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Presented by:

BENABDALLAH Abdelali

TLIBA Mohamed El Azouzi

BEN AMOUR Hicham

SELATNA Mouad

Subject

Power output prediction of a photovoltaic (PV) module using artificial neural network

Thesis examination committee:

Dr. LABIOD Chouaib	President
Dr. MILOUDI Khaled	Examiner
Dr. MOHREM Abdelkrim	Examiner
Mr. KEDDOUDA Abdelhak	Supervisor

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Dedications

To our dear parents with all our gratitude and love

For all these years of sacrifice and encouragement.

To our brothers and sisters and to all our families.

To all friends….

For everyone I love

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Nomenclatures

E	Energy solar	(Wh/m^2).
I	Current	(A)
V	Voltage	(V)
Voc	Open circuit voltage	(V).
Isc	short circuit current	(A).
FF	Form factor.	
Ipv	Photovoltaic current	(A).
Iph	Photon current (current generated by illumination)	(A).
Id	diode current	(A).
Q	Electrical charge	(1.6×10-19 C).
K	Boltzmann constant	(K=1.3854 × 10-23 J/K).
Rch	Load resistor	(Ω).
Rs	Series resistance of the cell	(Ω).
Rsh	Cell shunt resistance	(Ω).
T	cell temperature in	(Kelvin).
G	Insolation (solar radiation) or illumination	(W/m2)
Id1, Id2	Diode currents	(A).
A	Diode quality factor.	
V_t	junction thermal voltage	(J/C)
Is	Diode saturation current	(A)
H	Energy efficiency	
Iopt	The optimal current	(A).
Vopt	The optimum voltage.	
R	Resistive load	(Ω).
R_{SH}	are series and parallel resistors	(Ω)
$I_{ph,n}$	Short-circuit current of the cell under standard conditions	(A)
Pmax	Maximum power point	(W)
P	Power supplied by the PV module	(W)
Tc	PV cell temperature	(°C)

ABBREVIATIONS

PV	Photovoltaic
ANN	Artificial neural network
AC	Alternating current
DC	Direct current
AI	Artificial intelligence
WS	Wind speed
ML	Machine learning
MPPT	Maximum power point tracker
MSE	Mean square error
PWM	pulse width modulator
P&O	Disturb and Observe.
RMSE	Root Mean Square Error

GENERAL INTRODUCTION

GENERAL INTRODUCTION

Among the renewable energy sources (RES), solar energy has the greatest energy potential and photovoltaic arrays allow electrical energy to be produced directly from sunlight; Furthermore, during the operation phase, energy is produced without the consumption of fossil fuels or noise, and poses no health and environmental risks. These features will make photovoltaic devices one of the most important technologies based on the exploitation of renewable energy sources. However, the technological and environmental benefits of photovoltaic technology are hampered by economic and technical factors. It makes the high cost of production and installation.

Photovoltaic technology is possible for the client only if there are public financing opportunities. Furthermore, there are various concerns associated with PV modules, such as the effect of being connected to the grid. Some studies have been done on this topic, for example, but in general, there is little information on this topic. The most severe disturbance caused by connecting a large amount of PV generation to the grid can be encountered when a group of cloud swallows an area with a large concentration of PV generators. This may result in a large and somewhat abrupt variance in the photovoltaic output. The condition can be exacerbated if this change in radiation occurs during a rapid increase in pregnancy. For these reasons, it is clear that the availability of reliable predictive tools is very important for the deployment of PV technologies, to improve the performance of PV systems at the planning and operation stage and finally to properly assess the economic return. In order to evaluate the real performance of PV panels, it is very important to correctly predict the power output; an increase of even a few degrees of the PV panel along with a decrease in solar radiation can significantly reduce the conversion efficiency of the system and thus reduce energy production. In fact, an important consideration in achieving the efficiency of photovoltaic panels is to evaluate the performance for any weather conditions and to match the maximum power point. Several methods based on MPPT (Maximum Power Point Technology) have been reported in the literature, and many others have applied empirical correlations to evaluate the thermoelectric performance of a PV system. However, these methods require detailed knowledge of the physical parameters of the photovoltaic system and manufacturing specifications.

Another approach is represented by adaptive systems. An adaptive system is a system that is able to adapt its behavior to changes in its environment or in parts of the system itself. An adaptive system, such as Artificial Neural Networks (ANN), does not require any physical definitions of the PV array but should allow prediction, in a fast and reliable procedure, of the power output of the atmospheric variable PV module. This paper presents a model of artificial neural networks that best predicts the production of PV energy. The authors tested the use of an ANN to predict the power output of a PV panel using data monitored at a test facility.

In the first chapter, we will discuss a general study about the basic concepts and definitions of photovoltaic cells and the artificial neural network, and previous studies on this topic.

In the second chapter, we will discuss the mathematical formulas or equations for photovoltaic cells and the artificial neural network.

While we will discuss in the third chapter the description of the equipment and devices through which we obtain the measured data and experimental results (atmospheric temperature, solar panel temperature, solar radiation intensity and wind speed), and then we will discuss the results obtained in the Matlab program.

CHAPTER I : GENERALITIES AND LITERATURE REVIEW

I.1 Introduction

The prediction of photovoltaic production using an artificial neural network is affected by several factors such as temperature, humidity, wind and many other factors. As photovoltaics and artificial neural network have many pros and cons.

Where, in this chapter, we will study and define the basic concepts of photovoltaic cells such as the working principle and types, as well as training and applications architecture for the artificial neural network.

I.2 Photovoltaics

The term "photovoltaic" comes from the Greek, "photos" means light and "Volta" surname of the Italian physicist (Alessandro Volta) who invented the electric battery in 1800 and gave his name to the unit of measurement of electric voltage, the volt. In 1905, Einstein discovered that the energy of these quanta of light is proportional to the frequency of the electromagnetic wave. The use of solar cells began in the 1940s. The space domain needs energy without on-board fuel. Research is intensifying on photovoltaics. In 1954, BELL Laboratories created the first photovoltaic cell with an efficiency of 6%.

Space is becoming the test bed for photovoltaic technology. The high manufacturing costs of the cells and their mediocre yields do not yet allow them to be exploited on a large scale. It took until the 1970s for governments and industry to invest in photovoltaic technology [1].

I.2.1 Photovoltaic system

Electrically connected individual solar cells are called a photovoltaic module as this is done to increase their energy production. The cells are encapsulated so as to protect the consumer from electric shock, and protected from the environment, and the influences that are most important in the photovoltaic modules or arrays [2].

- Losses due to mismatched solar cells interconnections
- Module temperature
- PV modules failure modes

The surface material of the cells should be impermeable to water, have good resistance to impacts as it is stable under prolonged exposure to UV rays, and have low thermal resistance. In addition, the reflection from the front surface should be low. To reduce this reflection, an anti-reflective coating can be applied to the top surface, but there is a problem with the durability of these coatings. A technique that can be used instead, is to "rough" or texture the surface. However, this technology is more likely to stick dust and dirt to the top layer of the units, and therefore "self-cleaning" is less, with the benefit of reducing reflection by losses outperforming the contamination of the top surface [2]. A representation of how the different terms from PV cells to arrays can be seen in figure I 1.

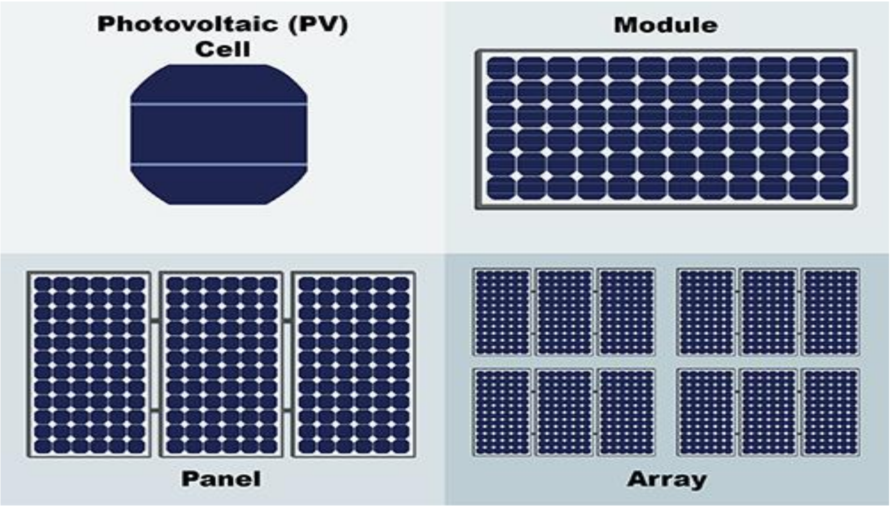

Figure I-1: form solar to arrays

A PV module is a form of many photovoltaic cells, a PV series has many modules connected in series and several photovoltaic modules (chains) form a group PV where a photovoltaic system is formed from many photovoltaic arrays connected to the aging and at home or to the power grid. A simplified grid-connected PV-system is illustrated in figure I 2.

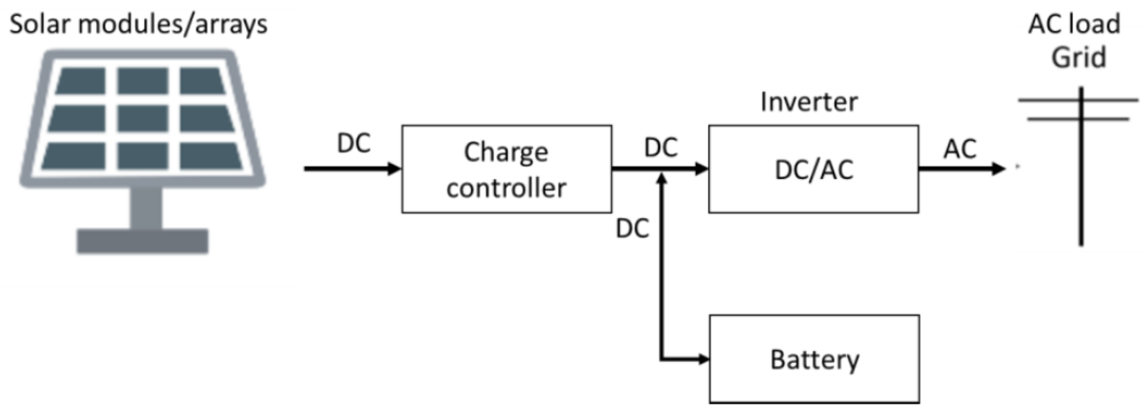

Figure I-2: simplified schematic of grid-connected PV sestem

Figurer I 2illustrates how solar (PV) modules or arrays are connected to a charge controller that again is connected to a DC/AC inverter and/or batteries. Solar cells produce direct current (DC), which needs to be converted into alternating current (AC) if it is to be fed to the electricity grid. DC energy can be stored in a battery or used in e.g. home appliances. The charge controller with MPPT (maximum power point tracker) or PWM (pulse width modulator) is typically used and is needed if a battery is connected to the system. The charge controller determines if the power generated from the solar modules is needed to charge the batteries, used in home appliances or fed to the grid. The controller is preventing the battery from overcharging and makes sure the electricity stored in the battery does not to get back to the solar modules during no-production periods [3].

