PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

MINISTRY OF HIGH EDUCATION AND SCIENTIFIC RESEARCH

UNIVERSITY YAHIA FARES OF MEDEA



Faculty of Technology
Department of Electrical Engineering
MASTER MEMORY

Branch: Automatic

Specialty: Automatic and systems

Theme:

Estimation of Photovoltaic System Parameters via Metaheuristic Algorithms

Presented by :

- **ABDENNEBI ZAKARIA**
- **GHEBGHOUB AYMEN**

Under the supervision of :

- **Dr. Amel Abbadi**
- **Prof. Fethia Hamid**

2023 / 2024

ملخص

يهدف هذا العمل إلى تقدير وتحديد المتغيرات الخلايا الكهروضوئية باستخدام خوارزميات WOA وGWO وBWOA وMPA بناءً على نموذج الصمام الثنائي الفردي ونموذج الصمام الثنائي المزدوج. تؤثر المتغيرات الكهربائية المختلفة للنموذج المكافئ للخلية الكهروضوئية بشكل مباشر على الخصائص I-V وP-V للوحدات الكهروضوئية. تم اختبار الخوارزميات في دراسة على خلايا RTC France Silicon الشمسية، مما يكشف عن أن خوارزمية MPA تتمتع بقدرة تنافسية عالية وفعالة في تقدير المتغيرات، مع جذر متوسط مربع الخطأ أفضل لمعظم قيم القياس. وتوصلت هذه الطريقة إلى طريقة تقليدية أفضل لتقدير المتغيرات من حيث التقارب والدقة، مما يوفر حلولاً عالمية مثالية.

الكلمات المفتاحية: أنظمة الخلايا الشمسية، الوحدة الكهروضوئية، الأدلة العليا، تقدير المتغيرات، تحديد المتغيرات، نموذج الصمام الثنائي الفردي، نموذج الصمام الثنائي المزدوج، وظيفة جذر متوسط مربع الخطأ.

ABSTRACT

This work aims to estimate and identify the parameters of photovoltaic cells using WOA, GWO, BWOA, and MPA algorithms based on the single diode model and the double diode model. The different electrical parameters of the equivalent model of a photovoltaic cell affect directly the characteristics I-V and P-V of the PV modules. A study tested algorithms on RTC France Silicon Solar Cells, revealing the MPA algorithm as highly competitive and efficient in parameter estimation, with a better root mean square error for most measurement values. That method attains a better conventional method for parameter estimation in terms of convergence and accuracy, which provide global optimal solutions.

Keywords: Solar cell systems, Photovoltaic (PV) module, Metaheuristic, Parameters estimation, Parameters identification, Single-diode model, Double-diode model, RMSE function.

RÉSUMÉ

Ce travail vise à estimer et identifier les paramètres des cellules photovoltaïques à l'aide des algorithmes WOA, GWO, BWOA et MPA basés sur le modèle à diode unique et le modèle à double diode. Les différents paramètres électriques du modèle équivalent d'une cellule photovoltaïque affectent directement les caractéristiques I-V et P-V des modules PV. Une étude a testé des algorithmes sur des cellules solaires au silicium RTC France, révélant que l'algorithme MPA est hautement compétitif et efficace dans l'estimation des paramètres, avec une meilleure erreur quadratique moyenne pour la plupart des valeurs de mesure. Cette méthode atteint une meilleure méthode conventionnelle d'estimation des paramètres en termes de convergence et de précision, qui fournit des solutions optimales globales.

Mots clés : systèmes de cellules solaires, module photovoltaïque (PV), métaheuristique, estimation des paramètres, identification des paramètres, mode monodiode, mode double diode, fonction RMSE.

Acknowledgements

First and foremost, we would like to thank God for giving us the strength, courage, and perseverance needed to complete our studies. His presence has been an invaluable source of inspiration and motivation.

Our sincerest thanks also go to our parents, who have always believed in us and provided unwavering support. Their love, encouragement, and sacrifices have played a crucial role in our success.

We extend our deepest gratitude to our exceptional dissertation directors, **Dr. Amel Abbadi** and **Prof. Fethia Hmidia**, for their unwavering guidance and invaluable mentorship throughout this transformative academic journey. Their expertise, patience, and unwavering belief in our potential have been instrumental in shaping our understanding and propelling us towards the successful completion of our research endeavors.

We would also like to thank the members of the dissertation committee who have honored us by examining this work and dedicating their valuable time. Their constructive comments and pertinent suggestions have allowed us to improve the quality of our dissertation and make it a more complete work.

Finally, we cannot forget all the teachers and administrative staff who have contributed to our education and development throughout our academic careers. Their courses, advice, and support have been essential for our intellectual and personal growth.

We are grateful to all the people who, directly or indirectly, have contributed to the completion of this work. Each of you has played an important role in our journey, and we want to express our deepest gratitude.

This dissertation is the result of hard work and close collaboration. It represents a significant milestone in our lives, and we are proud to share it with you.

Thank you again to all.

Zakaria & Aymen

Table of Contents

Abstract……..…I

Acknowledgements II

Table of Contents……...……...…. III

List of Figures VI

List of Tables VII

List of Abriviations..... VIII

General Introduction.....1

Chapter I Photovoltaic System Overview

I.1 Introduction.....4

I.2 Solar energy.....4

I.3. Solar radiation.....4

1.3.1 Types of Solar radiation 4

1.3.1.1 Direct radiation 4

1.3.1.2 Diffuse radiation 4

1.3.1.3 Reflected solar radiation 5

1.3.1.4 Global reach 5

I.3.2 Photovoltaic solar energy 5

I.4 Photovoltaic effect 6

I.4.1 PV cell power.....7

I.4.2 Photovoltaic cells 7

I.4.2.1 Ideal model 8

I.4.2.2 Practical one-diode model 8

I.4.2.3 Practical two-diode model 9

I.4.3 Different types of photovoltaic panal : 9

I.4.4 Module characteristics 10

I.5 Effects of outside variables on a solar panel 11

1.5.1 The effect of illumination 11

1.5.2 Influence of temperature 12

I.6 The PV generator.....12

I.6.1 Parallel Photovoltaic cell association 13

I.6.2 Photovoltaic cells in series 13

I.6.3 The photovoltaic array 14

I.6.4 Solar panel protection 15

I.6.5 Blocking diode 16

I.7 Advantages and disadvantages of photovoltaic energy **16**
I.8 Conclusions **17**

Chapter II Metaheuristic Optimization Algorithms

II.1 Introduction **19**
II.2 Definition of optimization **19**
II.2.2 Objective function 20
II.2.3 Meta-heuristics 20
II.3 Whale Optimization Algorithm (WOA) **21**
II.3.1 Inspiration 21
II.3.2 Mathematical model and optimization algorithm 23
II.3.2.1 Encircling prey 23
II.3.2.2 Bubble-net attacking method 24
II.3.2.3 Shrinking encircling mechanism 24
II.3.2.4 Spiral updating position 24
II.3.2.5 Search for prey 25
II.3.3 Advantages and disadvantages of WOA 27
II.4 Grey Wolf Optimization Technique (GWO) **27**
II.4.1 Inspiration 28
II.4.2.1 Encircling or blockading prey 29
II.4.2.2 Hunting 30
II.4.2.3 Searching for prey 31
II.4.6 Pseudocode of the GWO Algorithm 31
II.4.7 Advantages and disadvantages of GWO 33
II.5 Black Widow Optimization Algorithm (BWO) **34**
II.5.1 Inspiration 35
II.5.2 The mathematical modeling of the BWOA 36
II.5.3 Pseudocode of the BWOA algorithm 37
II.5.4 Advantages and disadvantages of BWOA 38
II.6 Marine Predators Algorithm (MPA) **39**
II.6.1 Inspiration 40
II.6.2 Procedure of Marine Predators Algorithm 41
II.6.3 The MPA technology 41
II.6.4 MPA optimization process 42
II.6 Marine memory saving 44
II.6.6 Pseudocode of the MPA algorithm 45
II.6.7 Advantages and disadvantages of MPA 46
II.7 Conclusion **47**

Chapter III Results and Discussion

III.1 Introduction **49**

III.2 Mathematical models of Photovoltaic cell **49**

III.2.1 Single Diode Model (SDM) 49

III.2.2 Double Diode Model (DDM) 50

III.2.3 PV module model 51

III.3 RMSE objective function **52**

III.3.1 For SDM of PV cell 52

III.3.2 For DDM of PV cell 52

III.3.3 For SDM of PV module 53

III.3.4 For DDM of PV module 53

III.4 Results and Discussion **53**

III.4.1 RTC France Silicon Solar cell identification 54

III.4.2 Results of SDM 54

III.4.2 Results of DDM 57

III.4.3 Statistics analysis 59

III.4.4 Convergence analysis 60

III.5 Conclusion **62**

General Conclusion **64**

List of bibloigraphic references **66**

List of Figures

Chapter I

Figure I.1 Types of solar radiation [8]. 5
Figure I.2 Photovoltaic effect [14]. 7
Figure I.3 Photovoltaic cells 8
Figure I.4 Equivalent circuit of an ideal model PV cell. 8
Figure I.5 Equivalent circuit of a single-diode cell. 9
Figure I.6 Equivalent circuit of a two-diode cell. 9
Figure I.7 Photovoltaic cell types [17]. 10
Figure I.8 Influence of illumination on the I-V characteristic [19]. 11
Figure I.9 Influence of temperature on the P-V characteristic [19]. 12
Figure I.10 Main composing part of the solar photovoltaic generator [21]. 13
Figure I.11 Characteristics resulting from a grouping pf np cells in parallel [22]. 13
Figure I.12 Characteristics resulting from a grouping of np celle in series [23]. 14
Figure I.13 Association of modules in series and in parallel. 14
Figure I.14 Solar panel in series and in parallel. 15
Figure I.15 Module protection diodes. 16

Chapter II

Figure II.1 Classification of optimization methods[30] 20
Figure II.2 Metaheuristics' general flowchart[29] 20
Figure II.3 The schematic of the spiral bubble-net attacking strategy [33] 22
Figure II.4 Bubble net search shrinking encircling mechanism[34]……..……24
Figure II.5 Flowchart od WOA algorithm. 26
Figure II.6 Hierarchy of grey wolf [35]. 28
Figure II.7 Hunting conduct of grey wolves 30
Figure II.8 Flow-chart of GWO algorithm. 32
Figure II.9 Life cycle of black widow spider**[**42**].** 36
Figure II.10 Flowchart of BWOA algorithm. 38
Figure II.11 MPA's optimization phases[47]. 41
Figure II.12 Flowchart of MPA algorithm. 46

Chapter III

Figure III.1 Equivalent circuit of DDM solar cell. [2]. 48
Figure III.2 Equivalent circuit of DDM solar cell [2]. 49
Figure III.3 Equivalent circuit of the PV module[2]. 50
Figure III.4 The measured data and estimated data data obtained by BWOA on single diode model. 54
Figure III.5 The measured data and estimated data data obtained by GWO on single diode model. 55
Figure III.6 The measured data and estimated data data obtained by MPA on single diode model. 55
Figure III.7 The measured data and estimated data data obtained by WOA on single diode model. 55
Figure III.8 The measured data and estimated data obtained by BWOA on double diode model. 56
Figure III.9 The measured data and estimated data obtained by BWOA on double diode model. 57
Figure III.10 The measured data and estimated data obtained by MPA on double diode model. 57
Figure III.11 The measured data and estimated data obtained by WOA on double diode model. 57
Figure III.12 Convergence curves for single diode model of France silicon solar cell. 59
Figure III.13 Convergence curves for double diode model of France silicon solar cell. 60

List of Tables

Table III.1 Upper and lower bound of the SDM,DDM parametrs. 53
Table III.2 The best values of the identified parameters for SDM of the RTC France silicon solar cell. 54
Table III.3 The best values of the identified parameters DDM of the RTC France silicon solar cell. 56
Table III.4 Single diode statistical analysis. 58
Table III. 5 Double diode statistical analysis 58
Table III.6 The calculated values of current and power. 60

List of Abriviations and symbols

PV	Photovoltaique panel
IR	Infrared Rays
VR	Visible Rays
WOA	Whale Optimization Algorithm
GWO	Grey Wolf Optimization
BWOA	Black Widow Optimization Algorithm
MPA	Marine Predator Algorithm
DDM	Double-Diode model
SDM	Single-Diode model
Iph	The photo current
Rs	Series resistance
Rsh	Shunt resistance
I_d	The diode current
n	Junction ideality factor
D	Diode
FF	Form factor
Voc	Open-circuit voltage
Max_Iter	Symbolizes the maximum number of iterations
I-V	The current-voltage
P-V	The power-voltage
Isc	Short-circuit current
RMSE	Root mean square error
min	Represents the lowest value of RMSE
mean	Corresponds to the average value of RMSE
max	The worst value
STD	The standard deviation of the RMSE values
r	Random number
$\vec{A},\ \vec{C}, \vec{D}$	Coefficient vectors
$X*$	Position vector of the best solution
X	Position vector
b	Constant for defining the shape of the logarithmic spiral
l	Random number uniformly distributed in the range of [−1, 1]
p	Probability for each encircling way
$Xrand$	Randomly chosen position of whale agent
X_p	The position vector of the victim
X_α	The best search agent

X_β	The second-best search agent
X_δ	The third best search agent
$\vec{\mathrm{p}}_{\mathrm{i}}(\mathrm{n}+1)$	The new position of a search agent
$\vec{\mathrm{p}}_{\mathrm{best}}(\mathrm{n})$	The previous iteration best search agent
q	The randomly generated float number
$\vec{p}_i(n)$	The position of the current search agent
$\mathrm{fitness}_{\mathrm{worst}}$	The current generation worst fitness value
$\mathrm{fitness}_{\mathrm{best}}$	The current generation best fitness value
$\mathrm{fitness(i)}$	The i^{th} search agent's current fitness
$\overrightarrow{X^I}$	A vector of top predators
$\overrightarrow{\mathrm{X}_{\mathrm{min}}}$, $\overrightarrow{\mathrm{X}_{\mathrm{max}}}$	The upper and lower limit of design variable
rand	Random vector that its upper and lower bounds ∈ [0, 1]
n , d	The agent's number and dimensions
$X_{i,j}$	The j^{th}dimension of i^{th} prey
P	Constant number initialized to 0.5
R	Designates vector of uniform random number in the range [0,1]
$\overrightarrow{R_B} \otimes \overrightarrow{Elite_\iota}$	Denotes the Brownian move of the predator
$\vec{\mathrm{U}}$	Denotes the binary vectors
r1, r2	Signifies the indexes of the prey matrix
$\overrightarrow{R_L}$	Vector of random numbers based on Lévy distribution.
I_{sd}	The diode saturation current (A)
V_m	The measured voltage (V)
I_m	The measured current (A)
k	Represents the Boltzmann constant
Vt	The thermal voltage
T	The temperature measured in Kelvin
q	The electron charge
I_{sd1}, I_{sd2}	The saturation currents (A) of the diode 1 and diode 2
$n1$, $n2$	Denote the ideality of the diode 1 and 2.
N_s	The number of series cells.
N_p	The number of parallel solar cells.
N	Depicts the total numbers of observations in experimental I-V data.
X	Decision variable vector.

General Introduction

As PV systems are considered reliable and promising renewable energy sources, they are expected to play a key role in the future among power generation systems. Thus, PV systems are popular research areas. A solar cell is the most basic unit of a PV system. Several solar cells are interconnected in series and/or parallel to compose a PV module. PV modules are connected in series to form a PV string. PV strings are also connected in parallel to form a PV array [1].

Solar cells are one of the ways to take advantage of solar energy, so significant attention went to modeling photovoltaic (PV) cells. Several parameters define the nonlinear electrical model of a solar cell, which must be studied in depth to design PV systems. It is vital to understand the current-voltage graph (I-V) before using PV cells. In addition to determining PV's parameters, picking a few points from this curve can also help. Based on the number of diodes, different parameter models are presented. Three different types are available: single diodes, double diodes, and three diodes [2].

The estimation of parameters in PV modules is one of the important items in the development of solar energy. This occurs due to the nonlinear behavior of the relationship between current and voltage; such variables as outputs are crucial in solar cells [3].

The number of computed parameters varies according to the model used, for SDM and DDM, the number of variables is five and seven, respectively. They are extracted with two passes: The first way is the traditional analytic method, and the second way is with the use of meta-heuristic algorithms. The traditional analytical methods are considered a typical solution for estimating the solar cell variables, such as WOA, GWO, BWOA, and MPA.

Many studies have been recently used in solar PV systems. The main concern was to find a correctly estimated estimation of the PV system model parameters, i.e., finding the best parameters of the solar cells as well as PV units to develop a precise I-V description curve and correctly design the PV system. The PV parameter can be found using three methodologies: analytical, numerical, and metaheuristic [4].

Metaheuristic algorithms are global optimization techniques that do not impose any restrictions on the problem formulation and have the ability to solve various complex problems. Since the photovoltaic cell has non-linearity in current-voltage, power-voltage, and intrinsic parameters, deterministic methods cannot extract parameters accurately based on current, voltage, and current derivatives with respect to the voltage at short-circuit current, maximum power, and open-circuit

voltage [5]. Convexity, continuity, and differentiability constraints are among the model limitations imposed by the derivation; also, the approximations decrease accuracy. The use of metaheuristic, bioinspired optimization algorithms for minimization processes has drawn a lot of interest because of their significant promise in contemporary global optimization solutions for nonlinear and complex systems. Stochastic techniques, called metaheuristics, are influenced by a range of natural occurrences. When used to identify parameters for solar and photovoltaic models, they have proven to be a viable substitute for deterministic approaches.

This work aims to extract and identify the parameters of photovoltaic cells using metaheuristic algorithms named WOA, GWO, BWOA, and MPA.

The first chapter of our thesis is devoted to a review of solar radiation and the photovoltaic effect. We will detail the operating principle of a solar cell, as well as that of photovoltaic modules. In the second chapter we present the metaheuristic algorithms and see the mathematical model of these algorithms. In the third chapter, an experimental validation was carried out to test these algorithms and identify the parameters of the RTC FRANCE SILICON SOLAR CELL type of the panel. The present study showed that the MPA is highly competitive and demonstrates better efficiency in parameter identification compared to other optimization algorithms. The root mean square error (RMSE) obtained by the MPA is better than the other errors for most measurement values in the case of single- and double-diode models.

Chapter I
Photovoltaic System Overview

I.1 Introduction

Solar energy has a beneficial impact on the environment and health compared to fossil fuels, and it is therefore considered as a green and clean energy source. The cost of photovoltaic (PV) panels is falling rapidly, while fossil fuel prices are rising and may eventually run out. This led to the popularity of solar energy systems which were attractive only for certain applications in remote and isolated areas [6].

I.2 Solar energy

The sun constantly releases a large amount of radiant energy into the solar system. The distance between the earth and the sun is approximately 150 million kilometers and the speed of light is just over 300,000 km/s [7]. The Earth intercepts a tiny fraction of the solar energy emitted into space. The concept of solar energy is to harness this vast energy reserve, directly converting sunlight into electricity.

I.3. Solar radiation

Definition of solar radiation: it is the energy that the sun emits into interplanetary space. When we talk about the amount of solar energy reaching the earth's surface, we use concepts of irradiance. Solar irradiation is the energy received per unit area over time (J/m^2), the power received in a given time. Similarly, solar irradiance is the power received in an instant - it is expressed in watts per square meter (W/m^2).

1.3.1 Types of solar radiation

1.3.1.1 Direct radiation

Direct radiation is the solar radiation that reaches the earth’s surface directly from the sun, without diffusion through the atmosphere. Pyrheliometer is a device that measures the density of direct radiation. The pyrheliometer must be equipped with a device to direct it continuously towards the sun.

1.3.1.2 Diffuse radiation

It consists of light diffused by the atmosphere (air, cloud cover, aerosols). Dispersion is the phenomenon of division of parallel rays into a number of rays Go in a different direction. It can be measured by a pyranometer with a screen that blocks the sun.

1.3.1.3 Reflected solar radiation

This albedo can be important when the soil is particularly reflective (water, snow). It is characterized by a coefficient proper to the nature of the bond called Albedo 0.

