



PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA
MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
ECHAHID HAMMA LAKHDAR UNIVERSITY OF EL OUED



Faculty of Technology

MASTER ACADEMIC DEGREE
Specialty: Electrical networks
Level: 02 Master

End of study dissertation
Presented for graduation from

**A Comparative study between different MPPT
algorithms for PV system**

Presented by:

- ❖ DAHA ADEM
- ❖ BESSEI MOHAMMED BACHIR

The defence was made before a jury consisting of:

<i>President</i>	<i>D.r. Ilyas Chouki</i>	<i>MCA</i>	<i>University of El-Oued</i>
<i>Examiner</i>	<i>D.r. Boughala Mohamed Salah</i>	<i>MCA</i>	<i>University of El-Oued</i>
<i>Protractor</i>	<i>D.r. Toumi Dgaafar</i>	<i>MCA</i>	<i>University of El-Oued</i>

Academic Year : **2025 / 2026**

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

شكر وتقدير

الحمد لله الذي بنعمته تتم الصالحات، وبفضله تُذلل الصعاب وتُثال المقاصد، أما بعد:

بفضل الله تعالى، بلغنا محطة مهمة من مسيرتنا العلمية، نضع بين أيديكم ثمرة جهد طويل، وسعي متواصل، وسهر ليلٍ حافلة بالأمل والعزيمة.

ولا يسعنا في هذا المقام إلا أن نتقدم بجزيل الشكر وعظيم الامتنان إلى أستاذنا الفاضل الدكتور تومي جعفر، الذي لم يبخل علينا بعلمه وخبرته، وكان نعم الموجّه والداعم. فقد كان لتوجيهاته السديدة، وملاحظاته القيّمة، وصبره في المتابعة، الأثر البالغ في إتمام هذا العمل وإخراجه بهذه الصورة.

كما نتقدم بخالص الشكر والتقدير إلى عائلتنا الكريمة، التي كانت لنا السند والداعم، ووفرت لنا بيئة محفزة على العمل والاجتهاد، ونثمن تفهمهم وصبرهم خلال فترات الغياب والانشغال.

ولا ننسى أن نعبر عن عميق امتناننا لأصدقائنا الأعزاء، الذين رافقونا خلال هذه الرحلة، فكانوا عوناً لنا في لحظات الصعوبة، ومصدر دعم وتشجيع في كل خطوة.

وفي الختام، نتوجه بالشكر لكل من كان له أثر طيب في مسيرتنا، وإن لم نذكره بالاسم، فله منا كل التقدير والعرفان، فمكائنته في القلب أسمى من أن تحيط بها الكلمات

Chapter I

MODELLING OF A PHOTOVOLTAIC GENERATOR

I.1. Introduction.....	4
I.2. Principle of photovoltaic conversion	4
I.2.1. Photovoltaic effect	4
I.2.2. Photovoltaic cells	5
I.2.3. Photovoltaic generator	14
I.3. MATLAB simulation of a photovoltaic generator	18
I.3.1. Choice of panel	21
I.3.2. Influence of Different Parameters	22
I.4. Conclusion	24

Chapter II

MPPT CONTROL AND THE DC-DC CONVERTER

II.1. Introduction	26
II.2. Direct connection between the PV array and the load	26
II.3. Optimal operation of a GPV	26
II.4. (DC/DC) Converter	27
II.5. Modelling of the boost chopper.....	27
II.6. Maximum Power Point Tracking Method.....	31
II.6.1. Definition of MPPT in a photovoltaic solar system.....	32
II.6.2 Summary of the various MPPT encountered in the literature.....	32

II.6.3. P&O Perturbation and Observation Algorithm.....	33
II.6.4. P&O ALGORITHM.....	34
II.7. Biological foundations.....	36
II.7.1. Biological Basics.....	36
II.7.2. Structure of the biological neuron.....	36
II.8. Principles of an artificial neural network.....	37
II.8.1. Activation functions	38
II.8.2. Architecture of neural networks.....	40
II.8.3. Learning.....	41
II.8.4. The -perceptron.....	44
II.9. Choosing the network structure.....	47
II.9.1. Presentation of the two algorithms used for training the proposed neural network.....	50
II.9.2. Training using the backpropagation algorithm.....	50
II.9.3. Training using the Levenberg- Marquardt algorithm.....	51
II.9.4. Validation: “ generalisation ability”.....	52
II.10. Conclusion.....	53

Chapter III

Simulation of MPPT algorithms using neural networks and the P&O algorithm

III.1 Introduction.....	55
III.2. Simulation results of the neural MPPT approach.....	56
III.3. Comparison of control technique results (neural network, P&O)	56
III.4. Conclusion.....	62

List of figures

I.1 Operating principle of a PV cell.....	5
I.2 : Equivalent circuit of a PV cell.....	7
I.3 : Static I(V) characteristics, (a) I(V) of a photodiode, (b) I(V) of a PV cell.....	8
I.4 : Optimal operating point of a PVcell.....	11
I.5 : Effect of series and shunt resistors on the I(V) characteristic.....	12
I.6: Effect of temperature on the I(V) characteristic[9] Effect of illuminance.....	13
I.7: Effect of illuminance on the I(V) characteristic.....	14
I.8: PV panel consisting of NSM cells in series and NPM cells in parallel Structure of a panel (b) Photovoltaic solar panel	14
I.9: Characteristics of a PV panel (a) I(V) characteristics, (b) P(V) characteristic.....	15
I.10: Characteristics of a series array of PV cells.....	16
I.11: Characteristics of a parallel array of PV cells.....	17
I.12: PV array consisting of NS modules in series and NP strings in parallel.....	18
I.13: Equivalent circuit of a PV cell without a shunt resistor.....	19
I.14: P-V characteristics of 50 W PV array with variation of irradiance.....	22
I.15: P-V characteristics of 50 W PV array with variation of irradiance.....	23
I.16: I-V characteristics of 50 W PV array with variation of irradiance.....	23
I.17: P-V characteristics of 50 W PV array with variation of temperat.....	23
II.1: Direct connection between a GPV and a load.....	26
II.2: Ideal circuit of the boost chopper.....	27
II.3: Equivalent circuit for the closed switch.....	27
II.4 : Equivalent circuit for the open switch.....	28
II.5: Waves in boost converters. (a) the voltage across the inductor; (b) the current through the inductor; (c) the current through the diode; (d) the current through the capacitor.....	29
II.6: Basic photovoltaic conversion chain with a static converter controlled by an MPPT controller on any load [18]	32
II.7: Application of the P&O algorithm to the PPV(VPV) characteristic [17]	33
II.8: P&O MPPT algorithm.....	35

II.9: Ideal switch voltage over a switching period T_s	35
II.10: Biological neuron.....	36
II.11: principle of an artificial neuron [23]	37
II.12: Heaviside function [26]. Fig. III.4: Sign function [26]	38
II.13: Linear function [25]	39
II.14: Sigmoid function [25]	40
II.15: Non-looped network [26, 25]	40
II.16: Loop network [26,25]	41
II.17: Linear threshold neuron with a single decision cell [25]	45
II.18: Architecture of the proposed neural network.....	48
II.19: General structure of the neural network in MATLAB Simulink.....	49
II.20: Internal structure of the first layer with a hidden layer of the neural network in MATLAB Simulink	49
II.21: Evaluation of the mean squared error as a function of the number of training iterations (using the backpropagation method)	51
II.22: Training error during neural network training (using the Levenberg-Marquardtmethod).....	52
III. 1. Simulink model of neural network controller MPPT with DC-DC boost convert.....	56
III. 2. Output power at standard conditions with neural network controller and conventional algorithm (P&O).....	56
III.3. Output current at standard conditions with neural network controller (ANN) and conventional algorithm (P&O).....	57
III.4. Output voltage at standard conditions with neural network controller (ANN) and conventional algorithm (P&O).....	57
III.5. Output power at different irradiance values and fixed temperature of 25 °C with neural network controller (ANN) and conventional algorithm (P&O).....	58
III.6. Output current at different irradiance values and fixed temperature of 25 °C with neural network controller (ANN) and conventional algorithm (P&O).....	58
III.7. Output voltage at different irradiance values and fixed temperature of 25 °C with neural network controller (ANN) and conventional algorithm (P&O).....	59
III.8. Output power at different temperatures and fixed irradiance of 1000 W/m ² with neural network controller (ANN) and conventional algorithm (P&O).....	59

III.9. Output current at different temperatures and fixed irradiance of 1000 W/m ² with neural network controller (ANN) and conventional algorithm (P&O).....	59
III.10. Output voltage at different temperatures and fixed irradiance of 1000 W/m ² with neural network controller (ANN) and conventional algorithm (P&O).....	60

List of tables

I.1. Settings for the BP-SX150S panel in S.T.C..... 21

II.1. Comparison table of MPPT controllers. 37

III-1. The analogy between biological neurons and artificial neurons 61

GENERAL INTRODUCTION

1. INTRODUCTION

Energy is the basis of all human activity. Today, a large proportion of global energy demand is met by fossil fuels. However, fossil fuel reserves are limited. Some developed countries have turned to nuclear energy, although this is not within the reach of all nations, particularly developing countries, and carries the risk of serious accidents. Indeed, the growth in global energy demand, the inevitable depletion of fossil fuel resources in the medium to long term, and the environmental damage caused by these energy sources have prompted the development of new, renewable energy sources, thereby ensuring sustainability and environmental protection, which has become a matter of great importance. [1]

The use of photovoltaic solar energy appears to be a necessity for the future. Indeed, solar radiation is the most abundant energy resource on Earth. The amount of energy released by the sun (captured by the Earth) in one hour could be sufficient to meet global energy needs for a year. In order to make better use of this energy and optimise its collection by photovoltaic panels, it is necessary to know the distribution of solar irradiance at the proposed site for the photovoltaic installation, under different orientations and inclinations. [1]

A photovoltaic generator can operate within a wide range of output voltage and current, but it can only deliver maximum power at specific values of current and voltage. Indeed, the generator's I-V characteristic depends on solar irradiance and temperature. These climatic variations cause the maximum power point to fluctuate. Because of this fluctuation, one or more controlled static converters are often inserted between the generator and the load to track the maximum power point. [2]

These controllers, known as MPPT (Maximum Power Point Tracking) controllers, are linked to the inverter, which acts as the interface between the PV generator and the load by ensuring that the former delivers its maximum power. MPPT techniques are used in photovoltaic systems to maximise the power output of the photovoltaic panel by continuously tracking the maximum power point, which is not easy to achieve; indeed, this tracking problem remains the subject of much research. Consequently, several methods have been developed and utilised. In this work, we develop an intelligent and innovative method, combining intelligent (neural) techniques aimed at tracking the maximum power point, as well as improving the responses obtained with

previously developed classical algorithms, regardless of variations in climatic conditions (sunlight, temperature, etc.)etc.), even under the most unfavourable conditions. The simulation results obtained have shown that the neural network technique yields good results and that this controller is efficient and highly robust.[2]

2. Organisation of the thesis

This thesis, comprising three chapters, is organised as follows:

- In the first chapter, we detail the principle of photovoltaic conversion, including the photovoltaic effect, photovoltaic cells and photovoltaic generators. We then describe in detail the mathematical model of the PV system. Next, we present simulations showing the effects of irradiance and temperature on the PV system's performance.
- In Chapter 2, we examined maximum power point tracking (MPPT) techniques, focusing on the Perturb and Observe (P&O) algorithm and neural networks, whilst explaining the working principle and characteristics of each technique.
- In Chapter 3, we simulated the P&O algorithm and neural networks and applied them to the photovoltaic system, presenting the results and conducting a comparative study of the two techniques in terms of tracking speed, stability and maximum power point extraction efficiency.
- At the end of this thesis, we provide a general conclusion

CHAPTER I
GENERAL INFORMATION
ON PHOTOVOLTAIC
GENERATORS
PHOTOVOLTAIC

I.1. Introduction

The conversion of solar radiation into electricity through the photovoltaic process is one way of harnessing solar energy. Generating electricity using clean methods has become a vital necessity in a world where the environment is threatened by pollution and the greenhouse effect [3]. Photovoltaics (PV) is a clean and inexhaustible energy source. It is an essential component of renewable energy that can help the world meet its ever-growing energy needs, whilst limiting the rise in greenhouse gas emissions and reducing environmental pollution.

In other words, photovoltaics is an intermittent energy source. It is an attractive solution as a replacement for or complement to conventional sources of electricity supply due to its many advantages [3]:

- It is a reliable source that requires little maintenance;
- It provides electricity using the sun's free and renewable energy;
- It requires no fuel;
- It is silent, non-polluting and environmentally friendly;
- It has a lifespan of around 25 year;

I.2.Principle of photovoltaic conversion

In the next section of this chapter, we will examine and analyse the electrical properties (current, voltage and power) of PV cells. First, we will briefly outline the structure and operation of a PV cell and module; we will also examine the electrical behaviour of these cells, which form the basic building blocks of PV generators. [4]

I.2.1.Photovoltaic effect

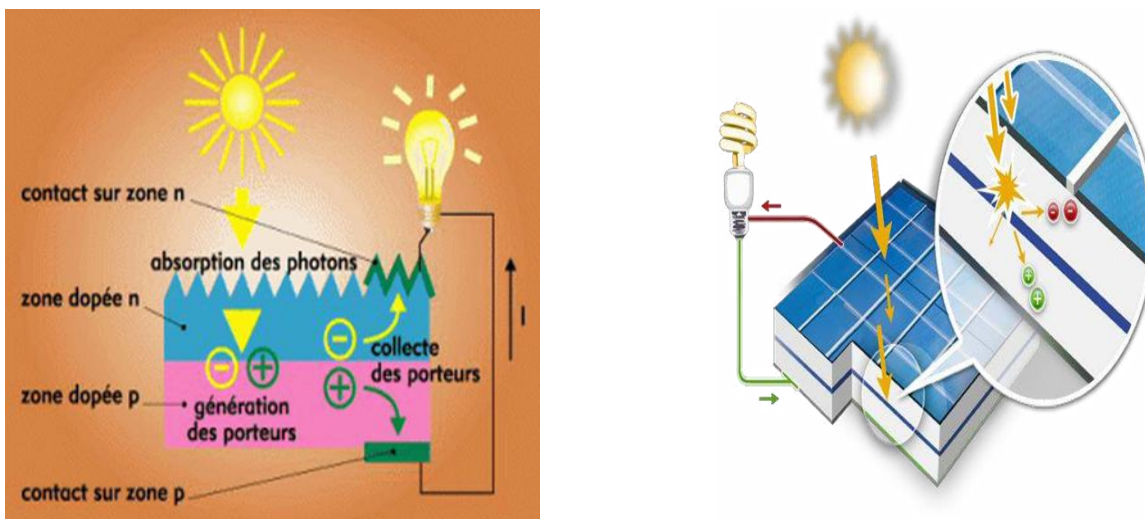
This involves converting the energy contained in sunlight into electrical energy using a sensor made of materials sensitive to the energy contained in photons. At the most basic level, this sensor takes the form of a cell known as a PV cell. The photovoltaic effect was first observed by the French physicist Edmond Becquerel [3]. However, it was not until the 1950s that researchers at Bell Laboratories in the United States succeeded in manufacturing the first photovoltaic cell, the primary or basic component of a photovoltaic system [4].

I.2.2. Photovoltaic cells

A PV cell, also known as a photovoltaic cell, is an electronic component made using semiconductor materials that have the unique property of generating electricity when exposed to light. It is generally made from silicon in its various forms. [5].

I.2.2.1. Structure and operating principle of a cell

The basic structure of a PV cell consists of two layers of silicon, one P-type (doped with boron) and the other N-type (doped with phosphorus), thus creating a PN junction with a potential barrier. The N-type region is covered by a metal grid which acts as the cathode, whilst a metal plate (back contact) covers the other side of the P-type region of the crystal and acts as the anode [3]. When photons are absorbed by the semiconductor, they transfer their energy to the atoms at the PN junction. Thus, the atoms are bombarded by the photons constituting the light (Fig. (I.1)), and under the effect of this bombardment, the electrons in the valence layers tend to be knocked out of their orbits. This then creates a potential difference between the two layers. This potential difference can be measured between the positive and negative terminals of the cell, via a load.



[1] Fig. I.1: Operating principle of a PV cell

A photovoltaic cell is therefore, by definition, a basic electrical generator.

It directly converts light into electricity.

Different types of cells :

Various solar cell technologies are currently being developed; over 90% of annual solar cell

production is based on crystalline silicon [5]. Depending on their base material, cells can be divided into three groups:

- Monocrystalline silicon cells
- Polycrystalline silicon cells
- Amorphous silicon cells

Monocrystalline cells :

These have the highest efficiency (15–22%) but are also the most expensive due to their complex manufacturing process. [4]

Polycrystalline cells :

As they are simpler to manufacture, their production costs are lower; however, their efficiency is lower (13–20%) [5].

Amorphous cells :

They have a low efficiency (5%) [5] but require only very thin layers of silicon and are inexpensive. They are commonly used in low-power devices such as solar-powered calculators.

It should be noted that, regardless of the material used, the efficiency of PV conversion can reach up to 40% [5]. These low efficiencies, linked to the materials technology, constitute the first major problem in the exploitation of solar energy [3]. Thanks to new materials such as cadmium telluride (CdTe), gallium arsenide (GaAs) and copper indium selenide (CIS), solar cells with efficiencies of 40% have been developed in the laboratory [3].

I.2.2.2. Electrical model of a PV cell

A. Equivalent circuit of a cell :

Modelling the behaviour of a PV cell draws on the properties of solar radiation and those of semiconductors.

In the literature, there are several mathematical models of a photovoltaic cell, the aim of which is to obtain the current-voltage (I-V) characteristic for the analysis and evaluation of

photovoltaic module performance. These models differ from one another in terms of the chosen structure of the PV panel and the number of parameters involved in calculating the current-voltage pair. The single-diode model is the most traditional and the most commonly used. It employs a current generator to model the incident light flux and a diode to account for the cell's polarisation phenomena. To account for physical phenomena at the cell level, the model is supplemented by two resistors, a series resistor R_s and a shunt resistor R_{sh} . The series resistance is due to the contribution of the base resistances, the junction front, and the front and rear contacts. The shunt resistance characterises the leakage currents from the junction along the cell's periphery: it is reduced as a result of the penetration of metallic impurities into the junction (especially if it is deep), during the deposition of the metal grid or the contact pads on the back surface of the cell [4]. Fig. (I.2) shows the electrical equivalent circuit of a cell. This figure demonstrates that the current generated by a cell is equal to the sum of three currents.

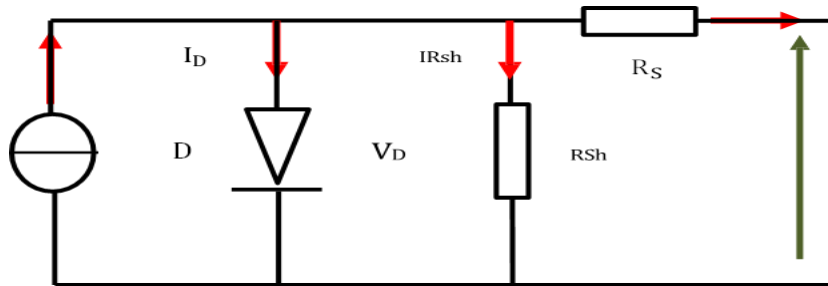


Fig. I.2: Equivalent circuit of a PV cell [4].

B. Electrical characteristic (current-voltage) of a cell :

As shown in Fig. (I.3), the static characteristic of a cell is that of a photodiode but in generator mode [5,7]. The $I(V)$ curve of the solar cell passes through three important points:

- The short-circuit current I_{cc} ;
- The open-circuit voltage V_{co} ;
- Point M, which represents the point of maximum power.

The $I(V)$ characteristic of a PV cell is divided into three parts [8]:

- Region (a), where the cell behaves as a current generator I_{cc} proportional to the irradiance G ;

- Region (b), where the cell behaves as a voltage generator V_{co} ;
- Region (c), where the internal impedance of the generator varies rapidly.