I.2.2 Photovoltaic Technology

Photovoltaics are devices that produce electricity directly from electromagnetic radiation. The devices are made of semiconductor materials, which conduct electricity under certain conditions, so they are neither conductive nor insulators. The most common semiconductor material is silicon, often what is combined with other elements to improve its delivery, in a process known as doping. Controlled amounts of certain impurity ions are added to the ultra-pure material to produce a doped semiconductor.

Impurity ions of lower valences enter the solid Si network and become electron acceptor sites, which trap free electrons. These traps have an energy level within the band gap, but close to the valence band. The absence of free electrons results in positively charged states called holes that move through the material as carriers. With these impurity ions of the electron acceptor, the semiconductor is called a p-type (positive) material, with holes like majority carriers. On the other hand, atoms with large valence (such as phosphorous) are electron donors, yielding an n (negative) substance. with an excess of conductive electrons as majority carriers [4]

An electron free to move throughout the crystal is said to be in the conduction band of the crystal, because free electrons are the medium by which electricity flows. Conduction band electrons and holes are fundamental to the electrical behavior of photovoltaic cells. Although the generation of electrons and holes by light is the central process in the effect total PV, but it does not produce current by itself.

A photovoltaic cell contains a barrier created by opposing electric charges facing each other on either side of the junction. This potential barrier selectively separates light-generated electrons and holes, causing more electrons to be sent to one side of the cell, and more holes to the other. This charge separation determines a potential difference between the two ends of the cell, which can be used to drive an electric current in an external circuit.[5]

If we connect the n-type side to the p-type side of the cell by means of an external circuit, then current flows through the circuit because this reduces the light-induced charge imbalance in the cell. This current from the cell is inherently direct current (DC) Figure I 3. Illustrates the functioning of a typical PV cell.

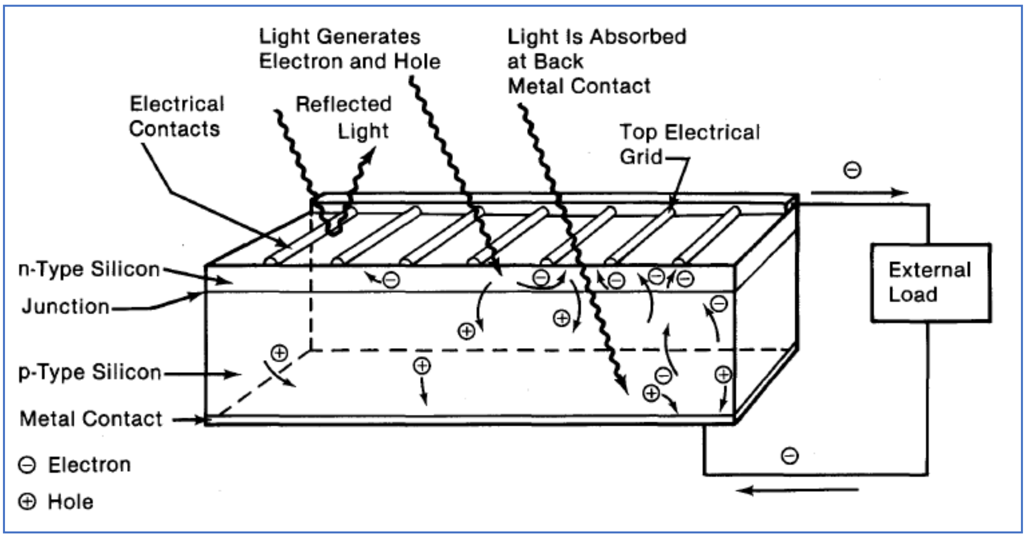

Figure I-3: light incident on the cell creates electron-hole pairs which are separated by the potential barrier creting a voltage drives a current through an external circuit

I.2.2.1 Semiconductors

Electricity is difficult to transmit in it as a solid, and its electrical conductivity is controlled by adding other elements in small quantities. A semiconductor is the electrical resistance between conductors and insulators. An external electric field can also change the degree of resistance of a semiconductor. Semiconductor is the basis of modern electronics, which includes radio, computers, phones, and many other devices. Electronic parts that work with semiconductors include transistors, solar cells, diodes, LEDs, silicon AC rectifiers, and analog and digital integrated circuits.[6].

Solar panels are the biggest example of devices powered by semiconductor materials, because they convert light energy into electrical energy [7].

I.2.2.2 PN junctions

Made by joining n-type semiconductors with p-type semiconductors, such as silicon saturated with phosphorous and silicon saturated with boron. Subject to an electric field in a PN junction connected to an external circuit, the electron-hole pairs will separate and the excited electrons will begin to move in a certain direction: an electric current is generated. The direct electrical current created by very fine metal wires connected together is then collected and directed to the next cell. The current is added as it passes from cell to cell down to the terminals of the board, and can then be added to those other panels connected in "fields".[8].

I.2.2.3 Photovoltaic effect

The photoelectric effect is the generation of voltage and electric current in a material when exposed to light. It is a physical and chemical phenomenon [9]

The photoelectric effect is closely related to the photoelectric effect. For both phenomena, light is absorbed, causing an electron or other charge carrier to be excited to a higher energy state. The main difference is that the term photoelectric effect is now commonly used when the electron is ejected from the material (usually in a vacuum) and the photoelectric effect is used when the excited charge carrier is still present inside the material. In both cases, an electric potential (or voltage) is produced by the separation of charges, and the light must have sufficient energy to overcome the excitation potential barrier. Typically the physical essence of the difference is that PV emission separates charges by ballistic conduction and PV emission separates by diffusion, but some concepts of "hot-carrier" PV devices blur this distinction.

I.2.3 Solar cell materials

According to the definition of a hemorrhoid,[10] There are three different physical structures divided by the size of the crystal grains; Crystalline, polycrystalline and amorphous The three different material structures are illustrated in Figure I 4 and represents the arrangements of the atoms for each material. The following descriptions of the materials are based on Wenham et al.[3].

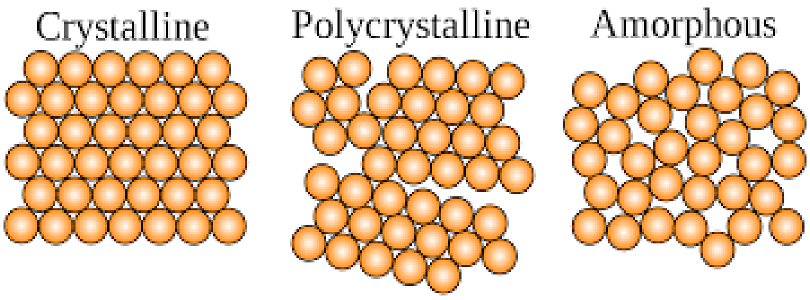

Figure I-4: materail structure

I.2.3.1 Monocrystalline cells

These are the ones with the best return (15-22%) but also the ones with the least cost. Rise due to complex manufacturing [11]

I.2.3.2 Polycrystalline cells

Its design is easier, its manufacturing cost is lower, but its production is lower (13-20%)[12]

I.2.3.3 Amorphous cells

They have a low yield (5%) [12] but require only a very small thickness of silicone and have a low cost. They are commonly used in small consumable products such as solar calculators regardless of the materials used, the photovoltaic conversion yield can reach 40% [12] These low yields related to the material technology, constitute the first major problem of solar energy exploitation thanks to the new material technology of cadmium telluride (CdTe), gallium arsenide (GaAs) In addition to copper disodium and indium selenide (CIS), solar cells producing 40% in vitro were able to emerge [13].

I.2.4 Maximum power

By varying the environment temperature and radiation, the maximum power is variable in I Figure I 5 since the maximum power available for solar arrays is constantly changing with atmospheric conditions, the real-time maximum power point tracker is the indispensable part of the PV system. MPPT charts for tracking maximal power points suggested in the technical literature. [14] can be divided into three different categories [15]

.Direct methods.

.Artificial intelligence methods.

.Indirect methods.

In direct methods, which are also known as true search methods, the MPP is searched by continuously jamming the PV array operating point. Within this category, Perturb and Observe P&O [16] Hill Climbing HC [17]and Incremental Conductance INC [18] schemes are widely applied in PV systems. P&O scheme involves perturbing the operation voltage of the PV array to reach the MPP. Analogous to P&O scheme, hill climbing method perturbs the duty cycle of the dc-dc interface converter. Simplicity is the main feature of these methods; however, intrinsic steady state oscillation limits these methods to low-power applications. Reduced steady state oscillation is possible with the incremental conductance method, which is based on the fact that the slope of the power versus voltage is zero at the MPP. 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.

Indirect methods rely on extracting the MPP of the array from its output properties. The OCV partial open circuit voltage [19] and short circuit current [20] diagrams provide a simple and effective method for obtaining an MPP.