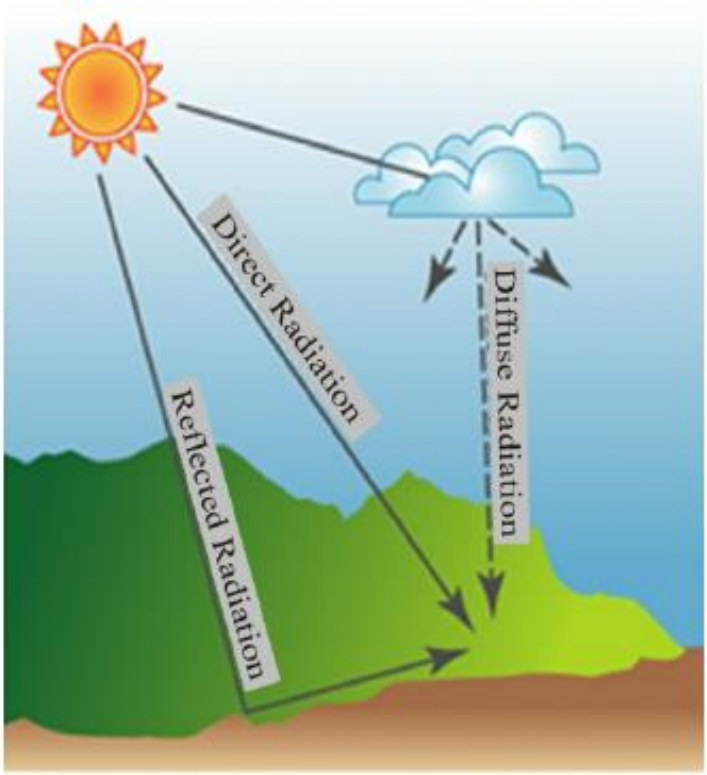


Figure I.1 Types of solar radiation [8].

1.3.1.4 Global Reach

Global radiation is the sum of all radiation received, including radiation reflected from the ground and objects on its surface. It is measured by a pyranometer or solarimeter without a screen. Weather stations generally measure horizontal global radiation by a horizontal pyranometer in the required location.

I.3.2 Photovoltaic solar energy

Solar energy can often be used directly by converting it into electricity using photovoltaic solar cells, where this method is classified as a form of direct use of solar energy. The photovoltaic effect generates an electric motive force, or electrical tension, in a semiconductor device due to the absorption of the luminous radiation when connected to an electrical circuit. Or through the production and capture of heat using thermal cells [9].

I.3.3 History of Photovoltaic cells

The first conventional photovoltaic cells were produced in the late 1950s, and throughout the 1960s, they were principally used to provide electrical power for earth-orbiting satellites. In the 1970s, improvements in the manufacturing, performance, and quality of PV modules helped to reduce costs and opened up a number of opportunities for powering remote terrestrial applications, including battery charging for navigational aids, signals, telecommunications equipment, and other critical low-power needs.

In the 1980s, photovoltaics became a popular power source for consumer electronic devices, including calculators, watches, radios, lanterns, and other small battery-charging applications. Following the energy crisis of the 1970s, significant efforts also began to develop PV power systems for residential and commercial uses, both for stand-alone, remote power as well as for utility-connected applications. During the same period, international applications for PV systems to power rural health clinics, refrigeration, water pumping, telecommunications, and off-grid households increased dramatically and remain a major portion of the present world market for PV products. Today, the industry's production of PV modules is growing at approximately 25 percent annually, and major programs in the U.S., Japan, and Europe are rapidly accelerating the implementation of PV systems on buildings and their interconnection to utility networks [10].

In the first half of the 20th century, the Chaplin-Fuller-Pearson team developed a new type of photovoltaic cell made of semiconductors. In the early 1950s, they used silicon wafers to create photovoltaic cells with efficiencies as high as 6%. After further research, the efficiency of photovoltaic cells currently on the market has been increased to 17% [11].

I.4 Photovoltaic effect

The photovoltaic effect used in solar cells enables the direct conversion of light energy from the sun's rays into electricity by generating and transporting positive and negative electrical charges in a semiconductor material under the effect of light. This material comprises two parts separated by the PN junction, one of which is doped N-doped, with an excess of electrons, and the other, P-doped, with a deficit of electrons. When the former is brought into contact with the latter, electrons in excess in the N material diffuse into the P material. The initially N-doped zone becomes positively charged, and the initially P-doped zone becomes negatively charged.

Fig I.2 illustrates the principle of the PV effect in a PV cell. Essentially, sunlight is composed of photons, which can be considered discrete units of the energy stored in light. A PV cell is made from semiconductor materials with a p-n junction. When solar radiation strikes in a solar cell, part of the photons can be absorbed by the cell, resulting in the production of electron-hole pairs in the cell. If an external circuit is formed, the voltage difference drives the electrons from the n-side to the p-side of the junction. Consequently, the electric current is formed in the external circuit [13].

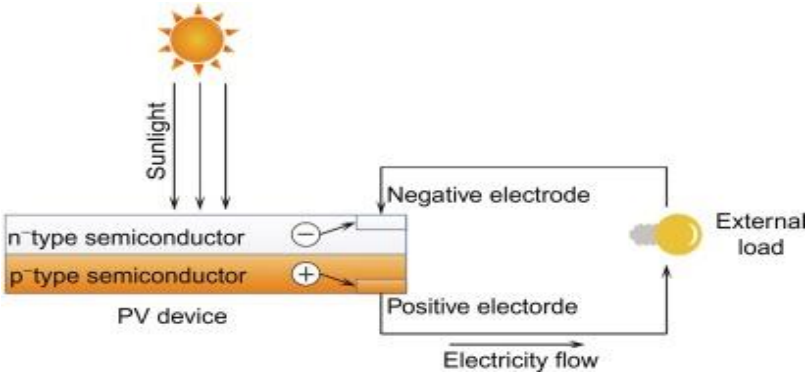


Figure I.2 Photovoltaic effect [14].

I.4.1 PV cell power

Under fixed ambient operating conditions (illuminance, temperature, ambient air circulation speed, etc.), the electrical power P(W) available at the terminals of a PV cell is [12]:

$$P = VI \tag{I.1}$$

P(W): Power supplied by the PV cell.

V(V): Voltage measured across the PV cell.

I(A): Current delivered by the PV cell.

I.4.2 Photovoltaic cells

Photovoltaic cells are semiconductor devices generally made from silicon in its various forms. They do not use any fluids or corrosive substances, and there are no moving parts. They generate electricity as long as they are exposed to solar radiation. They are virtually maintenance-free, non-polluting, and noiseless. For this reason, photovoltaic cells are the greenest and safest method of producing electricity [15].

A solar cell is a converter that converts solar energy into electrical energy. Its structure is based on the PN junction, i.e., it's made up of two layers: a P layer and an N layer. Based on a silicon semiconductor, the solar cell is an instantaneous converter that supplies

electrical energy if it receives solar energy in the form of radiation. The size of each cell can vary from a few square centimeters to 100 cm^2.



Figure I.3 Photovoltaic cells

I.4.2.1 Ideal Model

The equivalent circuit of an ideal PV cell is shown in Figure I.4. It includes a current source (Iph), which models the photocurrent associated with a diode in parallel, which models the PN junction, and determines the voltage. There are different types of solar cell model.

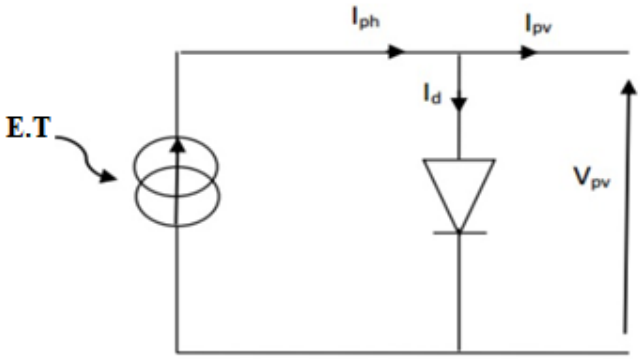


Figure I.4 Equivalent circuit of an ideal model PV cell.

I.4.2.2 Practical one-diode model

Figure I.5 shows the equivalent diagram of the actual solar cell, which accounts for parasitic resistive effects resulting from manufacturing. The components of this equivalent diagram are a shunt resistor (Rsh), which characterizes a leakage current between the top grid and the rear contact, which is typically much greater than (Rs); a diode (D) characterizes the junction; a current source (Iph) characterizes the photo-current; and a series resistor (Rs) represents Joule effect losses.

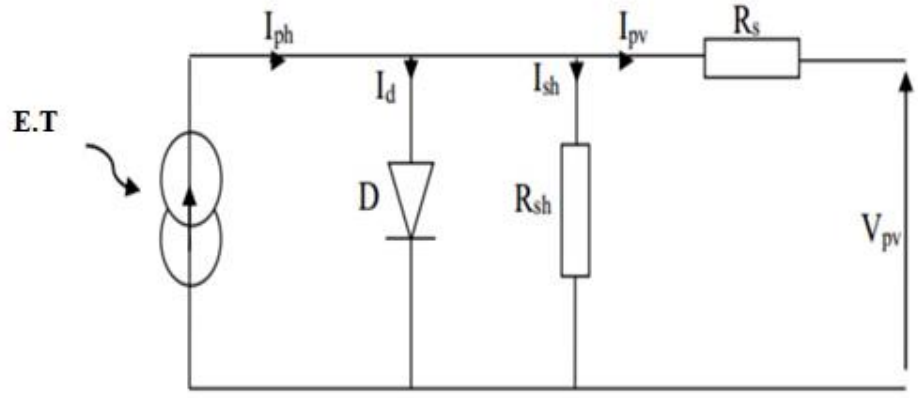


Figure I.5 Equivalent circuit of a single-diode cell.

I.4.2.3 Practical two-diode model

This model is represented by the equivalent electrical diagram shown in Figure I. 6. A current source modeling the luminous flux and losses is modeled by two resistors, a shunt resistor Rsh and a series resistor Rs, and two diodes for cell polarization and minority carrier recombination losses.

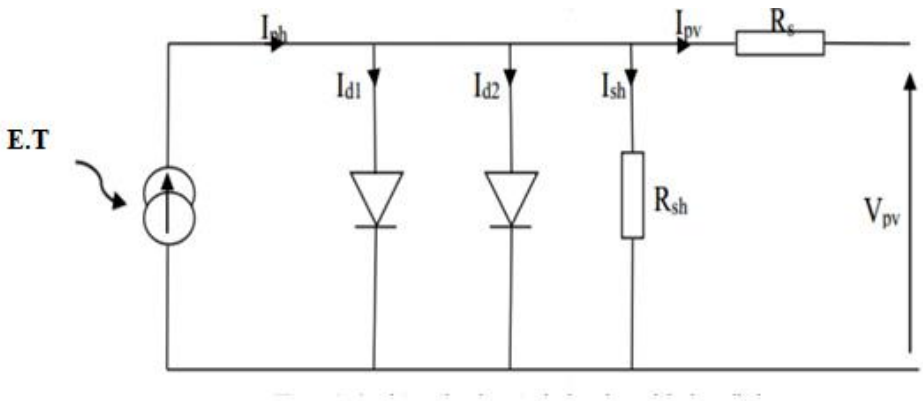


Figure I.6 Equivalent circuit of a two-diode cell.

I.4.3 Different types of photovoltaic panel:

Photovoltaic cells are typically made by sandwiching silicon layers with other elements like boron, gallium or phosphorus to generate an electric field that permits the flow of electricity when joined with a wire. The different types of photovoltaic panel:

a) **Monocrystalline solar modules**: Is a solar panel comprising monocrystalline solar cells. The panel derives its name from a cylindrical silicon ingot grown from single-crystal

silicon of high purity in the same way as a semiconductor. As the cell is composed of a single crystal, it provides the electrons with more space to move for better electricity flow.

b) Polycrystalline solar modules: currently have the best ratio(quality/price). This is why they are most commonly used. They are highly productive and long-lived (over 35 years).

c) Amorphous solar modules: Definitely have a bright future due to their flexibility and good yield (better yield in low light conditions). However, the yield of amorphous silicon is divided by two compared to lenses, so the solution requires a larger area for the same installed power. Furthermore, the price per square meter installed is lower than that of solar panels made of crystalline cells [16].

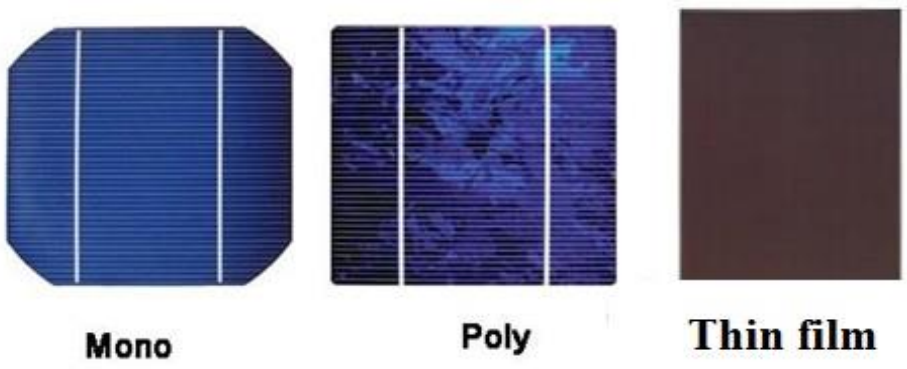


Figure I.7 Photovoltaic cell types [17].

I.4.4 Module characteristics

Modules are generally slim, solid, rectangular units (a couple of centimeters thick), with the following characteristics [18]:

- **Peak power, P_C:** Maximum electrical power that the module can deliver under standard conditions (25°C and 1000 W/m² illumination).
- **The I=f (V) characteristic:** Curve representing the current I delivered by the module as a function of the voltage at its terminals.
- **Open-circuit voltage, V_{OC}:** Voltage at module terminals in the absence of any current, for "full sun" illumination.
- **Short-circuit current, I_{CC}:** Current delivered by a short-circuited module for "full sun" illumination.
- **Optimum operating point, P_m (V_m, I_m):** When peak power is maximum in full sunlight, Pm = Vm × Im.
- **Efficiency:** Ratio of optimum electrical power to incident radiant power.

- **Form factor:** this is the ratio between optimum power and maximum power. It is calculated to define the efficiency of the solar cell. The Form Factor is the real measure of the I-V characteristic. Its value is greater than 0.7 for a good cell. It decreases with increasing cell temperature. It is obtained as follow :

$$FF = \frac{\mathrm{Vm} \times \mathrm{Im}}{\mathrm{Vco} \times \mathrm{ICC}} \tag{I.2}$$

I.5 Effects of outside variables on a solar panel

Temperature and irradiance have a direct impact on the properties of photovoltaic cells, also called PV generators.

1.5.1 The effect of illumination

The current-voltage (I-V) characteristics of a solar module at various illumination levels at a constant temperature of 25°C are depicted in Figure I.8 which demonstrates that:
- There is a proportionality between the short-circuit current (Icc) and illumination.
- The relationship between open-circuit voltage (Voc) and lighting is not very strong. At acertain installation, it might be regarded as constant.

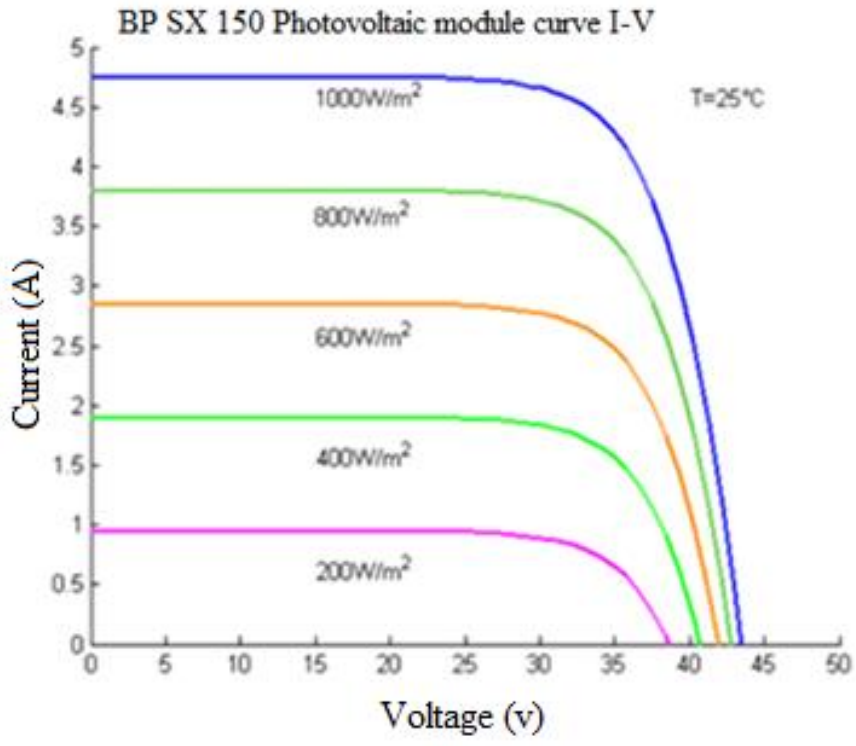


Figure I.8 Influence of illumination on the I-V characteristic [19].

1.5.2 Influence of temperature

PV generator characteristics are also impacted by temperature. With a fixed illuminance of 1000 W/m2, Figure 1.9 displays the properties of a photovoltaic generator as a function of temperature, demonstrating that:

- Open-circuit voltage Voc decreases with increasing temperature.
- The short-circuit current Icc increases with temperature. This increase is minimal compared to the decrease in voltage. The influence of temperature on Icc can be neglected in most cases.

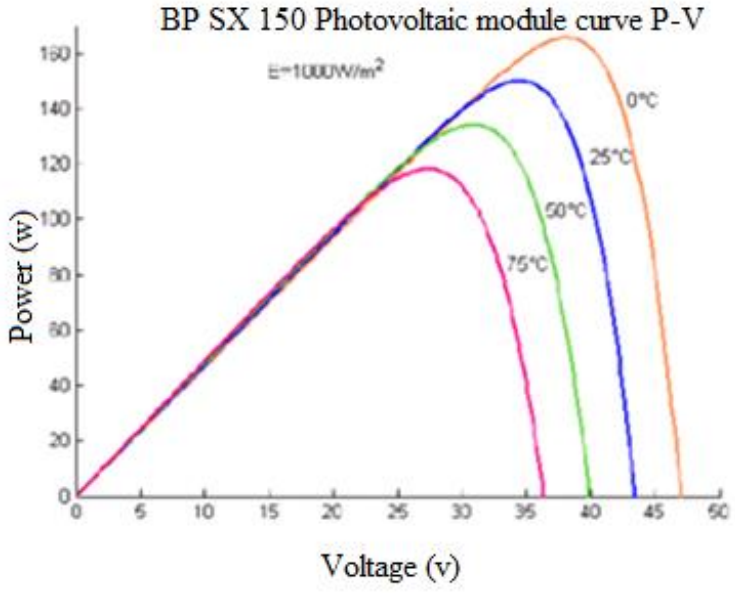


Figure I.9 Influence of temperature on the P-V characteristic [19].

I.6 The PV generator

A photovoltaic generator is a set of equipment set up to exploit photovoltaic energy in order to meet support needs. Depending on the desired power, the modules can be assembled into panels either in series and/ or in parallel to form a "photovoltaic field".

A photovoltaic generator consists of a set of PV modules that are themselves composed of a series and/or parallel assembly of elementary PV cells in order to obtain desired electrical characteristics such as power, short-circuit current, and Voc open circuit voltage. For a number of applications, the continuous current produced by a photovoltaic generator is converted using an alternating current inverter [20].

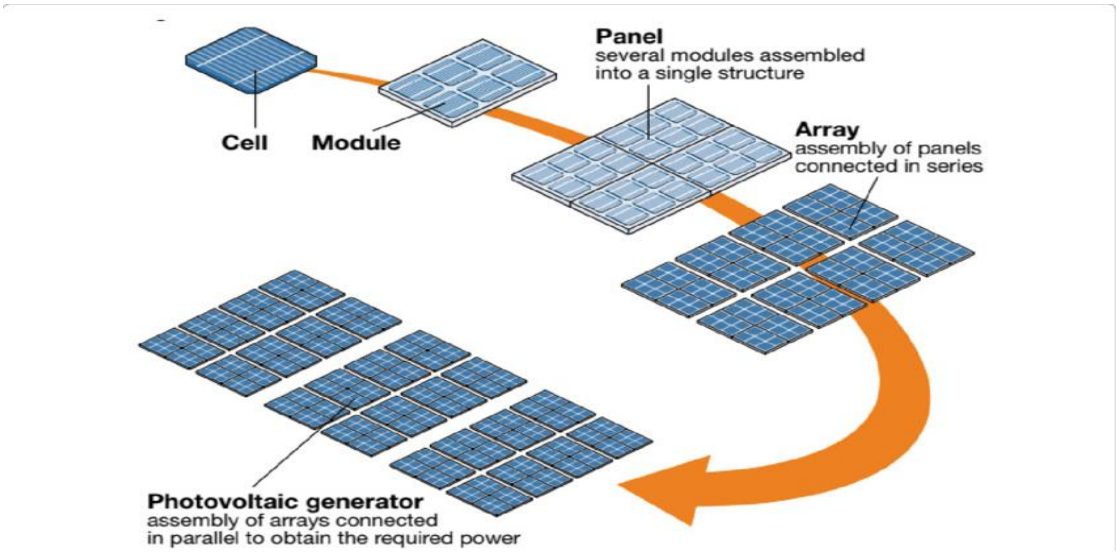


Figure I.10 Main composing part of the solar photovoltaic generator [21].