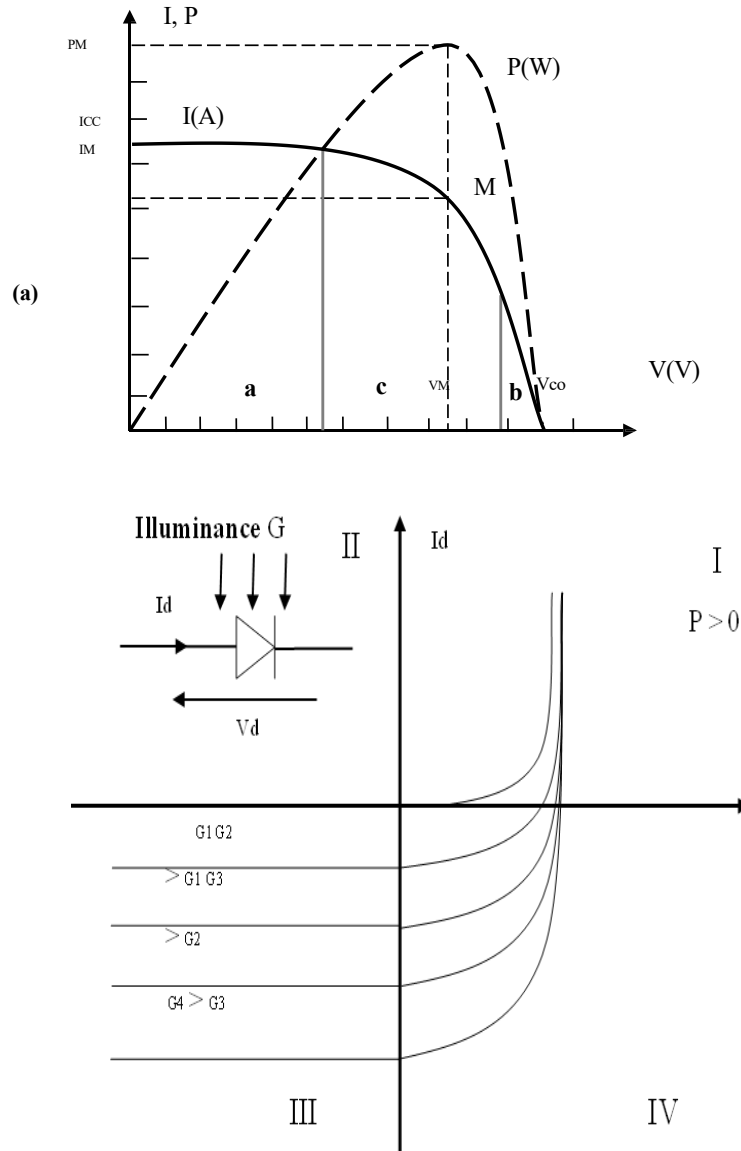


Fig. 1.3: Static $I(V)$ characteristics, (a) $I(V)$ of a photodiode, (b) $I(V)$ of a PV cell [6].

A. Determination of the various parameters :

A cell is characterised by various parameters that help us plot the $I(V)$ and $P(V)$ characteristics of a PV cell. These parameters can be internal or external. Internal parameters

These are parameters derived from equations that allow us to obtain the $I(V)$ characteristic of a photovoltaic cell. When the sides of the circuit are connected to a load R , a current I flowing through the circuit causes a potential difference to arise.

Kirchhoff's law allows us to write the following relationship:

Where:

$$I = I_{ph} - I_D - I_{Rsh} \quad (I.1)$$

- I is the current supplied by the cell;

- I_{ph} is the photocurrent, which is proportional to the illuminance G ; it also corresponds to the short-circuit current I_{cc} , defined as follows:

$$I_{ph} = I_{cc} \left(\frac{G}{1000} \right) \quad (I.2)$$

- I_D represents the bias current of a diode; it is given by:

$$I_D = I_s \left(e^{\frac{V - R_s I}{V_T}} - 1 \right) \quad (I.3)$$

Where:

I_s : is the current dependent on temperature T and the electrical parameters of the junction.

V_T : is the thermodynamic potential defined by:

$$V_T = \frac{AKT}{q} \quad (I.4)$$

T : is the actual cell temperature in Kelvin

- I_{Rsh} is the current flowing through the resistor R_{sh} . It is given by:

$$I_{Rsh} = \frac{V + R_s I}{R_{sh}} \quad (I.5)$$

From equation (I.1), we obtain the expression for the $I(V)$ characteristic of the chosen model:

$$I = I_{cc} \left(\frac{G}{1000} \right) - I_s \left(e^{\frac{(V - R_s I)}{V_T}} - 1 \right) - \frac{(V - R_s I)}{R_{sh}}$$

These parameters can be determined from the $I(V)$ curves, or from the characteristic equation (I.6). The most common are as follows:

1. Short-circuit current I_{cc} :

This is the current obtained by short-circuiting the cell terminals (taking $V = 0$ in the equivalent circuit). It increases linearly with the cell's irradiance and depends on the illuminated area, the wavelength of the radiation, and the temperature [9]. This current is identical to the photocurrent I_{ph} . By setting the voltage V to zero in equation (I.6), we obtain [8,9].

$$I_{cc} = I_{ph} - I_s \left(e^{\frac{R_s I_{cc}}{V_T}} - 1 \right) - \frac{R_s I_{cc}}{R_{sh}} \quad (I.7)$$

For photovoltaic cells with low series resistance, the term $I_s \left(e^{\frac{R_s I_{cc}}{V_T}} - 1 \right)$

in front of I_{ph} . The approximate expression for the short-circuit current then becomes:

$$I_{cc} = \frac{I_{ph}}{1 + \frac{R_s}{R_{sh}}} \quad (I.8)$$

2. Open-circuit voltage V_{co} :

This is the open-circuit voltage at which the current output by the cell is zero (it is the maximum voltage of a photovoltaic cell). It depends on the potential barrier and the shunt resistance. It decreases with temperature and varies slightly with light intensity. It is expressed analytically by the following formula [4]:

$$V_{co} = V_T * \ln \frac{I_{ph}}{I_s} + 1 \quad (I.9)$$

If the series resistance is zero and the shunt resistance is infinite, expression (I.9) becomes:

$$V_{co} = V_T * \ln \frac{I_{ph}}{I_s} \quad (I.10)$$

It is noted that for a silicon photovoltaic cell, the V_{co} voltage is in the range of 0.55 to 0.6.

3. Optimal power and form factor [8,9] :

The maximum effective power $P_M = V_M I_M$ is obtained by optimising the product of current and voltage.

$$\frac{I_M}{V_M} = - \left(\frac{dI}{dV} \right)_{-M} \quad (I.11)$$

As for the form factor FF (also known as the curve factor, fill factor, or *(fill factor)*), it is defined by:

$$FF = \frac{V_M . I_M}{V_{co} . I_{cc}} \quad (I.12)$$

This factor shows the deviation of the $I(V)$ curve from a rectangle (of length V_{co} and width I_{cc}) corresponding to the ideal photovoltaic cell. The values of I_M and V_M are obtained from equations (I.7) and (I.11). To do this, we distinguish between two cases:

- If R_{sh} is infinite, the derivation leads to the r
- solution of a non-linear equation in I_M using a numerical method, and thus enables

the calculation of V_M ;

- If R_{sh} is considered finite, the derivation leads to the solution of a non-linear equation in V_M using a numerical method.

4. Efficiency :

The power $P = I V$ is zero in short-circuit and open-circuit conditions. It reaches a maximum when tracing the $I(V)$ characteristic. This maximum P_M can be determined by plotting the $I(V)$ characteristic and the hyperbolas of constant power on the same graph. The optimal operating point corresponds to the point of tangency of the two curves, as shown in Fig. (I.4).

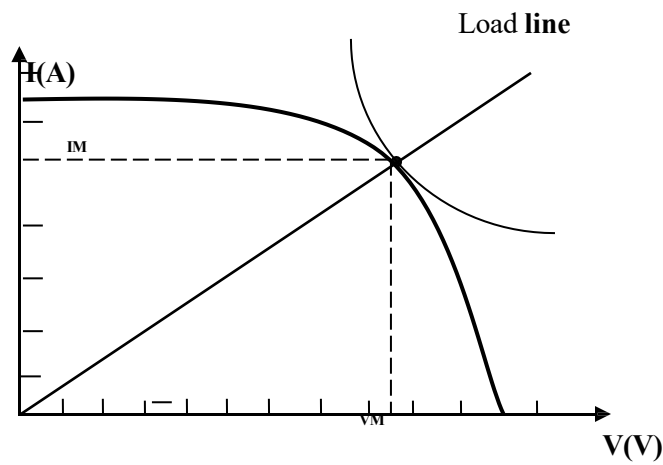


Fig. I.4: Optimal operating point of a PV cell [8]

The efficiency of the photovoltaic cell is given by:

$$\eta = \frac{P_M}{P_0} \quad (\text{I.13})$$

P_0 is the incident power. It is equal to the product of the irradiance and the total surface area of the photovoltaic cells. For silicon, the efficiency is less than 14%. The line passing through the origin and the point of maximum power has a slope that corresponds to the optimal load of the photovoltaic cell, as shown in Fig. (I.4)[3, 8, 9].

B. Parameters influencing the current-voltage (I-V) characteristic :

Four parameters influence the electrical behaviour of a photovoltaic cell or generator:

- Series resistance R_s ,
- Shunt resistance R_{sh} ,
- Illuminance G ,
- Temperature T .

Influence of series and shunt resistances

The performance of a photovoltaic cell deteriorates in proportion to the magnitude of the series resistance or the smallness of the shunt resistance [8, 9]. Fig. (I.5-a) shows the influence of the series resistance on the cell's $I(V)$ characteristic. The dotted curve corresponds to a non-zero value of R_S . This influence is reflected in a decrease in the slope of the curve in the region where the cell operates as a voltage source. The corresponding voltage drop is related to the cell's internal resistance.

In the case of shunt resistance, which is directly linked to the manufacturing process, its influence is only noticeable at very low current values. Fig. (I.5-b) shows that this influence results in an increase in the slope of the cell's power curve in the region corresponding to operation as a current source. This arises from the fact that, in addition to the diode forward current, an additional current varying linearly with the applied voltage must be subtracted from the photocurrent. The shunt resistance is generally very high; if it decreases, a slight slope is observed near the short-circuit current point on the $I(V)$ characteristic (Fig. I.4). A shunt resistance that is too low will affect the cell's open-circuit voltage: a photovoltaic cell with a shunt resistance that is too low will no longer produce voltage under low illumination.

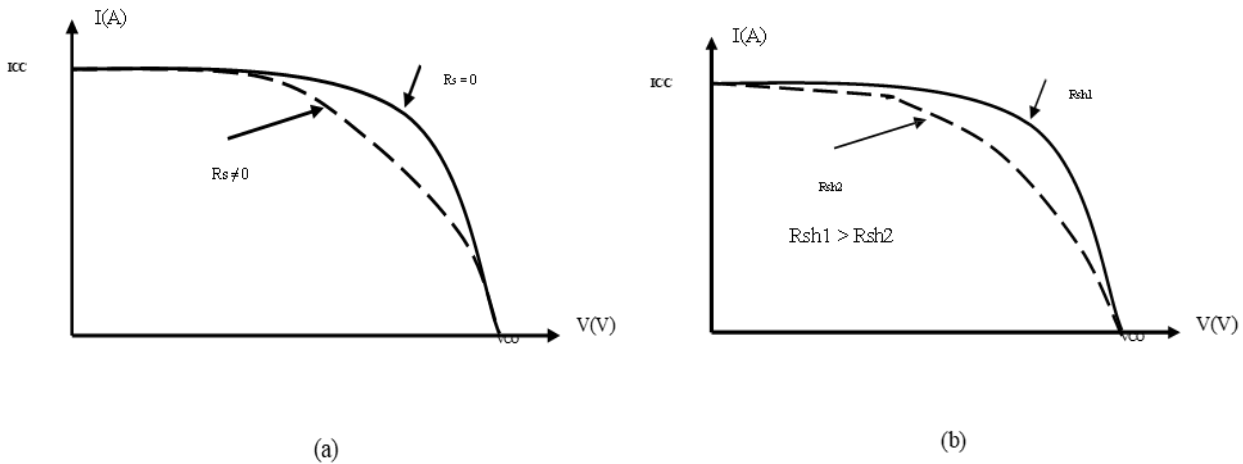


Fig. I.5: Effect of resistors, (a) in series, (b) in parallel, on the $I(V)$ characteristic [10]

Influence of temperature :

Temperature is a very important parameter in the behaviour of photovoltaic cells. Indeed, if the temperature increases, The increase in temperature also results in a decrease in the maximum available power, of the order of $5 \cdot 10^{-5} \text{ W/K}$ per cm^2 of cell, i.e. a variation of 0.35% per degree. The parameter T can be introduced into equation as shown by the following equation [6,9]

$$I = I_{cc} \left(\frac{G}{1000} \right) + a(T - T_{ref}) - I_s \left(e^{\frac{q(V + R_s I)}{nKT}} - 1 \right) - \frac{V + R_s I}{R_{sh}} \quad (\text{I.14})$$

a : Coefficient characterising the variation in power as a function of temperature.

T_{ref} : Module temperature under standard conditions ($T = 298.15 \text{ K}$, $G = 1000 \text{ W/m}^2$).

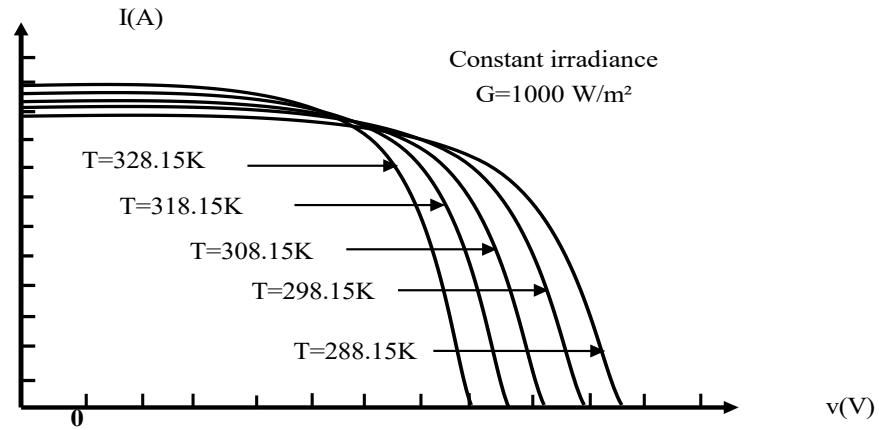


Fig. I.6: Effect of temperature on the $I(V)$ characteristic [9]
Effect of illuminance

The photocurrent I_{ph} is practically proportional to the illuminance or luminous flux G . The current $I_d(V_d)$, which by definition is the forward current of the junction in the dark, normally remains unchanged. This applies only to cells that do not utilise solar radiation concentration or that operate under low concentration. In fact, the carrier density and the saturation current are affected by variations in temperature and irradiance. The photocurrent generated in a photovoltaic cell is also proportional to the surface area S of the junction exposed to solar radiation. However, the open-circuit voltage is independent of these factors and depends solely on the quality of the material and the type of junction in question. Fig. (I.7) shows the $I(V)$ characteristics of a photovoltaic cell (PN junction on 57 mm diameter monocrystalline silicon) at 25°C and under various illuminance levels G . Each of these values of luminous flux corresponds to a maximum electrical power that the solar cell could supply. Note also the slight decrease in open-circuit voltage V_{co} following a drop in luminous flux [6,9].

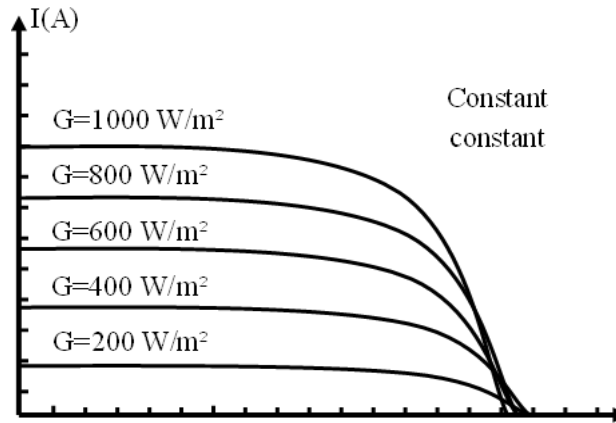


Fig. I.7: Effect of irradiance on the I(V) characteristic[9]

I.2.3. photovoltaic generator

A single cell measuring a few dozen square centimetres delivers a maximum of a few watts at a very low voltage (in the region of 0.6V to 0.8V), as this is the PN junction voltage. In order to increase the operating voltage and thus the power available across the entire array of cells. The cells are connected in series/parallel, resulting in what is known as a photovoltaic generator (PVG) [11].

I.2.3.1. PV module

A. Structure of a PV panel :

Connecting several PV cells in series and/or in parallel results in a photovoltaic generator (PVG), also known as a PV module or panel. When cells are connected in series, the voltages of each cell add together, increasing the total voltage of the photovoltaic generator. On the other hand, if the cells are connected in parallel, it is the current that increases [9]. Fig. (I.8) shows a series/parallel connection of PV cells.

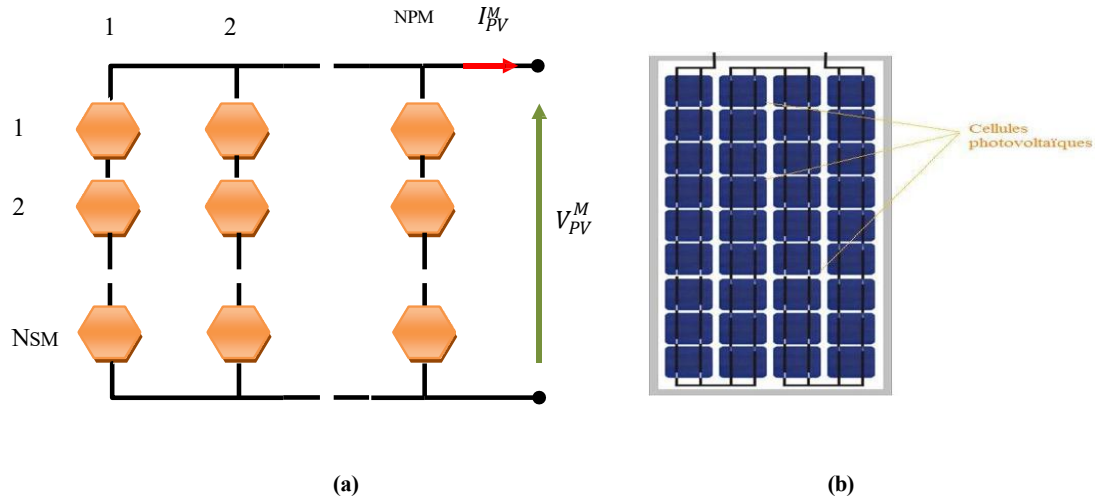


Fig. I.8: PV panel consisting of NSM cells in series and NPM cells in parallel

(a) Panel structure (b) Photovoltaic solar panel [9].

The $I(V)$ operating curve of a module is derived from the operating curve of a single cell by scaling the x-axis. The performance of a PV generator is determined from these characteristic curves. Fig. (I.9) shows the electrical characteristics $I(V)$ and $P(V)$ of a PV panel.

