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THEME

Identification of an autonomous photovoltaic system using radial basis function (RBF) networks

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بسم الله الرحمن الرحيم

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Dedication

I have the great honor of dedicating this modest work to:

To my dear father, to whom I owe my education and instruction. His presence in all circumstances has often reminded me of the sense of responsibility.

To my dear mother, for her concern for me and who surrounded me with her tenderness, always ready to sacrifice herself for her children.

And to all my loved ones.

To all my friends.

To all my colleagues in the Electronic class, Instrumentation Electronic option, year 2023-2024.

And to everyone who knows me and counts on me...

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General Introduction

The global consumption of electricity observed in recent decades is strongly linked to the development of industry and transmission. Natural gas, oil, coal, and uranium are examples of non-renewable resources that are used to generate a significant portion of the world's electricity today. When compared to human regeneration rates, theirs is incredibly slow. As a result, there is a rather short-term non-zero danger of these resources running out [1].

However, there is a negative environmental impact associated with this kind of energy use. For hydrocarbons, like coal, substantial emissions of greenhouse gases are produced on a daily basis, contributing significantly to both increased pollution and climate change. The aforementioned fact compels us to progressively explore inventive methods to offset the energy shortfall and mitigate the adverse effects on the ecosystem. As a result, both energy providers and government agencies are calling for the development of non-polluting sources based on renewable energy [2].

We refer to solar energy as renewable energy. Earth receives breathtaking light energy from the sun. However, the issue lies in the fact that the shape energy takes on does not always correspond to its useful form. We need to employ energy conversion procedures because of this. Photovoltaic solar cells, for instance, use light energy from the sun to create electrical energy.

Photovoltaic are promising because of their intrinsic qualities: their operating costs are very low ,their maintenance requirements are limited, they are reliable, quiet and relatively easy to install. Moreover, in some stand-alone applications, photovoltaic are very practical compared to other energy sources, especially in places that are difficult to access and uneconomical for the installation of traditional power lines [3].

Today, the necessity for a cheap, dependable power source in remote areas is what is driving the worldwide photovoltaic (PV) market. For a great deal of purposes, photovoltaic are only the most economical option. These applications include water pumping on farms, emergency call centers on campuses or universities, isolated systems serving cottages or remote households, utilities, and the military Motorways [4].

The objective of this thesis is to create an artificial neural network model which makes a prediction of the power produced by a photovoltaic system with a certain value of temperature and radiation, the objective of which is to develop photovoltaic (PV) systems.

Artificial neural networks play a crucial role in photovoltaic (PV) systems, covering several aspects of their design, management and optimization. In particular, the prediction of the power produced by photovoltaic systems facilitates efficient energy management. Which helps to adjust consumption according to planned production and maximize the use of available solar energy, allowing power grid operators to better balance supply and demand, thereby reducing the need for solar energy sources, Emergency energy helps plan energy supply and manage energy reserves, particularly for periods of low sunlight, facilitates the planning of investments and maintenance operations by predicting periods of maximum and minimum production [5].

This thesis is organized as follows:

In the first chapter is devoted to the identification of dynamic systems we will see the identification methods including global optimization technique called Aliénor and the steps necessary for successful identification.

In the second chapter, we present reminders on renewable energies and in particular photovoltaic systems and the components which makes them in general, including the types of photovoltaic cells and the advantages and disadvantages of a photovoltaic system.

The third chapter focused on artificial neural networks and the results obtained from the program we created based on radial basis function (RBF). We explored the architecture of an artificial neural network, the types of these networks and we explored how to learn a neural artificial networks as well as its advantages and disadvantages. included the implementation and performance evaluation of the RBF model in identifying and predicting the behavior of a photovoltaic system under various conditions

Finally, we close this work with a general conclusion which summarizes the results obtained and perspectives for the future continuity of this work.

Chapter I

Identification of dynamic systems

Introduction

The topic of identification of dynamic systems, has been at the core of modern control, following the fundamental works of Kalman. Realization Theory has been one of the major outcomes in this domain, with the possibility of identifying a dynamic system from an input-output relationship. The recent development of machine learning concepts has rejuvenated interest for identification [6].

Identification is an experimental method that uses techniques and algorithms to manipulate experimental resources with the goal of modifying the model's parameters to make the model behave like the system. This chapter covers the fundamental ideas behind the parametric identification of dynamic systems as well as a number of frequently used identification techniques and how they are used [7].

I.1 Principle of identifying a dynamic systems

Identifying a system entails putting forth a model structure based on the measurements acquired and figuring out its parameters. so that, when both systems are exposed to the same input.(the model's behavior corresponds to that of the real system)[8].

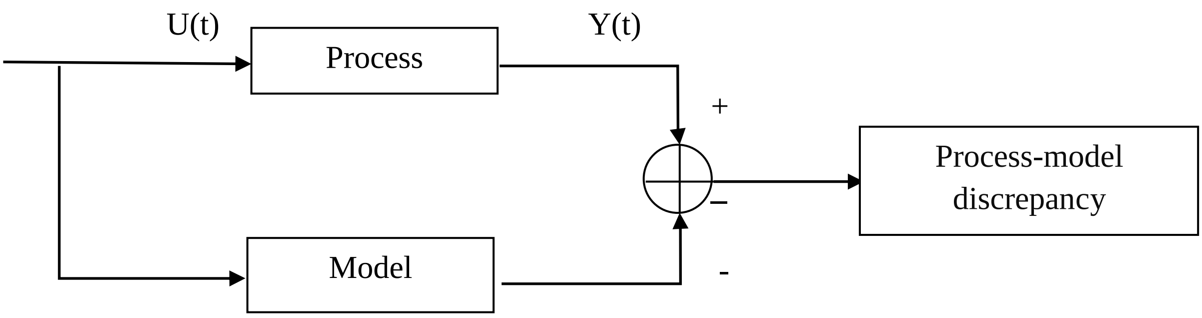


Figure III.1 Schematic of dynamic system

I.2 Identification steps

To identify a dynamic systems, one must follow the identification steps illustrated in Figure (I.1).

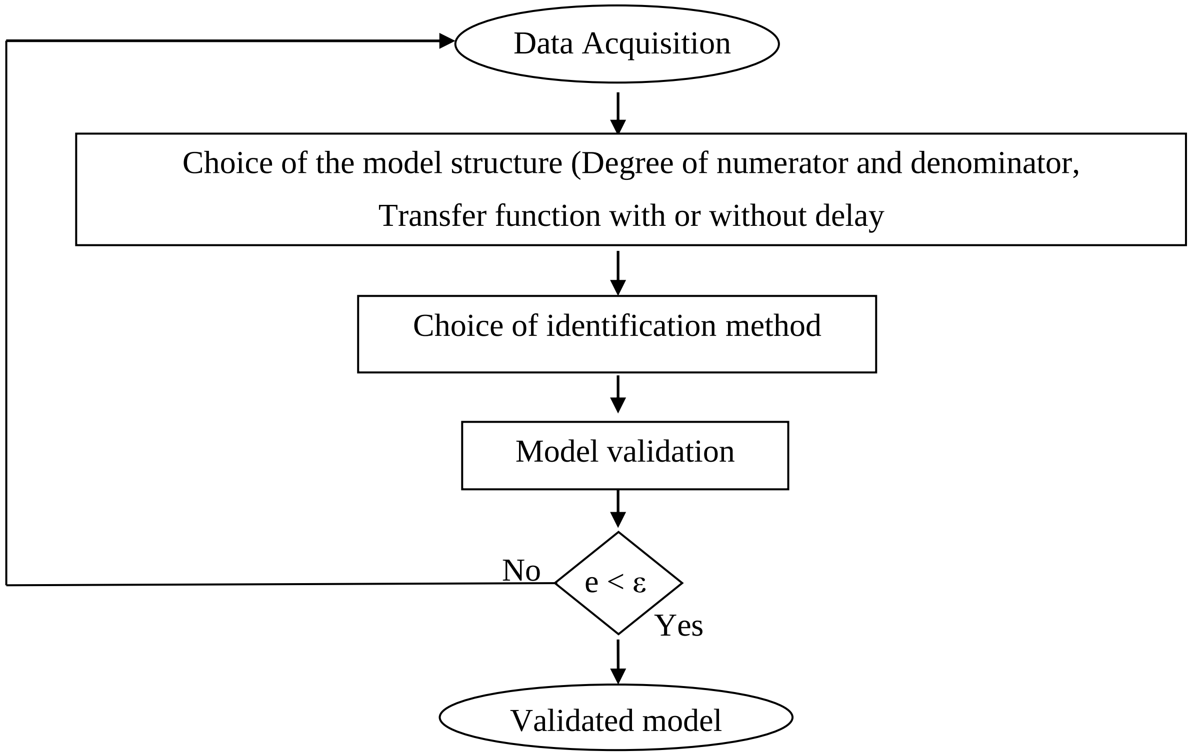


Figure I.2 Identification steps

I.2.1 Data Acquisition

Comprehending a system's behavior in real time is crucial for an efficient identification. This entails selecting an entry acting as an excitation signal whose spectrum density can stimulate the system's overall dynamics to identify [9].

Among the excitation signals that can be injected as an input:

- Constant signal.
- Unit step signal.
- Sinusoidal signal.
- Rectangular signal.
- Impulse signal.
- Pseudo-random binary sequence "PRBS".

I.2.1.1 Illustration of the importance of the excitation signal

To illustrate the importance of the input signal for the system to be identified, consider a first-order system with a transfer function described by a static gain k = 1 and a time constant T = 8 seconds [10].

Different types of input are injected into this process, as shown in Figure I.2:

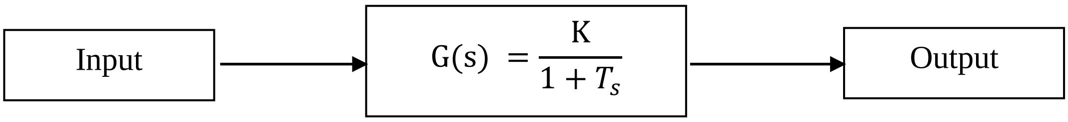


Figure I.3 Process representation

The results obtained for each signal are represented in the table I.1:

Table I.1 Parameters obtained for different input types

signal	Constant signal	Unit step signal	Rectangular signal	Impulse signal	PRBS
Static gain K	1.0048	1.0033	0.9980	1.6826	1
Time constant T	3.3098	7.6879	8.0671	4.4800	7.98

Table I.1 displays the parameters K and T identified after exciting the system with a constant, a unit step, a rectangular input, an impulse, and a pseudo-random binary sequence (PRBS). The results indicate that the PRBS signal is the most effective, with identified parameters very close to the actual values. This highlights the importance of choosing an excitation signal rich in frequencies.

I.2.2 Choice of the model structure

Choosing the model structure, or the sequence in which to choose the transfer function's numerator and denominator, is the second stage in the identification process. This stage is implemented using data from a tangible experiment. A model structure can be selected by applying an impulse input to the real system under identification and analyzing the shape of the step response [11].

I.2.3 Choice of identification method

Noise frequently tampers with the measured output when the excitation signals have low amplitudes. This kind of noise generates biases (errors in parameter estimation), and it is often challenging to accurately define it. As a result, each time, an assumption on its structure must be made before selecting a suitable estimation algorithm [12].

I.2.4 Model validation

Verifying if the discovered model can accurately represent the real system is the last stage of the identification procedure. This is accomplished by setting a tolerance and computing the error between the identified system's response and the real system's response to the identical input. The model is deemed validated if the estimated error is smaller than the predetermined tolerance. If not, the identification procedure needs to be done over from the beginning [13].

I.3 Identification methods

We have parametric method and non-parametric method.

These methods are classified by categories as they are represented in the table II.2:

Table I.2 identification methods

Parametric method	Non-paremetric method
1/Graphical method ➢ Method based on time responses (Strejc and Broida). ➢ Method for systems with integration. ➢ Method for oscillatory systems.	Method based on frequency responses.
2/Numerical method ➢ Method of least squares. ➢ Recursive least squares method.	Methods based on impulse responses .

I.3.1 Numerical method

Even if analytical approaches cannot precisely solve functions and equations found in theory or practice, we aim to find an approximate numerical solution that can be obtained in a finite number of processes.

As a result, we concentrate on numerical techniques based on the application of algorithms to precisely determine the parameters of our model following the graphical analysis [14].

I.3.1.1 The application of the method of least squares

To find the parameters, we must first start with the standard formulation of least squares, assuming that the calculated variable $\hat{y}(x)$ is given by the following model:

$$\hat{y}(x) = \theta_1 \emptyset_1 (x) + \theta_2 \emptyset_2 (x) + \cdots + \theta_n \emptyset_n (x) \tag{1.1}$$

When:

$\theta 1, \theta 2, \dots \theta n$: These are the parameters to be determined.

$\emptyset_1, \emptyset_2 \dots \emptyset_n$: These are known functions.

x_2, ..., x_n: These are explanatory variables.

n: The number of measurements.

We seek to determine the model parameters such that the calculated values $\hat{y}_i$ from the variables xi are as close as possible to the measured valuesy_i. When the precision is the same for all measurements, the parameters must satisfy the minimization of the following criteria:

$$j(\theta) = \frac{1}{2}\sum_{i=1}^{N} e_i^2 , \quad e_i = y_i - \hat{y}_i \tag{1.2}$$

The identified model is given in the form:

$$G(Z) = \frac{b_0+b_1 Z^{-1}+\dots+b_m Z^{-m}}{a_0+a_1 Z^{-1}+\dots+a_n Z^{-n}} = \frac{y(z)}{u(z)} \tag{1.3}$$

For $a_0 = 1$, the corresponding difference equation will be:

$$y(z) + a_1 y(z) Z^{-1} + a_2 y(z) Z^{-2} + \dots + a_n y(z) Z^{-n} = b_0 u(z) + \cdots + b_m u(z) Z^{-m} \tag{1.4}$$

$$y(k) = -a_1 y(k-1) - a_2 y(k-2) - \cdots - a_n y(k-n) + b_0 u(k) + \cdots + b_m u(k-m) \tag{1.5}$$

$$y(k+1) = -a_1 y(k) - a_2 y(k-1) - \cdots - a_n y(k-n+1) + b_0 u(k+1) + \dots \quad \dots + b_m (k-m+1) \tag{1.6}$$

We apply an input sequence {U(1), U(2), ... , U(N)} to the system and retrieve the corresponding measured variable sequence {y(1), y(2), ... , y(N)}.

The unknown parameters are grouped in the following vector:

$$\theta = [a_1 \ \dots \ a_2 \dots \ b_0 \ \dots \ b_m] \tag{1.7}$$

By introducing the regression vector $\emptyset$ (k + 1) such that:

$$\emptyset(k+1) = [-y(k) - (k-1) \dots - y(k-n+1) \ (k-1) \dots (k-m+1)] \tag{1.8}$$

The dynamic model is written in the form:

$$y(k+1) = \emptyset(k+1)\,\theta \tag{1.9}$$

In the least squares framework, the measurements y(k) ... y(k-n+1), u(k) ... u(k-m+1) are used to calculate (or predict) y(k+1):

$$\hat{y}(k+1) = \emptyset(k+1)\,\theta \tag{1.10}$$

Considering the points from 1 to N, we have (assuming n > m for simplicity):

$$y(n+1) = -a_1 y(n) - a_2 y(n-1) - \cdots - a_n y(1) + b_0 u(n) + \cdots + b_m u(n-m+1) \tag{1.11}$$

$$y(n+2) = -a_1 y(n+1) - a_2 y(n) - \cdots - a_n y(2) + b_0 u(n+1) + \cdots + b_m u(n-m+2) \tag{1.12}$$

$$y(N) = -a_1\, y(N-1) - a_2\, y(N-2) - \cdots - a_n\, y(N-1-n) + b_0 u(N+1) + \cdots + b_m u(n-m) \quad (1.13)$$

$$\begin{bmatrix} y(n+1) \\ y(n+2) \\ y(N) \end{bmatrix} = \begin{bmatrix} -y(n) - y(n-1) - y(n) \ldots - y(1) & u(n) \ldots \ldots u(n-m+1) \\ -y(n+1) - y(n) \ldots - y(2) \ldots & u(n+2) \ldots \ldots u(n-m+2) \\ \ldots\ldots \quad \ldots\ldots \quad \ldots\ldots. & \ldots\ldots\ldots \quad \ldots. \\ -y(N-1) - y(N-2) \ldots. -y(N-1-n) & u(N+1) \ldots u(n-m) \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \\ b_0 \\ \vdots \\ b_m \end{bmatrix} \quad (1.14)$$

$$y_N = \emptyset_N\, \theta_N \quad (1.15)$$

$$\theta_N = [\emptyset_N^T \emptyset_N]^{-1} \emptyset_N^T y_N \quad (1.16)$$

I.3.1.2 Recursive least squares methods

If a new measurement is received when using the non-recursive least squares approach, the entire calculation has to be done over. For this reason, recursive techniques are employed, enabling the computation of the model's parameter vectors' new values at each new instant [15].

