الجمهورية الجزائرية الديمقراطية الشعبية
République Algérienne Démocratique et Populaire

Ministère de l'Enseignement Supérieur
et de la Recherche Scientifique
Université Akli Mohand Oulhadj - Bouira -
Tasdawit Akli Muḥend Ulḥağ - Tubirett -

وزارة التعليم العالي والبحث العلمي
جامعة أكلي محند أولحاج
- البويرة -

Faculté des Sciences et des Sciences Appliquées

كلية العلوم والعلوم التطبيقية

Référence : ……………/MM/2021

المرجع:……/م م/ 2021

Mémoire de Master

Présenté au

Département : Génie Électrique
Domaine : Sciences and Technologies
Filière : **E**lectronique
Spécialité : Electronique des systèmes embarqués

Réalisé par :
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Théme

Artificial intelligence for parameter identification of a photovoltaic panel with a two-diode model

Soutenu le : **02/07/2024**

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Année universitaire : 2023-2024

Abstract:

Solar energy is a clean and inexhaustible source of energy. Photovoltaic panels are used to convert solar energy into electrical energy. Due to the importance of determining the unknown electrical parameters of solar panels to improve their performance, many techniques, models, and methods have been proposed by researchers. This thesis discusses the use of two methods to determine the unknown electrical parameters of a solar panel with a two-diode model. The first method involves simulated mathematical equations using MATLAB/Simulant software, and the second method involves using artificial intelligence algorithms. The obtained results under random daily conditions are presented in graphs and tables for a comparative study.

Keywords: parameter identification, photovoltaic panel, two-diode model, artificial intelligence.

ملخص :

الطاقة الشمسية هي مصدر طاقة نظيف لا ينضب .تستخدم الألواح الكهروضوئية لتحويل الطاقة الشمسية إلى طاقة كهربائية .ونظراً لأهمية تحديد المعلمات الكهربائية المجهولة للألواح الشمسية لتحسين أدائها، فقد تم اقتراح العديد من التقنيات والنماذج والأساليب من قبل الباحثين .تناقش هذه المذكرة استخدام طريقتين لتحديد المعلمات الكهربائية غير المعروفة للوحة شمسية بنموذج ثنائي الصمام . تتضمن الطريقة الأولى محاكاة المعادلات الرياضية باستخدام برنامج MATLAB/Simulant، أما الطريقة الثانية فتتضمن استخدام خوارزميات الذكاء الاصطناعي .تم عرض النتائج التي تم الحصول عليها في الظروف اليومية العشوائية في الرسوم البيانية والجداول لدراسة مقارنة.

الكلمات المفتاحية: تحديد المعلمة، الألواح الكهروضوئية، نموذج الثنائي الصمام، الذكاء الاصطناعي.

Résumé :

L'énergie solaire est une source d'énergie propre et inépuisable. Les panneaux photovoltaïques sont utilisés pour convertir l'énergie solaire en énergie électrique. En raison de l’importance de déterminer les paramètres électriques inconnus des panneaux solaires pour améliorer leurs performances, de nombreuses techniques, modèles et méthodes ont été proposés par les chercheurs. Ce mémoire discute de l'utilisation de deux méthodes pour déterminer les paramètres électriques inconnus d'un panneau solaire avec un modèle à deux diodes. La première méthode implique des équations mathématiques simulées à l'aide du logiciel MATLAB/Simulant et la deuxième méthode consiste à utiliser des algorithmes d’intelligence artificielle. Les résultats obtenus dans des conditions quotidiennes aléatoires sont présentés sous forme de graphiques et de tableaux pour une étude comparative.

Mots clés : identification des paramètres, panneau photovoltaïque, modèle à deux diodes, intelligence artificielle.

DEDICATIONS

I dedicate this modest work to yaya, my parents, my sweet children, my brothers and sisters, my lovely nephews and nieces, Hamza and Daou, my cousins, my big family, my dear friends, and to the memory of my uncle and my aunt.

THANKS

الحمد لله رب العالمين

إحتراماتي للشرفاء

This work was carried out within the faculty of sciences and applied sciences at the University of Bouira-Algeria.

First and foremost, I would like to thank my sister DjiDji and all the members of my extended family for their support and encouragement in bringing this modest work to fruition.

I would, of course, like to thank my supervisor, Dr. MADI Saida, the director of this thesis, for giving me the opportunity to explore the field of photovoltaic energy and artificial intelligence through this modest thesis.

I would also like to thank all the jury members for their interest in my work.

To all the teachers and everyone who helped me in one way or another, my deepest respect and gratitude.

Finally, I extend my thanks to all those who contributed to the completion of this work.

Table of Contents

Chapter III : Artificial intelligence for parameter identification of a photovoltaic panel with a two-diode model

List of figures

- **Chapter1:**

- **Chapter 2 :**

- **Chapter 3:**

List of tables

List of acronyms and symbols

- **Acronyms**

  - AI Artificial Intelligence.
  - ANN Artificial Neural Network.
  - CEO Chief Executive Officer.
  - E Solar energy, Irradiance, (W/m^2).
  - Estc Insolation under STC (Standard Test Conditions).
  - FF Fill Factor.
  - GA Genetic Algorithms.
  - I Photovoltaic panel's current, (A).
  - Ical Calculated current of the PV panel, (A).
  - Id1 Current of the diode1, (A).
  - Id2 Current of the diode 2, (A).
  - Imes Measured current of the PV panel, (A).
  - Impp Current at the maximum power point, (A).
  - Ip Current across the parallel resistance, (A).
  - Iph Photonic current, current generated by illumination, (A).
  - Isat1 Saturation current of the diode 1, (A).
  - Isat2 Saturation current of the diode 2, (A).
  - Isc Short circuit current, (A).
  - Iscd Datasheet's current of the PV panel, (A).
  - K Boltzmann constant, (1.3854×10^{-23} J/K).
  - K_{isc} Parameter used to adjust the value of the simulated short circuit current
  - K_i Temperature coefficient I_{sc}, % / (C°, K).
  - K_p Temperature coefficient P_{max}, % / (C°, K).
  - K_{rs} Parameter used to adjust the position of the simulated Mpp at NOCT.
  - K_v Temperature coefficient V_{oc}, % / (C°, K).
  - K_{voc} Parameter used to adjust the value of the simulated open circuit voltage.
  - MAE Mean Absolute Error.
  - MPP Maximum power point.
  - MSE Mean Squar Error.
  - NOCT Nominal operation Cell temperature.
  - Np Number of solar cells connected in parallel.

- Ns Number of solar cells connected in series.
- P Photovoltaic panel's power, (W).
- P_{cal} Calculated power of the PV panel, (W).
- P_{max} Maximum power of the PV panel, (W).
- P_{mes} Measured power of the PV panel, (W).
- PSO Particle swarm optimization.
- PV Photovoltaic.
- RMSE Root Mean Squar Error.
- Rp Parallel resistance of the solar cell, (Ω).
- Rs Series resistance of the solar cell, (Ω).
- Rsh Shunt resistance of the solar cell, (Ω).
- S The panel's surface, m^2.
- SOA Seagull optimization algorithms.
- STC Standard Test Conditions.
- T Ambient temperature, (K, °C).
- Tstc Junction temperature under STC conditions, (K).
- V Photovoltaic panel's voltage, (V).
- V_{cal} PV panel's calculated voltage, (V).
- V_{mes} PV panel's measured voltage, (V).
- V_{mpp} Voltage at maximum power point, (V).
- V_{oc} Open circuit voltage of the PV panel, (V).
- V_{ocd} PV panel's datasheet voltage, (V).
- V_{th1} Thermal voltage of the diode 1, (V).
- V_{th2} Thermal voltage of the diode 2, (V).
- n1 Ideality factor of the diode 1.
- n2 Ideality factor of the diode 2.
- q Electric charge of the electron, (1.6×10^{-19} C).
- rs Resistance used to adjust the position of the Mpp at STC.

- **Symbols**
  - η Efficiency.
  - Δ Delta.

General introduction

General introduction

The consumption of electrical energy has continued to increase since the advent of the industrial revolution, to the point where the pace of consumption has outpaced that of production. To address these deficiencies, humans have turned to alternative energy sources in search of a promising solution to meet current energy needs while committing to a transition towards a more sustainable and environmentally friendly future.

One such source is a photovoltaic (PV) system. One of its main characteristics is that it can be used in a wide variety of situations. A photovoltaic system can be installed on building rooftops, in large-scale solar farms, and in portable installations such as solar chargers. It can be adapted to many different environments.

The utility of photovoltaic energy in modern life is vast; it provides a clean and renewable source of electricity, thereby reducing dependence on fossil fuels and contributing to the fight against climate change and the preservation of air quality. Moreover, it offers an energy solution for remote or underserved regions via traditional electrical grids, thus improving access to electricity worldwide. Additionally, photovoltaic energy helps reduce electricity bills by generating a portion or all of the consumed electricity.

Photovoltaic electricity is produced through photovoltaic solar panels that convert the photon energy from the sun into electrical energy. These panels are designed in laboratories under specific conditions, namely: standard test conditions (STC) and nominal operating cell temperature (NOCT), and their parameters are determined from controlled experimental data under these conditions. However, the actual efficiency is often low. The manufacturer provides a technical datasheet for every photovoltaic panel, but not all parameters are included. The missing parameters in the PV panel's datasheet are essential for estimating and improving its performance and efficiency for real-world operation. These performances can be studied by providing an electrical model of the PV panel (modeling), from which its characteristic equation will be deduced [1, 2, 3].

The purpose of this thesis is to identify the unknown parameters of a photovoltaic panel using two methods. The first one is by implementing the mathematical equations proposed for each parameter using MATLAB/Simulink software. The second method is by using two artificial intelligence methods, namely: the neural network algorithm and the genetic algorithm. This thesis has been organized into three chapters, as follows:

- ***Chapter I:*** This chapter focuses on photovoltaic panels in a general manner. Various mathematical models with their corresponding characteristic equations have been introduced. In addition, the seven unknown parameters of the chosen PV panels have been estimated by mathematical equations that are implemented using MATLAB/Simulink software under STC and NOCT conditions. The obtained results have been presented in the form of tables and curves.

- ***Chapter II***: In this chapter, the artificial intelligence techniques used for the identification and optimization of the parameters in PV panels have been introduced and detailed.
- ***Chapter III***: The seven unknown parameters of a 50W PV panel have been estimated using two methods of artificial intelligence, namely the neural network algorithm and the genetic algorithm. The obtained results are compared with the measured values.

Finally, this work is concluded by a general conclusion.

CHAPTER I

GENERALITIES ON PHOTOVOLTAIC PANELS

Chapter I. Generalities on photovoltaic panels

I.1 Introduction

Photovoltaic panels, commonly known as solar panels, are devices that convert sunlight directly into electricity using semiconductor materials such as silicon and thin-film technologies.
A brief description of different photovoltaic technologies has been presented in this chapter. Then, different equivalent electrical circuits of the photovoltaic panel with their corresponding mathematical models have been presented. Finally, the seven unknown parameters of the different photovoltaic panels' sizes have been identified using MATLAB/Simulink software.

I.2 A photovoltaic solar panel

A photovoltaic panel is composed of solar cells, a basic unit that converts sunlight into electricity. These cells are typically made from silicon. They are connected either in series with the aim of increasing the photovoltaic panel's voltage, or connected in parallel with the aim of increasing the PV panel's current, or in both series and parallel (strings and branches) to increase both the voltage and the current of the photovoltaic panel [1, 4, 5, 6].

I.3 Photovoltaic panel’s types

Depending on the solar cell manufacturing technologies, there are three most popular types of photovoltaic panels, namely: mono-crystalline photovoltaic panels, poly-crystalline photovoltaic panels, and thin-layer photovoltaic panels [1, 5, 7].

I.3.1 Mono-crystalline photovoltaic panel

It is uniformly dark. The solar cells used in this type of panel are hexagonal and made with a single silicon crystal. This type of panel is very sensitive to high temperatures and has high efficiency.

I.3.2 Poly-crystalline photovoltaic panel

It is non-uniform and light blue in color. The solar cells used in this panel are square and made of several silicon crystals. This type of panel resists excessive temperatures and has a lower efficiency than monocrystalline.

I.3.3 Thin layer photovoltaic panel (amorphous)

It is called the second-generation technology of solar panels. It is dark gray. The solar cells used in this type of photovoltaic panel are made of silicon powder that is printed or sprayed on a sheet of glass or plastic in a thin layer. This panel has a lower efficiency than the two previous ones, which is why it is generally used in low-power devices.

Figure I.1 shows the different types of photovoltaic panels.

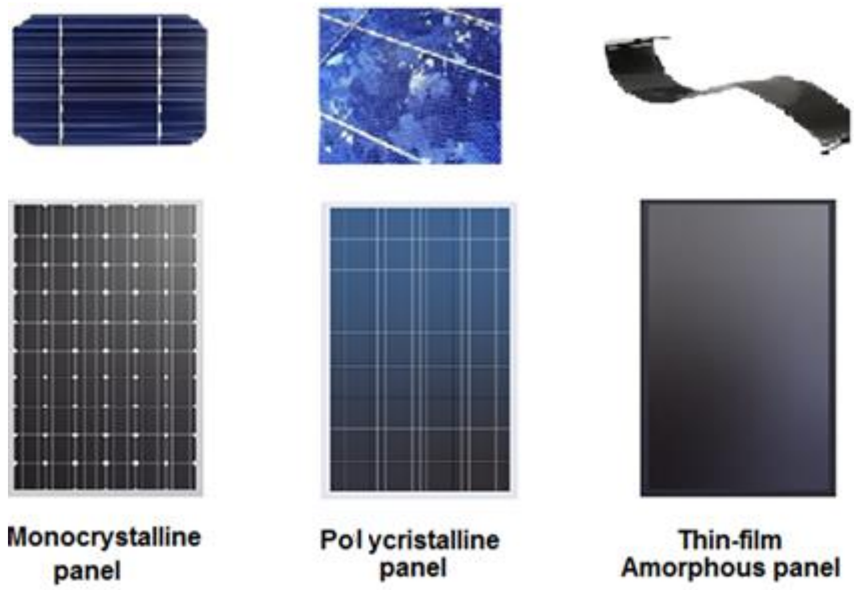


Figure I.1. Photovoltaic panel's types [1, 6, 7].

For good performance, the photovoltaic panels must be oriented towards the south and inclined from the ground at a certain angle so that the solar rays are perpendicular to the modules; this angle of inclination varies according to region and season [4].