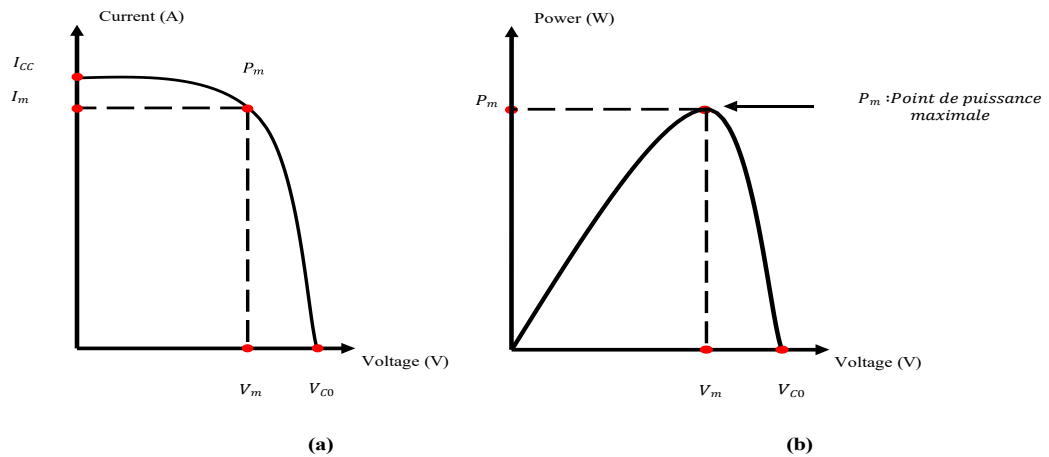


Fig. I.9: Characteristics of a PV panel, (a) $I(V)$ characteristics, (b) $P(V)$ characteristics [9]

It should be noted that in order to apply the $I(V)$ and $P(V)$ characteristics of a panel that will be homothetic at every point to the $I(V)$ or $P(V)$ curve of a PV cell, all the cells must be identical [6]. Thus, the $I(V)$ characteristic of a photovoltaic generator (GPV) has a point of maximum power (p_m).

Note :

The power of photovoltaic modules is expressed in peak watts. This represents the power that a module can supply when connected to its nominal (optimal) load, under an irradiance of 1000 W/m^2 and at a temperature of 25°C . For a silicon photovoltaic cell with a diameter of 10 cm, the peak power is $P_c \cong 1 \text{ W}$ [11].

B. Connection of photovoltaic cells :**Series connection :**

In a series connection, the same current flows through all the cells, and the resulting characteristic of the series connection is obtained by adding the voltages at a given current [4]. Fig. (I.10) shows the resulting characteristic obtained by connecting n identical cells in series

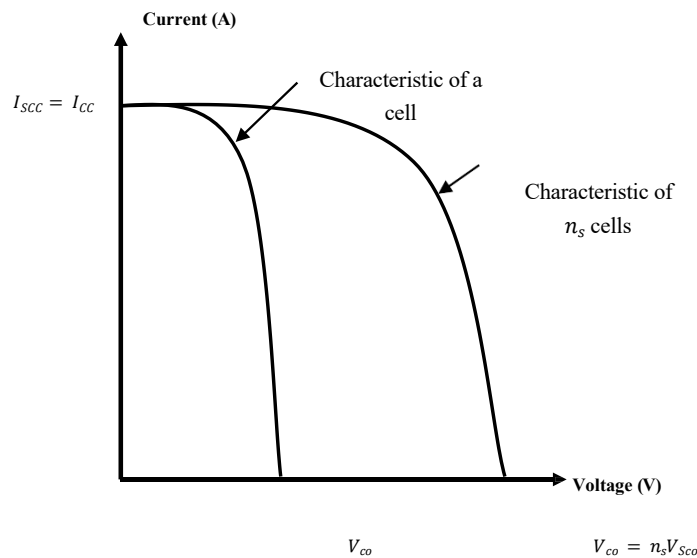


Fig. I.10: Characteristics of a series array of PV cells [4]

This figure shows that for a series array of n_s cells, the voltage V_{co} of the array increases by a factor of [4.9]:

$$V_{sco} = n_s V_{co} \quad (\text{I.15})$$

Parallel connection :

When identical cells are connected in parallel, the voltage across the branch is equal to the voltage of each module, and the current increases in proportion to the number of cells in parallel in the branch. The resulting characteristic is shown in Fig. (I.11) [8].

This figure shows that for n_p cells in parallel, the group current I_{cc} increases by a factor of [9]:

$$I_{pcc} = n_p I_{cc} \quad (I.16)$$

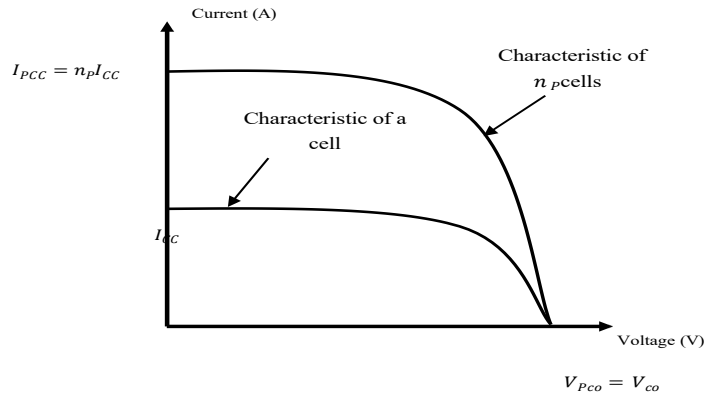


Fig. I.11: Characteristic of a parallel array of PV cells [4]

C. Advantages of a module :

PV modules perform the following functions [12]:

- Protection of cells against weather conditions;
- Mechanical protection and support;
- An electrical connection between the cells and the outside.

D. Positioning of solar panels :

One of the methods for increasing the overall efficiency of a PV system by maximizing the solar energy received is to improve energy capture efficiency through the correct orientation of the photovoltaic array modules. Solar panels should be positioned perpendicular to the sun, facing south in the northern hemisphere and north in the southern hemisphere. Solar collectors should be installed on the ground or on the roof, facing south, away from shaded areas. They must be tilted at an optimal angle to achieve the best possible result (maximum energy) [12].

I.2.3.2. PV fields

Currently, the power output of a module ranges from a few peak watts to several tens of peak watts. To increase the voltage and current to achieve higher power outputs, modules must be connected in series and/or in parallel via the connections in the junction box, which is equipped with the necessary safety features, thereby forming a PV array. As illustrated in Fig. (I.12), a PV array is, by definition, made up of modules of the same technology and with identical characteristics, electrically connected to one another either in series or in parallel [1]. Therefore, the current and voltage of a PV array consisting of N_S modules in series and N_P modules in parallel are:

$$V_{PV} = N_S V_M \quad (I.17)$$

$$I_{PV} = N_S I_M \quad (I.18)$$

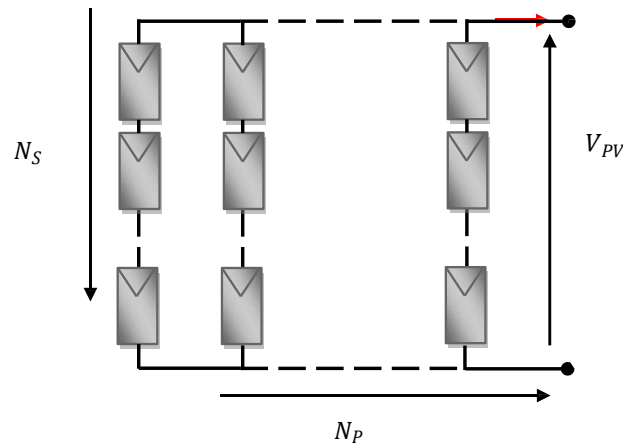


Fig. I.12: PV array consisting of N modules in series and N branches in parallel [7, 13]

I.2.3.3. Efficiency of a GPV photovoltaic generator

As with a cell, the efficiency of a photovoltaic generator (GPV) is the ratio of the maximum available power to the input power of the PV array, given by:

$$\eta_G = \frac{P_M}{P_e} \quad (I.19)$$

Where:

$$P_M = I_M V_M \quad \text{et} \quad P_e = G N_S N_P S$$

S : total surface area of the photovoltaic generator GPV.

N_S and N_P : number of modules in series and in parallel.

I.3. MATLAB Simulation of a photovoltaic generator

The PV generator essentially consists of one or more PV modules. These modules are formed by a series or parallel arrangement of PV cells that convert photovoltaic solar energy into electricity. To model a solar panel, we used MATLAB software as a testing and simulation tool. We implemented a programme in the form of a script file containing equations [I.17]–[I.31] from the equivalent circuit, which are necessary for plotting the $I(V)$ and $P(V)$ curves of a solar panel. According to [12], the shunt resistance can be neglected since it is usually very large compared to the series resistance, particularly for monocrystalline silicon cells; therefore, the circuit in Fig. (I.2) becomes:

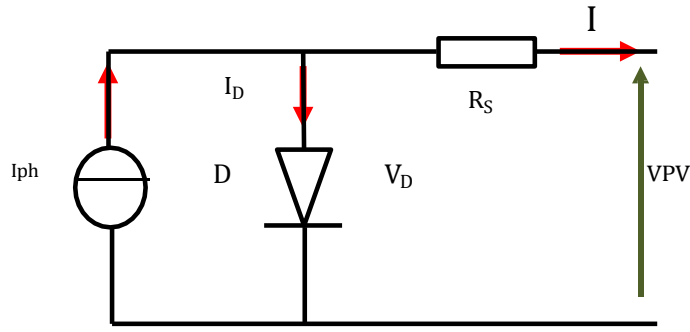


Fig. I.13: Equivalent circuit of a PV cell without shunt resistance [14].

Thus, equation (I.14) can be written as:

$$I = I_{cc} \left(\frac{G}{1000} \right) - I_s \left(e^{\frac{(V+R_s I)}{V_T}} - 1 \right) \quad (I.20)$$

The equation relating the current delivered by a PV module consisting of N_s cells connected in series and the voltage across its terminals is given :

$$I = I_{cc} \left(\frac{G}{1000} \right) - I_s \left(e^{\frac{(V+R_s I)}{V_T}} - 1 \right) \quad (I.21)$$

As :

$$V_T = \frac{N_s n K T}{q}$$

Taking into account the influence of irradiance and temperature, the steps to follow to plot the $I(V)$ curve of a PV panel are:

➤ *Calculation of the irradiance current I_{ph} :*

For a given temperature T , we have:

$$I_{ph} = I_{ph}(T_r) [1 + a \Delta T] \quad (I.22)$$

where:

$$\Delta T = T - T_r$$

T_r : Reference temperature, 298 K (25 °C).

a : coefficient of variation of the current as a function of temperature, as specified by the manufacturer.

$$I_{ph}(T_r) = I_{cc}(T_r) \frac{G}{G_0} \quad (I.23)$$

G_0 : Reference illuminance (1000 W/m²).

Therefore:

$$I_{cc} = I_{cc}(T_r)[1 + a \Delta T] \quad (I.24)$$

➤ *Calculation of the saturation current [15]:*

$$I_s = I_s(T_r) \left(\frac{T}{T_r}\right)^3 A e^{-bc} \quad (I.25)$$

Where: b and c are constants defined as follows:

$$b = \frac{E_g q}{AK} \quad (I.26)$$

$$C = \frac{1}{T} - \frac{1}{T_r} \quad (I.27)$$

Calculation of the series resistance R_s :

Various methods are proposed for calculating the series resistance [4,9], including:

$$R_s = -\frac{dv}{dI_{vco}} - \frac{1}{X_v} \quad (I.28)$$

Where:

$$X_v = \frac{I_s(T_r)}{VT(T_r)} e^{\frac{V_{cc}(T_r)}{VT(T_r)}} \quad (I.29)$$

➤ **Calculation of V_c :**

$$V_c = \frac{Va}{Ns} \quad (I.30)$$

Finally, to solve the non-linear characteristic equation (I.27), the following Newton-Raphson numerical method is used:

$$X_{n+1} = X_n - \frac{F(X_n)}{F'(X_n)} \quad (I.30)$$

Where X_n represents an iteration, X_{n+1} represents the next iteration, and $f(X_n)$ is the derivative of the function $f(X_n) = 0$.

$$F(I) = I - I_{ph} - I_s \left(e^{\frac{V+RsI}{VT}} - 1 \right) = 0 \quad (I.31)$$

The current I is therefore calculated as:

$$I_{n+1} = I_n - \frac{I_s \left(e^{\frac{V+RsI}{VT}} - 1 \right)}{-1 - I_{ph} \left(e^{\frac{V+RsI}{VT}} - 1 \right) \frac{Rs}{VT(T)}}$$

I.3.1. Choice of panel

We have chosen the BP-SX150S photovoltaic module because it offers the highest efficiency when compared with panels from other manufacturers; furthermore, its maximum voltage is higher, and it provides cost-effective power for general use through the direct operation of DC loads, or AC loads on systems equipped with an inverter. The module consists of 72 polycrystalline silicon cells connected in series to produce 150W of power.

I.3.1.1. Technical specifications of the BP-SX150S panel

Solar panel manufacturers specify the performance of their equipment under the following standard test conditions (STC).

- An AM 1.5 spectrum;
- An irradiance of 1000 W/m²;
- An ambient temperature of 25°C.

Based on the technical data sheets provided by the manufacturer and available in the appendix, we have determined the parameters of the selected panel, which we have set out in Table (I.1).

Rated Power	P _{nom}	150	W
Voltage at maximum power	V _{max}	34.5	V
Current at maximum power	I _{pm}	4.35	A
Open-circuit voltage	V _{co}	43.5	V
Short-circuit current	I _{cc}	4.75	A
Temperature coefficient (I _{cc})	a	0.065±0.015	mA/°C

Table I.1. Parameters of the BP-SX150S panel under STC conditions

Solar panel manufacturers specify the performance of their equipment under the standardised conditions mentioned above (STC). Based on these data and following the steps outlined in the previous paragraph, we have presented results for the modelling of the BP-SX150S panel.

I.3.2. Influence of Different Parameters

1. Effect of irradiance :

In Fig. (I.14) and Fig. (I.15), we present the results concerning the $I(V)$ and $P(V)$ characteristics of the panel at 25°C , obtained for various illuminance values.

Comparing these with the characteristics provided by the manufacturer (see the appendix), we observe good agreement between the actual (experimental) characteristics and those derived from simulation. For each different illuminance level, there corresponds a maximum power that the panel could supply; note also the slight decrease in open-circuit voltage following the decrease in luminous flux.

We also observe that the current is directly proportional to the irradiance at these illuminance levels.

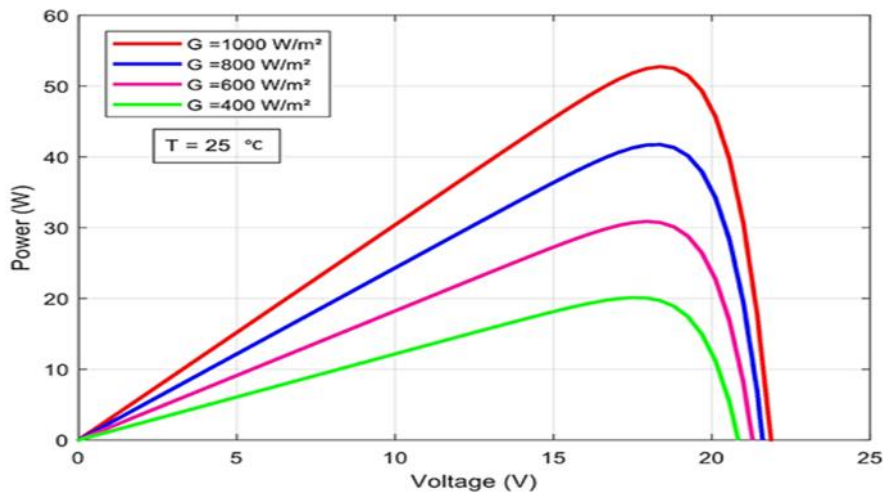


Fig. (I.14): P-V characteristics of 50 W PV array with variation of irradiance

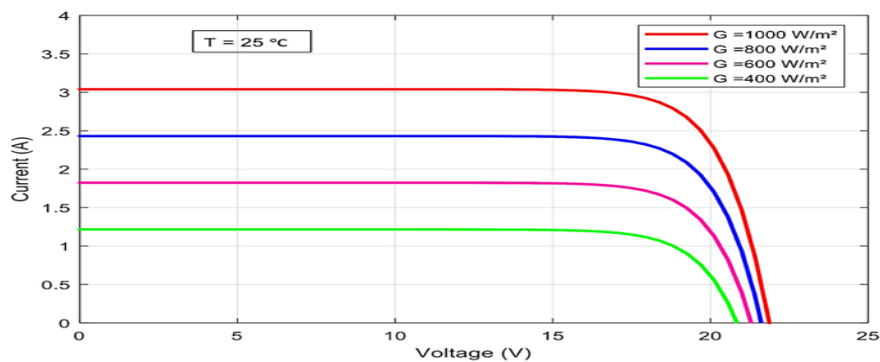


Fig. (I.15): I-V characteristics of 50 W PV array with variation of irradiance

2 . Influence of temperature :

Temperature is a very important parameter in the behaviour of PV cells. Fig. (I.16) and Fig. (I.17) illustrates the behaviour of the module under a fixed irradiance of 1000 W/m^2 , and at temperatures ranging from 25°C to 100°C . We observe that the current decreases with temperature, whereas the open-circuit voltage increases. This results in a reduction in the maximum available power.

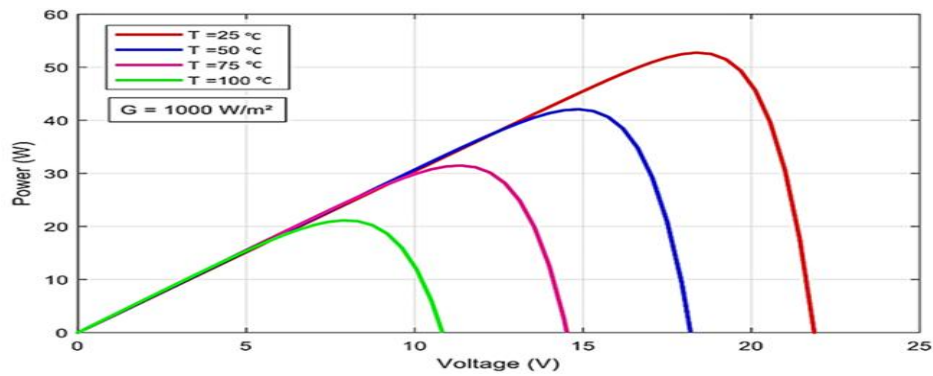


Fig. (I.16): I-V characteristics of 50 W PV array with variation of irradiance

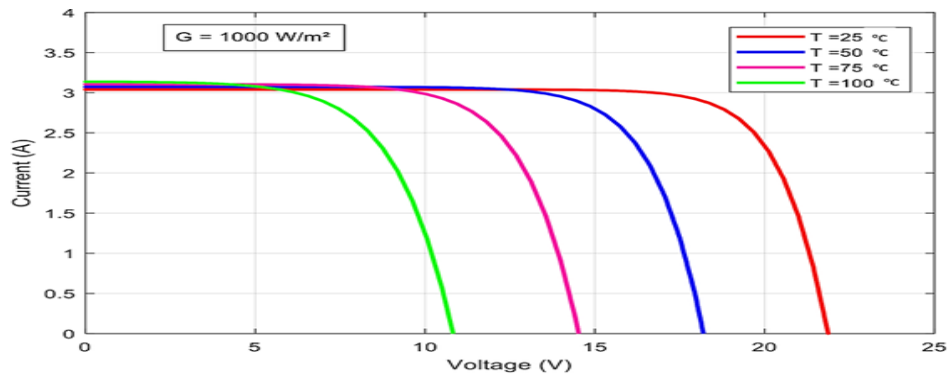


Fig. (I.17): P-V characteristics of 50 W PV array with variation of temperature

I.4. Conclusion

In this chapter, we are primarily interested in the operating principle of a PV cell and the analysis of its equivalent circuit. We then considered the various parameters of the equivalent circuit that enable us to plot the $I(V)$ and $P(V)$ characteristics of a photovoltaic cell and a photovoltaic generator. We have observed that the performance of a photovoltaic generator (PVG) is strongly influenced by meteorological conditions (temperature, irradiance), as well as by internal parameters such as series and parallel resistance. This study was carried out using MATLAB software, which is reliable for presenting results; we developed calculation programmes in the form of mathematical equations to plot the $I(V)$ and $P(V)$ characteristics. These studies were conducted on a BP-SX150S solar panel. The objective is to test the effect of key parameters that influence the modelling of a GPV.

