

الجمهورية الجزائرية الديمقراطية الشعبية

République Algérienne Démocratique et Populaire

وزارة التعليم العالي والبحث العلمي

Ministère de l'Enseignement Supérieur et de la recherche Scientifique

جامعة غرداية

N d'enregistrement :

Université de Ghardaïa

/...../...../...../...../.....



كلية العلوم والتكنولوجيا

Faculté de science et de la technologie

Département d'automatique et électromécanique

Mémoire de fin d'étude, en vue de l'obtention du diplôme

**Master**

**Domaine :** Science et Technologie

**Filière :** Automatique

**Spécialité :** Automatique

**Thème**

**Prediction of Solar radiation using recurrent neural network**

**Présenté par :** GUERBATI Abdessamed  
MORSLI Abderrazak

**Devant le jury composé de :**

<b>ZAGAOUI ABDALLAH</b>	<b>Prof</b>	<b>Université de Ghardaïa</b>	<b>Président</b>
<b>KIFOUCH ABDESLAM</b>	<b>MCB</b>	<b>Université de Ghardaïa</b>	<b>Encadrant</b>
<b>DJEMOUI Lalmi</b>	<b>MCA</b>	<b>Université de Ghardaïa</b>	<b>Co-encadrant</b>
<b>MOUSSA OUSSAMA</b>	<b>MAB</b>	<b>Université de Ghardaïa</b>	<b>Examineur</b>

**Année universitaire 2021/2022**

# Thanks

*First and foremost, praise and appreciation to Almighty God, who has enabled us to do this.*

*And give us the strength, patience, and health we need to go through these years of study.*

*This work would not have been feasible without him.*

*We would like to express our gratitude to **Mr. Kifouch Abdeslam**, our supervisor, for his efforts in providing us with valuable assistance and allowing us to complete the task.*

*We also want to express our gratitude to the University of Ghardaia, namely the Department of Science and Technology, as well as all of the professors and administrators who have taught us throughout the years.*

*Finally, we want to express our gratitude to everyone who assisted us in the creation of this work, whether directly or indirectly.*

## ***Dedications***

*We dedicate this work:*

*To our parents in testimony of their sacrifices and encouragement.*

*To our sisters and brothers for their support.*

*To our friends in memories of the good times spent together.*

***GUERBATI Abdessamed and MORSLI Abderrazak***

## ***Abstract:***

the main objectif of this research is to present an algorithm that can be used to predict a daily activity of solar radiation. Using a dataset that consists of temperature of air, time, humidity, wind speed, atmospheric pressure, direction of wind and solar radiation data.

this is done by using Neural Network (NN) technology to effectively predict solar radiation, and this technology imparts its ability to generate effective predictions with sufficient performance accuracy.

**Keywords:** Recurrent Neural Networks, Solar Radiation, prediction of solar radiation, artificial neural network, Temperature.

## ***Résumé:***

L'objectif principal de cette recherche est de présenter un algorithme qui peut être utilisé pour prédire une activité quotidienne de rayonnement solaire. Utilisation d'un ensemble de données comprenant la température de l'air, le temps, l'humidité, la vitesse du vent, la pression atmosphérique, la direction du vent et les données de rayonnement solaire.

Cela se fait en utilisant la technologie Neural Network (NN) pour prédire efficacement le rayonnement solaire, et cette technologie confère sa capacité à générer des prédictions efficaces avec une précision de performance suffisante.

**Mots clé:** Réseaux de neurones récurrents, rayonnement solaire, prédiction du rayonnement solaire, réseau de neurones artificiels, température.

## **ملخص:**

الهدف الرئيسي من هذا البحث هو تقديم خوارزمية يمكن استخدامها للتنبؤ بالنشاط اليومي للإشعاع الشمسي. باستخدام مجموعة بيانات تتكون من بيانات درجة حرارة الهواء والوقت والرطوبة وسرعة الرياح والضغط الجوي واتجاه الرياح وبيانات الإشعاع الشمسي.

وكل هذا يتم باستعمال تقنية الشبكة العصبية للتنبؤ بفعالية الإشعاع الشمسي، وتضفي هذه التقنية قدرتها على توليد تنبؤات فعالة بدقة أداء كافية.

**الكلمات المفتاحية:** الشبكات العصبية المتكررة، الإشعاع الشمسي، التنبؤ الإشعاع الشمسي، الشبكة العصبية الاصطناعية، درجة الحرارة.

## ***List of contents:***

Thanks	
Dedications	
Abstract	
List of figures	
INTRODUCTION.....	01
Chapter 1: artificial networks technical sketching	
1.1 Introduction .....	04
1.2 Biological Neuron.....	05
1.3Artificial Neuron.....	05
1.3.1The Link between biological and artificial neurons.....	05
1.4 Artificial neurons networks.....	07
1.4.1 Definition.....	07
1.4.2 History of neural networks.....	07
1.5 Structure of neural network.....	10
1.5.1Definition.....	10
1.5.2Types of neural network Structure.....	10
1.5.2.1 Feed-forwarded neural networks.....	10
1.5.2.2 Recurrent Neural Networks.....	11
1.5.2.3 Resonance Neural Networks.....	12
1.5.2.4 Self-organizing neural networks.....	13
1.6 Conclusion.....	14
Chapter 2: solar radiation and temperature	
2.1 Introduction.....	16
2.2Solar radiation.....	17
2.2.1 Radiation.....	17

2.2.2 Radiation component.....	17
2.2.3 Solar radiation .....	17
2.2.4 Penetration of solar radiation through the atmosphere.....	17
2.2.5 solar radiation data.....	19
2.2.5.1 solar radiation data sources.....	19
2.2.5.2 Measuring solar radiation data .....	20
2.2.5.3 physically-based models.....	22
2.2.6 solar radiation prediction.....	22
2.2.6.1 Variability and Predictability of Solar Radiation .....	22
2.2.6.2 Solar Irradiance Prediction using Measured Meteorological Parameters.....	23
2.3.temperature.....	25
2.3.1 Factors Controlling Temperature Distribution .....	25
2.3.1.1 The altitude .....	25
2.3.1.2 Distance from the sea .....	25
2.3.1.3 Air-mass and Ocean currents .....	25
2.3.2 Distribution of Temperature.....	26
2.3.3 Global Warming.....	28
2.3.4 sun and climate.....	29
2.3.5 effects of the atmosphere .....	30
2.3.6 Calculation of the surface temperature .....	31
2.4conclusion.....	32
<b>Chapter 3 Simulation and analysis</b>	
3.1Introduction.....	34
3.2MATLAB software.....	34
3.2.1 Starting MATLAB.....	34
3.2.2 Quitting MATLAB.....	35
3.2.3 About versions.....	35
3.2.4 Features of MATLAB R2015a.....	35
3.3 Neural networks on MATLAB.....	35
3.4 Study with nntool technology.....	36
3.5Conclusion.....	45
General conclusion.....	46
References .....	47

## ***List of figures***

### **Chaptre1**

Figure 1. Comparison between artificial and biological neuron.....	06
Figure 2. A model consists of classifying images of handwritten digits into 10 classes.....	07
Figure 3. The architecture of a simple perceptron.....	10
Figure 4. Structure of multi-layered perceptron.....	11
Figure 5. The architecture of a Recurrent Neural Network.....	12
Figure 6. Resonance Neural Network architecture.....	13
Figure 7. Architecture of a Self-Organizing Neural Network (the self-organizing map of Kohonen.....	14
Table 1. Important dates in the evolution of neural networks.....	09

### **Chaptre2**

Figure 1. Illustration of the effect of ozone on spectral surface UV irradiances.....	19
Figure 2. Summer Solstice.....	19
Figure 3. geographic distribution of potential climatic constrains to plant growth derived from long-term climate statistics.....	20
Figure 4. A schematic illustration of a pyranometer (a) and a pyrhelimeter (b).....	21
Figure 5. Typical target applications for irradiance forecasting and their respective spatial and temporal scales. (STPP = Solar Thermal Power Plants, PV = Photovoltaics). The blue area depicts the range for which the use of Numerical Weather Prediction models is appropriate.....	23
Figure 6: Time series prediction process.....	24
Figure 7. the solar farm.....	24
Figure 8. High resolution solar irradiance dataset.....	24
Figure 9. The distribution of surface air temperature in the month of January.....	27
Figure 10. The distribution of surface air temperature in the month of July.....	27
Figure 11. The range of temperature between January and July.....	28
Table 1. The absorption coefficient for solar radiation for some paints.....	32

### **Chaptre3**

Figure 1. MATLABcommandWindow.....	37
Figure 2. nntool'spage.....	37
Figure 3. the network by clicking.....	38

Figure 4. Train network preparation.....	39
Figure 5. Neural networks training.....	40
Figure 6. performance.....	40
Figure 7. regresion.....	41
Figure 8. Triningstate.....	41
Figure 9. two days .....	42
Figure 10. performance p.....	42
Figure 11. regresion smooth.....	43
Figure 12. stat smooth.....	43
Figure 13. estimate smooth (two days).....	44

## INTRODUCTION

The most important way to generate clean energy is to use solar panels, which require a specific amount of sunlight to produce a certain amount of energy. In our study, we try to help in this area by addressing changes in sunlight as a function of temperature changes (NN).

AND Exploration of data bases is a modern technology that aims to extract the information contained inside them. with concentrate our efforts in data bases on the most important facts in climatology and meteorology.

forecasting approaches focus on the formulation of future predictions such as temperature and natural solar radiation, as well as the examination of behaviors and trends.

Artificial Neural Networks (ANNs) have shown to be a useful tool for modeling linear and nonlinear systems without the requirement for programming.as in most conventional statistical methods, make implicit assumptions techniques to modeling ANNs are widely employed in today's world from many uses in a variety of fields of research and technology are two examples of engineering.

Recurrent Neural Networks (RNNs) are a type of neural network that are a subset of neural networks.

Neural networks in general They're beneficial in instances where you don't have a lot of time in data, there is a temporal link. To put it another way, when he information is provided in chronological sequence.

An RNN is a type of neural network. acquired by adding one or more Feed Forward ANNs to a Feed Forward ANN feedback links to preceding layers The A recurrent neural network's structure is defined by the presence of one or more additional nodes, often known as context in addition to the the structure of a recurrent neural network is characterized by the presence of one or many extra nodes, also named context units, beside the input layer. Such context units are connected to the hidden layer and hold the output of the neural network to feed it back to the hidden layer. That information is significant when the goal is a long-term prediction.

When there is temporal structure in the data, RNNs perform well in general. Otherwise, the recurrent neural network will interpret the short-term memory nodes as random noise.

The ability to accurately predict the incoming solar radiation is an important factor to improve the efficiency of a solar energy conversion system. One of the methods utilized to predict incoming

## *Introduction*

---

solar radiation is the use of an empirical model. The empirical model is a technique which uses meteorological parameters as inputs to predict future values of solar radiation.

The main shortcomings of the empirical model are its focus on long-term prediction, its reliance on existing meteorological data, as well as its inability to identify abnormalities and account for sudden changes in data.

Direct measurements of solar radiation at weather stations are the most accurate source of solar radiation data, provided that the equipment is well-maintained and regularly calibrated. Various methods have been developed to obtain solar radiation estimate for location, where is not directly measured. The simplest solution is to assign measured values from a nearby station or to use spatial interpolation methods.

The intensity of solar radiation on a particular location is influenced by several climatological measures and factors such as air temperature, sunshine duration, humidity, vapor pressure, and wind speed. Those factors and measures are important and essential to design and implement an automatic system for the prediction of global solar radiation on horizontal and surfaces. Many studies were made and others are still conducted in order to design and build such automatic prediction systems.

As a summary of the above, we discussed in the first chapter about the concept of neural networks and their types, while in the second chapter we explained what is solar radiation prediction and the elements used in this prediction, and for the third chapter we used the neural network technology in the MATLAB program to predict solar radiation.

We did all this to treat the following problem:

How to predict solar radiation using neural network technology? Is this technique accurate and error-free? And what are the factors that affect it?

**Chapter 1**  
**Artificial Networks Technical Sketching**

## **1.1 Introduction**

Due to the immense propagation of artificial neural networks in all tech-based systems, solar systems follow the trend. On this 1<sup>st</sup> chapter from our thesis; we will shed light on artificial neural networks, their connection and tie to biological neural networks and their historical evolution, finally we will dive into artificial neural networks types.

**1.2 Biological Neuron:**

A neuron is a cell composed of a cell body and a nucleus. The cell body branches to form what are called dendrites. These are sometimes so numerous that we then speak of dendritic hair or dendritic ramification. It is through the dendrites that information is conveyed from the outside to the soma, the body of the neuron. The information processed by the neuron then travels along the (single) axon to be transmitted to the other neurons. The transmission between two neurons is not direct. In fact, there is an intercellular space of a few tens of Angstroms ( $10^{-9}$  m) between the axon of the afferent neuron and the dendrites (we say a dendrite) of the efferent neuron. The junction between two neurons is called the synapse. Depending on the type of neuron, the length of the axon can vary from a few microns to 1.50 meters for a motor neuron. Similarly, dendrites measure from a few microns to 1.50 meters for a sensory neuron in the spinal cord. The number of synapses per neuron also varies considerably from several hundred to ten thousand.

**1.3 Artificial Neuron:**

An artificial neuron is a connection point in a neuronal artificial network. Such as biological neurons, artificial neurons have the ability to concoct input and transmit output to other nodes in the network. Technically, nodes are referred to as neurons, and the connections are distinguished by synaptic weights, which signify the significance of the connection. Synaptic weights vary as new input is received and processed, and this is how learning occurs.

In artificial and biological networks, when neurons sort the input they receive, they decide whether the output should be passed to the next layer as input or not. The decision to disseminate information or not is called bias and it is determined by an activation function built into the system. For example, an artificial neuron cannot transmit a signal output to the next layer only if its inputs (which are actually voltages) sum to a value greater than a particular threshold value. Because activation functions can be linear or nonlinear, neurons will often have a wide range of convergence and divergence. Divergence is the ability of a neuron to communicate with many other neurons in the network and convergence is the ability of a neuron to receive input from many other neurons in the network.

**1.3.1 The Link between biological and artificial neurons:**

Let us proceed to a simple comparison of the main steps of the perceptron algorithm with the constituent elements of biological neurons. This choice of algorithm is justified because it is as close as possible to the functioning of biological neurons and the interest of the algorithm Perceptron comes from a technique demonstrated in 1989 by George Cybenko, which consists of linking and stacking layers of perceptron to bring greater complexity. An algorithm of this type is

called Multilayer Perceptron, often abbreviated by the acronym MLP. The elements of biological neurons with the elements of the corresponding artificial neurons:

- Dendrite: weight of each input element is called weight vector (which adjusts during training) and  $x_i$  is called input vector.
- Cell body: application of an activation function  $f$  to the sum of the weighted inputs
- Axon: output of our model  $output = f(\sum w_i \cdot x_i) = f(\langle w/x \rangle)$

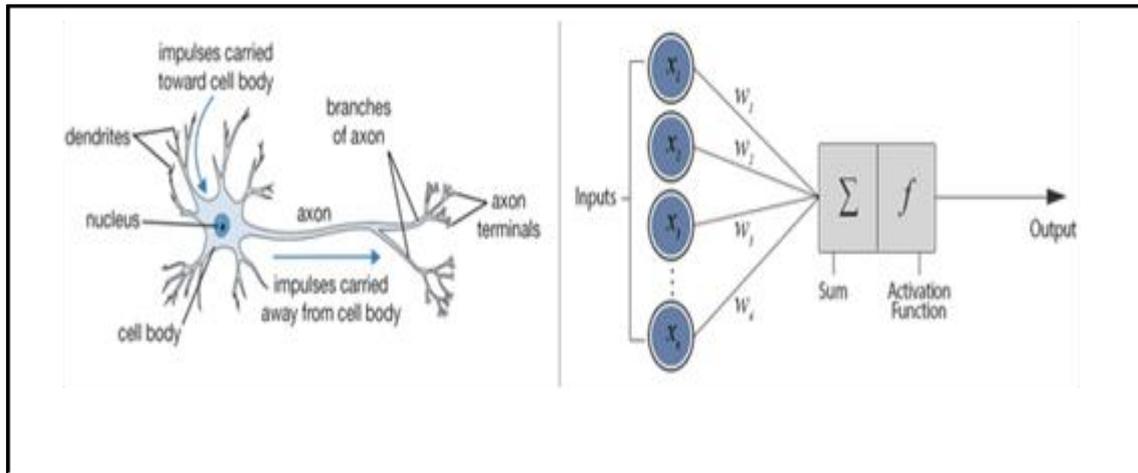


Figure 1. Comparison between artificial and biological neuron

In fact, the basic Perceptron technique is no longer employed since alternative algorithms, like as the (Support Vector Machine, in English), are far more efficient. Similarly, biological neurons are rarely employed alone; instead, they are frequently linked to other neurons.