I.4 Criteria for choosing a photovoltaic panel

The criteria for choosing a photovoltaic panel are given by the manufacturer under standard test conditions (solar irradiance E_{stc} = 1000 W/m^2, ambient temperature T_{stc} = 25 °C, and humidity 40 %) and the nominal operating cell temperature (solar irradiance E = 800 W/m^2 and ambient temperature T = 20 °C) [1].

- ***Maximum Power (Pmax):*** The maximum output power that the photovoltaic panel can produce under standard test conditions is typically measured in watts (W).
- ***Open-Circuit Voltage (Voc):*** The maximum voltage that the photovoltaic panel produces when no current is flowing is measured in volts (V).
- ***Short-Circuit Current (Isc):*** The current that flows through the photovoltaic panel when the output terminals are shorted is measured in amperes (A).
- ***Maximum Power Voltage (Vmp):*** The voltage that corresponds to the photovoltaic panel's maximum output power is measured in volts (V).

- ***Maximum Power Current (Imp):*** The current that corresponds to the photovoltaic panel's maximum output power is measured in amperes (A).
- ***Fill Factor (FF):*** The ratio of the actual maximum output power of the photovoltaic panel to the product of its open-circuit voltage and its short-circuit current. It measures the quality of the solar cell.
- ***Efficiency (η):*** It is the ratio of the electrical output power to the solar input power. It expresses as a percentage (%).
- ***Temperature Coefficient:*** It is the rate at which the photovoltaic panel's performance changes with temperature. It is typically expressed as a percentage per degree Celsius (%/°C).
- ***Nominal Operating Cell Temperature (NOCT):*** It is the temperature of the solar cells when the photovoltaic panel operates under specific conditions with solar irradiance equal to 800 W/m², an ambient temperature of 20 °C, and a wind speed of 1 m/s.
- ***Current-Voltage (I-V) Curve:*** It is a curve showing the relationship between the photovoltaic panel's current and output voltage under different conditions. It is used to determine the performance of the photovoltaic panel's characteristics and to design the photovoltaic system accordingly.
- ***Panel warranty:*** It is given in years for its operation and for its manufacturing technology.

I.5 Modeling of a photovoltaic panel

Photovoltaic cell modeling is important to the advancement of photovoltaic technology because it provides a better understanding of the inner workings of the solar cell and estimates the performance of the photovoltaic system under various environmental circumstances. This knowledge improves the performance of solar panels and allows for the creation of more efficient cells. The modeling of a solar panel is based on the electrical model circuit of the cell, taking into account the number of NS cells connected in series and the number of Np parallel branches, since the panel is a collection of cells connected in series and/or parallel [1, 2, 5, 6].

To create a model of a photovoltaic panel, the first step is to select the equivalent electrical circuit. That is, a diode and a current source, and each time element is added to get closer and closer to the real behavior of the photovoltaic panel. There are three most common electrical models that's have been proposed for this purpose, namely: single diode model, double diode model and three-diode model [1, 4, 5].

I.5.1. Equivalent electrical circuit of photovoltaic panel with a single diode model

The photovoltaic panel is represented by a current source in parallel with a diode and a parallel resistance Rp, in series with a series resistance Rs. The equivalent electrical circuit of this model will have five unknown parameters [1, 5, 8].

I.5.2. Equivalent electrical circuit of photovoltaic panel with a two-diode model

The photovoltaic panel is represented by adding a second parallel diode to the first model. This model considers the recombination of electrons at the cell surface by the second diode in addition to the diffusion phenomenon caused by the first diode. It also accounts for the voltage drop across the series resistance and the leakage current across the parallel resistance. The equivalent electrical circuit of this model will have seven unknown parameters [1, 2, 4, 5, 9].

I.5.3. Equivalent electrical circuit of photovoltaic panel with a three-diode model

The photovoltaic panel is represented by adding the third parallel diode to the second model. The added diode represents electron recombination between the metal and the semiconductor, as well as the diode leakage current due to recombination in the defect regions and grain sites [3]. The equivalent electrical circuit of this model will have nine unknown parameters.

I.6 Equivalent electrical circuit of a photovoltaic panel with a two-diode model

For our study, we focused on the representation of the photovoltaic panel's two-diode model with seven unknown parameters, see Figure I.2.
Based on figure I.2 and using Kirchhoff current law, the expression of the photovoltaic panel's current is given by equation (I.1).

$$I = I_{ph} - I_{d1} - I_{d2} - I_p \qquad (I.1)$$

Knowing that Iph is the photo current, Id1 and Id2 are the two currents across the two diodes 1 and 2, respectively, and they are given by the two equations (I.2) and (1.3).

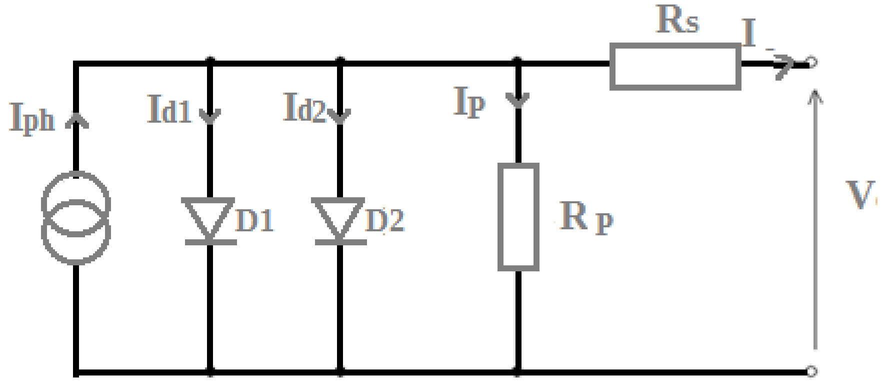


Figure I.2. Photovoltaic panel with two-diode model [1, 2, 4, 9].

$$Id1 = I_{sat1}\ \left[(\exp(\frac{(V+Rs*I)}{Vth1}) - 1\right] \tag{I.2}$$

$$Id2 = I_{sat2}\ \left[\exp\left(\frac{(V+Rs*I)}{Vth2}\right) - 1\right] \tag{I.3}$$

Knowing that V_{th1} and V_{th2} are the potentials of the junctions 1and 2, respectively. I_{sat1} and I_{sat2} are the saturation currents of the first diode and the second diode, respectively. In addition, Ip is the current across the parallel resistance Rp and it is given by the equation (I.4).

$$IP = \frac{(V-Rs*I)}{Rp} \tag{I.4}$$

The resulted photovoltaic panel's current-voltage characteristic equation is given by equation (I.5).

$$I = I_{ph} - I_{sat1}\ \left[(\exp(\frac{(V+Rs*I)}{Vth1}) - 1\right] - I_{sat2}\ \left[\exp\left(\frac{(V+Rs*I)}{Vth2}\right) - 1\right] - \frac{(V+Rs*I)}{Rp} \tag{I.5}$$

Multiplying this equation by the PV panel’s voltage results the photovoltaic panel’s power-voltage characteristic equation as given by the equation (I.6).

$$P = V * I \tag{I.6}$$

The two previous equations need seven parameters (I_{Ph}, n_1, n_2, I_{sat1}, I_{sat2}, R_S, R_P) to be estimated in order to plot the photovoltaic panel’s current-voltage and power-voltage characteristics. This is the aim of the following section.

I.7 Parameter identification of photovoltaic panel with a two-diode model

The modelling of the photovoltaic panel principally involves the extraction of the seven unknown parameters (I_{Ph}, n_1, n_2, I_{sat1}, I_{sat2}, R_S , R_P), that will be based on the following equations [10].
The values of the potentials of the junctions V_{th1} and V_{th2} can be obtained using the two expressions (I.7) and (I.8), respectively.

$$V_{th1} = \frac{n1*K*T*Ns}{q}\left(\frac{T}{Tstc}\right) * 0.7 \tag{I.7}$$

$$V_{th2} = \frac{n2*K*T*Ns}{q}\left(\frac{T}{Tstc}\right) * 0.7 \tag{I.8}$$

Knowing that; n1 and n2 are the ideality factor of the diode 1 and diode 2, respectively. K is Boltzmann constant which is equal to 1.38×10−23 J/K. T is the ambient temperature. N_s represents the number of photovoltaic cells connected in series. q is the charge of an electron which iq equal to 1.6×10^{-19} Coulombs. T_{stc} is the temperature at standard test conditions.

The values of the two saturation currents I_{sat1} and I_{sat2} can be obtained using the two expressions (I.9) and (I.10), respectively.

$$Isat1 = \frac{1}{2} * \frac{Isc*\left(\frac{(Rs+Rp)}{Rp}\right)-\frac{(Voc)}{Rp}*(1-\frac{(\exp\left(\frac{Isc*Rs}{Vth2}\right)-1)}{(\exp\left(\frac{Voc}{Vth1}\right)-1)})}{\left(\exp(\frac{Voc}{Vth1})-1\right)-(\exp\left(\frac{Isc*Rs}{Vth2}\right)-1)} \tag{I.9}$$

$$Isat2 = \frac{1}{2} * \frac{Isc*\left(\frac{(Rs+Rp)}{Rp}\right)-\frac{(Voc)}{Rp}*(1-\frac{(\exp\left(\frac{Isc*Rs}{Vth1}\right)-1)}{(\exp\left(\frac{Voc}{Vth2}\right)-1)})}{\left(\exp(\frac{Voc}{Vth2})-1\right)-(\exp\left(\frac{Isc*Rs}{Vth1}\right)-1)} \tag{I.10}$$

Knowing that I_{SC} is the short circuit current and V_{OC} is the open circuit voltage. Them values can be obtained using the following two equations.

$$\mathrm{Isc} = \mathrm{Iscd} * \left[1 + \frac{\mathrm{Ki}}{100} * \left(\mathrm{T} * \left(\frac{Tstc}{T}\right)^{-0.125} - Tstc\right)\right] * \left(\frac{Estc}{E}\right)^{Kisc} \tag{I.11}$$

$$\mathrm{Voc} = \mathrm{Vocd} * \left[1 + \frac{\mathrm{Kv}}{100} * \left(\mathrm{T} * \left(\frac{Tstc}{T}\right)^{1.25} - Tstc\right)\right] * \left(\frac{Estc}{E}\right)^{Kvoc} \tag{I.12}$$

With K_{ISC} is a parameter used to adjust the value of the short circuit current to be equal to the value of the data sheet's short circuit current, Isc_{data}. K_{VOC} is a parameter used to adjust the value of the open circuit voltage to be equal to the value of the data sheet's open circuit voltage, Voc_{data}.

In addition, the values of the series and parallel resistances can be estimated using the two equations (I.13) and (I.14), respectively.

$$\mathrm{Rs} = \mathrm{rs} * \frac{\mathrm{Np}}{Ns} * \frac{\frac{Pmax}{S*E}}{T*(\frac{-Kp}{100})} * \left(\frac{Tstc}{T} * \frac{Estc}{E}\right)^{KRs} \tag{I.13}$$

$$\mathrm{Rp} = 25 * (\frac{\mathrm{Ns}}{Np} * \frac{\frac{S*E}{Pmax}*T*\left(\frac{-Kp}{100}\right)}{\left(\frac{Tstc}{T}*\frac{Estc}{E}\right)}) \tag{I.14}$$

With K_{RS} is a parameter used to adjust the value of the series resistance to be obtained when the simulated maximum power point MPP is closer as possible as to the data sheet's MPP, $Pmax_{datasheet}$ The value of the photo current can be obtained using the equation (I.15).

$$Iph = \frac{Isc*\left(\frac{\mathrm{Rs+Rp}}{Rp}\right)*\frac{(\exp\left(\frac{Isc*Rs}{Vth2}\right)-1)*(\frac{Voc}{Rp})}{(\exp\left(\frac{Voc}{Vth1}\right)-1)})}{\left(\exp(\frac{Voc}{Vth1})-1\right)-(\exp\left(\frac{Isc*Rs}{Vth2}\right)-1)} \tag{I.15}$$

The identification method by Simulink involves entering the parameter values provided in the data-sheet of the panel as inputs, to obtain the two curves current-voltage and power-voltage at the output under the two conditions: standard test conditions (STC) and nominal operating cell temperature conditions (NOCT). This is done in these four following steps:

1. Vary the resistance rs under STC until the simulated Maximum Power Point MPP is as close as possible to the value of MPP of the datasheet. This value will be kept fixed for the remainder of the work.
2. Vary KIsc under NOCT conditions until the simulated short circuit current Isc equals to the datasheet 's short circuit current, Isc.
3. Vary Kvoc under NOCT conditions until the simulated open circuit voltage Voc equals to the datasheet's open circuit voltage, Voc.
4. Vary Krs under NOCT conditions until the simulated MPP is as close as possible to the datasheet's MPP.

Knowing that the values of the ideality factor of the two diodes n1 and n2 will be taken as 1.3 for monocrystalline type and 1.31 for polycrystalline type, respectively [10].

I.8 Results and discussion

The simulated values of the unknown parameters are obtained by implementing the equations (I.5) -(I.15) using MATLAB/Simulink.

The value of the absolute relative error for the maximum output power, $\Delta P_{\max}$ %, can be obtained using the following equation:

$$\Delta P_{\max}\ \% = \frac{|P_{max-Calculated} - P_{\max-\text{datasheet}}|}{P_{\max-\text{datasheet}}} * 100 \qquad (I.16)$$

With $P_{max-Calculated}$ is the calculated maximum output power of the photovoltaic panel and $P_{\max-\text{datasheet}}$ is the maximum output power of the photovoltaic panel given in its datasheet.

Table I.1 shows the datasheet values of the used photovoltaic panels and Table I.2 shows the obtained results under standard test conditions as well as under nominal operating cell temperature condition in addition to the resulted absolute relative errors.

Figures I.3-I.10 show the power-voltage and current-voltage curves of each used photovoltaic panel under standard test conditions as well as under nominal operating cell temperature conditions.

Table I.1 : The datasheet's parameters for the used photovoltaic panels.

PV panels	CS6P 270W Poly-crystalline		SW 270 Mono		SW 50 Poly RMA		50W Mono-crystalline	
	STC	NOCT	STC	NOCT	STC	NOCT	STC	NOCT
P_{max} (w)	270	196	270	194,9	50	35,9	50	37
I_{mp} (A)	8,75	6,97	8,42	6,74	2,75	2,2	2,87	2,33
V_{mp} (v)	30,8	28,1	32,1	28,9	18,2	16,3	17,45	15,89
I_{sc} (A)	9,32	7,55	8,90	7,19	2,95	2,38	3,08	2,50
V_{oc} (v)	37,9	34,8	38,3	34,5	22,1	19,8	22,60	20,66
Ns	60	60	60	60	36	36	36	36

Table I.2 : The obtained parameters of the used photovoltaic panels.