CHAPTER II

THE DC-DC CONVERTER AND MPPT CONTROL

II.1. Introduction

The output characteristics of a photovoltaic generator are non-linear and directly dependent on operating conditions such as: the level of solar irradiance and the ambient temperature. Furthermore, for a given operating condition, there is a single operating point at which the power supplied by the photovoltaic generator is at its maximum, known as the maximum power point (MPP). This point is, in turn, heavily dependent primarily on the level of solar irradiance and the ambient temperature.

II.2. Direct connection between the PV array and the load

Connecting a photovoltaic solar panel directly to a load remains the cheapest and most widespread operating principle. This approach essentially involves a photovoltaic array with a voltage V determined by the nominal voltage of the load to be powered. This choice is primarily due to the simplicity, reliability and low cost of the system. The presence of a reverse-current diode is essential to prevent the flow of reverse current towards the PV module (Fig. II.1).

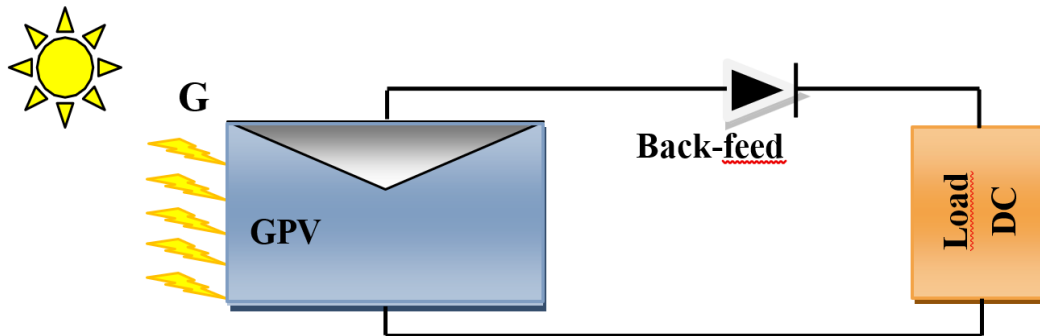


Fig. II.1: Direct connection between a GPV and a load.

II.3. Optimal operation of a GPV

Optimal operation of a PV system is important for increasing the efficiency of solar panels. The performance of a PV system is non-linear and varies with ambient temperatures and irradiance. Consequently, MPPT technology is required to obtain the maximum power from a PV system in order to improve its efficiency. In other words, to maximise the power delivered to the load connected to the generator terminals.

II.4. (DC/DC) Converter

Switches are static DC-DC converters that generate a variable DC voltage from a fixed DC voltage source. The chopper consists of capacitors, inductors and switches. Ideally, none of these components consume power, which is why choppers have high efficiency. Generally, the switch is a MOSFET transistor, a semiconductor device operating in either the cut-off or saturation mode. [19].

If the semiconductor device is in the cut-off state, its current is zero, hence its power dissipation is zero. If the device is in the saturated state, the voltage drop across its terminals will be almost zero and consequently the power loss will be very small. [19].

II.5. Modelling of the boost chopper

Also known as a step-up chopper or booster. It allows the PV voltage to be adapted to the load requirements by varying the duty cycle D . The input to the chopper is a DC current source and the output is a DC voltage load (energy sink); see Figure II.8 (a).

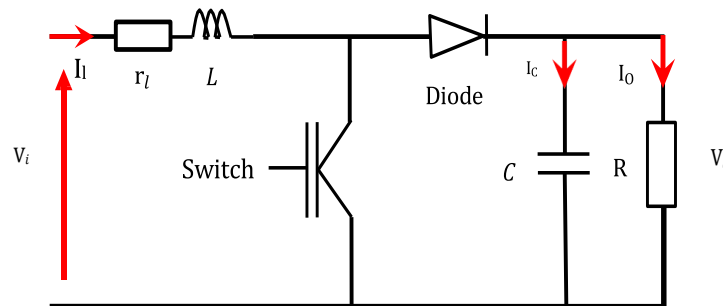


Fig. II.2: Ideal circuit of the boost chopper.

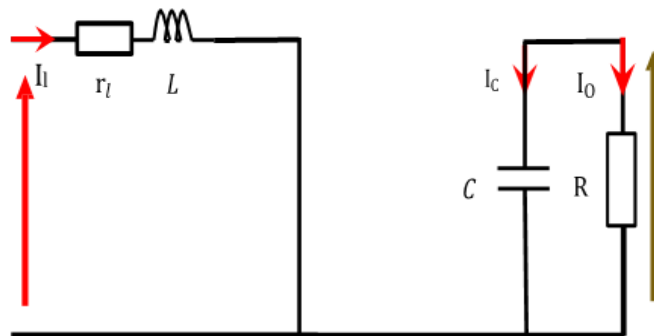


Fig. II.3: Equivalent circuit for the closed switch

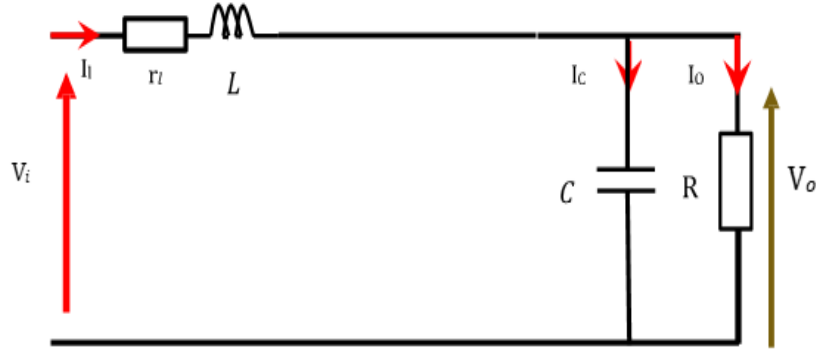


Fig. II.4: Equivalent circuit for the open switch

- Relationship between voltage and current [20] :

The following constraints are assumed:

1. The steady-state condition holds.
2. The switching period is T , and the time DT for the switch to be closed and open for $(1-D)T$.
3. The current through the inductor is continuous (always positive).
4. The capacitor is very large, and the output voltage V_o remains constant.
5. The components are ideal.

- Analysis for the closed switch [20] :

When the switch is closed, Figure (II.9), the diode is blocked, and by applying Kirchhoff's law to a loop containing the source, the inductor and the closed switch, we obtain:

$$V_L = V_S = L \frac{di_L}{dt} \quad (II.2)$$

The rate of change of current is constant, so the current increases linearly as long as the switch is closed, as shown in Figure (II.11). The change in current across the inductor is calculated by:

$$\frac{\Delta i_L}{\Delta t} = \frac{di_L}{dt} = V_S \quad (II.3)$$

The solution for Δi_L when the switch is closed

$$(\Delta i_L)_{\text{closed}} = \frac{V_S D i_L}{L} \quad (II.4)$$

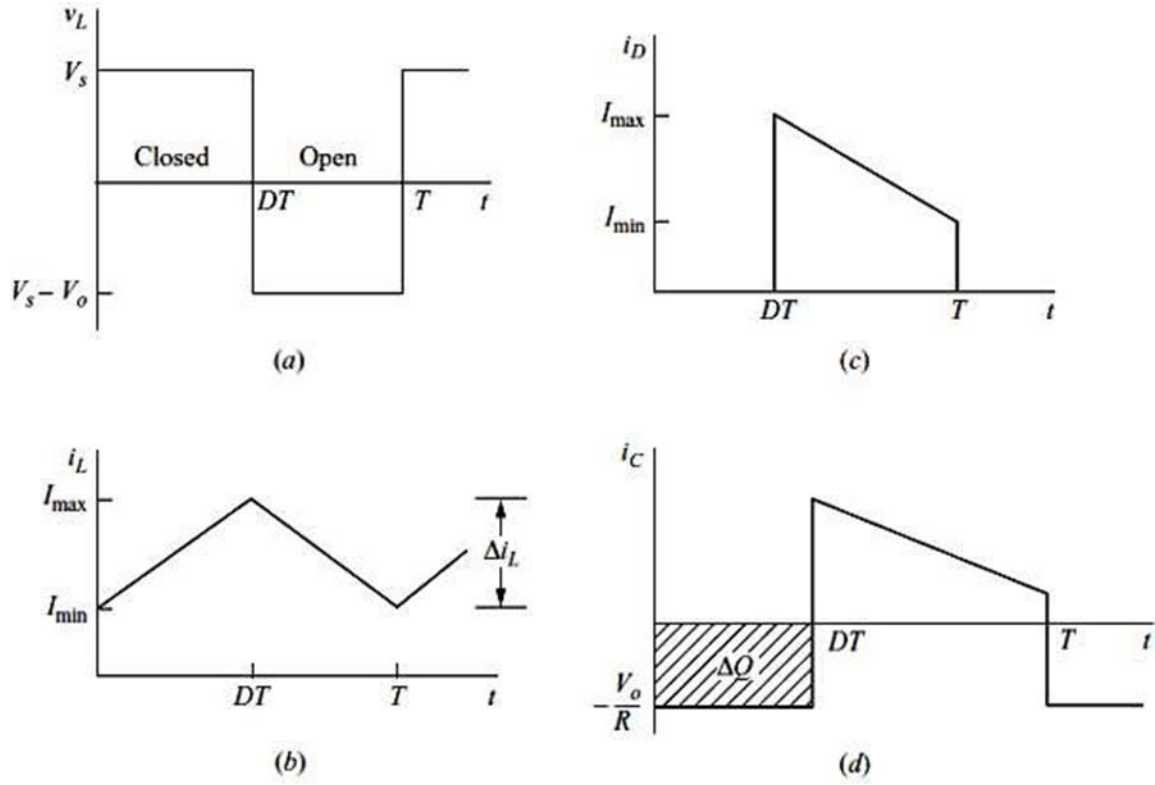


Fig. II.5: Waves in boost converters. (a) the voltage across the inductor; (b) the current through the inductor; (c) the current through the diode; (d) the current through the capacitor.

- Analysis for the open switch :

When the switch is open, Figure (II.10), the current through the inductor cannot change instantaneously; therefore, applying Kirchhoff's law to a loop containing the source, the inductor and the closed switch, we obtain:

$$V_L = V_s - V_o = L \frac{di_L}{dt} \quad (II.5)$$

The rate of change of current is constant, so the current varies linearly as long as the switch is open. The change in the current through the inductor is calculated by:

$$\frac{V_s - V_o}{L} = \frac{\Delta i_L}{\Delta t} \quad (II.6)$$

We solve for Δi_L :

$$\frac{\Delta i_L}{\Delta t} = \frac{\Delta i_L}{(1-D)T} = \frac{V_s - V_o}{L} \quad (II.7)$$

$$\Delta i_{Lopen} = \frac{(V_s - V_o)(1-D)T}{L} \quad (II.8)$$

For steady-state conditions, the change in the inductance current must be zero. Using equations (II.4) and (II.8).

$$(\Delta i_L)_{\text{Closed}} + \Delta i_{L_{\text{open}}} = 0 \quad (\text{II.9})$$

$$\frac{V_s D T}{L} + \frac{(V_s - V_o)(1-D)T}{L} \quad (\text{II.10})$$

The solution for V_o :

$$V_s (D + 1 - D) - V_o (1 - D) = 0 \quad (\text{II.11})$$

$$V_o = \frac{V_s}{(1-D)} \quad (\text{II.12})$$

Thus, the average voltage across the inductor must be zero for a periodic operation.

The expression for the average voltage across the inductor over a switching period:

$$V_L = V_s D + (V_s - V_o)(1-D) = 0 \quad (\text{II.13})$$

The average current through the inductor is determined by comparing the average power delivered by the source with the average power absorbed by the load, where the two powers must be similar.

The output power is :

$$P_o = \frac{V_o^2}{R} = V_o I_o \quad (\text{II.14})$$

And the input power is $V_s I_s = V_s I_L$. We equating the input power with the output power and using equation (II.9) :

$$V_s I_L = \frac{V_o^2}{R} = \frac{[V_s / (1-D)]^2}{R} = \frac{V_s^2}{R(1-D)^2} \quad (\text{II.15})$$

By solving for the average inductor current, the current I_L can be expressed as :

$$I_L = \frac{V_s}{R(1-D)^2} = \frac{V_o^2}{V_s R} = \frac{V_o I_o}{V_s} \quad (\text{II.16})$$

The maximum and minimum currents through the inductor are determined by using the average value and the variation in current from equation (II.4) :

$$I_{\text{MAX}} = I_L + \frac{\Delta i_L}{2} = \frac{V_s}{R(1-D)^2} + \frac{V_s D T}{2L} \quad (\text{II.17})$$

$$I_{\text{MIN}} = I_L - \frac{\Delta i_L}{2} = \frac{V_s}{R(1-D)^2} - \frac{V_s D T}{2L} \quad (\text{II.18})$$

Equation (II.9) is derived on the assumption that the inductance current is continuous, always

positive. Therefore, it is necessary for the current I_{MIN} to be positive for the inductance current to be continuous; thus, the range between the continuous inductance current and the discontinuous inductance current is determined by [21] :

$$I_{MIN} = 0 = \frac{V_s}{R(1-D)^2} - \frac{V_s DT}{2L} \quad (II.19)$$

$$\frac{V_s}{R(1-D)^2} = \frac{V_s DT}{2L} = \frac{V_s D}{2Lf} \quad (II.20)$$

The minimum value of the inductance and the switching frequency for a DC current in the boost converter is :

$$(L)_{MIN} = \frac{D(1-D)^2}{2} R \quad (II.21)$$

$$(Lf)_{MIN} = \frac{D(1-D)^2}{2f} R \quad (II.22)$$

- Output voltage ripple :

The preceding equations are derived on the assumption that the output voltage is constant; this implies an infinite capacitance. In practice, infinite capacitance results in a fluctuation in the output voltage, or ripple.

The output voltage ripple can be calculated from the form of the capacitor current, shown in Figure (II.7) (d):

$$|\Delta Q| = \frac{V_0}{R} DT = C \Delta V_0 \quad (II.23)$$

$$\Delta V_0 = \frac{V_0 DT}{RC} = \frac{V_0 D}{RCf} \quad (II.24)$$

This implies :

$$C = \frac{D}{R((\Delta V_0)/V_0)f} \quad (II.25)$$

II.6. Maximum Power Point Tracking Method

To achieve better efficiency in the operation of photovoltaic generators, the technique known as maximum power point tracking (MPPT) is used; this involves optimally transferring all the electrical power to be extracted from this photovoltaic energy source to the load to be powered. It must be used in any application utilising

these generators, and becomes necessary and even indispensable according to the theory of optimal power transfer. The control techniques employed for maximum power point tracking are [16]

II.6.1. Definition of MPPT in a photovoltaic solar system

MPPT technology is a control system combined with a matching stage that enables a non-linear electrical generator to operate in such a way as to continuously produce its maximum power. MPPT systems are generally used with photovoltaic generators or wind turbines. An MPPT controller is then used to control the power converter linking the load and the photovoltaic panel, so as to continuously supply the maximum power to the load [17].

Fig. (II.2) shows a photovoltaic conversion chain with a static converter controlled by an MPPT controller and an arbitrary load.

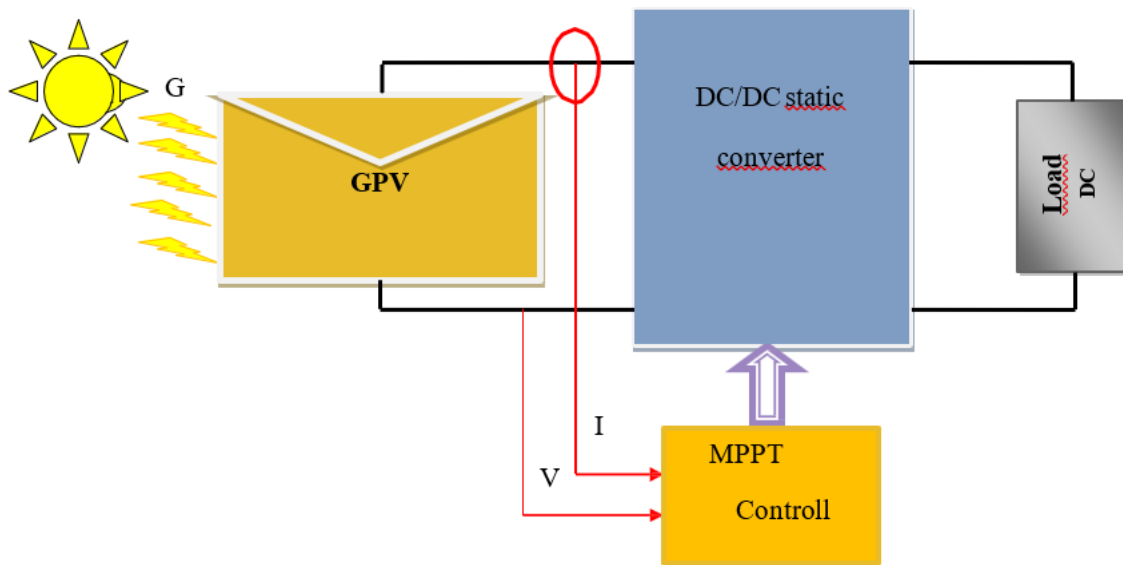


Fig. II.6: Basic photovoltaic conversion chain with a static converter controlled by an MPPT controller on any load [18].

II.6.2. Summary of the various MPPT encountered in the literature

Various publications on the operation of MPPT-type controllers have appeared regularly in the literature since 1968, the year the first control law of this kind was published, adapted for a photovoltaic renewable energy source. Given the large number of publications in this field, we have classified the various existing MPPT techniques,

grouping them according to their basic principle. In addition to the principle, the classification was carried out according to criteria such as the accuracy of the search or its speed, in order to make a comparative evaluation [18].

II.6.3. P&O Perturbation and Observation Algorithm

The P&O method works by periodically perturbing the PV panel voltage, with a small amplitude around its initial value (ΔV), and observing the resulting variation in PV power.

Thus, it can be deduced that if a positive increase in the V_{PV} voltage results in an increase in the P_{PV} power, i.e. $\Delta P > 0$, as illustrated in Fig. II.3, the voltage disturbance shifts the operating point towards a point closer to the MPP, and the voltage is continued to be disturbed in the same direction. This will shift the operating point until the MPP is reached.

If, on the other hand, the power decreases, $\Delta P < 0$, the operating point moves away from the MPP. In this case, the voltage must be perturbed with an algebraic sign opposite to the previous one to move the operating point until the MPP is reached.

Based on these various analyses of the consequences of a voltage variation on the power-voltage characteristic $P_{PV}(V_{PV})$, it is then easy to locate the operating point relative to the PPM, and to make the latter converge towards maximum power through an appropriate control command.

In summary, if, following a voltage disturbance, the PV power increases, the direction of the disturbance is maintained. Otherwise, it is reversed to resume convergence towards the new MPP [17].

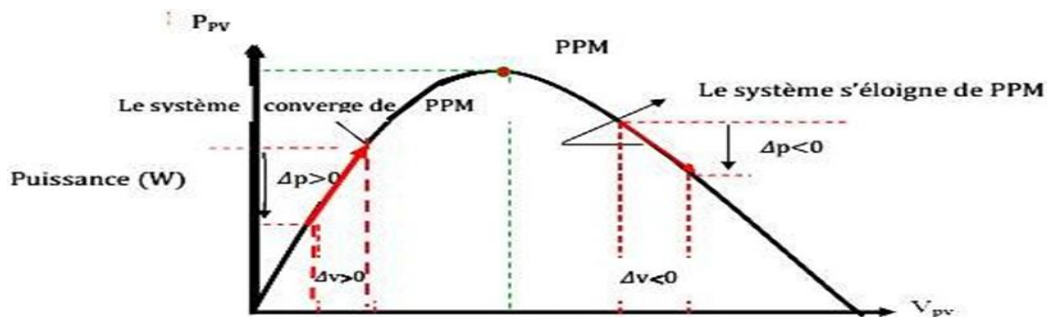


Fig. II.7: Application of the P&O algorithm to the PPV(VPV) characteristic [17].