The estimation of the parameters at (N+1) can be computed using the following two vectors:

$$y_N = [\mathrm{Y}(1)\ \mathrm{Y}(2) \quad \mathrm{Y}(\mathrm{N})]^T \quad (1.17)$$

$$\emptyset_N = [\emptyset(1)\ \emptyset(2) \quad \emptyset(\mathrm{N})]^T \quad (1.18)$$

Using the non-recursive relation over a given duration N, we have:

$$\theta_N = [\emptyset_N^T \emptyset_N]^{-1}\ \emptyset_N^T\ y_N \quad (1.19)$$

Thus, for a horizon of N+1 measurements, we will have the following relations:

$$\theta_{N+1} = [\emptyset_{N+1}^T\ \emptyset_{N+1}]^{-1} \emptyset_{N+1}^T Y_{N+1} \quad (1.20)$$

With:

$$\mathrm{Y}_{(N+1)} = [\ \mathrm{y}_N \quad \mathrm{y}(\mathrm{N}+1)\ ]^T \quad (1.21)$$

$$\emptyset_{(N+1)} = [\ \emptyset_N \quad \emptyset(\mathrm{N}+1)\ ]^T \quad (1.22)$$

To simplify the writing, we introduce the matrix $\mathrm{p}_{(N+1)}$ as follows:

$$p_{N+1} = [\emptyset_N^T\ \emptyset_{N+1}]^{-1} \quad (1.23)$$

This gives:

$$p_{N+1}^{-1} = [\emptyset_N^T \ \emptyset^T(\text{N+1})][\emptyset_N \quad \emptyset(\text{N}+1)]^T$$

$$= \ \emptyset_N^T \emptyset_N + \ \emptyset^T(\text{N+1}) \ \emptyset(\text{N}+1) \tag{1.24}$$

If we define:

$$p_{N+1}^{-1} = \emptyset_N^T \emptyset_N \tag{1.25}$$

We will have the following relation:

$$[p_{N+1}^{-1}]^{-1} = [\ p_N^{-1} + \ \emptyset^T(\text{N}+1)\emptyset(\text{N}+1)]^{\ -1} \tag{1.26}$$

We get:

$$p_{N+1} = \text{p}_N - \frac{\text{p}_N \emptyset^T(\text{N+1})\emptyset(\text{N+1})}{1+\emptyset(\text{N+1})\text{p}_N \emptyset^T(\text{N+1})} \tag{1.27}$$

For the calculation of θ_{N+1} ,we have :

$$\theta_{N+1} = \text{p}_{N+1}[\emptyset_{N+1}^T \text{y}_{(N+1)}] = \text{p}_{N+1}[\emptyset_N^T \ \emptyset^T(\text{N+1})][\ y_N \quad \text{y}(\text{N}+1)]^T$$

$$= \text{p}_{N+1}[\emptyset_N^T y_N + \emptyset^T(\text{N}+1)\text{y}(\text{N}+1)] \tag{1.28}$$

With

$$\emptyset_N = \text{p}_N \ \emptyset_N^T \ y_N \tag{1.29}$$

We can then write:

$$p_N^{-1} \ \theta_N = \ \emptyset_N^T \ y_N \tag{1.30}$$

Therefore:

$$\theta_{N+1} = \text{p}_{N+1}[p_N^{-1} \ \theta_N + \emptyset^T(\text{N}+1)\text{y}(\text{N}+1)] \tag{1.31}$$

Replacing p_N^{-1} with what we found previously, we will have:

$$\theta_{N+1} = \text{p}_{N+1}[p_{N+1}^{-1} - \emptyset^T(\text{N}+1)\emptyset(\text{N}+1)] \ \theta_N + \emptyset^T(\text{N}+1)\text{y}(\text{N}+1)$$

$$= \theta_N - \ \text{p}_{N+1} \ \emptyset^T(\text{N}+1)\theta_N + \text{p}_{N+1}\emptyset^T(\text{N}+1)\text{y}(\text{N}+1)\theta_N + \text{p}_{N+1} \ \emptyset^T(\text{N}+1)$$

$$[y(\text{N}+1) - \ \emptyset^T(\text{N}+1)\theta_N \ ] \tag{1.32}$$

Therefore, we obtain the following relation:

$$\theta_{N+1} = \theta_N + \text{k}_{N+1}[\text{y}(\text{N}+1) - \emptyset(\text{N}+1) \ \theta_N] \tag{1.33}$$

Therefore:

θ_{N+1}: New parameter estimation.

θ_N: Previous parameter estimation.

k_{N+1}: Adaptation gain.

with :

$$k_{N+1} = p_{N+1}\, \emptyset^T(N+1) \tag{1.34}$$

$y(N+1)$: Prediction of the output at N+1.

$\emptyset(N+1)\,\theta_N$: Prediction of the outputs preceded.

I.4 Identification and optimization using Intelligent Algorithms

I.4.1 Particle Swarm Optimization(PSO)

I.4.1.1Definition

Particle Swarm Optimization (PSO) is a stochastic optimization method for non-linear functions, based on the reproduction of social behavior. PSO is a relatively recent algorithm in computational learning, introduced by James Kennedy and Russell Eberhart in 1995. It bears some resemblance to evolutionary computation[16].

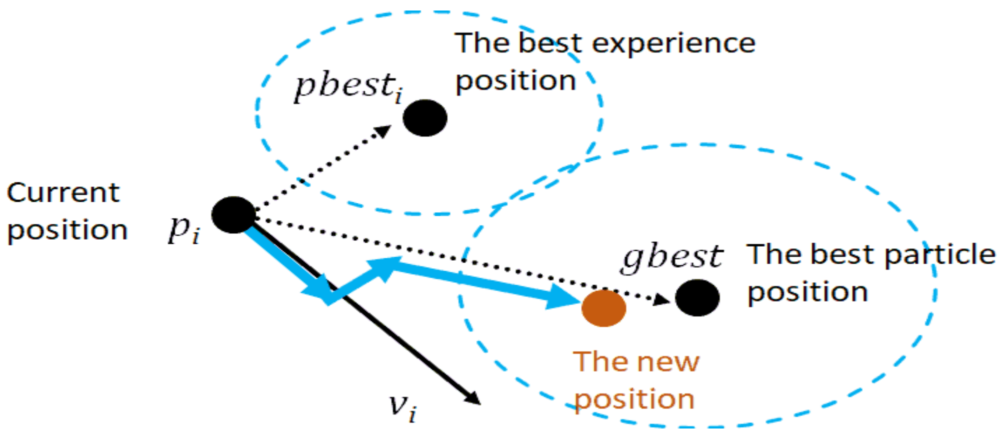


Figure I.4 visual representation of PSO algorithm

I.4.1.2 The origin of PSO

The origin of this method comes from observations made during computer simulations of group flights of birds and schools of fish. These simulations highlighted the ability of individuals in a moving group to maintain an optimal distance between each other and to follow a global movement relative to the local movements of their neighbors [17].

I.4.1.3 Principle of Particle Swarm Optimization

This social behavior, based on the analysis of the environment and the neighborhood, constitutes a method for finding an optimum by observing the trends of neighboring individuals. Each individual seeks to optimize their chances by following a trend moderated by their own experiences. Indeed, we can observe relatively complex dynamics of movement in these animals, even though individually each individual has limited intelligence and only local knowledge of their situation in the swarm. An individual in the swarm only knows the position and speed of its closest neighbors.

Therefore, each individual uses not only its own memory but also the local information about its closest neighbors to decide on its own movement [18].

I.4.1.4 Basic Principle of PSO

In PSO, each individual in the population is called a “particle,” while the population is known as a swarm. It is important to note that a particle can benefit from the movements of other particles in the same population to adjust its position and velocity during the optimization process. Each individual uses the local information it can access about the movement of its nearest neighbors to decide on its own movement. Very simple rules such as stay close to other individuals, go in the same direction, and move at the same speed are sufficient to maintain the cohesion of the entire group [19].

At the start of the algorithm, a swarm is randomly distributed in the search space, with each particle also having a random velocity. Then, at each time step:

- Each particle can evaluate the quality of its position and keep track of its best performance.
- Each particle can query some of its neighbors and obtain from each of them their best performance.
- At each time step, each particle chooses the best of the best performances it is aware of, modifies its velocity based on this information and its own data, and moves accordingly.

With the limited information it has, a particle must decide its next move, which is to decide its new velocity. To do this, it combines three pieces of information:

- Its current velocity.
- Its current best position.
- The best performance (velocity and position) of its neighbors.

I.4.1.5 Formulation

The swarm of particles consists of n particles, and the position of each particle represents a solution in the search space. The particles change states according to the following three principles:

- Maintain their inertia
- Change state based on their most optimistic position
- Change state according to the most optimistic position of the group

The position of each particle is influenced by both its own most optimistic position during its movement (individual experience) and the most optimistic position of the particle in its vicinity (global experience) [20].

I.4.2 The Biogeography-Based Optimization (BBO) algorithm

The Biogeography-Based Optimization (BBO) algorithm, developed by Dan Simon in 2008, is inspired by studies on the spatial distribution of plant and animal species and the causes of their distribution and extinction. It deals with how species richness (number of species) is maintained in an island system that is subject to immigration and on which species go extinct. When an island cannot easily support the population of a species, members migrate to new islands and undergo speciation [21].

A good solution to the optimization problem is an island with a large number of species, which corresponds to an island with a low HSI. In the BBO algorithm, each habitat has its own rates of immigration and emigration representing the species coming to and leaving the island. These parameters are influenced by the number of species (S) on the island [22].

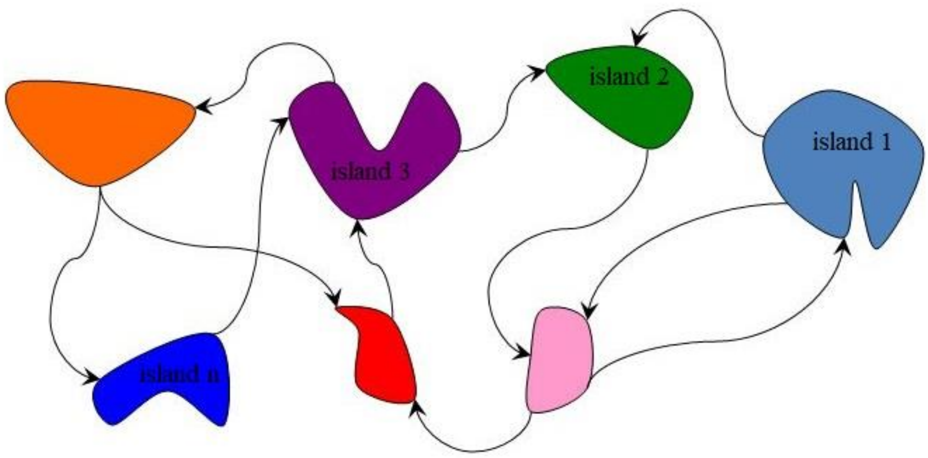


Figure I.5 Over view of the BBO algorithm

I.4.2.1 Principle of the BBO algorithm

BBO is an algorithm based on a population of individuals called islands (or habitats). Each island represents a possible solution to the problem to be solved. The fitness of each island is determined by its HSI (Habitat Suitability Index), which is a measure of the quality of a candidate solution. Each island is represented by Suitability Index Variables (SIVs). A high HSI of an island indicates good performance on the optimization problem, while a low HSI indicates poor performance [23].

The operation of BBO is based on migration and mutation. The initial population represents the search space, and it is generated randomly. The evaluation of the initial population leads to the migration of some individuals, and the offspring will be mutated. Migration creates a new set of individuals, and mutation determines the proportion of the population that will be renewed at each generation. The best individuals found are preserved through elitism (selection). The new offspring replace the parents to form a new population [24].

I.4.3 Ant Colony Optimization

Ant Colony Optimization (ACO), designed by Dorigo, is inspired, as its name suggests, by the behavior of ants when they search for food and optimize the path between their nest and the food found. Indeed, ants use their environment to communicate with each other, using a stigmergic mechanism whereby they deposit pheromones on the ground to indicate to other ants the path they have taken to reach the food. Thus, others can follow the pheromone trail to find the food source [25].

I.4.4 Artificial immune system

The optimization by artificial immune systems (AIS) was born in the 1980s thanks to the work of Farmer, Packard, and Perelson. AIS mimics the functioning of the human immune system. Indeed, the latter aims to protect the body from external pathogens such as bacteria or viruses [26].

I.4.5 Genetic algorithms

Genetic Algorithms (GA) are adaptive strategies and global optimization techniques. They are the first, most well-known, and most widely used among evolutionary methods. Genetic algorithms were originally developed in the 1960s at the University of Michigan by John Holland and his team, who conducted research on adaptive and robust systems. They were initially used with binary representations, where crossover and mutation operators play a major role. Genetic Algorithms form one of the main classes of Evolutionary Algorithms, proposed and developed by Holland. They are based on modern theories of natural evolution and use a combination of reproduction (crossover and mutation) and selection to generate individuals increasingly adapted to their environment, and therefore optimal solutions [27].

I.4.6 Fuzzy logic

Fuzzy logic is an extension of conventional Boolean logic, and the fuzzy logic technique is a strategy based on these ideas. Rather than employing rigid binary values (true or false), it uses degrees of truth to handle imprecise or uncertain data. The following are some salient features of the fuzzy logic method [28].

I.4.6.1 Basic Principle

- **Degrees of Truth**: Unlike classical logic where a statement is either true (1) or false (0), fuzzy logic allows for intermediate values between 0 and 1.

I.4.6.2 Main Components

- **Fuzzy Variables**: These are variables whose values are not precise but rather defined by fuzzy sets.
- **Membership Functions**: These define the degree to which a value belongs to a fuzzy set.
- **Fuzzy Rules**: These are in the form of "if-then" statements and allow relationships between variables to be formulated.

I.4.7 Artificial neuron network

A neural network can be considered as a mathematical model of distributed processing, composed of several elements of non-linear computation (neurons), operating in parallel and connected to each other by weights [29]. Artificial neural networks are highly connected networks of elementary processors operating in parallel. Each elementary processor calculates a unique output based on the information it receives. Artificial neurons are often used in the form of networks that differ according to the type of connections between the neurons; around fifty types can be enumerated. Examples include the Rosenblatt perceptron, Hopfield networks, multi-layer perceptron, radial basis function … etc [30].

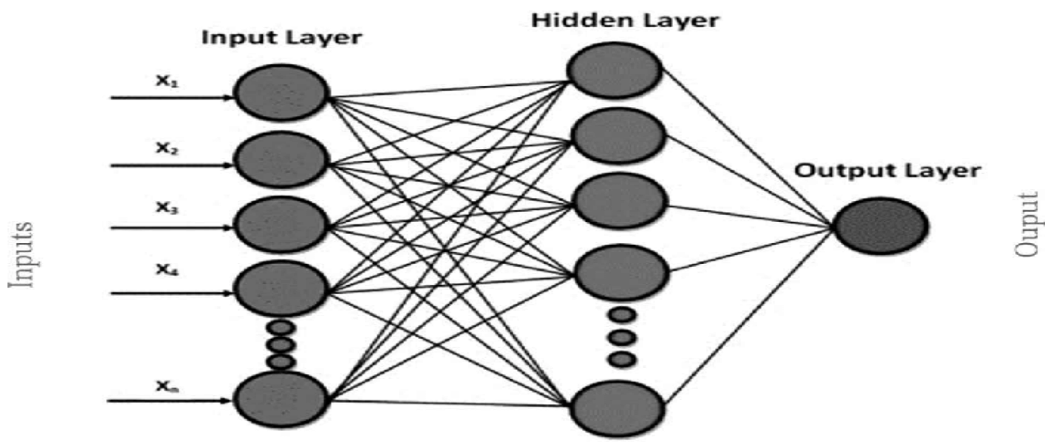


Figure I.6 Artificial neuron network

In this thesis, we will use artificial neural networks to identify our dynamic system. In the third chapter, we will try to provide different types of artificial neural networks, the essential concepts to understand the architectures, the functioning, and the applications of artificial neural networks, as well as their learning methods.

Conclusion

This chapter presents various methods for calculating the parameters of a dynamic behavior model. We have classified these methods into several categories: methods based on a step response, which do not yield highly precise results but provide information about the system's dynamics; least squares methods, which are not the best but can offer an analytical solution; and the model-based method, which directly achieves the identification objective. The model-based method is widely used in practice as the identification problem is formulated as an optimization problem, with the parameters to be identified using a global optimization technique called Aliénor.

Chapter II
Photovoltaic solar energy

Introduction

Photovoltaic solar energy is produced by directly converting sunlight into electrical current through the use of cells that are usually made of silicon crystalline. In terms of industry and technology, this technology is still cutting edge. Non-toxic silica is a type of silicon, one of the most prevalent materials on Earth. By combining multiple cells in series or parallel, a photovoltaic generator (PVG) is created with a non-linear current-voltage characteristic, featuring a maximum power point. These days, generated electricity can be stored in batteries or used immediately to power a load [31].

The term "photovoltaic" comes from the Greek "photo," which means light, and the term "voltaic," which is derived from the name of the Italian physicist Alessandro Volta (1754–1827), who made important contributions to the understanding of electricity. Consequently, light electricity is what "photovoltaic" literally means.

I I.1 Photovoltaic cells history

The photovoltaic effect was initially noticed by scientists in the 1800s, which is when photovoltaic (PV) or solar cells got their start. But it wasn't until Bell Laboratories created the first useful silicon solar cell in 1954, with an efficiency of 4% to 6% [32].

PV cells were first mostly employed in space applications, such satellite power. Not until the oil crisis of the 1970s did interest in renewable energy, particularly solar power, begin to grow. As a result, PV cells are being used to generate power on land.

The efficiency of photovoltaic cells has advanced significantly since the 1950s. While research cells have achieved efficiency of up to 47.1%, commercial PV cells can now attain up to 22% to 23%.

These days, PV cells are employed in many different fields, such as the transportation, commercial, and residential sectors. It is anticipated that the use of PV cells will continue to increase as costs come down and technology advances.

II.2 Advantages and Disadvantages of solar energy

II.2.1 Advantages

- ✓ Electricity generated is environmentally friendly and aligns with sustainable development principles
- ✓ It is a renewable energy source as it is inexhaustible on a human scale.
- ✓ It can be used in developing countries without access to an electrical grid.

II.2.2 Disadvantages

- ✓ Current photovoltaic cells have limited efficiency (around 10% for most users), resulting in modest power output.
- ✓ The market is specialized but growing.
- ✓ Energy generation is restricted to daylight hours, while residential demand peaks at night.
- ✓ Storing this energy is complex and costly with current battery technologies.
- ✓ Lifespan typically ranges from 20 to 25 years, after which the crystallized silicon in the cells degrades.
- ✓ Costs are tied to peak power capacity.

II.3 The efficiency

One of the standards for this kind of sensor's quality is its PV cell's efficiency. As a result, by setting an operational temperature, pressure, and kind of light spectrum, this measurement is performed in accordance with exact requirements. In order to be able to compare the various cell performances objectively, we are just discussing here the total efficiency of converting photons into electrons, translated by the electrical power delivered by the PV cells, compared to an illumination of 1000 W/m² [33].

The material used and the losses associated with the technique employed to create a cell determine the efficiency. Silicon (Si) is one of the most widely used materials and is inexpensive due to its different crystalline forms (monocrystalline, polycrystalline, or amorphous).

PV panels with monocrystalline cells are the photovoltaic cells of the first generation. They are composed of high-purity silicon crystals.

II.4 Electrical model of a photovoltaic cell

The equivalent circuit of a solar cell in the dark is shown in Figure I.1 it is equivalent to a current generator I_{ph} that is linked to a diode in parallel. In this circuit, there are two parasitic resistances. These resistances affect the cell's I-V characteristics in a particular way:

- ✓ The series resistance (R_s) represents the contact and connection resistance.
- ✓ The shunt resistance (R_{sh}) connected in parallel represents the leakage current.
- ✓ A diode in parallel that models the PN junction.