PV panels	**270W Poly-crystalline**		**SW 270 Mono**		**SW 50 Poly RMA**		**50W Mono-crystalline**	
	STC	**NOCT**	**STC**	**NOCT**	**STC**	**NOCT**	**STC**	**NOCT**
rs(Ω)	159,14566	159,14566	125,862	125,862	269,33594	269,335944	430,2205967	430,2205967
Krs	//	-0,09225	//	-0,5654	//	-0,6844	//	-0,6187
Kvoc	//	-0,365	//	-0,451	//	-0,472	//	-0,38
Kisc	//	-0,9305	//	-0,955	//	-0,941	//	-0,914
V_{th1} (v)	1,413	1,366	1,402	1,356	0,8478	0,8196	0,8414	0,8134
V_{th2} (v)	1,413	1,366	1,402	1,356	0,8478	0,8196	0,8414	0,8134
I_{sc} (A)	9,32	7,55	8,90	7,19	2,95	2,38	3,08	2,50
I_{ph} (A)	9,32	7,551	8,90	7,19	2,95	2,381	3,08	2,501
V_{oc} (v)	37,9	34,8	38,3	34,5	22,1	19,8	22,60	20,66
R_s (Ω)	0,3637	0,4728	0,2522	0,2799	0,6039	0,6514	1,012	1,109
R_p (kΩ)	10,94	6,768	12,48	7,720	11,5	6,899	10,630	6,575
I_{sat1} (A)	$1,047*10^{-11}$	$3,261*10^{-11}$	$6,114*10^{-12}$	$3,177*10^{-11}$	$7,047*10^{-12}$	$3,844*10^{-11}$	$3,323*10^{-12}$	$1,162*10^{-11}$
I_{sat2} (A)	$1,047*10^{-11}$	$3,261*10^{-11}$	$6,114*10^{-12}$	$3,177*10^{-11}$	$7,047*10^{-12}$	$3,844*10^{-11}$	$3,323*10^{-12}$	$1,162*10^{-11}$
I_{mp} (A)	8,8663	7,14225	8,5023	6,8353	2,80285	2,25262	2,90812	2,3517
V_{mp} (v)	30,3958	27,42244	31,7892	28,497	17,8568	15,91923	17,2212	15,7429
P_{max} (w)	269,4983	195,8579	270,281	194,7864	50,0499	35,86	50,0813	37,0239
ΔP_{max}%	**0,00063**	**0,000459**	**0,00036**	**0,00020**	**0,00019**	**0.00006**	**0,00039**	**0,0005**

The simulated values represented in Table I.2 show that these mathematical equations allowed the identification of electrical parameters for various monocrystalline and polycrystalline panels with an absolute relative error of the maximum output power ranging from 0.00006 to 0.00063. In this range, the smallest value under standard test conditions is obtained for the polycrystalline type, which indicates the best identification, while for 270 W photovoltaic panels, the best identification is obtained for the monocrystalline type. In addition, the calculated values of the photocurrent, the open-circuit voltage, and the short-circuit current for each used photovoltaic panel are equal to the datasheet's values. Moreover, the values of the maximum output power and its corresponding current and voltage are close to the datasheet's values.

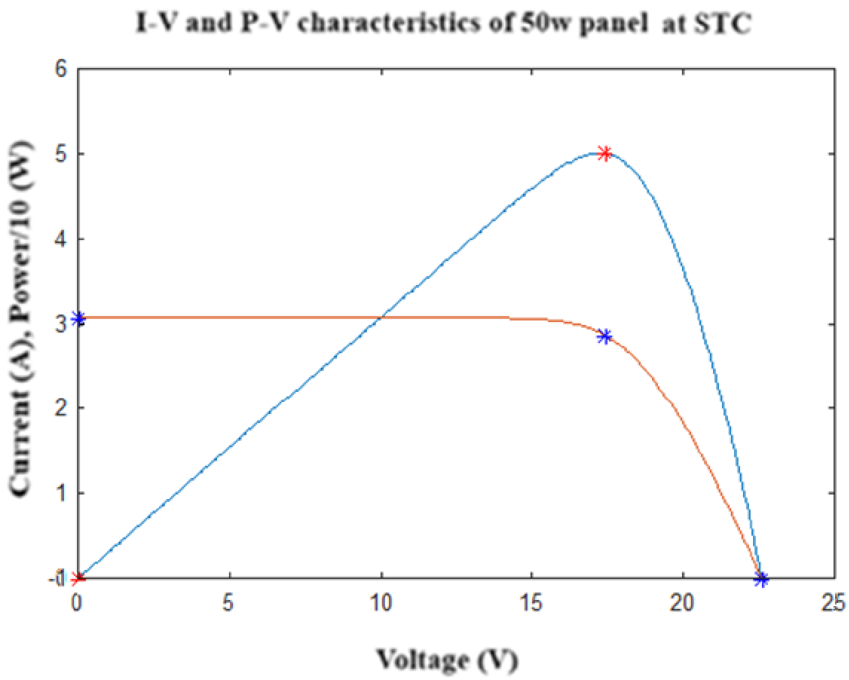


Figure I.3. Current–voltage and power–voltage curves under STC for 50W mono-crystalline photovoltaic panel.

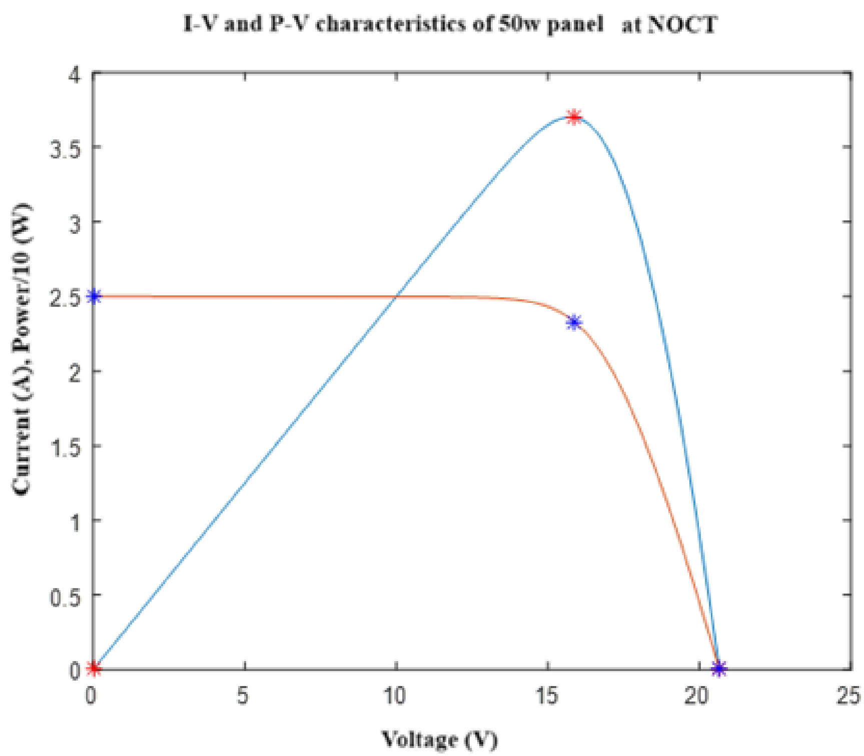


Figure I.4. Current–voltage and power–voltage curves under NOCT conditions for 50 W mono-crystalline photovoltaic panel.

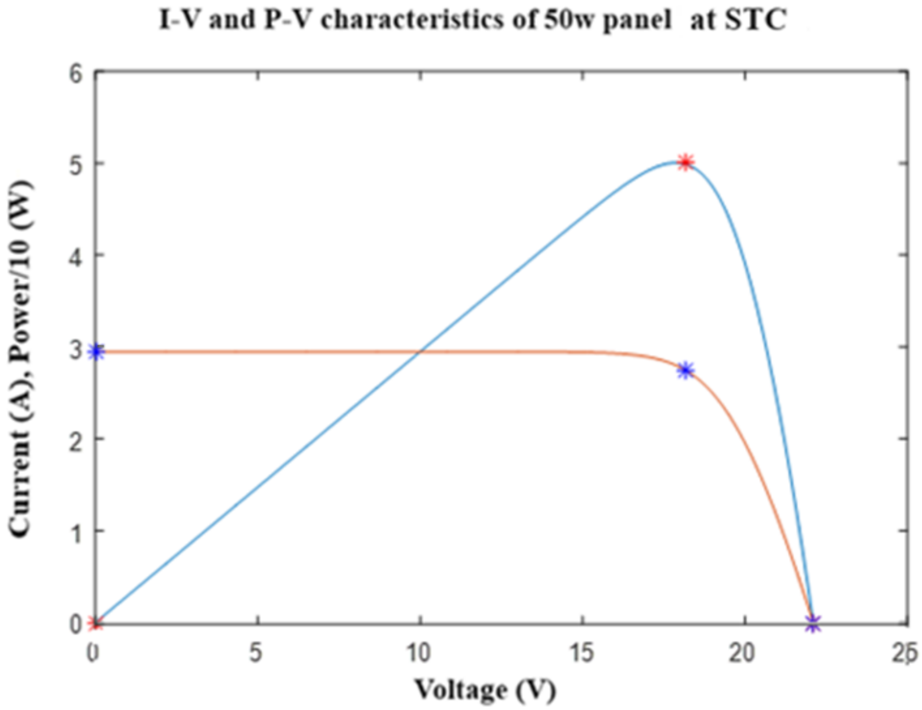


Figure I.5. Current–voltage and power–voltage curves under STC for 50 W poly-crystalline photovoltaic panel.

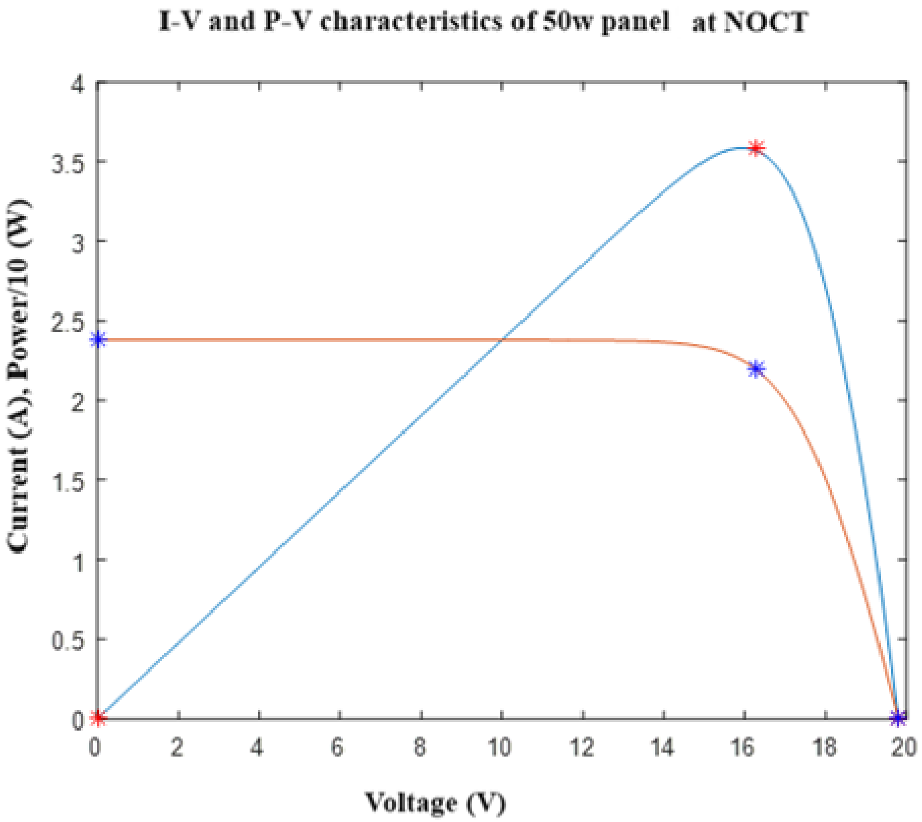


Figure I.6. Current–voltage and power–voltage curves under NOCT conditions for 50W poly-crystalline photovoltaic panel.

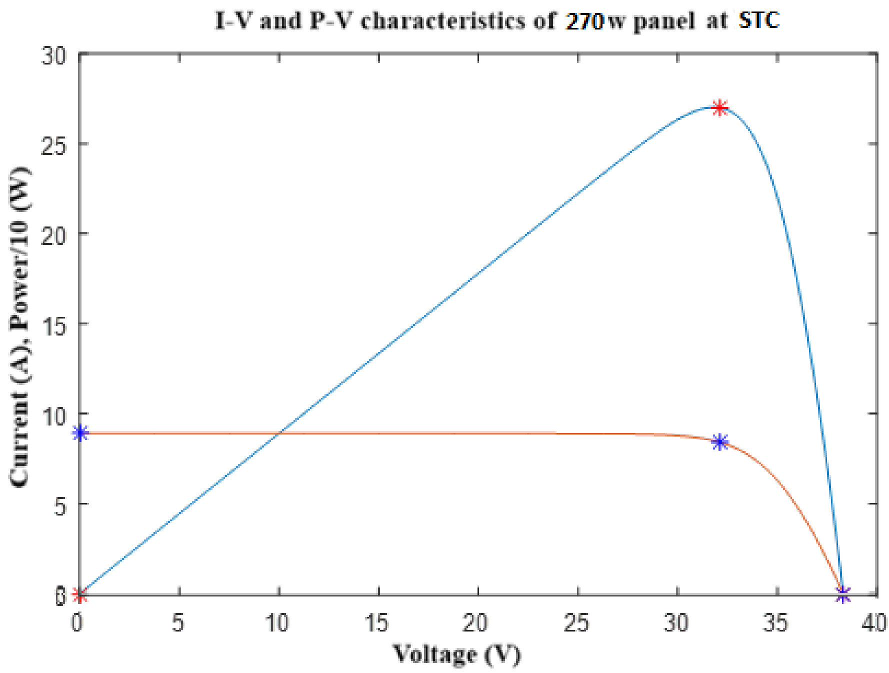


Figure I.7. Current–voltage and power–voltage curves under STC for 270W mono-crystalline photovoltaic panel.