The approach entails categorizing (into ten types) photographs of handwritten numbers. The green squares represent our model's inputs, the gray circles represent perceptrons, and the arrows indicate linkages.

In general, our model's last layer is employed to form the desired output. We attempt to forecast the likelihood of each class in this case since we have a classification challenge (number 0, number 1, etc.). Because there are ten classes, the last layer includes ten neurons and a "SoftMax" activation function that allows a probability to be returned.

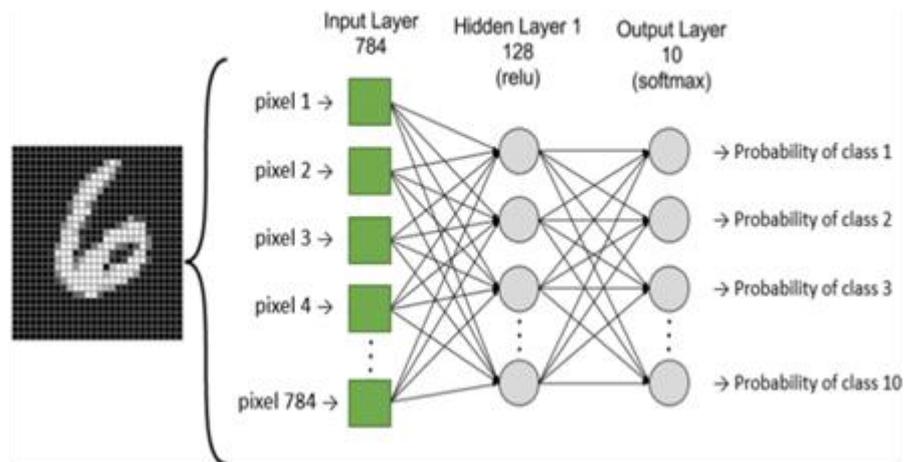


Figure 2. A model consists of classifying images of handwritten digits into 10 classes

## 1.4. Artificial neurons networks:

### 1.4.1. Definition:

A neural network is an oriented graph, made up of a set of units, carrying out initial processing, structured in the form of successive inter-connected layers capable of exchanging information via structured links.

The artificial models proposed from a connectionist point of view are based on the structure and the global comportment of the biological model. Hence, the principle of interconnection and parallelism is always respected without taking into account the principle of structuring. Based on this principle, neural networks have been successful.

Artificial neural networks (ANNs) are densely connected networks of elementary processors that operate in parallel. Based on the information it receives as input, each elementary processor generates a unique output.

### 1.4.2. History of neural networks:

When the science of cybernetics appears a while ago, the main objective was to give the machine a certain level of intelligence similar to that of the human being. The history of networks of artificial neurons began 75 years ago. The table 1 present significant dates on the history of the evolution of neural networks.

With ups and downs, real success only emerged about thirty years ago. Since then, artificial neural networks have established themselves as one of the best approaches to heterogeneous information

analysis. It also presents itself as a solution to problems whose formalization is complex or even impossible. As a result, artificial neural networks are frequently used in the field of forecasting, pattern recognition and data reconstruction and correction as well as in the field of robotics. In 1943, McCulloch and Pitts proposed the first model of a formal neuron: a neuron with binary behavior. The biological neuron model presented by James in 1890 inspired their model. The latter had introduced the concept of associative memory. Then, with the formal model, McCulloch and Pitts demonstrated the possibility of solving complex arithmetic logic problems using the concept of neural networks. The idea assumes that the brain is equivalent to a Turing machine. In 1949, the famous American physiologist Hebb took up James's idea. Based on Pavlov's theory, he presented a learning rule for neural networks. We are talking about Hebb's rule used by several neural algorithms.

The idea is based on the modification of the characteristics of the inter-neuronal connections (often-called weights) during the learning phase. The first successes of artificial neural networks appeared in 1958, with the famous Perceptron model proposed by Rosenblatt. Inspired by the visual system, he managed to develop a two-layer artificial neural network: a perception layer (retina) and a decision-making layer. Given the technological means of the time, it was a master stroke to operate an artificial system capable of learning through experience. A second exploit saw the light of day two years later. An automation engineer named Widrow presents the Adaptive Linear Elements (ADALINE) model. With a structure similar to that of the perceptron, ADELIN integrates a new learning function known today as the gradient back-propagation algorithm. After a relative success, the publication of Minsky and Papert in 1969 led to a disinterest in this field. The study they publish highlights the limits of Perceptrons to deal with nonlinear problems. This criticism has had a great influence on the diversion of research (especially financially) mainly towards other approaches such as rule-based systems. For 13 years, research in the field of artificial neural networks remained in the shadows. But some researchers, such as Kohonen and Grossberg, continued their research disguised under the guise of various names.

(Adaptive signal processing, pattern recognition, modeling in neurobiology, etc.). The revival of research on artificial neural networks arrived in 1982. The physicist Hopfield presented studies proposing a new theory of operation allowing to increase the possibilities of treatment with artificial neural networks. This new model based on looped learning (still used today for certain neural algorithms) has revived interest in artificial neural networks without having lifted the problem of the limits exposed by Minsky and Papert. In the same year, Kohonen proposed his self-organizing map "SOM" as one of the best classification approaches. On the other hand, in 1983 Fukushima et al. introduce a new neural model called Neocognitron used for handwritten character recognition.

The removal of the limits of the perceptron is obtained with the proposal of the Boltzmann machine in 1983. On the other hand, the effectual use of this model is made difficult by extremely long convergence times. Between 1985 and 1986, significant progress appeared with the proposal of the gradient back-propagation algorithm. This idea was created independently by three sets of researchers: Parker, Rumelhart, and Le cun. The proposed algorithm is now the foundation of the learning function of the well-known Multi-Layer Perceptron (MLP), which has been widely used since its discovery. Since, the research has been aggressively relaunched.

The use of neural networks will surge in the 1990s. Several models based on the perceptron method and gradient back-propagation are suggested. The concept of developing and dynamic neural networks has also piqued the curiosity of researchers.

It is much more freeing for the other layers of our model, and it is especially critical that the activation functions of the perceptrons be non-linear in order to complicate its model. The tanh or ReLU activation functions are the most commonly employed in practice.

Table 1: Important dates in the evolution of neural networks. (1)

Date	Author	Event
1890	James	An introduction to the notion of associative memory, law of learning
1943	McCulloch et Pitts	Modeling of a biological neuron into a formalized neuron
1949	Rosenblatt	Proposal of the Perceptron model - First neuro-component.
1960	Widrow	Development of the ADALINE model inspired by the Perceptron.

1969	Minsky et Papert	Highlighting the limits of the Perceptron - Abandonment of research.
1967-1981	Grossberg, Kohonen, etc...	Discreet research period.
1982	Hopfield	Relaunch of research with the presentation of the Hopfield model - Theory of the functioning and possibilities of neural networks.
1983	Fukushima, Mirvake et Ito	Proposal of the Neocognitron neural model used for the recognition of handwritten characters.
1985-1986	Parker, Rumelhart et Le Cun	Development of multilayer neural networks and proposal of the gradient back-propagation algorithm.

## 1.5 Structure of neural network

### 1.5.1 Definition:

Architecture is a critical concept that influences the categorization of ANNs. The term structure is frequently used as a synonym for architecture in the literature. Each architecture has its own organizational structure that is tailored to a certain set of applications.

A neural network can take several forms based on the type of data it processes, as well as its complexity and manner of processing the input.

Architectures have advantages and disadvantages that can be combined to achieve the best outcomes. The choice of architecture is so critical and is mostly decided by the goal.

### 1.5.2 Types of neural network Structure.

#### 1.5.2.1 Feed-forwarded neural networks:

Feed-forwarded (forward propagation) networks and multilayer networks (data crosses the input network at the output without backtracking information) (multilayer perceptron).

Because it just has two layers, the input layer and the output layer, the simple perceptron is called simple. The network is activated when input data is received. In this network, data is processed between the input and output layers, which are all interconnected. As a result, the integral network only has a weight matrix. Because the simple perceptron only has a single weight matrix, it can only be used as a linear classifier to separate the collection of data into two discrete groups.(2)

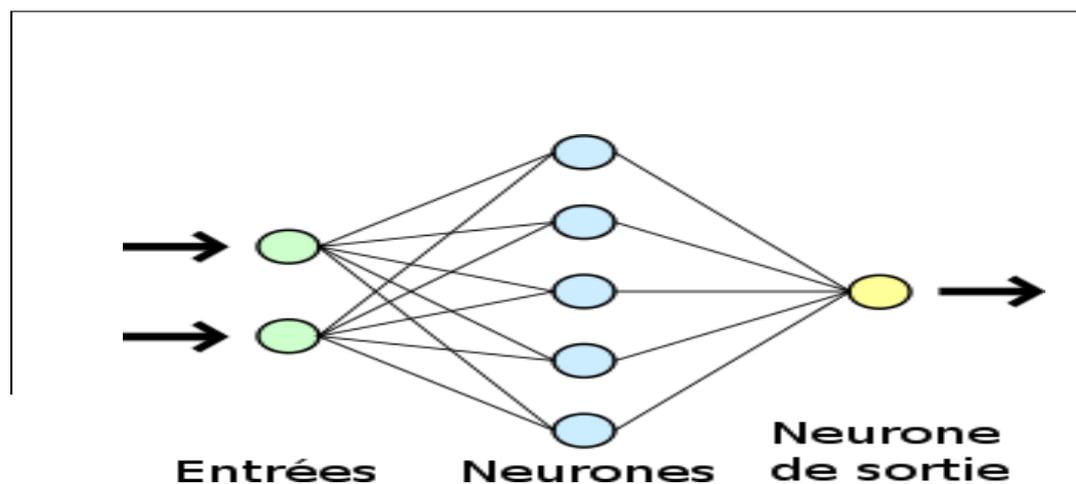


Figure 3. The architecture of a simple perceptron

The multilayer perceptron has a similar construction. An input layer receives information and an output layer sends it out. Unlike the ordinary perceptron, the multilayer perceptron has one or more "hidden" layers between the input and output layers. The number of layers in the network correlates to the number of weight matrices. As a result, a multilayer perceptron is better suited to dealing with nonlinear functions.

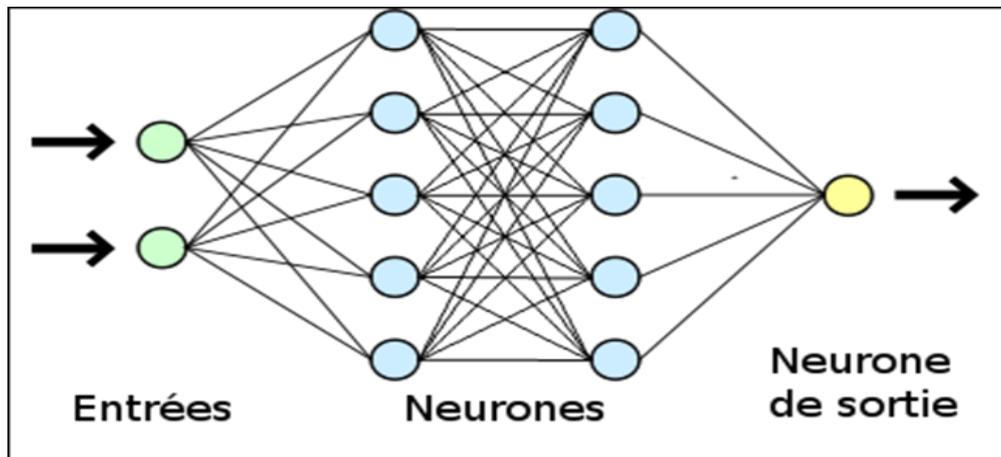


Figure 4. Structure of multi-layered perceptron

It is feasible to establish numerous different neural networks dedicated to each processing part of the information for the processing of complex and very variable information. Convolutional neural networks are the name for several types of neural networks. These networks can be thought of as a collection of data segments that eventually process all of the data (e.g., image, video, text processing).

### 1.5.2.2 Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are neural networks that process information in cycles. These cycles allow the network to process the information several times by returning it to the network each time.

The capacity of Recurrent Neural Networks to take into account contextual information following the repeat of the same information processing is their strength. The network is self-maintained by this dynamic.

One or more layers make up a recurrent neural network. The most well-known single-layer recurrent neural network is the Hopfield model (temporal network).

Multi-layer recurrent neural networks are distinguished by the presence of pairs (input/output) such as perceptrons between which data propagates both forward and backward.

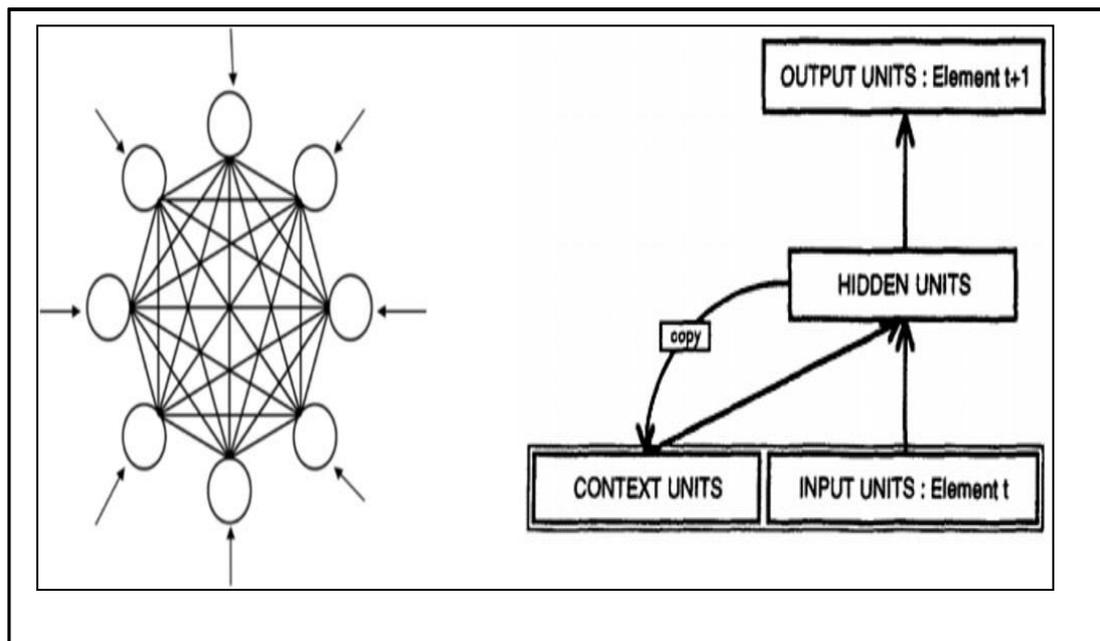


Figure 5 The architecture of a Recurrent Neural Network.