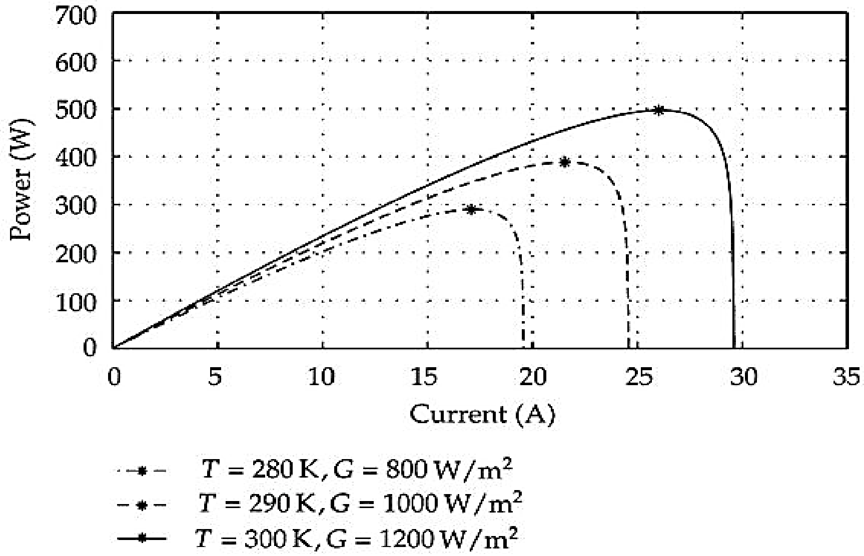

Figure I-5: P_I characteristic of PV

I.2.5 Efficiency

Solar cell efficiency refers to the portion of energy in the form of sunlight that can be converted via photovoltaic cells into electricity by the solar cell.

The efficiency of the solar cells used in a photovoltaic system, along with latitude and climate, determine the annual energy production of the system. For example, a solar panel with an efficiency of 20% and an area of 1 m 2 will produce 200 kWh/year under standard test conditions if exposed to standard test conditions with a solar irradiance value of 1000 W/m2 for 2.74 hours a day. . Solar panels are usually exposed to sunlight for longer than that on a given day, but solar radiation is less than 1000 W/m2 for most of the day. Solar panels can produce more when the sun is high in the sky and will produce less in cloudy conditions or when the sun is low in the sky. The sun sets in the sky in winter. In a highly productive solar region such as central Colorado, which receives an annual saturation of 2000 kWh/m2/ [21] this panel is expected to produce 400 kWh of energy annually. However, in Michigan, which receives only 1,400 kWh/m²/year [21] annual energy productivity will drop to 280 kWh for the same panel. In northern European latitudes, yields are much lower: 175 kWh of annual energy production in southern England under the same conditions.[22]

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Several factors influence the value of cell conversion efficiency, including its reflectance, thermodynamic efficiency, charge carrier separation efficiency, charge carrier collection efficiency, and conduction efficiency values. [23].

I.2.6 Effect of climatic condition on photovoltaic performance

I.2.6.1 Effect of the intensity of solar radiation on the output of the solar cell

Solar radiation indirectly affects the voltage and current of the solar cell, since a higher value of the intensity of solar radiation also activates the temperature of the solar cell. The higher the intensity of solar radiation, the external voltage supporting the cell, the sun, its beginnings, the less affected by solar radiation [24].

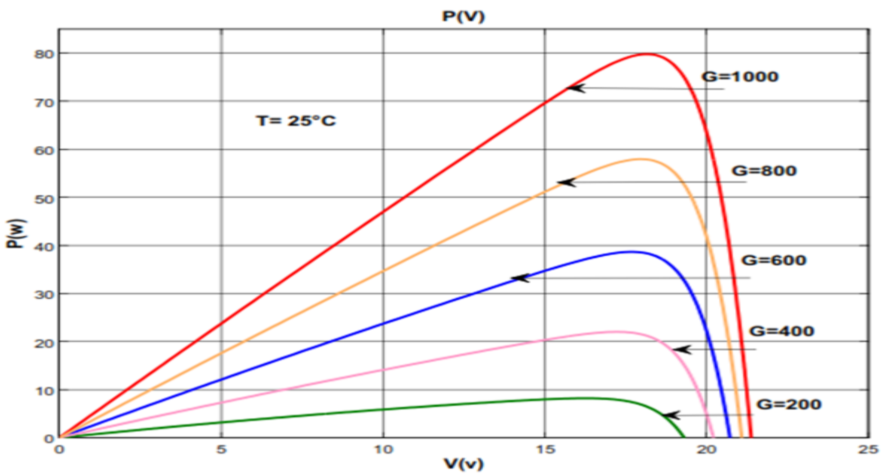


Figure I-6: the effect of the intensity of solar radiation on the properties of (P_V)

I.2.6.2 temperature effect

Higher temperature leads to higher temperature The open circuit voltage of the photovoltaic cell, which results in a slight increase in the short circuit of the solar cell, [25]as shown in the Figure I 7

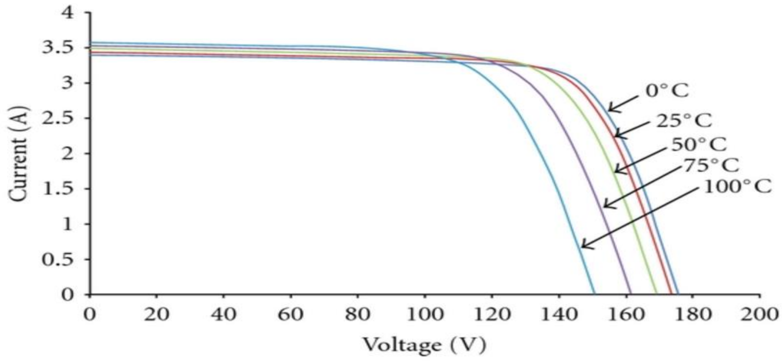


Figure I-7: the effect of temperature on properties of (V_I)

I.2.6.3 Wind effect

The wind movement does not directly affect the performance of the solar cell, but rather effects the surface temperature of the solar cell and thus affects the its internal temperature. And since the wind movement affects the convection currents and thus works to raise the heat transfer coefficient in pregnancy, which in turn helps in the transfer of heat from the cell surface to the external environment, and this leads to a decrease in the internal temperature cell and thus improves its efficiency [26].

I.2.6.4 Shadow Effect

The shade that may form on the solar panels is one of the most important factors that must be taken into consideration when building systems The solar panel, as the shade formed on the surface of the solar panel reduces the amount of solar radiation falling on the panel and thus lead to a decrease in the electrical energy produced by the solar panel, as the value of the electrical energy produced is proportional to With the size and shape of the shadow formed on the surface of the solar panel [27].

I.2.7 Advantage and disadvantage of photovoltaic

I.2.7.1 Advantages [28] [29]

- Reliable system
- Low cost of operation and maintenance
- Low maintenance
- Free energy source
- Clean Energy

- Does not cause environmental impacts Environmental friendly
- Potential to mitigate emissions of greenhouse gases

I.2.7.2 Disadvantages [30] [31]

- Limitations in the availability of systems on the market
- High initial cost
- Needs a relatively large area of installation
- High dependence on technology development
- Geographical conditions (solar irradiation)

I.3 Artificial Neural Networks

A thorough understanding of the architecture of neural networks is important to avoid disappointing results and, thus, identify and establish better parameters to improve the network performance. Therefore, this section describes the fundamentals of artificial neural networks [32]

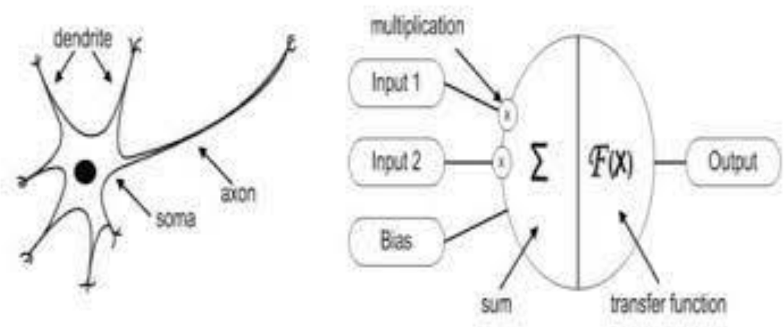


Figure I-8: biologic and artificial neuron designs

The design and functionality of artificial neurons arise from the observation of complex biological neurons in which distributed information is processed in parallel by the mutual dynamic repetitions of neurons. Accordingly, there are some similarities between biological neural network and artificial neural network and one can check them in Figure I 8. In biological neurons, information enters the neuron through the dendrites, the soma processes it and passes it through the axon. Similarly, in an artificial neural network, the information comes from the inputs being weighed. Thus, in the artificial nervous body, the weighted inputs and biases are collected and processed by the transmission function. After it is processed, the information is passed through the outputs

Different learning rules can be chosen and applied, therefore, the weights and biases are parameters that are adjustable so that the input/output of the neuron achieves a certain end. In any artificial neural network model, it is important to consider the structure of the nodes, the network topology, and the learning algorithm. Therefore, a broader view of mathematics, fundamentals and algorithms will be presented [32].

I.3.1 Artificial Intelligence

Artificial intelligence is an area of computing that is primarily focused on transferring anthropomorphic intelligence and thinking into machines that can help humans in many ways. Artificial intelligence was the term John McCarthy used in 1956. Artificial intelligence has slowly spread and become stronger in many fields such as engineering, mathematics, physics and technology, all of which have led to the current massive transformation in this field that we are witnessing now.[33]

This is an idea that suggests that a machine can acquire intelligence. It includes areas such as machines that can learn on their own, adapt to certain conditions and self-correct their mistakes. That is, machines may think on their own without being coded using commands.[34].

I.3.2 Machine learning (ML)

It is the study of computer algorithms that can improve automatically through experience and using data [35] and is considered a part of artificial intelligence. Machine learning algorithms build a model based on data samples, known as training data, in order to make predictions or decisions without being explicitly programmed to do so.[36]Machine learning algorithms are used in a variety of applications, such as medicine, email filtering, speech recognition, and computer vision, where it is difficult or unfeasible to develop traditional algorithms to perform the required tasks [37]

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of Mathematical Optimization introduces methods, theory, and areas of application in the field of machine learning. Data mining is a related field of study, with an emphasis on exploratory data analysis through unsupervised learning.[38].Some machine learning applications use data and neural networks in a way that mimics the functioning of the biological brain. [39] In its application across business problems, machine learning is also referred to as predictive analytics.