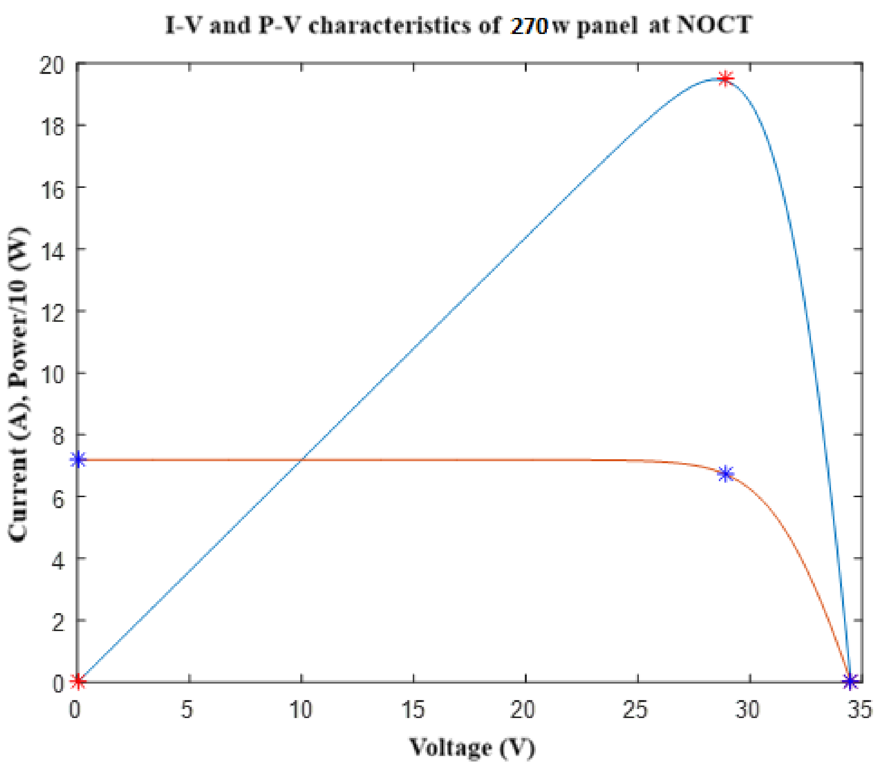


Figure I.8. Current–voltage and power–voltage curves under NOCT conditions for 270W mono-crystalline photovoltaic panel.

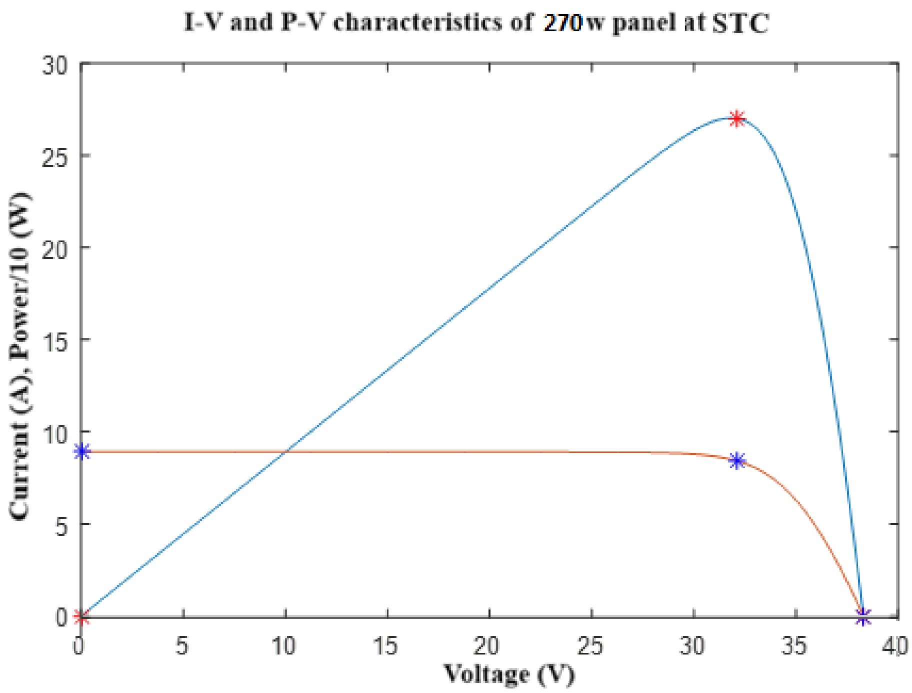


Figure I.9. Current–voltage and power–voltage curves under STC for 270 W poly-crystalline photovoltaic panel.

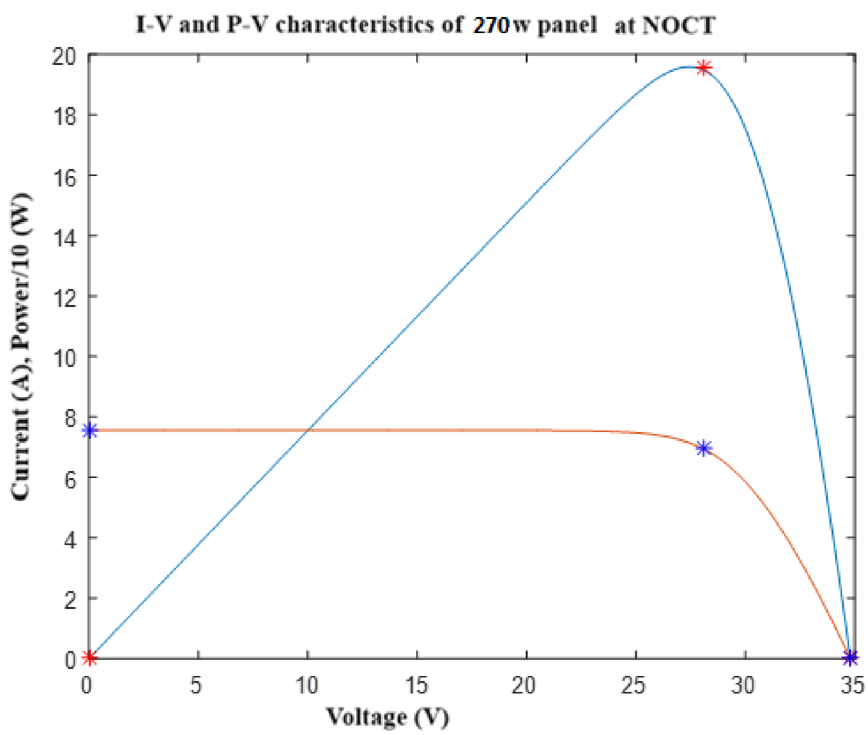


Figure I.10. Current–voltage and power–voltage curves under NOCT conditions for 270 W poly-crystalline photovoltaic panel.

Figures I.3–I.10 show that the curves of the current–voltage drawn from the calculated values pass perfectly through the three points, namely: short-circuit current, open-circuit voltage, and the maximum power point of the datasheet.

I.9 Conclusion

In this chapter, the unknown parameters of two types of photovoltaic panels have been identified by implementing the mathematical equations using MATLAB/Simulink software.

This method seems good and yields results with acceptable absolute relative error; however, the adjustment of the variable to get the simulated values as close as the datasheet's values is too time-consuming and exhausting. Not to mention that reading data from graphs is done visually, making it susceptible to errors. Therefore, in the next chapters, we will resort to artificial intelligence to identify these parameters.

CHAPTER II

ARTIFICIAL INTELLIGENCE AT THE SERVICE OF PHOTOVOLTAIC ENERGY

Chapter II. Artificial intelligence at the service of photovoltaic energy

II.1. Introduction

Photovoltaic energy is an inexhaustible and promising energy source, produced by solar panels. Given that, identifying the electrical parameters of photovoltaic panels is crucial for improving their efficiency. Many researchers have turned to various identification techniques, from classical to artificial ones.

In a general sense, artificial intelligence (AI) means the simulation of human behavior. In other words, it makes it possible for machines to mimic humans through algorithms and mathematical functions.

The introduction of artificial intelligence to identify the parameters of photovoltaic panels marks a significant advancement in the field of solar energy. Unlike classical techniques, which often rely on complex mathematical models and iterative calculations that can be sensitive to measurement errors, artificial intelligence techniques allow for the processing of massive volumes of data to extract precise information about the performance of solar panels within a well-defined timeframe [21].

The importance of artificial intelligence in this field lies in its ability to improve the accuracy, speed, and reliability of identifying PV panel parameters using techniques such as machine learning and artificial neural networks [11-22], fuzzy logic [25-30], neuro-fuzzy networks [20], metaheuristics inspired by natural phenomena (genetic algorithms [20, 31, 32, 33, 34, 35, 38], ant colony algorithms [37], PSO (particle swarm optimization) algorithms[3, 38], grey wolf algorithm [39], bat algorithms [40], SOA seagull optimization algorithms [41]…etc.).

In this chapter; the artificial intelligence techniques used for solar energy systems, namely: (1) Artificial neural networks, (2) Fuzzy logic and (3) Genetic algorithms have been explained.

II.2 Artificial neural network

An artificial neural network is a computer system composed of multiple algorithms whose functioning is inspired by the operation of biological neurons in the human brain.
Figure I.1 shows the biological neuron and its artificial equivalent [12, 13].
The perceptron shown in Figure II.1.b is inspired by the biological neuron in Figure II.1.a, where the dendrites of the biological neuron correspond to the inputs of the artificial neuron, and the axon of the biological neuron corresponds to the output y of the artificial neuron. The cell body is represented in the artificial neuron with two mathematical operations: Aggregation and Activation [12, 13, 14, 16, 19, 20].

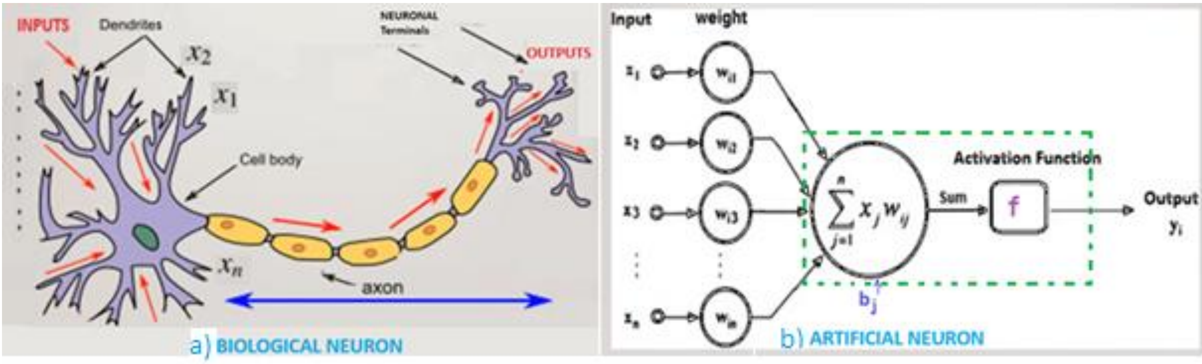


Figure II.1. The representation of the biological neuron [14, 23] and the artificial neuron [12, 19, 24].

- The aggregation sums the products of each entry with its corresponding weight.

$$Z=W1*X1 + W2*X2 +.... + W_n*X_n + b \qquad (II.1)$$

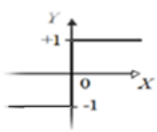
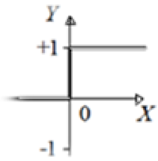
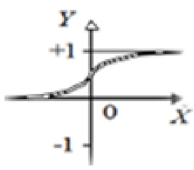
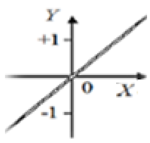
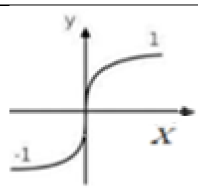
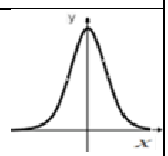
With; bj: the bias; Z is the signal after aggregation; Wi are the weights; X is the inputs vector.

- The activation A of the neuron depends on the activation function applied to the signal Z after aggregation. It can be either excitatory or inhibitory, according to the inequality given by the equation (II.2).

$$\begin{cases} \text{If Z} > \text{ threshold, then A} = 1 \text{ (excitatory signal)} \\ \qquad \text{Otherwise, A} = 0 \text{ (inhibitory signal)} \end{cases} \qquad (II.2)$$

Table II.1 shows various activation functions of the artificial neural network, from the sign function to the Gaussian function.

Table II.1. Transfer functions used in artificial neural networks [11, 12, 14, 18].

Activation function	Sign	Step	Sigmoid	Linear	Hyperbolic	Gaussian
The appearance						
Input/output function	A=1 x≥0 A=-1 x<0	A=1 x≥0 A=0 x<0	$A = \frac{1}{1+e^{-x}}$	A=x	A= tangh(αx)	$A = e^{-x^2}$

II.2.1 Neural network architecture

The architecture of the neural network varies depending on the complexity of the task to be performed as well as the nature of the data to be processed [14].

The neural network can be simple (an input layer and an output layer), as it is composed of an input layer, one or more hidden layers, and finally an output layer (multilayer network) [11, 14, 15, 17]. The hidden layers apply mathematical transformations to the input values within the network, with each neuron considered a computational unit [14, 16].

Figure II.2 shows a neural network from a mathematical perspective.

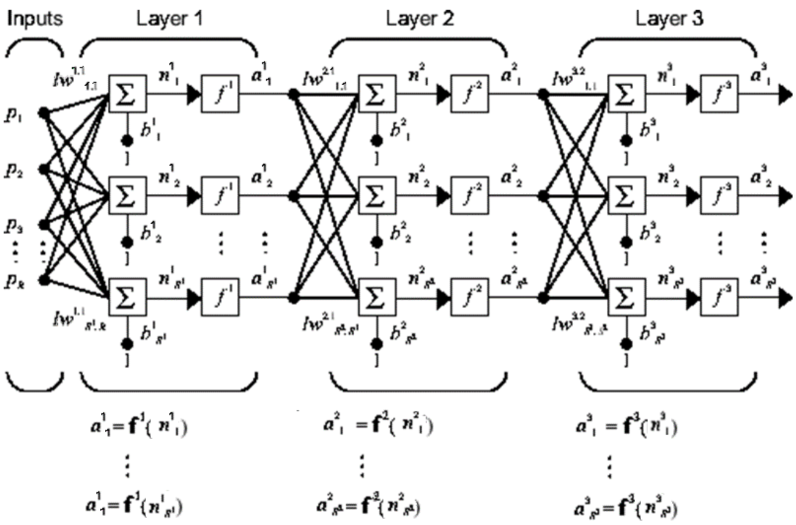


Figure II.2. Mathematical representation of an artificial neural network [13].

