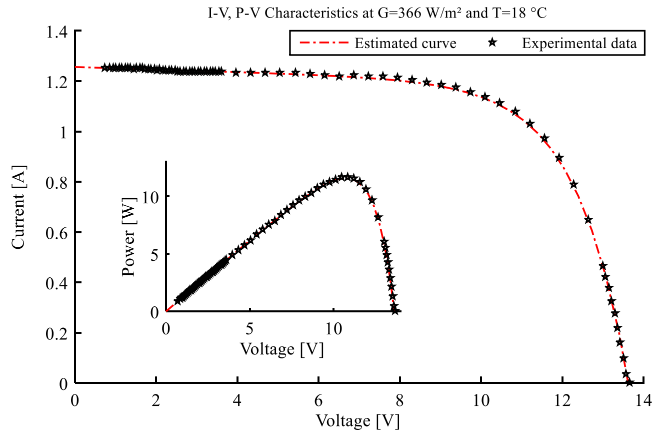

Fig. 8. Correspondence between measured and estimated I-V and P-V curves.

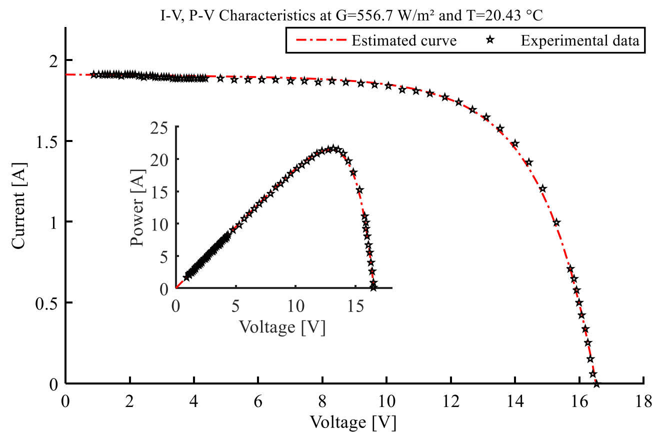

Fig. 9. Correspondence between measured and estimated I-V and P-V curves.

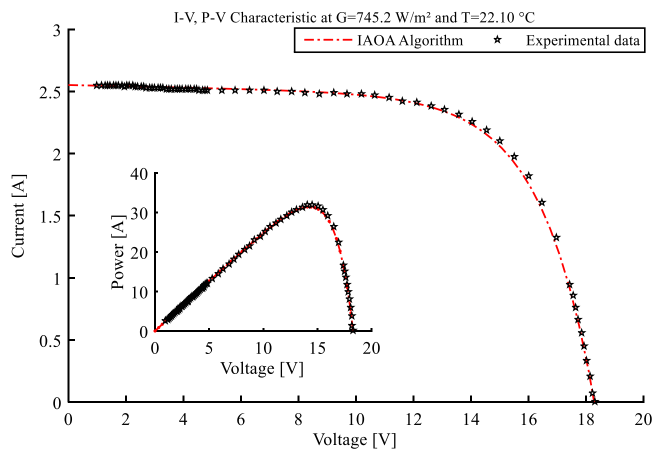

Fig. 10. Correspondence between measured and estimated I-V and P-V curves.

can be improved according to a high level of confidence, which increases industrialization and the exploitation of photovoltaic technologies. The seven parameters related to the equivalent electrical circuit are consequently extracted by introducing the general operating condition. Table 4 depicts the estimated parameters of the DDM at G= 745.2 W/m^2, T = 22.10 °C, and G= 902 W/m^2, T = 23.87 °C, respectively. Table 5 shows the statistical results related to the RMSE, MAE, and NRMSD for all presented cases.

Table 3
Statistical analysis of the obtained results of the DDM.

Algorithms	$MinF_{obj,DDM}$	$MaxF_{obj,DDM}$	$AveF_{obj,DDM}$	$SDF_{obj,DDM}$
VCS	0.31567	0.31693	0.31622	0.00062
GSA	0.49424	0.56884	0.54253	0.04187
WOA	0.31531	0.31618	0.31581	0.00045
SCA	0.31558	0.31621	0.31599	0.00035
MVO	0.31492	0.31594	0.31560	0.00058
SSA	0.31487	0.31537	0.31504	0.00028
AO	0.31458	0.31464	0.31461	$6.447e^{-05}$
AOA	0.31529	0.31735	0.31617	$6.711e^{-04}$
IAOA	**0.31455**	0.31498	0.31460	$\mathbf{9.537e^{-06}}$

Table 4
Estimated parameters of the DDM under different Irradiance (G) and Temperature (T) conditions.