I.6.1 Parallel Photovoltaic cell association

In a grouping of cells connected in parallel, the cells are subjected to the same voltage, and the resulting characteristic of the grouping is obtained by adding the currents.

If you want a PV module with a higher output current, you can either use PV cells with a larger surface area and higher efficiency, or combine several PV cells with similar characteristics in parallel. Figure I.11 illustrates the resulting characteristics (Ipcc,Vpoc) obtained by associating in parallel np identical cells :

$$I\text{pcc} = n\text{p} * I\text{cc} \quad \text{and} \quad V\text{poc} = V\text{oc} \tag{I.3}$$

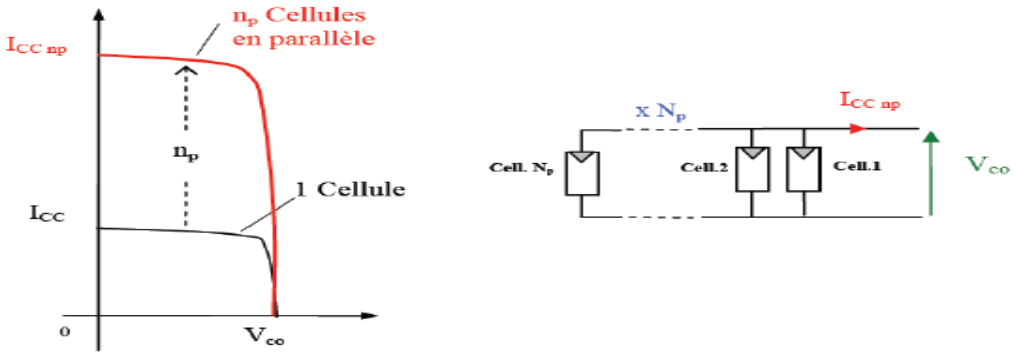


Figure I.11 Characteristics resulting from a grouping pf np cells in parallel [22].

I.6.2 Photovoltaic cells in series

In a series module, the cells have the same current flowing through them, and the resulting characteristic of the series array is obtained by summing the voltages at a given current.

Figure I.12 illustrates the resulting characteristic (*I*sco, *V*sco) obtained by associating identical cells *n*s in series:

$$Isco = Icc \text{ and } Vsco = ns * Vco \quad (I.4)$$

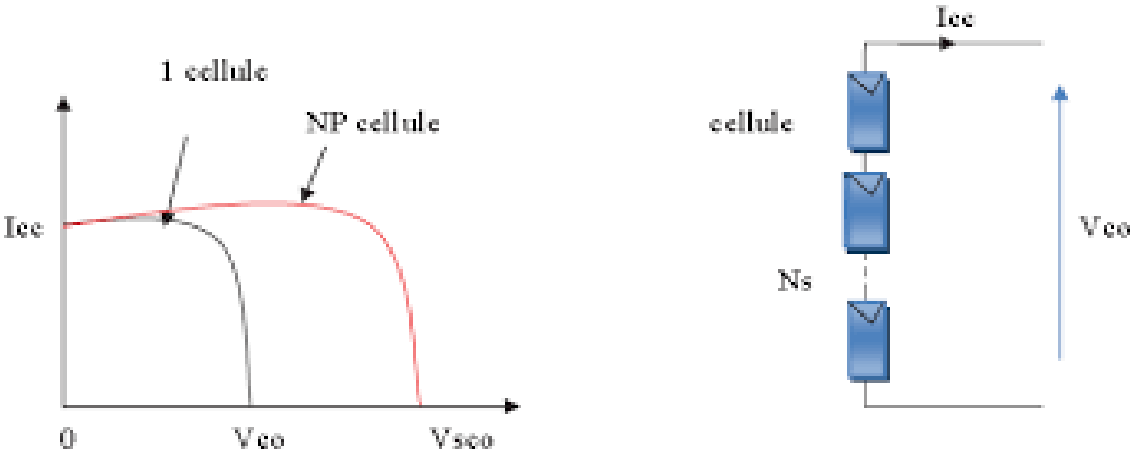


Figure I.12 Characteristics resulting from a grouping of *n*p celle in series [23].

I.6.3 The photovoltaic array

To supply the voltage and current required by the system, the photovoltaic array generally comprises a number of modules made up of several photovoltaic cells, connected in series and in parallel (Figure I.13).

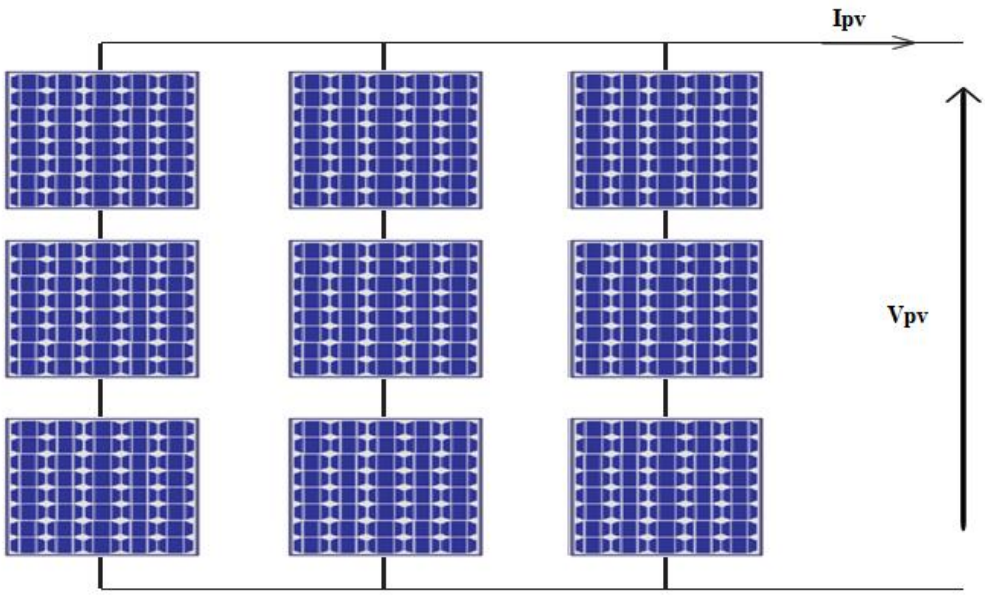


Figure I.13 Association of modules in series and in parallel.

First, the modules are connected in parallel to form units, then the units formed are wired in series. (Figure I.14).

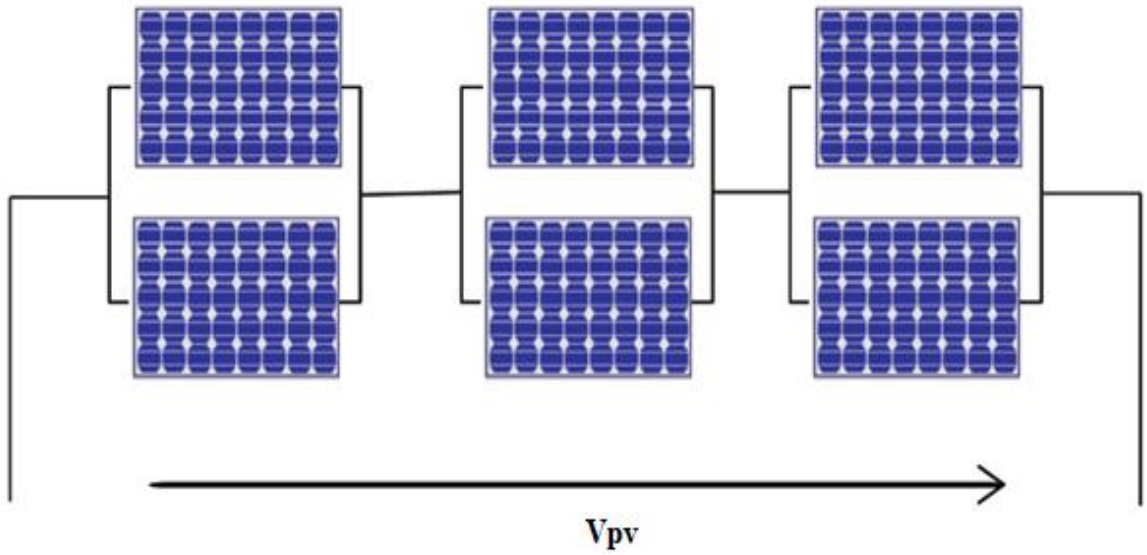


Figure I.14 Solar panel in series and in parallel.

I.6.4 Solar panel protection

To convert a panel into a module, protection diodes must be added (Figure 1.15). To illustrate the usefulness of protection diodes, we distinguish between two types of PV cell assembly:

Parallel and series. In a parallel array, the cells are subjected to the same voltage, and the currents are added together. Under unfavorable conditions (non-uniform illumination and open circuit), a weak cell may be subjected to the reverse current generated by the other cells, thus dissipating significant power and being destroyed. To avoid this problem, a blocking diode be added in series to prevent any reverse current.

On the other hand, in a series grouping, the current is constant and the voltages add up. Under certain conditions of non-uniform illumination and close-to-short-circuit operation, a cell can be subjected to the voltage of the other cells applied in reverse, and so operate as a receiver, dissipating significant power and being destroyed if the thermal stress is too great or if the avalanche voltage is exceeded. To avoid this effect, a blocking diode be connected in parallel to the terminals of an elementary assembly of no more than 30 or 40 silicon cells. The spontaneous firing of this parallel diode as soon as a reverse voltage appears at the terminals of the assembly limits the latter to the diode voltage and thus the energy dissipated [24].

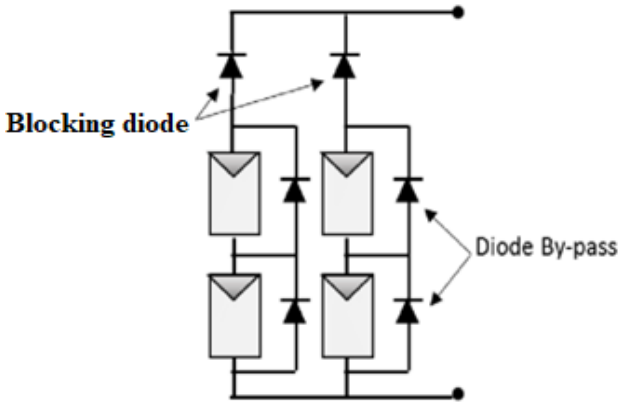


Figure I.15 Module protection diodes.

I.6.5 Blocking diode

For a multi-strings PV system, the generated voltage of some strings could be different from the others. Under this circumstance, the PV string with lower voltage can dissipate a reversed current, originally generated from the other strings. A similar situation could lead to energy reduction and a PV string damage. The most commonly used strategy to protect the system from the reversed current, is to connect a blocking diode in series of each PV string [25].

I.7 Advantages and disadvantages of photovoltaic energy

The main advantages of this energy resource are:

- It's clean, non-polluting, non-emitting of greenhouse gases and produces no waste.
- It uses reliable, long-life components that require little maintenance.
- It requires very low operating costs, thanks to low maintenance and the employment of a small, non-highly qualified workforce.

Whereas the main disadvantages of this resource are:

- The manufacture of photovoltaic solar panels requires cutting-edge technology and costly investment in equipment and research and development.
- As an intermittent energy source, electricity production is unstable and unpredictable, depending on the amount of sunlight.
- The lifespan of photovoltaic installations is only 20 to 30 years. However, the efficiency of photovoltaic cells decreases with time and operating conditions.

I.8 Conclusions

In this chapter, we presented general information about solar energy, the construction of different types of solar cells, their effects and operating principle, and the advantages and disadvantages of solar energy systems.

Chapter II
Metaheuristic Optimization Algorithms

II.1 Introduction

Estimating photovoltaic parameters is a complex process that requires the use of efficient methods to obtain accurate results. The electrical parameters of a photovoltaic cell, such as diode saturation current (Id), series resistance (Rs), shunt resistance (Rp), and ideality factor (a), directly influence the electrical behavior of the PV module. However, these parameters are generally not supplied by the manufacturer, making their estimation essential for analyzing the performance of a PV system, that are different methods estimate these parameters. that are different methods to estimate these parameters.

Metaheuristic algorithms are optimization techniques that are designed to find an adequate solution for a broad range of optimization problems. These algorithms stand out from other optimization techniques in several ways. Firstly, they are derivative-free, meaning that they do not require any sort of calculation of derivatives in the search space, as opposed to gradient-based search techniques. This makes metaheuristic algorithms much simpler, more flexible, and more capable of avoiding local optima, making them highly effective for handling challenging optimization tasks. The stochastic nature is another characteristic of metaheuristic algorithms, which implies they begin the optimization process by generating random results [26].

The Whale Optimization Algorithm (WOA), the Grey Wolf Optimization Algorithm (GWO), the Black Widow Optimization Algorithm (BWOA), and the Marine Predator Algorithm (MPA) are among the photovoltaic parameter estimation strategies that will be covered in this chapter. These algorithms are based on natural methods that have been inspired by the natural world, such as tracking Predator marine, tracking gray wolves, tracking black widows, and tracking whale migration.

In summary, photovoltaic parameter estimation is a complex process that requires the use of efficient methods to obtain accurate results. Natural algorithms, such as WOA, GWO, BWOA, and MPA, offer a promising approach to estimating these parameters and improving the performance of photovoltaic systems.

II.2 Definition of Optimization

An optimization problem is defined as the search for the minimum or maximum (optimum) of a given function. We can also find optimization problems in which the variables

of the function to be optimized are constrained to evolve in a certain part of the search space. In this case, we have a particular form of what is known as a constrained optimization problem [27].

II.2.1 Classification of optimization methods

An optimization problem is solved using optimization methods whose classification is illustrated in Figure II.1

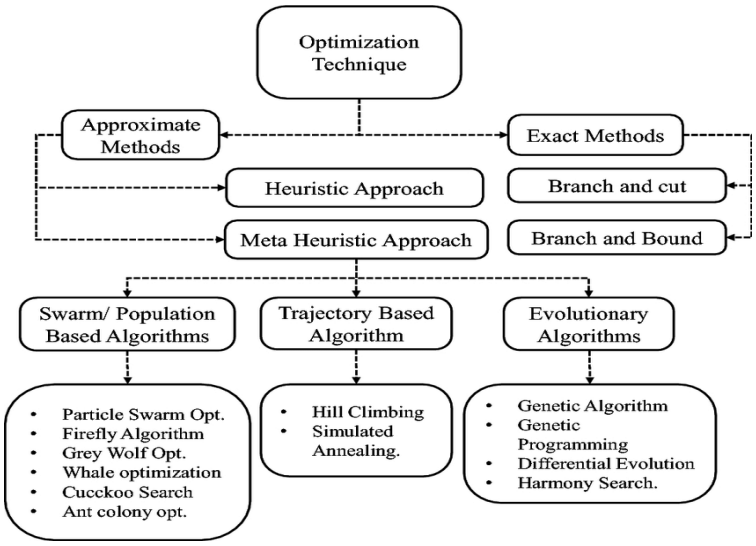


Figure II.1 Classification of optimization methods [30].

II.2.2 Objective function

Target function is the term used for the function f (also known as the fitness function, cost function, or optimization criteria). The optimization method will need to determine an optimal value for this function.

II.2.3 Meta-heuristics

Meta-heuristics appeared in the 1980s and form a family of optimization algorithms aimed at solving difficult optimization problems, for which no more efficient classical method is known. They are generally used as generic methods that can optimize a wide range of different problems, without requiring major changes to the algorithm employed [28].

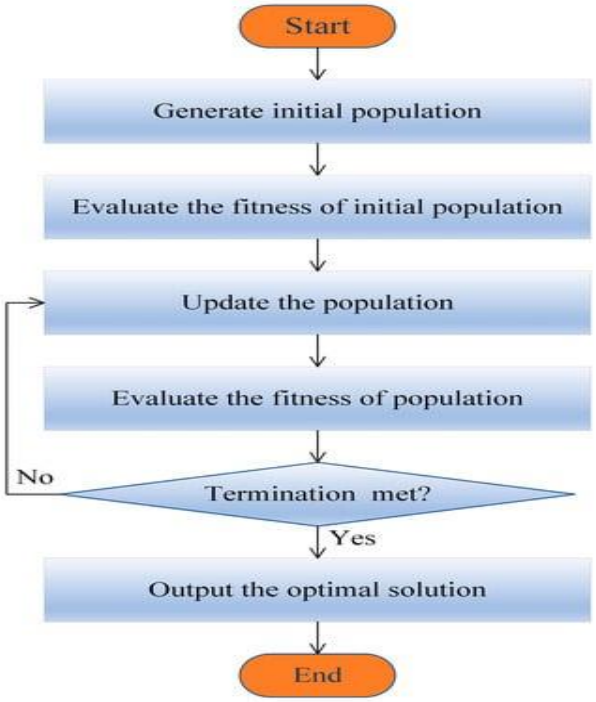


Figure II.2 Metaheuristics' general flowchart [29].

II.3 Whale optimization algorithm (WOA)

The Whale Optimization Algorithm (WOA) is an intelligent optimization algorithm. Proposed by Australian researchers in 2016; the algorithm is inspired by the bubble network hunting techniques used by humpback whales to solve complex optimization problems.

The algorithm comprises three main operators to simulate the prey search, prey encirclement, and bubble network hunting behaviors of humpback whales.

II.3.1 Inspiration

In the meta-heuristic algorithm, a newly purposed optimization algorithm called the Whale Optimization Algorithm (WOA) is inspired by the bubble-net hunting strategy. The algorithm describes the special hunting behavior of humpback whales. The whales follow the typical bubbles, causing the creation of a circular or '9-shaped path' while encircling prey during hunting. Simply bubble-net feeding and hunting behavior could be understood such that the humpback whale went down in water for approximately 10–15 meters and then, after the start of producing bubbles in a spiral shape, encircled prey and then followed the bubbles and moved upward on the surface [31].

Whales are fancy creatures. They are considered the biggest mammals in the world. An adult whale can grow up to 30 m long and 180t in weight. There are 7 different main species of this giant mammal, such as killer, minke, sei, humpback, right, finback, and blue. Whales are mostly considered predators. They never sleep because they have to breathe on the surface of the oceans. In fact, half of the brain only sleeps. The interesting thing about whales is that they are considered highly intelligent animals with emotions. According to Hof and Van Der Gucht, whales have common cells in certain areas of their brains similar to those of humans called spindle cells. These cells are responsible for judgment, emotions, and social behaviors in humans. In other words, the spindle cells make us distinct from other creatures. Whales have twice as many of these cells as an adult human, which is the main cause of their smartness. It has been proven that whales can think, learn, judge, communicate, and become even more emotional than humans, but obviously with a much lower level of smartness. It has been observed that whales (mostly killer whales) are able to develop their own dialect as well. Another interesting point is the social behavior of whales. They live alone or in groups. However, they are mostly observed in groups. Some of their species (killer whales, for instance) can live in a family over their entire life period. One of the biggest baleen whales is the humpback whale (Megaptera novaeangliae). An adult humpback whale is almost the size of a school bus. Their favorite prey are krill and small fish herds.

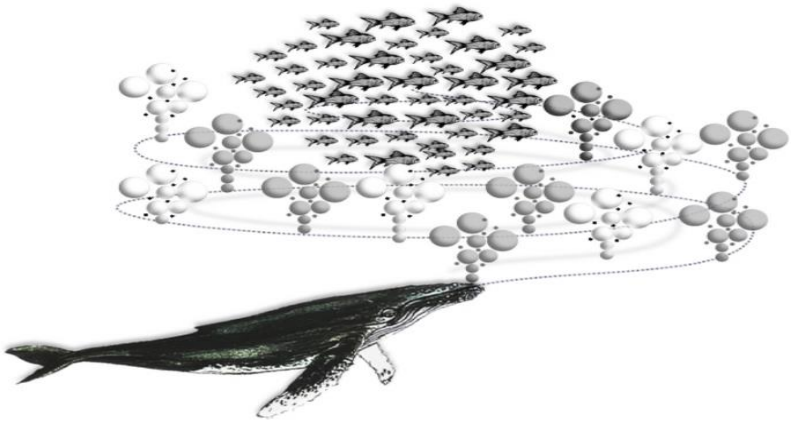


Figure II.1 The schematic of the spiral bubble-net attacking strategy [33].

Fig. II.3 shows this mammal. The most interesting thing about humpback whales is their special hunting method. This foraging behavior is called the bubble-net feeding method. Humpback whales prefer to hunt schools of krill or small fish close to the surface. It has been

observed that this foraging is done by creating distinctive bubbles along a circle or '9'-shaped path, as shown in Fig. II.3 [32].

II.3.2 Mathematical model and optimization algorithm

In this section the mathematical model of encircling prey, spiral bubble-net feeding manoeuvre, and search for prey is first provided. The WOA algorithme is then proposed.