### 1.5.2.3 Resonance Neural Networks

The name of the neural network refers to how it works once more. The activation of all neurons in resonant neural networks is reflected to all other neurons in the system. The name resonance comes from the fact that this return generates oscillations.

These neural networks, of course, can take many various forms with varying degrees of complexity. To take things a step further, consider Bidirectional Associative Memory, which allows two pieces of information of different natures to be associated, or the ART model (Adaptive Resonance Theory), which allows contextual information to interact with prior knowledge to identify or recognize items.

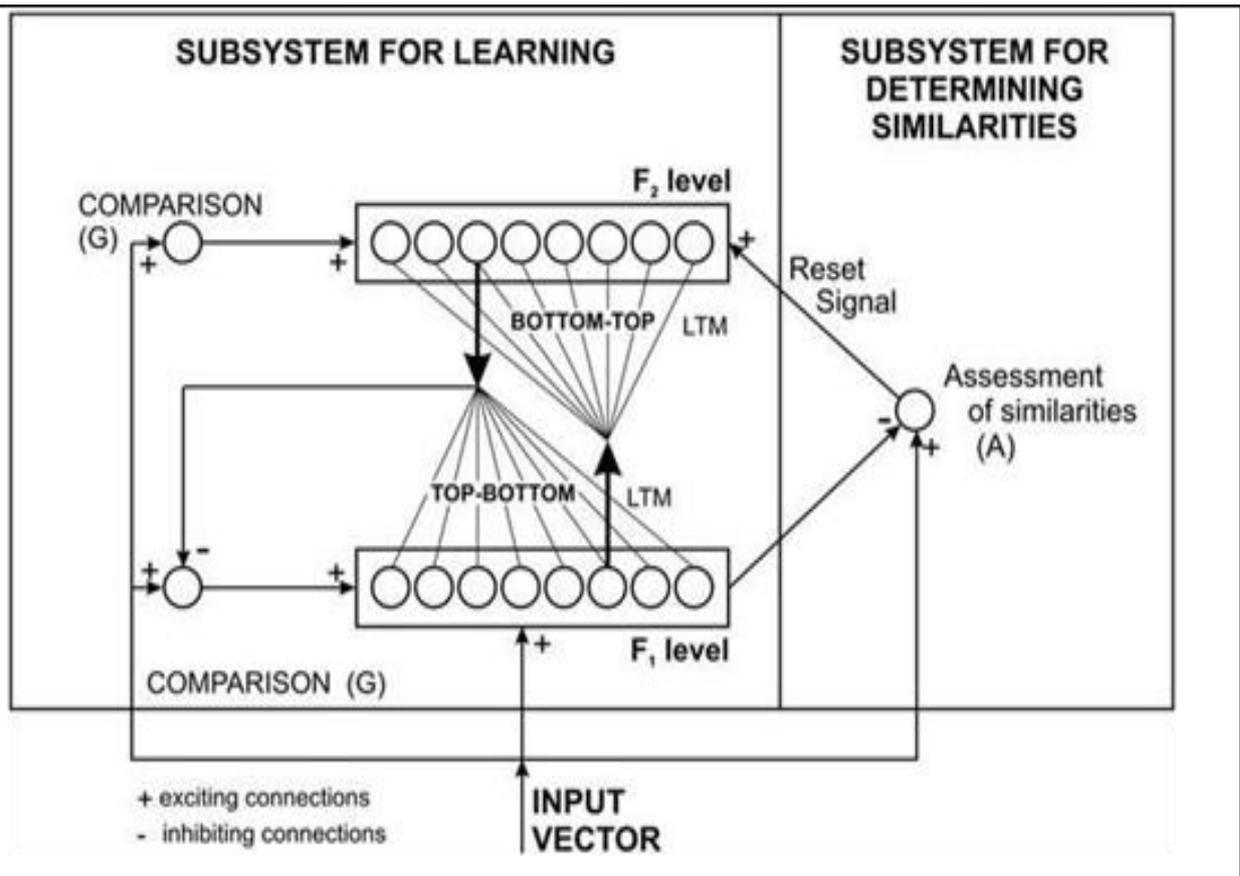


Figure 6. Resonance Neural Network architecture

#### 1.5.2.4 Self-organizing neural networks:

Self-organizing neural networks are particularly well adapted to the processing of spatial data. Self-organized neural networks may explore the distribution of data in broad domains using unsupervised learning approaches, such as for clustering or classification problems.

Kohonen's self-organizing map is arguably the most well-known model of this type of neural network.

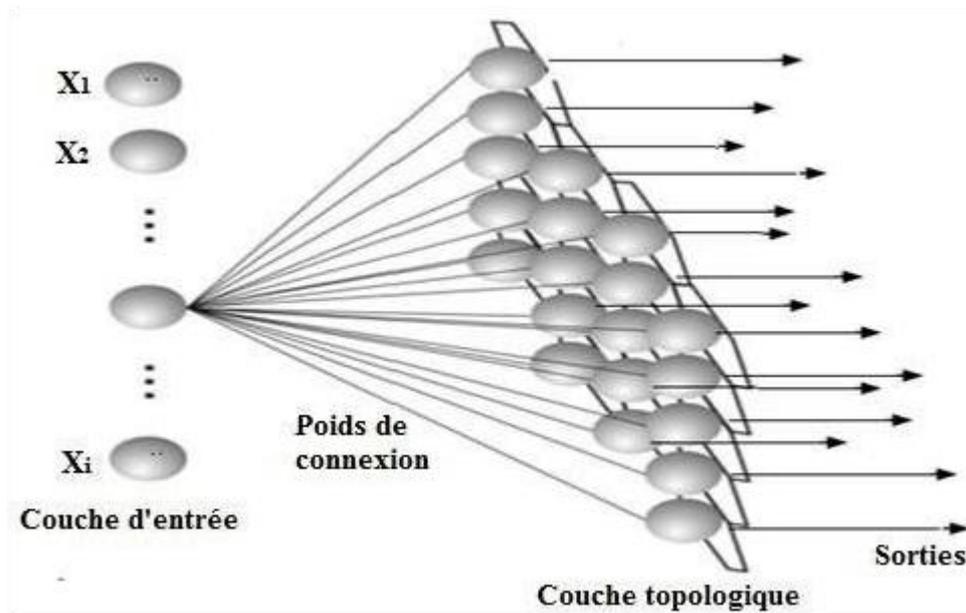


Figure 7. Architecture of a Self-Organizing Neural Network (the self-organizing map of Kohonen)

### 1.6 Conclusion:

On this introductory first chapter, we shed lights on the basics of artificial neural networks, starting from the original structural components of it, the biological neuron its implication in the process of building a neural network, then we illustrate the types of neural networks and explained them in graphs.

**Chapter 2:**  
**Solar radiation and temperature**

## **2.1 Introduction**

In this chapter we will discuss about the solar radiation, which is one of the sustainable energies most important, it can be transformed into heat or electric powers, and used for various solar applications, such as solar building, solar eating, heat pumps, air conditioning, agriculture, and research of atmospheric physics. In this case, a precise knowledge of the direct, diffuse, and global solar radiation components are required for the better exploiting solar energy. A solar radiation measurement in one site are obtained a through the radiometric stations which operate instantly and every day. Sadly, these systems cannot be available for all sites, so we use proven techniques to evaluate the solar radiation components, as the empirical modelling and intelligent techniques.

And we also try to show that the temperature plays in all the phenomena which have for seat the high and the middle atmosphere a most important role, whether it influences them directly or indirectly. This is how, for example, we have recently shown its importance essential in the question of atmospheric ozone, we have identified the Factors that Controlling Temperature Distribution and Calculation of the surface temperature.

## **2.2 Solar radiation**

### **2.2.1 Radiation**

The outflow and engendering of waves communicating energy through space or through some medium; for instance, the emanation and proliferation of electromagnetic, sound, or flexible waves. The energy sent through space or some medium; when unfit, generally alludes to electromagnetic radiation. Otherwise called brilliant energy. A flood of particles, like electrons, neutrons, protons, alpha particles, or high-energy photons, or a combination of these. (3)

### **2.2.2 Radiation component**

Because of scattering, radiation on Earth's surface consists of two components. Part of the incoming radiation is preserved as beam radiation, while the rest is scattered in the atmosphere and is either reflected back into space or reaches the ground as diffuse radiation. In contrast to beam radiation, which has a well-defined direction, diffuse radiation originates from all over the sky dome. Although diffuse radiation is most intense near the Sun, a good approximation is to assume that it is isotropic, uniformly distributed on all directions. (4)

### **2.2.3 Solar radiation**

Solar radiation, often called the solar resource or just sunlight, is a general term for the electromagnetic radiation emitted by the sun. Solar radiation can be captured and turned into useful forms of energy, such as heat and electricity, using a variety of technologies. However, the technical feasibility and economical operation of these technologies at a specific location depends on the available solar resource. (5)

### **2.2.4 Penetration of solar radiation through the atmosphere**

Penetration of solar radiation through the atmosphere depends on several factors, solar elevation, scattering on air molecules and clouds, absorption by trace gases such as ozone, aerosols and reflection properties at the Earth's surface. Considerable progress in this field has been achieved over the last decades. Accurate measurements of atmospheric ozone, which is the most important absorber in the UV part of the solar spectrum, have been performed with ground-based instruments for more than 70 years, and from space with satellites since the late 1970s. Measurements of the spectral distribution of the solar UV radiation reaching the Earth's surface are technically much more demanding than ozone measurements, and reliable time series are only available from the late 1980s. Measurements of the solar spectrum were performed on top of the Teide mountain, Tenerife, Spain, as early as 1888. Based on these spectral measurements the lower limit of the solar spectrum

was set to 292 nm. Cornu explained the lack of measurable solar radiation below this limit by strong absorption in the atmosphere. Hartley (1880) suggested that the atmosphere contained ozone and Fabry et al (1913) later confirmed this by accurate measurements. After the discovery of the Antarctic ozone ‘hole’ ozone layer has attracted increasing international interest, and measurements of atmospheric ozone and surface solar UV radiation are being carried out worldwide and regularly. Today, solar spectral surface UV radiation is monitored worldwide by accurate, ground-based instruments. Over the last two decades global estimates of solar UV variations and climatology at the surface have been calculated from satellite measurements of atmospheric backscattered solar UV using radiative transfer models. However, satellite surface UV instruments do not provide the same accuracy as ground-based instruments do, mainly because of the inability to measure ground reflection and aerosols near the Earth’s surface sufficiently well. Solar radiation reaching the Earth’s atmosphere is mainly in the wavelength range 200–4000 nm. Radiation below 400 nm is called UV radiation and is usually divided into UVC (200–280 nm), UVB (280–315 nm) and UVA (315–400 nm). The World Health Organization recommends to separate UVB and UVA at 315 nm. This has been widely adopted by the geophysical scientific community. However, one should be aware that separation at 320 nm is still used by many authors in other scientific disciplines. Ozone is a strong absorber in the UVC, and even with a strongly depleted ozone layer as found under the Antarctic ozone ‘hole’, virtually no UVC radiation can be observed at the Earth’s surface. The absorption by ozone is weaker in the UVB allowing a fraction of this radiation to reach the Earth’s surface. The UVB level is strongly dependent on the amount of atmospheric ozone. UVA is nearly insensitive to ozone variations because absorption by ozone is weak in this wavelength region. The effect of ozone on the spectral distribution at the Earth’s surface under clear atmospheric conditions at sea level is illustrated in figure1. In this section, we give a brief overview of the present knowledge of how different factors affect the solar radiation penetrating into the Earth’s surface, and how surface UV the determined by direct measurements as well as by indirect methods, varies in space and time. (6)

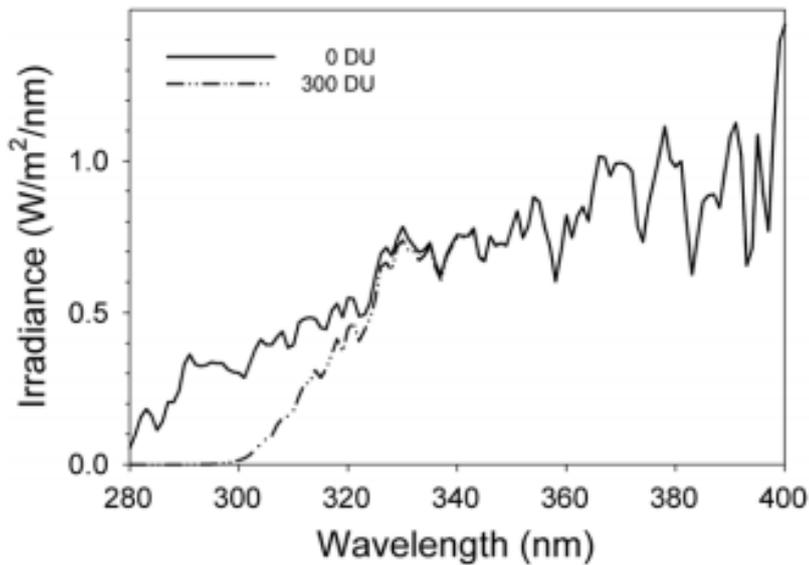


Fig1: Illustration of the effect of ozone on spectral surface UV irradiances

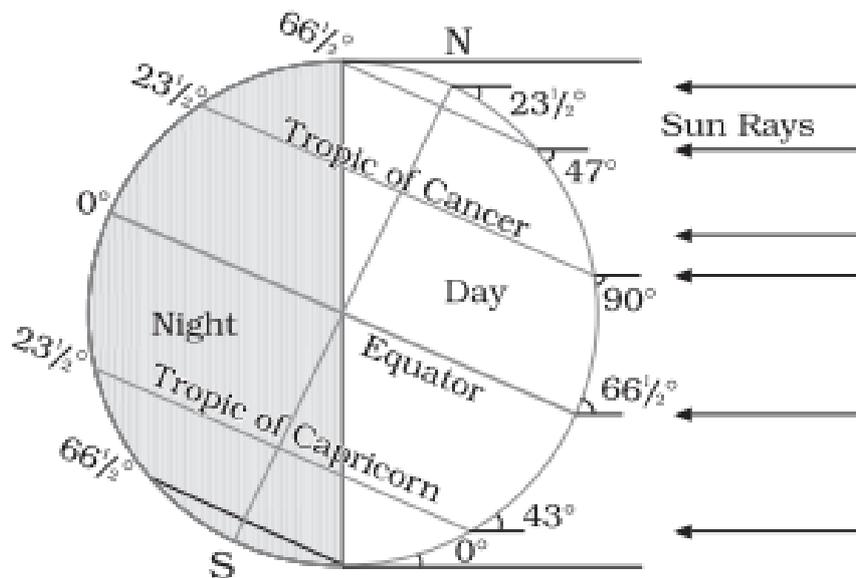


Fig2:Summer Solstice

## 2.2.5 solar radiation data

### 2.2.5.1 solar radiation data sources

Direct measurements of solar radiation at weather stations are the most accurate source of solar radiation data, provided that the equipment is well-maintained and regularly calibrated. Various methods have been developed to obtain solar radiation estimate for location, where is not directly measured. The simplest solution is to assign measured values from a nearby station or to use spatial interpolation methods.