Alg.	*VCS*	*GSA*	*WOA*	*SCA*	*MVO*	*SSA*	*AO*	*AOA*	*IAOA*
Par.	G= 366 W/m^2, T = 18 °C								
I_{ph}	1.261	1.269	1.260	1.259	1.265	1.260	1.259	1.258	1.256
R_s	0.463	0.348	0.451	0.168	0.151	0.341	0.45	0.35	0.51
R_{sh}	78.71	485	180	87	350	145	210	150	200
I_{01}	$1.4e^{-05}$	$1.50e^{-05}$	$7e^{-05}$	$1.1e^{-04}$	$8e^{-05}$	$1.45e^{-05}$	$1.5e^{-05}$	2.2^{-04}	$1.37e^{-05}$
I_{02}	$1.4e^{-05}$	$1.45e^{-05}$	$7e^{-05}$	$1.1e^{-04}$	$8e^{-05}$	$1.45e^{-05}$	$1.5e^{-05}$	2.2^{-04}	$1.37e^{-05}$
a_1	1	1.03	1.1	1.56	1.5	1.02	1.1	1.6	1
a_2	1	1	1.52	1.2	1.12	1	1.1	1.25	1
V_{mp}	10.385	11.055	10.385	10.720	10.60	10.718	10.720	10.717	10.720
I_{mp}	1.034	1.100	1.073	0.991	1.082	1.071	1.070	1.069	1.068
V_{oc}	13.40	13.735	13.40	13.735	13.60	13.39	13.40	13.37	13.40
I_{sc}	1.256	1.268	1.258	1.255	1.265	1.262	1.261	1.260	1.258
	G= 566.7 W/m^2, T = 20.43 °C								
I_{ph}	1.94	1.916	1.95	1.94	1.945	1.922	1.919	1.92	1.910
R_s	0.57	0.68	0.511	0.17	0.571	0.854	0.45	0.35	0.491
R_{sh}	148	150	125	70	120	238	250	300	500
I_{01}	$8.9e^{-06}$	$9e^{-06}$	$7e^{-05}$	$8e^{-06}$	$8e^{-06}$	$8e^{-05}$	$7e^{-05}$	$6.5e^{-05}$	$6e^{-05}$
I_{02}	$8.93e^{-06}$	$7.5e^{-06}$	$7e^{-05}$	$8e^{-06}$	$8e^{-06}$	$8e^{-05}$	$7e^{-05}$	$6.5e^{-05}$	$6e^{-05}$
a_1	1.06	1.1	1.52	1.35	1.14	1.42	1.43	1.2	1.4
a_2	1.18	1.32	1.29	1.08	1.1	1.35	1.29	1.23	1.3
V_{mp}	12.730	13.735	13.065	12.730	12.60	12.730	12.730	12.722	12.730
I_{mp}	1.700	1.659	1.603	1.756	1.675	1.611	1.616	1.625	1.681
V_{oc}	16.080	16.750	16.750	15.745	15.700	16.415	16.415	16.408	16.415
I_{sc}	1.937	1.914	1.946	1.968	1.944	1.919	1.920	1.927	1.909
	G= 745.2 W/m^2, T = 22.10 °C								
I_{ph}	2.594	2.591	2.50	2.597	2.582	2.522	2.549	2.576	2.551
R_s	0.572	0.685	0.514	0.493	0.571	0.254	0.331	0.302	0.305
R_{sh}	147	199.7	300	150	120	200	150	160	200
I_{01}	$8e^{-06}$	$3.5e^{-06}$	$9.5e^{-05}$	$7e^{-06}$	$8e^{-06}$	$3.75e^{-05}$	$9.75e^{-05}$	$4.5e^{-05}$	$6.3e^{-05}$
I_{02}	$8e^{-06}$	$3.5e^{-06}$	$9.5e^{-05}$	$7e^{-06}$	$8e^{-06}$	$3.75e^{-05}$	$9.75e^{-05}$	$4.5e^{-05}$	$6.3e^{-05}$
a_1	1.186	1.08	1.5	1.2	1.2	1.35	1.54	1.4	1.45
a_2	1.181	1.08	1.5	1.2	1.2	1.35	1.54	1.4	1.45
V_{mp}	14.40	14.405	14.07	14.74	14.60	14.07	14.07	14.07	14.07
I_{mp}	2.275	2.285	2.158	2.287	2.240	2.188	2.188	2.188	2.188
V_{oc}	17.755	17.42	18.09	18.425	18.20	17.755	17.755	17.755	17.755
I_{sc}	2.592	2.589	2.498	2.594	2.581	2.520	2.520	2.520	2.520
	G= 902 W/m^2, T = 23.87 °C								
I_{ph}	3.104	3.126	3.11	3.10	3.00	3.093	3.045	3.040	3.051
R_s	0.333	0.595	0.351	0.169	0.351	0.174	0.331	0.354	0.305
R_{sh}	70.19	85.72	90	80	70	98	90	100	70
I_{01}	$6.55e^{-06}$	$6e^{-05}$	$7e^{-05}$	$2.9e^{-05}$	$2e^{-06}$	$7.8e^{-06}$	$8e^{-06}$	$7.5e^{-06}$	$6.5e^{-06}$
I_{02}	$6.55e^{-06}$	$6e^{-05}$	$7e^{-05}$	$2.9e^{-05}$	$2e^{-06}$	$7.8e^{-06}$	$8e^{-06}$	$7.5e^{-06}$	$6.5e^{-06}$
a_1	1.305	1.607	1.55	1.45	1.13	1.30	1.54	1.50	1.35
a_2	1.281	1.584	1.55	1.42	1.13	1.30	1.22	1.38	1.23
V_{mp}	16.080	16.080	15.41	15.745	15.70	16.08	16.07	16.06	16.08
I_{mp}	2.652	2.616	2.601	2.593	2.562	2.678	2.676	2.674	2.678
V_{oc}	20.10	20.435	19.43	19.765	19.3	20.09	2.11	2.08	20.10
I_{sc}	3.099	3.122	3.106	3.096	2.998	3.090	3.087	3.085	3.090