The following describes the four different ways that neurons in the network are connected to each other [11, 13, 14, 16, 17]:

- ✓ **Static multilayer network:** Each neuron in the previous layer is connected to the input of each neuron in the next layer, but there is no connection between neurons in the same layer, as shown in Figure II.3.a.
- ✓ **Local multilayer network:** Each neuron in the previous layer is not connected to all the neurons in the next layer, as shown in Figure II.3.b.
- ✓ **Recurrent multilayer network:** One or more neurons of the next layer or the output layer are connected to the input of the neurons of the same layer or of the previous layers, as shown in Figure II.3.c.
- ✓ **Complex multilayer networks:** Each neuron is connected to all the neurons in the network and to itself, as shown in Figure II.3.d.

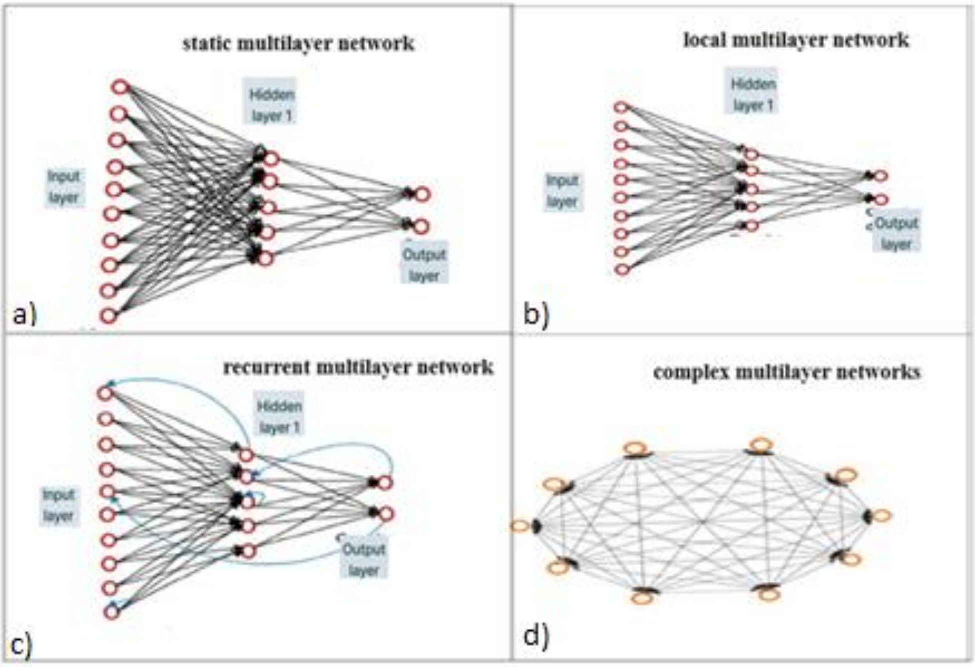


Figure II.3. Different types of connections between neurons of the ANN [14, 16, 17, 18].

II.2.2 Realization of a neural network

The implementation of a neural network for supervised learning involves the following steps [11, 16, 17, 22]:

- Choosing a network architecture suitable for the task and the dataset.
- Initializing the weights (Wi) and biases with random values.
- Forwarding input data through the neurons from one layer to another by performing calculations and applying activation functions each time. The output is the result of these random values assigned to the weights.
- Calculating the loss function (error measurement) at the network output, which calculates the difference between the values predicted by the network and the given values that should be obtained.
- Backpropagation of the measured error (back propagation) through the neural network using the backpropagation algorithms.
- Updating the weights to minimize the error at the network output using optimization rules, previously calculated gradients, and the learning rate.
- Data validation and testing: these previous steps are repeated multiple times, and at the end of each iteration, the resulting model is validated on data not seen during training (validation data) to check for overfitting. Finally, the model is evaluated on data not seen during training (test data) to verify its generalization with new data.

II.2.3 Learning of neural networks

Once the architecture is defined, artificial neural networks are often trained using various learning techniques, which are a phase of network development where synaptic weight values are adjusted by learning algorithms to best fulfill the intended task. Several types of learning are distinguished [11, 13, 14, 16, 17, 19, 22]:

II.2.3.1 Supervised learning

In this type of learning, pairs of data (inputs and corresponding outputs) are provided to the network. The synaptic weights of the network are adjusted to minimize the error signal, which consists of the difference between the obtained output value and the desired value. In this case, the network is forced to converge towards a specific final output by exploiting many examples associated with target values.

II.2.3.2 Unsupervised Learning

In this type of learning, there is no a priori knowledge about the information to be obtained, meaning that data analysis is performed without associated target values. In this case, the network is free to converge to any final output.

II.2.3.3 Reinforcement Learning

Reinforcement learning is a behavioral learning model. The algorithm receives feedback from data analysis and guides the user towards the best result. This type of learning is based on the principle of reward and punishment that the model receives while interacting with a dynamic environment, so the algorithm adjusts its behavior to maximize rewards.

II.2.3.4 Deep Learning

Deep learning is a subcategory of machine learning that incorporates complex neural networks with multiple layers to iteratively learn data. Complex deep learning neural networks are designed to emulate the functioning of the human brain and are often used in applications such as image recognition, speech recognition, computer vision, automatic translation, enterprise CEO robots, etc.

The learning and updating of weights are done by certain rules, such as Hebb’s rule, Widrow-Hoff’s rule and some optimization algorithms such as gradient descent algorithms, least square, etc. Not to mention that the cost function calculation in a neural network depends on the type of problem you are trying to solve. Generally, it is chosen to be a local error for each observation than it is generalized for all the observation. Many methods for calculation of the cost function, have been proposed such as: Cross-Entropy Loss, Mean Squared Error (MSE), Mean Absolute Error (MAE), etc.

II.2.4 Advantages of neural networks

The advantages of neural networks can be summarized in the following points [16]:

- They are extremely efficient in modelling complex and nonlinear data.
- They can be used for a wide range of tasks, including classification, regression, image segmentation, text generation, automatic translation, and more.
- The operations performed by neurons in a neural network can be highly parallelized, allowing for fast execution.
- They can be updated with new data without requiring a complete redesign of the model.
- They provide real-time response.

II.2.5 Disadvantages of neural networks

The disadvantages of neural networks can be summarized in the following points [16]:

- Some neural network models are large and require a lot of storage.
- Deep neural networks often require large amounts of data to be effectively trained.
- Input data for neural networks may require significant preprocessing for normalization.
- There is no precise rule for choosing the exact number of neurons, weights, and other network parameters.
- It is almost impossible to predict how the neural network makes its decisions.

II.3 Fuzzy logic

Fuzzy logic is an extension of Boolean logic. Based on the linguistic baths (big, small, medium, hot, cold, lukewarm, etc.) of human reasoning, it enables the analysis of imprecise and uncertain data. It doesn't require a precise understanding of the system's mathematical model. In binary logic, a variable can only be in two states: 0 (false) or 1 (true), but in fuzzy logic, a variable can be in different states than true or false (rather true, almost false, … etc.) [25, 26, 29].

II.3.1 Fuzzy System Architecture

The fuzzy system is composed of three steps (see Figure II.4), namely: fuzzification, fuzzy rules and inferences, and defuzzification. These steps are briefly explained in the following sentences [25, 26, 27, 28, 30, 42]:

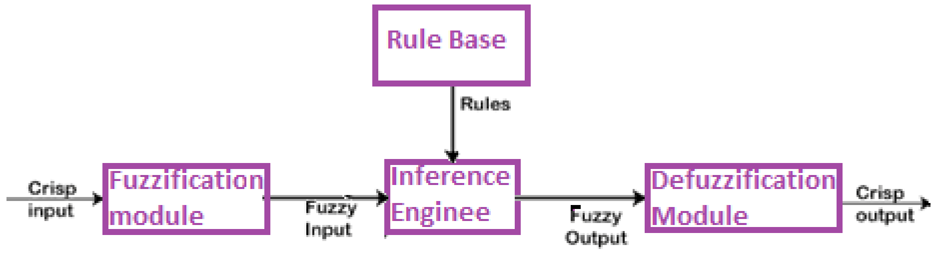


Figure II.4. Architecture of the fuzzy system.

- **Fuzzification:** Fuzzification converts numerical input data into fuzzy (linguistic) values. Before this can be done, fuzzy sets (linguistic variables) must be defined to represent the input variables and their membership degrees.
- **Fuzzy rules and inferences:** In this phase, fuzzy input variables are processed using IF-THEN rules . Fuzzy inference then applies operations to these rules to handle uncertainty and determine fuzzy output variables. A table of inference rules is created, listing conditions (IF) and conclusions (THEN).
- **Defuzzification:** This step is devoted to the calculation and decoding of linguistic variables (fuzzy) at the output into real (numerical) values by applying membership functions as during fuzzification. The most commonly used methods for defuzzification steps are the center of area method, the maximum method, the surface method, and the height method.

II.3.2 The Fundamentals of Fuzzy Logic

The basics of fuzzy logic are summarized in the following points [27, 30, 42]:

- **The operators of fuzzy logic:** They represent logical operations between the belonging functions of fuzzy values. There is complement, union and intersection.
- **Fuzzy variables:** Fuzzy logic is based on fuzzy variables (e.g., temperature, speed, etc.) with fuzzy values (e.g., hot, cold, warm, fast, medium, slow, etc.) in the universe of discourse (e.g., from 0°C to 100°C, from 0 km/h to 100 km/h, etc.).
- **Membership functions**: It is a curve that informs us about the degree of belonging to a certain fuzzy class (linguistic value).

Some forms of the functions of belonging are represented in figure II.5.

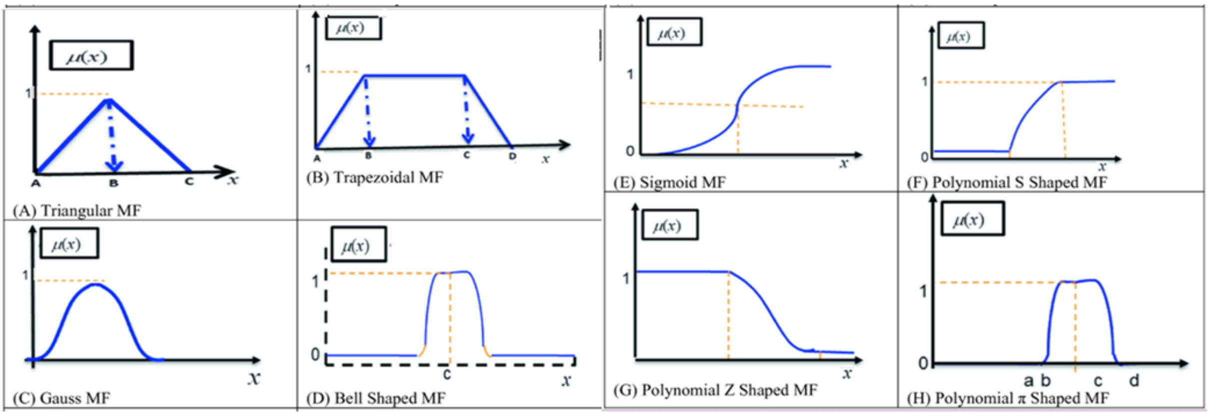


Figure II.5. The membership functions.

II.3.3 Advantages of fuzzy logic

The advantages of the fuzzy logic can be summarized in the following points [28]:

- A condition can be in a state other than true or false.
- Rules are stated in natural human language.
- It is easy to implement and allows for solving problems where data is uncertain.

II.3.4 Disadvantage of fuzzy logic.

The disadvantages of fuzzy logic can be summarized in the following points [28]:

- Adjustment techniques are primarily human-based, so they may not be precise.
- Its performance depends on expertise.
- Lack of a general theory that rigorously characterizes stability and robustness.

II.4 Genetic algorithms

Genetic algorithms are metaheuristic methods based on the population approach, which simultaneously process multiple solutions to converge towards better solutions. Genetic algorithms are optimization search techniques inspired by the natural selection process observed in biological evolution. By using an approach based on evolutionary theory, genetic algorithms generate an initial population of potential solutions, and then evolve them over successive generations using genetic operators such as selection, crossover, and mutation [31, 33, 34].

II.4.1 Organization of the Genetic Algorithm

In order to apply genetic algorithms, a population of individuals is required. Each individual has a chromosomal chain that directs his or her behavior, and these chromosomes are made up of genes that have properties that modify the way the individual will behave in the face of the problem. In addition, these individuals will be subject to selection, and only those who have advantageous characteristics in the face of the problem to be solved will survive [33, 34].

Figure II.6 shows the five steps of the genetic algorithms, staring from a bit to finish with a population

.

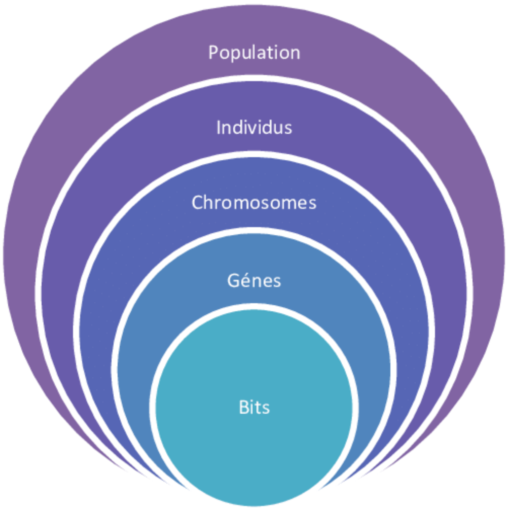


Figure II.6. Hierarchical levels of the genetic algorithm [34].

II.4.2 Principles of the Genetic Algorithms

The detailed description of how a genetic algorithm operates have been cited below [31, 33, 34]:

II.4.2.1 Coding

This step involves modelling the data in a way that can be processed by genetic algorithms. Data encoding can be in binary, real, or gray code, depending on the task at hand. Each gene of a chromosome receives a unique code.

II.4.2.2 Population generation

Defines an initial population of potential solutions. These solutions, called individuals or chromosomes, are typically represented by a coding in the form of bit strings, vectors, or other data structures. The initial population is generated randomly, and its choice influences how quickly the algorithm converges to the optimal solution.

Figure II.7 shows an example of a generation of a population where the genes are coded in binary.