However, density of solar radiation measurements is often not sufficient for reliable interpolation. A different approach, which is not directly based on measured solar radiation at nearby station, is to model solar radiation. Satellite observation have also provided alternative means to derive (7)

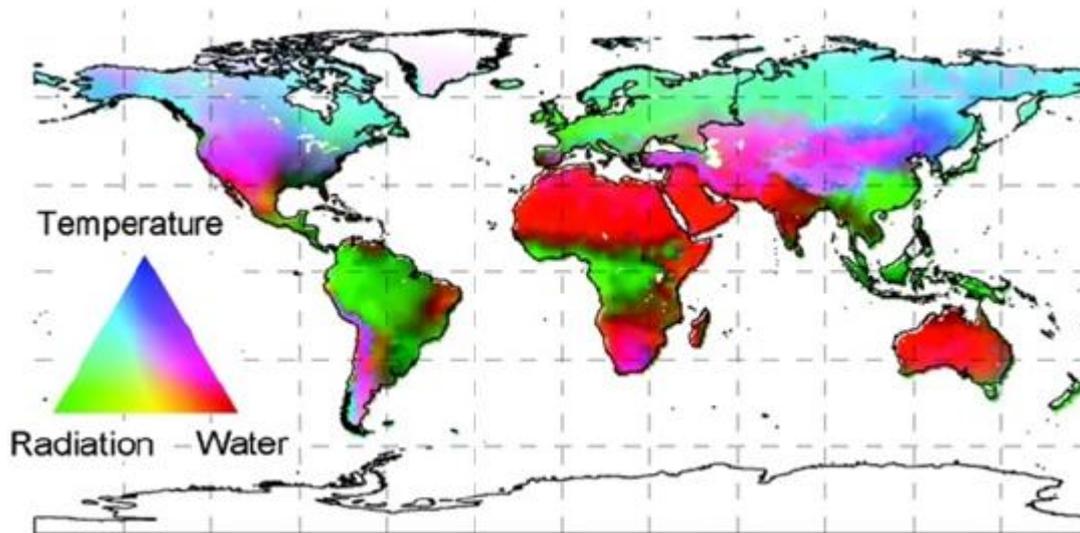


Fig3: geographic distribution of potential climatic constraints to plant growth derived from long-term climate statistics

### 2.2.5.2 Measuring solar radiation data

Determination of solar irradiance on tilted surfaces typically starts from measurements in the horizontal plane. Solar radiation is commonly measured by two main classes of instruments: pyrheliometers and pyranometers.

A pyrheliometer measures solar radiation coming directly from the Sun and a small portion of the sky around the Sun at normal incidence.

In this device sunlight typically enters through a window to a thermopile (a device that converts heat to electricity). The electrical signal that is generated can be recorded and converted into  $W/m^2$ . The window of the pyrheliometer acts as a filter that only lets through sunlight in the  $0.3-3 \mu m$  range. The pyranometer measures total hemispherical (diffuse plus beam) solar radiation, usually on the horizontal plane. This means that the device must give an unbiased response to radiation from all directions. It consists of a thermopile sensor that is horizontally oriented and a glass dome that limits the wavelength range, as in the pyrheliometer. The glass dome preserves the  $180^\circ$  view and shields the thermopile from air convection.

Schematic illustrations of a pyranometer and a pyrheliometer are shown in Figure 4.

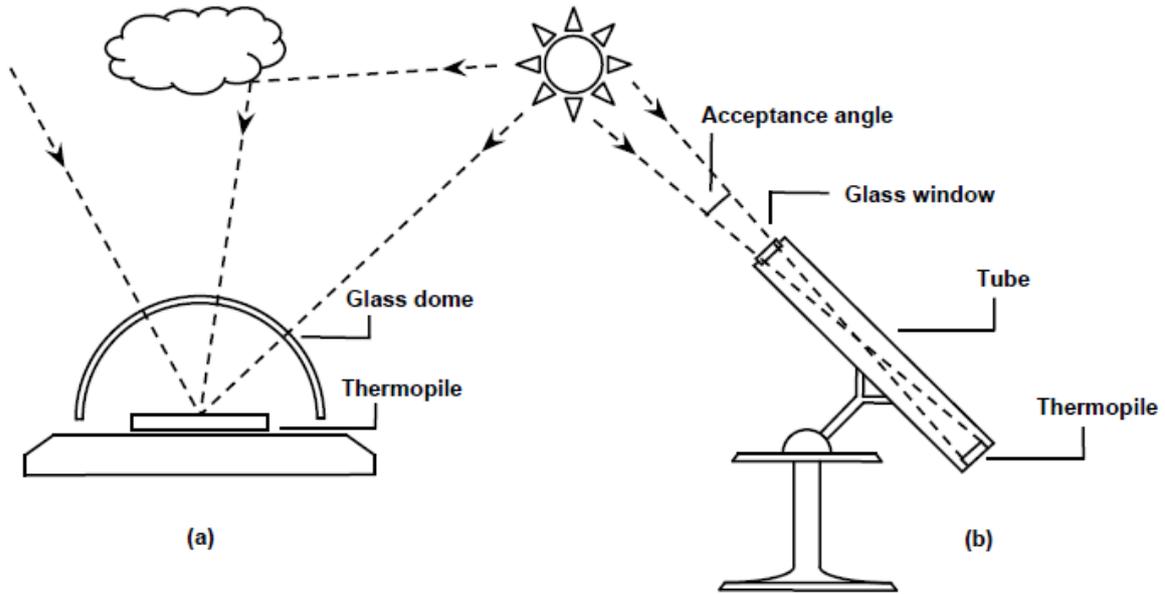


Fig 4: A schematic illustration of a pyranometer (a) and a pyrheliometer (b)

While pyrheliometers only measure normal-incidence beam radiation, global or diffuse radiation can be measured with pyranometers. To measure diffuse radiation a shading ring is attached to the pyranometer to block beam radiation. A correction factor is then used to compensate for the loss of view. Beam radiation on the horizontal surface can indirectly be measured by two pyranometers, one measuring diffuse and one measuring global, and then be obtained as the difference between global radiation and diffuse radiation

In the following, we will deal with average radiative flux over some period of time, typically one hour, which is how monitored data are available.

This means that the available radiation is integrated over both time and wavelengths. We will denote integrated and averaged radiation by the letter  $I$  (8)

$$I = \frac{1}{t_2 - t_1} \int_{t_1}^{t_2} G(t) dt$$

Monitored radiation is available in time series, and the equations below are all applied one time step at a time. The time  $t$  always refers to the midpoint of the monitored time interval:

$$t = \frac{t_1 + t_2}{2}$$

We will assume that we have the beam and diffuse radiation components ( $I_b$ ) and ( $I_d$ ) on the horizontal plane. From these we want to obtain the beam, diffuse and ground-reflected radiation components ( $I_{bT}$ ), ( $I_{dT}$ ) and

( $I_{gT}$ ) on a tilted planar surface. Expressed in global radiation we wish to go from radiation on the horizontal plane:

$$I = (I_b) + (I_d)$$

to radiation on the tilted plane:

$$I_T = I_{bT} + I_{dT} + I_{gT}$$

The basic strategy is to find the incidence angles of radiation on the horizontal and tilted surfaces, which are used to weight beam radiation, and the view factor of the tilted plane, which determines the incident isotropic radiation on the tilted plane.

### 2.2.5.3 physically-based models

Physically-based models employ algorithms to model the transfer of solar radiation through the atmosphere based on known relationships and laws from physics. Solar radiation transferring through the atmosphere is absorbed by gases and scattered by molecules, aerosols, and cloud particles. Due to the complexity of the radiative transfer and high temporal and spatial variability of atmospheric composition, the physically-based models require numerous input parameters in order to locally tune them. Physically-based models generally rely on estimates of atmospheric composition derived from numerical weather prediction models. (9)

## 2.2.6 solar radiation prediction

### 2.2.6.1 Variability and Predictability of Solar Radiation

Solar radiation varies according to a combination of predictable annual and daily cycles, and irregular (though not entirely unpredictable) changes in weather. The annual and daily average variation is predictable within certain bounds; hourly variation over the course of a day is more difficult to predict. Certain events such as major forest fires and, even more significantly, volcanic eruptions, can produce unexpected declines in solar irradiance for extended periods of time. Satellite-based forecasting models are currently being developed and are aimed at reliably providing hourly forecasts on a day-ahead basis. Variability poses a challenge to large-scale integration of solar resources with the electric grid, but satellite-based and other forecasting models are currently being developed which can reliably provide hourly forecasts on a day-ahead basis. (10)

### 2.2.6.2 Solar Irradiance Prediction using Measured Meteorological Parameters

It is necessary to have an accurate knowledge of the various components of solar energy available at the locations of interest for its effective and efficient utilization. These components of solar energy are sunshine duration, maximum ambient temperature, latitude, longitude, relative humidity, day of the year, daily clear sky global radiation, total cloud cover, temperature, clearness index, altitude, months, average temperature, average cloudiness, average wind velocity, atmospheric pressure, extra-terrestrial radiation, evaporation, reference clearness index, mean diffuse radiation, mean beam radiation, soil temperature. Out of these, global radiation is the most important component of solar radiation as it gives the total solar availability at a given place. It is measured only at a few locations because of the high cost involved in the purchase of various equipments and maintenance thereof. Due to financial constraints, lack of human and technical resources, the meteorological measurements in general and solar radiation in particular, is limited to few locations. In Bangladesh, there are some sunshine recording stations situated generally in towns and cities. Most of the developing countries have the similar problem to measure the actual solar radiation for useful utilization in various solar energy applications. Hence, to estimate these parameters at locations with no measurements, mathematical, statistical, and other techniques like neural networks, genetic algorithms, wavelets etc. are being used globally. Most of these techniques need historical solar radiation data from which necessary data for a particular location and application can be derived.

(11)

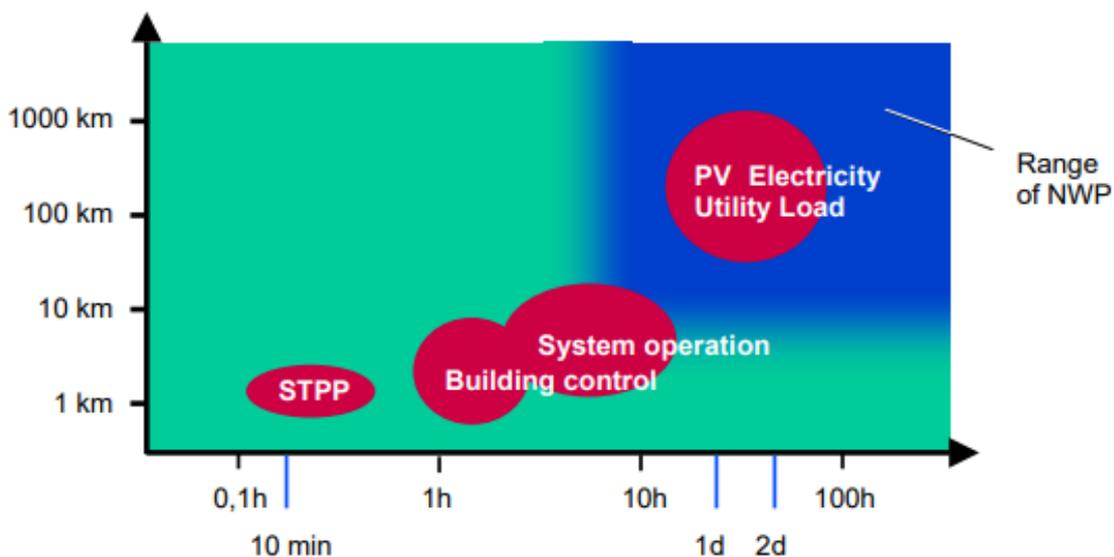


Fig. 5: Typical target applications for irradiance forecasting and their respective spatial and temporal scales. (STPP = Solar Thermal Power Plants, PV = Photovoltaics). The blue area depicts the range for which the use of Numerical Weather Prediction models is appropriate.

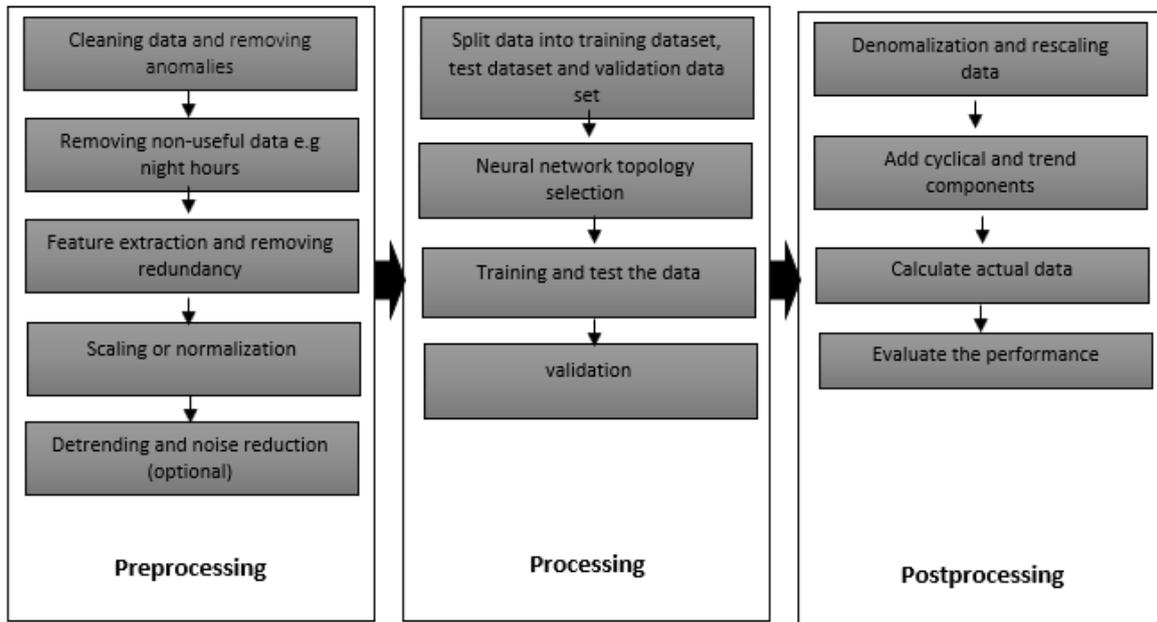


Fig6: Time series prediction process



Fig7: the solar farm

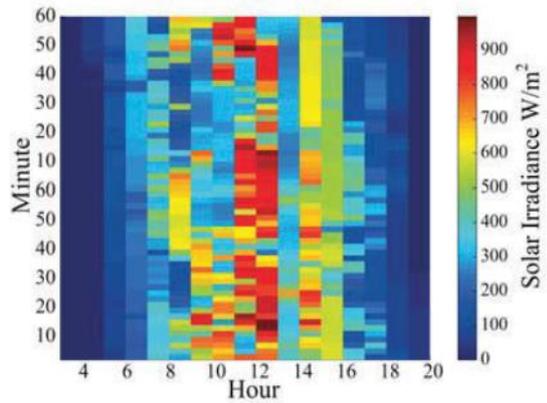


fig 8: High resolution solar irradiance dataset.

## **2.3temperature**

The interaction of insolation with the atmosphere and the earth's surface creates heat which is measured in terms of temperature. While heat represents the molecular movement of particles comprising a substance, the temperature is the measurement in degrees of how hot (or cold) a thing (or a place) is.(12)

It is also defined as an increasing function of the degree of thermal agitation of particles (in the kinetic theory of gases), by the equilibrium heat transfer between several systems or by entropy (in thermodynamics and in statistical physics). Temperature is an important variable in other disciplines: meteorology, climatology, medicine, and chemistry.

The most common temperature scale is the degree Celsius, in which water freezes at 0°C and boils at about 100°C under standard pressure conditions. In countries using the imperial (Anglo-Saxon) system of units, the degree Fahrenheit is used (freezing at 32°F and boiling at 212°F). The unit of the international system of units, of scientific use and defined from the absolute zero, is the kelvin (common name derived from William Thomson's name, Lord Kelvin). (13)

### **2.3.1 Factors Controlling Temperature Distribution**

The temperature of air at any place is influenced by the latitude of the place; the altitude of the place; distance from the sea, the air-mass circulation; the presence of warm and cold ocean currents; local aspects.