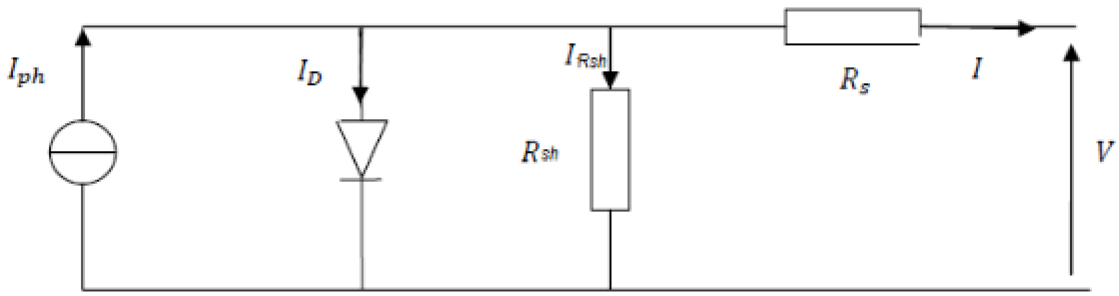


Figure II.1 Electrical equivalent diagram of the PV cell with one diode

The Kirchhoff's law allows us to write the following relation:

$$\mathrm{I}_{ph} = \mathrm{I}_{d} + \mathrm{I}_{Rsh} + I \quad \text{so} \quad I = \mathrm{I}_{ph} - \mathrm{I}_{d} - \mathrm{I}_{Rsh} \tag{2.1}$$

The resulting expression for the current-voltage characteristic after all calculations is:

$$I = \mathrm{I}_{ph} - \mathrm{I}_{sat}\,[e^{\frac{\mathrm{v}+(\mathrm{I}*\mathrm{Rs})}{\mathrm{nVt}}} - 1] - \frac{\mathrm{V}+(\mathrm{I}*\mathrm{R}_{s})}{\mathrm{R}_{sh}} \tag{2.2}$$

The expressions for I_{ph} (the photocurrent) and I_{sat} (the diode saturation current) are given by:

$$\mathrm{I}_{ph} = [\,\mathrm{I}_{sc} + (\,\mathrm{k}_i * (T - 273))] * \frac{G}{1000} \tag{2.3}$$

$$\mathrm{I}_{sat} = (\,\mathrm{I}_{sc} \; * e^{\frac{\mathrm{V}_{c0}}{\mathrm{nVt}}} - 1) * (\frac{T}{298})^{3} * \; e^{\frac{\mathrm{q}*\mathrm{E}_{g}*(\frac{1}{298}-\frac{1}{T})}{\mathrm{n.K}}} \tag{2.4}$$

When:

I_{ph}: Photocurrent produced.

I_{sat} : Diode saturation current.

R_{s}, R_{sh} : The series resistance and the shunt resistance, respectively.

K: Boltzmann constant ($1.3806488 * 10^{-23}$ J/k).

Q: Electron charge ($1.6 * 10^{-19}$ C).

$\mathrm{v}_t = \frac{kt}{q}$ Thermal voltage at temperature T.

k_i : Constant.

n: Ideality factor of the junction.

T: Effective cell temperature in Kelvin.

E_g: Energy gap (for crystalline silicon is equal to 1.12 eV).

G: radiation W/m².

II.5 Electrical characteristics of a photovoltaic cell

These parameters can be determined from current-voltage curves or from the characteristic equation.

The most common ones are as follows:

II.5.1 Short circuit current (Isc)

When this current is present, there is no voltage across the PV generator or cell. This current equals the photocurrent I_{ph} in the perfect condition, which has infinite shunt resistance and zero series resistance. Otherwise, by setting the voltage (V) to zero in the I_v equation, we obtain[34]:

$$I_{sc} = I_{ph} - I_{sat}\, e^{\frac{q(I_{sc} * R_{sh})}{nKT}} - 1 - \frac{(I_{sc} * R_s)}{R_{sh}} \tag{2.5}$$

For most cells (whose series resistance is low), we can neglect the term.

[$I_{sat}\, e^{\frac{q(I * R_S)}{nKT}} - 1$] in front of I_{ph}. The approximate expression of the short-circuit current and then:

$$I_{sc} \cong \frac{I_{ph}}{1+\frac{R_s}{R_{sh}}} \tag{2.6}$$

II.5.2 Open circuit voltage (v_{c0})

This is the voltage v_{c0} at which the current supplied by the photovoltaic generator is zero (it is the maximum voltage of a solar cell or photovoltaic generator).

(2.7)

In the ideal case, its value is slightly less than:

$$v_{c0} = v_t\, Ln \frac{I_{ph}}{I_{sat}} + 1 \tag{2.8}$$

II.5.3 PV cell power

Under fixed ambient operating conditions (irradiation, temperature, ambient air circulation speed, etc.), the electrical power P (W) available to terminals of a PV cell is:

$$P= VI \tag{2.9}$$

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

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

I (A): Intensity delivered by the PV cell [35].

II.5.4 Maximum power of a PV cell

For an ideal solar cell, the maximum power p_{max} would therefore correspond to the open-circuit voltage v_{c0} multiplied by the short-circuit current I_{sc}:

$$p_{max} = v_{c0} I_{sc} \tag{2.10}$$

p_{max} (W): The power supplied by the PV cell.
v_{c0} (V): The open circuit voltage measured across the PV cell.
I_{sc} (A): The short-circuit intensity delivered by the PV cell.

The PV cell's characteristic curve is more "rounded" Figure II.2. The voltage at the maximum power point vp_{max} is lower than the circuit voltage open (v_{c0}), and the supplied current Ip_{max} is lower than the short circuit current (I_{sc}) at the same voltage. The power at this moment is expressed as follows:

$$p_{max} = v_{pmax} I_{pmax} \tag{2.11}$$

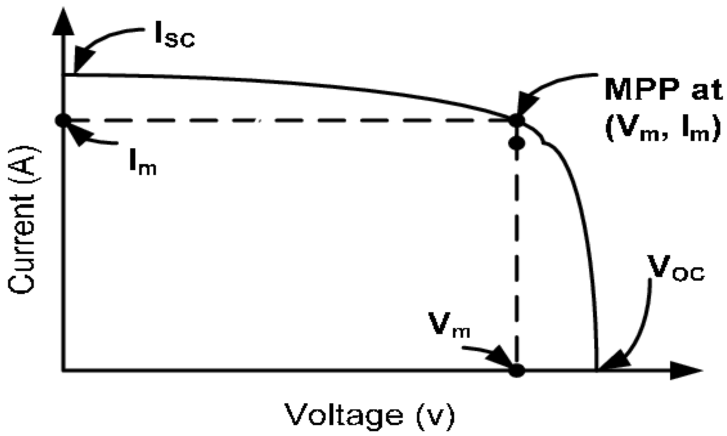


Figure II.2 maximum power point MPP

II.5.5 The fill factor

The fill factor (FF), sometimes referred to as the curve factor or fill factor, is the product of the open-circuit voltage v_{c0} and the short-circuit current I_{sc}. Put another way, it's the maximum power that an ideal cell can provide. The cell's quality is indicated by the fill factor. the closer it is to unity, the more efficient the cell is. For effective cells, it usually hovers around 0.7 and drops with temperature. It is described as follows and represents the impact of losses brought on by the two parasitic resistances, R_s and R_{sh}[36]:

$$FF = \frac{p_{max}}{v_{c0}\, I_{sc}} = \frac{v_{max}\, I_{max}}{v_{c0}\, I_{sc}} \tag{2.12}$$

II.6 The photovoltaic module

To produce more power, solar cells are assembled to form a module Figure I.3. Series connections of several cells increase the voltage for the same current, while paralleling increases the current while maintaining the tension. These cells are protected from humidity by encapsulation in a polymer EVA (ethylene-vinyl-acetate) shown (II.3) and protected on the front surface of a glass, hardened with high transmission and good mechanical resistance.

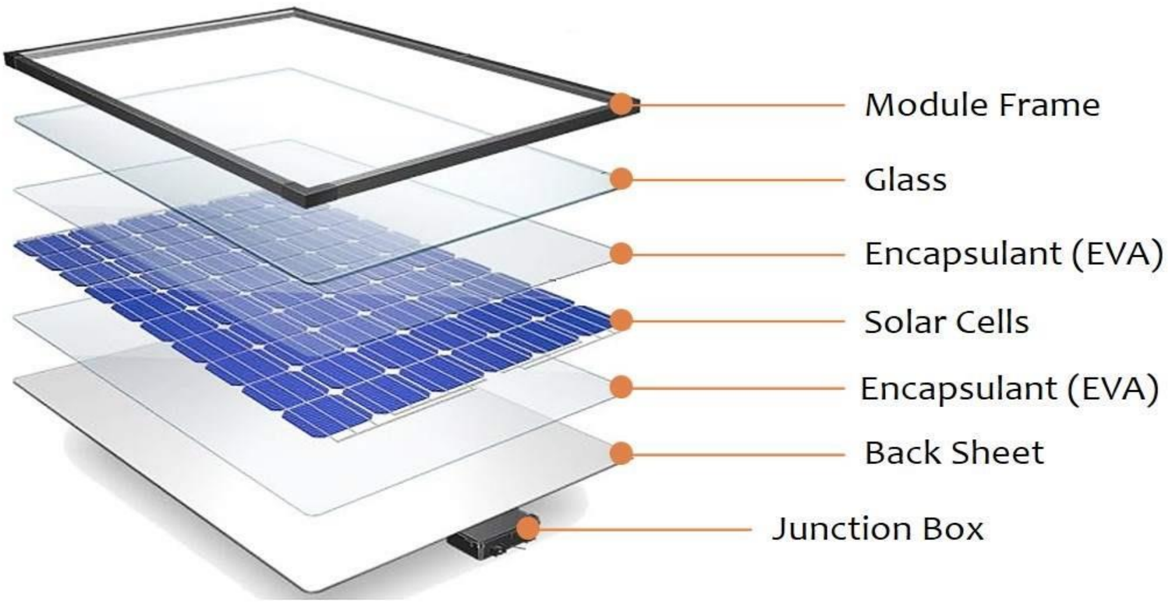


Figure II.3 Photovoltaic Module

II.6.1 Characteristics of a Photovoltaic module

- ✓ Peak power, Pc, represents the maximum electrical power that a module can provide under standard conditions (25°C and an irradiance of 1000 W/m²).
- ✓ Short-circuit current, I_{sc}., is the current delivered by a module in short-circuit conditions under full sunlight.
- ✓ Optimum operating point, (U_m, I_m), is reached when the peak power is maximum under full sunlight. $P_m = U_m * I_m$.
- ✓ Efficiency is the ratio of the optimal electrical power to the incident radiation power.
- ✓ Fill factor is the ratio between the optimal power P_m and the maximum power that the cell can have: $v_{c0} * I_{sc}$.

II.7 From the cell to the photovoltaic generator

The electrical power produced by an industrialized cell is very low, typically ranging from 1 to 3 watts with a voltage of less than one volt.

Due to its low voltage, a single cell is insufficient to function as a standalone PV generator. Cells are sold as photovoltaic modules in order to raise the voltage. The majority of module producers connect 36 cells in series.

Currently the power of a module is from a few peak watts to a few tens of peak watts. To obtain higher powers, it is necessary to associate modules in series-parallel to have a PV generator. [37].

II.8 Operating principle of a photovoltaic installation

The principle of operation of a photovoltaic solar installation is relatively simple: it involves converting sunlight into electricity. This process is based on a physical phenomenon called the photovoltaic effect. The photovoltaic effect occurs when a photon is absorbed in a material made up of doped p-type (positive) and n-type (negative) semiconductors, forming a p-n (or n-p) junction. Due to this doping, an electric field is permanently present in the material. When an incident photon interacts with the electrons of the material, it transfers its energy to the electron, freeing it from its valence band and subjecting it to the intrinsic electric field. Under the influence of this field, the electron migrates towards the upper surface, leaving behind a hole that migrates in the opposite direction. Electrodes placed on the upper and lower surfaces allow the electrons to be collected and to perform electrical work to reach the hole on the front surface [38].

A photovoltaic cell is made up of one of these materials, typically silicon, and designed in such a way that the emitted electrons are collected to form an electric current. The cells are assembled to create a current that is sufficiently high to be used. This assembly of cells is called a photovoltaic module or, more commonly, a solar panel.

II.9 Types of photovoltaic solar cells

There are different types of photovoltaic solar cells, and each type has its own efficiency and cost. Solar cells can be divided into three groups, based on the base material used:

- ✓ Monocrystalline cells
- ✓ Polycrystalline cells

- ✓ Thin-film cells

II.9.1 Monocrystalline cells

Ultra-pure silicon is melted to form silicon blocks. The whole crystalline structure is aligned uniformly in a monocrystalline. After that, the silicon block is cut into wafers, which are usually 200 mm to 300 mm thick. In order to optimize the solar module's surface area, circular cells are divided into square elements. 152 mm is the typical side length of these cells. Doping, applying contact surfaces, and adding an anti-reflection layer are all steps in the production process[39].

Industrially produced monocrystalline cells have an efficiency ranging from 15% to 18%, making them the most efficient cells currently available. However, their production requires more energy and time compared to polycrystalline cells. Despite their high efficiency, monocrystalline cells have some drawbacks:

- ✓ The production process is laborious, challenging, and therefore costly.
- ✓ A significant amount of energy is needed to obtain a pure crystal.
- ✓ The payback period for the energy investment is long (up to 7 years).

FigureII.4 Monocrystalline solar cell

II.9.2 Polycrystalline cells

The base material is ultra-pure silicon, which is melted. However, for the production of polycrystalline solar cells, monocristals are not grown, but the molten silicon is cooled down in a controlled manner in a square mold. During the cooling process, the crystals orient themselves irregularly, forming the typical shimmering surface of polycrystalline solar cells. The square silicon blocks are cut into wafers 200 to 300 mm thick. Applying contact surfaces, doping, and the anti-reflection layer finish the production process. The solar cell's characteristic blue surface is caused by the anti-reflection layer because blue light absorbs more light than it reflects.

The efficiency of polycrystalline solar cells ranges from 13% to 16%.Polycrystalline cells are characterized by[40]:

- ✓ Lower production cost.
- ✓ Requires less energy.
- ✓ Efficiency of 13% and up to 20% in the lab.

Figure II.5 Polycrystalline solar cell

II.9.3 Thin-film cells (Amorphous)

Originating from Greek, "amorphous" implies "without form." Elements with irregularly shaped atoms are referred to as amorphous in physics. Atoms are referred to as crystals if their structure is organized.

A supporting medium, like glass, is coated with silicon to create amorphous solar cells. At that point, the silicon's thickness ranges from 0.5 to 2 µm. As a result, not only is a very small amount of silicon necessary, but carving silicon blocks by hand is also not required. Amorphous solar cells have an efficiency of only 6% to 8%.

Figure II.6 Thin-film solar cell

II.9.4 High efficiency multi-junction cells

Nowadays, most inorganic photovoltaic cells consist of a simple PN junction. In this junction, only photons with energy equal to or greater than the material's energie gap (denoted as Eg in V) can create electron-hole pairs. In other words, the photovoltaic response of a single-junction cell is limited to the energy of the photon. Only the portion of the solar spectrum with photon energy greater than the material's absorption gap is useful, so lower-energy photons are not usable. Moreover, even if the photon energy is sufficient, the probability of interacting with an electron is low. Thus, most photons pass through the material without transferring their energy. A well-known technological solution to limit these losses is to use multilevel systems, stacking junctions with decreasing energy gaps. This approach allows for the exploitation of almost the entire solar spectrum with very high conversion efficiencies [41].

Figure II.7 High efficiency multi-junction solar cell

II.9.5 Other cell types

There are other types of photovoltaic technologies currently on the market or under study, the main ones being:

II.9.5.1 Flexible cells

Based on a production process similar to that of thin-film technologies, these cells are made by depositing an active material layer onto a thin plastic substrate, making them flexible. This opens up a range of applications, particularly for building integration (roofing) and domestic applications.

II.9.5.2 Concentrated photovoltaic

Certain cells are engineered to function under concentrated sunlight. These cells are positioned within a collector that concentrates sunlight onto them using a lens. The objective is to minimize the use of semiconductor photovoltaic material while maximizing sunlight utilization. Their efficiency typically falls between 20% and 30%.

II.10 Photovoltaic cell association

II.10.1 Serial association

In a grouping of Ns cells in series, the resulting characteristic of the grouping is obtained by adding the elementary voltages of each cell, while the current crossing cells remains the same. Figure I.8 shows the resulting characteristic (I_{scc}, v_{sc0}) with:

$$I_{scc} = I_{sc} \text{ and } v_{sc0} = n_s * v_{c0} \tag{2.13}$$

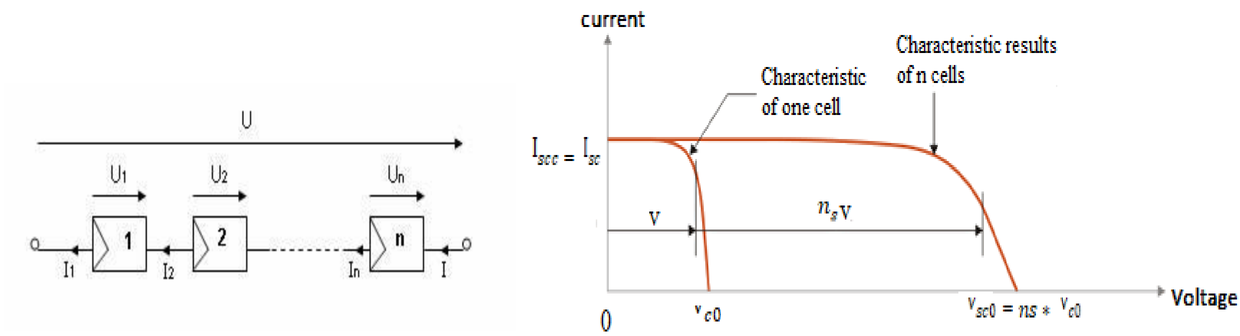


Figure II.8 serial association of PV cells

II.10.2 Parallel association

In a group of Np cells in parallel, the cells are subject to the same voltage and the resulting characteristic of the grouping is obtained by the addition of the currents.

Figure I.9 shows the resulting characteristic (I_{psc}, v_{pc0}) With:

$$I_{psc} = n_p * I_{sc} \ et \ v_{pco} = v_{c0} \tag{2.14}$$

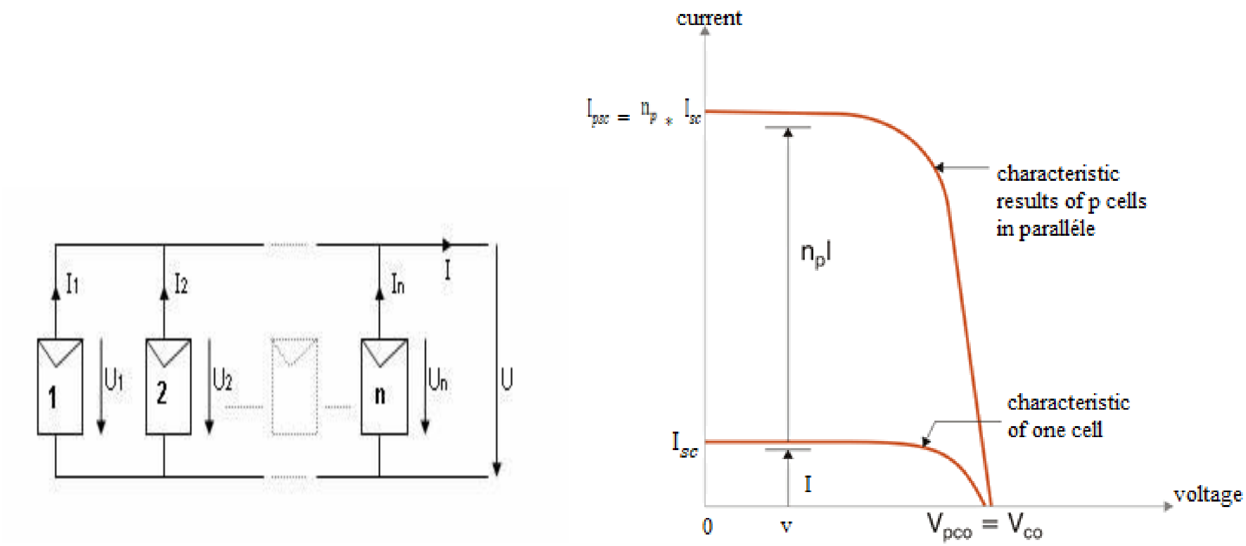


Figure II.9 parallel association of PV cells

II.11 Behavior of a photovoltaic generator

A photovoltaic generator's behavior can be affected by a number of factors, including temperature variations throughout the array, uneven irradiation, and cell design. These differences may result in imbalances that compromise the generator's dependability and performance [42].