I.3.3 Regression

The regression task can be considered as a curve fitting problem, where the output variable is a discrete variable that takes values in an interval in the real axis or in a region in the plane of complex numbers. Having a data set that includes training points for yi and xi, where I can represent any real number above 1, it is possible to estimate a function f, whose graph fits the data[40]. If a new data point with an unknown output value occurs, the function can be used from the trained model to predict its output value Figure I.9 the effect of temperature on properties of (V_I) shows a simple example of linear regression where a new point is predicted using the function that is tailored to fit the available training data set.

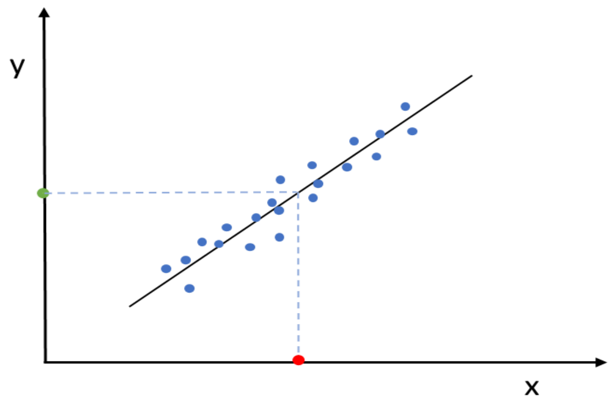


Figure I-9: linear regression example

The blue points in. Figure I.9 represents the training data and the red points on the x-axis represents a new point to the data set. The green point is the new output value ŷ,

I.3.3.1 Linear regression

In statistics, linear regression is a linear approach to modeling the relationship between a standard response and one or more explanatory variables (also known as dependent and independent variables). The case of one of the explanatory variables is called simple linear regression. For more than one process, the process is called multiple linear regression [41] and this term differs from multivariate linear regression, in which multiple correlated variables are predicted, rather than a single standard variable [42] .

I.3.3.2 Nonlinear regression

Nonlinear regression is characterized by the fact that the prediction equation is nonlinearly dependent on one or more unknown parameters. While linear regression is often used to build a purely empirical model, nonlinear regression typically arises when there are physical reasons to believe that the relationship between response and predictors follows a particular functional form [43].

I.3.4 Artificial Neural Network Architecture

A typical neural network contains a large number of artificial neurons called units, which are arranged in a series of layers. In a typical artificial neural network, different layers are formed

Input layer - contains those units (artificial neurons) that receive input from the outside world where the network will learn, recognize, or otherwise manipulate. Output layer - contains mod Hidden Layer - These units are located between the input and output layers. The function of the hidden layer is to convert the input into something that the output unit can use in some way.

Connecting neural networks, which means that each hidden neuron is completely connected to each neuron in its previous (input) and next (output) layerules that respond to information about how any task has been learned.[44].

I.3.5 Training

A key aspect in the implementation of artificial neural networks is the training. This process must be well designed so that the network successfully learns a task. However, one should understand that a precise definition of training is difficult to achieve because there is no direct approach on how to do [45] this learning process consists in the adjustment of the weights under some learning rules. Essentially, the free parameters from a network are adapted, through a stimulation process. When a group of patterns is presented, the network typically learns

The connection weights and the performance is improved by iteratively updating the weights. The network learns to recognize the pattern inherent to the training signals.

I.3.6 Applications of ANN

Artificial neural networks have found applications in many disciplines due to their ability to reproduce and model nonlinear processes. Application areas include system identification and control (vehicle control, lane prediction [46] process control, natural resource management), quantum chemistry [47] general game playing [48] pattern recognition (radar systems, face identification, signal classification [49] 3D reconstruction [50] object recognition and more), sensor data analysis [51] sequence recognition (gesture, speech, handwritten and printed text recognition[52]), medical diagnosis, finance [53] (e.g. automated trading systems), data mining, visualization, machine translation, social network filtering [54] and e-mail spam filtering. ANNs have been used to diagnose several types of cancers [55] and to distinguish highly invasive cancer cell lines from less invasive lines using only cell shape information [56].

I.3.7 Advantages and disadvantages ANN [57]

I.3.7.1 Advantages of ANN

►Storing information on the entire network: Information such as in traditional programming is stored on the entire network, not on a database. The disappearance of a few pieces of information in one place does not prevent the network from functioning.

► Ability to work with incomplete knowledge: After ANN training, the data may produce output even with incomplete information. The loss of performance here depends on the importance of the missing information.

► having fault tolerance: Corruption of one or more cells of ANN does not prevent it from generating output. This feature makes the networks fault tolerant.

► having a distributed memory: In order for ANN to be able to learn, it is necessary to determine the examples and to teach the network according to the desired output by showing these examples to the network. The network's success is directly proportional to the selected instances, and if the event cannot be shown to the network in all its aspects, the network can produce false output.

► Gradual corruption: A network slows over time and undergoes relative degradation. The network problem does not immediately corrode immediately.

I.3.7.2 Disadvantages of ANN

► Hardware dependence: Artificial neural networks require processors with parallel processing power, in accordance with their structure. For this reason, the realization of the equipment is dependent.

► unexplained behavior of the network: This is the most important problem of ANN. When ANN produces a probing solution, it does not give a clue as to why and how. This reduces trust in the network.

► Determination of proper network structure: There is no specific rule for determining the structure of artificial neural networks. Appropriate network structure is achieved through experience and trial and error.

► Difficulty of showing the problem to the network: ANNs can work with numerical information. Problems have to be translated into numerical values before being introduced to ANN. the display mechanism to be determined here will directly influence the performance of the network. This depends on the user's ability.

I.4 Literature review

Gómez et al [58] studied Photovoltaic Power Prediction Using Artificial Neural Networks and Numerical Weather Data, The main objective of this study was to evaluate the applicability of the GDAS flux numerical weather model as a replacement for in situ weather measurements to model the power outputs of a photovoltaic system. Three training and testing scenarios, with different combinations of monitoring and GDAS weather data, were used to feed and evaluate the performance of one prediction model using a multilayer perceptron ANN algorithm. Solar irradiation and air temperature were the main input variables, while PV power production was the only predicted output. Bias errors on individual days tended to be compensated when considering more complete temporal samples. This happened both on the weather inputs and the PV power outputs. Mean RMSE values of 2.9% and 9.9% on PV outputs were achieved for the most representative testing sample in the first and second scenarios, respectively. A comparison led to the conclusion that most of the power prediction errors were due to the approximate nature of the GDAS solar irradiation data. However, the 100.00 W/m2 mean RMSE error achieved for this weather variable was in accordance with other solar irradiation forecast methodologies included in the bibliography. The neural network model used was shown to model the real power system with solid

Saberian,et al [59],studied Modelling and Prediction of Photovoltaic Power Output Using Artificial Neural Networks Power prediction for photovoltaic panels is needed for accurate power planning. In this paper, the generated power of a solar panel has been estimated using mathematical equations. Afterward, the meteorological data and estimated power have been used for training GRNN and FFBP. Both of these neural networks have shown good modelling performance; however,FFBP has shown a better performance compared to GRNN

Dolaraand et al[60]studied A Physical Hybrid Artificial Neural Network for Short Term Forecasting of PV Plant Power Output Forecasting tools play a crucial role for solving problem related to RES energy integration in smart grid models. In this paper a new hybrid forecasting method, by means of an artificial neural network mixed with the clear sky solar radiation model is presented. The results from the error assessment, according to the error definitions here explained, lead to the conclusion that the hybrid method is more accurate than just the ANN even changing some settings in the neural network. Besides it has been emphasized that the accuracy of these methods, ANN above all, is strictly related to the historical data preprocessing phase and to the accuracy of the historical weather forecast data used for the training phase. The trend of the errors clearly shows how the accuracy in all the considered day-types is higher with PHANN in comparison to the ANN method, although in partially cloudy and cloudy days the overall efficiency decreases. Some improvements are therefore connected to the reliability of the weather forecast and to the pre-processing of the raw data used to train the network. Additional research directions for future works will include day clustering in the training dataset, to properly forecast the next day production according to the specific day-types.

Lee et al [61] studied Recurrent Neural Network-Based Hourly Prediction of Photovoltaic Power Output Using Meteorological Information, by using the experiment results from a real-world dataset, although the proposed ANN-based model fails to result in better performances compared to the conventional models, the proposed DNN-and LSTM-based models outperform them. Especially, the LSTM-based model shows quite successful performances for most of the experiment settings. Moreover, for the days that involve many changes of PV power outputs, the proposed LSTM-based model yields much better results than the others. In this paper, the PV power outputs on a particular day are assumed to be independent of those on another day, while the output at a particular hour depends on that during its previous hour. We note that incorporating information from previous hours and previous days would be helpful to improve prediction quality as suggested in, but it becomes very difficult due to the increased parameters to be learned. Therefore, to improve the performances of the proposed LSTM-based model in Section 2.3, we plan to utilize these information through enhancing techniques for more sophisticated prediction learns as a future study. Further, based on the models suggested in this paper, we plan to further improve the proposed models towards PV power output prediction without metrological information. Since there still exist many areas where such detailed metrological information is unavailable, we believe that these prediction models are much practical

Konjić et al [62] studied Artificial Neural Network Approach to Photovoltaic System Power Output Forecasting Results demonstrate that simple artificial neural network, such as MLP trained by LM learning algorithm, is able to predict the PV power output with acceptable accuracy. In terms of needed database for model development, it was shown that seasonal database is more suitable than yearly database. In the paper, data of summer seasons was used. However, the same procedure could be repeated for other seasons. Presented models with up to three hidden layers, four neurons per layers and tansig and logsig activation functions gave approximately similar errors in the case of seasonal database. Confidence interval was adopted around forecasting curve. The result offers a high confidence level of prediction that is important and useful for system operation, planning and power management.