#### **2.3.1.1 The altitude**

The atmosphere is indirectly heated by terrestrial radiation from below. Therefore, the places near the sea-level record higher temperature than the places situated at higher elevations. In other words, the temperature generally decreases with increasing height. The rate of decrease of temperature with height is termed as the normal lapse rate. It is 6.5°C per 1,000 m.

#### **2.3.1.2 Distance from the sea**

Another factor that influences the temperature is the location of a place with respect to the sea. Compared to land, the sea gets heated slowly and loses heat slowly. Land heats up and cools down quickly. Therefore, the variation in temperature over the sea is less compared to land. The places situated near the sea come under the moderating influence of the sea and land breezes which moderate the temperature.

#### **2.3.1.3 Air-mass and Ocean currents**

Like the land and sea breezes, the passage of air masses also affects the temperature. The places, which come under the influence of warm airmasses experience higher temperature and the places

that come under the influence of cold air-masses experience low temperature. Similarly, the places located on the coast where the warm ocean currents flow record higher temperature than the places located on the coast where the cold currents flow (14)

### **2.3.2 Distribution of Temperature**

The global distribution of temperature can well be understood by studying the temperature distribution in January and July. The temperature distribution is generally shown on the map with the help of isotherms. The Isotherms are lines joining places having equal temperature. Figure 9 (a) and (b) show the distribution of surface air temperature in the month of January and July. In general, the effect of the latitude on temperature is well pronounced on the map, as the isotherms are generally parallel to the latitude. The deviation from this general trend is more pronounced in January than in July, especially in the northern hemisphere. In the northern hemisphere the land surface area is much larger than in the southern hemisphere. Hence, the effects of land mass and the ocean currents are well pronounced. In January the isotherms deviate to the north over the ocean and to the south over the continent. This can be seen on the North Atlantic Ocean. The presence of warm ocean currents, Gulf Stream and North Atlantic drift, make the Northern Atlantic Ocean warmer and the isotherms bend towards the north. Over the land the temperature decreases sharply and the isotherms bend towards south in Europe. It is much pronounced in the Siberian plain. The mean January temperature along 60° E longitude is minus 20° C both at 80° N and 50° N latitudes. The mean monthly temperature for January is over 27° C, in equatorial oceans over 24° C in the tropics and 2° C - 0° C in the middle latitudes and -18° C to -48° C in the Eurasian continental interior. The effect of the ocean is well pronounced in the southern hemisphere. Here the isotherms are more or less parallel to the latitudes and the variation in temperature is more gradual than in the northern hemisphere. The isotherm of 20° C, 10° C, and 0° C runs parallel to 35° S, 45° S and 60° S latitudes respectively. In July the isotherms generally run parallel to the latitude. The equatorial oceans record warmer temperature, more than 27°C.

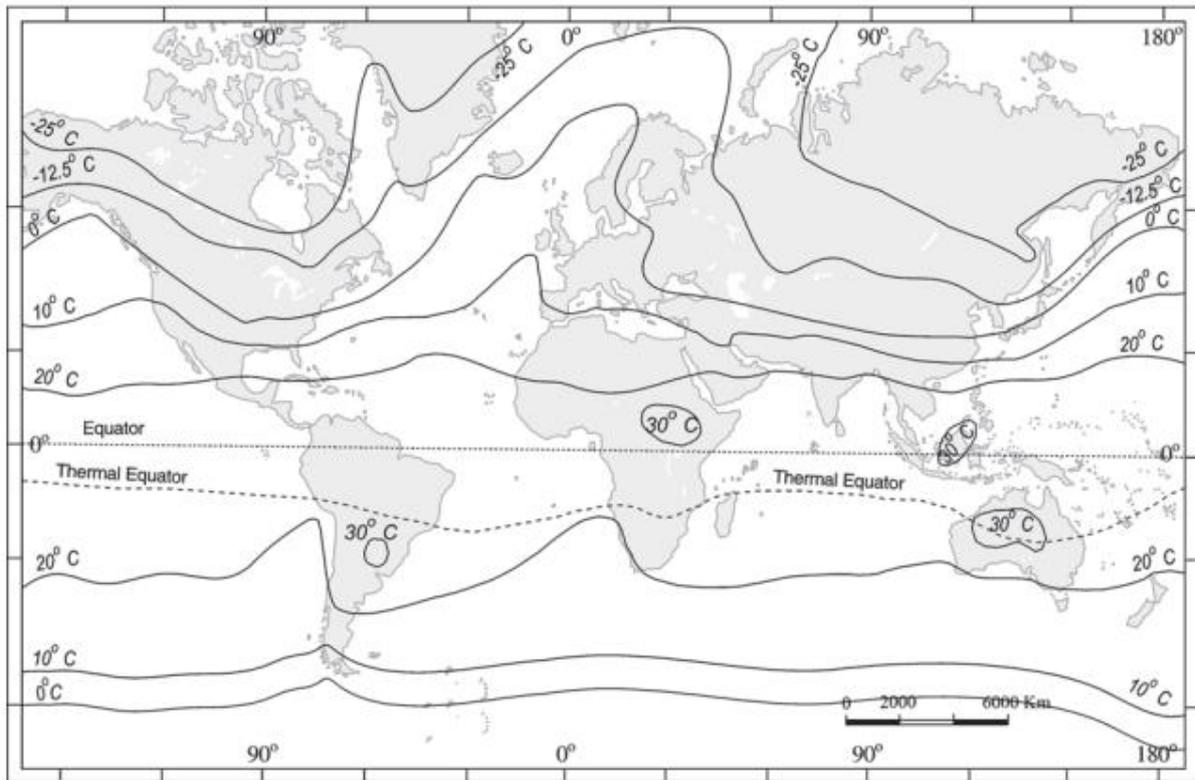


Figure 9 (a): The distribution of surface air temperature in the month of January

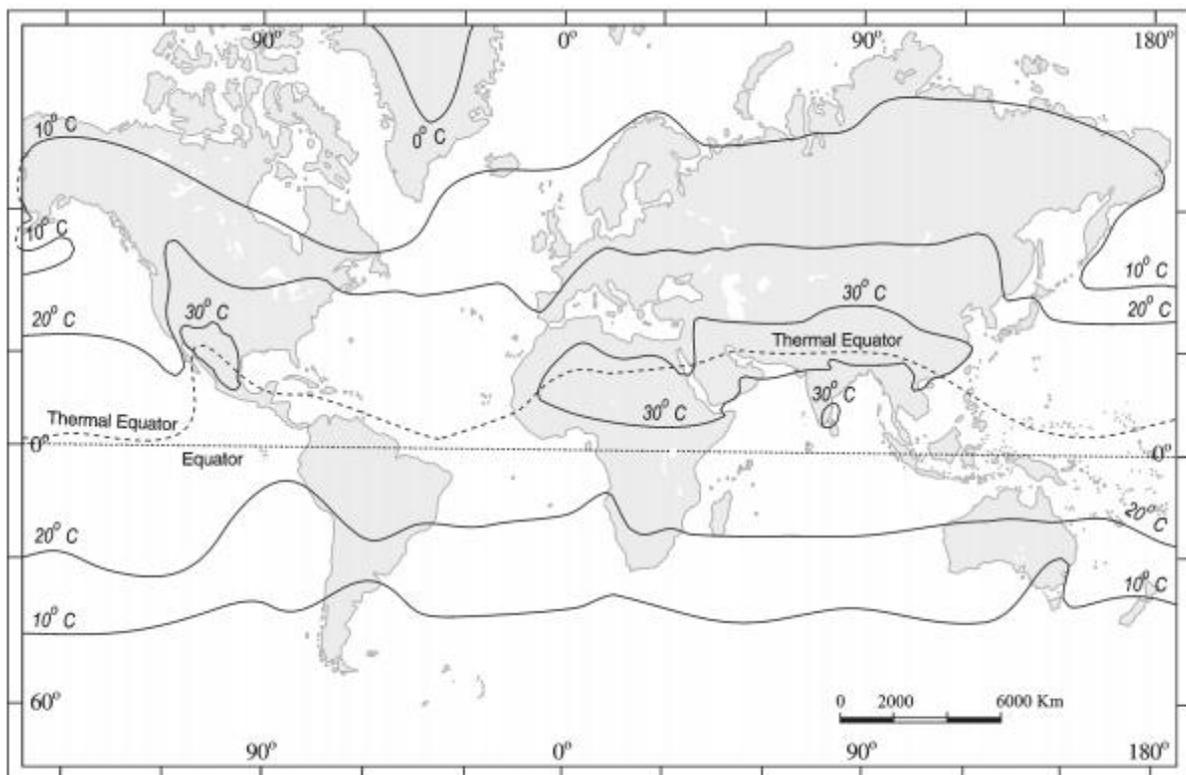


Figure 10 (b): The distribution of surface air temperature in the month of July

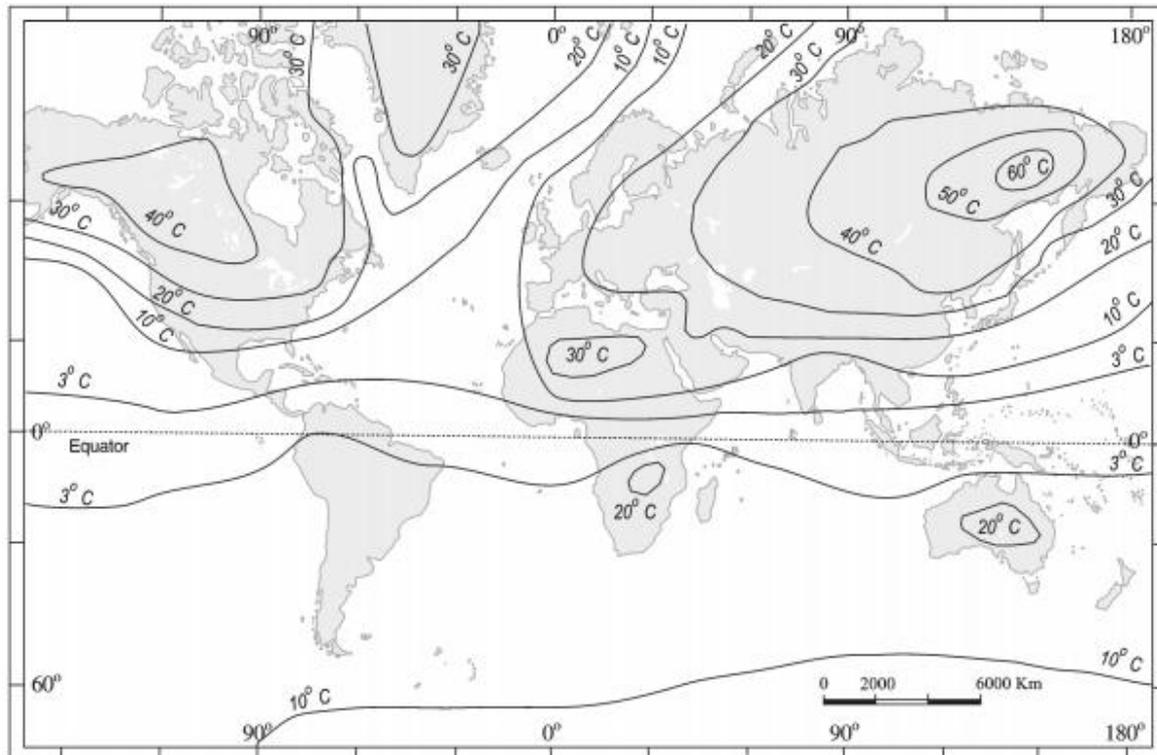


Figure 11: The range of temperature between January and July

### 2.3.3 Global Warming

The atmosphere contains number of component gases: 78.08% nitrogen (N<sub>2</sub>), 20.95% oxygen (O<sub>2</sub>), 0.93% argon, 0.038% carbon dioxide (CO<sub>2</sub>) and some other traces. About 1% could be water vapor varying with climate. These gases have maintained a constant average earth temperature by a natural balance as they radiate out the same amount of energy as that coming in. Any change in the concentration of particular gases in the atmosphere can prevent heat from being radiated out into space and upset this fine balance. The atmospheric gases which are able to absorb and trap in energy in a recycle to heat up the earth are known as the greenhouse gases. The natural constituent greenhouse gases are water vapor, which causes about 36-70% of the of the heating, carbon dioxide (CO<sub>2</sub>) about 9-26%, methane (CH<sub>4</sub>) about 4-9%, and ozone about 37%.

Solar radiation has important effect on ozone, O<sub>3</sub>, the molecule with three oxygen atoms, in atmosphere. Ozone is very rare in our atmosphere, averaging about three molecules for every 10 million air molecules. In spite of this small amount, O<sub>3</sub> plays a vital role in the atmosphere. O<sub>3</sub> molecules in the upper atmosphere (stratosphere) and the lower atmosphere (troposphere) are chemically identical, but play different roles in the atmosphere and effects on earth habitants. Stratospheric ozone (often referred to as "good ozone") plays a beneficial role by absorbing most of the biologically damaging ultraviolet, called UV-B, sunlight. Without the filtering action of the

ozone layer, more UV-B would penetrate the atmosphere and would reach the earth's surface. The absorption of ultraviolet radiation by ozone creates a source of heat and is the reason for temperature rise as one goes to higher altitudes. Ozone thus plays a key role in the temperature structure of the earth's atmosphere. On the other hand, surface-level tropospheric ozone (often called "bad ozone") has destructive nature. It reacts strongly with other molecules and high levels of ozone are toxic to living systems when comes in to direct contact. Studies show harmful effects of ozone on crop production, forest growth, and human health. (15)

### **2.3.4 sun and climate**

Sun and climate Meteorological records show that the global average surface air temperature has increased about 0.8 °C during the last 150 years. Longer term climatic variations, on the other hand, have been inferred from a variety of proxy climate indicators, including growth rings in trees. Because tree growth depends partly on temperature, the width of an individual tree ring can be used to identify paleotemperature trends. Many reconstructions of the past climate have been published in the last 15 years. Some of them seem to show very little past climate variability, while other more recent ones show larger variability. Obviously, climate changes have been spatially uneven, and different forcing mechanisms, both anthropogenic and natural ones, will have different spatial signatures. The Sun may influence climatic trends in several ways: a change in the total solar irradiance (TSI) may directly produce terrestrial temperature responses on time scales of years to centuries. A change in UV irradiance may modulate the stratospheric ozone level and atmospheric circulation, and then indirectly, terrestrial temperatures and terrestrial UV spectra on time scales of years to centuries. Direct and indirect influence may be caused by solar and cosmic ray particles, modulated by the solar wind and the magnetic field of the Sun. These particles interact with the atmosphere through nuclear collisions producing secondary particles which can penetrate deeper into the atmosphere and act as seeds for cloud formation. Solar variability as a source of climate forcing is a hot topic. Many attempts have been made to link various aspects of solar variability to climatic changes. Since the Sun is the ultimate driver of the climate system, and since it has a variable emission, it seems natural to look for the source of climate variability in the Sun itself. In recent years there has been a growing concern about the possible anthropogenic forcing of climate change through the increasing atmospheric content of greenhouse gases. This has made the connection between solar variability and global climate change a very controversial research area (16).

### 2.3.5 effects of the atmosphere

46 percent is absorbed by earth's surface on average, but this value varies significantly from place to place depending on cloudiness surface type, and elevation in there is persistent cloud cover, as exists in some equatorial regions much of the incident solar radiation is scattered back to space and very little is absorbed by earth's surface.

Water surfaces have low reflectivity (4-10 percent) except in low solar elevations and are the most efficient absorbers.

Snow surfaces on the other hands have high reflectivity (40-80 percent) and so are the poorest absorbers

High attitude desert regions consistently absorb higher than average amounts of solar radiation because of the reduced effect of the atmosphere above them.