II.11.1 Influence of sunlight

A decrease in sunlight leads to a reduction in the creation of electron-hole pairs, resulting in a current change in darkness. The current of the solar panel is equal to the difference between the photocurrent and the dark diode current. As sunlight decreases, there is a proportional decrease in the solar current I_{sc}accompanied by a very slight decrease in voltage v_{c0} leading to a shift of the solar panel's P_{max} point towards lower powers [43].

The following graphs represent I(V) and P(V) curves for different operating irradiations of the PV module at constant temperature:

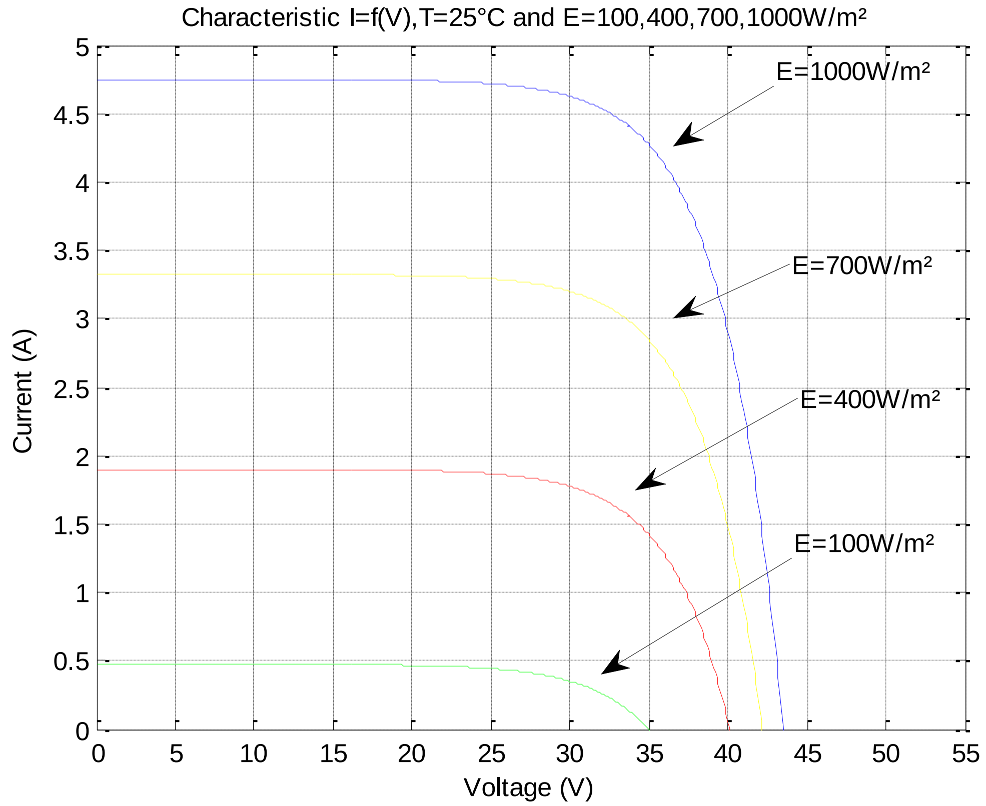


Figure II.10 Influence of sunlight in characteristic I=f (V)

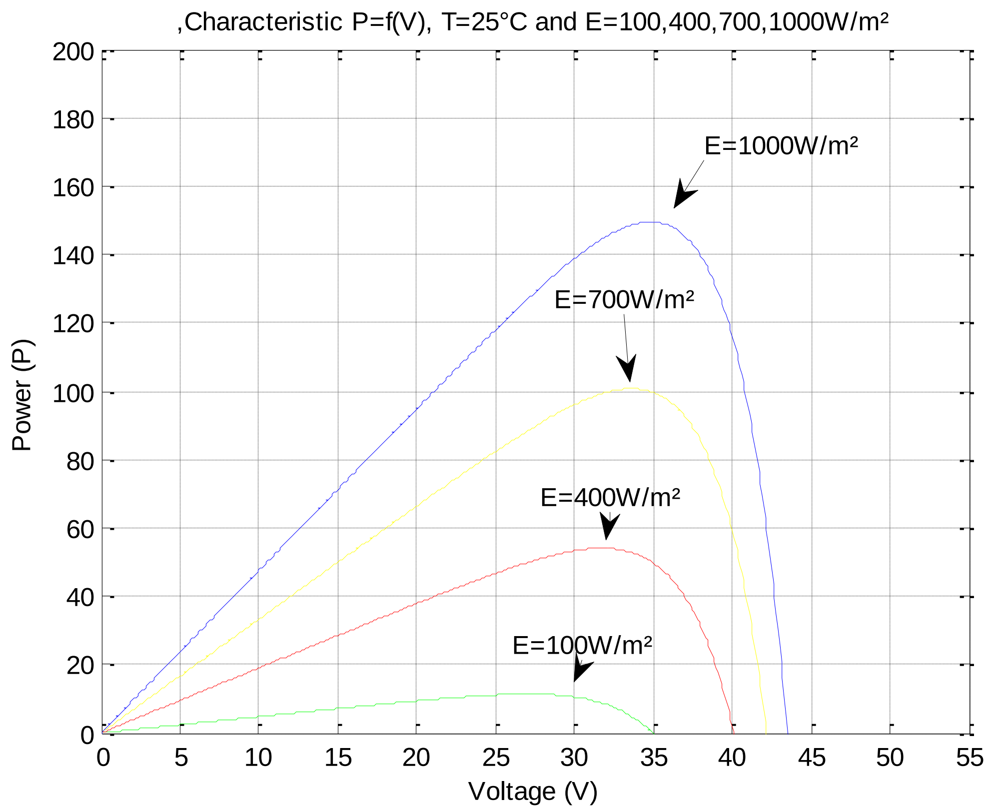


Figure II.11 Influence of sunlight in characteristic P=f (V)

It is clear that the value of the short-circuit current is directly proportional to the intensity of the radiation. However, the open-circuit voltage does not vary in the same proportions but remains almost identical even at low irradiance.

This implies that:

- ✓ The optimal power of the cell (p_{max}) is practically proportional to the irradiance.

II.11.2 Influence of temperature

We observe that the current delivered by each cell depends on the internal temperature of the PN junction that makes up the PV cell. Considering the warming of a PV module from 0°C to 75°C, and assuming that the rear temperature of each cell is close to the PN junction temperature, the temperature's influence can be considered. It is noted that the open-circuit voltage decreases as the temperature increases. Consequently, there is a loss of available power at the PV module terminals [44].

The following graphs represent I(V) and P(V) curves for different operating temperatures of the PV module at constant irradiation:

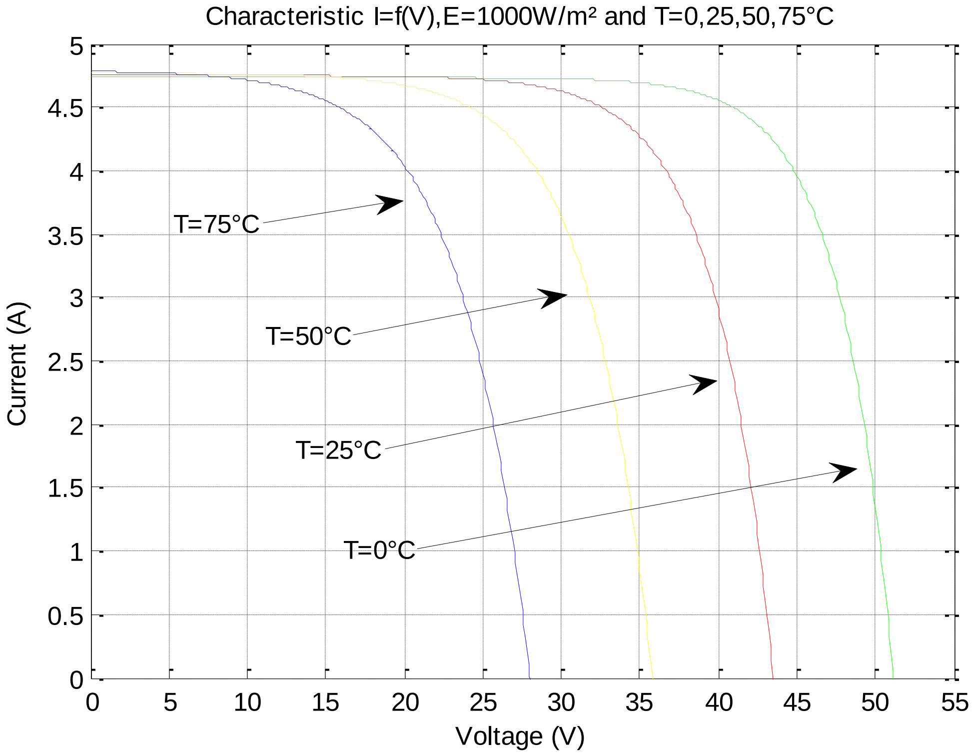


Figure II.12 Influence of temperature in characteristic I=f (V)

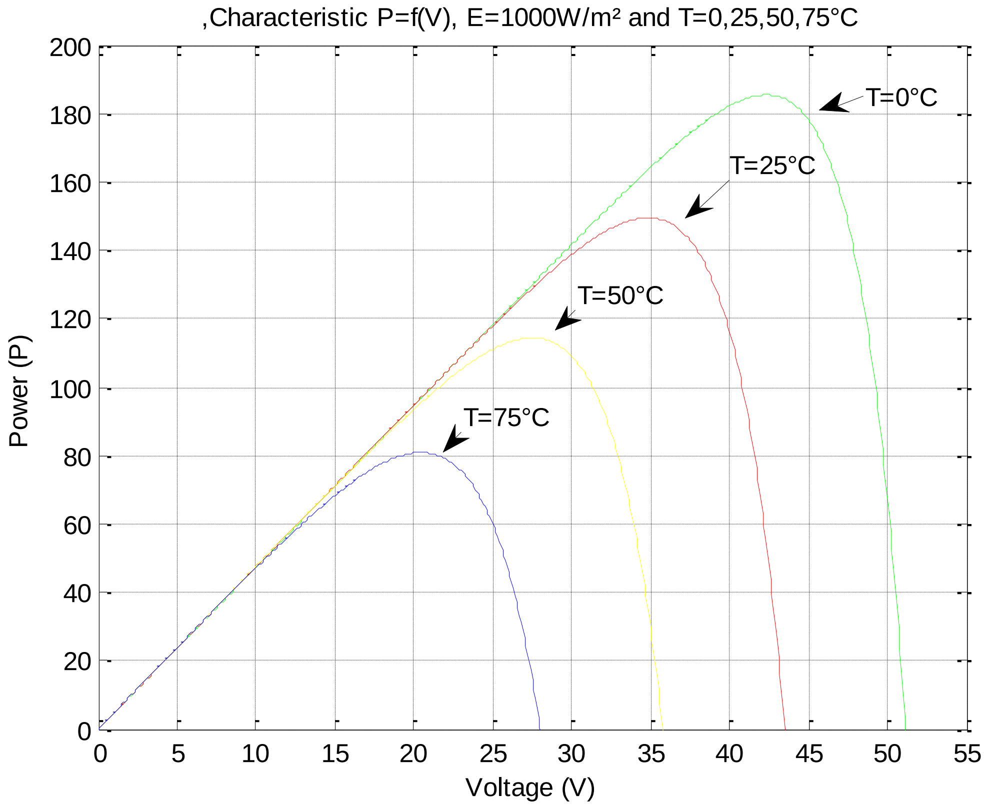


Figure II.13 Influence of temperature in characteristic P=f (V)

We observe that temperature has a negligible influence on the value of the short-circuit current. However, the open-circuit voltage decreases significantly as the temperature increases.

The variation in site temperature must be considered while constructing an installation. It is significant to note that for every degree above 25°C that the cell temperature rises, the panel's power drops by about 0.5%.

II.12. Application of photovoltaic systems

- **Solar air conditioning**

The term "solar air conditioning" describes a group of techniques used to cool a building primarily by sun energy. Solar heat collected by solar thermal collectors or the electrical energy generated by photovoltaic panels can be used for air conditioning.

- **Hybrid electrification (photovoltaic-wind)**

Two renewable energy sources wind and photovoltaic are combined and used in this hybrid system to produce electricity.

A solar subsystem with an AC/DC converter is part of the hybrid system, enabling it to continuously track the maximum power point. Wind energy is transformed into electricity using a wind turbine. A DC bus is connected to both energy sources. Batteries provide for storage. An inverter is used to link the load to be powered, which can be either direct or alternating [45].

- **Photovoltaic pumping**

To be brought to the surface, groundwater needs to be pumped. Therefore, the need for a pump and thus a reliable source of energy such as photovoltaic is necessary.

- **Seawater desalination**

One of the solutions to address the lack of drinking water is desalination plants. It is a process that removes salt from salty or brackish water to make it potable.

II.13 off grid photovoltaic system:

A PV system is a complete set of PV equipment for converting sunlight into electricity. The PV generator, the battery, the regulator, the converter, and the load are typically its five primary elements.

II.13.1 The photovoltaic panel

The group of interconnected photovoltaic cells forms the PV module or panel, which is responsible for capturing sunlight and converting it into electricity.

II.13.2 The regulator (charge controller)

The regulators are put in place with the aim of ensuring longevity of the system. Storage, therefore minimizing the installation cost.
Indeed, a regulator is responsible for:

- ✓ Controlling the overcharging and discharging of the battery.
- ✓ Ensure optimization of the system from an energy point of view where it constitutes an energy transfer node between module, storage and use [46].

To function, a regulator needs an indicator which informs it about the state of charge of the batteries. It must maintain the state of charge of the batteries between two thresholds: a high threshold and another bottom. The choice of thresholds depends on the characteristics of the batteries and the conditions of use.

A regulator is defined by:

- ✓ Amperage in Ampere.
- ✓ Voltage in Volt.

II.13.3 The solar battery

Its job is to store the current generated by the panel so that the system can function independently. Its lifespan is defined by the number of charge-discharge cycles. It is characterized by:

- ✓ Amperage in ampere-hours (Ah).
- ✓ Voltage in volts.

II.13.4 The energy converter (inverter)

It converts the direct current generated by solar panels into alternating current and output voltage (12 V, 24 V... 48 V) to 220 V. Its characteristics include the output voltage in volts and the nominal power in watts.

II.13.5 Load

It encompasses all of the functions performed by different gadgets linked to the solar energy system. Given the energy efficiency requirements of photovoltaic systems, it is crucial to define the criteria on which the choice of loads to be used will be based: continuous or alternative load [47].

Conclusion

In this chapter, we presented the principle of converting solar energy into electrical energy using photovoltaic cells, the main characteristics and technologies of the components of a PV generator, as well as the different configurations of photovoltaic systems and their applications.

Chapter III

Artificial neural networks and Results

Introduction

The development of artificial neural networks stems from a desire to understand and mimic the capabilities of the human brain. Intelligence, learning, memorization, massive parallel processing of information, and flexibility are all qualities attributed to the brain, sought after for the synthesis of various intelligent and complex artificial systems [48].

The concept of artificial neural networks originated in the 1940s, drawing an analogy with the human nervous system. These networks are built upon the neural function, as neurons are recognized as the cellular components responsible for information processing in the brain.

III.1 History of Artificial Neural Networks

The first modeling of a neuron dates back to 1943. It was presented by McCulloch and Pitts. The interconnection of these neurons allows for the calculation of several logical functions. In 1949, Hebb proposed the first mechanism for the evolution of connections, called (by analogy to biological systems) synapses. The combination of these two methods allowed Rosenblatt in 1958 to describe the first operational model of neural networks: the perceptron. This is capable of learning to calculate a large number of Boolean functions, but not all of them. Its theoretical limitations were highlighted by Minsky and Papert in 1969. Since 1985, new mathematical models have allowed these limitations to be overcome, giving rise to the multilayer networks that we will study in more detail [49].

III.2 Biological neuron

Neurons, numbering in the hundreds of billions, are the basic cells of the central nervous system. Each neuron receives nerve impulses through its dendrites (receptors), integrates them to form a new nerve impulse, and transmits it to a neighboring neuron via its axon (transmitter),as shown in Figure III.1:

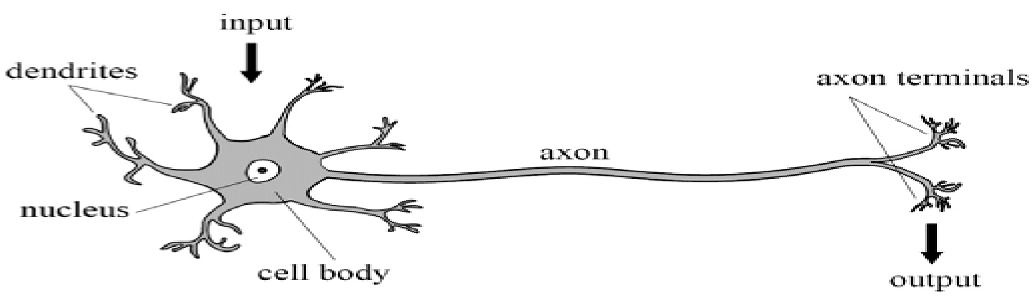


Figure III.1 Biological neuron

A neuron is a cell that can transmit information to other neurons through its various connections (synapses). The human brain is the best model of an extremely fast multifunctional machine [50].

III.2.1 Features of biological neuron

- Receiving signals from neighboring neurons.
- Integrating these signals.
- Generating a nerve impulse (nerve message).
- Conducting it.
- Transmitting it to another neuron capable of receiving it.

II.2.2 Structure of biological neuron

A neuron consists of three parts:

- Dendrites: receive messages.
- Cell body: generates the action potential (response).
- Axon: transmits the signal to the next cells.
- Synapse: allows cells to communicate with each other, and also plays a role in modulating signals that pass through the nervous system.

III.3 Formal neuron

In an artificial neural network, each neuron is a basic processor Figure III.2 It receives a variable number of inputs from upstream neurons. Each of these inputs is associated with a weight representing the strength of the connection. The neuron has a single output, which then branches out to feed a variable number of downstream neurons [51].