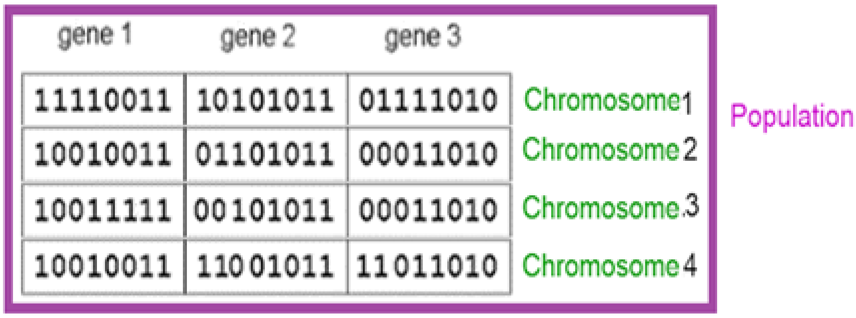


Figure II.7. Binary representation of the genes of a chromosome.

II.4.2.3 Evaluation

Evaluates each individual in the population based on a predefined criterion, often referred to as a fitness function. This function measures how "good" each individual is in relation to the optimal solution sought.

Example of evaluation:

Consider the following mathematical equation:

$$3\,x^2 + 4\,y = 76 \qquad \text{(II.3)}$$

With (x,y) represents the pair solution or the individual, where x and y take their values from 0 to 9. The fitness function is given by the equation (II.4).

$$F(x) = 3\,x^2 + 4\,y - 76. \qquad \text{(II.4)}$$

with a randomly generated population given as **(x,y) : [(9, 2), (1, 5), (8, 3), (6, 4), (7, 4)].** This population is composed of five chromosomes.

The calculated fitness value for the chromosome (9, 2) will be given by the following equation:

$$f\,(9, 2) = 3 * 9^2 + 4 * 2 - 76 = 175 \qquad \text{(II.5)}$$

In this example, the evaluation function is computed for each individual or solution pair (x, y).

The error to be minimized by genetic algorithms is calculated by several expressions depending on the objective of the optimization. Therefore, there are some common types of error expressions:

- The mean square error, given by the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(predicted - valculated)^2 \qquad \text{(II.6)}$$

- The root-mean-square error, given by the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(predicted - valculated)^2} \qquad \text{(II.7)}$$

- The mean absolute error, given by the following equation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(predicted - valculated) \tag{II.8}$$

Knowing that n is the number of elements being compared.

II.4.2.4 Selection

Selects the fittest individuals for reproduction, meaning the selection of parents from the previously generated population. Individuals with better fitness values have a higher probability of being selected, thus simulating the process of natural selection. Individual selection is performed by different operators: roulette wheel selection, tournament selection, stochastic selection, uniform selection, and elitist selection.

II.4.2.5 Reproduction

Produces a new generation of individuals by combining the characteristics of the selected individuals (parent 1 and parent 2). This is mainly done through two genetic operators

- **Crossover operator**: Two parental individuals are selected, and some of their genetic information is exchanged to create offspring. There can be a single-point crossover, a two-point crossover, or a uniform crossover (by mask).

Figure II.8. shows the operation of the crossover between parents to give birth to new children.

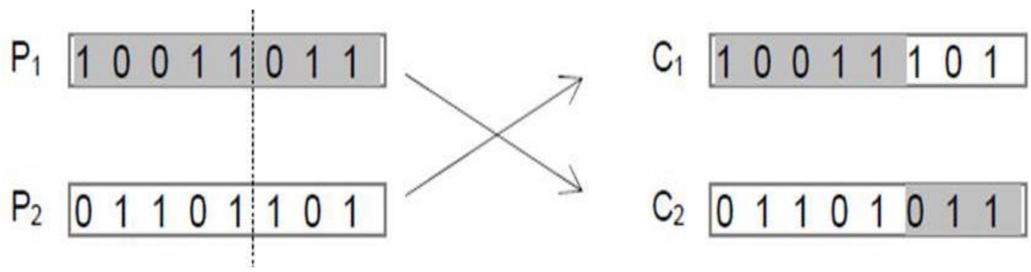


Figure II.8. The operation of crossing between two parents.

- **Mutation operator**:

Random and rare modifications are made to certain individuals in the population, introducing an inversion of one or more bits of the gene (see figure II.9).

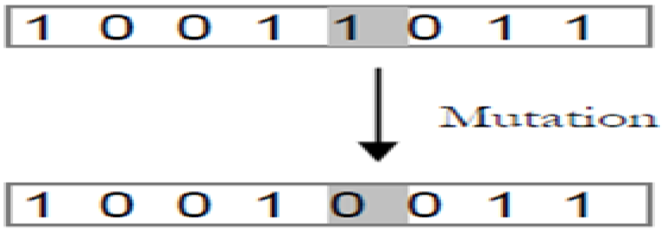


Figure II.9. The mutation of a gene.

II.4.2.6 Replacement

Keeps the population size steady by replacing the older generation (parents) with the younger generation (offspring). The new generation of people can be chosen to use several tactics, like complete replacement or partial replacement, depending on fitness.

II.4.2.7 Termination

Repeat the select, reproduce, and replace steps for a predefined number of generations until a predetermined termination condition is met. This condition can be a convergence criterion (that means stagnation of fitness improvement) or a predefined time limit.

II.4.2.8 Convergence criteria

The end of the algorithm will be reached when any of the following conditions are satisfied:

- If the algorithm has converged to the same solution after several generations,
- If the number of iterations reaches the set build number,
- If the normalized error of the best chromosome has the smallest value.

Figure II.10 shows the different steps of generation a GA with its different operators, starting with the parent to the new generation (children).

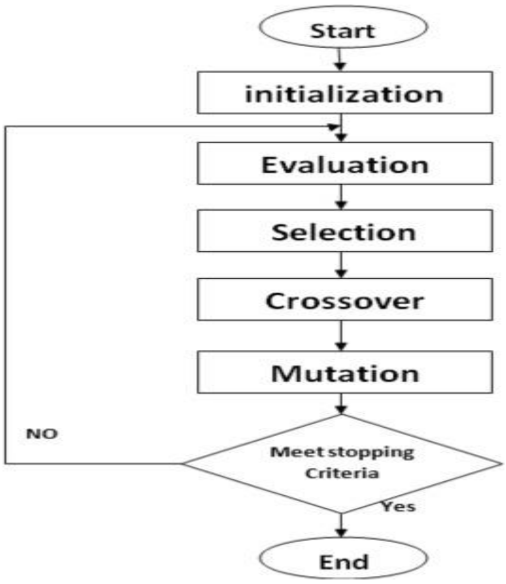


Figure II.10. The steps of generating genetic algorithms.

II.4.3 Advantages of genetic algorithms

The advantages of genetic algorithms can be summarized in the following points [31, 34]:

- They are fast and can deal with multiple solutions at once.
- They are able to efficiently exploit a large parameter search space.
- They have a great ability to find the global optimums of optimization problems.
- In photovoltaic panels, genetic algorithms offer a powerful approach to identifying the photovoltaic panel parameters by optimizing model performance.

II.4.4 Disadvantages of genetic algorithms

The disadvantages of genetic algorithms can be summarized in the following points [31, 34]:

- They do not give the exact solution, but the optimal one.
- The accuracy of the results depends on the parameters manipulated by the algorithm.
- Genetic algorithms sometimes converge on an individual with a very high adaptation value.

II.5 Conclusion

This chapter has covered three artificial intelligence techniques for determining a solar panel's electrical parameters. The three techniques are the neural network algorithm, fuzzy logic, and the genetic algorithm.

The next chapter will focus on two techniques of artificial intelligence, namely the neural network algorithm and the genetic algorithm. Those techniques will be used to estimate the unknown parameters of a solar panel with a two-diode model.

CHAPTER III

ARTIFICIAL INTELLIGENCE FOR PARAMETERS IDENTIFICATION OF A PHOTOVOLTAIC PANEL WITH A TWO-DIODE MODEL

Chapter III. Artificial intelligence for parameters identification of a photovoltaic panel with a two-diode model

III.1 Introduction

In the previous chapter, various artificial intelligence techniques that are used to identify the unknown parameters of a two-diode photovoltaic panel were introduced. Three artificial intelligence techniques were detailed, namely: neural networks, fuzzy logic, and genetic algorithms.
In this chapter, the neural network technique and genetic algorithms will be used to identify the unknown parameters of a 50-watt photovoltaic panel with a two-diode model. Starting with an introduction of the used photovoltaic panel and its electrical characteristics, then defining and applying the two chosen methodologies separately to identify the unknown parameters. Finally, at the end of each identification, the results are discussed

III.2 Characteristic of the used panel

The identification of the unknown parameters of a photovoltaic panel using artificial neural networks and genetic algorithms will be applied on a 50W Suntech photovoltaic panel. This panel comprised of 36 cells connected in series. The experimental values, which is the dataset of the panel, were collected at a temperature of 17 °C and an irradiance of 1176 W/m^2. The dataset of the panel consists of 601 measured voltage values (V_{mes}) and 601 measured current values (I_{mes}) [10] and the datasheet of the 50W Suntech photovoltaic panel is shown in Table III.1.

Table III.1: Datasheet of the 50W Suntech photovoltaic panel.

Parameters	Datasheet value
Isc (A)	3.2
Voc (V)	21.8
Ipmax (A)	2.9
Vpmax (V)	17.5
Pmax (W)	50.75

III.2 1. Identification using the neural network's method

The implementation of the neural network is carried out using programming code in MATLAB 2015, following these steps:

III.2.1.1. Implementation of the neural network

1. **Data Preparation**: The input and output data of the photovoltaic panel dataset are pre-processed before being fed into the network. This involves transposing the data into matrices using the apostrophe (‘) to avoid matrix dimension incompatibility. Then, the data are normalized using the ***MinMax*** function following the equation (III.1)

   $$Xnorm = \frac{\text{Xoriginal} - \text{Xmin}}{\text{Xmax} - \text{Xmin}} \qquad \text{(III.1)}$$

   The resulting values are within the [0,1] range to standardize their scales and facilitate the convergence of the optimization algorithm.
2. **Definition of the network architecture**: The network is of the Backpropagation type (it is used for training feedforward neural networks by adjusting weights based on the gradient descent method to minimize the error, so it requires a loss function to calculate the error). The network learning is supervised since its main task is optimization (the predicted output should resemble a given real output). The neural network is defined with an input layer, two hidden layers of ten neurons each, and an output layer. The network is set by the ***fitnet*** function and trained using ***trainlm***, its chosen learning algorithm is ***Levenberg-Marquardt***. This algorithm is widely used for effectively training neural networks for optimization tasks, minimizing the associated cost function based on *residuals*. It combines gradient descent technique when far from the solution and Gauss-Newton when close to the solution, enabling it to converge rapidly towards an optimal solution [30, 31].
3. **The chosen activation functions**: they are the sigmoid ***logsig*** for the two hidden layers and ***purelin*** for the output layer.

   Figure III.1 shows the architecture of the implemented neural network.

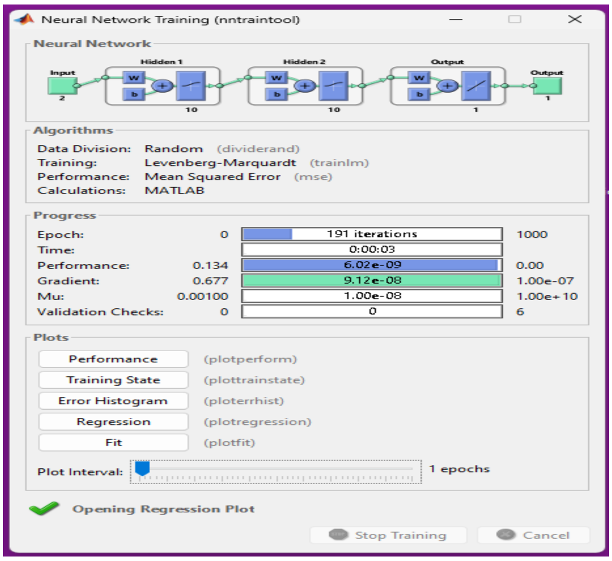


Figure III.1. Architecture of the ANN.

4. **Division of data into sets:** The data in the dataset is divided into 70% data for training, 20% data for testing, and 10% data for validation.
5. **Initialization of weights and biases:** The weights and biases of the neural network, as well as the learning rate, are initialized randomly by the algorithm at the beginning and then adjusted over time.
6. **Definition of the cost function:** The error calculation is carried out by the ***fmincon*** instructions, and the chosen cost function to be minimized is obtained by the ***mean Square Errors*** :

$$\boldsymbol{Cost} = \frac{1}{n}\sum_{i=1}^{n}(Pi - P'i)^2 \quad \text{(III.2)}$$

where n is the total number of observations, Pi is the actual value for observation i of the measured power, and P'i is the predicted value for observation i of the calculated power.
7. **Training of the neural network:** The network is trained with the data from the dataset, which means the measured current I_{mes} and the measured voltage V_{mes}.
8. **Cross-validation**: After the training, the algorithm will use 10% of the dataset (validation data) to evaluate the network's performance and detect if there is an overfitting.
9. **Testing Phase**: After the validation, the chosen model is tested on 20% of the dataset (test data) to assess if the network generalizes well to new data.

Figures III.2 and III.3 show the training result obtained at the 191st iteration at a time of 3s under Windows 10 on an ASUS intel-i5 VivoBook of RAM = 8 GO.

Figure III.2 of the regression diagrams shows that there is agreement between the predictions and the true values, that is, the values predicted by the network either during training or testing follow all their targets. The training and testing ratio exceeds 0.9%.

Figure III.3 shows that the evolution curves of the MSE error during training, testing, and validation almost overlap. The three performance curves converge to a value of 10^{-9} at the 191st epoch. This result indicates successful training, although the training stopped at the 191st epoch as the gradient reached its limit.