Choice of MPPT algorithm :

Table (II.1) shows a comparison of the various MPPT techniques, the principles of which we have outlined above.

An analysis of these various research methods shows that the performance of an MPPT controller cannot be reduced to a single parameter η_{MPPT} which is defined as the MPPT efficiency.

II.6.4. P&O ALGORITHM

The P&O method is a widely used approach in the field of MPPT techniques because it is simple. It requires only measurements of the PV panel's output voltage V_{PV} and its output current I_{PV} , and can therefore immediately identify the maximum power point by generating a reference voltage V_{ref} at its output.

As its name suggests, the P&O method works by varying V_{PV} and observing its impact on the change in the PV panel's output power.

Figure (II.6) is a flowchart of the P&O algorithm. This algorithm is designed to run on a computer, and so at each cycle of the algorithm, V_{PV} and I_{PV} are measured to calculate $P_{PV}(k)$. This value of $P_{PV}(k)$ is compared with that of $P_{PV}(k-1)$, which was calculated in the previous iteration. If the output power has now increased since the last measurement, the output voltage disturbance will continue in the same direction as that taken in the last cycle.

If the output power has decreased since the last measurement, V_{PV} is perturbed in the opposite direction to that of the previous iteration. V_{PV} is thus perturbed at each MPPT cycle. When the maximum power point is reached, V_{PV} oscillates around the optimal value V_{OP} . This causes a power loss that increases with the size of the perturbation step. If this step size is large, the MPPT algorithm will respond quickly to sudden changes in operating conditions, but power losses will be significant when operating conditions are stable or changing slowly. In other words, if the step size is small, power losses under stable or slowly changing operating conditions will be lower, but the system will not be able to respond quickly to rapid changes in temperature or sunlight [19].

The disadvantage of the P&O MPPT technique is that, in the event of a rapid change in illumination conditions, this method may shift the operating point in the wrong direction.

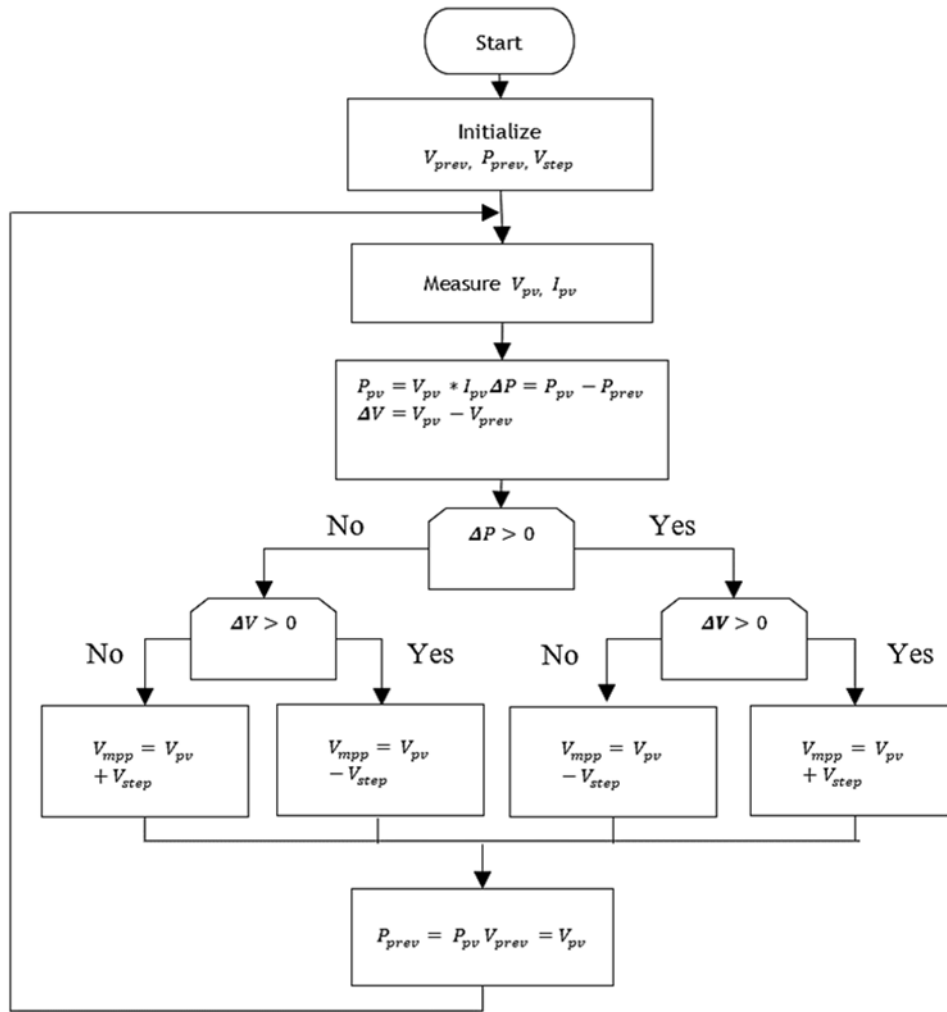
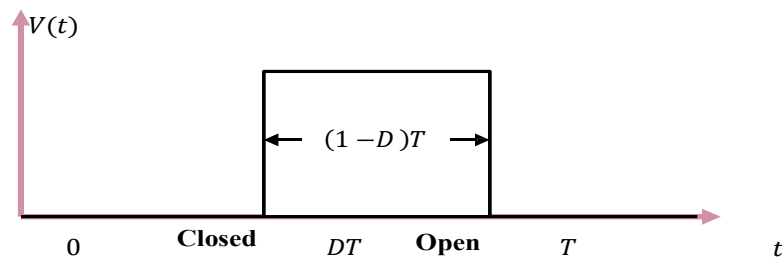


Fig. II.8: P&O MPPT algorithm.

As shown in Fig. (II.7), during the operation of the chopper, the switch is closed for a closing time equal to DT , and opened for an opening time equal to $(1-D)T$, where:

- Test the switching period, which is equal to $1/f$.
- D is the duty cycle of the switch ($D \in [0.1]$).

Fig. II.9: Ideal switch voltage over a switching period T_s .

II.7. Biological foundations

The brain consists of approximately 10^{12} interconnected neurons, with 1,000 to 10,000 synapses per neuron. Not all neurons are identical, nor do they behave in the same way. In our work, we focus on the fundamental principles necessary for understanding how neural networks function [23].

II.7.1. Biological Basics

A neuron is a particularly complex cell specialised in processing electrical signals. Its role is to receive, store and transmit information, Fig. III.1. A neuron can be divided into three main regions: the cell body, the dendrites and the axon [23].

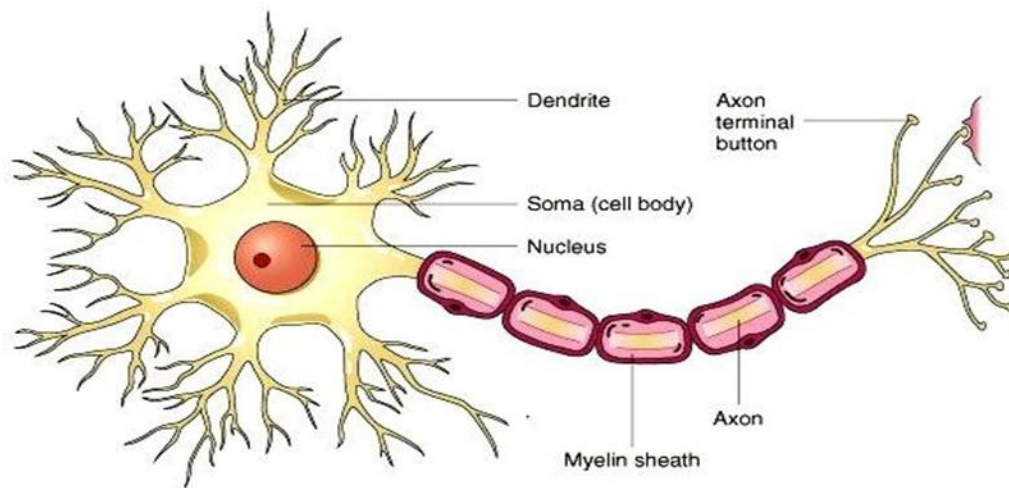


Fig. II.10: Biological neuron.

II.7.2. Structure of the biological neuron

II.7.2.1 The cell body :

It contains the neuron's nucleus as well as the biological machinery necessary for enzyme synthesis. This spherical or pyramidal cell body thus contains the other molecules essential to the cell's life. It measures a few micrometres in diameter [23,24].

II.7.2.2 The dendrites :

These are fine extensions that branch out from the neuron and form a vast network of branches. The signals sent are received by the dendrites. They are a few tens of micrometres in length [23,24].

II.7.2.3 The axon :

The processed information is transmitted outwards along the axon; the signals leave the neuron via the terminal tree of the axon. Unlike the dendrites, which branch out around the neuron, the axon is longer and branches at its.

II.8. Principles of an artificial neural network

- no concept of time
- synaptic weight: real coefficient
- summation of signals arriving at the neuron
- output obtained after applying a transfer function

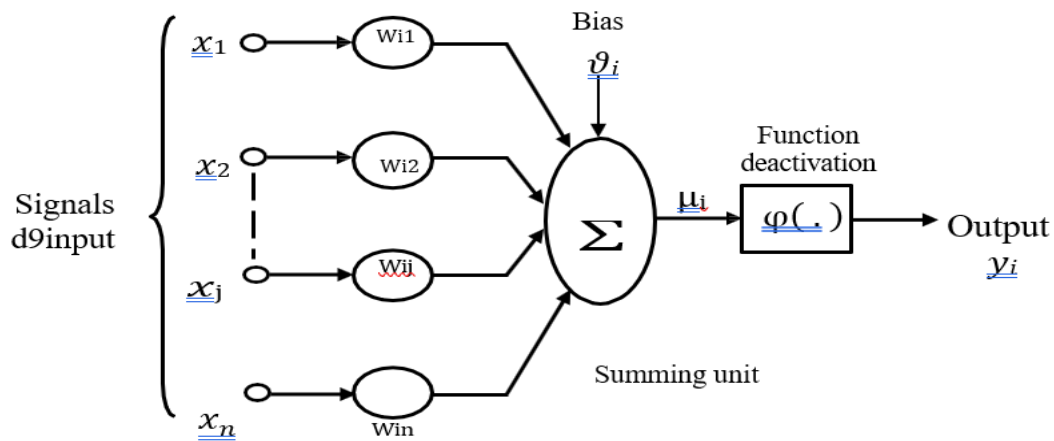


Fig. II.11: principle of an artificial neuron [23].

There is a clear analogy (Table III-1) with biological neurons:

Biological neurons	Artificial neurons
Synapses	Weighted connections
Axons	Outputs
Dendrites	Inputs
Summator	Activation function

Table III-1. The analogy between biological neurons and artificial neurons.

II.8.1. Activation functions

This function allows the internal state of the neuron to be defined based on its total input. We cite a few functions that are frequently used as examples [25].

II.8.1.1.Binary threshold function :

Heaviside function Fig. (III.2) defined by:

$$h(x) = \left. \begin{array}{l} 1, x \geq 0 \\ 0, \text{if no} \end{array} \right\} \quad (\text{III.1})$$

Sign function Fig. (II.3) defined by:

$$\text{sgr}(x) = \left\{ \begin{array}{l} 1, x \geq 0 \\ 0, \text{if no} \end{array} \right. \quad (\text{III.2})$$

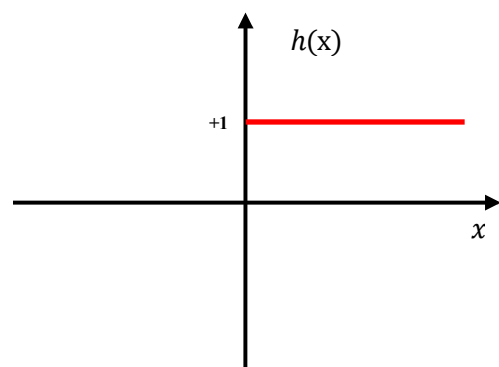
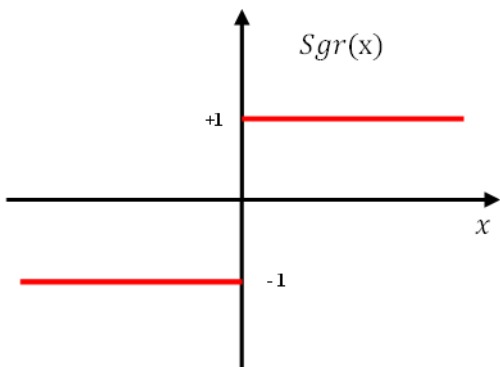


Fig. II.12: Heaviside function [26]. Fig. III.4: Sign function [26].

The threshold introduces non-linearity into the neuron's behaviour; however, it limits

the range of possible responses to two values [25].

II.8.1.2.Linear function :

This is one of the simplest activation functions; its function is defined by [25]:

$$f(x)=x \quad (III.3)$$

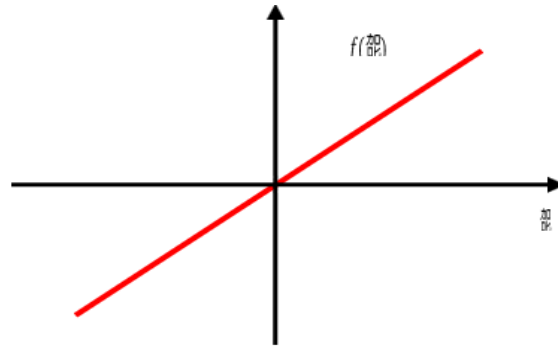


Fig.II.13: Linear function [25].

II.8.1.3.Linear function with a single threshold or multiple thresholds :

It can be defined as follows:

$$f(x) = \begin{cases} x, & x \in [u, v] \\ V, & \text{if } x \geq v \\ u, & \text{if } x \leq u \end{cases} \quad (III.')$$

II.8.1.4.Sigmoid function :

It is equivalent to the continuous linear function. Being continuous, it is differentiable; moreover, its derivative is simple to calculate. Fig. (III.5) shows that it is defined by:

$$f_1(x) = \frac{1}{1+e^{-x}} \quad (III.5)$$

$$f_1(x) = \frac{1}{1+e^{-x}} \quad (III.6)$$

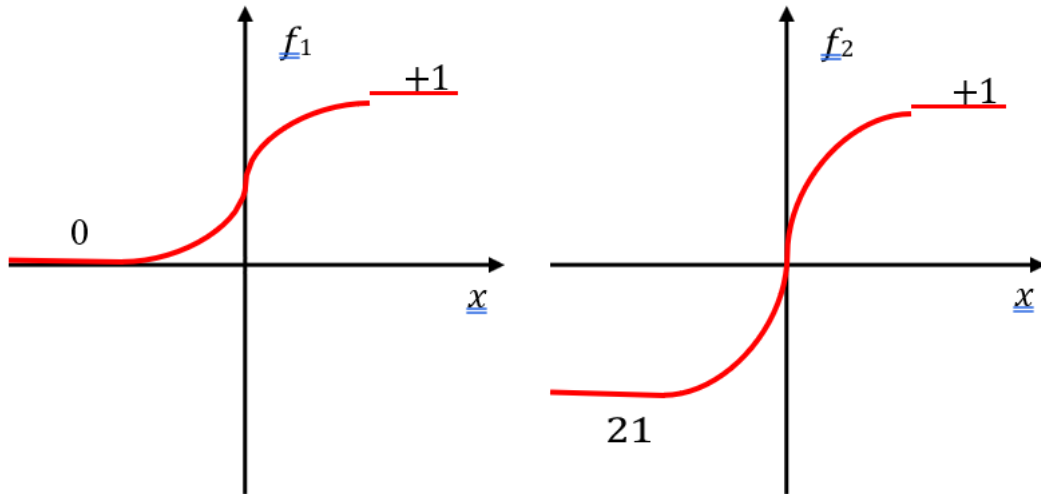


Fig. II.14: Sigmoid function [25].

II.8.2. Architecture of neural networks

II.8.2.1. Non-recurrent networks :

These are unidirectional networks with no feedback (feedforward). The output signal is obtained directly following the application of the input signal. If not all neurons are output neurons, they are referred to as hidden neurons [27].

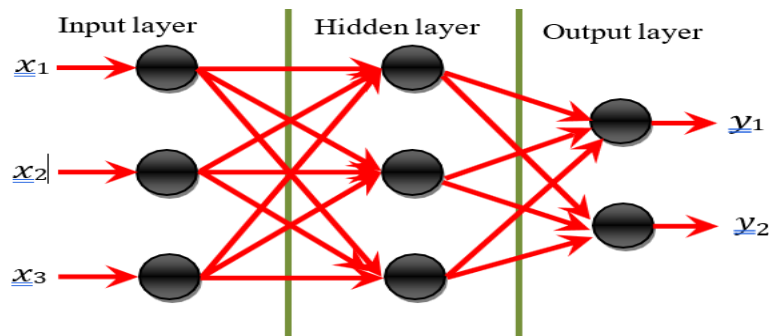


Fig. II.15: Non-looped network [26, 25].

II.8.2.2. Looped networks :

These are neural networks with feedback (feedback networks or recurrent networks) [26, 25].

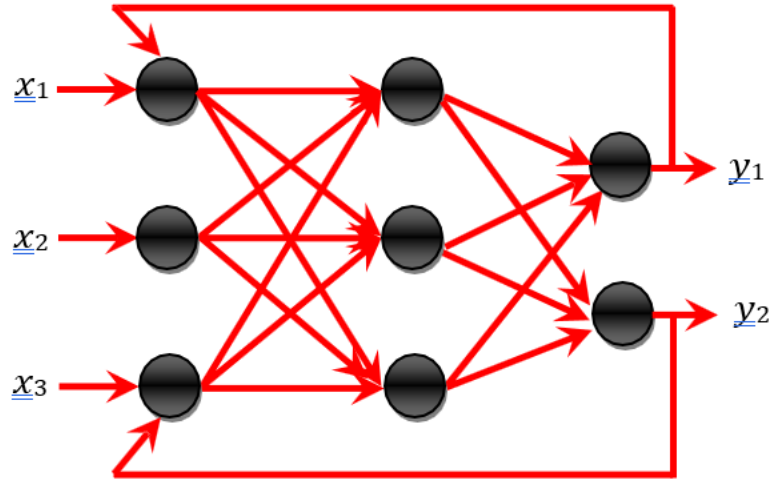


Fig. II.16: Loop network [26,25].

II.8.3. Learning

II.8.3.1. Types of learning :

Learning and adaptation are two essential characteristics of neural networks. The role of learning is to optimise the weights of each connection. There are numerous rules for modifying connection weights and thus achieving correct learning once the training phase is complete. The network must be capable of making the correct associations for input vectors that it has not learnt. This is one of the key properties of neural networks, as it enables the recognition of similar patterns; this is the recognition phase. Learning techniques can be classified into three categories [26,25]:

II.8.3.2. Supervised learning :

A supervisor or teacher provides the network with input/output pairs. They train the network on all these pairs using a learning method such as backpropagation of the error gradient, by comparing the actual output of the network with the desired output for each pair. Learning is complete when all input-output pairs are recognised by the network. This type of learning is found, amongst others, in the perceptron [26].

II.8.3.3. Unsupervised learning :

This type of learning involves automatically detecting patterns present in the examples provided and adjusting the connection weights so that examples with the same pattern characteristics produce the same output. Kohonen's self-organising networks are the best-known examples of unsupervised learning networks [26].