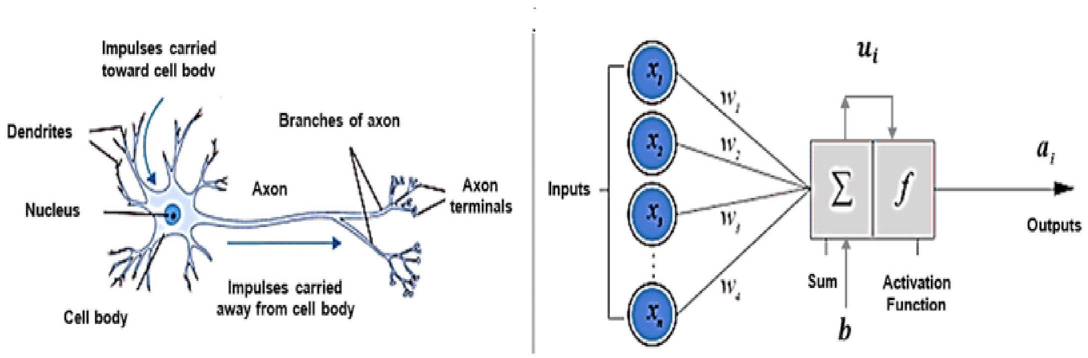


Figure III.2 Biological neuron / artificial neuron matching

In summary, a formal neuron simply computes a weighted sum of its inputs, adds a threshold to this sum, and passes the result through a transfer function to obtain its output.

$$S = \sum_{i=1}^{n} w_{i.}\, x_i + b_i \qquad (3.1)$$

$$y = f(S) \qquad (3.2)$$

With:

x_i: Components of the input vector.

$w_{i.}$: Components of the synaptic weight vector.

b_i: Bias.

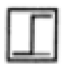
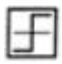
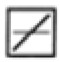
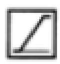
S: Weighted sum, also called potentials.

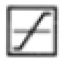
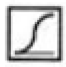
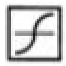
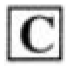
f: Activation function.

y: Neuron output.

Various functions can be used as the transfer function of a neuron, as shown in Table III.1 The most commonly used ones are the "threshold," "linear," "sigmoid," and "hyperbolic tangent" functions.

Table III.1 transfer functions

Name	input/output Relation	Icon	matlab function
Hard limit	Y=0 $s < 0$ Y=1 $s \geq 0$		hardlim
Symmetrical hard limit	Y= -1 $s < 0$ Y=1 $s \geq 0$		hardlims
Linear	Y = s		purelin
Saturating linear	Y=0 $s < 0$ Y=s $0 \leq s \leq 1$ Y=1 s> 1		stalin

Symmetric saturating linear	Y= -1 $s < 0$ Y=s $\leq s \leq 1$ Y=1 $s > 1$		stalins
Positive linear	Y=0 $s < 0$ Y=S $s \geq 0$		poslin
Log-sigmoid	Y= $\frac{1}{1+e^{-S}}$		logsig
Hyperbolic tangent sigmoid	Y=$\frac{e^{S}-e^{-S}}{e^{S}+e^{-S}}$		tansig
competitive	Y=1 neuron with max S Y=0 all auther neurons		compet

III.4 Artificial Neural Networks

The layer of an artificial neural network refers to a group of neurons that operate in parallel and are typically all connected to the same inputs. These networks consist of various layers, such as input layers, hidden layers, and output layers. Each layer plays a specific role in processing information within the neural network.

- **Input Layer:** This is the first layer of the network. Each neuron in this layer represents an input feature and directly receives the input values.
- **Hidden Layers:** These are intermediate layers between the input layer and the output layer. They do not directly receive the input data or produce the final output of the network. They perform nonlinear transformations of the data to learn useful representations.
- **Output Layer:** This is the last layer of the network. It produces the final output of the network after the data has been transformed by the hidden layers.

III.5 Neural Network Architectures

III.5.1 Static networks

In a static neural network, one (or more) algebraic function of its inputs is realized by composing the functions performed by each of its neurons. In such a network, the flow of information travels from the inputs to the outputs without feedback.

In static neural networks, time is not a factor in their functionality. If inputs remain constant, so do outputs. The computation time for each neuron's function is negligible, allowing it to be considered instantaneous. This is why static networks are often referred to as "static networks".

III.5.2 Dynamic networks

Unlike static neural networks, whose connection graph is acyclic, dynamic neural networks can have arbitrary connection topologies, including loops that feedback one or more outputs to the inputs.

III.5.3 A convolutional neural network (CNN)

Convolutional neural networks are widely used tools for deep learning. They are particularly well-suited for images as inputs, although they are also used for other applications such as text, signals, and other continuous responses. They differ from other types of neurons in several ways.

III.6 Neural Networks Classification

III.6.1 MLP

The most popular artificial neural network is the Multilayer Perceptron (MLP), which was developed by Werbos and Rumelhart. It represents the most common and simplest model of a non-linear network. In an MLP network, neurons are grouped into layers, with the first and last layers called the input layer and output layer, respectively. Between these two layers, there can be one or more hidden layers.

The training of an MLP is done with a supervised method using the backpropagation algorithm. The backpropagation algorithm adjusts the synaptic coefficients of the network in the opposite direction of the gradient of the error criterion JN, using only input/output data. Indeed, the error at the output of the network results in incorrect values for several synaptic weights. Thus, the main objective of a learning algorithm is to assign credit for each synaptic weight in the network and correct its value. The backpropagation algorithm achieves this by propagating errors from the output to the input through the network [52].

III.6.2 Hopfield Network

John Hopfield presented the network's architecture and explained how computational skills may be developed in a paper titled "Neural network and physical system with emergent collective computation abilities," which was published in 1982. He provided an example of an associative memory that his network can use. Separable, and the output is limited to either 0 or 1[53].

He claims that the system looks for stable states, or attractor states, within its state space. As nearby states get closer to a stable condition, mistakes can be fixed and incomplete data can be filled in.

III.6.3 The single-layer perceptron

The most basic type of neural network, the single-layer perceptron simulates visual experience. Retinal cells, decision cells, and association cells make up its three primary components. This network employs an all-or-nothing activation function (0 or 1). With the perceptron, learning can be accomplished by a variety of previously established techniques. The association and decision cells are separated by a single layer of tunable weights. The uses of the perceptron are restricted. It can only be used for classifications in which the variables are separable linearly. Secondly, the result can only be one of two values: 0 or 1[54].

III.6.4 Jordan network

The oldest recurrent network is the Jordan network. Its goal is to carry out a series of actions in response to a task that the user provides. The task doesn't change while the sequence is being executed, but the network has to know where it is in the series. In order to accomplish its duty, it needs a context memory, which is represented by a layer known as the context layer[55].

III.6.5 The Kohonen network

The Kohonen network, also known as the Kohonen Self-Organizing Map (SOM). This map makes it possible to depict in a limited number of dimensions the structure seen in high-dimensional data. It is a very helpful preprocessing method that makes the representation space smaller. In essence, the topological map is made up of an output neuron competitive layer. A layer of input neurons feeds these neurons. The map's learning rule is unsupervised [56].

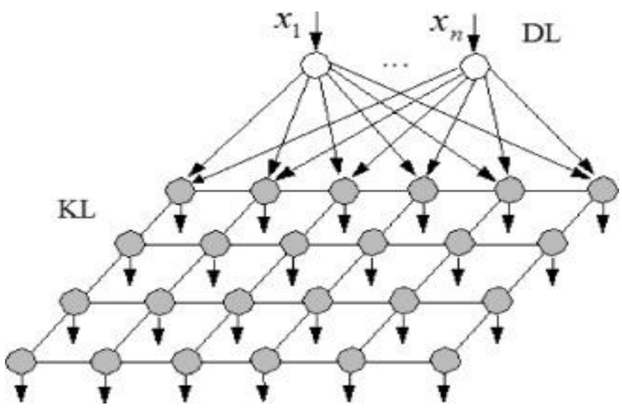
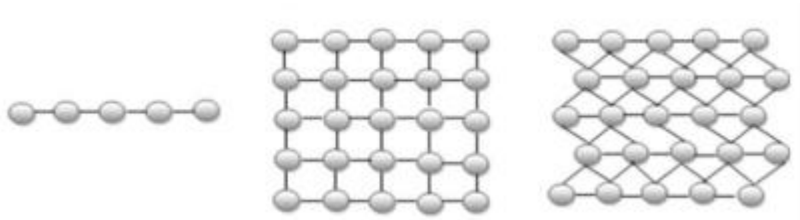


Figure III.3 Architecture of kohnen network

The three neighborhood types shown in Figure III.4 are linear, rectangular, and triangular neighborhoods, which are frequently utilized for Kohonen maps.



(a) (b) (c)

Figure III.4 Three types of neighborhoods: (a) linear, (b) rectangular, (c) triangular

III.6.6 Elman network

Elman introduced the Elman network in 1990, as shown in the following graphic. The Jordan network and this network are extremely similar.

The difference between Jordan and Elman models lies simply in the connection that gives the network its recurrent nature: in Elman's ANN, the loop is located at the hidden layer level, whereas it is between the output layer and the hidden layer in Jordan's ANN [57].

III.6.7 Radial Basis Function (RBF) Networks

After MLPs, RBF networks are arguably the most popular kind of neural networks. RBF networks and MLPs share numerous similarities. Initially, all of the neurons are fully connected to the units in the following layer, and they also have forward unidirectional connections. They are unlooped neural networks as a result.

They also have the same structure as Multilayer Perceptron. The RBF network is a three-layer network, with an input layer, one hidden layers composed of kernel functions, and an output layer, whose neurons are typically driven by linear activation functions[58].

Because of its architecture, this network primarily employs the competitive and error corrective learning rules. It may use a learning technique that simultaneously incorporates supervised and unsupervised learning. Compared to the Multilayer Perceptron, this network performs as well as or better.

Furthermore, their faster and simpler learning make them tools of choice for several types of applications, including classification and function approximation. However, this network has not been as extensively researched as the Multilayer Perceptron.

Function approximation is one of the most common uses of artificial neural networks. The general framework of the approximation problem is as follows: assuming the existence of a relationship between several variables (the inputs) and an output variable. Since this relationship is unknown, we try to construct an approximator (black box) between these inputs and this output. To achieve these different steps, we try to use radial basis function (RBF) networks. These networks are capable of providing a local representation of space through basis functions (this is the particularity of RBF networks), whose influence is restricted to a certain area of space. Several radial functions can be used, but the most common is a Gaussian-like function. Linear combinations of Gaussian functions have been used since the 1960s to build interpolations or function approximations. RBF models are related to many other approaches are used in pattern recognition as well as in the study of function approximation [59].

Layered RBF networks can be used in the case of function classification problems and are capable of approximating any non-linear continuous function with any degree of precision.

$$\hat{y}= \sum_{i=1}^{l} e^{(-\frac{v^2}{\sigma^2})} \tag{3.3}$$

$$v_j(x) = \|c_j - x\| = \sqrt{\sum_{i=-1}^{n}(x_i - c_{ji})^2} \tag{3.4}$$

V(x) is the distance between the centers of the neurons and their input vectors.

$$\sigma = \frac{v}{\sqrt{2s}} \tag{3.5}$$

σ: The standard deviation.

III.7 How to choose your architecture

A number of factors need to be taken into account in order to select the best architecture for a given application, including:

- The nature of the data to be processed (dynamic, static).
- Available hardware and/or software resources for implementing the network.
- The intended function (diagnostic, prediction, recognition etc).
- Learning times that correspond to the amount of time required prior to beginning the decision-making process and treating the network as an expert.
- The work necessary to get the datasets ready for testing and training.
- Temporal constraints generally associated with real-time applications (certain types of neural networks, such as the "Boltzmann machine," requiring random draws and an indefinite number of calculation cycles before stabilizing the output result, present more constraints than other networks for real-time use).

III.8 Network design steps

To build a neural network, the first step is not to choose the type of network but to carefully select the training, testing, and validation datasets. Only then does the choice of network type come into play. To clarify the process, here are the key steps that should guide the creation of a neural network, chronologically:

III.8.1 Determination of the inputs/outputs of the neural network

For any model design, the selection of inputs must consider two essential points:

- The intrinsic dimension of the input vector should be as small as possible. In other words, the input representation should be as compact as possible while retaining essentially the same amount of information. Additionally, it's important to ensure that the different inputs are independent [60].
- All information presented in the inputs should be relevant to the quantity being modeled. Therefore, they must have a real influence on the output value.

III.8.2 Selection and preparation of the samples

The process of developing a neural network always begins with the selection and preparation of data samples. As in data analysis cases, this step is crucial and will help the designer determine the most appropriate type of network to solve the problem. The way the sample is presented conditions: the type of network, the number of input cells, the number of output cells, and how to conduct learning, testing, and validation (Bishop, 1995).

III.8.3 Elaboration of the network structure

The structure of the network depends closely on the type of samples. It is necessary to first choose the type of network: a standard perceptron, a Hopfield network, a basic function network, a Time-Delay Neural Network (TDNN), a Kohonen network, an ARTMAP.

III.8.4 Learning

Learning is a numerical optimization problem. It consists of calculating the optimal weights of the different connections using a sample. The most commonly used method is backpropagation, which is generally more economical in terms of the number of arithmetic operations required to evaluate the gradient : input values are entered into the input cells, and based on the error obtained at the output (the delta), the weights assigned to the connections are corrected[61].

It is a cycle that is repeated until the network's error curve is increasing (care must be taken not to over train a neural network, which will then become less efficient). There are other learning methods such as Quick Prop, for example. But the most commonly used method is still backpropagation.

III.8.5 Validation and Testing

Once the network is trained, it is important to conduct tests to verify that it reacts correctly. There are several methods for validation, such as cross-validation, bootstrapping, etc. However, for testing purposes, in the general case, a portion of the sample is simply set aside from the training sample and kept for out-of-sample testing. It can be required to change the design of the network or the training set if the network's performance is not up to par.

III.9 Type of learning

III.9.1 Supervised learning

In this type of learning, we have a set of examples (called the training set) which are pairs of (input, desired output). For each example, we present an input to the network, calculate an output, and compare it with the desired output, which gives us the error made by the network. Using this error, we adjust the weights of the network, then calculate the new error, and so on until the error is below a chosen threshold [62].

III.9.2 Unsupervised learning

There are cases where we do not have information about the classes in the training set. This lack of knowledge can have several causes, such as a lack of information about the data or the volume of information being too large to be labeled manually. It is in these cases that unsupervised learning is useful.

Unsupervised learning is the only type of learning that can explain learning in the biological system. This training process maps a given class of input vectors that share a common property to a particular output. However, initially, we cannot know the corresponding output for a class of input vectors.

Unsupervised learning is a different technique where no output variable is determined. The network categorizes the input variables on its own.

Unsupervised learning is generally applied to recurrent networks. It is well suited for modeling complex data (images, sounds, etc.), where the rules governing the behavior of the system to be modeled by neural networks are less precise. There are several rules for supervised learning: supervised learning with the perceptron rule and learning with radial basis function (RBF) networks[63].

III.9.3 Reinforcement learning

Reinforcement learning is a technique similar to supervised learning, but instead of providing desired results to the network, it is given a grade (or score) that measures the network's performance after a few iterations. In other words, supervised learning requires a supervisor to dictate to the network which action is correct in a given situation. However, in reinforcement learning, the network does not have a supervisor; it interacts with the environment, which provides quantitative feedback on the values of its actions. Reinforcement learning helps overcome some of the limitations of supervised learning. It is a form of supervised learning, but with a scalar satisfaction index instead of a vector error signal. This type of learning is inspired by the work in experimental psychology by Thorndike (1911)[64].

The two properties, "trial and error search" and "long-term reward," are the two most important characteristics of reinforcement learning.

III.10 Learning rules

III.10.1 Hebb's law

Based on the results of neurobiological observation experiments:

Neurons that fire together wire together. The synaptic weights of neurons whose activities are synchronized are higher. When two connected units are operational at the same time, the strength of the connection increases.

The following equations can be used to model Hebb's law:

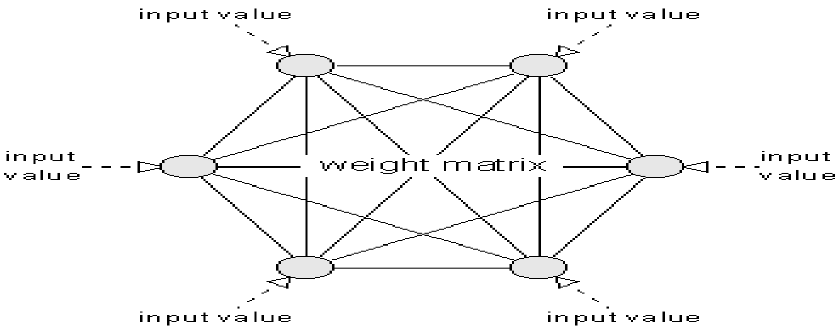


Figure III.5 Architecture of a Hopfield structure

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij} \tag{3.6}$$

Such as:

$$\Delta w_{ij} = \varepsilon \, . \, x_i \, . \, x_j \tag{3.7}$$

x_j: Output value of neuron j.

x_i : Output value of neuron i.

ε : A positive constant representing the learning rate (epsilon) or decayed.

III.10.2 Widrow-Hoff's Adaline Law (Delta Rule)

It calculates the difference between the output value and the desired value to adjust the synaptic weights. It uses an error function, called "the mean squared error," based on the differences used for weight adjustment**.**

This law is also a modified version of Hebb's law. It uses the principle of error correction, which guides certain neural network learning algorithms.

$$E= d_i - x_j \tag{3.8}$$

If the output is less than the desired response, for example, the weight of the connection should be increased, assuming that unit j is excitable (equal to 1). This rule can be expressed as follows:

$$\Delta w_{ij} = \varepsilon\,(d_i - x_i\,)x_j \tag{3.9}$$

With:

x_i :Output and x_j input.

d_i : Desired response by the human expert.

III.10.3 Cascade correlation rule

A learning method called the cascade correlation algorithm adds hidden neurons to the network piecemeal until their positive effects become negligible. The two steps that this rule follows are as follows:

- Training without Hidden Layer: Initially, a traditional learning technique is used to train the system without a hidden layer.
- Training Additional Neurons: Next, in order to lower the network's residual error, a limited number of extra neurons are trained. These neurons' weights are adjusted by the learning rule that is applied. The neuron that performs the best is chosen and added to the network. To give the network time to adjust to the new resource, step 1 is repeated.
- This method seeks to progressively construct a network structure that can effectively represent intricate relationships in the data [65].

III.10.4 Backpropagation rule

Invented by Rumelhart, Hinton, and Williams in 1986, this rule is used to adjust the weights from the input layer to the hidden layer. It can also be seen as a generalization of the delta rule for nonlinear activation functions and for multilayer networks. The weights in the neural network are initially set to random values. Then, a dataset is considered, which serves as a training sample. Each sample has target values that the neural network should reach when presented with the same sample [66].

III.11 Application

- Actually, there are applications for neural networks in a number of fields, including computer science, electronics, hydrology, neuroscience, and cognitive science. Neural network research holds great potential for artificial intelligence, with applications across various domains.
- Industry: neural networks are used for quality control, defect detection, correlation between data provided by multiple sensors, and analysis of signatures or handwriting.
- Finance: Credit attribution, investment selection, and forecasting and modeling of market movements (exchange rates, currency values, etc.).
- Information technology and telecommunications: data compression, picture, audio, and noise recognition patterns.
- Environment: Resource management, chemical analysis, resource forecasting and modeling, meteorological and hydrological forecasts [67].