II.3.2.1 Encircling prey

Humpback whales can recognize the location of prey and encircle them. Since the position of the optimal design in the search space is not known a priori, the WOA algorithm assumes that the current best candidate solution is the target prey or is close to the optimum. After the best search agent is defined, the other search agents will hence try to update their positions towards the best search agent. This behavior is represented by the following equations:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_t^* - \vec{X}_t\right| \quad \text{(II. 1)}$$

$$\vec{X}_{t+1} = \vec{X}_t^* - \vec{A} \cdot \vec{D} \quad \text{(II. 2)}$$

where t indicates the current iteration, A and C are coefficient vectors, X^* is the position vector of the best solution obtained so far, X is the position vector. X^* should be updated in each iteration, if there is a better solution. The coefficient vectors A and C are calculated as follows:

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r} - \vec{a} \quad (II. 3)$$

$$\vec{C} = 2 \cdot \vec{r} \quad (II.4)$$

where $\vec{a}$ is a variable linearly decrease from 2 to 0 over the iterations in both exploration and exploitation phases. Exploration is related to global search exploring the search space looking for good solutions while exploitation is related to local search to refine the solution avoiding big jumps on the search space. r is a random number [0, 1].

II.3.2.2 Bubble-net attacking method

The bubble-net attack phase mimics the behavior of the humpback whale as it spirals upwards during feeding. During this phase, the whale approaches the predicted prey location in a spiral path. The following mathematical formula can be used to describe this behavior:

II.3.2.3 Shrinking encircling mechanism

This technique is employed by decreasing linearly the value of $\vec{a}$ from 2 to 0 over the course of iterations, causing fluctuation in A in the interval [−1, 1]. The new position of a search agent is anywhere between the original position of the agent and the position of the current best agent. Figure II.4 shows the possible positions from (X, Y) towards (X^*, Y^*) that can be achieved by $0 \leq A \leq 1$ in a 2D space.

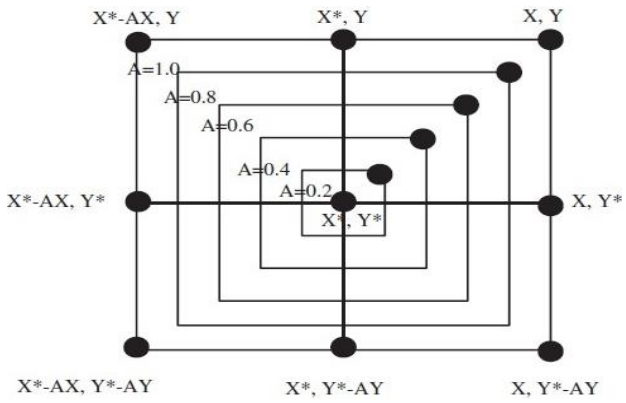


Figure II. 2 Bubble net search shrinking encircling mechanism [34].

II.3.2.4 Spiral updating position

To update the position of whale located at (X, Y) and prey located at (X^*, Y^*), a spiral equation is introduced to mimic the helix-shaped movement of hump- back whales b, which is described as

$$\vec{X}_{(t+1)} = D' \cdot \mathrm{e}bl \cdot \cos(2pl) + \vec{X}_t^* \qquad \text{(II.5)}$$

where $D' = X^*(t) - X(t)$ and indicates the distance of the ith whale to the prey (best solution obtained so far), b is a constant.

For defining the shape of the logarithmic spiral, l is a random number in [−1, 1]. There is a probability of 50% to choose either the shrinking encircling mechanism or the spiral model to update the position of whales.

$$\vec{X}_{(t+1)} = \begin{cases} \vec{X}_t^* - \vec{A} \cdot \vec{D} & \text{if } p < 0.5 \\ D' \cdot ebl \cdot \cos(2pl) + \vec{X}_t^* & \text{if } p \geq 0.5 \end{cases} \quad \text{(II.7)}$$

where p expresses random number between [0, 1].

II.3.2.5 Search for prey

Exploration is expressed as follows:

$$\vec{D} = \vec{C} \cdot \vec{X}_{rand} - \vec{X} \quad \text{(II.8)}$$

$$\vec{X}_{(t+1)} = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \quad \text{(II.9)}$$

Vector A take the values >1 to enforce exploration.

Algorithm 1. Whale Optimization Algorithm

```
Input Number of MaxIter and Population etc
Initialize the whales population Xi (i = 1, 2, ..., n)
Initialize a, A, C, l and p
Calculate the fitness of each search agent
X*= the best search agent
while (it < MaxIter)
    for each search agent
        if (p < 0.5)
            if (|A| < 1)
              Update the position of the current search agent
            else if (|A| ≥ 1)
                 Select a random search agent (X_rand) Update the
                  position of the current search agent
                search agent
              End
        else if (p ≥ 0.5)
              Update the position of the current search
        End
    End
    Calculate the fitness of each search agent
    Update X* if there is a better solution
    It=it+1
```

11 : Update a, A, C, l and p

12 : **end while**

13 : **return** X*

The pseudo code of the WOA algorithm is presented in algorithm 1 From theoretical stand point, WOA can be considered a global optimizer because it includes exploration/exploitation ability. Furthermore, the proposed hyper-cube mechanism defines a search space in the neighborhood of the best solution and allows other search agents to exploit the current best record inside that domain. Adaptive variation of the search vector A allows the WOA algorithm to smoothly transit between exploration and exploitation: by decreasing A, some iterations are devoted to exploration ($|A| \geq 1$) and the rest is dedicated to exploitation ($|A|<1$).

Remarkably, WOA includes only two main internal parameters to be adjusted (A and C).

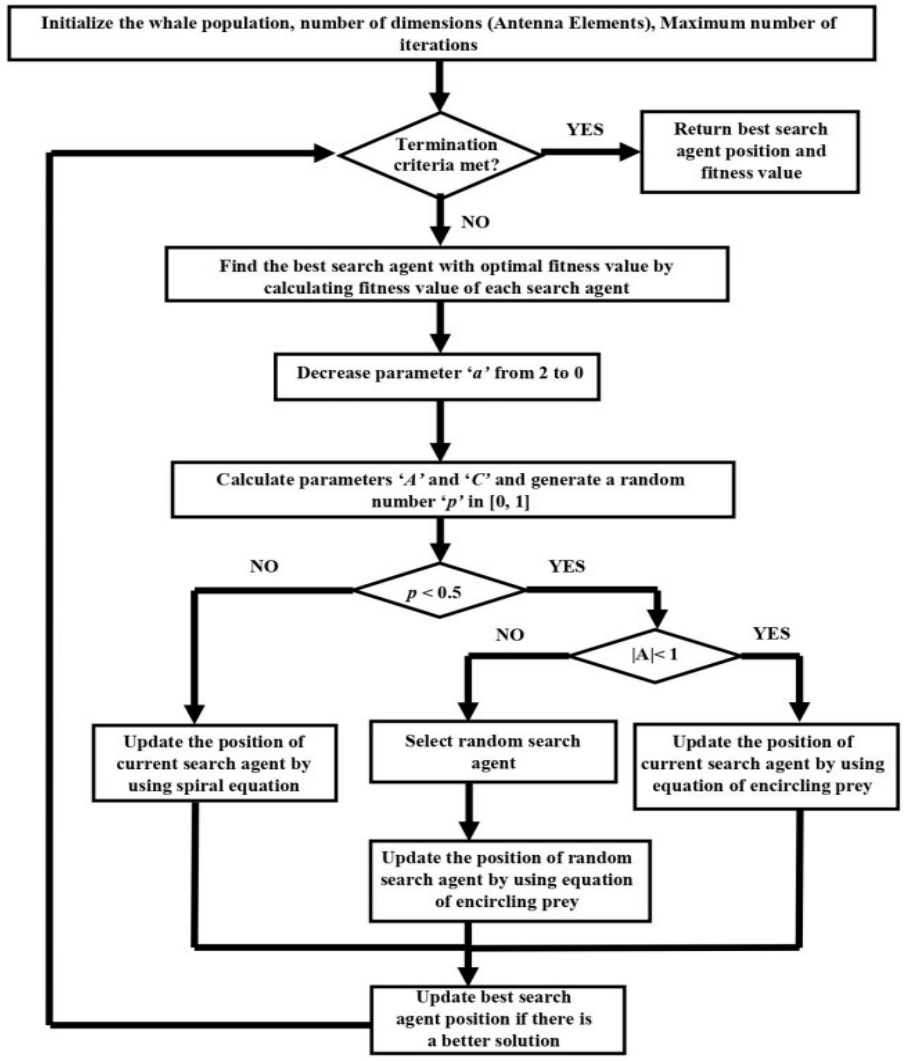


Figure II.3 Flowchart od WOA algorithm.

II.3.3 Advantages and disadvantages of WOA

a) Advantages:

- **Flexibility:** The Whale Optimization Algorithm (WOA) is designed to solve complex optimization problems, including multivariate and constraint problems.
- **Efficiency:** WOA has been demonstrated to be efficient in solving optimization problems, particularly in the fields of engineering, robotics and system optimization.
- **Robustness:** The algorithm is designed to be robust to perturbations and changes in optimization parameters.
- **Ease of use:** WOA is easy to implement and use, even for non-optimization experts.
- **Performance:** WOA has been shown to offer competitive performance with other optimization algorithms, notably genetic algorithms and swarm search algorithms.

b) Disadvantages:

- **Complexity:** The WOA algorithm is designed to be complex, which can make it difficult to implement and use.
- **Dependence on data quality:** The WOA algorithm is dependent on the quality of the input data, which can affect its performance.
- **Parameter sensitivity:** The WOA algorithm is sensitive to optimization parameters, which may require fine-tuning of these parameters to achieve optimal results.
- **Limits to scalability:** The WOA algorithm may be limited in its ability to handle large-scale optimization problems.
- **Lack of documentation:** Documentation of the WOA algorithm may be limited, making it difficult to use for new users.

II.4 Grey Wolf Optimization Technique (GWO)

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

In GWO, there are four types of grey wolves such as alpha (α), beta (β), delta (δ) and omega (ω) and they have very strict social dominant hierarchy as shown in Fig. 3, where dominance of wolves decreases from top to bottom.

Alpha is the first level and is the leader of the pack. Beta is the second level on the hierarchy of wolves and help alpha wolves to make a decision. Delta is the third level in the

pack, delta wolves have to succumb alpha and beta, but they dominate omega. Omega wolves have the lowest position in the pack. They always have to succumb to all other dominant wolves. Fig II.6 shows the gray wolf social hierarchy [34].

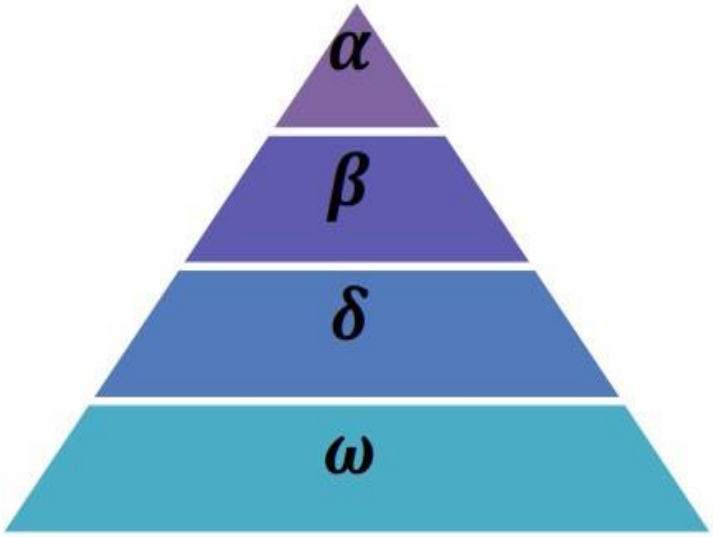


Figure II.4 Hierarchy of grey wolf [35].

II.4.1 Inspiration

They live in packs of four to nine groups, and that can vary based on their ancestors. Wolves have body language and communication like bees. Barking and howling are used for warning and long-distance communication, respectively. A wolf used to challenge its travel companion by growling or laying its ears back on its head. In the group, there are male and female hierarchies. The grey wolves are of four different types, namely alpha, beta, delta, and omega. The most dominant over the entire pack is the male alpha grey wolf type. The alpha male and male-only have babies that breed. At the age of three, the young wolf becomes a teenager and joins the pack or leaves for hundreds of miles to find its own land. At birth, their pups can't see or hear and approximately weigh one pound. They work on a strict socially dominant hierarchy [36].

The alpha is mainly responsible for making decisions like hunting, sleeping, searching for a place, and so on. The (alpha) wolves are not absolutely the strongest members of the pack, but they are the best in terms of controlling the pack.

The beta wolves are second in the hierarchy of grey wolves; they are subordinate or deputy wolves after alpha wolves and help alpha wolves in decision-making or other events.

Beta wolves can replace or lead if one of the alpha wolves passes away, becomes sick, is seriously wounded, or is too old. The respect is tensed up to alpha wolves, but they (beta wolves) give authority to other lower-level wolves as well. They are considered counselors to the alpha wolves and punishment givers to the others. Omega are the lowest-ranking wolves; they act as scapegoats; they are the weakest wolves; and, in a hierarchal manner, they eat after all the wolves that live in the pack; they are sometimes babysitters in the pack. The delta wolves are called subordinate because they must submit to alpha and beta wolves, but, on the other hand, they dominate omega wolves.

II.4.2 Mathematical modeling and the proposed algorithm

In order to improve the application of the grey wolf optimizations, the mathematical modeling of hunt strategy, social behavior, pursuing, surrounding, tracking, and attacking prey are examined in this part.

II.4.2.1 Encircling or blockading prey

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. According to Muro et al, the main phases of grey wolf hunting are as follows:

- Tracking, chasing, and approaching the prey.
- Following, encircling, and harassing the prey until it stops moving.
- Attacking the target.

Wolves encircle the target during the chase. The encircling is modeled by the Equations (III.10) and (III.11):

$$\overrightarrow{D} = \overrightarrow{IC} \cdot \vec{\chi}_P(t) - \vec{x}(t)I \quad \text{(II.10)}$$

$$\vec{X}_{(t+1)} = \vec{\chi}_P(t) - \vec{A} \cdot \overrightarrow{D} \quad \text{(II.11)}$$

where t represents the current iteration, $\vec{A}$, $\vec{C}$, and $\overrightarrow{D}$ are coefficient vectors, $\vec{\chi}_P$ is the position vector of the victim, and $\vec{x}$ is the position vector of a grey wolf $\vec{A}$ and $\vec{C}$, as computed through these two equations:

$$\vec{A} = 2a.\overrightarrow{r_1} \quad \text{(II.12)}$$

$$\vec{C} = 2 * \vec{r}_2 \cdot \overrightarrow{x_p} \quad \text{(II.13)}$$

II.4.2.2 Hunting

Components of a linearly reduce from 2 to 0 through the iterations and $\vec{r_1}$ and $\vec{r_2}$ as random vectors in [0,1]. The pursuit is habitually directed by the leader alpha (α) followed by beta (β) and delta (δ) which can sometimes contribute in chasing. (δ) and (ω) look after the injured wolves in the group. Alpha (α) is considered the best result owing to the best information of the place of the target, while beta (β) and delta (δ) are the second and the third best solutions respectively in designing GWO. (ω) is the last best. Therefore, the first three best solutions obtained so far are saved and the other search agents (including ω) are obliged to update their positions according to the position of the best search agent. When the prey stops moving, the wolves terminate the chase by attacking it, as shown in Figure II.7.



Figure II.5 Hunting conduct of grey wolves.

In this regard, the following formulas are applied: (**A**) approaching and pursuing target, (**B**–**D**) following, encircling and disturb the target, (**E**) attacking the target.

$$\overrightarrow{D_\alpha} = |\overrightarrow{C_1} \cdot \overrightarrow{x_\alpha}(t) - \vec{x}_1| \quad \text{(II.14)}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1\vec{D}_\alpha \quad \text{(II.15)}$$

$$\overrightarrow{D_\beta} = |\overrightarrow{C_2} \cdot \overrightarrow{x_\beta}(t) - \vec{x}(t)| \quad \text{(II.16)}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2\vec{D}_\beta \quad \text{(II.17)}$$

$$\overrightarrow{D_\delta} = |\overrightarrow{C_3} \cdot \overrightarrow{x_\delta}(t) - \vec{x}(t)| \quad \text{(II.18)}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \quad \text{(II.19)}$$

Therefore, the updated position of all search agents is given by:

$$\vec{X}_{(t+1)} = \frac{(\vec{X}_1+\vec{X}_2+\vec{X}_3)}{3} \quad \text{(II.20)}$$

II.4.2.3 Searching for prey

The searching process of the wolves mostly depends on the movements or the position of alpha, beta, and delta wolves to look for the prey in a diverging manner and, they attack the prey in a converging way. In the divergence case, the mathematical modeling is done by using random values of $A > 1$ or $A < -1$ to force the search agent to move away (diverge) from the prey. The exploration situation is applied in this case and allows the grey wolf optimization (GWO) algorithm to word widely explore the prey. C is another prominent factor in exploration. It is very helpful especially during the final iterations in case the local minimum stagnation problem occurs. C with values range in [0,2] can be considered as an obstruction effect to approach prey in the natural world. This obstacle or obstruction in nature generally happens during the hunting period of wolves and that precludes them from swiftly and accurately approaching their prey.

II.4.6 Pseudocode of the GWO Algorithm

The pseudocode of the GWO algorithm and its flowchart is presented in figure as follow (Figure II.8):

Algorithm 2 GWO

1: Initialize the grey wolf population X_i, i = 1, n
2: Initialize a, A and C
3: Calculate the fitness of each search agent
4 : X_α=the best search agent
5: X_β = the second best search agent
6 : X_δ= the third best search agent
7 : while t < max number of iteration do
8: for each search agent do
9 : Randomly initialize r_1 and r2

```
        Update the position of the current search agent
    End
    Update a, A and C
    Calculate the fitness of all search agents
    Update Xα . Xβ and Xδ
    t=t+1
End while
return Xα
```

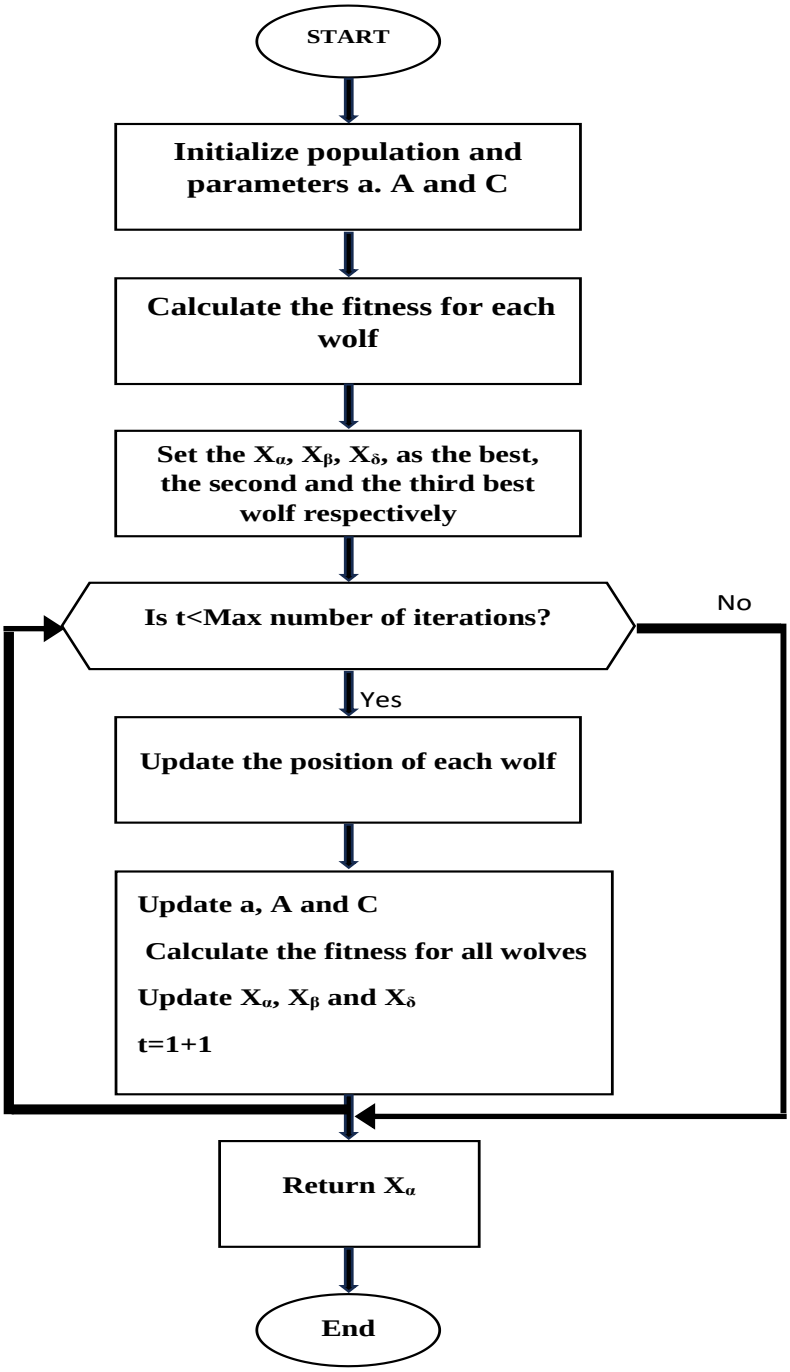


Figure II.6 Flowchart of GWO algorithm.