Lo Brano et al [63] studied Artificial Neural Networks to Predict the Power Output of a PV Panel PV module in real conditions. Data used to train the networks were acquired using two different types of PV modules connected to calibrated electrical loads. Climatic variables were acquired by means of a weather station. The performances evaluation of the ANNs was performed by comparing the prediction with the real power output and the errors were generally contained within the 0.05–1% of the module peak power output. ANNs with simpler architecture generally required longer training time while more complex ANNs have requested shorter training time. Results show that adaptive techniques are able to predict the power output of a PV panel with great accuracy and short computational time. These algorithms can play a dominant role concerning remote management of PV in a probable future when this technology will be extremely widespread in the territory

Wang et al [64] studied Improved artificial neural network method for predicting photovoltaic output performance to ensure the safety and stability of power grids with photovoltaic (PV) generation integration, it is necessary to predict the output performance of PV modules under varying operating conditions. MANN, to predict the output performance of a PV module under varying operating conditions. The four-ANN model is built with different solar irradiance and module temperatures. Each neural network is a traditional three-layer feed-forward neural network. The inputs are the solar irradiance and module temperature, and the outputs are the fives parameters of the single diode model. The neural network is trained using experimental data under different operating conditions. Using the proposed method, the I–V characteristics are determined from the solar irradiance and temperature without solving any nonlinear implicit equation the proposed MANN is applied to experimental data and compared with a single-ANN. The results indicate that proposed MANN method has a more accurate output performance prediction, including the I–V and P–V curves and the maximum power point, than the single-ANN

Celik et al [65]studied artificial neural network modeling and experimental validation of operating current for single-crystal PV modules.

. The success of analytical models largely depends on the accuracy of some characteristic parameters of photovoltaic cells, such as Rso and Rsho, which are not provided by module manufacturers and it is a laborious process to determine their exact values.

. The five-variable model in use is currently one of the most popular analytic models in reading and writing. With the current results given by the mean absolute error values, it can be concluded that although the model provides reasonable accuracy in most cases, there is still room for improvement. To improve the analytical models, they suggested quantifying the models' sensitivity to cell temperature with higher accuracy, especially at solar noon, when most energy is produced on a given day.

. It is evident from the literature that artificial neural networks are increasingly being applied to solve a variety of engineering problems including time-series prediction, control, modeling, optimization, etc. The generalized neural network regression model has been successfully used in the present article to predict the operating current of a PV module. They chose the realized regression neural network as the most successful model from a number of networks, such as Multilayer Perceptron, Generalized Feed forward and Multilayer Perceptron.

. The general conclusion is that, as indicated by the average absolute error percentage values, the neural network generalized regression model resulted in a more accurate stream prediction than the five-variable analytical model. Therefore, it can be used for design and/or optimization purposes for PV systems

Sun et al. [66]studied a research on a short-term module temperature prediction model based on BP neural network for PV prediction, and it has a significant impact on the prediction accuracy of PV that can help the power network to accommodate more renewable energy resources. However, the unit temperature is affected by many factors and exhibits strong variability and discontinuity, which means that it is very difficult to predict the unit temperature in a direct way. Using the stepwise method, we can reduce the difficulties by dividing the direct prediction procedure into several independent steps. Meanwhile, the physical significance of the effect on the temperature of the PV module can be represented more clearly. Moreover, the BP neural network is suitable for the properties of influencing factors and mapping the relationship between factors and unit temperature. Thus, they proposed a unit temperature stepwise prediction model based on the BP neural network and the stepwise prediction method in this paper. The result of comparison with the traditional direct model shows that the proposed stepwise model shows better performance than the direct model. Provides a potential basis for further study.

I.5 Motivation

Nowadays, renewable energy sources have become of paramount importance in power gen- eration due to concerns regarding greenhouse gas emissions and environmental pollution issues that are consequences of excessive consumption of fossil fuel energy sources. Moreover, fossil fuel energy sources are limited and will run out someday in future. There-fore, it’s necessary to look for other sources of energy to substitute fossil fuels. By end of 2018, in some locations electricity generation from new wind and photovoltaic (PV) plants had become more economical than power generation from fossil fuel-fired plants. Also, in some places building new wind and solar PV plants cost less than continuing execution of current existing fossil fuel power plants. Since solar energy is a clean, available, free and renewable source of energy, deployment of PV panels has increased in recent years in order to generate electricity from solar energy. Due to interest of countries in investment of renewable sources of energies, it is likely that installment of PV panels continue to increase.

I.6 Conclusion

From what we studied, we found that predicting the power output of a photovoltaic (PV) unit using an artificial neural network has several effects, including wind, temperature, humidity and solar radiation intensity.

Where we have provided state-of-the-art system, general information about photovoltaics and artificial neural network (configuration, operating principle, characteristics, etc.), as well as advantages and disadvantages of photovoltaic and artificial neural network.

CHAPTER II : MATHEMATICAL MODELING

II.1 Introduction

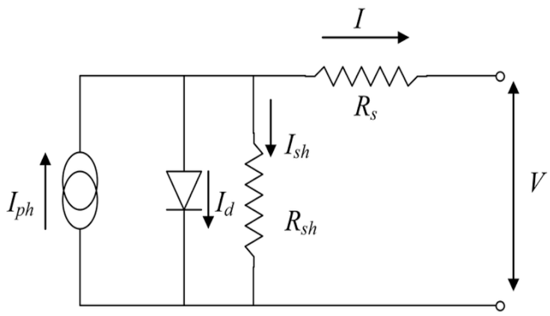
Photovoltaic energy is the result of converting solar radiation into electricity through photovoltaic panels, a group of solar cells linked in series.

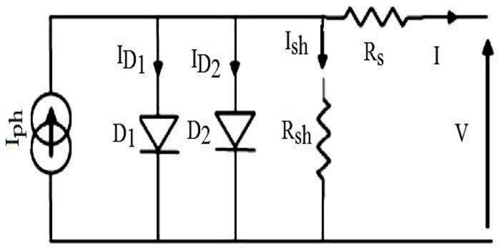
In this chapter, we will present different equations for the photovoltaic cells and the artificial neural network, where we will observe the mathematical equations for current, voltage, and energy P and the learning process of the artificial neural network.

II.2 Modeling of the photovoltaic cell

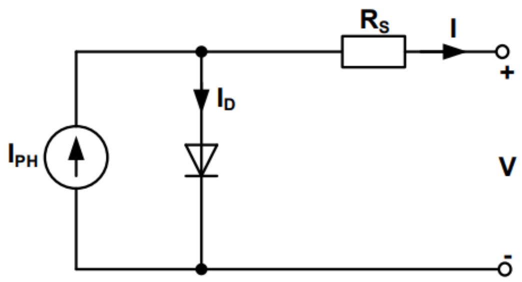
II.2.1 Electrical models of PV panels

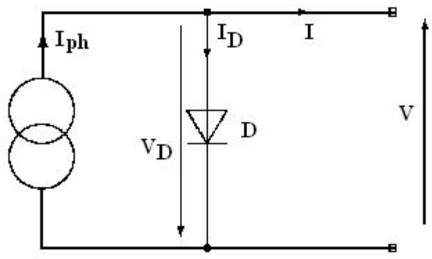
Photovoltaic modeling can be done according to different levels of complexity. It is a matter of obtaining an equivalent circuit for a photovoltaic cell. There are several types of models for modeling solar cells. Each model will give the different types of mathematical equations due to the different number of components in the circuit. Figure II.1 shows four types of photovoltaic cell models.





a) General model b) Double diode model





c) Appropriate model d) Simplified model

Figure II-1: equivalent diagram of a PV cell

The single diode model offers a good compromise between simplicity and precision. This model has a current source, I_{Ph}, which depends on solar radiation and temperature, a diode in parallel whose inverse saturation intensity depends on the temperature and a resistance in RS series, which represents the effect of internal resistance and cell contacts. We can introduce more complexity into the model by additionally introducing a resistor in parallel with diode Rsh [67]The appropriate model was also used in a modeling to accomplish verification with the manufacturer's data sheet [68].

$$I = I_{ph} - I_d - I_{RH} \qquad \text{II.1}$$

According to the general model, we have this equation:

$$\mathrm{I} = I_{PH} - I_S\left[EXP\left(\frac{q(V + R_S I)}{KT_C A}\right) - 1\right] - \left(\frac{(V + R_S I)}{R_{RH}}\right) \qquad \text{II.2}$$

The appropriate model

$$\mathrm{I} = I_{PH} - I_S\left[EXP\left(\frac{q(V + R_S I)}{KT_C A}\right) - 1\right] \qquad \text{II.3}$$

IPH is current produced by cells

q = 1.6 × 10^{-19} C electron charge;

K= 1.38 × 10^{-23} J/K Constant

Tc is the working temperature of the cell;

A is a quality factor of the diode, normally between 1 and 2;

Rs and RSH are series and parallel resistors

The photo current produced by the modules depends linearly on the solar irradiation and is also under the influence of temperature

$$I_{PH} = \left(I_{ph,n} + K_I \Delta T\right) + \frac{G}{G_N} \qquad \text{II.4}$$

$$I_{ph,n} = I_{SC,n} \qquad \text{II.5}$$

With G: Lighting (W/m^2)

T: Temperature (K)

$I_{ph,n}$: Short-circuit current of the cell under standard conditions

Gn = 1000 W/m^2 and T =25°C =298 K

$$I_S = I_{RS}(\frac{T_C}{T_{ref}})^3 EXP\left[\frac{qT_G\left(\frac{1}{T_{ref}} - \frac{1}{T_C}\right)}{KA}\right] \qquad \text{II.6}$$

Where I_{Rs} is the reverse saturation current, E g is the bang-gap energy [69]

$$I_S = \frac{I_{SC,n}}{EXP\left(\frac{qI_{OC,n}}{N_C KAT_C}\right) - 1} \qquad \text{II.7}$$

From equation (6) and (7), we get:

$$I_S = \frac{I_{SC,n} + K_I \Delta T}{EXP\left(\frac{V_{OC,n+}K_V \Delta T}{V_t * K}\right) - 1} \qquad \text{II.8}$$

$$V_t = \frac{N_S K T_C}{q} \qquad \text{II.9}$$

II.2.2 Maximum power

The power supplied to the external circuit by the PV module under illumination depends on the load impedance; an external resistance is placed across the terminals of the unit. This force is the maximum operating point Pmax (Iopt, Vopt) of the current voltage [70]

$$P_{opt} = I_{opt}V_{opt} \qquad \text{II.10}$$

II.2.3 Energy efficiency

It is the ratio between the maximum electrical energy provided by a $P_{opt}(I_{opt},V_{opt})$ photovoltaic cell and the incident solar energy. Given by:

$$\eta = \frac{P_{opt}}{P_{inc}} = \frac{I_{opt}V_{opt}}{P_{inc}} \qquad \text{II.11}$$