III.12 The advantages and disadvantages of neural networks

III.12.1 Advantages

- Robustness to noisy data: Neural networks can effectively handle noisy and incomplete data, making them suitable for real-world environments where data may be imprecise.
- Simulation of diverse behaviors: Neural networks can model a wide variety of complex behaviors, making them useful in many application domains.
- Fault tolerance: Neural networks can often continue functioning even in the presence of failures or damage to some neurons, thanks to their ability to self-organize and compensate for damage.
- Automatic weight calculation: Once configured and trained, neural networks can automatically calculate the weights of connections, simplifying the use of the network in practical applications.
- Generalization: Neural networks can generalize from training data to make predictions or classifications on new data they have never seen before[68].

III.12.2 Disadvantages

- Opacity of results: As they do not provide easily interpretable explanations for their decisions, unlike decision tree methods.
- Long training time: Training a neural network can be computationally intensive and time-consuming, especially for large or complex networks.
- Complex representation: Understanding the internal workings and representations learned by a neural network can be challenging due to its complex structure.
- Long learning period: It may take a significant amount of time to train a neural network to achieve satisfactory performance, especially for complex tasks or large datasets.
- Risk of local minima: During training, neural networks can get stuck in suboptimal solutions called local minima, which can hinder their ability to learn the best model.
- Difficulty in explaining results: Neural networks can produce accurate results, but explaining how and why they make certain predictions or classifications can be challenging without prior knowledge or understanding of the network's inner workings.

III.13 Simulation results

MPPT algorithms are crucial in photovoltaic applications because the MPP of a solar panel fluctuates with the solar irradiation and temperature, Since the maximum available energy of solar arrays continuously changes with the atmospheric conditions, a real-time maximum power-point tracker is the indispensable part of the PV system. Proposed maximum power point tracking (MPPT) schemes in the technical literature can be divided into three different categories [69]:

- Direct methods.
- Artificial intelligence methods.
- Indirect methods.

In the direct methods, which are also known as true seeking methods, the MPP is searched by continuously perturbing the operating point of the PV array .Under this category, Perturb and Observe (P&O) [70]. Artificial intelligence and indirect methods have been proposed to improve the dynamic performance of MPP tracking. Concentrating on nonlinear characteristics of the PV arrays, the artificial intelligence methods. Provide a fast, and yet, computationally demanding solution for the MPPT problem as shown in the following Figure III.6:

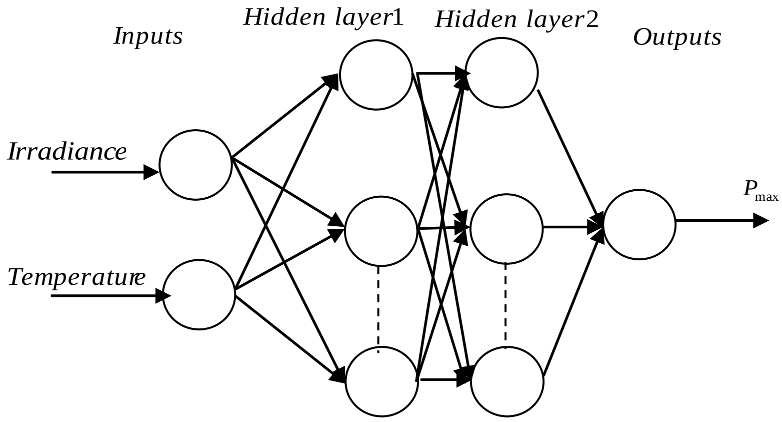


Figure III.6 Proposed ANN structure for MPPT

The indirect methods are based on extracting the MPP of the array from its output characteristics [71].

Table III.2 Electrical parametrs of the BP SX 150S PV array at 25°C,1000W/m²

Electrical characteristics	Value
Maximum Power (P_{mpp})	150 W
Voltage at P_{mpp} (V_{mpp})	34.5 V
Current at P_{mpp} (I_{mpp})	4.35 A
Short-circuit current(I_{sc})	4.75 A
Open-circuit voltage(V_{oc})	43.5 V
Temperature coefficient of I_{sc}	(0.065 $\pm$ 0.015)%/°C
Temperature coefficient of V_{oc}	-(160 $\pm$ 20)mV/°C
Number of cells series (N_S)	72

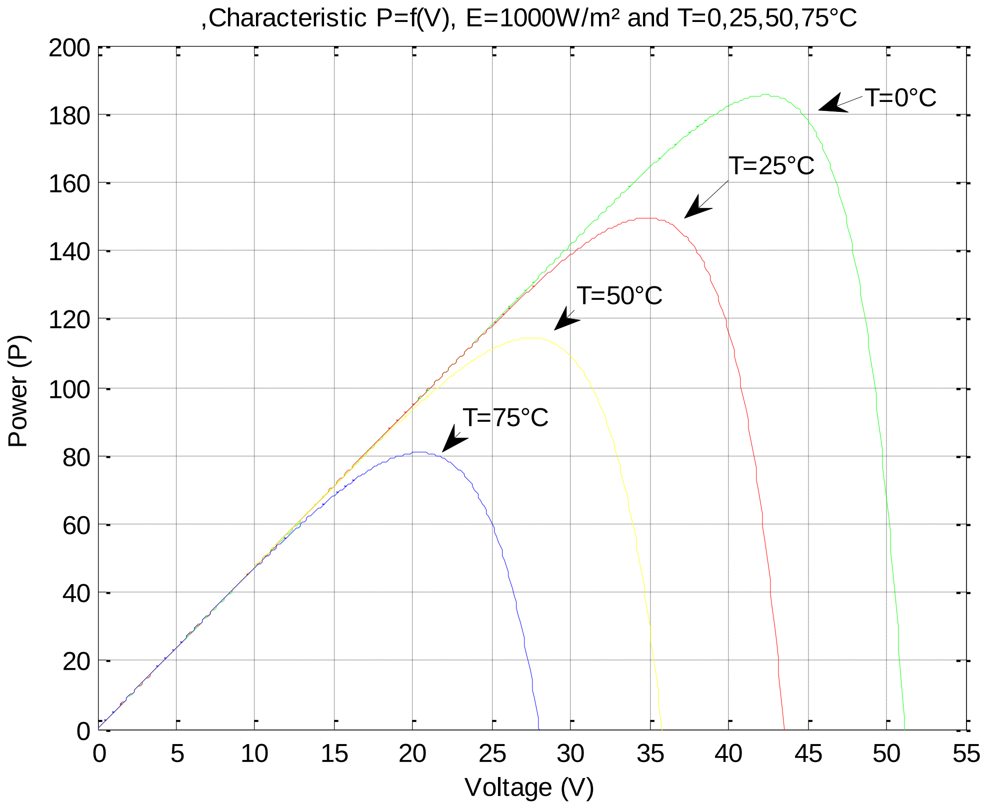
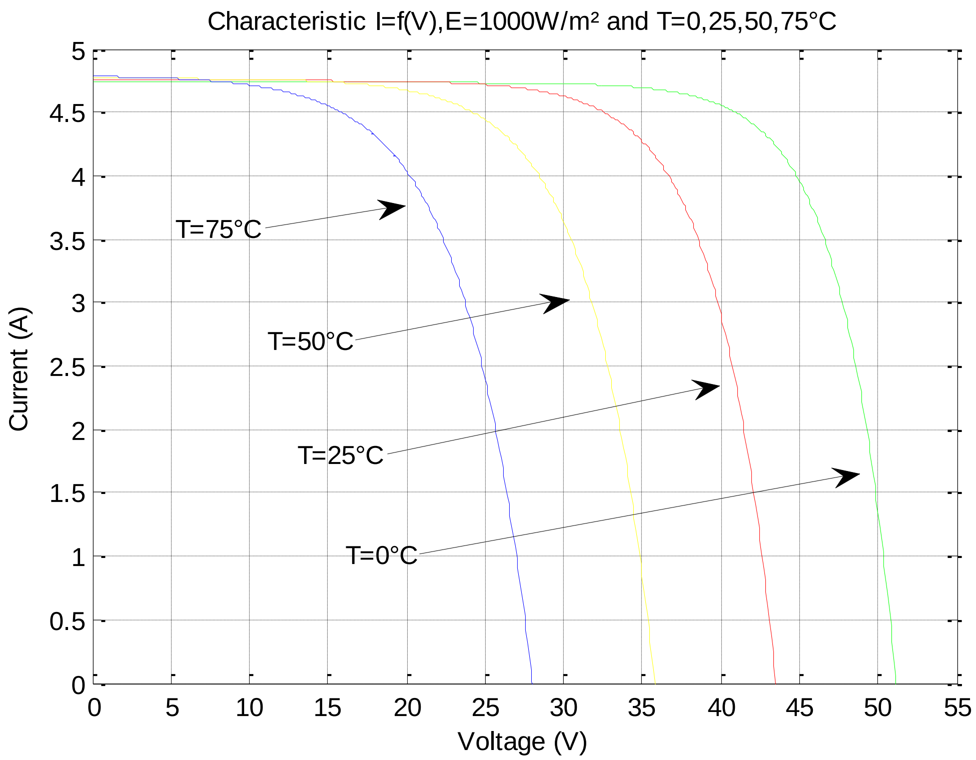


Figure III.7 Characteristic of PV ,P=f(V).



FigureIII.8 Characteristic of PV,I=f(V).

In our proposed design, we incorporate a two-layer radial basis function (RBF) neural network technique that predicts the PV array voltage at which maximum power is attainable. These networks develop a non-linear relationship between the input and output, with a hidden layer that functions with preferences similar to those of neurons in our brain. The hidden layer in our model is an RBF neural network. The input parameters are T (temperature) and E (radiation).

III.13.1 Learning step

The size of the input training matrix reaches 360 by 2 Inputs which ensure high accuracy of the model.The simulated model characteristics are shown in Table III.3.

Table III.3 Architecture of RBF Model

Model	Output / Structure	MPP
RBF	Number of hidden layers	1
	Algorithm	Least square
	Number of Neurons	40
	Activation function	Gaussian
	Adjusted Gain	150
	Dataset	360
	Training time (S)	3.37(s)
	Number of iterations	40
	MSE	$1.5302e$-004

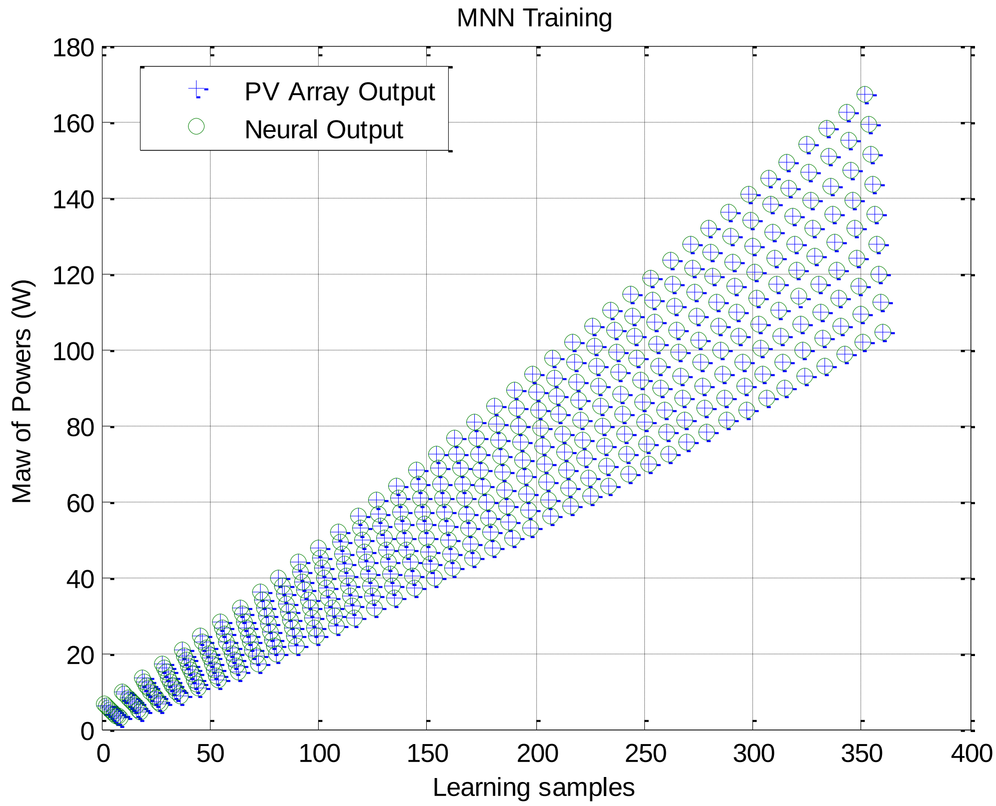


Figure III.9 Training Data

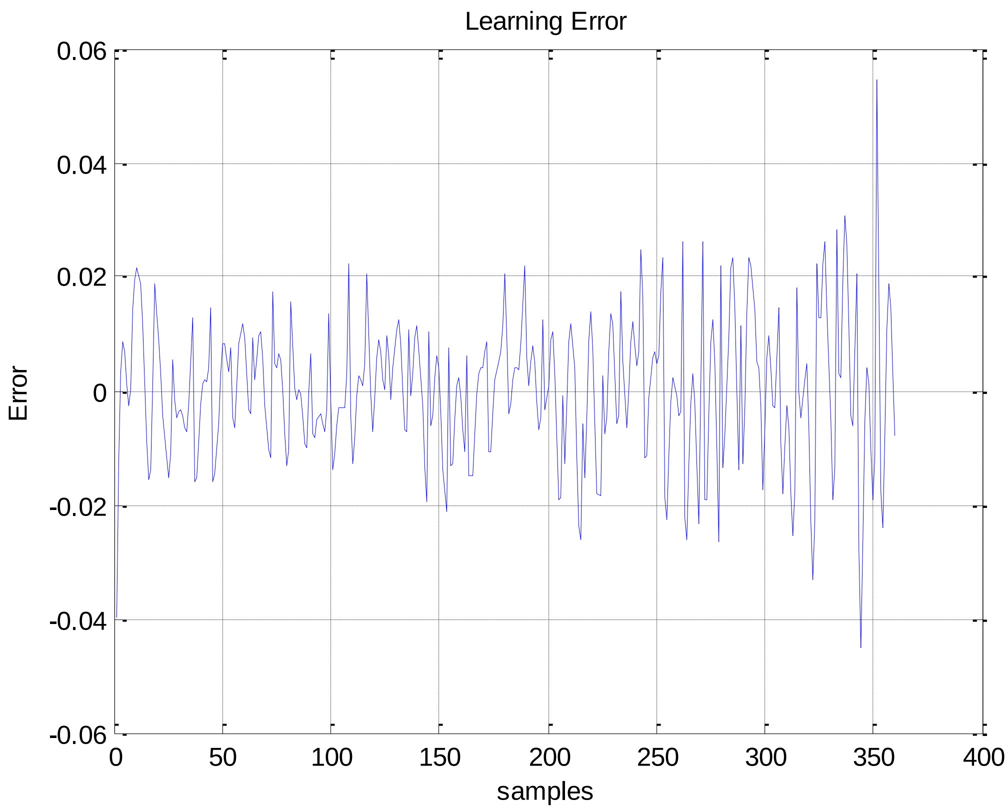


Figure III.10 Training Error MSE = 1.5302e-004

III.13.2 Validation step

Now we verify that the neuronal network model after learning are actually able to predict the desired output for values given at the entry which are not used in the learning. We always should compare the true output of the networks with the model of the PV for comparisons using mean square error (MSE). For this we study three cases.

This section interprets the results obtained from the identification of a photovoltaic system using a Radial Basis Function (RBF) neural network. The analysis focuses on the performance of the RBF model in terms of Maximum Power Point Tracking (MPPT).

This analysis concentrates on three specific cases:

- The radiation varies, and the temperature is constant.
- The temperature varies, and the radiation is constant.
- Both radiation and temperature vary.

In each case, there are several tests, and each scenario has a graph presenting the errors values.

Case 01 : the irradiation varies and the temperature is constant.