Regarding the statistical analysis of the obtained results, the two first cases (G=366 W/m^2, T = 18 °C, and G=556.7 W/m^2, T = 20.43 °C) have been analyzed and presented for the DDM. From Table 5, which presents the comparison study in terms of Error, it can be shown that IAOA has the minimum Error of RMSE, MAE, and NRMSD followed by the AO, SSA and then AOA algorithms. For

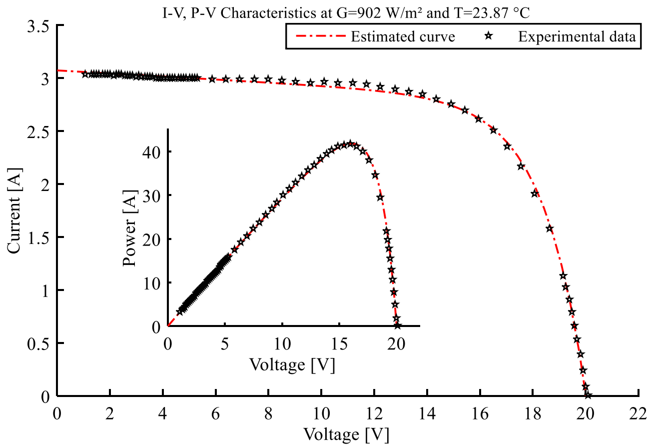

Fig. 11. Correspondence between measured and estimated I-V and P-V curves.

Table 5
Comparison study in terms of Error for all algorithms.