Where P_{inc} is equal to the product of the illumination and the total surface of the solar cells. This parameter reflects the quality of conversion of solar energy into electrical energy [70]

II.2.4 Form factor

Known as the curve factor or the fill factor or the so-called form factor, it is the ratio between the maximum power provided by a P_{opt} cell (I_{opt}, V_{opt}) and the product of the short circuit current, I_{cc}, at the open circuit voltage V_{co}, i.e. the maximum power for an ideal cell. The form factor indicates the quality of the cell; the closer to unity the higher the cell efficiency, it was about 0.7 for efficient cells; it decreases with temperature. It is defined by [71]:

$$FF = \frac{P_{opt}}{I_{cc}V_{co}} = \frac{I_{opt}V_{opt}}{I_{cc}V_{co}} \qquad \text{II.12}$$

II.3 Mathematical formulation of artificial neural network

II.3.1 Transfer function

The activation function or transmission function controls the output amplitude of neurons and is based on the interactions of neurons with input values and depends on the activity level of neurons. This hypothesis is founded on the biological model, where each neuron is to some extent active at all times. Essentially, a neuron is activated when the network input exceeds the unique maximum value of the gradient assigned to the activation function, known as the threshold. Accordingly, near the set value, the activation function has a rather sensitive reaction. The activation function depends on the neuron's previous activation state and external input and is defined as

$$aj(t) = factj(net(t); aj(t-1), oj) \qquad \text{II.13}$$

This equation demonstrates how the network input net previous activation state $aj(t - 1)$ and the influence of the thresholOj is transformed into a new activation state$aj(t)$ It must be emphasized that though the threshold values are different for each neuron, the activation function embraces all neurons Two of the most commonly used activation functions in neural networks are the logistic and hyperbolic tangent function. Both functions are used because of the simplicity in finding its derivatives. Usually, these functions are applied in the hidden layer of the network. The logistic function

$$sigmoid(x) = \frac{1}{(1 + e^{-x})} \qquad \text{II.14}$$

Takes the input with any value between plus and minus infinity and maps the output to the range values (0, 1). The hyperbolic tangent: also takes the input with any value between plus and minus infinity and squashes

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad \text{II.15}$$

The output into the range -1 to 1. The selection of the activation function provides nonlinear limits to the hidden neurons and influences the performance of the networks. To avoid bad performances, one usually pre-processes the input data, for example, by normalizing the data

Another relevant function is the linear function

$$f(x) = x \qquad \text{II.16}$$

Where the inputs and outputs range from minus infinity to plus infinity, which it is generally used in the output layer of the network.

II.3.2 Neural Networks Architecture

A neuron is a non-linear and specific function of its input. The formation of nonlinear functions of two or more neurons is a neural network. The following sections introduce the different categories of neural networks

II.3.2.1 Feedforward Neural Networks

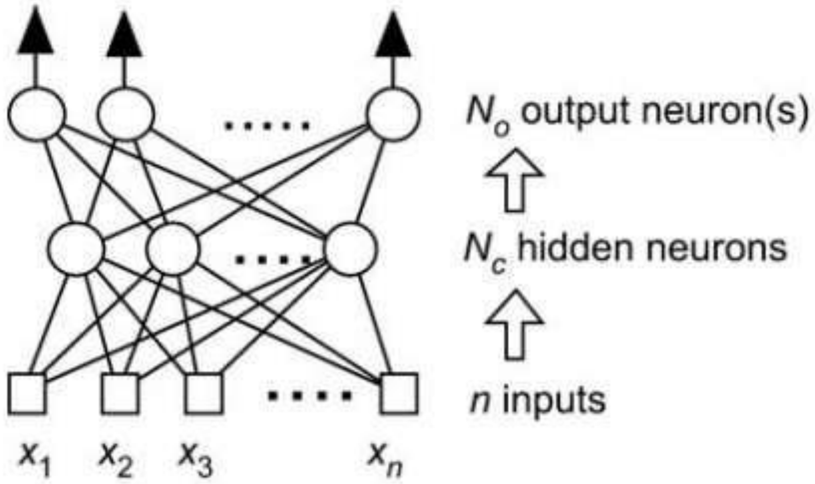


Figure II-2: feedforward neural network withe n inputs a layer of Nc hidden neurons and N0 output neurons [32]

A Feedforward neural network is a nonlinear function of its inputs, which is the configuration of the functions of its neurons. As Figure II.2 Shows, information via the connected neurons runs only in the forward direction, from input to output. Graphically, the vertices are the neurons and the edges are the connections; these types of networks do not have back loops. The term communication is obviously taken figuratively because the computations for each neuron are executed as software.

II.3.2.2 Multilayer Networks

The majority of neural network applications use multilayer networks with a structure akin to the figure in Figure II.2, which shows how the network computes the N0 functions of the network's input variables; each output is a nonlinear function of the nonlinear functions computed by the hidden neurons. In other words, in the Feedforward neural network the nonlinear functions N0 are calculated based on the previous calculation of the NC functions computed by the hidden neurons

Feeder neural networks are static neural network models, i.e. models applied to processes where the setting for each segment is determined in advance, and is not changed for that segment using in-process feedback. [72]

The following equations and Figure II.3 provide the structure and computations required to generate the output of individual multi-layer artificial neural networks.

$$n_1 = F_1(w_1 x_1 + b_1) \quad \text{II.17}$$

$$n_2 = F_2(w_2 x_2 + b_2) \quad \text{II.18}$$

$$n_3 = F_2(w_2 x_2 + b_2) \quad \text{II.19}$$

$$n_4 = F_3(w_3 x_3 + b_3) \quad \text{II.20}$$

$$m_1 = F_4(q_1 n_1 + q_2 n_2 + b_4) \quad \text{II.21}$$

$$m_2 = F_5(q_3 n_3 + q_4 n_4 + b_5) \quad \text{II.22}$$

$$y = F_6(r_1 m_1 + r_2 m_2 + b_6) \quad \text{II.23}$$

$$\begin{aligned} y = F_6[r_1(F_4\big[q_1 F_1[w_1 x_1 + b_1] + q_2 F_2[w_2 x_2 + b_2]\big] + b_4 + \cdots \\ + r_2\big(F_5\big[q_3 F_2[w_2 x_2 + b_2] + q_4 F_3[w_3 x_3 + b_3]\big] + b_6\big] \end{aligned} \quad \text{II.24}$$

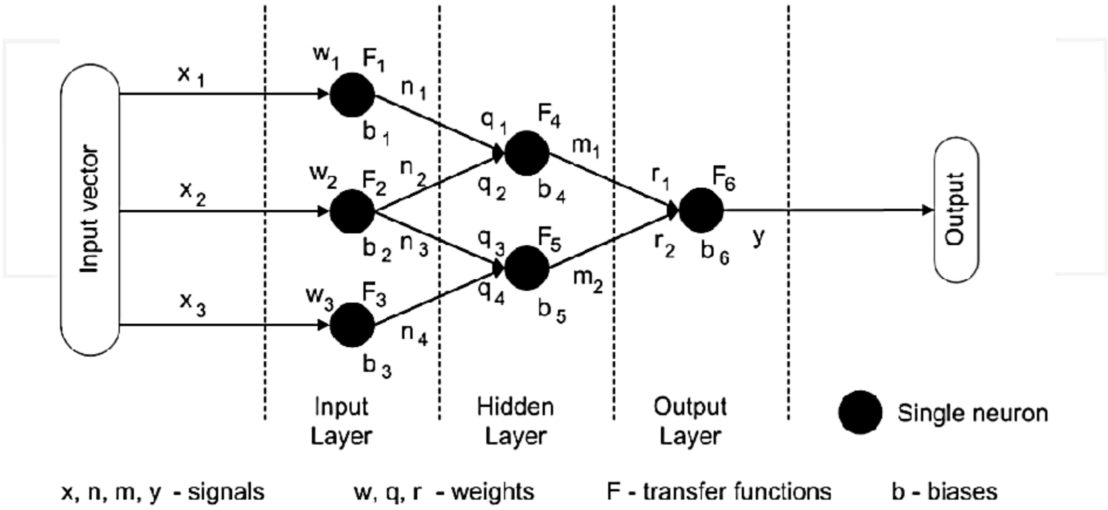


Figure II-3: multilayer artificial neural network [32]

II.3.3 Artificial neural network training

This network becomes ready for training once the network is structured for a specific application. To start this process, the initial weights are chosen randomly. After that, training or learning begins. There are two methods of training - supervised and unsupervised. Supervised training includes a mechanism for providing the network with the desired output either by manually “arranging” the performance of the network or by providing the desired output with the input. Unsupervised training is where the network must understand the input without outside help. The vast majority of networks use supervised training. Unsupervised training is used to do some initial characterization of the input [73].

II.3.4 Training Algorithm

One of the most important achievements in neural network training is the development of the steepest descent algorithm, also known as the inverse error algorithm. For each example in the training set, the algorithm calculates the error using a predefined error function, that is, the difference between the actual output and the desired output. After this process, the error is propagated again through the hidden nodes to adjust the weights of the inputs. This procedure is completed when the network approaches the minimum error resolution. Although this algorithm is widely used in neural networks, it presents some limitations, notably slow convergence and traps easily in local minima. [74] Where the gradient is very steep, step sizes should be taken small so that they do not go outside the required minimum. On the other hand, for a small fixed step size, the training process will be very slow when the gradient is gentle. The classic 'fault valley' can also occur when the curvature of the fault surface has different directions and thus can lead to slow convergence. However, the slow convergence of the steepest regression methods can be greatly improved by the Gauss-Newton algorithm which is able to find suitable step sizes for each direction and can converge very quickly by using the second derivatives of the error function to evaluate the surface error curvature. However, calculating the second derivatives poses computational complexity.