➢ $200\text{w}/m^2 \le \text{E} \le 1000\text{w}/m^2$ and T = 25°C

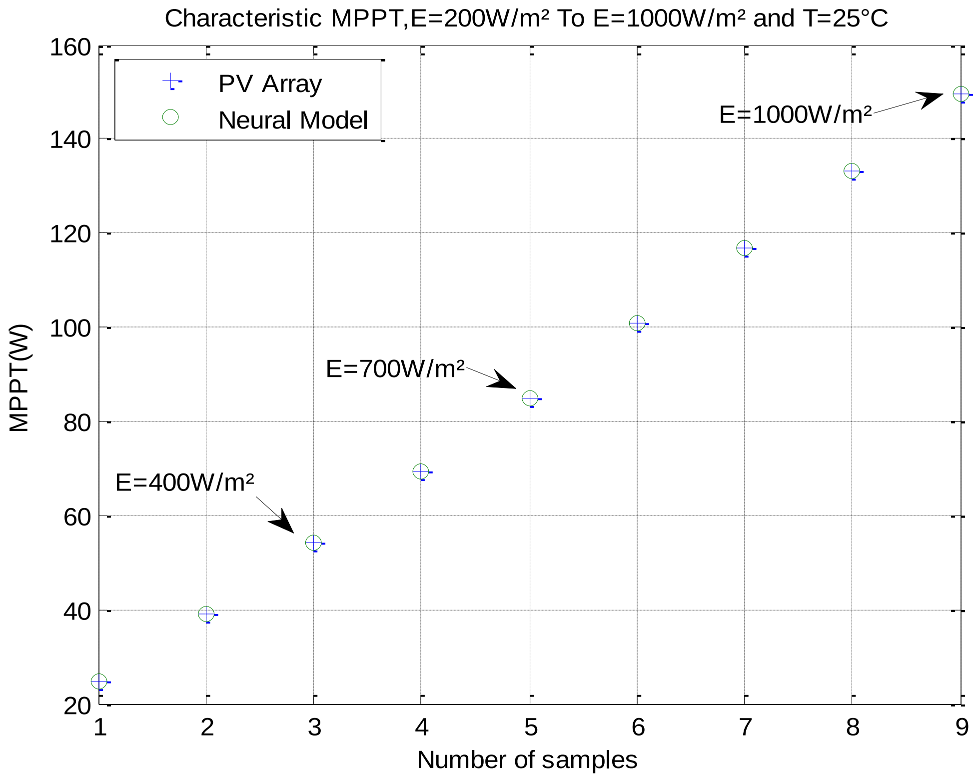


Figure III.11 'O' Neural Model and '+' PV Array MPPT for T = 25 °C

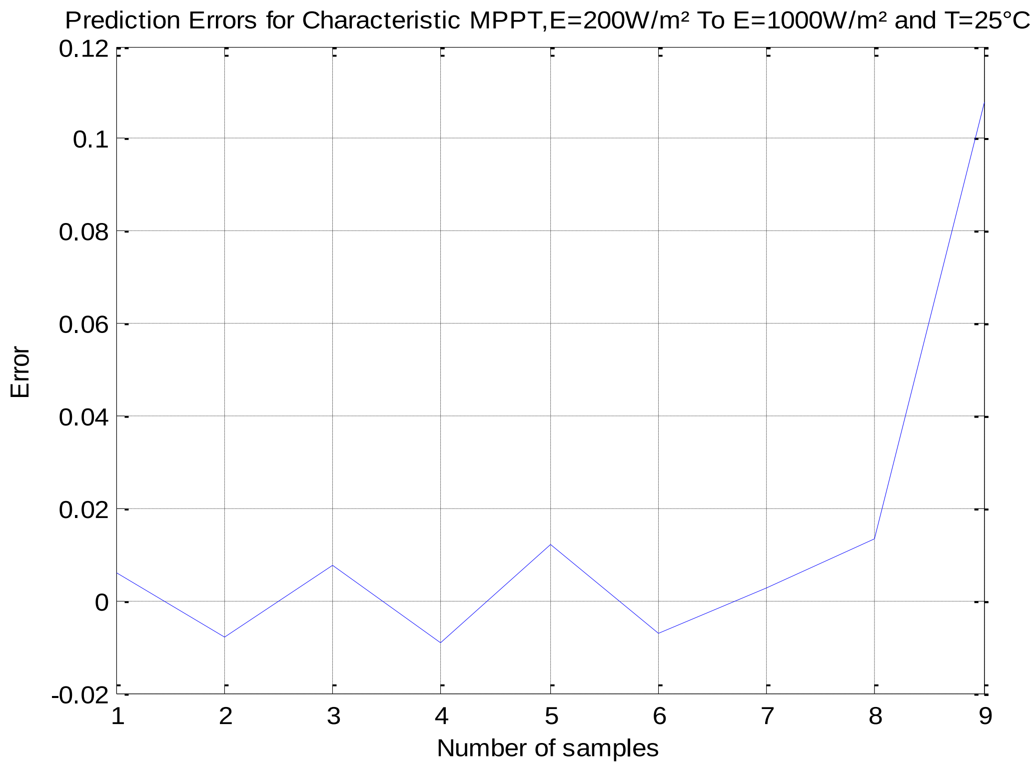


Figure III.12 MSE= 0.0014

- $150 \text{w}/m^2 \leq \text{E} \leq 950 \text{w}/m^2$ and T = 60°C

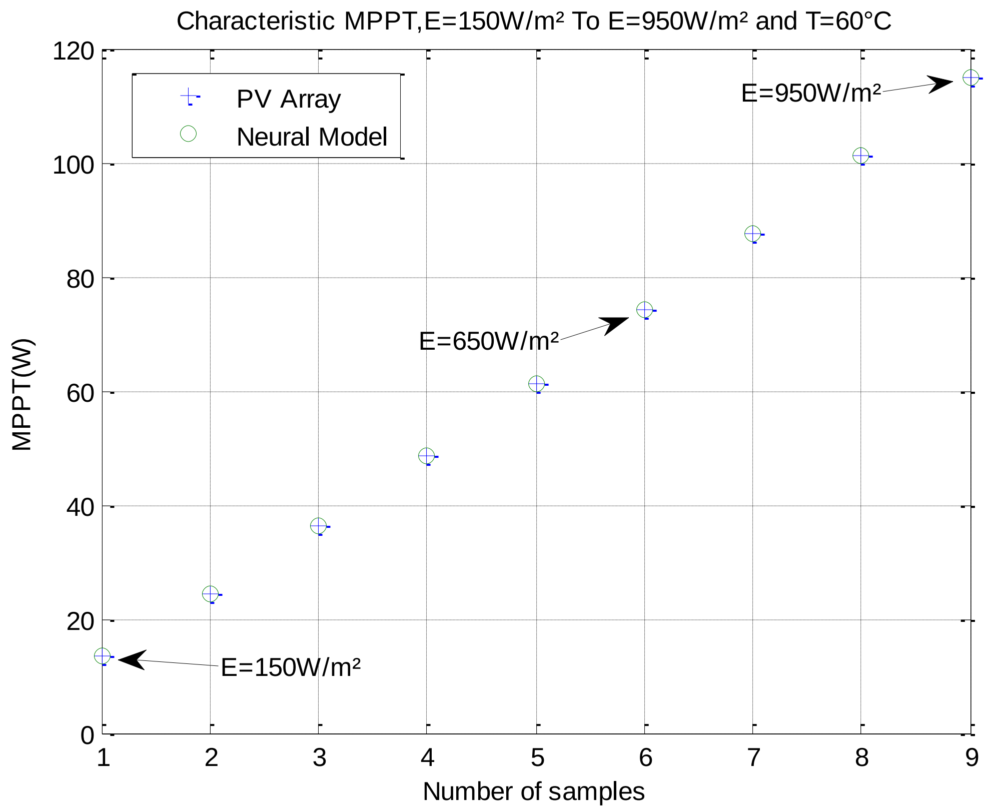


Figure III.13 'O'Neural Model and'+' PV Array MPPT for T = 60°C

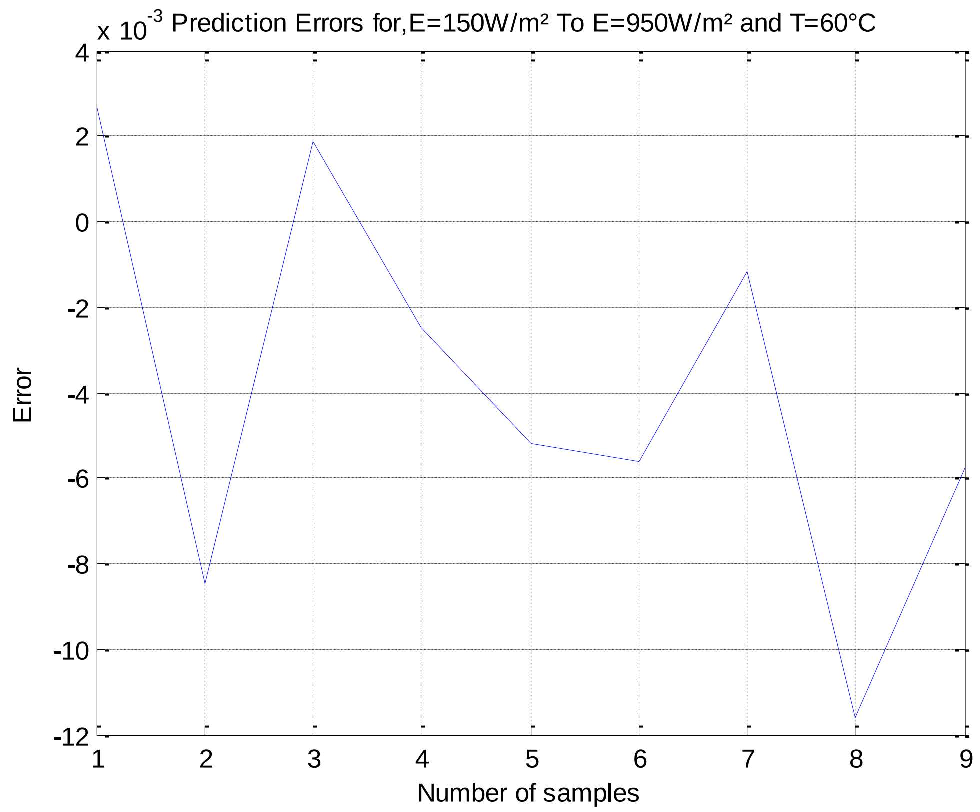


Figure III.14 MSE= 3.5143e-005

Case 02: The temperature varies and the irradiation is constant.