II.8.3.3.1. Self-supervised learning :

The neural network evaluates its own performance without the help of a ‘teacher’. An object is presented at the input of the neural network, and the class to which this object belongs is specified. If the network does not classify it correctly, it measures the error itself and propagates this error back to the input. The network performs as many iterations as necessary until the correct answer is obtained [25].

II.8.3.4 Learning methods :

In expert systems, the expert’s knowledge is in an enumerated form; it is expressed as rules. In the case of neural networks, knowledge is distributed. It is encoded in the connection weights, the network topology network, the transfer functions of each neuron, the thresholds of these functions, and the learning method used. There are a number of learning methods [26]:

II.8.3.4.1. Hebb’s rule :

This is the oldest learning method (1949), inspired by biology. It reflects the strengthening of connections linking two activated neurons. If at least one of the two neurons is not activated, the weight of the connection remains unchanged [25].

II.8.3.4.2. Backpropagation of Error Gradient Algorithm :

This algorithm is used in feedforward networks, which are layered neural networks comprising an input layer, an output layer, and at least one hidden layer. There is no recursion in the connections, and no connections between neurons within the same layer. The principle of backpropagation involves feeding an input vector into the network, calculating the output by propagating through the layers from the input layer to the output layer via the hidden layers. This calculated output is compared with the desired output, yielding an error. From this error, the error gradient is calculated and propagated from the output layer back to the input layer, hence the term ‘backpropagation’. This allows the network weights to be adjusted and thus enables learning. The operation is repeated for each input vector until the stopping criterion is met [26,25].

II.8.3.4.2.1. Advantages and disadvantages of error gradient backpropagation :

➤ **Advantages :**

This was one of the first algorithms developed for training feedforward multi-layer neural networks. It addresses a shortcoming of the perceptron algorithm, which is unable to modify the weights of the hidden layers, where computational implementation poses no difficulties.

➤ **The Drawbacks :**

Regarding the algorithm:

The error gradient backpropagation algorithm follows the descent of the error gradient: a local minimum can quickly halt the search for global optima:

The importance of choosing the learning rate. If the learning rate is too high, the network dynamics will oscillate around the optimum; if it is too low, convergence is slow.

II.8.3.4.3. The LEVENBERG-MARQUARDT algorithm :

Among the quasi-Newton family of algorithms, the LEVENBERG-MARQUARDT method [28-29] is a standard algorithm for optimising the quadratic error due to its properties of rapid convergence and robustness. It is based on non-linear least squares techniques and the GAUSS-NEWTON algorithm with restricted neighbourhood.

The main reason for choosing the LEVENBERG-MARQUARDT (LM) algorithm is the size of the Hessian matrix, which depends on the amount of data in the training set, the lower computational cost, and the guarantee of rapid convergence to a minimum such that:

$$P_k = [J a_k^T J a_k + \mu_k I_n]^{-1} J a_k^T r_k \quad (\text{III.7})$$

Among the neighborhood-restricted methods, the FLETCHER method [30-29] was selected and developed.

The variable μ_k , which appears in the positive-definite modified Hessian

$$H_K = G_K + \mu_K I_K, \text{ is controlled by the ratio } R = \frac{\Delta J_K}{\Delta Q_K}$$

$$\Delta J_K = J(W_K) - J(W_K + S_K) \quad (\text{III.8})$$

Where

$$\Delta Q_K = Q(0) - Q(S_K) \quad (\text{III.9})$$

and the elliptic function:

$$Q(S) = J(W_K) + g(W_K)^T S = \frac{1}{2} S^T H_K(W_K) S \quad (\text{III.10})$$

This ratio tends towards 1 as the cost function approaches the osculating quadratic curve. Training is terminated when a minimum is reached, either based on a stopping criterion on the cost function or on the minimum value of the gradient norm.

Algorithm :

Initialisation of the weights W_0 by a uniform distribution according to Beale's rule [29] with $u_0 > 0$

The solution is given by the algorithm for the $k^{\text{ème}}$ iteration:

- 1) Derive from W_K et μ_K , calculate g_K et H_K
- 2) Solve $-g_K = H_K S_K$
- 3) Review by $J(W_K + S_K)$ et R_K

Calculate the parameter μ_K

1. If $R_K \leq 0.25$ alors $\mu_{K+1} = 4\mu_K$
2. If $R_K \leq 0.75$ then $W_{K+1} = W_K$ otherwise $W_{K+1} = W_K + S_K$

The constants for the threshold values of R_K are empirical.

Where:

J : Is the cost function.

$$H_K = G_K + \mu_K I_n \quad \text{where } I_n \text{ is an } n \times n \text{ identity matrix} \quad (\text{III. 11})$$

$$g_k = J a_K^T r_k \text{ (Gradient), avec } J a_{i,j} = \frac{\partial r_i}{\partial w_{j,k}} \quad (\text{III. 12})$$

$$G_K = J a_K^T r_k \text{ (Hessien), et } S_k = \sum_{i=1}^{NS} r_{i,k} \nabla^2 r_{i,k} \quad (\text{III. 13})$$

Where the residual vector: $r_{i,K} = t_{i,K} - O_{i,K}$, $i = 1 \dots S$, $k = 1 \dots N$, $r_i = |r_i|$

r vector i, K , instantaneous error between the theoretical response $t_{\bar{a}}$ and the calculated response O_i of the $i^{\text{ème}}$ output neuron and $1^{\text{ème}}$ stimulus. N is the number of stimuli. S is the number of network outputs. The gradient and the Hessian are derived from the Jacobian matrix of the residual vector of dimension $N \times W$ (total number of weights) for the $K^{\text{ème}}$ iteration.

II.8.4. The -perceptron

Since the results of the work by McCulloch and Pitts (1943) [26,25], which led to the definition of the formal neuron, as well as those of Hebb, explaining the effects of learning, memory and conditioning based on groups of cells. To explain these learning effects, Hebb

proposed that cells learn to modify the strength of the connections linking them, depending on their simultaneous activity. Some researchers had the idea of using models of neurons and synaptic development to simulate neural networks. The first robust model was presented in 1959 by F. Rosenblatt; this was the perceptron, in other words a network reduced to a single formal neuron [25].

II.8.4.1. Description :

Perceptrons are feedforward networks with the following structure: a layer of fixed connections situated between the input units (the retina) and the association units. The second layer connects the association units and the output units: it is on these weights that the adaptation acts. In the perceptron, there is only one layer that varies as a result of adaptation. In the perceptron neuron, a threshold activation function is used. The model of the perceptron's linear threshold neuron, comprising a decision cell connected to N input cells, is shown in Fig. (III.9).

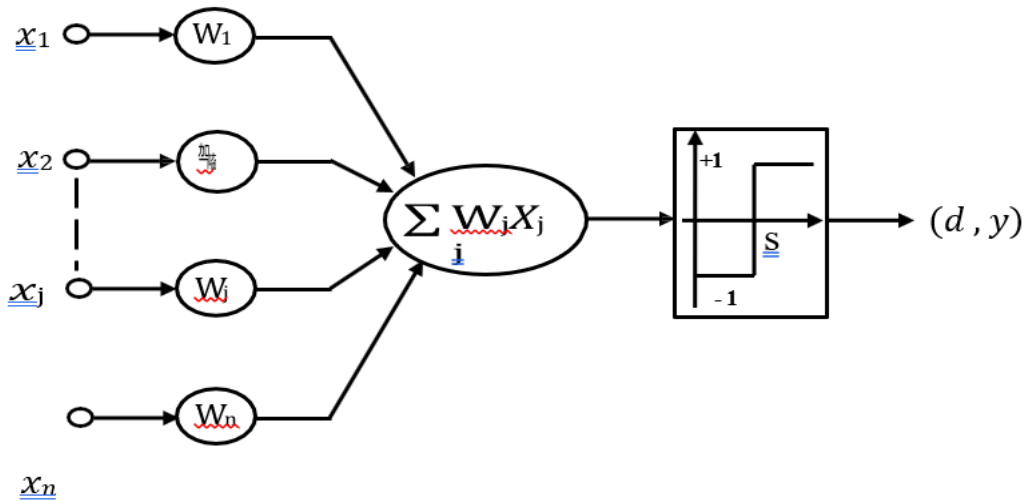


Fig. II.17: Linear threshold neuron with a single decision cell [25].

The linear threshold neuron therefore partitions the input vectors submitted to it into two domains. The boundary between these two domains is defined by the condition:

$$S = \sum_j W_j X_j \quad (\text{III.14})$$

Where S denotes the threshold of the decision cell. Indeed, for $\sum_j W_j X_j > S$, the neuron outputs 1.

For $\sum_j W_j X_j < S$, it responds with -1

The boundary separating these two domains will therefore be a hyperplane.

II.8.4.2. Multilayer Perceptron (MLP) :

Perceptrons are the most common type of artificial neural network; they consist of three layers: the first is the input layer, the second is known as the hidden layer, and the last is the output layer. The first layer is made up of feedforward neurons, whilst the other layers are composed of several neurons known as hidden neurons; the neurons from one layer to another are connected by synaptic weights. Each hidden neuron acts as a cell that performs a weighted sum of the inputs X_{ij} to neuron j , using the synaptic weights W_{ij} corresponding to these inputs. Its output is then obtained via the function $f(j)$, known as the activation function. This function is generally increasing, monotonic and bounded. The most commonly used are saturating functions and sigmoid functions. We have added input terms X_{ij} corresponding to the bias. There is no fixed rule for determining the network architecture; the number of neurons in the input and output layers is determined by the number of inputs and outputs, respectively. Thus, it has been shown that networks with a single hidden layer serve as an approximation tool. In our case, information propagates from the input layer to the output layer, which provides a real response ($\hat{y}$) corresponding to the desired output (y). In summary, to teach a task to this network (weight adaptation), we must present it with a pair of examples (inputs/outputs) or (U_{com}, y).

Weight learning is achieved through backpropagation of the error (x) between the network's output ($\hat{y}$) and the desired value (y) (minimisation criterion). The algorithm enabling such learning is known as the Windrow–Hoff ‘backpropagation algorithm’; it is based on the gradient method. All these methods involve minimising a function relating to the mean squared error. This learning algorithm enables the determination of the changes in synaptic weights $\Delta W_{j,i}(k)$ and biases $\Delta b_{j,i}(k)$. It can be expressed by the following relations [26-25]:

$$\Delta W_{j,i}^m(n) = n \epsilon_j(n) \frac{\partial F_m}{\partial U_j^m(n)} (U_j^m(n)) (X_i(n))^T \quad (\text{III.15})$$

$$\Delta b_{j,i}^m(n) = n \epsilon_j(n) \frac{\partial F_m}{\partial U_j^m(n)} (U_j^m(n)) \quad (\text{III.16})$$

$X_i(n)$: represents the input vector of neuron (i) in layer m ; the update equation for these synaptic weights and biases is based on the following relationship:

$$W_{j,i}^m(n+1) = W_{j,i}^m(n) + \Delta W_{j,i}^m(n) \quad (\text{III.17})$$

$$b_j^m(n+1) = b_j^m(n) + \Delta b_j^m(n) \quad (\text{III.18})$$

The calculation of the activation values of the input units is expressed symbolically as:

$$\text{Net}_j^i(n) = \sum_{i=1}^p W_{j,i}^1(n) U_{ab,i}^1(n) + b_j^i(n) \quad (\text{III.19})$$

$$Y_j^i(n) = F_1[\text{Net}_j^1(n)] \quad (\text{III.20})$$

II.8.4.2.1. Implementation of PMC networks :

Consider a network comprising an input layer with n neurons, an output layer with m neurons, and one or more hidden layers. Suppose we have a training set consisting of k pairs of vectors: We will follow an approach adopted by Wierenga and Kluytmans (1994), which consists of four main steps [25]:

- Step 1: set the number of hidden layers.
- Step 2: determine the number of neurons per hidden layer.
- Step 3: Select the activation function.
- Step 4: Select the learning programme.

II.9. Choosing the network St :

Fig. (III.2) clearly shows that our network consists of three layers, namely:

- An input layer consisting of two neurons, whose role is to transmit the input values corresponding to the variables (G, T) to the next layer, known as the ‘hidden layer’;
- A hidden layer with ten neurons, each with a selected activation function of the tangent sigmoid type
- An output layer with a single neuron representing the reference voltage of the PV module, whose activation function is of the identity or ‘linear’ type

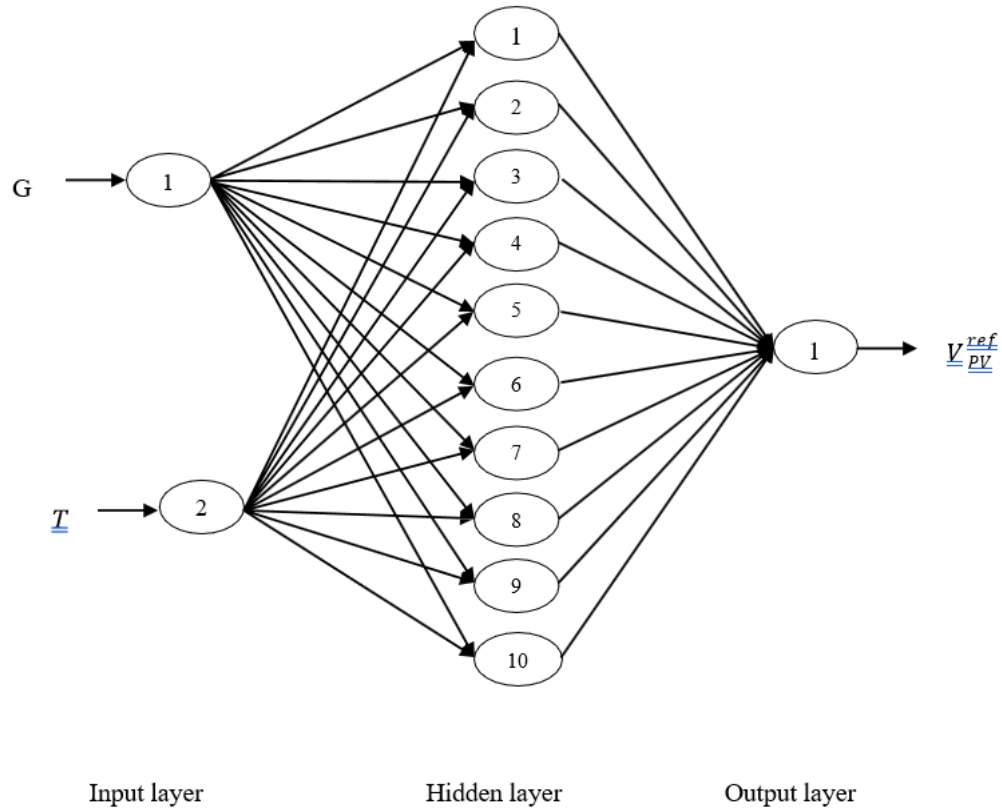


Fig. II.18: Architecture of the proposed neural network.

The number of neurons in the hidden layer was optimised empirically during the training phase. Indeed, tests showed that the most stable structure is one comprising ten neurons.

It should also be noted that the choice of activation function for the hidden layer was not made arbitrarily, but was selected following several tests which showed that the tangent sigmoid function converges more rapidly than the exponential sigmoid function during the training phase.

In addition, two other parameters must also be optimised, namely:

The number of epochs, which represents the duration of training, and the training performance, which is the minimum difference between the values presented to the network (or ‘input-output patterns’) and the values obtained. This training was carried out using the backpropagation algorithm, which will be detailed later.

Furthermore, the second stage, after proposing the optimal architecture obtained—which consists of selecting the number of hidden layers, the number of neurons per layer, and

the activation functions of our neural network—involves training it offline using two different algorithms. To this end, the general structure of the neural network in Simulink is illustrated in Figures (III.11) and (III.12).

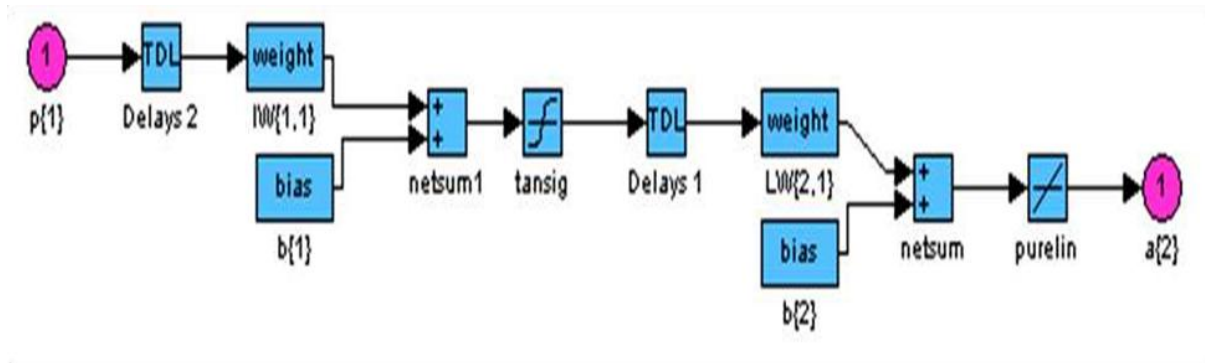


Fig. II.19: General structure of the neural network in MATLAB Simulink.

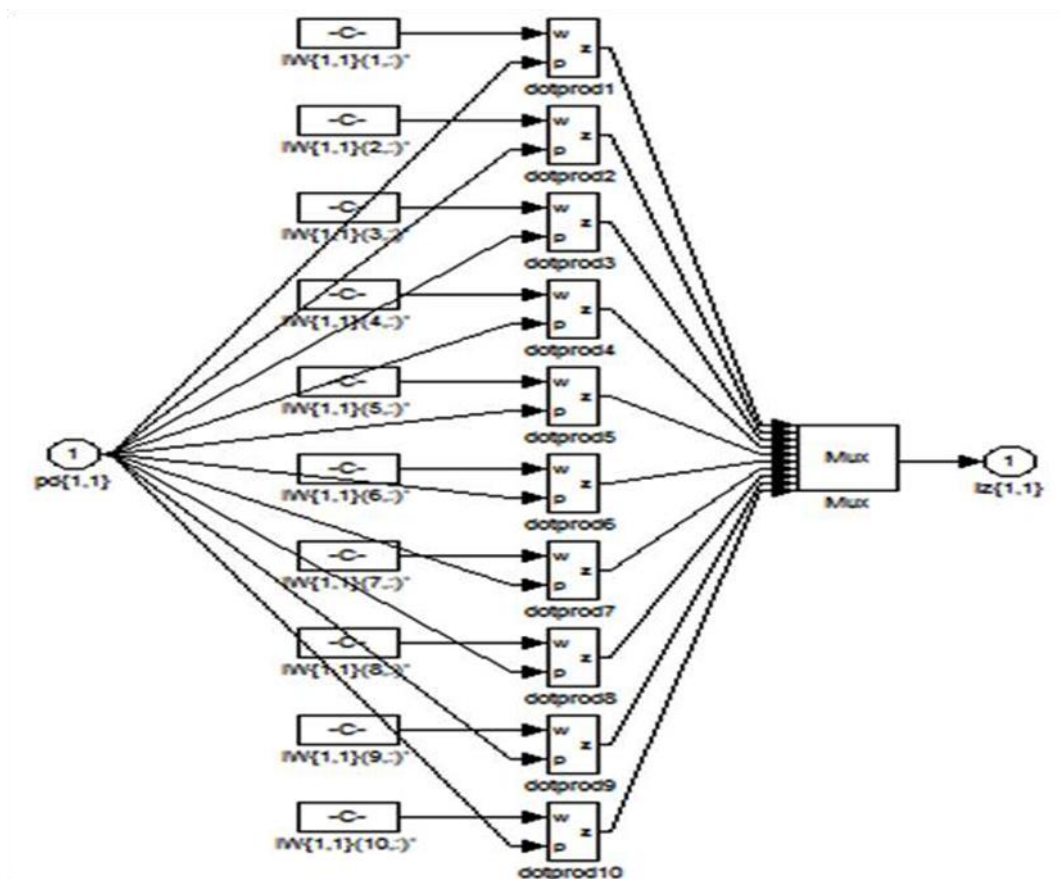


Fig. II.20: Internal structure of the first layer with a hidden layer of the neural network in MATLAB Simulink.