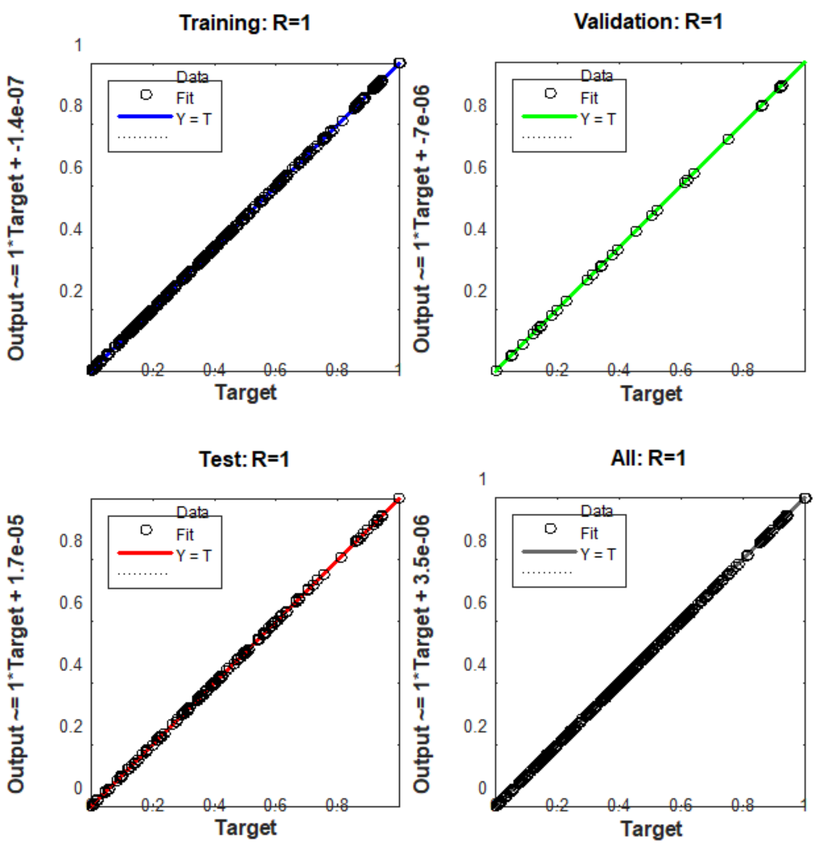


Figure III.2. Regression diagram produced during the training of the network.

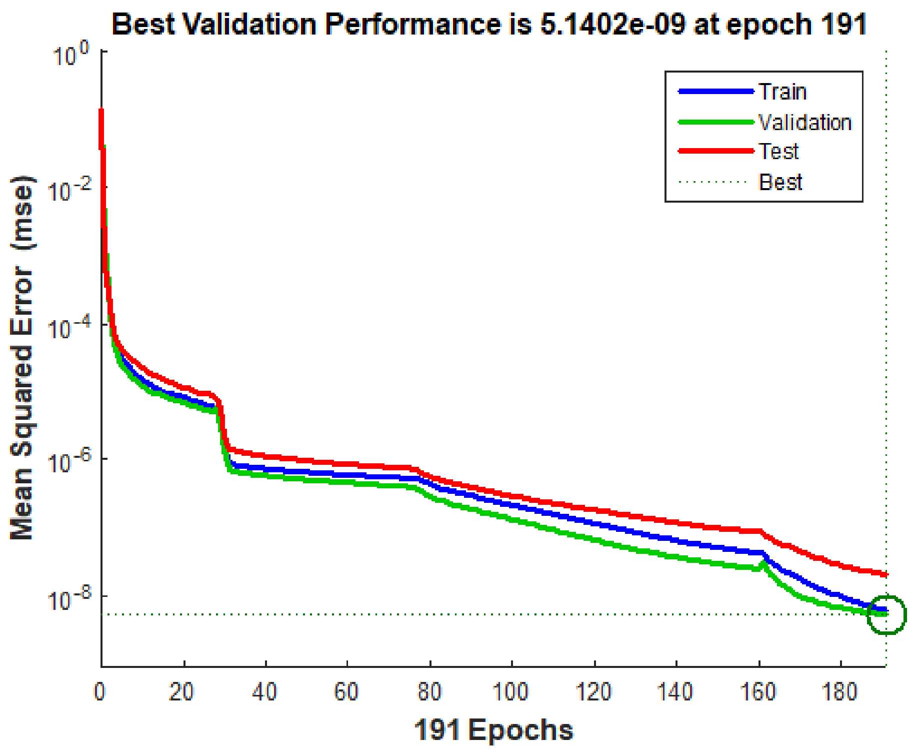


Figure III.3. Performance curves or MSE evolution curves.

The steps of the neural network training process are summarized in the flowchart shown in Figure III.4.

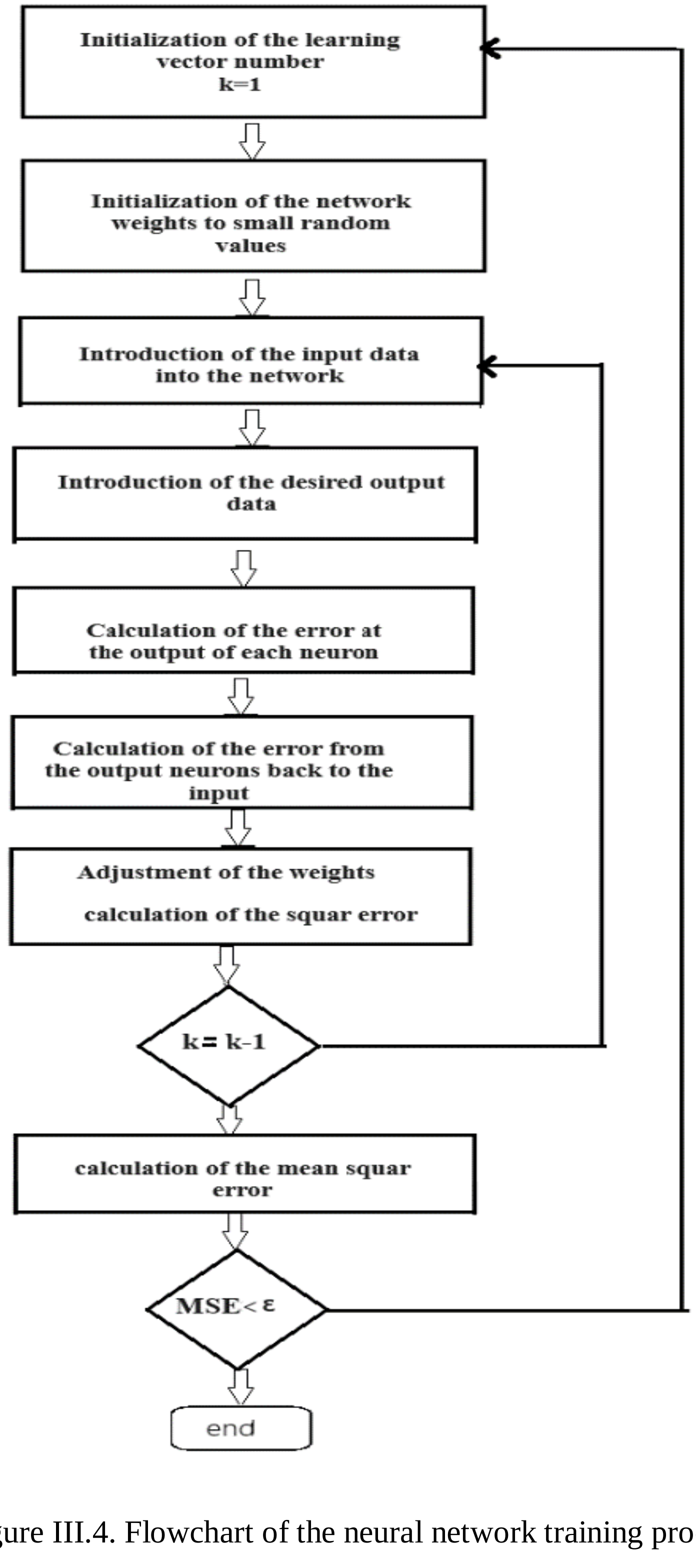


Figure III.4. Flowchart of the neural network training process

III.2.1.2 Identification and results

The neural network is trained and utilized to estimate the seven unknown parameters of a 50W photovoltaic panel. As a result, the parameter evaluation function will be the photovoltaic panel's output power equation. Knowing that the power (P) from the solar panel dataset serves as the neural networks' output, and that the current (I) and voltage (V) from the solar dataset serve as the neural networks' inputs. The model given to the neural network is the equation of power (I.6) where I is given by the equation (I.5).

The obtained results after applying the neural network algorithm are shown in Table III.2. The power-voltage characteristic curves that are generated using the neural network algorithm and the dataset are shown in Figure III.5.

Table III.2: Experimental values and predicted values by the neural network.

	Measured values [10]	Estimated values using Simulink [10]	ANN values at 619th epochs and 404th epochs
Iph(A)	/	3.0651783	3.063
$Isat_1$(A)	/	$32.7536*10^{-09}$	$1.9772*10^{-08}$
$Isat_2$(A)	/	$32.7536*10^{-9}$	$2.2712*10^{-08}$
Vth1=	/	1.1135299	1.0922
Vth2=	/	1.1135299	1.0938
Rs (Ω)	/	0.52187354	0.55275
Rp (Ω)	/	3109.020864	3000.3349
Impp (A)	2.811	2.8321	2.811
Vmpp (V)	15.408	15.2933	15.408
Pmax (w)	**43.3119**	**43.31215493**	**43.3120 (619 epochs)**
			43.3119 (404 epochs)
Isc (A)	/	3.0646637	/
Voc (V)	/	19.663987	/
ΔP_{max}%	**/**	**$6.16*10^{-4}$**	**$2.30*10^{-4}$ (619 epochs)**
			0 (404 epochs)

In this study, it is important to note that the neural network is calculating the power, while the current and voltage values are provided by the dataset. The maximum power point's voltage (Vmpp) and current (Impp) calculated by the neural network are those given in the dataset.

The Absolut relative error in the maximum power point (Pmax) is calculated using the following formula:

$$\Delta P_{max}\ \% = \frac{|P_{max-Calculated} - P_{\max-\text{ Measured}}|}{P_{\max-\text{ Measured}}} * 100 \qquad \text{(III.3)}$$

The measured maximum power corresponds to the 82nd observation of the measured voltage and the 82nd observation of the measured current. The calculated neural network's maximum power is displayed at the 82nd observation of the calculated values shown in the MATLAB results window. At the maximum power point, which corresponds to the 82nd observation, the measured voltage, Vmpp, is 15.408V and the measured current, Impp, is 2.811A from the dataset. The calculated value of the neural network for the maximum power is equal to 43.3120 W after 619 epochs.

Therefore, the calculated values of the maximum power by the neural network are close to those provided in the dataset. Additionally, the identified values of unknown parameters by the neural network are close to those estimated using Simulink blocks.

Figure III.5 shows the obtained power-voltage curve using the neural network technique. Based on this figure, the predicted values by the neural network technique closely follow the curve of the measured values.

Figure III.6 represents the block of different results generated by the neural network after identifying the unknown parameters at the 404 epochs. This figure shows that the testing processus is getting bad after the 50^{th} epoch, that means the network doesn't generalize well with new data after the 50^{th} epoch, even if there is no overfitting and the training is still good.

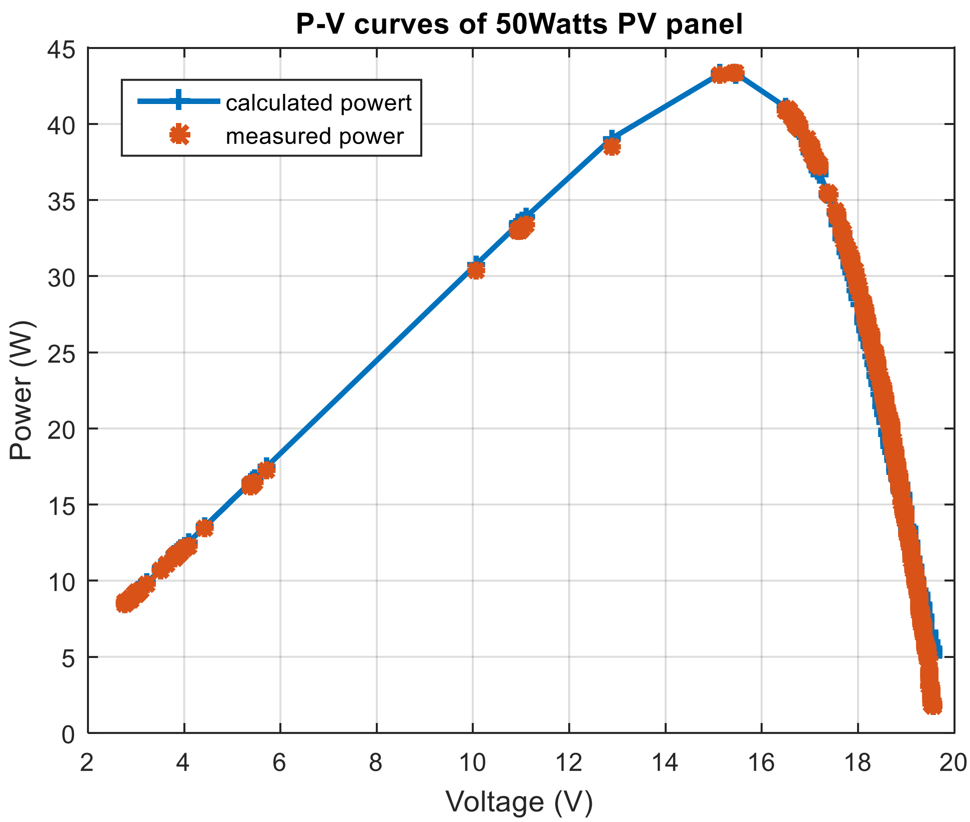


Figure III.5. Power-voltage curves for 50 W Suntech photovoltaic panel under random daily conditions.