- 20°C ≤ T ≤ 60°C and E=1000w/m^2

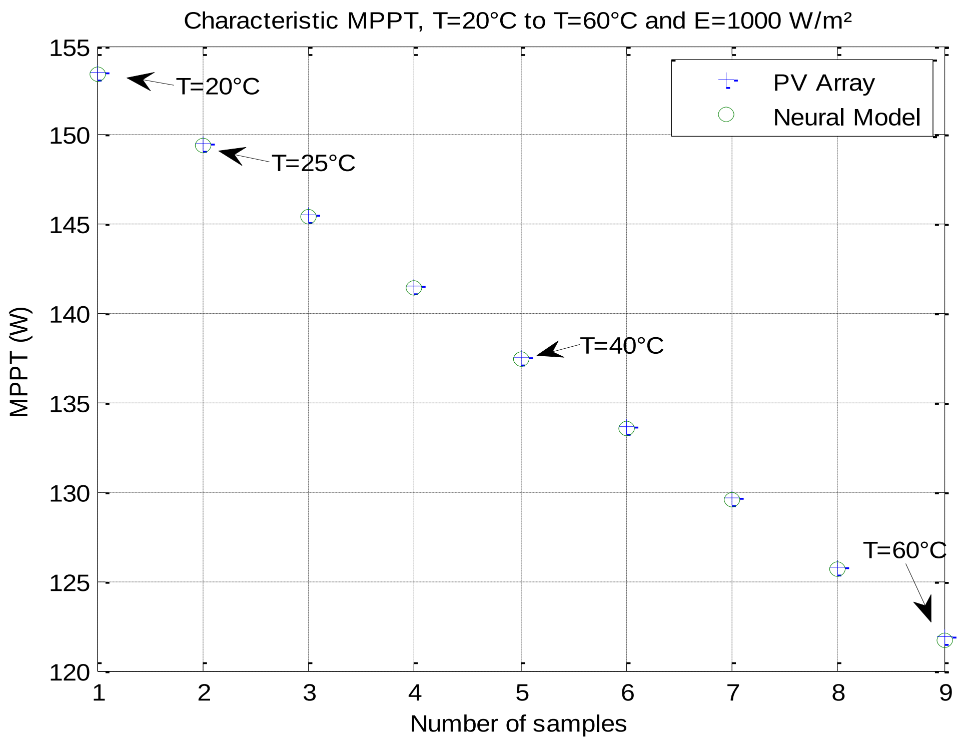


Figure III.15 'O'Neural Model and'+' PV Array MPPT for E=1000w/m^2

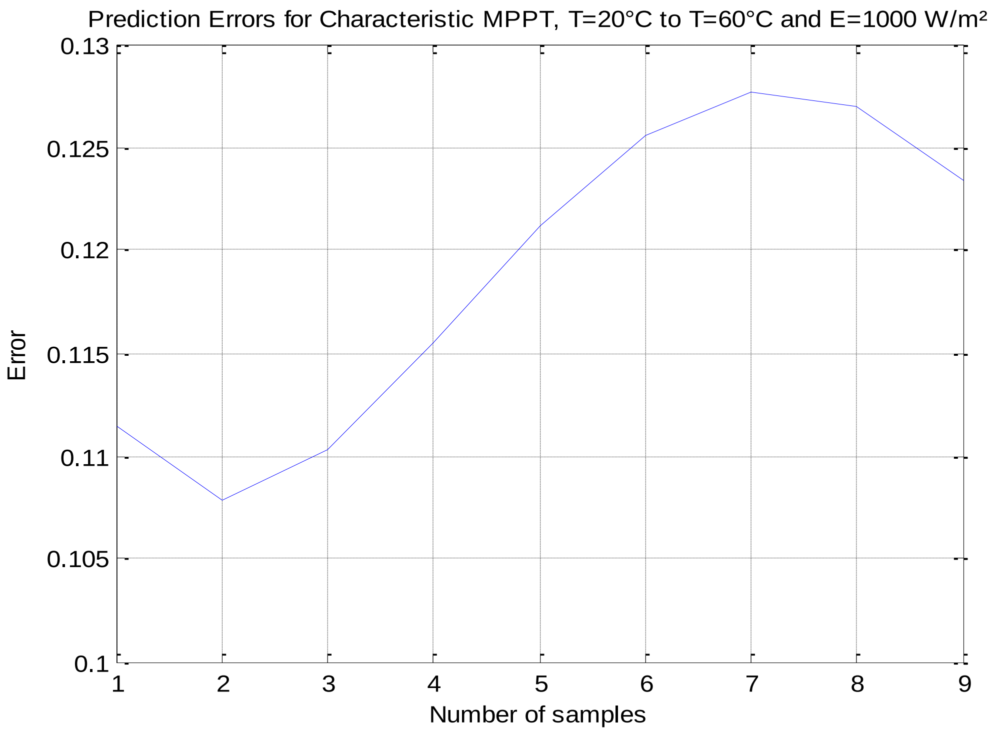


Figure III.16 MSE= 0.0142

➢ $20°C \leq T \leq 70°C$ and $E=600w/m^2$

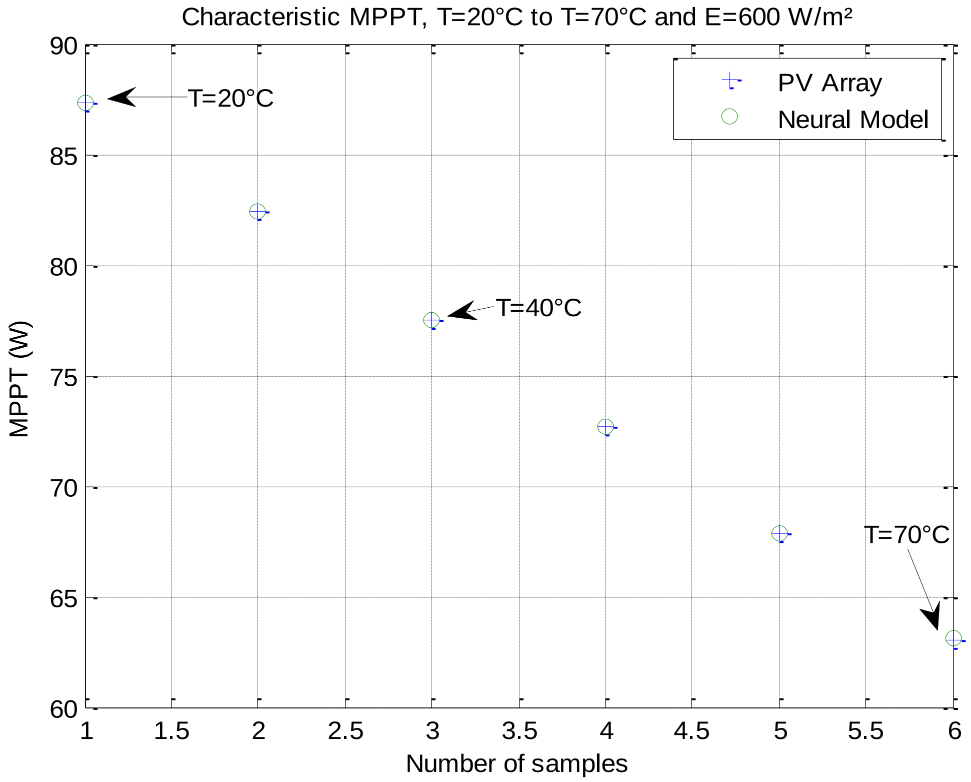


Figure III.17 'O'Neural Model and'+' PV Array MPPT for E=600w/m²

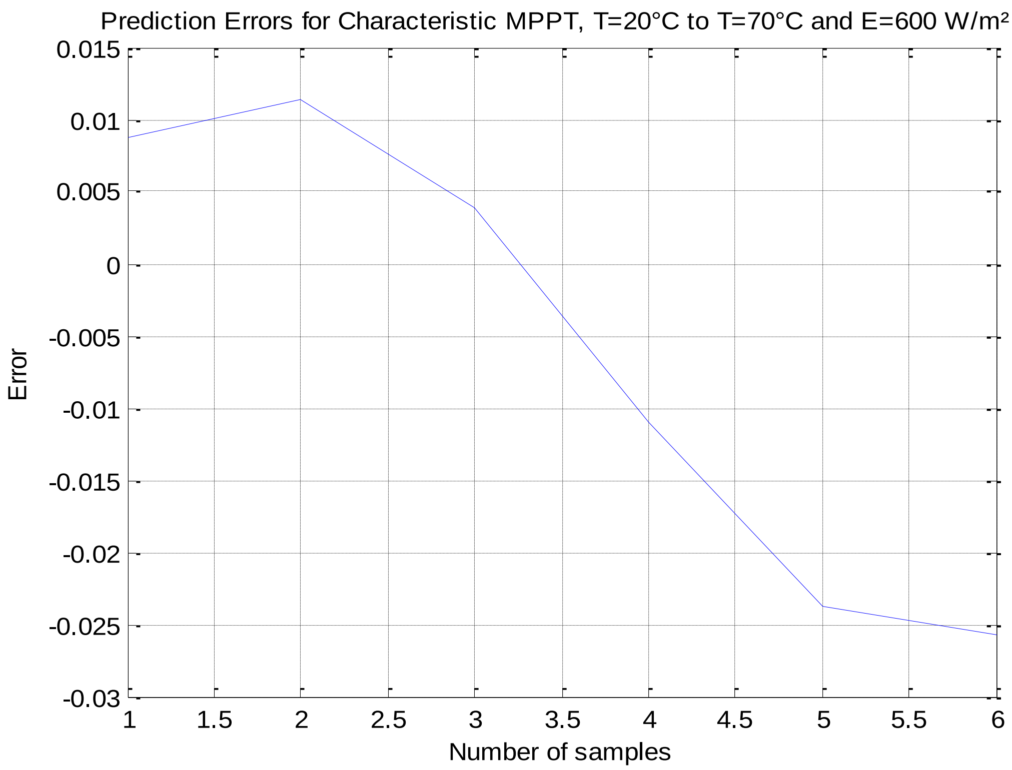


Figure III.18 MSE=2.6195e-004

➢ 23°C ≤ T ≤ 72°C and E=500w/m^2

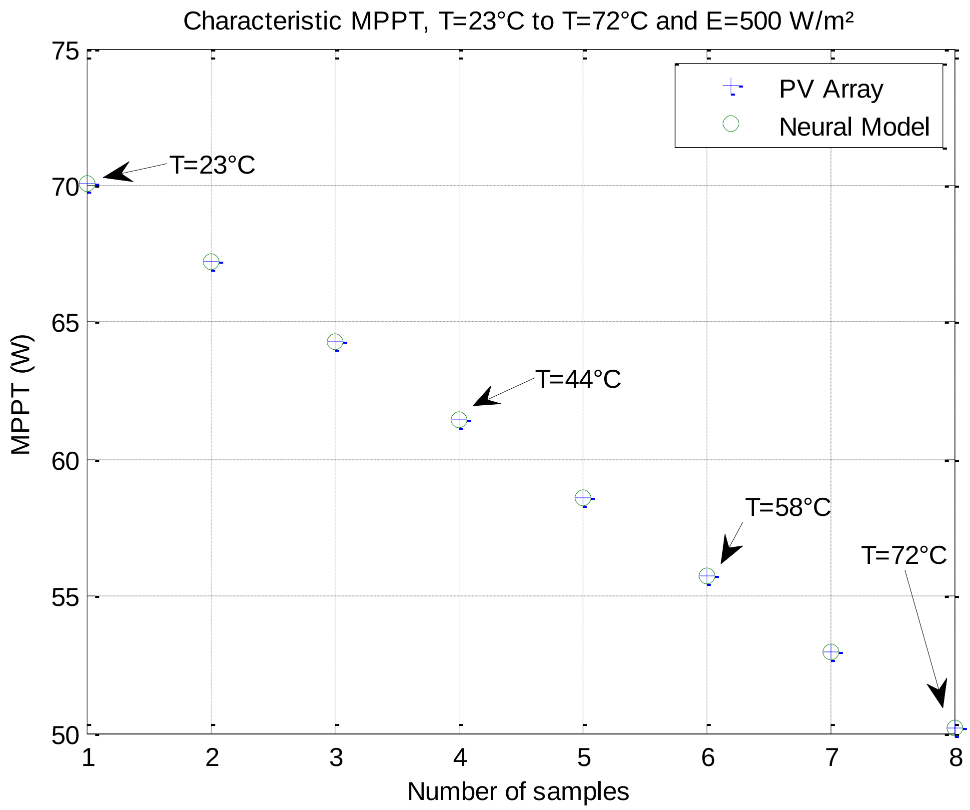


Figure III.19 'O'Neural Model and'+' PV Array MPPT for E=500w/m^2

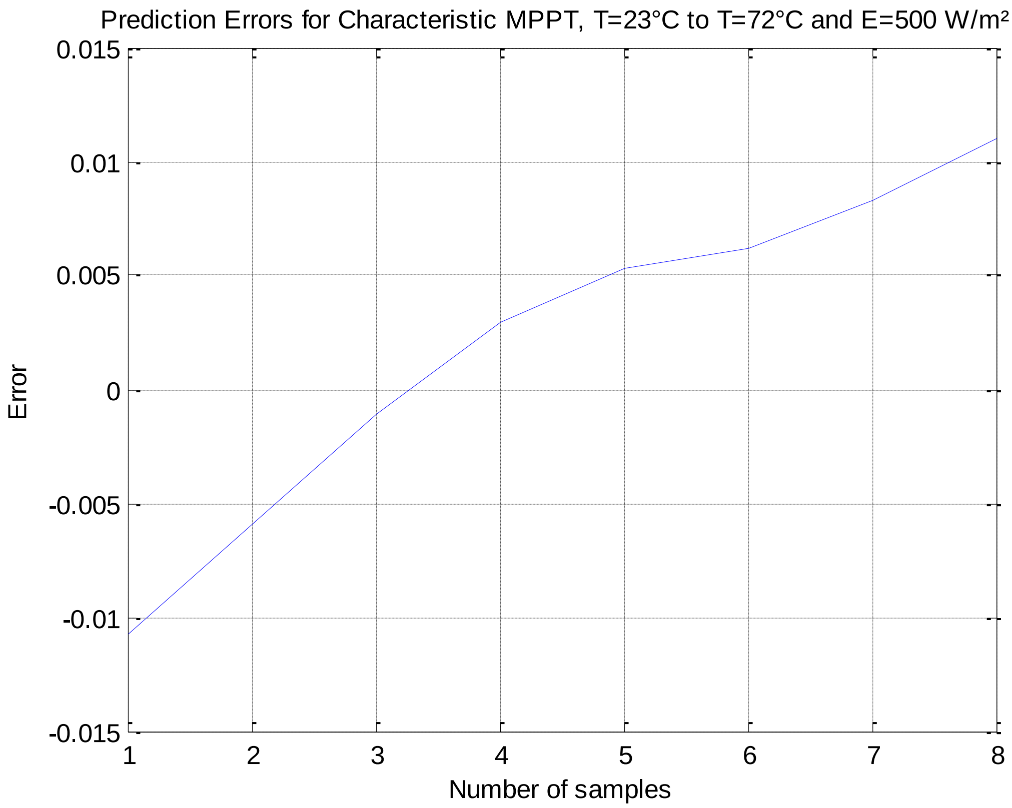


Figure III.20 MSE=5.2089e-005

Case 03: The temperature varies and the irradiation varies too.

➢ $0°C \leq T \leq 60°C$ and $100w/m^2 \leq E \leq 700w/m^2$

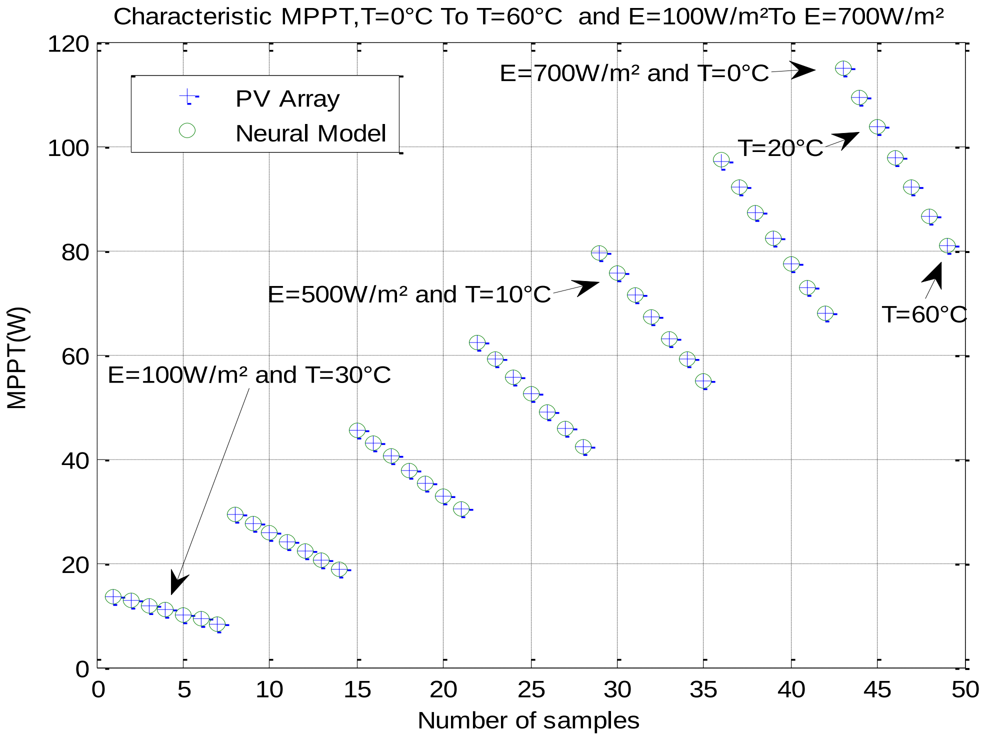


Figure III.21 'O'Neural Model and'+' PV Array MPPT for T and E varie

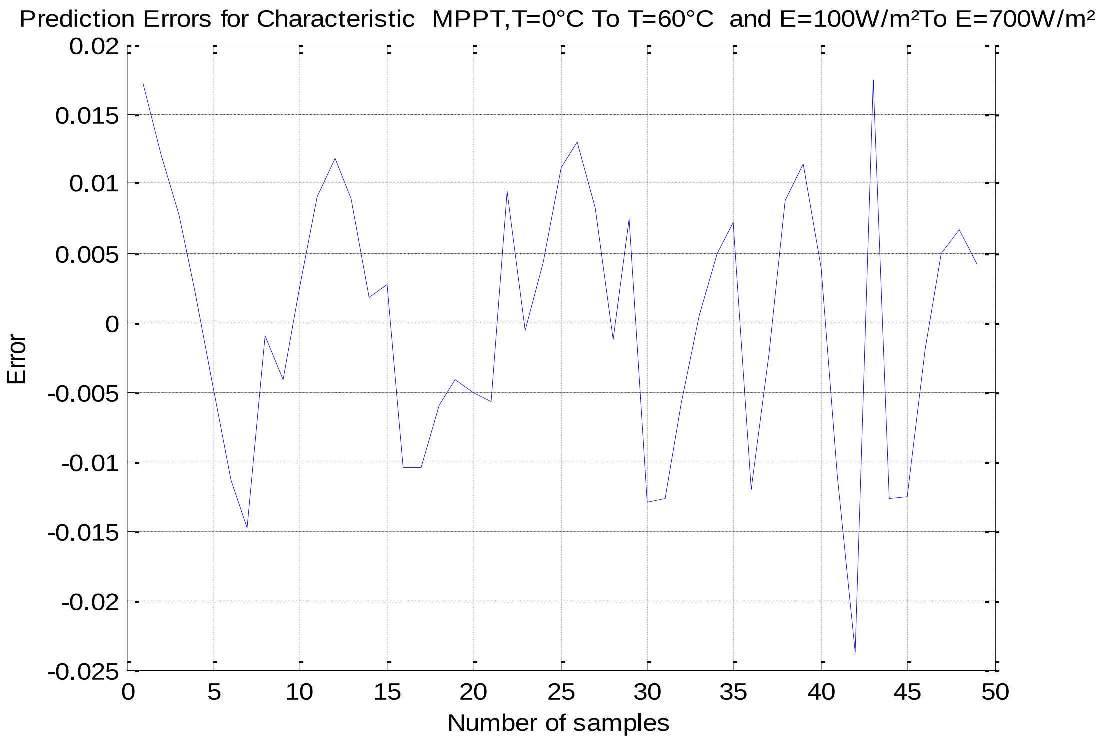


Figure III.22 MSE=8.7042e-005

➢ $0°C \le T \le 48°C$ and $100w/m^2 \le E \le 700w/m^2$

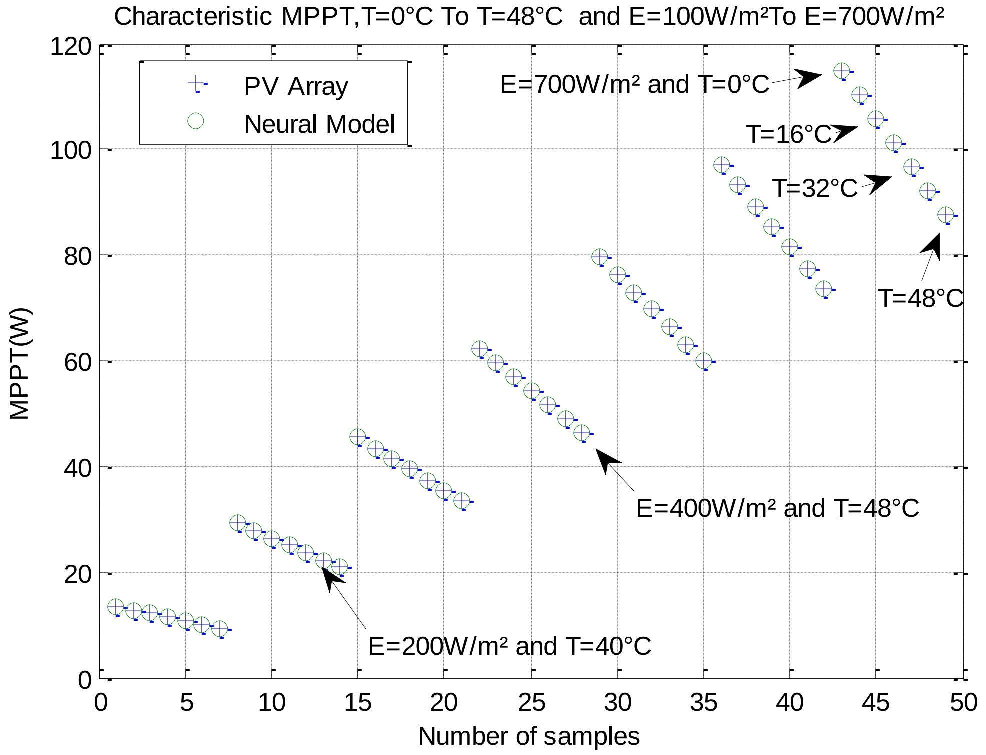


Figure III.23 'O'Neural Model and'+' PV Array MPPT for T and E varie

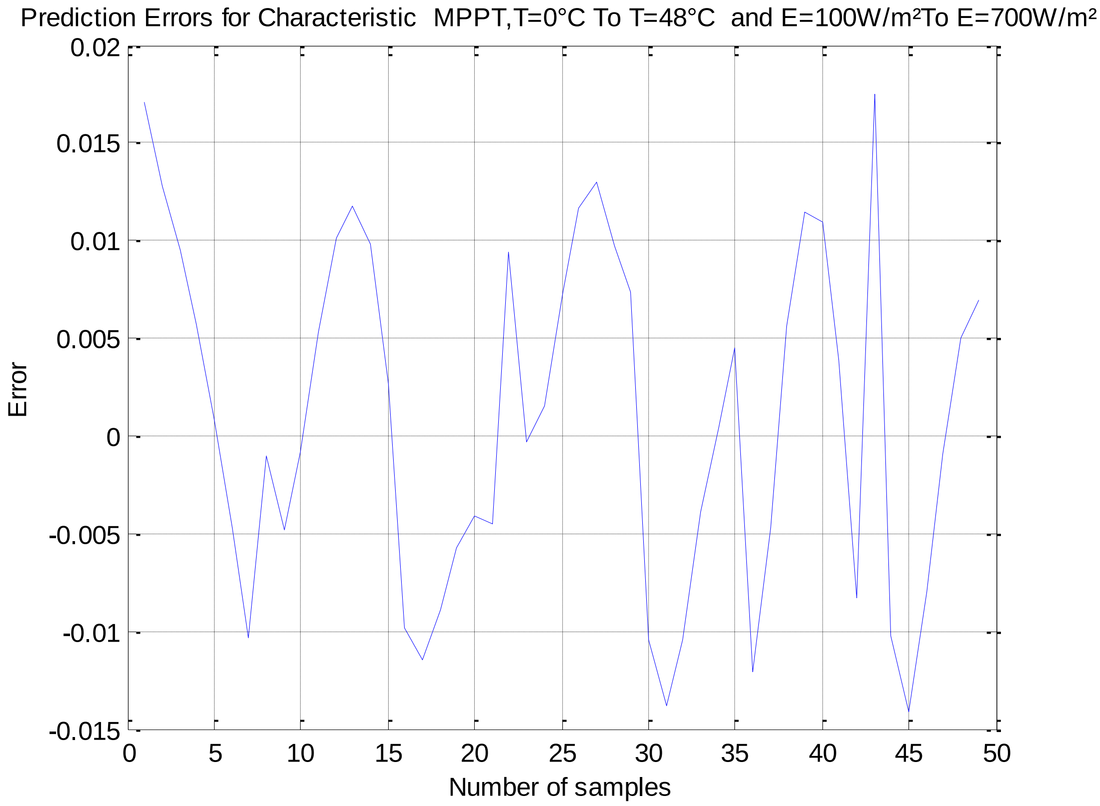


Figure III.24 MSE=7.7643e-005

III.13.3 Results Interpretation

In order to show the validation of the presented RBF model, three comparisons between the PV and our RBF model, corresponding to the following cases have been made and obtained results are discussed.

- **Case 01:** The radiation varies, and the temperature is constant.

The MPP of RBF model and our Real PV system are represented in Figures [11,13], respectively. Random combinations of values of (E,T) are taken that have not been used in training. The horizontal axis represents the index of the sample points from 1 to 9. The percentage errors between the desired outputs calculated from PV and the outputs of RBF Model are presented in Figures [12,14]. The absolute value of percentage error in MPP is less than 0.04 % for RBF.

- **Case 02:** The temperature varies, and the radiation is constant.

The MPP of RBF model and our Real PV system of are represented in Figures [15,17,19], respectively. Random combinations of values of (E,T) are taken that have not been used in training. The horizontal axis represents the index of the sample points from 1 to 9,1 to 6 and 1 to 8 respectively. The percentage errors between the desired outputs calculated from PV and the outputs of RBF Model are presented in Figures [16,18,20]. The absolute value of percentage error in MPP is less than 0.03 % for RBF.

- **Case 03:** Both radiation and temperature vary

In this difficult case the MPP of RBF model and our Real PV system of are represented in Figures [21,23], respectively. Random combinations of values of (E,T) are taken that have not been used in training. The horizontal axis represents the index of the sample points from 0 to 50. The percentage errors between the desired outputs calculated from PV and the outputs of RBF Model are presented in Figures [22, 24]. The absolute value of percentage error in MPP is less than 0.04% for RBF.

In our results by testing the errors between the real model of PV and our desired one with all possible cases of variation of the irradiation and the temperature, it can be seen that the applied RBF is capable to predict the MPPT of the PV panel for any set of input values (E,T) within their defined domain of variations with performance reached 95.98 % as presented in all figures without any aditional Metaheuristic technique or renforcement ,compared to all cited references and technics results .

Conclusion

In this chapter, we began with a historical overview of the origins of neural networks and their development up to the present day. Then, we discussed the architectures of neural networks, covering both static and dynamic networks. Following this, we addressed the classification of neural networks. We also delved into the considerations for choosing an architecture and moved on to the steps involved in designing a neural network. Before concluding with the advantages and disadvantages, we explored the types of learning and their rules, as well as their applications**.**

General conclusion

The efficiency, stability and reliability of a photovoltaic energy are considered major factors for establishing this energy resource on the market. In this work, common maximum power point tracking technique, based on artificial neural network using the RBF (Radial basis function) has been proposed for a grid-connected PV system to maximize the output power of a PV array. The aim has also been improving the stability and reliability of a PV power conversion, with a certain value of temperature and radiation.

We began this thesis with identification of dynamic systems we explored methods for identifying and understanding the complex behavior of a dynamic system. Among these methods, we examined Least Squares, Recursive Least Squares, Particle swarm optimization, fuzzy logic as well as the steps necessary for successful identification.

We then presented the photovoltaic systems and their main characteristics, their different main components. Then we presented the different parameters and equations allowing the design of a photovoltaic installation for a specific site.

The last part of our work addresses an in-depth study about artificial neural networks, we simulated a code that predicts the power produced by a photovoltaic system.

The output power of the photovoltaic generator (GPV) depends on several climatic factors, such as irradiation and temperature. However, real-time tracking of the optimum operating point (MPP) is required to optimize system performance. In this work, we studied an intelligent modeling neural network to extract the maximum power from the PV Array. The simulation results demonstrated that our RBF network learned well, confirming this by the test values which gave very approximate power values or almost equal to the real power values produced by the solar panels. The characteristics of the PV were taken from electrical parameters of the BP SX 150S for learning the network.

In this thesis, MPPT identifier has been developed to improve the average tracking efficiency, increase the stability and enhance the reliability of a grid-connected PV system. However, there are other challenges that need further solutions, if investing in this type of energy resource is to become more attractive, some suggestions being as follows:

- Enhanced tracking efficiency of a PV system under rapidly changing atmospheric conditions has been demonstrated in this current work. It would prove beneficial to improve the PV system performance under a partial shading condition. This condition happens when there is a shading, which can be caused by tree shadow or dust, i.e. on part of the PV array. In this case, the PV array will generate several MPPs. Hence, the total generating efficiency of the installed PV array decreases. To solve this issue, an MPPT controller based on the PSO algorithm could be used.

- A fault situation is considered one of the major challenges facing large-scale PV systems when connected to the grid. This issue can cause a dynamic stability problem with voltage rise. However, disconnection of faulty units could cause the system to malfunction. To address this issue, advanced active control and advanced reactive control would need to be employed.

Finally the main recommendation that can be made for the future investigation, is the implementation of a physical model for the artificial neural network MPPT technique using microcontrollers and testing it on a real PV Array.

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