An additional 23 percent or so the incident solar radiation is absorbed on average in the atmosphere, especially by water vapor and clouds at lower altitudes and by ozone (O<sub>3</sub>) in the stratosphere.

Absorption of solar radiation by ozone shields the terrestrial surface from

Harmful ultraviolet light and warms the stratosphere producing maximum temperatures of -15 to 10 c° (5 to 50 f°) at an altitude of 50 km (30 miles).

Most atmospheric absorption takes place at ultraviolet and infrared wavelengths, so more than 90 percent of the visible portion of the solar spectrum with wavelengths between 0.4 and 0.7 μm (0.00002 to 0.00003 inch), reaches the surface on a cloud-free day visible light, however is scattered in varying degrees by cloud droplets air molecules and dust particles. . Blue and red sunsets are in effect attributable to the preferential scattering of short (blue) wavelengths by air molecules and small dust particles. Cloud droplets scatter visible wavelengths impartially (hence, clouds usually appear white) but very efficiently, so the reflectivity of clouds to solar radiation is typically about 50 percent and may be as high as 80 percent for thick clouds. The constant gain of solar energy by earth's surface is systematically returned to space in the form of thermally emitted radiation in the infrared portion of the spectrum.

The emitted wavelengths are mainly between 5 to 100 μm (0.0002 and 0.0004 inch) and they interact differently with the atmosphere compared with the shorter wavelengths of solar radiation.

Very little of the radiation emitted by earth's surface passes directly through the

Atmosphere. Most of it is absorbed by clouds, carbon dioxide, and water vapor and is then reemitted in all directions. The atmosphere thus acts as a radiative blanket over earth's surface hindering the loss of heat to space.

The blanketing effect is greatest in the presence of low clouds and weakest for clear cold skies that contain little water vapor without this effect the mean, surface temperature of 15 c° (59° f) would be some 30° C colder conversely as atmospheric concentrations of carbon dioxide methane

chlorofluorocarbons and other absorbing gases continue to increase, in large part owing to human activities surface temperatures should rise because of the capacity of such gases to trap infrared radiation. The exact amount of this temperature increase however remains uncertain because of unpredictable changes in other atmospheric components especially cloud cover. An extreme example of such an effect (commonly dubbed the greenhouse effect) is that produced by the dense atmosphere of the planet Venus, which results in surface temperatures of about 475°C (887° F). this condition exists in spite of the fact that the high reflectivity of the Venusian clouds cause the planet to absorb less solar radiation than Earth. (17)

### 2.3.6 Calculation of the surface temperature

The temperature a surface reaches under the influence of solar radiation is dependent not only on the total solar radiation but also on the air velocity at the surface and on the absorption coefficient of the surface. During a day the surface temperature normally increases due to the solar radiation and will therefore be higher than the surrounding air temperature. Heat exchange with surrounding air increases with increasing air velocity at the surface. The highest surface temperatures can therefore be expected at calm, windless weather conditions. The heat exchange between the surface and the surrounding air can be characterized by the surface coefficient of heat exchange or the  $\alpha$ -value. Normally an  $\alpha$ -value of 20 W/ (m<sup>2</sup>.K) for free convection (heat exchange due to differences in temperature between surface and surrounding air) is used. The amount of solar radiation absorbed by a surface depends on the absorption coefficient of the surface; because wooden window frames are mostly painted the absorption of solar radiation depends on the absorption coefficient of the paint ( $a$ ). The absorbed total solar radiation can be calculated by:

$$I_{tot} = a \cdot (I_{dn} + I_{ds}) \cdot \cos(I)$$

Dark paints have a higher absorption coefficient than light-colored paint. In table 1 some absorption coefficients are given for different colored paints. (18)

<b>Colour of the paint</b>	<b>Absorption coefficient</b>
White	0.25
Crème	0.35
Light yellow	0.45
Light green	0.50
Grey	0.75
Black	0.97

Table 1: The absorption coefficient for solar radiation for some paints

## **2.4.conclusion**

Temperature and radiation are among the most important natural elements that positively affect humans, such as clean energy production and agriculture and the theft, such as global warming issues..., and depending on usage, and therefore the studies are continuing in this field from major universities and institutes to achieve appropriate solutions for optimal use of these elements

**Chapter 3:**  
**Simulation and analysis**

### 3.1 introduction

In this chapter, we process data using some MATLAB features such as nntool..., the MATLAB environment is in the form of a Workspace, where a command interpreter performs operations and MATLAB functions. The sources of these are available, written in MATLAB “language”, even in C or in Fortran. The user can modify them as he wishes, but by drawing inspiration from them, he can above all create and add his own functions, neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, network function is largely determined by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements.

### 3.2 MATLAB software

MATLAB is a programming language that engineers and scientists use to study and build systems and products that change the world. The MATLAB language, a matrix-based language that allows the most natural expression of computational mathematics, is at the heart of MATLAB.

With MATLAB we can: analyze the data and create algorithms, create applications and models, by deploying to enterprise applications and embedded devices, as well as integrating with Simulink and Model-Based Design, MATLAB also allows you to take your ideas from study to production.

MATLAB is used by millions of engineers and scientists for a variety of applications in industry and academia, including deep learning and machine learning, signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology (19).

#### 3.2.1 Starting MATLAB

We can follow these steps to change the startup directory:

- 1- Right-click on the MATLAB shortcut icon and select Properties from the context menu.

The Properties dialog box for matlab.exe opens to the Shortcut page.

- 2- Enter the new startup directory in the Start in field and click OK.

The next time you start MATLAB using that shortcut icon, the current directory will be the one you specified in step 2.

3- When we Allow the program to begin. Allow the program to begin. the most online interpreter and the Help pane are crucial. If this continues, If MATLAB Help does not appear, go to the Help tab and select MATLAB Help. That's all there is to it; the online assistance is incredibly user-friendly and helps you to obtain the information you require. a thorough understanding of the software.... Most The online interpreter and the Help pane are crucial. If this continues, If MATLAB Help does not appear, go to the Help tab and select MATLAB Help. That's all there is to it; the online assistance is incredibly user-friendly and helps you to obtain the information you require. a thorough understanding of the software.

You can make multiple shortcuts to start MATLAB, each with its own startup directory, and each startup directory having different startup options. (20)

### 3.2.2 Quitting MATLAB:

To end your MATLAB session, type quit in the Command Window, or select File → Exit MATLAB in the desktop main menu. (21)

### 3.2.3 About versions: MATLAB R2015a

### 3.2.4 Features of MATLAB R2015a:

1. Can connect the controllers with signals easily.
2. New dashboard section included in Simulink library.
3. Can easily add displays and controls into your models.
4. A new range called Simulink Time Scope included.
5. Sample time becomes simpler.

MATLAB is available for several platforms (Windows, Macintosh, Unix, Linux).

## 3.3 Neural networks on MATLAB

In most cases, neuronal networks are adjusted or entrapped so that a certain entry leads to a specific target exit. A situation like this is depicted here. The network is then adjusted based on a comparison of the sortie and the target, until the network's output matches the target. Typically, many of these entrée/cible pairs are used to construct a network in this supervised learning environment. (22)

The training by lots of a network takes place by making weight and bias changes based on a whole set (lot) of entry vectors. Following the presentation of each individual vector of entry, incremental training modifies the weight and bias of a network based on the needs. Progressive training is often known as "online training" or "adaptive training."

Neuronal networks have been developed to perform complicated functions in a variety of applications, including form recognition, identification, classification, speech, vision, and control systems. A list of available applications.

Neuronal networks can now be used to solve problems that are difficult for traditional computers or humans to solve. Throughout the toolbox, the focus is on neuronal network paradigms that are being built or are already being used in technical, financial, and other practical applications.

Although supervised training methods are commonly used, other networks can be created using non-supervised training approaches or direct conception methods. Non-supervised networks can be used to identify data groups, for example. Several forms of linear networks and Hopfield networks are designed directly. In conclusion, there are many different sorts of design and learning strategies that can be used to expand a user's options.

The field of neuron networks has a five-decade history, but it wasn't until the last ten years that it found a strong application, and the field continues to grow at a rapid pace. As a result, it differs significantly from the domains of control or optimization, where the terminology, the foundational mathematics and design procedures have been solidly established and applied for many years. We don't think of the neural network toolbox as a straightforward collection of well-established procedures. We hope that it will be a useful tool for industry, education, and research, one that will assist users in determining what works and what doesn't, as well as one that will aid in the development and expansion of the field of neuron networks. Because the field and the equipment are so new, this toolkit will explain the procedures, show how to apply them, and provide examples of their successes and failures. We believe that understanding paradigms and how to apply them is essential to a successful and satisfying use of this toolbox, and without it, user complaints and requests will overwhelm us. So please bear with us if we provide a lot of instructional material. We hope you will find this material useful.

### **3.4 Study with nntool technology**

To begin, we'll walk you through how to use the nntool technology using the following forms:

MATLAB command for Windows:

Data to be chosen There are 29 variables and one target in the current data. You can either copy the data to MATLAB or utilize the import option.

Because columns must be rows, data must be split into target (response or output) and input data (variables).

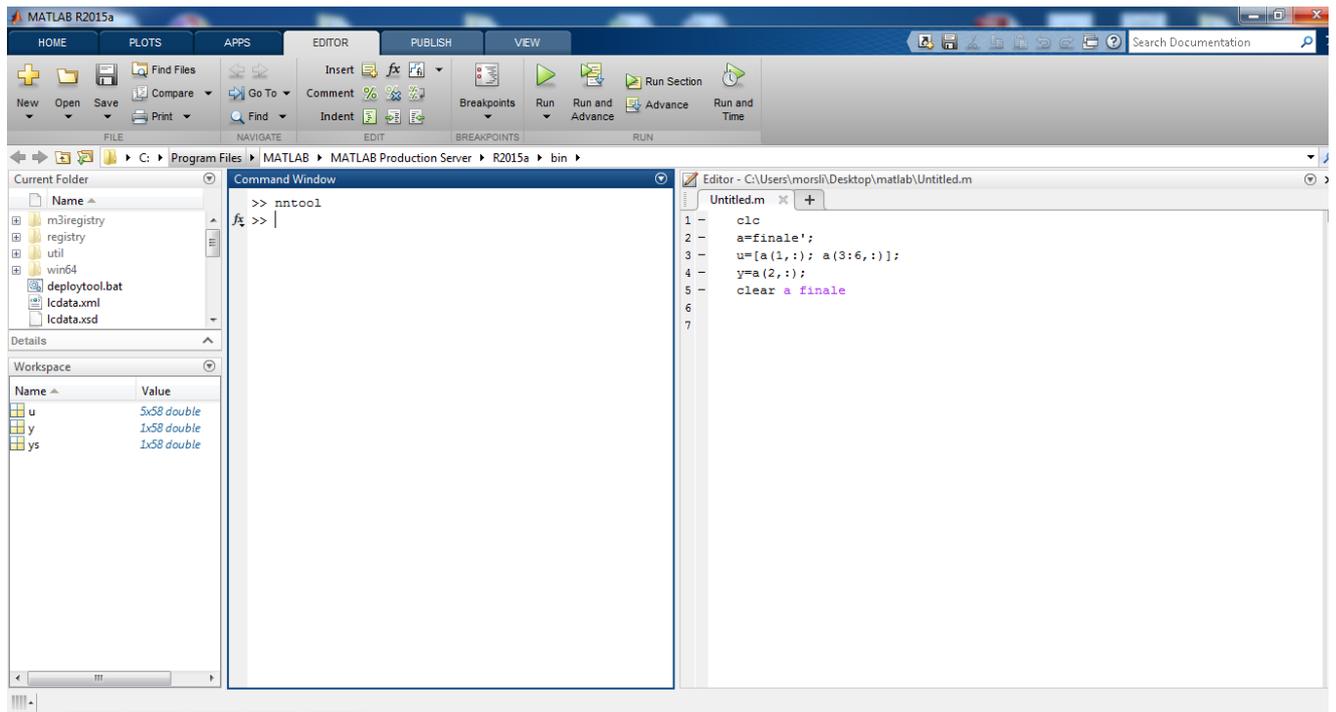


Figure1. MatlabcommandWindow

Type in the command window

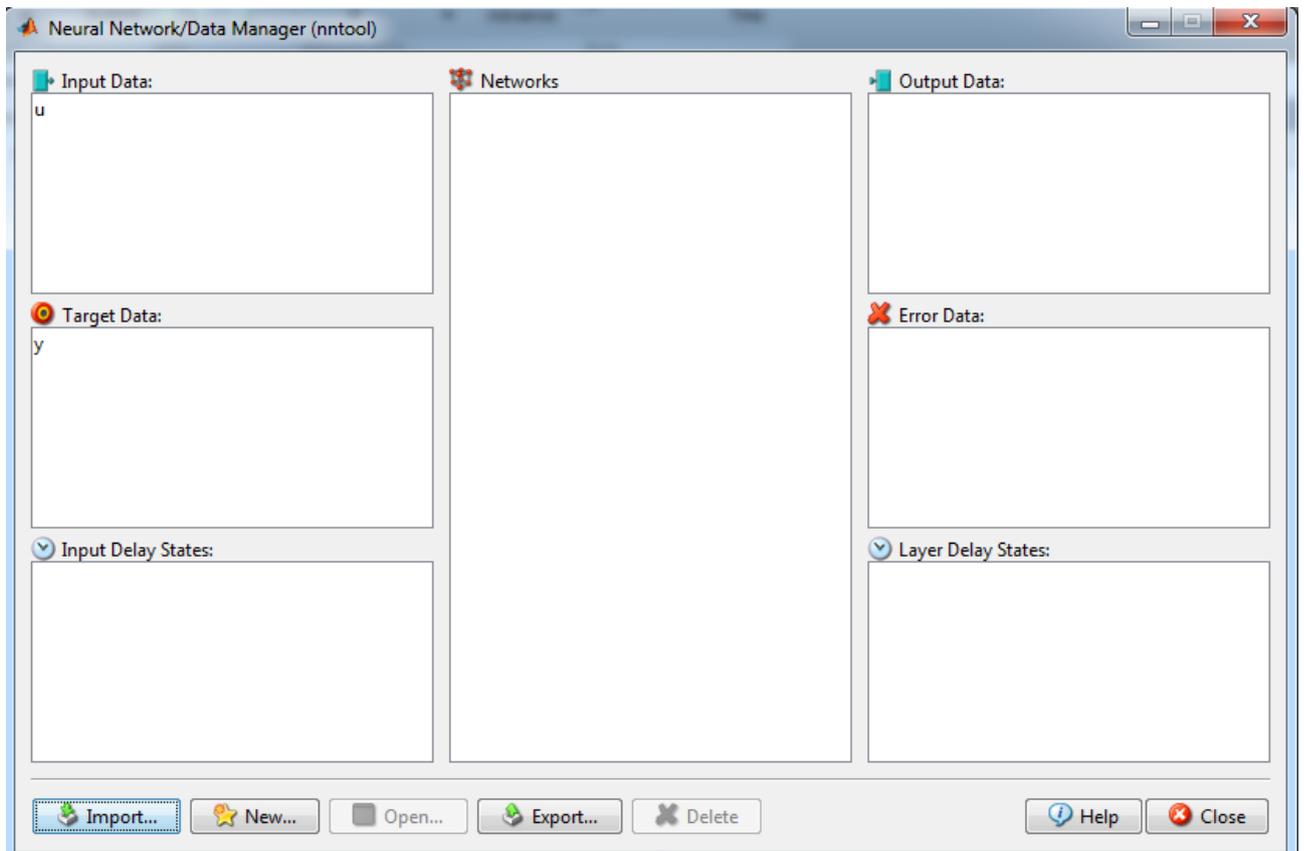


Figure 2. nntool's page

Now create the network by clicking on new from network type we can choose the desired network type here I choose feedback with backpropagation select the entry. Output and training and learning algorithms (functions)