II.4.7 Advantages and disadvantages of GWO

a) Advantages:

- **Flexibility:** The Grey Wolf Optimization (GWO) algorithm is designed to solve complex optimization problems, including multivariate and constraint problems.

- **Efficiency:** GWO has been shown to be effective in solving optimization problems, particularly in the fields of engineering, robotics and systems optimization.
- **Robustness**: The algorithm is designed to be robust to perturbations and changes in optimization parameters.
- **Ease of use:** GWO is easy to implement and use, even for non-optimization experts.
- **Performance:** GWO has been shown to offer competitive performance with other optimization algorithms, notably genetic algorithms and swarm search algorithms.
- **Simplicity:** GWO is known to be a simple algorithm to implement, with few parameters to adjust.
- **Diversity:** The GWO algorithm is designed to maintain population diversity, which is essential to avoid stagnation in local regions.

b) Disadvantages :

- **Slow convergence:** GWO can be slow to converge on the optimal solution, which can be a drawback for high-complexity optimization problems.
- **Paucity of exploration:** GWO may have difficulty exploring regions of the search space, leading to stagnation in local regions.
- **Data quality dependency:** GWO is dependent on the quality of input data, which can affect its performance.
- **Parameter sensitivity:** GWO is sensitive to optimization parameters, which may require fine-tuning of these parameters to achieve optimal results.
- **Limits to scalability:** GWO may be limited in its ability to handle large-scale optimization problems.

II.5 Black Widow Optimization Algorithm (BWO)

The black widow optimization algorithm (BWOA) is a novel bio-inspired metaheuristic optimization algorithm that mimics the mating and cannibalistic behavior of black widow spiders. Some key points about the BWOA [38]:

- It is used to estimate the parameters of photovoltaic cells and panels, which is important for improving the accuracy and efficiency of solar energy systems.
- Analytic methods have limitations in extracting photovoltaic cell parameters, so metaheuristic algorithms like BWOA are used as they can better explore the search space and avoid local optima.

- The BWOA has shown superior or equal performance compared to other state-of-the-art metaheuristic algorithms in determining photovoltaic cell and panel parameters, with up to 16.5% improvement in accuracy.
- The BWOA has advantages such as easy implementation, better convergence speed, and flexibility in optimization patterns due to its unique operators like "cannibalism"[39].
- The BWOA has been applied to problems like virtual machine migration in cloud computing to optimize energy consumption, cost, and load.

Overall, the black widow optimization algorithm is a powerful metaheuristic technique that can outperform other algorithms in various optimization problems, especially those involving photovoltaic systems and cloud computing.

II.5.1 Inspiration

Black Widow is a population-based optimization algorithm entitled BWO it is a modern optimization method proposed by Vahideh Hayyolalam et al. in 2020, which is inspired by the unique mating behavior of black widow spiders. The algorithm simulates the life cycle of black widow spiders and has numerous advantages in terms of convergence speed, fitness optimization and the avoidance of local optimality [40].

It's an evolutionary system that mimics the peculiar way black widow spiders mate. During the day, the female one stays hidden, and at night she weaves her web. The female black widow marks specific areas of her net with pheromone to draw in the male whenever she feels the need to mate. After a male joins the web, the female eats it during or after mating, at which point she moves the eggs into her egg sac. A female may deposit up to ten egg sacs, with around 250 eggs in each. The young emerge from the egg and practice sibling cannibalism. They may even swallow their mother, but they only hang around in her web for a little while. Those that are strong and fit survive because of this cycle.

The reasons and results of sibling cannibalism are still not well understood. It affects the population-level by reducing the number of surviving spiderlings, but with appended implications for the general fitness of the cannibal and its parents. Spiderlings that eat their mother can have very good survival rates than the ones that do not [41].

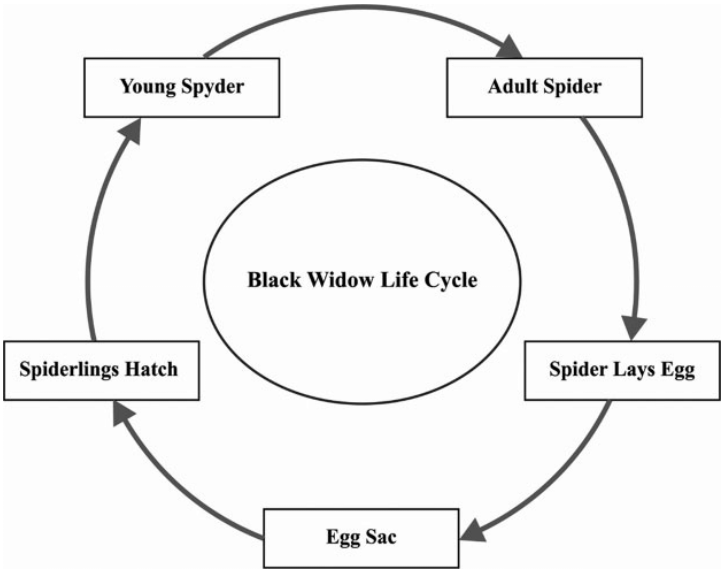


Figure II.7 Life cycle of black widow spider [42].

II.5.2 The mathematical modeling of the BWOA

Movement: as indicated in equation (II.21) the spider's moves inside the web were characterized as linear and spiral.

$$\vec{p}_i(n+1) = \begin{cases} \vec{p}_{best}(n) - q\vec{p}_{r_1}(n) & if\ rand() \leq 0.3 \\ \vec{p}_{best}(n) - \cos(2\pi\delta)\vec{p}_i(n) & for\ other\ circumstance \end{cases} \quad \text{(II.21)}$$

where, $\vec{p}_i(n+1)$ is the new position of a search agent, $\vec{p}_{best}(n)$ is the previous iteration best search agent, q represents the randomly generated float number between [0.4,0.9], r_1 varies between 1 and the maximum size of search agents generated by a random integer number, $\vec{p}_{r_1}(n)$ position of the r_1 search agent, with $i \neq r1$, δ is the randomly generated float number in the interval [−1.0,1.0], $\vec{p}_i(n)$ is the position of the current search agent.

Pheromones: pheromone is a significant phenomenon in the mating of spiders. A female spider with low pheromone rates indicates a hungry cannibal spider. Male spiders typically do not prefer female spiders with low pheromone rates. For low pheromone rates, scores of 0.3 or below, it would be substituted by another female spider. Based equation (II.22), the spider updates its position and moves towards an option to avoid the female spiders with low pheromone rates. The equation represents the pheromone rate value.

$$pheromone\ (i) = \frac{(fitness_{worst} - fitness(i))}{(fitness_{worst} - fitness_{best})} \quad \text{(II.22)}$$

where, $fitness_{worst}$ is the current generation worst fitness value, $fitness_{best}$ is the current generation best fitness value, $fitness(i)$is the ith search agent's current fitness value.

Updating of search agent:

$$\vec{p}_i(n) = \vec{p}_{best}(n) + \frac{1}{2}[\vec{p}_{r_1}(n) - (-1)^{\gamma} * \vec{p}_{r_2}(n)] \quad \text{(II.23)}$$

where $\vec{p}_i(n)$ is the low pheromone rate search agent is going to be modified, r_1 and r_2 are random integer numbers derived between 1 and the maximum size of search agents, provided $r_1 \neq r_2$, $\vec{p}_{r_1}(n)$, $\vec{p}_{r_2}(n)$- r_1, r_2 chosen search agents, $\vec{p}_{best}(n)$is best past iterations best search agent, y is a randomly generated binary number, $y \in \{0,1\}$.

II.5.3 Pseudocode of the BWOA Algorithm

The pseudocode of the BWOA algorithm (algorithm 3) is given below and its flowchart is presented in Figure II.10:

Algorithm 4 Black widow optimization algorithm (BWOA).

```
Begin procedure
Generate the initial population
while iteration < Max Number of Iterations do
    Initialization random of parameters q and B, where 0.4 ≤ q 50.9 and-1.0 ≤8 ≤1.0
        if random <0.3 then
            p⃗best(n) − qp⃗r1(n)
        else
            p⃗best(n) − cos(2πδ)p⃗i(n)
        end if
    Compute pheromone for each search agen
    Update search agents that have low pheromone value
    Calculate p⃗best the fitness of Preys using the objective function
        If p⃗new < p⃗best then
            p⃗best = p⃗new
        end if
    iteration iteration+1
end while
Display p⃗best the best optimal solution
end procedure
```

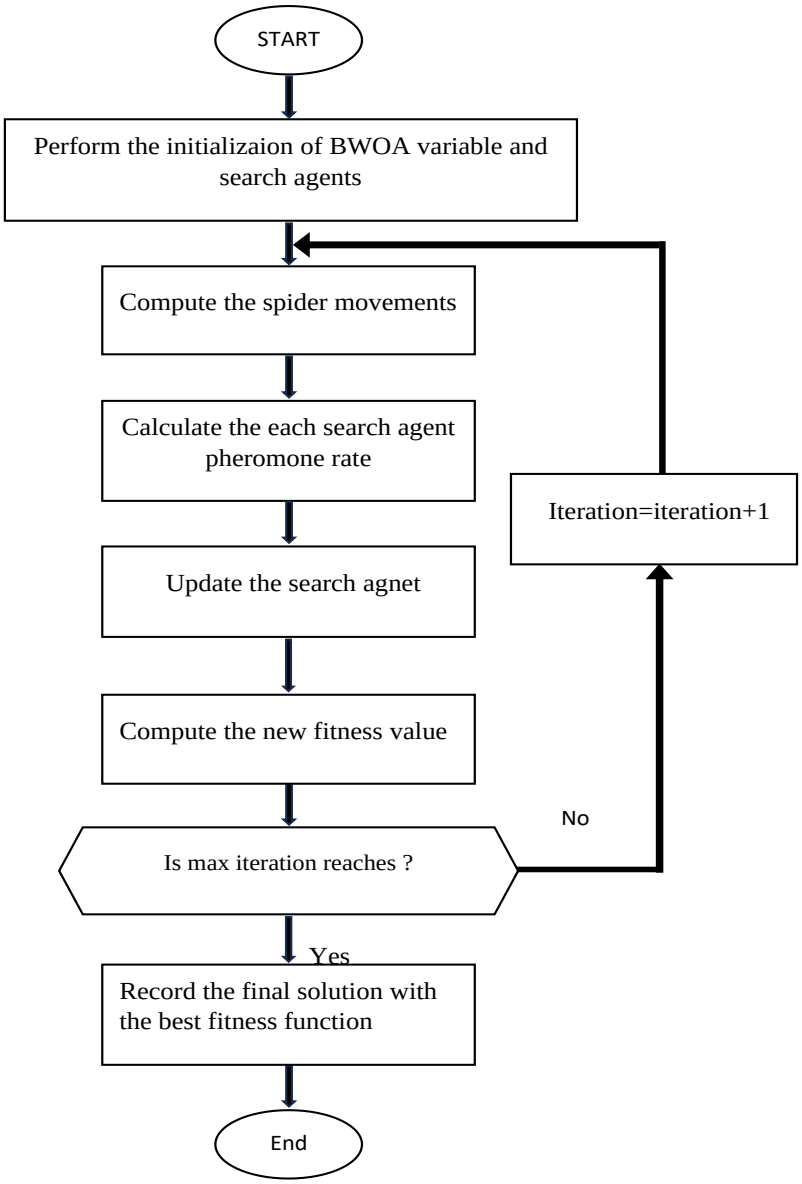


Figure II.8 Flowchart of BWOA algorithm.

II.5.4 Advantages and disadvantages of BWOA

a) Advantages:

- **Efficiency:** The Black Widow Optimization (BWO) algorithm has been demonstrated to be efficient in solving optimization problems, particularly in the fields of engineering, robotics and system optimization.
- **Flexibility:** BWO is designed to solve complex optimization problems, including multivariate and constraint problems.
- **Robustness:** The algorithm is designed to be robust to perturbations and changes in optimization parameters.

- **Ease of use:** BWOA is easy to implement and use, even for non-optimization experts.
- **Performance:** BWOA has been shown to offer competitive performance with other optimization algorithms, notably genetic algorithms and swarm search algorithms.
- **Diversity:** The BWO algorithm is designed to maintain population diversity, which is essential to avoid stagnation in local regions.
- **Adaptability:** BWOA is able to adapt its crossover and mutation parameters to strike a balance between exploration and search intensification.

b) Disadvantages:

- **Complexity:** The BWO algorithm is designed to be complex, which can make it difficult to implement and use.
- **Dependence on data quality:** BWOA is dependent on the quality of the input data, which can affect its performance.
- **Parameter sensitivity:** BWOA is sensitive to optimization parameters, which may require fine-tuning to achieve optimal results.
- **Limits to scalability:** BWOA may be limited in its ability to handle large-scale optimization problems.
- **Perturbations:** The BWO algorithm may be sensitive to perturbations in the optimization parameters, which may affect its performance.
- **Random initiation:** The BWO algorithm uses random initiation, which can lead to a loss of quality solutions during the search.
- **Loss of quality solutions:** The BWO algorithm may lose quality solutions during the search, which may affect its performance.

II.6 Marine Predators' Algorithm (MPA)

The Marine Predator Algorithm (MPA) is a new intelligent Optimization algorithm based on the foraging pattern of marine organisms. The Marine Predator Algorithm, which has the benefits of a simple structure, few parameters, and ease of implementation, solves the optimization problem by mimicking the laws of marine organisms foraging for prey, including sharks, toucans, sunfish and swordfish [43].Recently, the MPA has been broadly employed to tackle numerous optimization problems in various research areas and has confirmed its supremacy over a large number of the metaheuristic algorithms regard to

convergence speed and accuracy thanks to its simplicity, flexible implementation and few adjustable parameters requirements[44].

This algorithm is employed to work out on abundant optimization problems specifically Mathematical and Engineering Optimization problems, Image processing, Photovoltaic Systems, Fog Computing, Wind-Solar Generation System. MPA is formulated based on the different foraging strategy opted by the ocean predators and optimal encounter rates policy in biological interaction [45].

II.6.1 Inspiration

MPA is a new natural metaheuristic algorithm simulated in 2020 by Faramarzi et al. This is driven by the dominant feeding pattern of oceanic predators and the optimal politics of confrontation in predator-prey relationships in marine ecosystems. In the MPA, the predator is looking for the prey and at the same time the prey is looking for its own food. Predator and prey are seen as search agents. Marine predators follow the most appropriate strategy to increase the amount of prey found in marine ecosystems. In the stochastic process of metaheuristic algorithms like MPA, the next location is based on the current location and the transition probability to the next location. Different strategies have been proposed to describe the behavior of marine predators. However, the compromise between the Lévy strategy and the Brownian helps to find the best optimization strategy that describes the MPA optimization process. The predator-prey ratio is a key factor in moving from one stage of the optimization process to the next. High gear ratio is prominent in the first stage, while uniformity and low gear ratio are visible signs in the second and third stages.

MPA is a powerful heuristic algorithm with several advantages such as fewer design variables, simple procedure, low computational load, significant convergence speed, near-global solution, flexibility, problem-independence, and gradient-free nature. Recently, the MPA approach has been successfully applied in many fields for design optimization. MPA was developed to develop a robust strategy for large-scale PV system reconfiguration to reduce partial shading on PV system performance.

In addition, MPA has been applied to predict confirmed Covid-19 cases. Therefore, MPA can be called an excellent algorithm that can be applied to solve many problems in power systems.

II.6.2 Procedure of Marine Predators Algorithm

MPA follows a similar framework compared to other metaheuristics. It employs a set of candidate solutions for a given optimization problem. Several mechanisms are used to improve this set, from being random to having solutions approximately close to the global optimum of the problem on hand. There are three main phases in MPA as follows [46]:

- **Phase 1:** High velocity, in which the speed of a marine predator is higher than a prey. The best course of action for predators in this phase is to stay put and not change their location, whether the prey is moving in a Lévy or Brownian pattern.
- **Phase 2:** Same velocity, in which the speed of a marine predator is identical to that of a prey. In this phase, when the prey is moving in a Lévy pattern, the most effective strategy for the predator is to adopt a Brownian motion.
- **Phase 3:** Low velocity, in which the speed of a marine predator is less than a prey. In this phase, the Lévy motion is the best to adopt.

Fig II.10 illustrates the three MPA's optimization phases graphically:

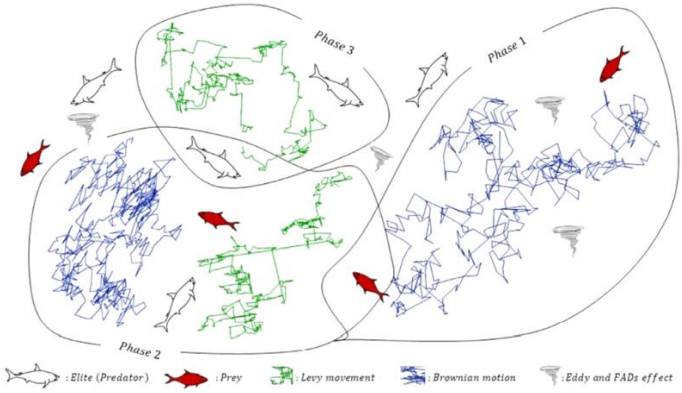


Figure II.9 MPA's optimization phases [47].

II.6.3 The MPA technology

MPA depends on the survival of the fittest strategy, in which predators have to select the optimum theory to exceed the confrontation rates related to the prey. In MPA, the predator is looking for the prey, and at the meantime, the prey itself is searching for its food. Generally, the foraging strategy of many animals is a stochastic strategy, in which the next location relies on the current location and the probability transition to the next position. This optimal strategy has been developed by the marine ecosystem and has been selected by predators for surviving. The marine creatures, including sharks, swordfish, and tunas exhibit Lévy-like behavior in

searching for prey, as the optimal search strategy for patchy prey in nature. The predators employ a Lévy approach in areas having lower gathering of prey and they use the movement of Brownian in an environment correlated to bountiful prey.

The MPA is a population-based approach. The initial randomization of the MPA is similar to different meta-heuristics algorithms, in which the candidate's position is updated as follows:

$$X_0 = X_{min} + rand(X_{max} - X_{min}) \tag{II.24}$$

where X_{max} and X_{min}represent the upper and lower limit of design variable, respectively, and rand represents a random vector that its upper and lower bounds ∈ [0, 1].

According to the survival of the fittest strategy, top predators have highly gifted in the foraging process. Therefore, the optimal solution is specified as a top predator to arrange Elite. Such Elite supervises of seeking and finding the prey related to the knowledge of prey's locations.

$$Elite = \begin{bmatrix} X_{1,1}^{I} & \cdots & X_{1,d}^{I} \\ \vdots & \ddots & \vdots \\ X_{n,1}^{I} & \cdots & X_{n,d}^{I} \end{bmatrix}_{n \times d} \tag{II.25}$$

where $\overrightarrow{X^I}$ is a vector of top predators that reproduced n times to arrange Elite. The variables n and d represent the agent's number and dimensions, respectively. Such Elite is updated for each iteration if the top predator is replaced by another one that is better.

The Prey is arranged similar to the Elite's dimension, in which the predators update their positions related to it. Simply, the initialization process establishes the initial Prey, where the fittest predator arranges the Elite. The Prey is depicted by the following:

$$Prey = \begin{bmatrix} X_{1,1} & \cdots & X_{1,d} \\ \vdots & \ddots & \vdots \\ X_{n,1} & \cdots & X_{n,d} \end{bmatrix}_{n \times d} \tag{II.26}$$

where $X_{i,j}$ is the j^{th}dimension of i^{th} prey. The optimization process mainly depends on the Elite and the Prey. Notably, the MPA applies random variables and operators for searching along with avoiding stuck into local minima.

II.6.4 MPA Optimization Process

Subsequently with the MPA formulation, MPA optimization needs to be addressed and, in this regard, the entire optimization procedure is divided broadly into three major stages taking

into account different velocity ratio however yet impersonating the life-cycle of predator as well as prey. Three different stages are highlighted as Stage I, II and III .

Stage I: "Whenever the predator navigates quicker than prey". (High velocity ratio).

Stage II: "Whenever the predator and prey navigate almost with the same velocity". (Unit velocity ratio).

Stage III: "Whenever the predator navigates slower than prey". (Low velocity ratio).

In first stage, in a scenario wherein the predator is steering quicker than the prey, the velocity ratio is considered high, thereby the best strategy that can be adopted by the predator is to stop and not move at all. The mathematical formulation of the same is depicted.