As a third step, we decided to examine the impact of the choice of training algorithm on training performance in terms of convergence speed (minimisation of the quadratic error), using two different algorithms, namely:

the backpropagation algorithm and the Levenberg-Marquardt algorithm.

II.9.1. Presentation of the two algorithms used for training the proposed neural network

As previously mentioned, once the architecture has been chosen, the ANN must undergo a training phase. This involves calculating the synaptic weights in such a way that the outputs of the neural network, for the examples used during training, are as close as possible to the ‘desired’ outputs. These correspond to the values of the data for the function we wish to approximate or to the output of the process we wish to model.

The training of our network was carried out using two different algorithms:

- Backpropagation algorithm;
- Levenberg-Marquardt algorithm.

II.9.2. Training using the backpropagation algorithm

The development of the network is based on supervised learning using the backpropagation algorithm. It should be noted that this algorithm has been used with great success in a number of complex applications. During this phase, the backpropagation error gradient backpropagation algorithm seeks the weights W_i that minimise the mean (MSE) between the target value and the value estimated by the model, governed by the following equation:

$$EQM = \frac{1}{2} \sum (V_{PV}^{ref} - V_{PV}^{mes})^2$$

In other words, the weights W_i are continuously adjusted as long as the EQM error exceeds a certain threshold value corresponding to the acceptable output accuracy.

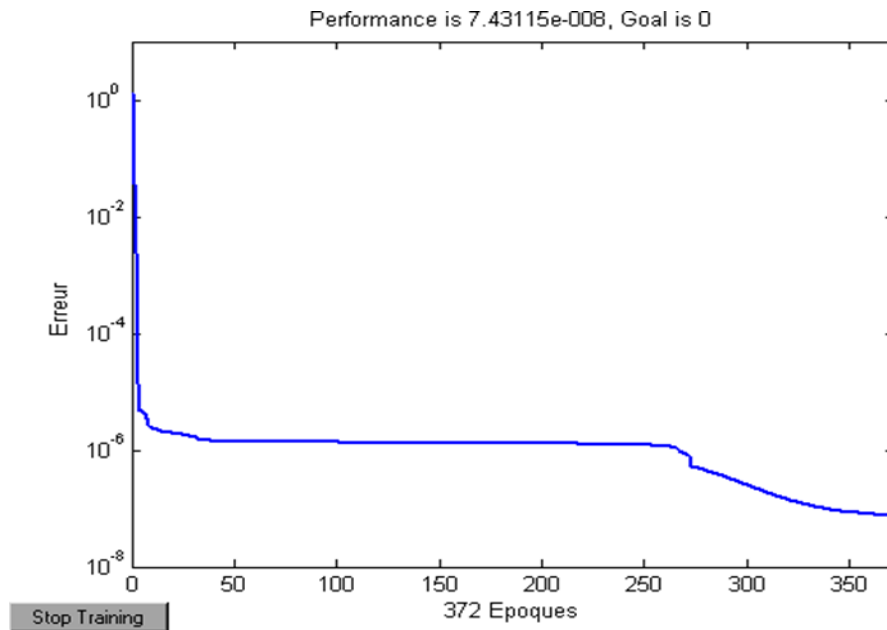


Fig. II.21: Evaluation of the mean squared error as a function of the number of training iterations (using the backpropagation method).

The adjustment of the connection weights, represented by the matrices [W1] and [W2], is carried out based on the stimuli present at the network's input. The aim is to find the connection weights appropriate to the data that ensure convergence towards the desired output.

Once the learning process is complete, the weights are no longer modified, which corresponds to the optimal ANN structure.

II.9.3. Training using the Levenberg- -Marquardt algorithm

On the other hand, and with a view to comparing performance with the previous backpropagation method, the system will now be trained using the Levenberg-Marquardt method.

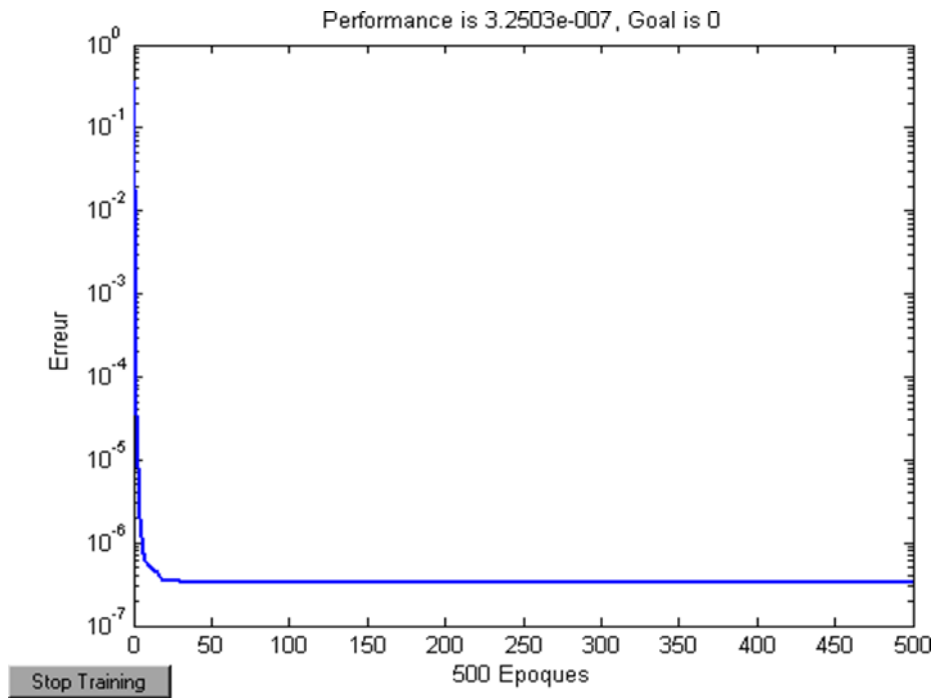


Fig. II.22: Training error during neural network training (using the Levenberg-Marquardt method).

The results clearly show that the target error was achieved by this method with a high convergence rate and a high approximation capacity. For this reason, we will adopt this algorithm for the remainder of the work.

II.9.4. Validation: “ generalisation ability”

The evaluation of the network’s generalisation ability is carried out on the validation set, using input-output pairs not belonging to the training set. That is to say, after completing the training and determining the network weights required to calculate to assess the network’s generalisation ability.

The photovoltaic system used comprises the following blocks:

A photovoltaic generator, a boost chopper, a current regulator, a voltage regulator and a neural MPPT controller

II.10.Conclusion

In this chapter, we have studied the photovoltaic module and its performance, as well as DC-DC converters used in photovoltaic systems, such as the boost chopper. We also described the Maximum Power Point Tracking (MPPT) control of these converters in order to determine the point at which the photovoltaic generator power is maximized, using the Perturb and Observe (P&O) algorithm.

Results concerning the output power of the photovoltaic generator and the output voltage were obtained. However, this technique has some drawbacks, such as response time and oscillations in steady-state operation at the maximum power point.

In contrast, the Artificial Neural Network (ANN) algorithm is considered one of the modern intelligent approaches that offers superior performance in tracking the maximum power point. It is characterized by its ability to learn and adapt to rapid changes in environmental conditions such as solar irradiance and temperature, which helps reduce oscillations and improve response speed compared to the P&O algorithm. Moreover, this technique allows for higher accuracy in identifying the maximum power point, thereby improving the overall efficiency of the photovoltaic system. However, it requires greater complexity in terms of design and training, as well as sufficient data to ensure good performance.

CHAPTER III

Simulation of MPPT algorithms using neural networks and the P&O algorithm

III.1. Introduction

In this chapter, a maximum power point tracking (MPPT) system will be simulated using MATLAB/Simulink, whilst examining the performance of artificial neural networks by analysing response speed, tracking accuracy, and the stability of power output under various operating conditions, with the aim of improving the performance of photovoltaic systems and increasing their efficiency.

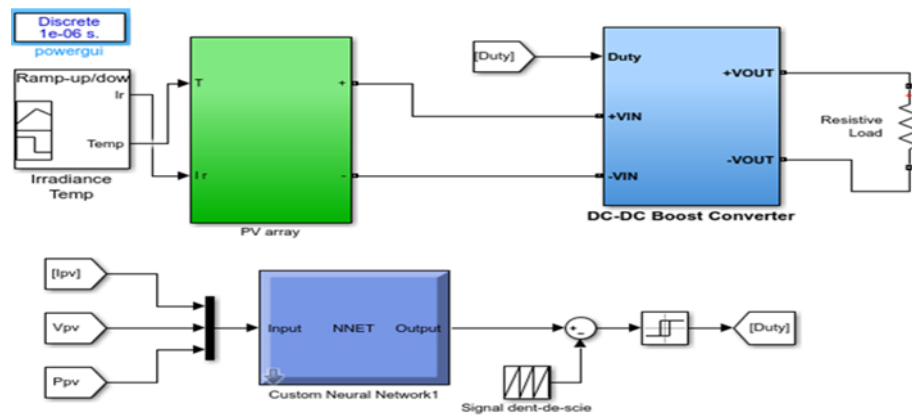
Maximum power point tracking (MPPT) systems are of great importance within photovoltaic systems, given the impact of climatic variations, such as changes in solar irradiance and temperature, on the efficiency of solar cells and the electrical power extracted from them. It has therefore become necessary to rely on control techniques capable of ensuring that the system operates as close as possible to the maximum power point with the greatest possible accuracy, whilst minimising energy loss and improving system stability.

Artificial neural networks are among the most important artificial intelligence technologies used in MPPT systems, due to their ability to handle non-linear systems and rapid changes in operating conditions. This technology also relies on the principle of learning and training to predict optimal values and control the system with high accuracy, thereby improving response speed and reducing oscillations compared to traditional methods

Through this study, a complete model of the photovoltaic system will be developed, incorporating the photovoltaic generator, a DC-DC converter, and a neural network algorithm within the MATLAB/Simulink environment. The system will be subjected to various operating conditions to evaluate its performance and study the behaviour of power, voltage, and current as climatic conditions change.

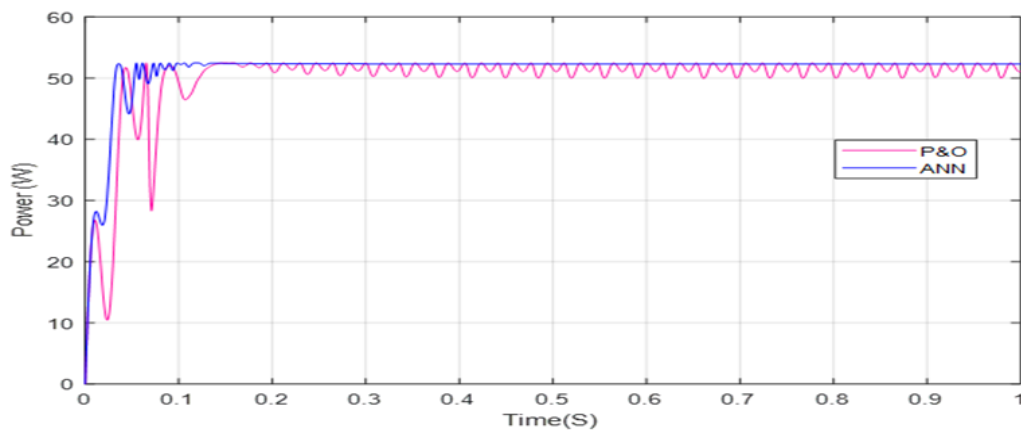
Finally, this study aims to highlight the effectiveness of artificial neural networks in improving the performance of photovoltaic systems, and to demonstrate the role of intelligent control techniques in enhancing the efficiency and stability of modern solar energy systems.

III.2. Simulation



III. 1. Simulink model of neural network controller MPPT with DC-DC boost convert

III.3. Comparison of control technique results (neural network, P&O)

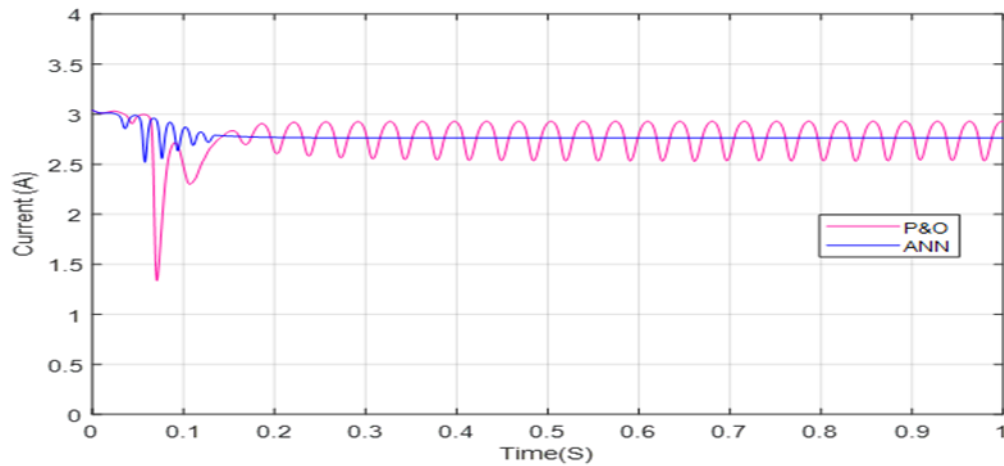


III. 2. Output power at standard conditions with neural network controller and conventional algorithm (P&O)

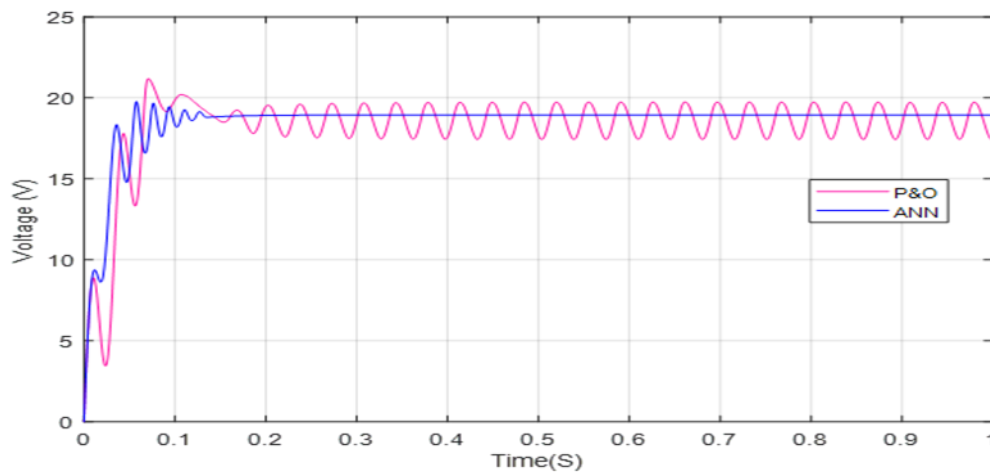
To further assess system performance, additional simulations were carried out under variable irradiance levels of 800 W/m², 900 W/m², and 1000 W/m² at a constant temperature of 25 °C.

The corresponding results are presented in the following figures, demonstrating the ANN controller's ability to adapt effectively to changes in irradiance while maintaining stable power output and high tracking accuracy. Second Scenario: To evaluate the proposed

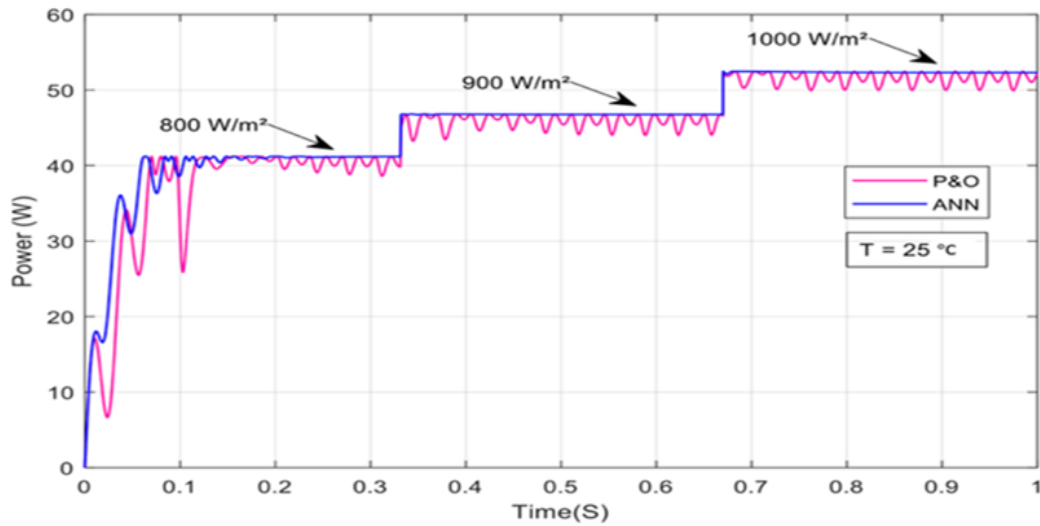
system's performance, simulations were conducted under varying solar irradiance levels (800 W/m^2 , 900 W/m^2 , and 1000 W/m^2) while maintaining a constant temperature of 25°C . The corresponding results demonstrate the capability of the neural network controller to respond effectively to changes in solar input while preserving stable output power and accurate maximum power tracking.