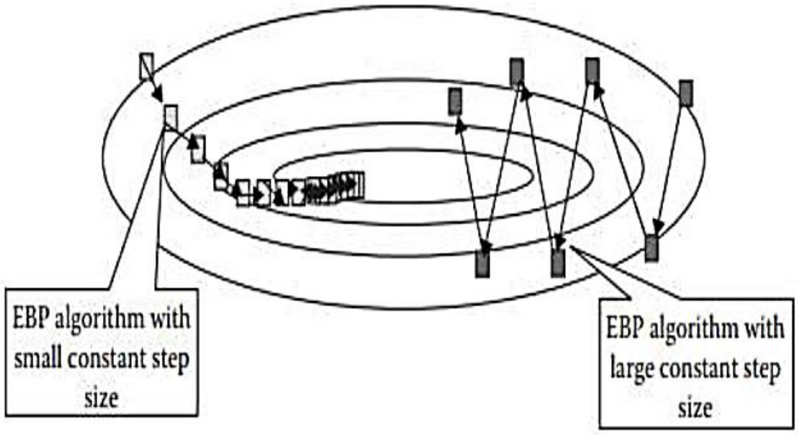


Figure II-4: steepest descent method with different learning constants the trajectory on the left is for small learning constant that leads to slow convergence the trajectory on the right is for large learning constant that causes oscillation

To solve these problems other learning algorithms such as Levenberg-Marquardt have been proposed which are suitable for small and medium-sized problems and have fast and stable convergence when compared to other methods. It combines extreme slope and Gauss-Newton algorithms. It has the stability of the steepest grades and the speed of the Gauss-Newton, but it is more powerful than the Gauss-Newton. The idea is to combine the two training processes so that the algorithm around the region with a complex curvature turns into the steepest descent algorithm, until the local curvature is suitable to complete a quadratic approximation; later, to speed up convergence, the algorithm roughly becomes the Gauss-Newton algorithm [75].

II.3.5 Backpropagation

Backpropagation is mostly used for training a feedforward neural network. It is believed to be the most accurate because it improves on itself by learning more [76] It was first invented in 1969 by Bryson and ho but was mostly ignored until the mid-1980s with famous article called Learning representations by back-propagating errors. Backpropagation is performed after an input vector is fed into the network to produce an actual network's output, and the actual output is compared with the desired output. If there is no difference between the two outputs, no further training is necessary, otherwise, the output is backpropagated and the weights are updated using gradient descent to reduce the differences between the actual output and the desired output.[77] Backpropagation is only used for computing the gradients of the cost function (error) through the network as it is mostly misunderstood for the whole learning algorithm in the network. To compute the partial derivatives of cost functions which composes of known gradients, the chain rule of calculus is used

The mathematical expression for backpropagation algorithm can be expressed as the partial derivative ∂C/∂w of the cost function C with respect to the weight w and bias b in the network [76]

II.3.6 Test performance of the model

Then, the next step was testing the performance of the developed ANN Model. In order to evaluate the ANN model proposed in this study, three error statistics used which were; the mean squared error (MSE), the mean absolute percentage error (MAPE), and root mean squared error (RMSE). The MSE represents the error between the actual and prediction output. Then, the MAPE was as accuracy indicator for the neural network. RMSE was used indicate the efficiency of the develop ANN Model in prediction. A large positive RMSE indicates that there was a big deviation in the predicted data from the measured data and the lower RMSE show the accurate of the prediction output. It also represents the measurement of the variation of the predicted data around the measured data [78] All the errors formula expressed in a percentage as defined as follow:

$$MSE = [0.5(Actual - Predict)^2] * 100\% \qquad \text{II.25}$$

$$MAPE = \left[\frac{1}{N}\sum\left(\frac{Actual - Predict)}{Actual}\right)\right] * 100\% \qquad \text{II.26}$$

$$RMSE = \left[\sqrt{\frac{1}{N} \quad \sum(Predict - Actual)^2}\right] * 100\% \qquad \text{II.27}$$

II.4 Conclusion

In the end, we got to know and introduced from the knowledge of the mathematical equations of PV (electrical models of PV panels, voltage, current, maximum power, efficiency) and artificial neural network (transmission function, neural network architecture, learning, training and backpropagation).

CHAPTER III : EXPERIMENTAL SETUP, RESULTS AND DISCUSSION

III.1 Introduction

In this chapter we will present a case study of this work first and describe the devices used for measurement in the studied experiment. In order for ANN models to be based on valid data points, since there are many weather parameters that are measured in situ such as ambient temperature, wind speed, and solar radiation, it would be appropriate to Investigate any of the variables of interest to the model and if there are any lags associated with these variables, it is worth looking into. The method for creating a model will be a model-based approach to create an optimal number of hidden neurons and hidden layers, depending on the performance parameters. Models should be tested using predicted weather parameters to monitor models performance by also including potential errors from weather forecast deviations.

After that, the input selection will be presented first along with the specification of the ANN model. Relevant results Model training will then be presented, followed by the results of the models being tested with the forecast weather data obtained (solar radiation, air temperature, wind speed, solar panel temperature)

The obtained model representations will be discussed in matlab software. All performance parameters are calculated based on standardized data. All model structures will be referenced without including the number of input variables

III.2 Description of solar panels

A solar panel, solar electric panel, photovoltaic (PV) module or solar panel is a group of photovoltaic cells mounted in a frame for installation. Solar panels use sunlight as an energy source to generate direct current electricity. The array of photovoltaic modules is called PV panel, and the system of photovoltaic panels is called array. Arrays of photovoltaic system supply solar electricity to electrical equipment

Most solar panels (correctly called "modules") are aluminum framed, topped with tempered glass, and sealed by a waterproof backing. Sandwiched between the glass and the support layers are the photo-reactive cells themselves, often made of silicon. On the back of the unit is a junction box that may or may not contain two cables. If the junction box does not have cables, it can be opened to access the electrical terminals where wires can be connected to conduct the generated electricity away from the unit. If there are cables already in place, the junction box is usually closed and not accessible to the user. Sealed junction boxes are more common.

III.2.1 Solar Cell Characteristics

III.2.1.1 Electrical Characteristics

Table III.1: Electrical Characteristics Solar Cell

Characteristics	**JSP 160**
Open-Circuit Voltage (Voc)	22,70 V
Optimum Operating Voltage (Vmp)	18,60 V
Short-Circuit Current (Isc)	9,08 A
Optimum Operating Current (Imp)	8,61 A
Maximum Power at STC (Pmax)	160 W
Cell Efficiency	18,3 %
Module Efficiency	16,2%
Maximum system Voltage	1000 V DC
Operating temperature	-40C° to +85 C°
Power tolerance	0/ +3 %

STC: irradiance 1000(w/m²) module 25C°AM=1.5

III.2.1.2 Mechanical Characteristics

Table III.2: Mechanical Characteristics

Type of Cell	**Poly-Crystalline 156*156mm**
Cells array and number	4*9(36pcs)
Dimensions	1480*669*35mm Cable:4mm²
Weight	12kgs
Front glass	3.2mm tempered glass
Frame	Anodized aluminium alloy
Encapsulation	Glass/EVA/Cells/EVA/TPT
Relative humidity	0 to 100%
Resistance	227g steel ball fall down from 1m Height and 60m/s wind
Wind and snow load parameters	5400Pa

III.2.1.3 Temperature Coefficient

Table III.3: Temperature Coefficients

Parameter	Value
Nominal Operating Cell temperature	(NOCT46C°±2C°)
Temperature Coefficient of Pmax	-(0,47±0,05)%⁄k
Temperature Coefficient of Voc	-(0,075±0,01)%⁄k
Temperature Coefficient of Isc	-(0,055±0,01)%⁄k
Maximum series fuse⁄current rating	15A

Figure III-1: solar panels

III.3 Multimeter

It is an integrated electronic measuring device that contains a number of measuring devices in one device. This digital device can be of an analog design similar to a galvanometer pointer.

This all-in-one device basically includes the following devices:

Ammeter - to measure: electric current.

Voltmeter - to measure: electrical potential.

Ohmmeter - to measure: electrical resistance

III.3.1 The components

This durable multipurpose electronic device (or VOM) typically consists of the following components:

DC Balanced Bridge Amplifier, PMMC Meter.

Attenuated in the income stage to choose the correct effort range.

Standardized for converting AC input voltage to a proportional value of DC.

An internal battery, and an additional circuit that gives the ability to measure resistance. Function key to select different standard functions of the meter such as voltage, current, resistance.

Figure III-2: multimeter

III.4 Solar power meter pyr 1307

It is used to measure the intensity of the total radiation through the hemispherical vision range of the measuring device, and it contains two hemispheres of transparent optical glass concentric, the inner half blocking the infrared radiation coming from the outer half, and in the middle of the device there are a number of conductive thermocouples consecutively to form a heat column (English: Thermopile).

The hot connection of the thermocouples is painted black and located on the upper surface (I.e. exposed to sunlight coming through the atmosphere), and the cold junction is facing down into the device and blocked from the sun.

The device contains a white glossy protection disc in order to prevent the thermocouple from being affected by a source other than the solar radiation to be measured. This device is calibrated to measure the total radiation on the horizontal surface.

And the pyrometer can be used to measure the scattered radiation only, by shading the ray receiving surface in the device to prevent the arrival of direct rays. And in this way it can be said that by using this device it is possible in an indirect way to know both direct and scattered radiation

Figure III-3: solar power meter pvr 1307

III.5 Anemometer air velocity Air flow

An air tachometer measures air velocity and air pressure. An anemometer is an instrument for measuring the velocity or velocity of gases either in a confined flow, such as the flow of air in an air stream, or in unconfined flows, such as an atmospheric wind. To determine velocity, it detects changes in some physical properties of the fluid or the effect of the fluid on a mechanical device being introduced into the flow. Depending on the type of application, the air tachometer and anemometer are manufactured as a hot wire AV meter or a sinusoidal weather AV meter, both of which can measure air velocity and air pressure. Air velocity measurement results can be stored in memory, depending on the model. Air tachometer is ideal for taking quick or static measurements, including monitoring ventilation installations, checking processes, suitable for industry, private workshops, navigation enthusiasts, or other hobbies, etc. at some level, or component of velocity in a particular direction.

Figure III-4: anemometer with air flow &air velocity metal vane

III.6 BTM-4208SD

III.6.1 Description

12 channels Temperature recorder SD card data logger.

Data can be down load to the Excel, extra software is no need

* Auto data logger or manual data logger. Data and LCD Backlight is OFF):

Data logger sampling time range: 1 to 3600 seconds.

* Sensor type: J/K/T/E/R/S thermocouple.