$WhileIter < \frac{1}{3}$ Max_Iter then,

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_B} \otimes \left(\overrightarrow{Elite_l} - \overrightarrow{R_B} \otimes \overrightarrow{Prey_l}\right) i = 1, \ldots\ldots n \qquad \text{(II.27)}$$

Here $\overrightarrow{Prey_l} = \left(\overrightarrow{Prey} + P.\vec{R} \otimes \overrightarrow{Stepsize_l}\right)$ is a vector comprising of random numbers built on Normal distribution symbolizing the Brownian motion; $\otimes$ denotes entry-wise multiplication; P represents constant number initialized to 0.5; Iter is the current iteration; Mar_Iter symbolizes the maximum number of iteration and R designates vector of uniform random number in the range [0,1].

In Stage II, the scenario wherein the pace of predator as well as prey is almost the same, the velocity ratio is considered to be a unit velocity ratio, thereby the best strategy that can be rather need to be opted by Predator is the Brownian move and by the Prey is Levy move. Herein, predator is accountable for exploration nevertheless the prey is responsible for the exploitation.

$While \quad \frac{1}{3}Max_Iter < Iter < \frac{2}{3}Max_Iter \quad then,$

For the Population (Prey)

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_L} \otimes \left(\overrightarrow{Elite_l} - \overrightarrow{R_L} \otimes \overrightarrow{Prey_l}\right) i = 1, \ldots\ldots n/2 \qquad \text{(II.28)}$$

Here $\overrightarrow{Prey_l} = \overrightarrow{Prey_l} + P.\vec{R} \otimes \overrightarrow{Stepsize_l}\big)$ is a vector based on Levy distribution representing the Levy motion;

For the Population (Predator)

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_B} \otimes \left(\overrightarrow{R_B} \otimes \overrightarrow{Elite_l} - \overrightarrow{Prey_l}\right) i = \frac{n}{2}, \ldots\ldots n \quad \text{(II.29)}$$

Here, $\overrightarrow{Prey_l} = \overrightarrow{Elite} + P.CF \otimes \overrightarrow{Stepsize_l}$ is used to control the step size and is given as $CF = \left(1, -, \frac{Iter}{Max_{Iter}}\right)^{\left(2\frac{Iter}{Max_Iter}\right)}$ Multiplication $\overrightarrow{R_B} \otimes \overrightarrow{Elite_l}$ denotes the Brownian move of the predator.

In the third stage, in the scenario wherein predator moves slower than that of the prey, the velocity ratio is considered to be a low velocity ratio, thereby the best strategy that can be opted by the predator is Levy motion and the same is clearly depicted using

While $Iter > \frac{2}{3}$*Max_Iter then,*

$$\overrightarrow{Stepsize_l} = \overrightarrow{R_L} \otimes \left(\overrightarrow{R_L} \otimes \overrightarrow{Elite_l} - \overrightarrow{Prey_l}\right) i = 1, \ldots\ldots n \quad \text{(II.30)}$$

Here, $\overrightarrow{Prey_l} = \overrightarrow{Elite} + P.CF \otimes \overrightarrow{Stepsize_l}$; Multiplication $\overrightarrow{R_L} \otimes \overrightarrow{Elite_l}$ denotes the Levy move of the predator. Lastly, one important component that needs to be considered here in MPA is the cause of the behavioral change among the marine predators i.e., the environment concerns such as Eddy Formation or Fish Aggregating Devices commonly known as FADs effects. The FADs effect is mathematically depicted as shown in Eq II.31.

$$\overrightarrow{Prey_l} = \begin{cases} \overrightarrow{Prey_l} + CF[\overrightarrow{X_{min}} + \overrightarrow{R_L} \otimes (\overrightarrow{X_{min}} - \overrightarrow{X_{max}})] \otimes \vec{U} if r \leq FADs \\ \overrightarrow{Prey_l} + [FADs(1-r) + r](\overrightarrow{Prey_{r1}} - \overrightarrow{Prey_{r2}}) if r > FADs \end{cases} n \quad \text{(II.31)}$$

Here, FADs denote the probability for FADs effect on the optimization procedure initialized with value 0.2; $\vec{U}$ denotes the binary vectors with value 0 (if array is < FADs) and 1otherwise; r depicts random number ranging between [0, 1] ; $\overrightarrow{X_{min}}$ and $\overrightarrow{X_{max}}$ are the vectors containing lower and upper bounds of the dimensions and r1 and r2 signifies the indexes of the prey matrix.

II.6 Marine memory saving

Based on the highlighted points, marine predators have a good memory in reminding the place where they have been successful in foraging. This capability is simulated by memory

saving in MPA. After updating the Prey and implementing FADs effect, this matrix is evaluated for fitness to update the Elite. The fitness of each solution of the current iteration is compared to its equivalent in prior iteration, and the current one replaces the solution if it is more fitted. This process also improves the solution quality with the lapse of iteration and also simulates the returning of predators to the locations of the prey-abundant area with successful foraging.

II.6.6 Pseudocode of the MPA Algorithm

The pseudocode of the MPA algorithm (algorithm 4) is given below and its flowchart is presented in Figure II.12:

Algorithm 4 Pseudo-code of MPA

```
Input: Search agents(Prey) population Xi(i = 1, 2, ..., n),
Output: the optimal solution for the problem
Initialize the Preys
Calculate the fitness of Preys using the objective function
for iteration = 1: maximum number of iterations
Find the top predator and construct the Elite matrix.
for iteration = 1: maximum number of iterations
        if iteration < Maximum iteration/3
            Update Preys
        elseif iteration <2 Maximun iteration/3
            Update first half of the Preys
            Update second half of the Preys
        else
            Update Preys
        end
    Calculate the fitness of Preys using the objective function
    Find top predator and update the Elite matrix,
    Accomplish memory saving
    Update Preys
    Calculate the fitness of Preys.
    Find top predator and undate the Elite matris.
    Accomplish memory saving.
end for.
```

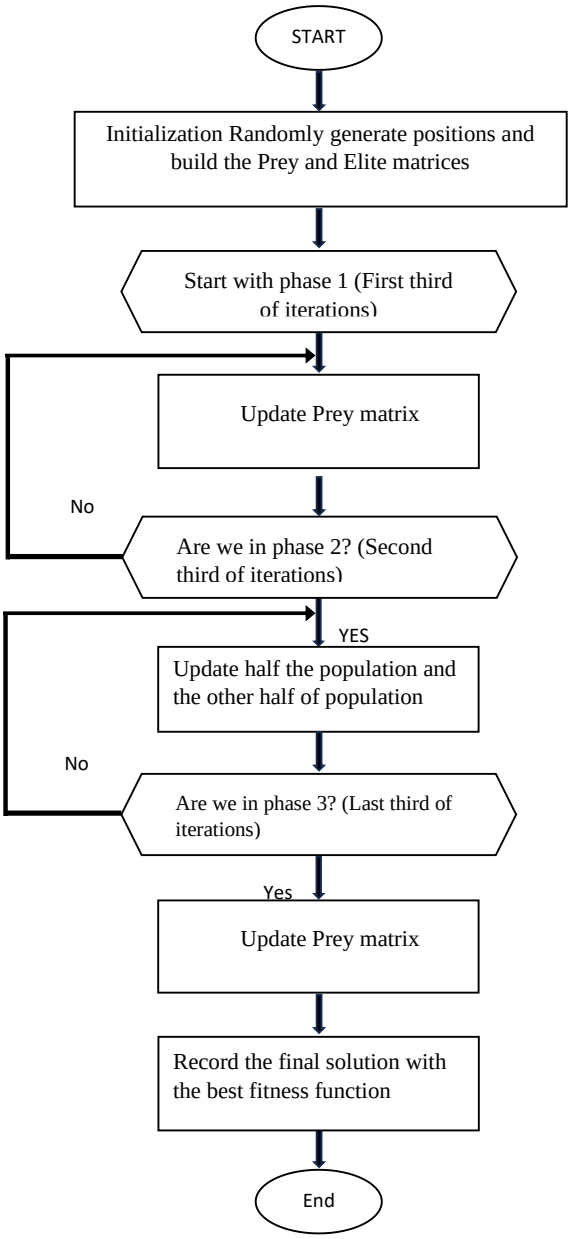


Figure II.10 Flowchart of MPA algorithm.

II.6.7 Advantages and disadvantages of MPA

a) Advantages:

Flexibility: The MPA algorithm is adaptable to different optimization problems and can be used to solve complex problems.

Speed: The MPA algorithm is fast and efficient at finding optimal solutions.

Robustness: The MPA algorithm is robust and can perform well even with noisy or imperfect data.

Diversity: The MPA algorithm can generate diverse and non-uniform solutions, which is useful for multi-objective optimization problems.

b) The main disadvantages of the marine predator algorithm (MPA) are:

MPA can easily fall into local optima due to lack of population diversity in the late stage of optimization [48].

II.7 Conclusion

This chapter explored the application of metaheuristic algorithms for photovoltaic model parameter estimation. Four algorithms have been considered:

- Whale optimization algorithm (WOA)
- Gray wolf optimization algorithm (GWO)
- Black widow optimization algorithm (BWOA)
- Marine predator optimization algorithm (MPA)

In conclusion, metaheuristic algorithms are a very effective parameter estimation method for photovoltaic models. They offer a robust and efficient approach that can be applied to a wide range of models and conditions.

Chapter III
Results and Discussion

III.1 Introduction

The simulation results are shown and fully explained in this chapter. The WOA, GWO, BWOA, and MPA algorithms are used to determine the electrical parameters of the single-diode and double-diode solar PV models, which include the RTC France silicon solar cell, by simulations on the MATLAB platform. The acquired simulation results demonstrate the approaches resilience and convergence efficiency for the four previously described models.

III.2 Mathematical Models of Photovoltaic Cell

Solar cell models describing the I-V characteristics typically contain one diode, two diodes. These detailed models are described as follows:

III.2.1 Single Diode Model (SDM)

A modified Shockley diode equation can describe a single diode model. It is widely used for modeling solar cells because it is simple to implement with 5 parameters (Iph, Id, n, Rsh, Rs). However, at low illuminations, the single diode model is particularly inaccurate in describing cell behavior. Figure III.1 shows a single diode model consisting of a current source in parallel with a diode, and the module shunt resistance controls the loss of currents at the junction within the cell [49].

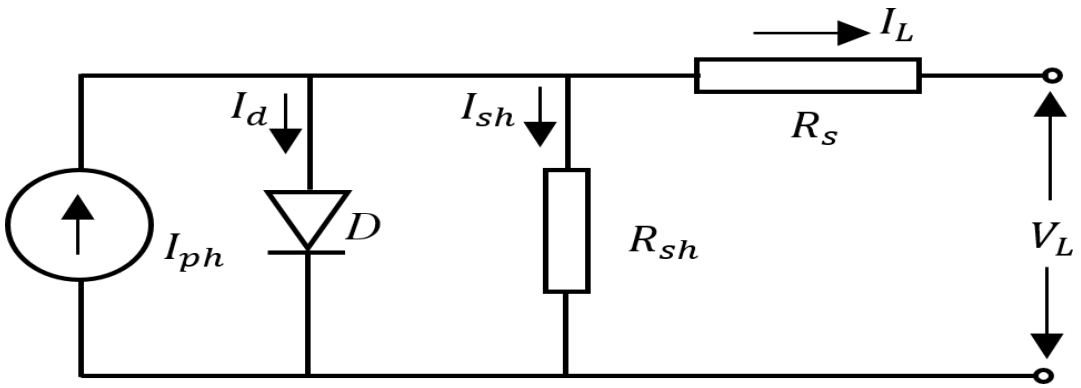


Figure III.1 Equivalent circuit of DDM solar cell [50].

$$I_L = I_{\text{ph}} - I_D - I_{\text{sh}} \quad \text{(III.1)}$$

Where I_{ph} , I_D, and I_{sh} represent the current of the independent current source, the diode current, and the current of shunt resistance. The diode current I_D is well defined by Shockley equation as

$$I_d = I_{\text{sd}}[exp(\frac{V_L+R_sI_L}{nV_t}) - 1] \quad \text{(III.2)}$$

Where I_{sd} , V_L, I_L are the diode saturation current(A), the measured voltage (V), and the measured current(A), respectively. The diode ideality factor is *n*, and the thermal voltage is represented by Vt and is calculated as

$$V_t = \frac{K.T}{q} \quad \text{(III.3)}$$

Where *k* represents the Boltzmann constant and equals (1.3806503×10ˆ-23 J/K), *T* is the temperature measured in Kelvin (T=33+273.15), and *q* is the electron charge (1.60217646 × 10 ˆ −19 C). The shunt resistance current is formulated as

$$I_{\text{sh}} = \frac{V_L+R_sI_L}{R_{\text{sh}}} \quad \text{(III.4)}$$

From equations III.1, III.2, III.3, and III.4, the output current of the solar cell can be calculated as

$$I_L = I_{\text{ph}} - I_{\text{sd}}[exp(\frac{V_L+R_sI_L}{nV_t}) - 1] - \frac{V_L+R_s.I_L}{R_{\text{sh}}} \quad \text{(III.5)}$$

In this equation, the unknown five parameters are *X*=(I_{ph} , I_{sd}, R_s, R_{sh}, and *n*) which have to be optimized.

III.2.2 Double diode model (DDM)

Figure III.2 shows the double-diode model as an additional diode is added in parallel with the current source. This additional diode can achieve higher accuracy than a single diode model, but with seven parameters, more computation is needed (I_{ph}, I_{d1}, Id_2, n_1, n_2, R_{sh}, R_s).

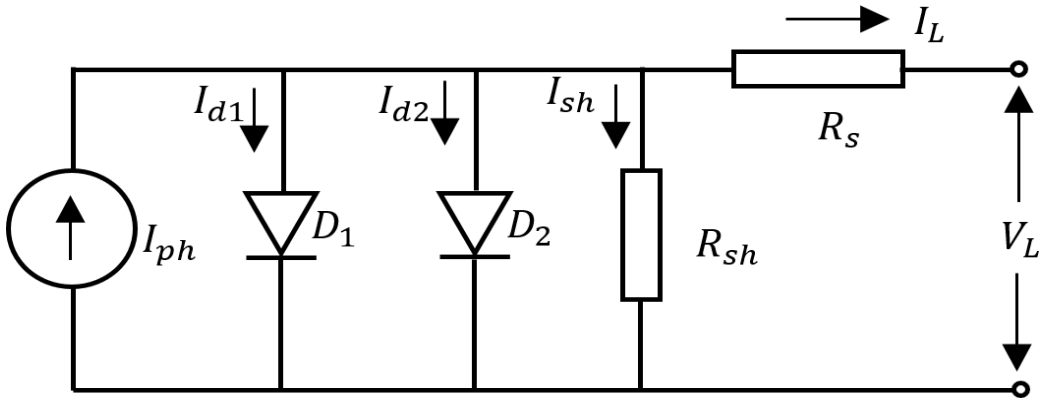


Figure III.2 Equivalent circuit of DDM solar cell [50].

$$I_L = I_{\text{ph}} - I_{D1} - I_{D2} - I_{\text{sh}} \quad \text{(III.6)}$$

$$I_{D1} = I_{\text{sd1}} \left[exp\left(\frac{V_L + R_S I_L}{n_1 V_t}\right) - 1 \right] \quad \text{(III.7)}$$

$$I_{D2} = I_{\text{sd2}} \left[exp\left(\frac{V_L + R_S I_L}{n_2 V_t}\right) - 1 \right] \quad \text{(III.8)}$$

$$I_L = I_{\text{ph}} - I_{\text{sd1}} \left[exp\left(\frac{V_L + R_S I_L}{n_1 V_t}\right) - 1 \right] - I_{\text{sd2}} \left[exp\left(\frac{V_L + R_S I_L}{n_2 V_t}\right) - 1 \right] - \frac{V_L + R_S I_L}{R_{\text{sh}}} \quad \text{(III.9)}$$

Where I_{sd1}, I_{sd2} are, respectively, the saturation currents (A) of the diode 1 and diode 2. $n1$ and $n2$ are denote the ideality of the diode 1 and 2, respectively. There are 7 unknown parameters within this model and have to be identified

X= (Iph, Isd1, Isd2, Rs, Rsh, $n1$ and $n2$).

III.2.3 PV module model

In a large PV generation system, PV modules are used as basic components rather than PV cells, because the output power of PV cells is limited at high voltage levels. Researchers have developed the PV module model so as to predict the I-V characteristics before modeling the whole system [51].

PV module model is build based on the configuration of SDM. It consists of a number of solar cells arranged in series or/and parallel to increase the efficiency of the energy solar cell. Ns describes the number of series cells, and Np presents the number of parallel solar cells. The modeling of the PV solar cell is described in Fig III.3, and the output current is calculated by the following expression:

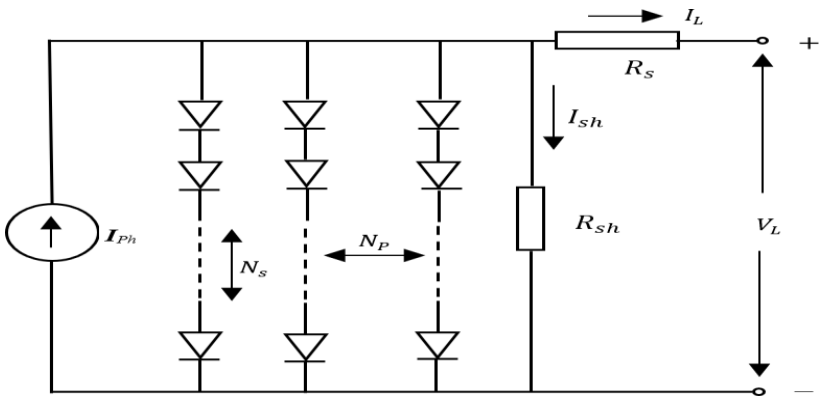


Figure III.3 Equivalent circuit of the PV module [50].

$$I_L = I_{\text{ph}}.N_p - I_{\text{sd}}.N_p[exp(\frac{V_L+R_S I_L.N_S/N_p}{nV_t}) - 1] - \frac{V_L+R_S.I_L.N_S/N_p}{R_{\text{sh}}.N_S/N_p} \quad \text{(III.10)}$$

$$V_t = \frac{N_S.K.T}{q} \quad \text{(III.11)}$$

The PVM model has five unknown parameters needed to be optimized similar to SDM which are X=(I_{ph}, I_{sd}, R_s, R_{sh}, and n).

III.3 RMSE objective function

As shown in the equivalent circuit of SDM, there are five unknown parameters represented in a solution vector of X=(I_{ph}, I_{sd}, R_s, R_{sh}, and n) to be identified. To solve the solar cell or PV module parameter estimation problem, an objective function needs to be defined and then optimized using a selected MA. Root mean square error (RMSE) is a popular objective function employed for the solar cell or PV module parameter estimation problem and it aims to minimize the errors between the experimental I-V data and simulated I-V data as follows [52]:

$$\text{RMSE} = \sqrt{\frac{1}{N_e}\sum_{i=1}^{N_e}(I_{measured} - I_{estimated})^2} \quad \text{(III.12)}$$

where N represents the number of the measured points. $I_{measured}$ and $I_{estimated}$ represent the measured and estimated solar cell current at point i, respectively.

III.3.1 For SDM of PV Cell

$$\begin{cases} f^n_{Solarcell}(V_l, I_l, X) = I_{ph} - I_{sd1}\left[exp\left(\frac{q(V_l+I_l R_s)}{n1kT}\right) - 1\right] - \frac{V_l+I_l R_s}{R_{sh}} - I_l \\ X = (I_{ph}, I_{sd1}, n1, R_s, R_{sh}) \end{cases} \quad \text{(III.13)}$$

There are five parameters in the equation expressed above that need to be identified: $I_{ph}, I_{sd1}, n, R_s, R_{sh}$.

III.3.2 For DDM of PV Cell

$$\begin{cases} f^n_{Solarcell}(V_l, I_l, X) = I_{ph} - I_{sd1}\left[exp\left(\frac{q(V_l+I_l R_s)}{n1\text{k}T}\right) - 1\right] - I_{sd2}\left[exp\left(\frac{q(V_l+I_l R_s)}{n2\text{k}T}\right) - 1\right] - \frac{V_l+I_l R_s}{R_{sh}} - I_l \\ X = (I_{ph}, I_{sd1}, I_{sd2}, n1, n2, R_s, R_{sh}) \end{cases} \quad \text{(III.14)}$$

There are seven parameters in the above equation which need to be identified:

$(I_{ph}, I_{sd1}, I_{sd2}, n1, n2, R_s, R_{sh})$.