Import,

$Y$  (Radiation) = target

$U$  (time) = input data) temperature- speed (m/sec) –humidity-atmospheric pressure)

### real time estimation:

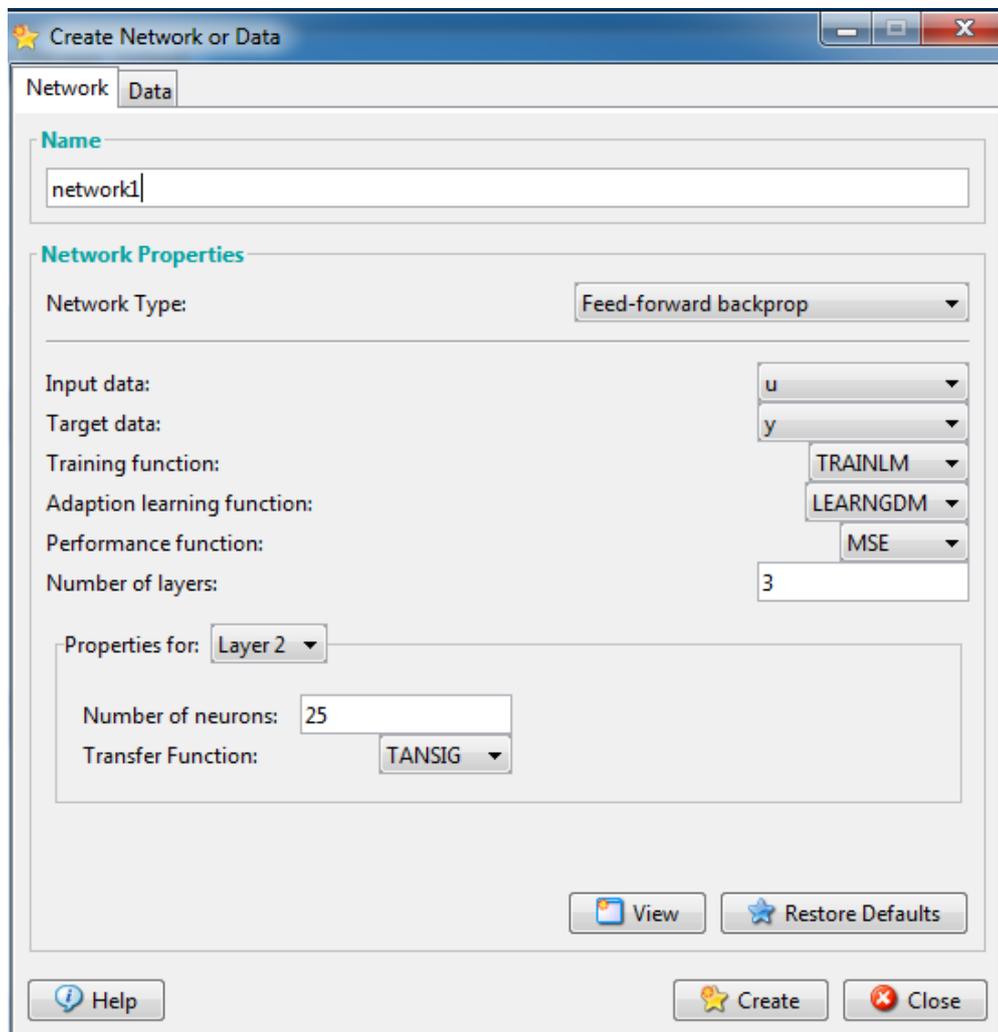


Figure 3. the network by clicking

import inputs (T) and target (R)

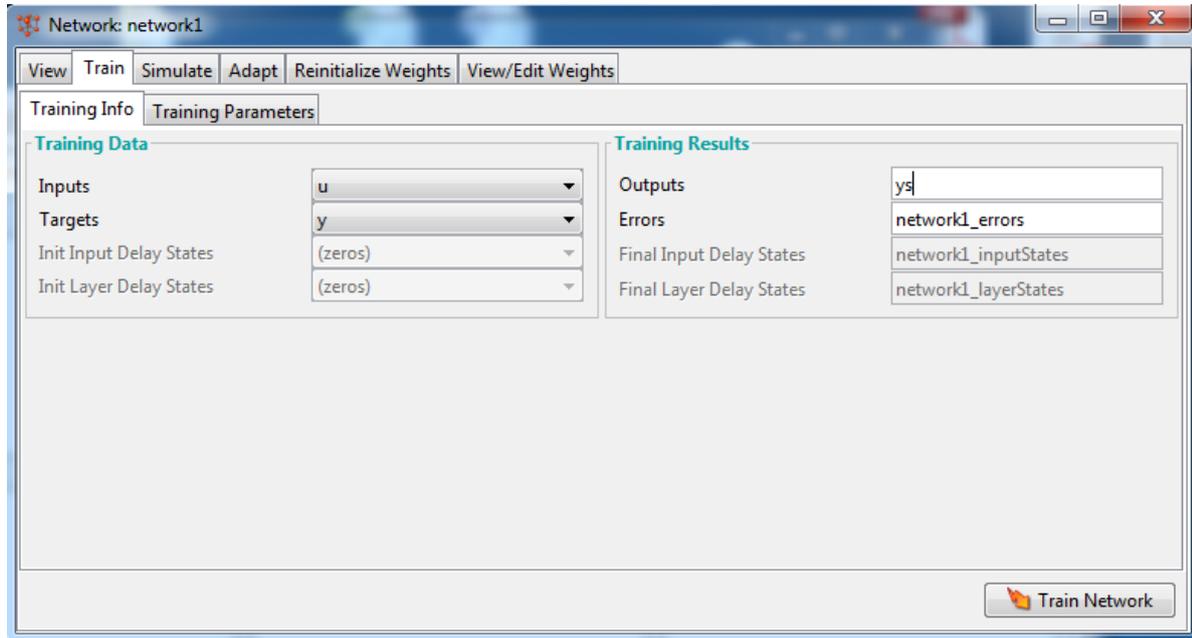


Figure 4. Train network preparation

We can see the data's training, testing, validation, and general regression, and we can train the network until we achieve a satisfactory fit:

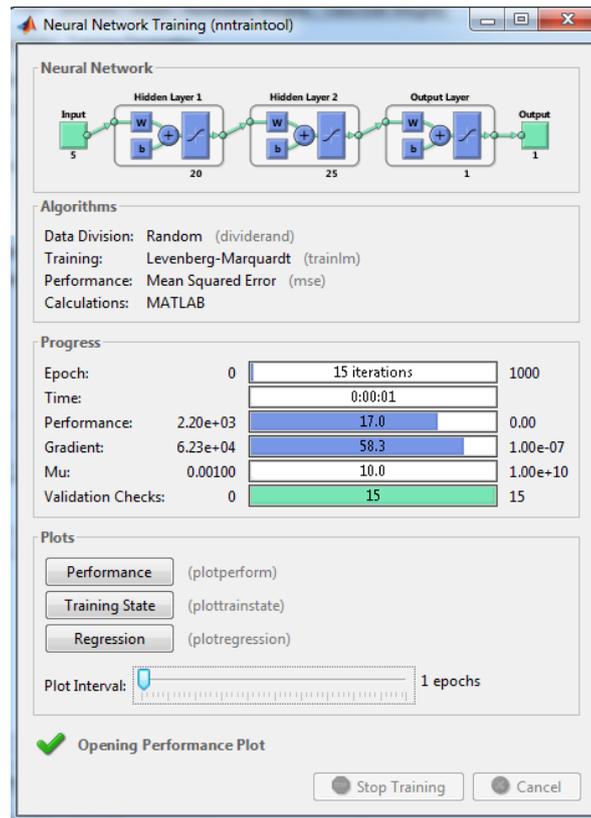


Figure 5. Neural networks training

The training graphs (Training):

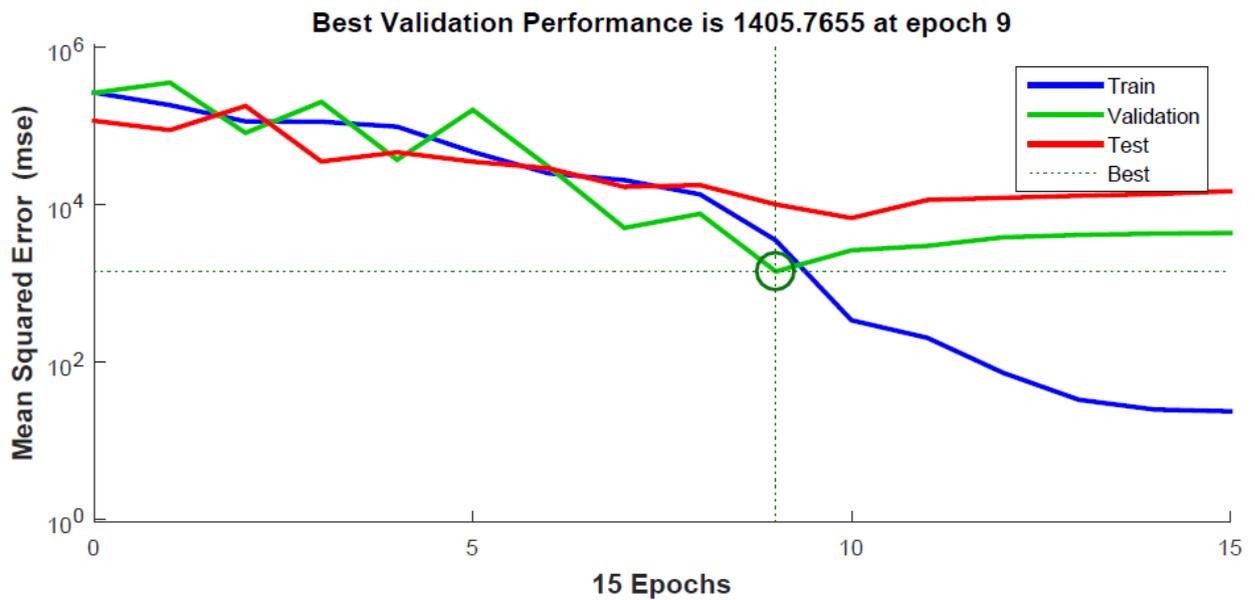


Figure 6. performance

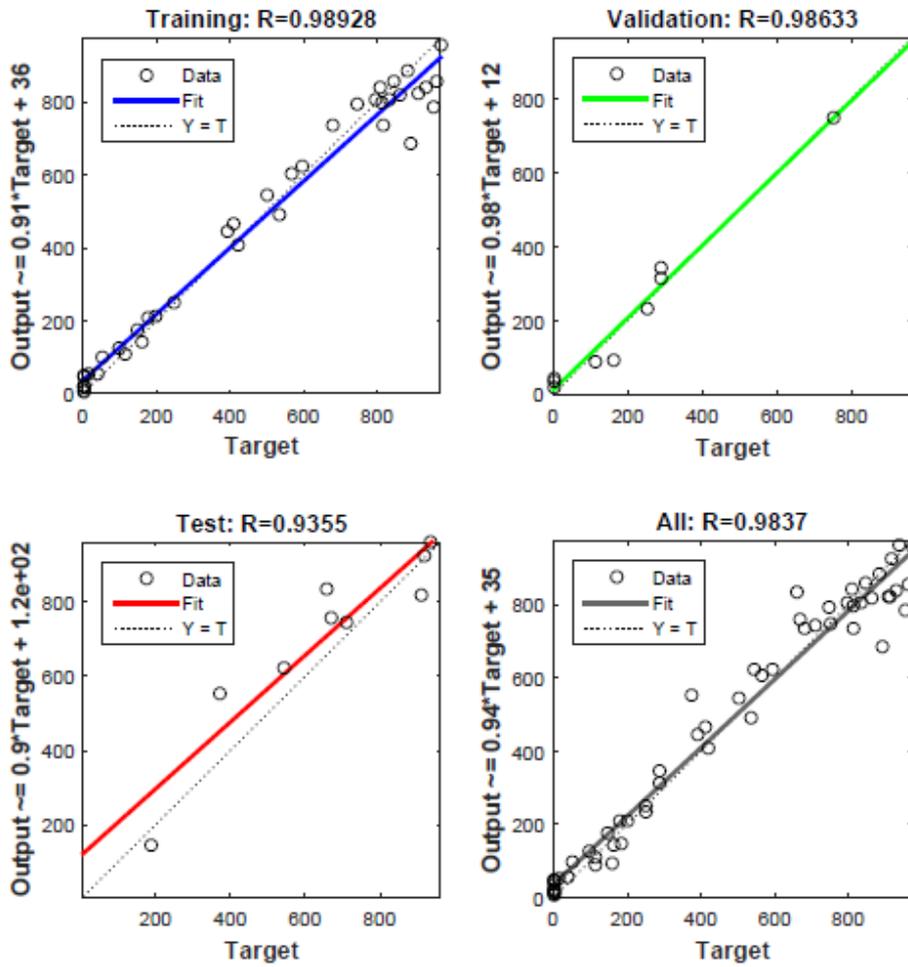


Figure 7. Regression

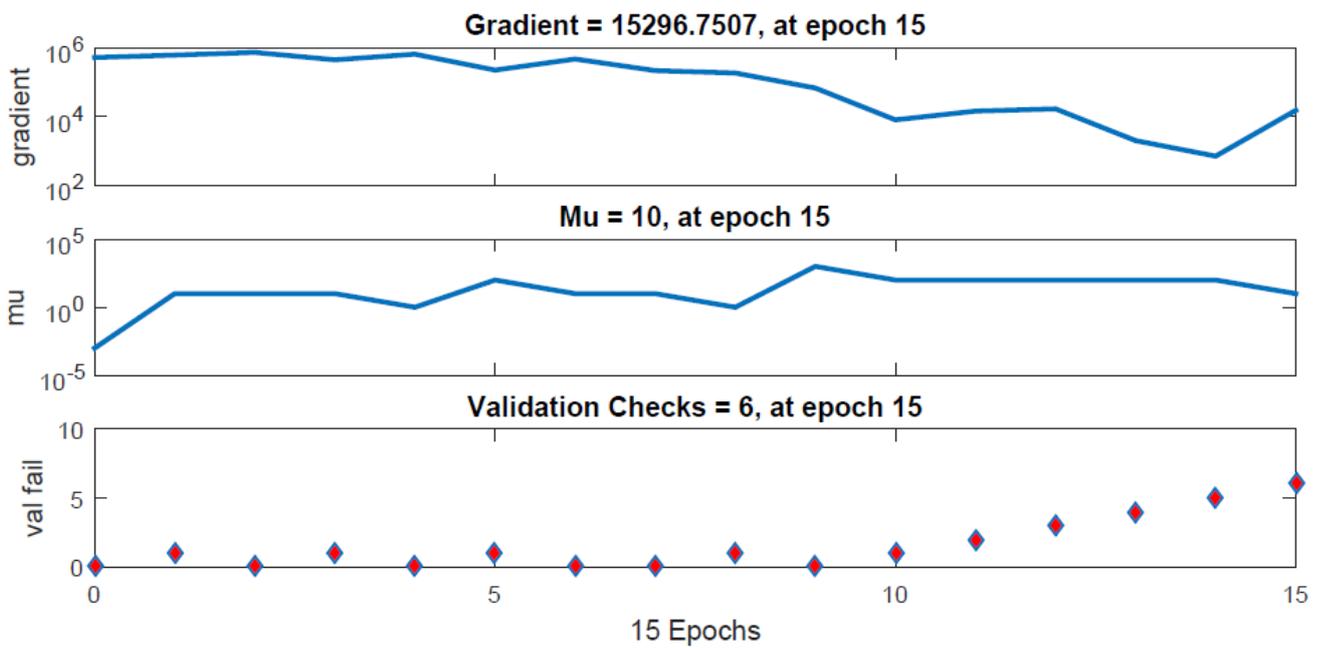


Figure 8. Training state

The difference between the actual radiation values (R) and the values predicted by (nntool) is (R) in the following figures, and the difference between them that we cross by (error) on different days with the change in the number of neurons and the number of layers, and we note the differences, if any:

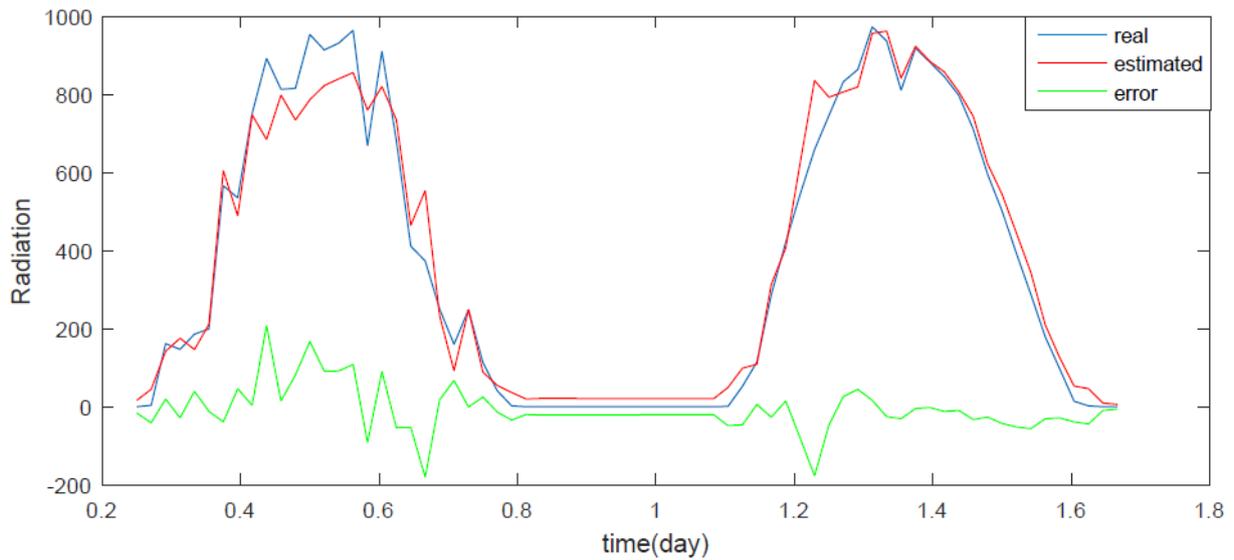


Figure 9. two days

Rms= $y - y_s = 64.7139$

MAE = 6%

**Fitted data tracking using the smooth:**

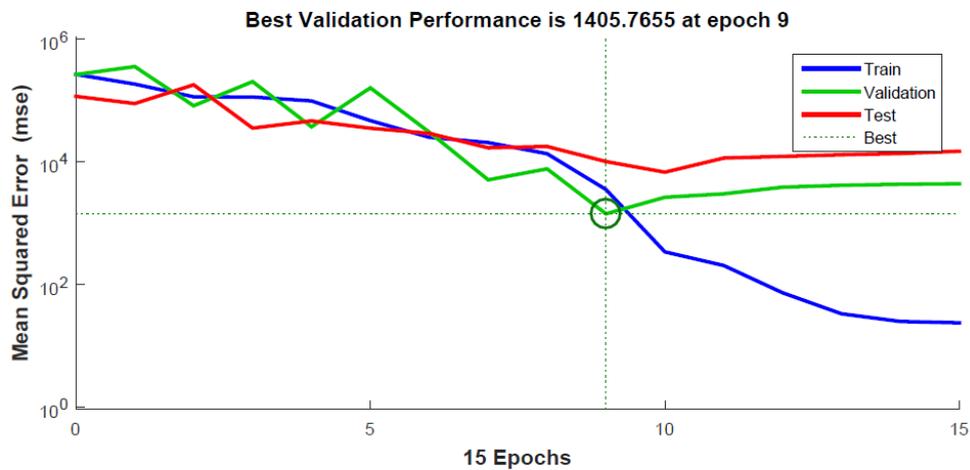


Figure 10. performance p

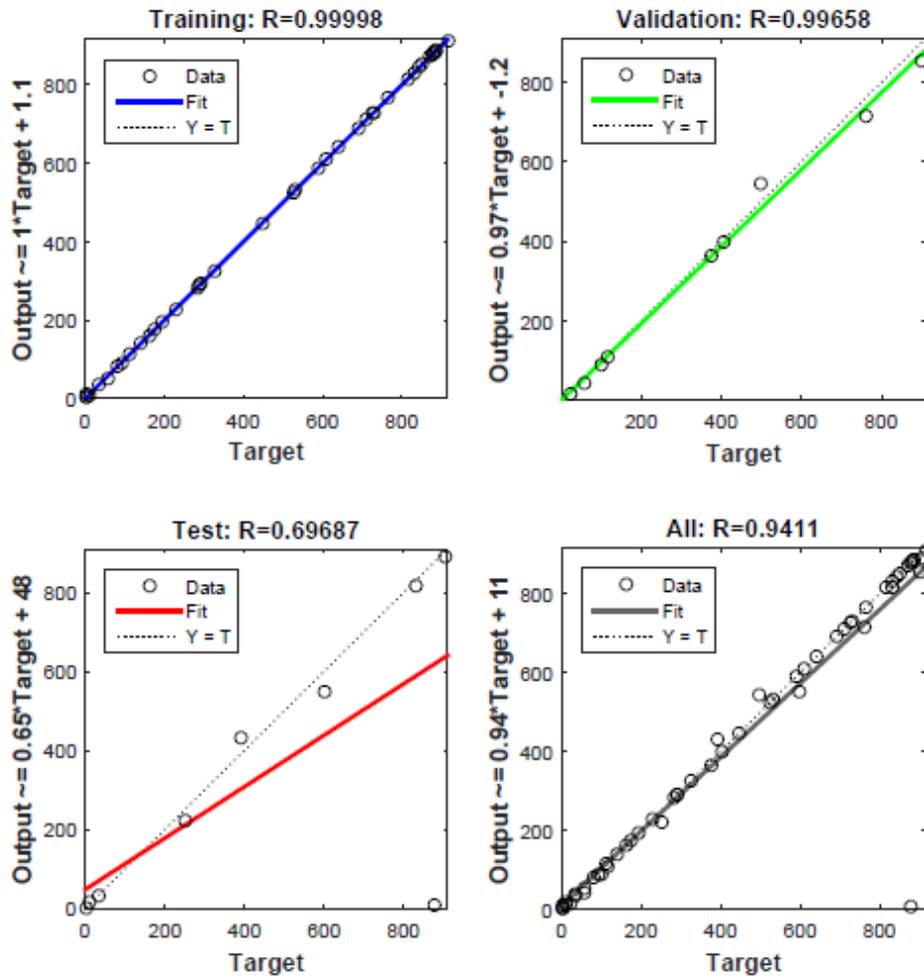


Figure 11. regression smooth

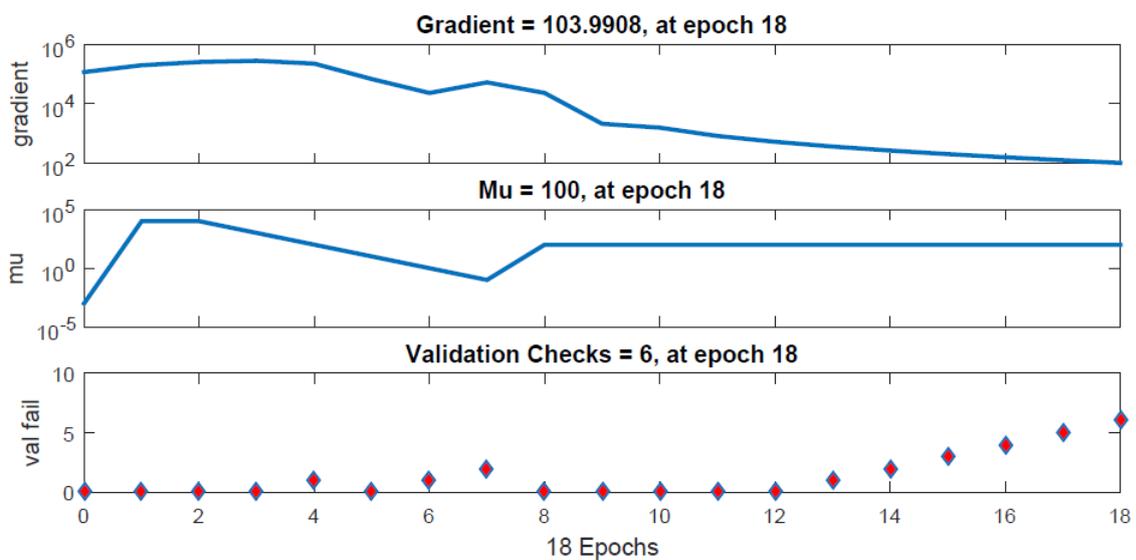


Figure 12. stat smooth

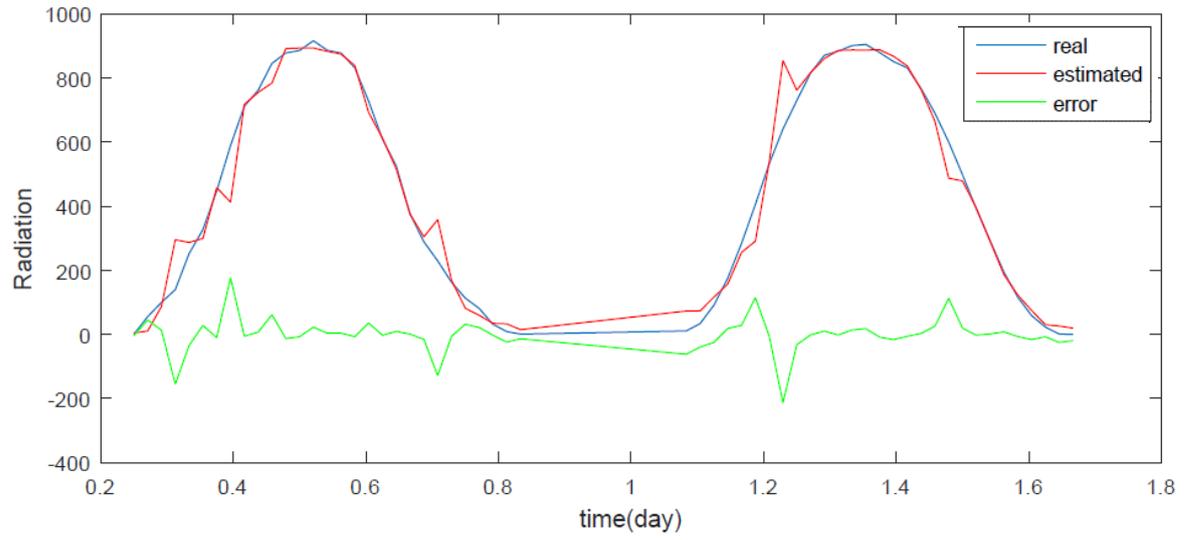


Figure 13. estimate smooth (two days)

**Observations:**

Between the curves, there is a difference in precision and mistakes. (Fig 13) smoothed.

We can see a huge variance in the value of the radiation in the first curve, but it quickly returns to its target value.

However, we can see that the second curve has a minor shift in the radiation value, but it returns to stability over time, whereas the third curve shows that the mistake is small and the desired value is nearly constant.

**Hypotheses:**

These changes may be due to:

- Weak nntool technology.
- or the number of neurons.
- The number of canapes

**Explanation:**

Following the research, we discovered that the modifications and errors were caused by changes in the number of neurons and layers, with the bigger the number, the higher the accuracy. On figure 11, we noticed it.

**3.5 Conclusion:**

From the results we obtained using the data set consisting of air temperature, Time, humidity, wind speed, atmospheric pressure, wind direction and solar radiation data, this was done using neural network (nntool) technology, and we recognized that the usage of this technology is vital and accurate in the field of predictions and data analysis.

## **General Conclusion**

In this research we tried to help in knowing how to predict solar radiation by knowing the natural temperatures as well as in order to produce clean energy, because of the correlation between the natural temperatures and radiation.

And we found that the prediction of solar radiation using the neural network technology (NN) to analyze and study the data, explaining the similarity of the technology with biological neurons,

We also talked about artificial and recurrent neurons and explained neural networks and types of structures.

For the second chapter, we talked about solar radiation and its effect on the atmosphere, temperatures and methods of calculating it.

In the last chapter, we discussed the use of technology (NN) and obtaining the curves and results used in the fields of energy production, and we got very accurate results and few errors, and this is due to the characteristics of this technology mentioned, and therefore it is possible to know the times and conditions of using power generators absolutely from knowing the temperature.

### References:

- (1) : Mehdi Abadi. Réalisation d'un réseau de neurones "SOM" sur une architecture matérielle adaptable et extensible à base de réseaux sur puce "NoC". Micro et nanotechnologies/Microélectronique. Université de Lorraine ; Université du Centre (Sousse, Tunisie), 2018. P10
- (2) : <https://www.juripredis.com/fr/blog/id-19-demystifier-le-machine-learning-partie-2-les-reseaux-de-neurones-artificiels> Seen 25/04/2022 17.50.
- (3) : Richard N. Henderson, **introduction of radiation**, Department of energy Portsmouth gaseous diffusion plant, annual site environmental report 2018, revision3, USA, 2020.
- (4) :JoakimWid\_en and Joakim Munkhammar, **Solar radiation theory**, uinversity of Uppsala,2019
- (5) :<https://www.energy.gov/eere/solar/solar-radiation-basics>, 28-04-2022-21:00.
- (6) :Juzeniene, Asta; Brekke and others, **Solar radiation and human health**, Reports on Progress in Physics, university of lund,2011 .
- (7) :Jedrzej s Bojanowski, **Quantifying solar radiation at the earth surface with meteorological and satellite data**,phd thesis, university of twente, Netherlands, 2014.
- (8) :JoakimWid\_en and Joakim Munkhammar, previous reference.
- (9) :Jedrzej s Bojanowski, previous reference.
- (10): Zhihong Pang, Fuxin Niu,Zheng O'Neill, **Solar radiation prediction using recurrent neural network and artificial neural network: A case study with comparisons**, article in renewbale energy, Elsevier, usa, 2020.
- (11) :Md. Shafiqul Islam, **prediction of solar irradiance for Bangladesh using neural network**, master thesis in engineering in electrical and electronic engineering, university of dhaka, Bangladesh, 2014.
- (12): M. Siraj Anwar and others, **Solar radiation. Heat balance and temperature**, previous reference.
- (13) :Aissaboudjrada, Younes djekaoua, **Prédictions des états des radiations par R.N récurrent(TDNN)**, mémoire master en Sciences et Technologies, université de ghardaia, 2020-2021.
- (14): M. Siraj Anwar and others, **Solar radiation. Heat balance and temperature**, previous reference

## *References*

---

- (15): Sultana N. Nahar, **Solar Irradiance of the Earth's Atmosphere**, university of ohio, article Department of Astronomy, USA,
- (16): Juzeniene, Asta; Brekke and others, the same reference.
- (17) :Britannica.com/science/climate-meteorology/solar-radiation-and-temperature 23-04-2022-22.30.
- (18): C.J.J. Castenmiller, **Surface temperature of wooden window frames under influence of solar radiation**, article in heron, Netherlands, 2004.
- (19) :<https://www.mathworks.com/discovery/what-is-matlab.html>, 15:33, 27-05-2022.
- (20) : Using matlab, MATLAB the language of technical computing, stanford university, version6, 1984.
- (21) : David Houcque , **Introduction to matlab for engineering students**, Northwestern University, version 1.2, august, 2005.