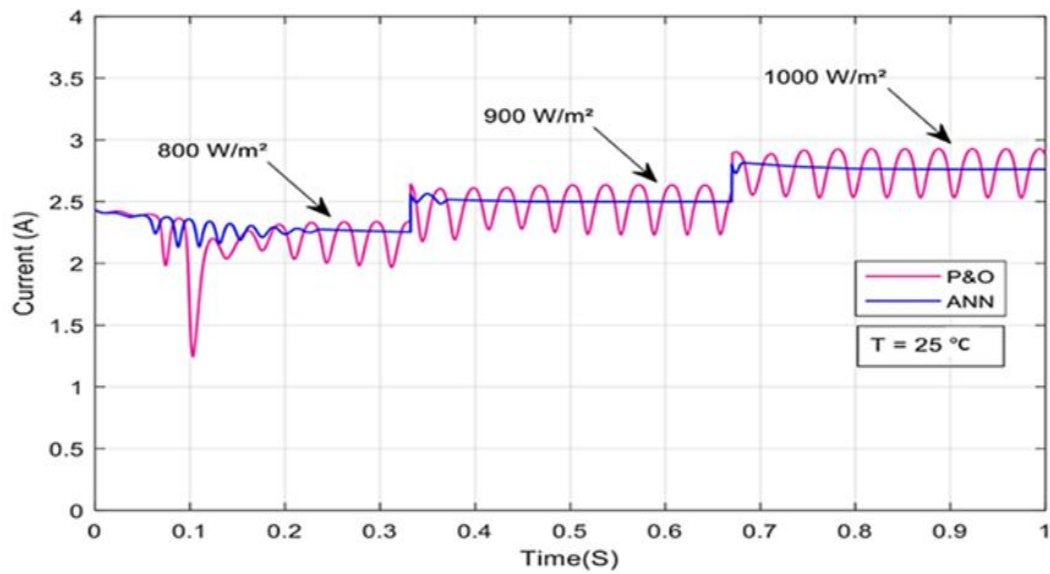
III.3. Output current at standard conditions with neural network controller (ANN) and conventional algorithm (P&O)



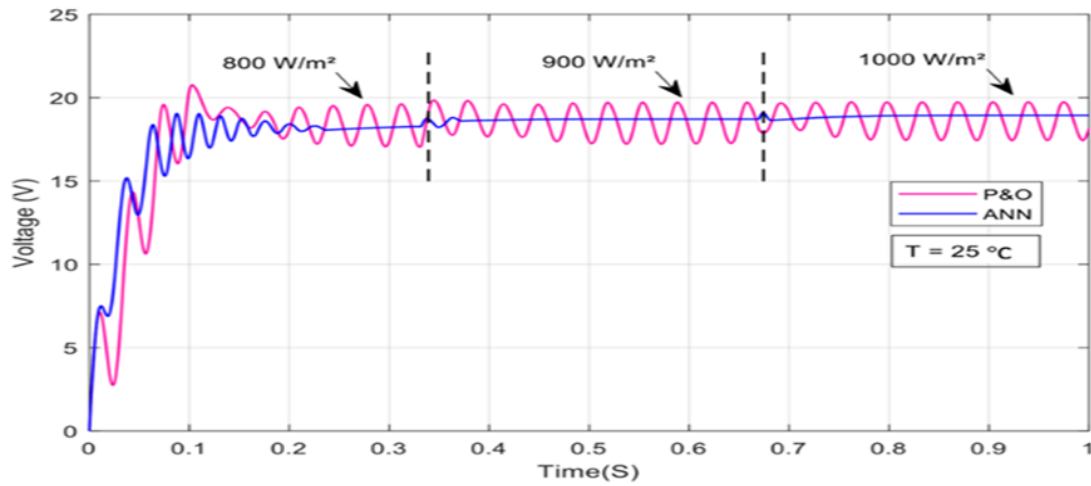
III.4. Output voltage at standard conditions with neural network controller (ANN) and conventional algorithm (P&O)



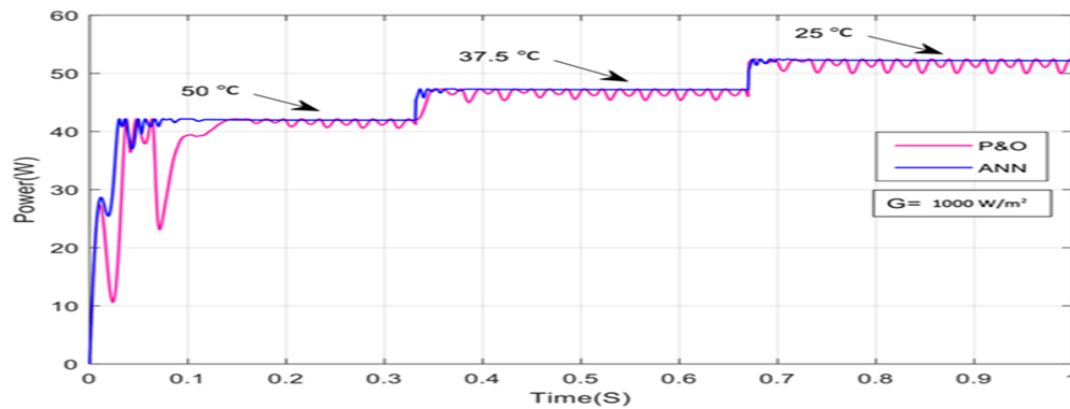
III.5. Output power at different irradiance values and fixed temperature of 25 °C with neural network controller (ANN) and conventional algorithm (P&O)



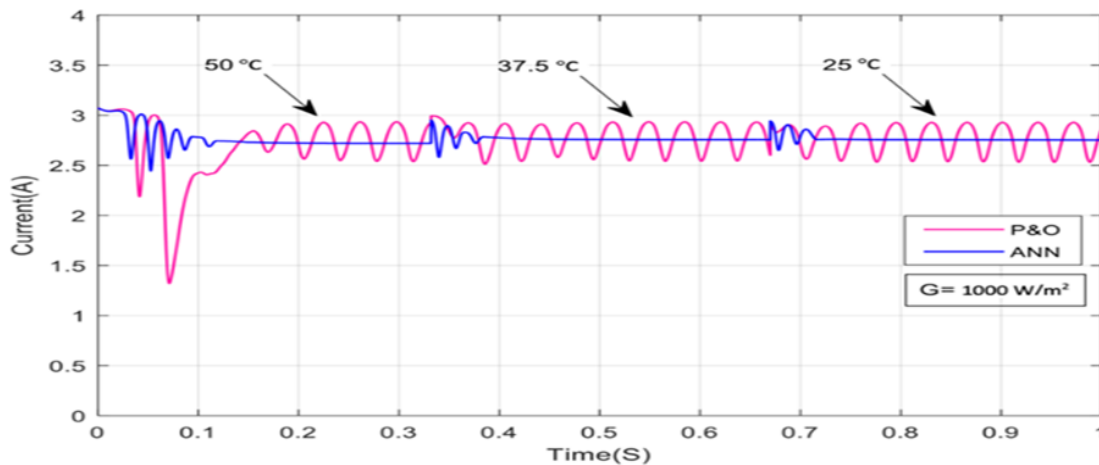
III.6. Output current at different irradiance values and fixed temperature of 25 °C with neural network controller (ANN) and conventional algorithm (P&O)



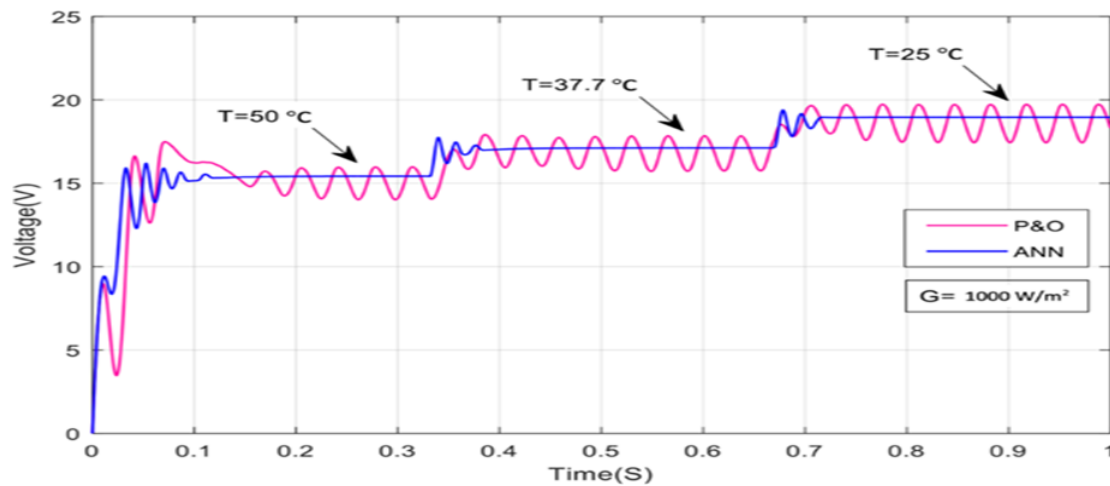
III.7. Output voltage at different irradiance values and fixed temperature of 25°C with neural network controller (ANN) and conventional algorithm (P&O)



III.8. Output power at different temperatures and fixed irradiance of 1000 W/m^2 with neural network controller (ANN) and conventional algorithm (P&O)



III.9. Output current at different temperatures and fixed irradiance of 1000 W/m^2 with neural network controller (ANN) and conventional algorithm (P&O)



III.10. Output voltage at different temperatures and fixed irradiance of 1000 W/m² with neural network controller (ANN) and conventional algorithm (P&O).

In the third test case, the impact of rapid temperature fluctuations on system performance was examined while maintaining constant solar irradiance a $G = 1000 \text{ W/m}^2$. The PV array temperature was varied between 25 °C, 37.5 °C, and 50 °C, as depicted in the corresponding figures 18-23. The obtained results indicate that the ANN-based MPPT controller preserves stable power delivery and consistently achieves accurate tracking of the maximum power point despite thermal disturbances.

Overall, the findings demonstrate that the ANN-driven MPPT strategy effectively adapts to changing environmental conditions. Compared with the conventional perturb and observe method, the neural-network-based controller exhibits faster transient behavior, enhanced tracking capability, and significantly reduced steady-state oscillations, highlighting its practical applicability in real photovoltaic systems.

III-1. The analogy between biological neurons and artificial neurons

MPPT	Efficiency η_{MPPT}	Advantages	Disadvantages
P&O	81.5%–96.5%	-A simple structure. -Easy to implement. -Few measurement parameters.	- Exhibits oscillations around the MPP. -Occasional loss of MPP tracking during rapid changes in .
Neural Network	95%–99%	- High tracking accuracy - Fast dynamic response - Suitable for nonlinear and complex PV system	- Requires training dataset - High computational complexity - Implementation cost is high

III.4. CONCLUSION

This work introduces an artificial neural network-based MPPT technique designed to improve the dynamic response and energy extraction efficiency of photovoltaic systems. The PV module was modeled using a single-diode representation derived from the electrical characteristics of its equivalent circuit. A DC–DC boost converter was integrated with the PV model to enable implementation of the ANN-based tracking mechanism.

The converter topology was analytically described to establish the relationship between duty cycle, load conditions, and the effective input impedance seen by the PV array. This configuration was subsequently developed and evaluated within the MATLAB/Simulink simulation environment.

Simulation results confirm that the proposed ANN-based MPPT approach delivers superior dynamic performance compared to the traditional P&O method. Specifically, it ensures faster convergence to the maximum power point, improved operational stability, and reduced oscillatory behavior under varying operating condition.

General conclusion:

In conclusion, this dissertation has presented a comprehensive and integrated study of photovoltaic (PV) systems, beginning with the fundamental operating principles of the PV cell and the analysis of its equivalent circuit, and extending to the modeling of the photovoltaic generator and the investigation of its electrical characteristics (I – V and P – V) under varying environmental conditions. The influence of key factors such as solar irradiance, temperature, and internal parameters, including series and shunt resistances, has been thoroughly examined. Simulation results obtained using the MATLAB/Simulink environment have demonstrated the significant impact of these parameters on the overall performance of the PV system, highlighting the necessity of adopting efficient techniques to optimize energy extraction.

Furthermore, DC–DC converters, particularly the boost converter, have been studied for their essential role in power adaptation and energy transfer optimization. Special attention has been given to Maximum Power Point Tracking (MPPT) techniques. The conventional Perturb and Observe (P&O) algorithm was analyzed, and its main limitations—such as steady-state oscillations around the maximum power point and relatively slow dynamic response—were identified.

In contrast, an Artificial Neural Network (ANN)-based MPPT approach was proposed and implemented as an advanced intelligent solution. Simulation results have confirmed its superior performance in terms of faster response, reduced oscillations, and higher accuracy in tracking the maximum power point, even under rapidly changing environmental conditions. Despite its higher complexity and the requirement for adequate training data, this method represents a promising and effective approach for enhancing the performance of photovoltaic systems.

Overall, photovoltaic energy stands out as a clean, renewable, and sustainable energy source capable of meeting the increasing global energy demand while mitigating environmental impacts. This work opens promising for future research focused on the development of more advanced intelligent control strategies and their validation under real operating conditions to ensure improved efficiency, reliability, and robustness of PV systems.

Bibliography

- [1] TRAHI Fatiha. 'Prediction of global solar irradiance for the Tizi-Ouzou region using artificial neural networks. Application for the design of a photovoltaic installation to power the Lampa research laboratory.' Master's thesis in Electronics, Mouloud Mammeri University of Tizi-Ouzou, 2011.
- [2] R.M. Erahi-Chenni. "Improvement of P&O control through synchronous battery current detection." ICESD Journal, pp. 113–121, 2019.
- [3] A. AZIZ, 'Electrical Properties of Inorganic and Organic Electronic Components: Design and Modelling of a Photovoltaic Chain for More Efficient Utilisation of Solar Energy', PhD Thesis, Paul Sabatier University, Toulouse III, France, 2016.
- [4] OUMNAD, 'Fundamental Electronics', Mohammadia School of Engineering, Website, <http://z.oumnad.123.fr>.
- [5] C. Hua and C. Shen, 'Comparative study of peak power tracking techniques for solar storage systems', IEEE Applied Power Electronics Conference and Exposition, 15–19 February, Anaheim, CA, USA, 2014.
- [6] P. ROUX, 'Simplified General Theory of Semiconductors', Website <http://philippe.roux.7.perso.neuf.fr/>.
- [7] Regional Directorates for Industry, Research and the Environment, websi <http://www.drire.gouv.fr/alsace/surete/didactique/atome.htm>
- [8] R. C. Neville, 'Solar Energy Conversion: The Solar Cell' Studies in Electrical and Electronic Engineering. Elsevier Scientific Publishing Company, Vol 1, New York, NY, 1978.
- [9] C. R. Sullivan and M. J. Powers, 'High-efficiency maximum power point tracker for photovoltaic arrays in a solar-powered race vehicle', The 1993 IEEE 24th Annual Power Electronics Specialists Conference, PESC Record, pp. 574–580, Seattle, WA, USA, 2011.
- [10] J. D. Van Wyk and J. H. Enslin, 'A study of a wind power converter with microcomputer-based maximum power control utilising an oversynchronous electronic Scherbius cascade', IEEE International Power Electronics Conference (IPEC-83), Vol. 1, pp. 766–777, Tokyo, 2020.
- [11] Z. BENDJELLOULI, 'Contribution to the Modelling of a Solar Cell', Master's Thesis, University of Bechar, Algeria, 2019.

- [12] M. ANGEL CID PASTOR, “Design and Implementation of Electronic Photovoltaic Modules”, PhD Thesis, National Institute of Applied Sciences of Toulouse, France, 2016.
- [13] A. Mezache and F. Soltani, ‘A novel threshold optimisation technique for CFAR detection in Weibull clutter using a fuzzy-neural network’, IEEE International Conference on Signal Processing and Communications (ICSPPC 2017), Dubai, United Arab Emirates, 24–27 November 2017.
- [14] M. DJARALLAH, “Contribution to the Study of Grid-Connected Residential Photovoltaic Systems”, PhD Thesis, University of Batna, Algeria, 2018.
- [15] M. L. LOUAZENE, ‘Technical and Economic Study of a Photovoltaic Pumping System at the Ouargla Site’, Master’s Thesis, El Hadj Lakhdar University of Batna, Algeria, 2008.
- [16] H. FATIHA and R. AICHA, “Modelling and Simulation of a Photovoltaic System”, Academic Master’s Thesis in Electrical Engineering, Kasdi Merbah University, Ouargla, 2014
- [17] C. CABAL, “Energy Optimisation of the Electronic Conversion Stage for Photovoltaic Power Conversion”, PhD Thesis, Paul Sabatier University, Toulouse III, France, 2008
- [18] S. A. TADJER, ‘Study of a Harmonic Compensation System Using a Photovoltaic Generator’, Master’s Thesis, Mouhamed Bougara University, Boumerdes, Algeria, 2008.
- [19] Z. M. Salameh, M. A. Casacca, and W. A. Lynch, ‘A mathematical model for lead-acid batteries’, IEEE Transactions on Energy Conversion, Vol. 7, No. 1, pp.2014.
- [20] Daniel Hart, *Power Electronics*, McGraw-Hill.
- [21] Bisker and Chiri, “Control of a Photovoltaic System in Off-Grid and Grid-Connected Modes”, Final Year Project, École Nationale Polytechnique, Algiers, June 2012

الملخص :

تهدف هذه المذكرة إلى تحسين كفاءة استخراج الطاقة من الأنظمة الكهروضوئية (PV) من خلال إجراء دراسة مقارنة معمقة بين خوارزمية التتبع التقليدية "الاضطراب والملاحظة (P&O)" وتقنية ذكية حديثة تعتمد على "الشبكات العصبية الاصطناعية (ANN)" وتنقسم المذكرة إلى ثلاثة فصول رئيسية:

الفصل الاول نمذجة المولد الكهروضوئي :

يتناول مبدأ التحويل الكهروضوئي والخصائص الكهربائية للخلايا والمجمعات الشمسية (I-V و P-V). ويستعرض محاكاة النظام عبر برنامج MATLAB لدراسة تأثير العوامل المناخية؛ حيث تبين أن التيار يتناسب طردياً مع شدة الإشعاع الشمسي، في حين يؤدي ارتفاع درجة الحرارة إلى انخفاض الجهد المتاح وبالتالي تقليص القدرة القصوى للمجمع.

الفصل الثاني تحكم MPPT والمحولات المستمرة-المستمرة:

يشرح دور محولات الرفع (Boost Converter) في موازنة الجهد ونقل الطاقة الكهروضوئية إلى الحمل بشكل مثالي. كما يستعرض بالتفصيل خوارزمية P&O التقليدية وعيوبها مثل التذبذب المستمر حول نقطة الطاقة القصوى وبطء الاستجابة الديناميكية. وفي المقابل، يقدم الأسس البيولوجية والرياضية للشبكات العصبية الاصطناعية، مع التركيز على تدريب الشبكة المقترحة خارج الخط (Offline) باستخدام خوارزميتي البث الخلفي للخطأ (Backpropagation) و"ليفنبرغ-ماركاردت" (LM)، حيث أظهرت الأخيرة سرعة تقارب ودقة أعلى.

الفصل الثالث (المحاكاة والمقارنة):

يركز على محاكاة نظام التتبع بالكامل في بيئة MATLAB/Simulink تحت ظروف تشغيل ديناميكية متغيرة (إشعاع وحرارة متقلبة) لتقييم استجابة التيار والجهد والقدرة.

الخاتمة العامة

أثبتت نتائج المحاكاة تفوق نظام التحكم القائم على الشبكات العصبية الاصطناعية (ANN) مقارنة بالأسلوب التقليدي (P&O). تميزت تقنية الشبكات العصبية باستجابة ديناميكية أسرع، ودقة تتبع عالية تتراوح بين 95% إلى 99% (مقارنة بـ 81.5% - 96.5% لخوارزمية P&O)، مع تقليص شبه تام للتذبذبات في حالة الاستقرار. على الرغم من تعقيد تصميمها وحاجتها لبيانات تدريبية ضخمة، فإنها تعد حلاً ذكياً وواعداً لرفع كفاءة واستدامة أنظمة الطاقة الشمسية.

الكلمات المفتاحية :

النظام الكهروضوئي (PV System) /تتبع نقطة الطاقة القصوى (MPPT) / الشبكات العصبية الاصطناعية (ANN) / خوارزمية الاضطراب والملاحظة (P&O) /محولات الرفع المستمرة-المستمرة (Boost Converter) / نمذجة ومحاكاة (Modeling and Simulation)

General Introduction :

This thesis focuses on optimizing energy extraction from photovoltaic (PV) systems by presenting a comparative study between the conventional Perturb and Observe (P&O) algorithm and an intelligent approach utilizing Artificial Neural Networks (ANN). The work is structured into three core chapters:

Chapter I (Modelling of a Photovoltaic Generator):

Covers the principles of PV conversion and the mathematical modeling of solar cells and arrays (I-V and P-V characteristics). MATLAB simulations analyze environmental impacts, showing that output current is directly proportional to solar irradiance, while rising temperatures degrade the open-circuit voltage and decrease overall maximum power output.

Chapter II (MPPT Control and the DC-DC Converter):

Investigates the modeling of a DC-DC boost converter used to step up voltage and match the PV array to the load. It outlines the classic P&O tracking mechanism and its limitations, such as steady-state oscillations and slow dynamic response. It then introduces the biological foundations of artificial neurons and details the proposed multi-layer perceptron architecture, trained offline using Backpropagation and Levenberg-Marquardt (LM) algorithms—where the LM method demonstrated superior convergence speed.

Chapter III (Simulation and Comparison):

Implements the full PV string simulation in MATLAB/Simulink under dynamic climate scenarios (varying irradiance and sudden temperature fluctuations) to evaluate current, voltage, and power responses.

General Conclusion:

Simulation results confirm that the ANN-based MPPT controller offers significantly better performance than the traditional P&O algorithm. The intelligent neural network exhibits faster transient response, minimizes steady-state oscillations around the Maximum Power Point (MPP), and yields a higher tracking efficiency of 95% to 99% (compared to P&O's 81.5% - 96.5%). Despite its structural complexity and heavy reliance on substantial

training datasets, the ANN strategy proves to be a robust and highly efficient solution for modern renewable solar energy applications.

Keywords

Photovoltaic System (PV) /Maximum Power Point Tracking (MPPT) /Artificial Neural Networks (ANN) /Perturb and Observe Algorithm (P&O)/ DC-DC Boost Converter