III.3.3 For SDM of PV Module

$$\begin{cases} f_{PVmodule}^{n}(V_l, I_l, X) = I_p N_p - I_{sd1} N_p \left[exp\left(\frac{q\left(V_l + \frac{R_S I_l N_S}{N_p}\right)}{n1kTN_s} \right) - 1 \right] - \frac{V_l + \frac{R_S I_l N_S}{N_p}}{\frac{R_{sh} N_S}{N_p}} - I_l \\ X = (I_p, I_{Sd1}, n1, R_s, R_{sh}) \end{cases} \quad \text{(III.15)}$$

III.3.4 For DDM of PV Module

$$\begin{cases} f_{PVmodule}^{n}(V_l, I_l, X) = I_p N_p - I_{sd1} N_p \left[exp\left(\frac{q\left(V_l + \frac{R_S I_l N_S}{N_p}\right)}{n1kTN_s} \right) - 1 \right] - I_{sd2} N_p \left[exp\left(\frac{q\left(V_l + \frac{R_S I_l N_S}{N_p}\right)}{n2kTN_s} \right) - 1 \right] \\ \quad - \frac{V_l + \frac{R_S I_l N_S}{N_p}}{\frac{R_{sh} N_S}{N_p}} - I_l \\ X = (I_{ph}, I_{sd1}, I_{sd2}, n1, n2, R_s, R_{sh}) \end{cases} \quad \text{(III.16)}$$

where *n* is the index of experimental point in given I-V data; *N* depicts the total numbers of observations in experimental I–V data; *X* is a decision variable vector consists of five unknown parameters to be optimized.

III.4 Results and Discussion

This section shows the results of calculations performed using MATLAB R2015a on a 1.80 GHz (1.99 GHz) Intel (R) Core (TM) i7-8565U CPU and 16 GB of memory. This section tests and validates the WOA GWO BWOA MPA approach that was used to extract solar PV parameters for SDM and DDM. Using the most modern and accurate metaheuristic algorithms, the results are compared. The best (minimum), mean (median), max (maximum), and standard deviation of the RMSE values are calculated after 500 iterations of the method. Before this, the RMSE was calculated for the single diode model and, in particular, for the RTC France solar cell based on parameters extracted from 30 methods reported in different published literature.

Table III.1 Upper and lower bound of the SDM, DDM parameters.

RTC FRANCE SOLAR CELL		
Parameters	**Lower bound**	**Upper bound**
1DM		
$I_{ph}(A)$	0	1
$I_{sd}(\mu A)$	0	1
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	100
n_1	1	2
2DM		
$I_{ph}(A)$	**0**	**1**
$I_{sd1}(\mu A)$, $I_{sd2}(\mu A)$	0	1
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	100
n_1, $n2$	1	2

III.4.1 RTC France Silicon Solar Cell Identification

The optimization techniques proposed have been used to obtain the parameters of the model of both the following commercial cells and photovoltaic panels: a standard (RTC France) silicon solar cell.

For the RTC France silicon solar cell, Table III.2 presents the results of the identification of five and seven parameters as well as the RMSE values of the SDM, DDM obtained by WOA, GWO, BWOA and MPA and other metaheuristic algorithms.

III.4.2 Results of SDM

The results of the decision parameters for single diodes estimated by implementing the WOA GWO BWOA MPA algorithm and the comparison with other methods for finding the best root mean squared error (RMSE) are illustrated in Table III.2. The optimization method that achieved the best RMSE of 9.860218e-04 is the MPA algorithm. This value is highlighted in Table III.2.

The order of algorithms based on the minimum value of the RMSE is MPA, BWOA, GWO and WOA. The I-V and P-V characteristics of the tested SDM were obtained based on the extracted results from the WOA, GWO, BWOA, and MPA in Table 2, suggesting that MPA achieves high performance and more accuracy in extracting the decision variables of SDM.

Figure III.4, Figure III.5, Figure III.6 and Figure III.7 presents the results of measured data and estimated data on single diode model.

Table III.2 The best values of the identified parameters for SDM of the RTC France silicon solar cell.

SDM

ALGORITM	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n_1	rmse
WOA	0.759945	0.657755	0.0335613	99.518	1.55636	3.2001e-03
GWO	0.763427	0.795979	0.0331395	49.2777	1.57872	7.5011e-03
BWOA [52]	0.7606026	1	0.0310645	100	1.604565	9.8602e-04
MPA	0.760782	0.309867	0.0365598	52.9215	1.477	**9.860218e-04**

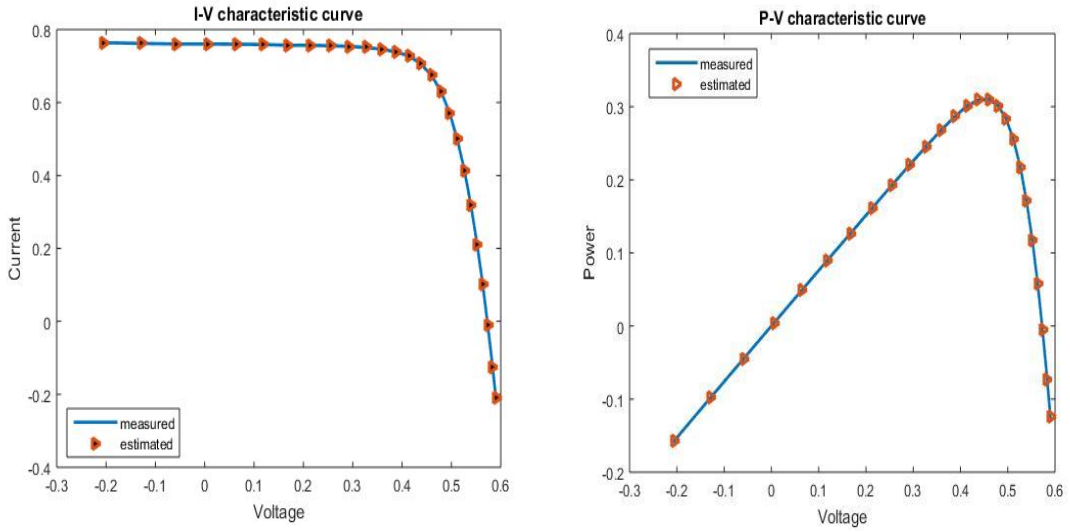


Figure III.4 The measured data and estimated data obtained by BWOA on single diode model.

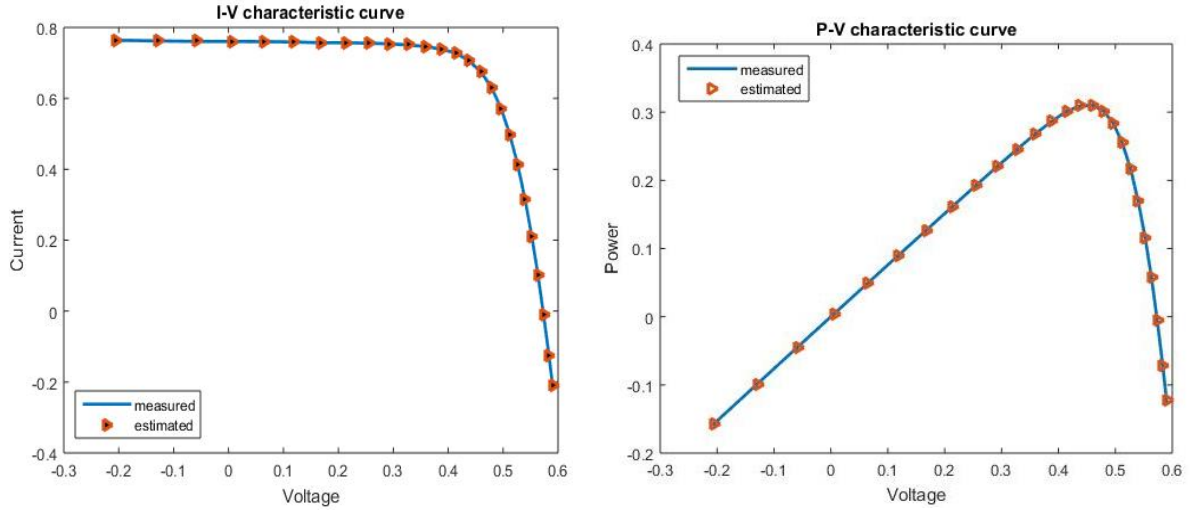


Figure III.5 The measured data and estimated data obtained by GWO on single diode model.

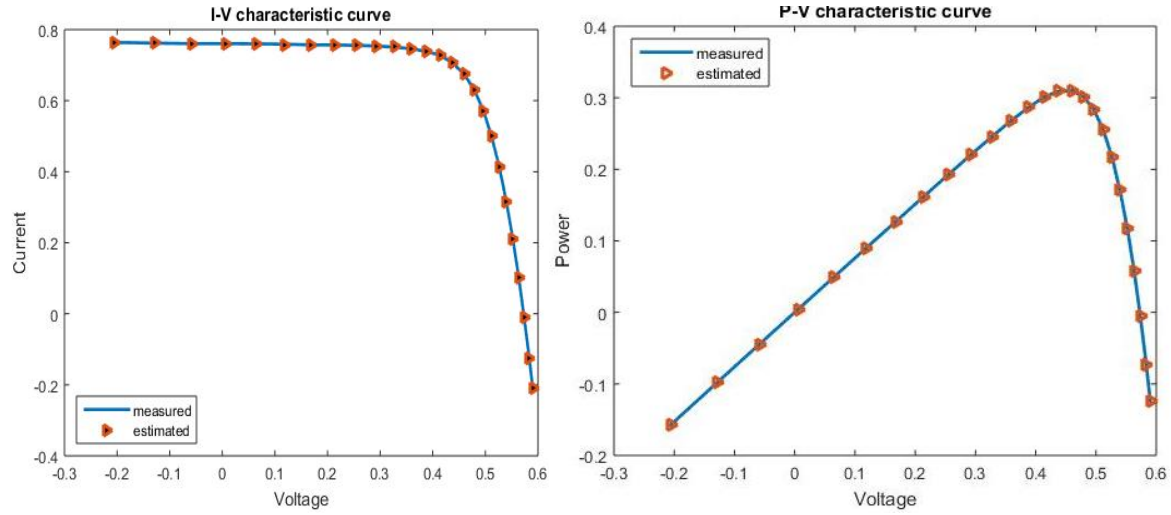


Figure III.6 The measured data and estimated data obtained by MPA on single diode model.

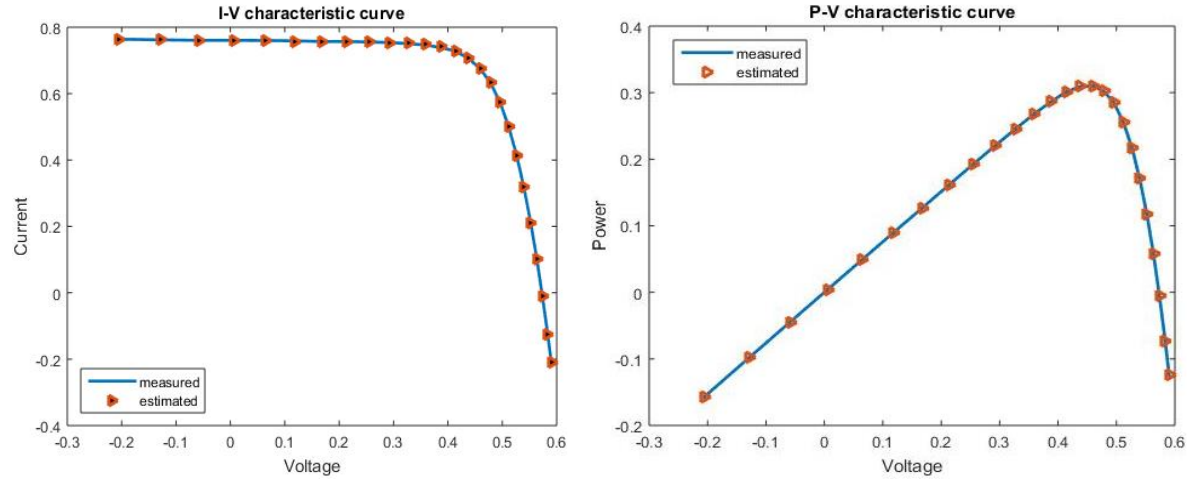


Figure III.7 The measured data and estimated data obtained by WOA on single diode model.

III.4.2 Results of DDM

The results of the decision parameters for diode diodes estimated by implementing the WOA GWO BWOA MPA algorithm and the comparison with other methods for finding the best root mean squared error (RMSE) are illustrated in Table III.3. The optimization method that achieved the best RMSE of 9.8248e-04 is the MPA algorithm.

Figure III.8, Figure III.9, Figure III.10 and Figure III.11 presents the results of measured data and estimated data on double diode model.

Table III.3 The best values of the identified parameters DDM of the RTC France silicon solar cell.

DDM

ALGO	$I_{ph}(A)$	$I_{sd1}(\mu A)$	$I_{sd2}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n_1	n_2	rmse
WOA	0.74852	0.01831	0.67998	0.01433	96.5035	1.3638	1.5885	3.1312e-03
GWO	0.76657	0.56611	0.07025	0.03427	27.2165	1.5569	1.5336	2.2124e-03
BWOA [52]	0.76086	0.57327	0.07886	0.04050	44.0913	1.8934	1.3576	9.8738e-04
MPA	0.76079	0.25116	0.34726	0.03668	54.1523	1.4600	1.9129	**9.8248e-04**

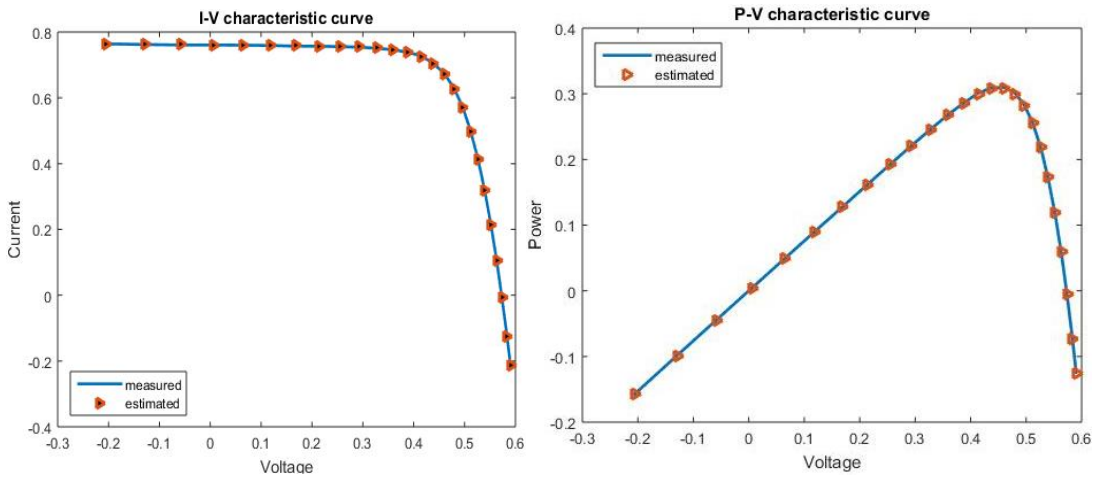


Figure III.8 The measured data and estimated data obtained by BWOA on double diode model.

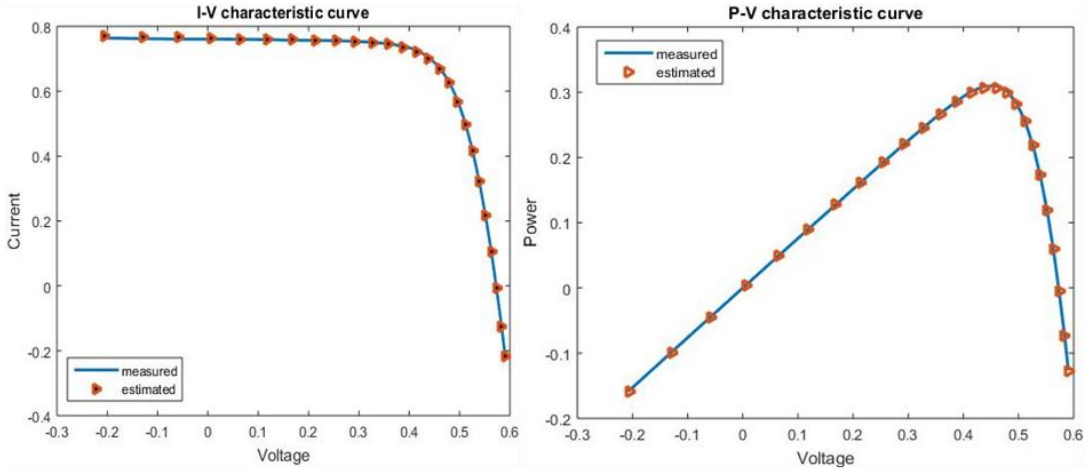


Figure III.9 The measured data and estimated data obtained by BWOA on double diode model.

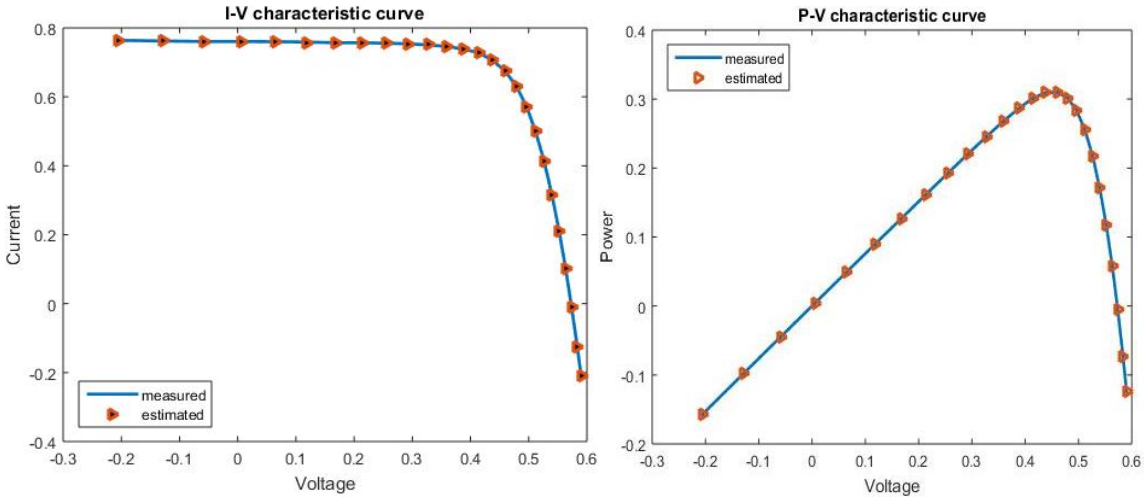


Figure III.10 The measured data and estimated data obtained by MPA on double diode model.

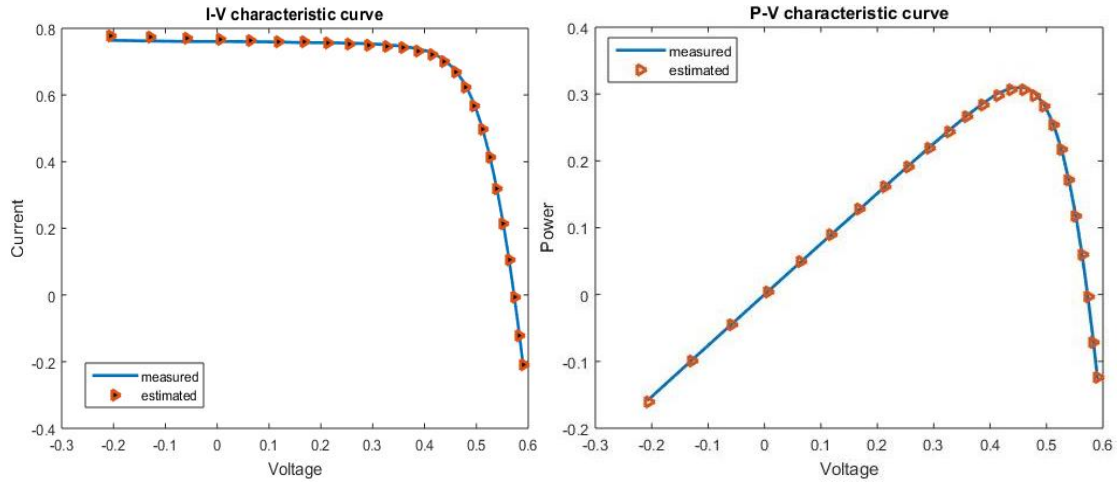


Figure III.11 The measured data and estimated data obtained by WOA on double diode model.

III.4.3 Statistics Analysis

In order to evaluate the robustness and reliability of the MPA algorithm, the statistical results obtained by WOA, GWO, BWOA, MPA. are presented in Table III.4.

These results include: RMSEmin, which represents the lowest value of RMSE; RMSEmean, which corresponds to the average value of RMSE; RMSEmax, which is the worst value; STD, which is the standard deviation of the RMSE values; and it indicates the reliability of the algorithm.