Algorithms	*RMSE*	*MAE*	*NRMSD*	*RMSE*	*MAE*	*NRMSD*
	G= 366 W/m^2, T = 18 °C			G= 566.7 W/m^2, T = 20.43 °C		
VCS	$1.814e^{-02}$	$2.095e^{-03}$	$1.443e^{-02}$	$3.717e^{-03}$	$4.291e^{-04}$	$1.918e^{-03}$
GSA	$4.759e^{-03}$	$5.496e^{-04}$	$3.752e^{-03}$	$3.828e^{-03}$	$4.4e^{-04}$	$2.000e^{-03}$
WOA	$1.309e^{-02}$	$1.512e^{-03}$	$1.041e^{-02}$	$8.413e^{-03}$	$9.715e^{-04}$	$4.322e^{-03}$
SCA	$1.939e^{-03}$	$2.239e^{-03}$	$1.545e^{-02}$	$3.790e^{-03}$	$4.376e^{-04}$	$1.985e^{-03}$
MVO	$7.741e^{-03}$	$5.098e^{-03}$	$4.125e^{-02}$	$2.024e^{-03}$	$1.277e^{-04}$	$1.041e^{-03}$
SSA	$1.141e^{-03}$	$1.317e^{-04}$	$9.065e^{-03}$	$8.818e^{-03}$	$1.018e^{-03}$	$4.593e^{-03}$
AO	$2.209e^{-03}$	$1.315e^{-04}$	$7.990e^{-04}$	$8.425e^{-03}$	$9.728e^{-04}$	$4.388e^{-03}$
AOA	$5.998e^{-03}$	$3.442e^{-03}$	$5.012e^{-03}$	$5.502e^{-03}$	$3.701e^{-04}$	$1.802e^{-03}$
IAOA	$\mathbf{1.132e^{-03}}$	$\mathbf{7.142e^{-05}}$	$\mathbf{8.944e^{-04}}$	$\mathbf{1.988e^{-03}}$	$\mathbf{2.295e^{-04}}$	$\mathbf{1.010e^{-03}}$
	G= 745.2 W/m^2, T = 22.10 °C			G= 902 W/m^2, T = 23.87 °C		
VCS	$3.309e^{-04}$	$4.512e^{-05}$	$1.013e^{-04}$	$4.7e^{-03}$	$5.418e^{-04}$	$1.5e^{-03}$
GSA	$1.884e^{-03}$	$2.175e^{-04}$	$7.274e^{-04}$	$5.312e^{-03}$	$3.287e^{-04}$	$5.619e^{-04}$
WOA	$9.4e^{-03}$	$10.84e^{-04}$	$3.757e^{-03}$	$2.1\ e^{-03}$	$2.443e^{-04}$	$6.811e^{-04}$
SCA	$6.381e^{-04}$	$7.368e^{-05}$	$2.459e^{-04}$	$3.981e^{-03}$	$4.597e\text{-}^{04}$	$1.286e^{-03}$
MVO	$2.475e^{-03}$	$1.562e^{-04}$	$9.589e^{-04}$	$2.714\ e^{-03}$	$1.713e^{-04}$	$9.050e^{-04}$
SSA	$7.611e^{-03}$	$8.788e^{-04}$	$3.020e^{-03}$	$1.397e^{-03}$	$1.613e^{-04}$	$4.521e^{-04}$
AO	$7.6e^{-03}$	$8.789e^{-04}$	$3.020e^{-03}$	$1.397e^{-03}$	$1.613e^{-04}$	$4.521e^{-04}$
AOA	$5.206e^{-03}$	$6.123e^{-04}$	$7.101e^{-03}$	$4.541e^{-03}$	$5.097e^{-04}$	$2.301e^{-04}$
IAOA	$\mathbf{3.623e^{-05}}$	$\mathbf{4.183e^{-06}}$	$\mathbf{1.397e^{-05}}$	$\mathbf{3.316e^{-04}}$	$\mathbf{3.829e^{-05}}$	$\mathbf{1.062e^{-04}}$

the NRMSD, the IAOA showed its high performance by the minimum of Error for all presented cases. These results prove that the proposed IAOA show a highly satisfactory performance than the original version of AOA and other conventional evolutionary algorithms.

6. Conclusion

The enhancement of the solar power generation covers the process towards getting high exploitation and integration of these energies. Based on previously published studies about identifying electrical parameters of photovoltaic models, which need to be improved to achieve a more satisfactory performance, this paper proposed a newly developed approach to resolve this issue. To accomplish the desired goals, the following contributions have been demonstrated:

- A new optimization algorithm called IAOA is proposed.
- The highlighting of real experimental data of I-V and P-V curves is investigated.
- Taking into account different operating conditions, extensive modeling of the DDM of photovoltaic cells/panels is presented.
- A statistical analysis of obtained results is employed to demonstrate the effectiveness of the proposed model.
- Compared with VCS, GSA, WOA, SCA, MVO, SSA, AO, and AOA algorithms, a high level of accuracy, reliability, and performance is achieved by the proposed IAOA algorithm.
- The superiority of IAOA is demonstrated in terms of RMSE, MAE, and RMSD for all presented cases.
- The proposed IAOA can achieve the lowest value of standard deviation by 9.537e-06.

The obtained results show that the proposed IAOA is better than any other since it includes less value of the presented DDM fitness function and a high level of performance characterizes. We recommend going more profound for the modeling procedure and improving these results by proposing other meta-heuristic algorithms for future work.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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