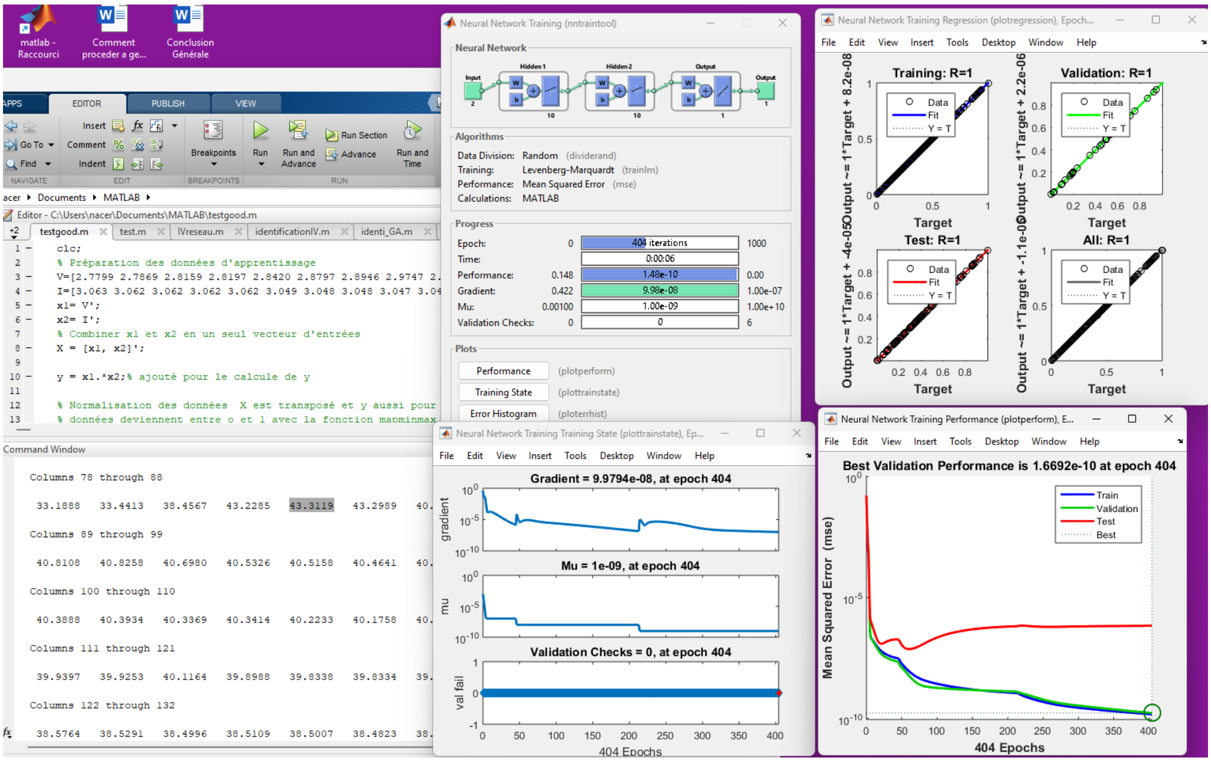


Figure III.6. Block of identifying unknown parameters using a neural network at 404 epoch.

III.2.2 Identification using Genetic Algorithms

The implementation of the genetic algorithms is carried out using a programming code in MATLAB 2015, following these steps:

III.2.2.1 Implementation of Genetic Algorithms

Identifying the parameters of a photovoltaic panel using genetic algorithms involves finding global minima by optimizing a certain function called the *fitness* function. The parameter ranges to be identified entail constrained optimization.

In this method, the parameters of the model to be identified are grouped into a vector called a chromosome, knowing that a set of chromosomes constitutes what is called a population. The operating principle of genetic algorithms is summarized in a flowchart shown in Figure III.7.

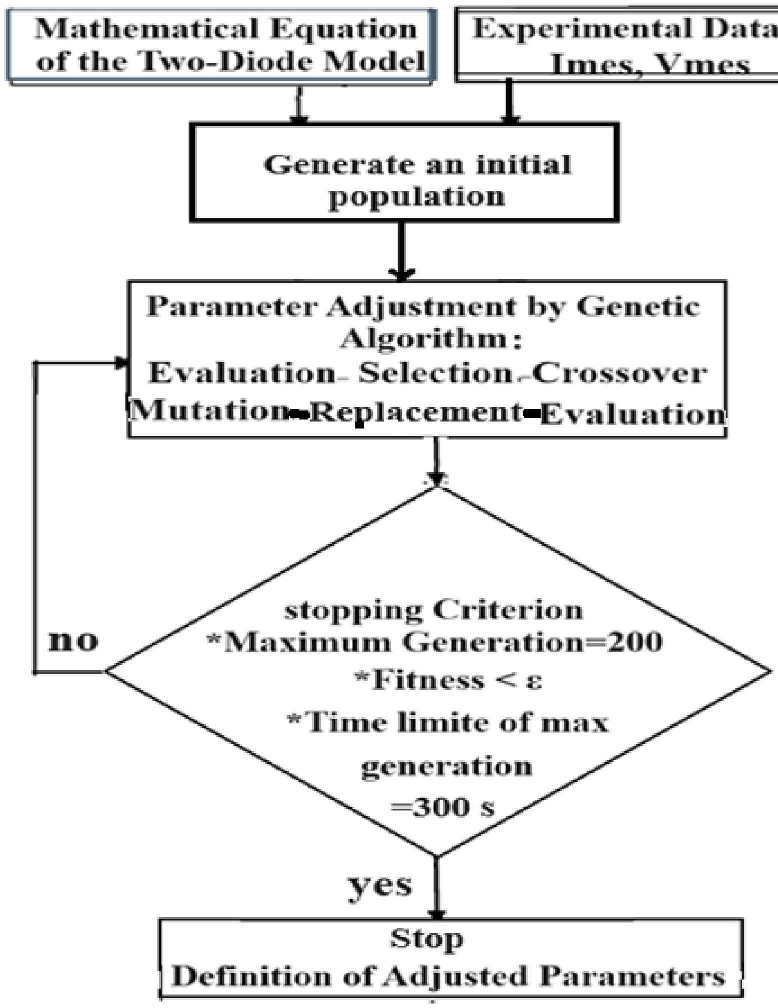


Figure III.7. Evolutionary flowchart of genetic algorithms.

The implementation of the genetic algorithm optimization is based on the following steps:

1. **Data Preparation**:

The data set of measured current and measured voltage is presented. Variation ranges (constraints) are defined for our parameters.

2. **Declaration of the fitness function**:

The fitness function, f, allows the evaluation of each individual (chromosome). In our case, the objective function to be minimized is given by the following equation.

$$\boldsymbol{Cost} = \sum_{i=1}^{n}(Ii - I'i)^2 \tag{III.4}$$

where Ii is the i^{th} observation of the measured current and Ii' is the i^{th} calculated current.
n is the total number of observations.

3. **Implementation of genetic algorithms and their options**:

Genetic algorithms are implemented using the ***gaoptimset*** function with the following options: generating a population of 100 individuals, limiting the number of generations to 200, limiting the execution time without improvement to 300 seconds, and for other options such as the type of selection, crossover, etc., the algorithm will choose default settings.

4. **Individuals' evaluation**:

After initializing the population with 100 individuals, each individual is evaluated based on its fitness function. Individuals are then selected to be the parents. These parents reproduce through various processes (crossover and mutation) to form a new generation that replaces the parents. The new generation (children) is evaluated too, so if it does not satisfy the required criteria, it will go through the same process as their parents, and this process continues until the required criterion is satisfied.

III.2.2.2 Identification and results

The obtained results for the 50W Suntech photovoltaic panel using genetic algorithms are presented in Table III.3. The curves of the measured current (dataset) and the calculated current using the genetic algorithm as a function of the photovoltaic panel's voltage are depicted in Figure III.8.

Table III.3: Experimental values and predicted values using genetic algorithms at a fitness of 0.688964.

	Measured values [10]	Estimated values using Simulink [10]	GA values at fitness = 0.688964
Iph (A)	/	3.0651783	3.0225
$Isat_1$ (A)	/	32.7536e-09	$9.0656*10^{-8}$
$Isat_2$ (A)	/	32.7536e-9	7.5733^{e}-10
Vth1	/	1.1135299	1.0130
Vth2	/	1.1135299	1,0168
Rs (Ω)	/	0.52187354	0.45233
Rp (Ω)	/	3109.020864	3728.4767
Impp (A)	2.811	2.8321	2.8055
Vmpp (V)	15.408	15.2933	15.408
Pmax (w)	**43.3119**	**43.31215493**	**43.2271**
Isc (A)	/	3.0646637	/
Voc (V)	/	19.663987	/
ΔP_{max}%	/	**$6.16*10^{-4}$**	**0.2**

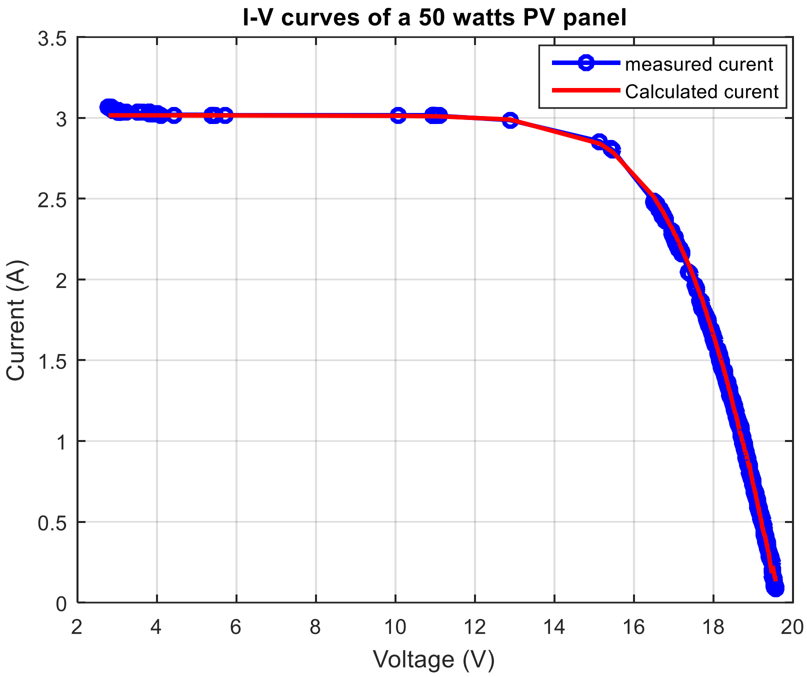


Figure III.8. Current-voltage curves obtained using the dataset values and genetic algorithms for Suntech 50 W photovoltaic panel.

Figure III.8 illustrates how closely the estimated current-voltage curve to the measured one. Knowing that, the used genetic algorithm calculates only the photovoltaic panel's current using the measured values of the current and the voltage, I_{mes} and V_{mes}, respectively. The absolute relative error of the maximum power obtained using the genetic algorithm can be obtained using the equation (III.3).

The 82nd observation in the dataset corresponds to the measured values of the voltage and current at the maximum power point (that means $V_{\mathrm{mpp-\,Mes}}$ = 15.408V, $I_{\mathrm{mpp-\,Mes}}$= 2.811A, and $P_{\mathrm{max-\,Mes}}$ = 43.3119 W). The corresponding calculated current at the maximum power point using genetic algorithms is very close to that measured ($I_{\mathrm{mpp-}\,Cal}$= 2.8055A, and $P_{\mathrm{max-}\,Cal}$ = 43.2271W). Knowing that the maximum power calculated is given by: $p_{\mathrm{max-}\,Cal} = 2.8055 * 15.408$.

It is noticed that the obtained results using genetic algorithm are close to the dataset value.

Figure III.9 shows the variation of the fitness function while the genetic algorithm calculates the current by adjusting the seven unknown parameters.

The fitness curve shown in Figure III.9 which represents the error made between the calculated and measured currents, is close to zero, which means a good prediction.

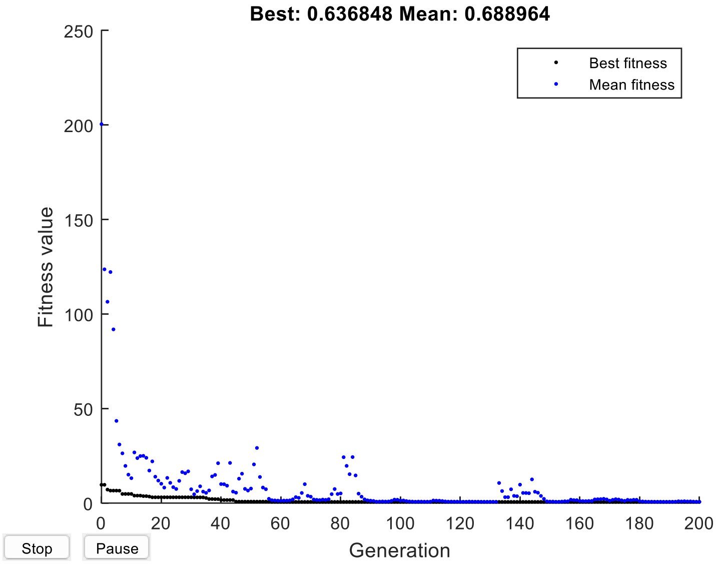


Figure III.9. The curve of fitness evolution during the generation.

III.3 Conclusion

The aim of this chapter is to identify the unknown parameters of a 50 W Suntech photovoltaic panel using a neural network algorithm and a genetic algorithm. Identification using the neural network algorithm is performed with the power-voltage characteristic equation for a photovoltaic panel with a two-diode model. In addition, identification using genetic algorithms is carried out with its current-voltage characteristic equation. Therefore, identification using artificial intelligence algorithms can be obtained based on both characteristic equations.

A neural network algorithm is a powerful and promising approach that can contribute to a better understanding and optimization of photovoltaic system performance. However, for their training and learning, a large amount of experimental data is required, and the choice of their structure must be varied until satisfactory results are obtained.

The use of genetic algorithms for identifying the electrical parameters of a photovoltaic solar panel is a common approach in modelling and simulating photovoltaic systems. While genetic algorithms may not provide the exact solution, they have proven their effectiveness in searching for a solution very close to the optimum.

GENERAL CONCLUSION

General conclusion

Photovoltaic energy is an essential source of renewable energy, offering significant advantages in terms of sustainability and reduction of carbon emissions. By converting sunlight directly into electricity using photovoltaic cells, this technology plays a crucial role in the global energy transition. To improve the performance of photovoltaic cells, various models and optimization methods have been proposed.

Among the different proposed photovoltaic cell models, the two-diode model is chosen in this work for its accuracy, as it considers the recombination effects of charge carriers in the junction and bulk regions, thus providing a better simulation of the actual performance of the cell.

Simulink, a widely used tool for modelling and analyzing photovoltaic systems, allows for the simulation of photovoltaic cell performance by integrating different components and operating conditions, thus facilitating the study and optimization of systems. However, in the case considered in this study, numerous mathematical equations (characterizing each parameter to be identified) are involved in creating the mathematical model of the PV cell. This requires considerable attention and time to implement the various blocks representing these equations and to achieve the desired results, the accuracy of which relies on the human visual system.

Artificial intelligence techniques, particularly artificial neural networks, surpass classical methods in identifying the electrical parameters of photovoltaic models. A neural network algorithm can learn and generalize from large amounts of experimental data without the need for extensive equations, enabling precise parameter estimation even in the presence of nonlinearities and noise in the data. In this work, a single characteristic equation was sufficient for identification using a neural network algorithm.

For better identification using artificial intelligence, the selection of initial options is crucial for ensuring the algorithm's rapid convergence to an optimal solution. For instance, in genetic algorithms, choosing the initial population is vital, and in neural networks, the selection of initial weight values is essential, but how to choose exactly these options?

In this dissertation, neural networks learning is done for a single 50-watt panel under specific well-defined conditions. It would be interesting to develop a neural network capable of learning the characteristics of multiple 50-watt panels of different technologies and predicting their unknown parameters without needing to alter its architecture each time.

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