The statistical results for the SDM and DDM of RTC France silicon solar cells are shown in Table III.4.

Table III.4 statistical analysis of SDM.

SDM

ALGORITM	Min	Mean	Max	Std
WOA	3.2001E−03	1.8170E−02	3.7773E−02	1.7746E−02
GWO	7.5011E−03	2.5617E−02	3.8160E−02	1.6071E−02
BWOA[52]	9.8602e-04	9.8602e-04	9.8602e-04	1.5016e-04
MPA	9.8602187789168e-4	9.860218778918169e-4	9.8602187789209e-4	1.4257E−09

Table III. 5 statistical analysis DDM.

DDM

ALGORITM	Min	Mean	Max	Std
WOA	3.1312E−03	4.5208E−03	5.4380E−03	1.2238E−03
GWO	2.2124E−03	1.6222E−02	3.7996E−02	1.9113E−02
BWOA[52]	9.8738574e-04	9.8738e-04	9.9765e-04	1.8284797e-04
MPA	9.8248E-4	9.8282E-4	9.8602	1.7186e-17

For SDM identified on the basis of MPA, it is found that the lowest RMSE value is reached after 500 iterations, with an STD of 1.4257E−09.

For the France RTC cell based on DDM, the best results are obtained by MPA, which records an RMSE of 9.8248E-4 and an STD of 1.7186e-17.

III.4.4 Convergence Analysis

Graphically illustrates the convergence patterns of the RMSE objective function for both SDM and DDM models of the R.T.C. France solar cell. Notably, the DDM exhibited faster and more efficient convergence compared to the SDM model.

For the SDM, Figure III.12 displays the best convergence speed for the separate runs regarding both WOA GWO BWOA and MPA. MPA algorithm shows a very high improvement compared to the other strategy for the different separate executions.

For DDM, Figure III.13 displays the best convergence speed for the separate runs regarding both WOA GWO BWOA and MPA. the MPA algorithm has the best convergence speed compared to the other algorithms.

Table III.6 represents the current measured and power measured of the RTC France silicon solar cell.

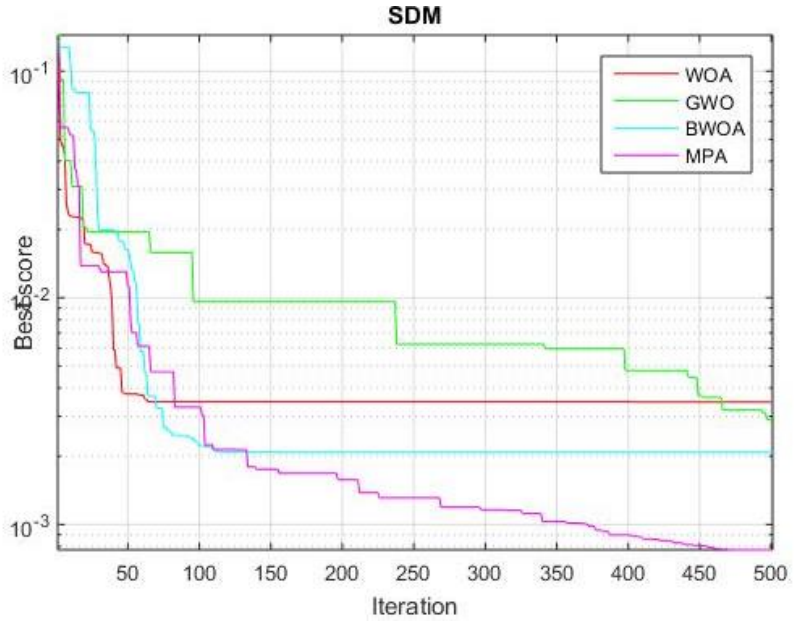


Figure III.12 Convergence curves for single diode model of France silicon solar cell.

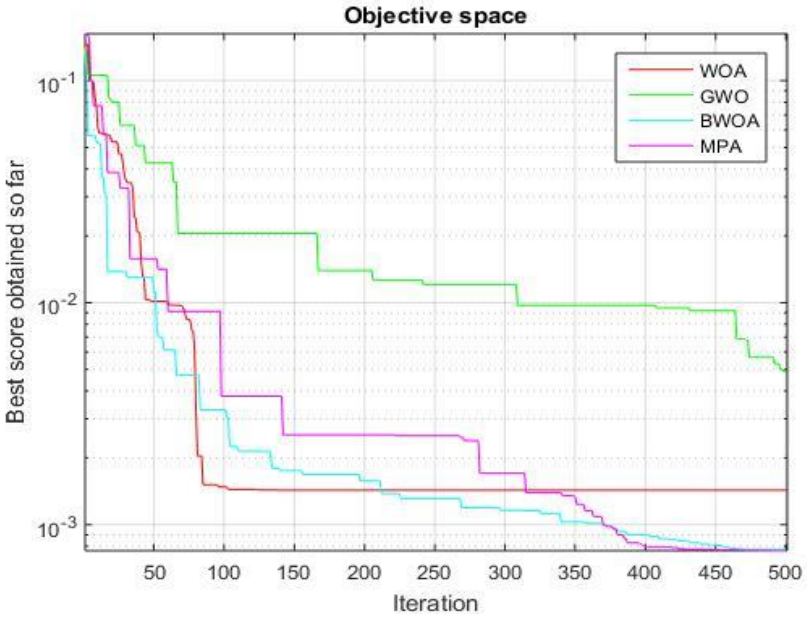


Figure III.13 Convergence curves for double diode model of France silicon solar cell.

Table III.6 The calculated values of current and power.

$I_{measured}$ (A)	$V_{measured}$ (V)
0.764	- 0.2057
0.762	- 0.1291
0.7605	- 0.0588
0.7605	0.0057
0.76	0.0646
0.759	0.1185
0.757	0.1678
0.757	0.2132
0.7555	0.2545
0.754	0.2924
0.7505	0.3269
0.7465	0.3585
0.7385	0.3873
0.728	0.4137
0.7065	0.4373
0.6755	0.459
0.632	0.4784
0.573	0.496
0.499	0.5119
0.413	0.5265
0.3165	0.5398
0.212	0.5521
0.1035	0.5633
-0.01	0.5736
-0.123	0.5833
-0.21	0.59

III.5 Conclusion

This work introduces the MPA GWO BWOA WOA as an innovative, enhanced evolutionary technique for solving optimization problems. The MPA algorithm is used to efficiently estimate PV characteristics for independent solar PV modules at RTC France Silicon Solar Cell. Using these algorithms, the MPA algorithm statistically outperforms several current optimization techniques. Compared to the three algorithms of GWO, BWOA, and WOA, the MPA algorithm is finding the lowest RMSE for both models of the SDM and DDM of RTC France Silicon Solar Cell. Given the great effectiveness of the MPA technique in the PV parameter estimation concern, it is advised that the provided method be examined for adequacy in future attempts to tackle power system operation and control optimization frameworks.

General Conclusion

General Conclusion

This research investigated the application of metaheuristic algorithms for photovoltaic parameter estimation. The results demonstrate that these algorithms are powerful tools for this complex task, offering several advantages over traditional methods.

The performance of a photovoltaic (PV) system can be deduced from the characteristics of its current-voltage relationships, but the parameters of the PV model are uncertain due to its multimodal, multivariable, and non-linear properties, so the PV model requires its parameters to be extracted with great accuracy and efficiency.

The utilization of metaheuristic algorithms presents a promising avenue for accurately estimating photovoltaic system parameters. Through the exploration of algorithms such as the Whale Optimization Algorithm (WOA), Grey Wolf Optimization Algorithm (GWO), Black Widow Optimization Algorithm (BWOA), and Marine Predator Algorithm (MPA), significant strides have been made in optimizing the performance and energy yield of photovoltaic systems. These algorithms offer versatile optimization strategies capable of addressing the complexity and variability inherent in photovoltaic systems, thus enabling more precise parameter estimation and enhanced system efficiency.

The Whale Optimization Algorithm (WOA) demonstrates its efficacy through its mimicry of the social behavior of humpback whales, leveraging exploration and exploitation phases to efficiently search the parameter space. Similarly, the Grey Wolf Optimization Algorithm (GWOA) draws inspiration from the cooperative hunting behavior of grey wolves, utilizing leader-following dynamics to converge towards optimal solutions. Meanwhile, the Black Widow Optimization Algorithm (BWOA) takes cues from the predatory tactics of black widow spiders, employing a symbiotic mating process to evolve solutions through population-based optimization. Additionally, the Marine Predator Algorithm (MPA) mirrors the hunting strategies of marine predators, integrating prey pursuit and swarm collaboration to navigate complex search landscapes.

The single-diode and double-diode PV models are widely used in the literature, namely RTC France. The performance of these algorithms is evaluated by static indices called min RMSE, max RMSE, mean RMSE, standard deviation, P-V, and I-V curves.

Metaheuristic algorithms, like WOA, GWO, BWOA, and MPA, effectively address the challenges associated with photovoltaic parameter estimation, including model non-linearity,

multi-objective optimization, and noise in measurement data. Among the investigated algorithms, MPA emerged as the most successful in accurately estimating photovoltaic parameters for the double-diode and single-diode models.

LIST OF BIBLIOGRAPHIC REFERENCES

[1] Yağan, Y. E., Vardar, K., & Ebeoğlu, M. A. (2018). Modeling and simulation of PV systems. *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE), 13*(2), 1-11.

[2] Malki, A., Mohamed, A. A., Rashwan, Y. I., El-Sehiemy, R. A., & Elhosseini, M. A. (2021). Parameter Identification of Photovoltaic Cell Model Using Modified Elephant Herding Optimization-Based Algorithms. *Applied Sciences, 11*(24), 11929.

[3] Shaban, H., Houssein, E. H., Pérez-Cisneros, M., Oliva, D., Hassan, A. Y., Ismaeel, A. A., ... & Said, M. (2021). Identification of parameters in photovoltaic models through a runge kutta optimizer. *Mathematics, 9*(18), 2313.

[4] Ghetas, M., & Elshourbagy, M. (2024). Parameters extraction of photovoltaic models using enhanced generalized normal distribution optimization with neighborhood search. *Neural Computing and Applications*, 1-18.

[5] Louzazni, M., Khouya, A., Amechnoue, K., Gandelli, A., Mussetta, M., & Crăciunescu, A. (2018). Metaheuristic algorithm for photovoltaic parameters: comparative study and prediction with a firefly algorithm. *Applied Sciences, 8*(3), 339.

[6] Shaikh, M. R. S. (2017). A review paper on electricity generation from solar energy.

[7] Farida, C., & Naima,G. (2018). *Dimensionnement d'un système photovoltaïque autonome* (Doctoral dissertation, Université Mouloud Mammeri).

[8] Chalkias, C., Faka, A., & Kalogeropoulos, K. (2013). Assessment of the direct sun-light on rural road network through solar radiation analysis using GIS.

[9] AHMED BOUBENIA. Analysis of hybrid renewable energy systems integrating Power-To-Gas Concept: Performances optimization based on artificial intelligence techniques University doctoral thesis. Boumerdes: University M'Hamed Bougara –Boumerdes,2019.

[10] Center, F. S. E., & Withers Jr, C. (2014). Assessment of Energy Efficient Methods of Indoor Humidity Control for Florida Building Commission Research.

[11] Bhavin K Madhu. Dynamic Analysis of Grid Connected Hybrid System of PV Panel and Wind Turbines for a Light Commercial Building. University Master's thesis. Tennessee: University of Tennessee at Chattanooga,2010,109p

[12] Alayat Mahmoud, Boucetta Issam. Maximisation de la production d'un système photovoltaïque à base de MPPT soumis à des éclairements différent .UNIVERSITE Annaba. 2017.

[13] Zhang, T., & Yang, H. (2018). High efficiency plants and building integrated renewable energy systems: Building-integrated photovoltaics (BIPV). Handbook of Energy Efficiency in Buildings: A LifeCycle Approach; Elsevier: Amsterdam, The Netherlands, 441-595.

[14] Zhang, T., & Yang, H. (2018). High efficiency plants and building integrated renewable energy systems: Building-integrated photovoltaics (BIPV). *Handbook of Energy Efficiency in Buildings: A Life Cycle Approach; Elsevier: Amsterdam, The Netherlands*, 441-595.

[15] Noureddine, B. E. N. B. A. H. A. (2022). *Université Batna 2–Mostefa Ben Boulaïd* (Doctoral dissertation, Université de Biskra).

[16] Muntaser Mohammed Nasser Ali AL-SHARFI, Ahmad khalid Abd Al-khalik YAHYA (2023). Inverter Control of The PV-Wind Hybrid System Grid-Connected by SRF Algorithm.UNIVERSITY YAHIA FARES OF MEDEA.

[17] Murphy, D. M., Eskenazi, M. I., White, S. F., & Spence, B. R. (2002, May). Thin-film and crystalline solar cell array system performance comparisons. In *Conference Record of the Twenty-Ninth IEEE Photovoltaic Specialists Conference, 2002.* (pp. 782-787). IEEE.

[18] BERREZIGA NASSIM, BABOU SMAIL. Commande direct par la méthode incremental conductance (inc-cond) d'un panneau photovoltaique .2018.

[19] Maoulida, F. A. H. A. D. Modélisation d'un module photovoltaïque de type bp sx 150 pour la génération d'énergie électrique.

[20] Đurin, B., Shpetim, L., Plantak, L., & Kranjčić, N. (2020). Using Solar Photovoltaic Energy for Irrigation: A Review of the Application. *Advances in environmental studies*, *4*(2), 358-367.

[21] Đurin, B., Shpetim, L., Plantak, L., & Kranjčić, N. (2020). Using Solar Photovoltaic Energy for Irrigation: A Review of the Application. Advances in environmental studies, 4(2), 358-367.

[22] Goar, N., & Mahmoudi, A. (2017). Réalisation d'un convertisseur DC/DC dans une chaine de conversion d'énergie photovoltaïque.

[23] BOUGANDOURA Djihane BOUDJENAH Hadjer. Implémentation software de l'algorithme bio-inspiré SOA pour la commande MPPT.Ecole National Polytechnique(2020).

[24] Abdellatif MAHAMMEDI. (2020). Contribution to the control of a Power Converter with Improved Topologies Associated with a Photovoltaic Generator Based on Advanced Techniques.Ziane (Doctoral dissertation, Achour University of Djelfa).

[25] GAROUDJA ILYES. FAULTS DETECTION AND DIAGNOSIS OF PHOTOVOLTAIC SYSTEMS USING ARTIFICIAL INTELLIGENCE TOOLS (Doctoral dissertation, Université BLIDA). 2018.

[26] Tomar, V., Bansal, M., & Singh, P. (2024). Metaheuristic Algorithms for Optimization: A Brief Review. *Engineering Proceedings*, *59*(1), 238.

[27]Ghaitaoui Essama,Ahmed Ben Khelifa Lahcene.Approches d'optimisation pour l'estimation des paramètres et Suivi du point de puissance maximale (MPPT) du Système photovoltaïque. University Ahmed draia-ADRAR,2022.

[28] Lachaal Bassim Araba Abderaouf, Optimisation et Classification des chemins d'apprentissageUniversité de 8 Mai – Guelma,2014.

[29] Gu, Z., Xiong, G., & Fu, X. (2023). Parameter extraction of solar photovoltaic cell and module models with metaheuristic algorithms: A review. *Sustainability*, *15*(4), 3312.

[30] Roni, M. H. K., Rana, M. S., Pota, H. R., Hasan, M. M., & Hussain, M. S. (2022). Recent trends in bio-inspired meta-heuristic optimization techniques in control applications for electrical systems: A review. *International Journal of Dynamics and Control*, 1-13.

[31] Trivedi, I. N., Pradeep, J., Narottam, J., Arvind, K., & Dilip, L. (2016). Novel adaptive whale optimization algorithm for global optimization. Indian Journal of Science and Technology.

[32] Mirjalili, S., & Lewis, A. (2016). Advances in engineering software the whale optimization algorithm, vol. 95.

[33] Nadimi-Shahraki, M. H., Zamani, H., Asghari Varzaneh, Z., & Mirjalili, S. (2023). A systematic review of the whale optimization algorithm: theoretical foundation, improvements, and hybridizations. *Archives of Computational Methods in Engineering*, *30*(7), 4113-4159.

[34] Mohamed, M., Abdullah, M., & Yahia, M. (2021). Parameters estimation of photovoltaic module using Grey Wolf optimization method. *Przegląd Elektrotechniczny*, *97*.

[35] Touabi, C., & Bentarzi, H. (2022). Photovoltaic panel parameters estimation using grey wolf optimization technique. Engineering Proceedings, 14(1), 3.

[36] Dagal, I., Akín, B., & Dari, Y. D. An improved constant current step-based grey wolf optimization algorithm for photovoltaic systems. *Journal of Intelligent & Fuzzy Systems*, (Preprint), 1-20.

[37] Somashekar, B., & Esther, B. P. (2017). Partial shading conditions for photovoltaic system using MPPT techniques. *International Journal of Recent Trends in Engineering& Research (IJRTER)*, *3*(06).

[38] Madhiarasan, M., Cotfas, D. T., & Cotfas, P. A. (2023). Black widow optimization algorithm used to extract the parameters of photovoltaic cells and panels. *Mathematics*, *11*(4), 967.

[39] Zhou, C. (2023). Black Widow Optimization Algorithm for Virtual Machines Migration in the Cloud Environments. *International Journal of Advanced Computer Science and Applications*, *14*(8).

[40] Wang, H., Zhang, C., & Wu, H. (2023). Shear Capacity Prediction Model of Deep Beam Based on New Hybrid Intelligent Algorithm. *Buildings*, *13*(6), 1395.

[41] Atchi Aymene ,Khaled Rayane. Identification of PV model parameters using experimental and nameplate data. University M'Hamed BOUGARA – Boumerdes,2016.

[42] Praveena, V., Vijayaraj, A., Chinnasamy, P., Ali, I., Alroobaea, R., Alyahyan, S. Y., & Raza, M. A. (2022). Optimal deep reinforcement learning for intrusion detection in UAVs. *Computers, Materials & Continua*, *70*(2), 2639-2653.

[43] Qi, C. (2024). Improved marine predators algorithm for engineering design optimization problems.

[44] Mugemanyi, S., Qu, Z., Rugema, F. X., Dong, Y., Wang, L., Bananeza, C., ... & Mutabazi, E. (2023). Marine predators algorithm: A comprehensive review. *Machine Learning with Applications*, *12*, 100471.

[45] Rai, R., Dhal, K. G., Das, A., & Ray, S. (2023). An inclusive survey on marine predators algorithm: Variants and applications. *Archives of Computational Methods in Engineering*, *30*(5), 3133-3172.

[46] Al-Betar, M. A., Awadallah, M. A., Makhadmeh, S. N., Alyasseri, Z. A. A., Al-Naymat, G., & Mirjalili,S. (2023). Marine predators algorithm: A review. Archives of Computational Methods in Engineering, 30(5), 3405-3435.

[47] Al-Betar, M. A., Awadallah, M. A., Makhadmeh, S. N., Alyasseri, Z. A. A., Al-Naymat, G., & Mirjalili,S. (2023). Marine predators algorithm: A review. Archives of Computational Methods in Engineering, 30(5), 3405-3435.

[48] Sun, C. J., & Gao, F. (2021). A tent marine predators algorithm with estimation distribution algorithm and Gaussian random walk for continuous optimization problems. *Computational Intelligence and Neuroscience*, *2021*.

[49] Malki, A., Mohamed, A. A., Rashwan, Y. I., El-Sehiemy, R. A., & Elhosseini, M. A. (2021). Parameter Identification of Photovoltaic Cell Model Using Modified Elephant Herding Optimization-Based Algorithms. *Applied Sciences*, *11*(24), 11929.

[50] Rai, N., Abbadi, A., Hamidia, F., Douifi, N., Abdul Samad, B., & Yahya, K. (2023). Biogeography-based teaching learning-based optimization algorithm for identifying one-diode, two-diode and three-diode models of photovoltaic cell and module. *Mathematics*, *11*(8), 1861.

[50] Ma, J. (2014). Optimization approaches for parameter estimation and maximum power point tracking (MPPT) of photovoltaic systems (Doctoral dissertation, University of Liverpool).

[51] Sharma, A., Sharma, A., Averbukh, M., Jately, V., Rajput, S., Azzopardi, B., & Lim, W. H. (2023). Performance investigation of state-of-the-art metaheuristic techniques for parameter extraction of solar cells/module. *Scientific reports*, *13*(1), 11134.

[52] ABDENNEBI Zakaria, GHEBGHOUB Aymen , ABBADI Amel ,HAMIDIA Fethia , DOUIFI Nadia . Parameters Estimation of Double Diode Model of Photovoltaic Cell Using Grey Wolf and Black Widow Optimization Algorithms. Journée d'Etude sur l'Exploitation des Energies Renouvelables pour la Sécurité Energétique de l'Algérie. University yahia fares of medea,2024.