Optional Accessories:

* Type K thermocouple probe CAT #:

TP-01, TP-02A. TP-03, TP-04

* SD Card

* USB cable, USB-01.

* Data Acquisition software,

* AC to DC 9V adapter

* Hard carrying case

* Kit does not contain an SD memory card

Figure III-5: BTM-4208 SD

III.7 Data

To employ and train an ANN, a large database of specific data that represents the analyzed physical system is required. To achieve this goal,

Where the physical data used to train the ANN was as follows:

Air temperature Tair [∘ C]

Cell temperature Tc [∘ C]

Solar irradiance G [W/m^2]

Wind speed W [m/s]

The thermal system of the photovoltaic units was measured using thermocouples (T type, fixed copper) installed on the front and rear solar panels via the BTM-4208SD, where the temperature was recorded every 1 minute

The solar radiation of the photovoltaic units was measured using a solar power meter pyr 1307, where the solar radiation intensity was measured every 5 minutes

The current and voltage produced by the solar panel were measured using a multitimeter, where the recording time was every 5 minutes.

Wind speed and air temperature were measured using the ANEMOMETR Air velocity Air flow instrument, with the recording time being every 5 minutes.

III.8 Data preprocessing

Figures 1 2 3 4 show the measured time series on 12 - 05 - 2022 for photovoltaic systems converted into power (watts). And raw data for meteorological time series respectively. Systems time series provide many observations, point this out mostly

Days in ELoued are affected by climatic factors (solar radiation, ambient temperature, wind speed and cloud formations). It is clear that the variation in the radiation time series is very compatible with the shape of the time series of the PV system. Also, it can be seen that this meteorological data is positively correlated with the time series of the PV system because the temperature increases when a sunny day is detected and the opposite is also verified.

There is a direct relationship between ambient temperature and solar radiation. Although the efficiency of photovoltaic cells decreases with temperature, the effect of solar radiation is more likely. Therefore, one can say that there is a relationship between PV production and ambient temperature.

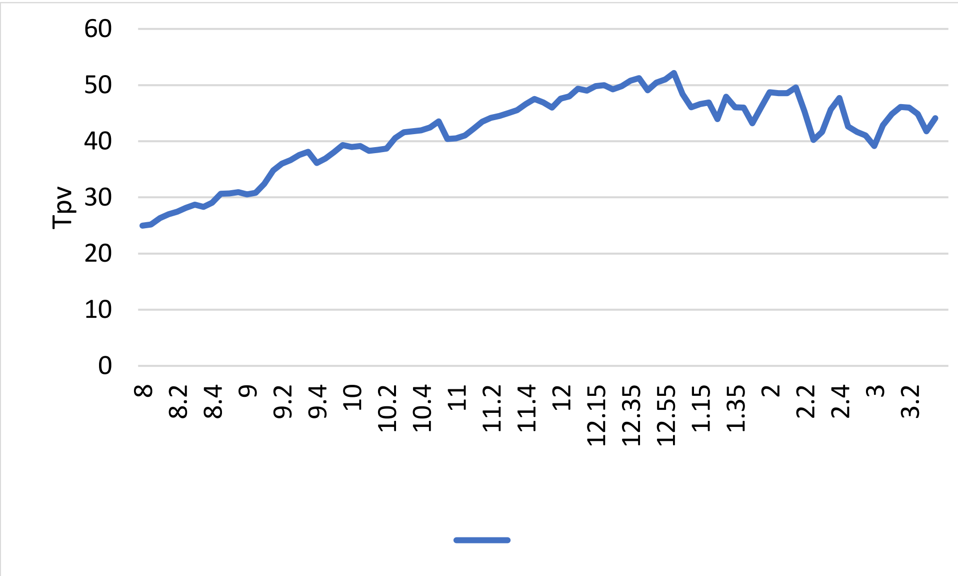


Figure III-6: solar panel temperature Tpv (C°) in terms of time (min)

Through the curve 1, we notice that the temperature of the solar panel Tpv is increasing over time [8:00, 12:55], reaching its peak (52 C°) at 1 o'clock in the afternoon, then we notice a decrease in the temperature of the solar panel in the rest of the time.

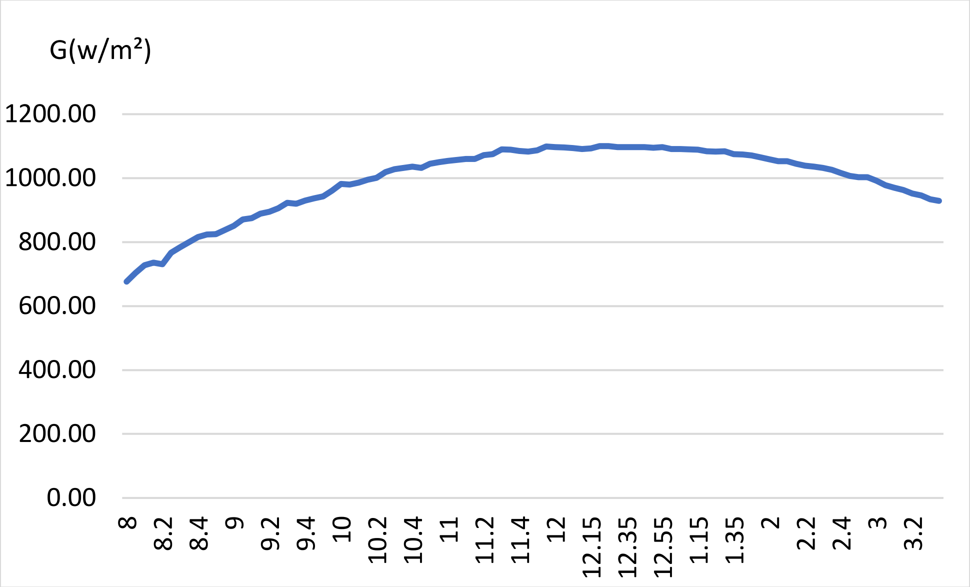


Figure III-7: intensity of solar radiation G (w/m²) in terms of time (min)

Through curve 2, we notice that the intensity of solar radiation increases over time, reaching its highest value (1100.13 W/m²) at 12.25 o'clock, then the intensity of solar radiation decreases during the rest of the time.

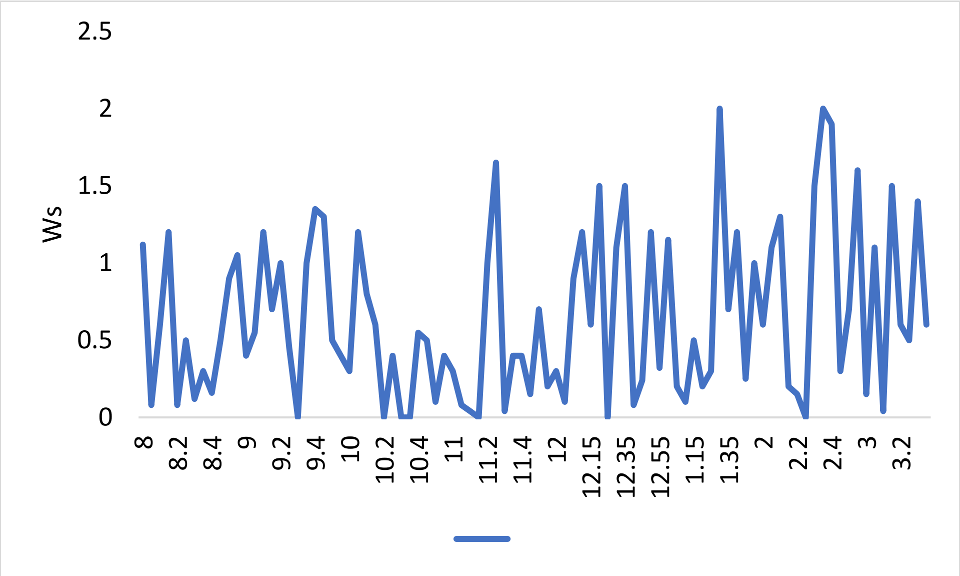


Figure III-8: wind speed Ws (m/s) in terms of time (min)

Through curve 3, we notice that the wind speed fluctuates during the measurement period, as this speed changes from one moment to another.

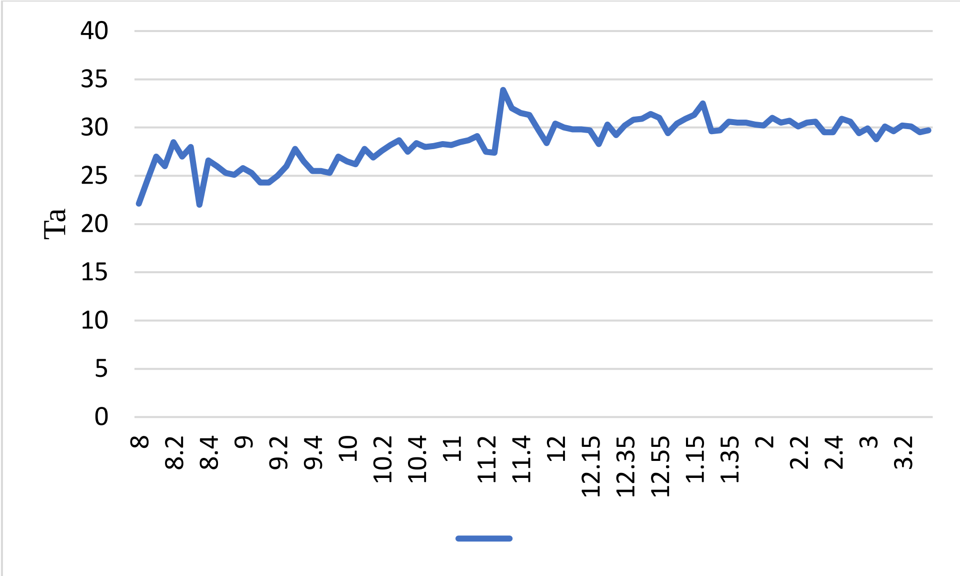


Figure III-9: atmospheric temperature Ta (C°) in terms of time (min)

Through the curve 4, we notice the increase in the temperature of the atmosphere Ta (C°) during time, reaching its maximum value in time11:30(min), then we notice a decrease in the temperature of the atmosphere in the rest of the time.

III.9 The non-linear relationship between input and output

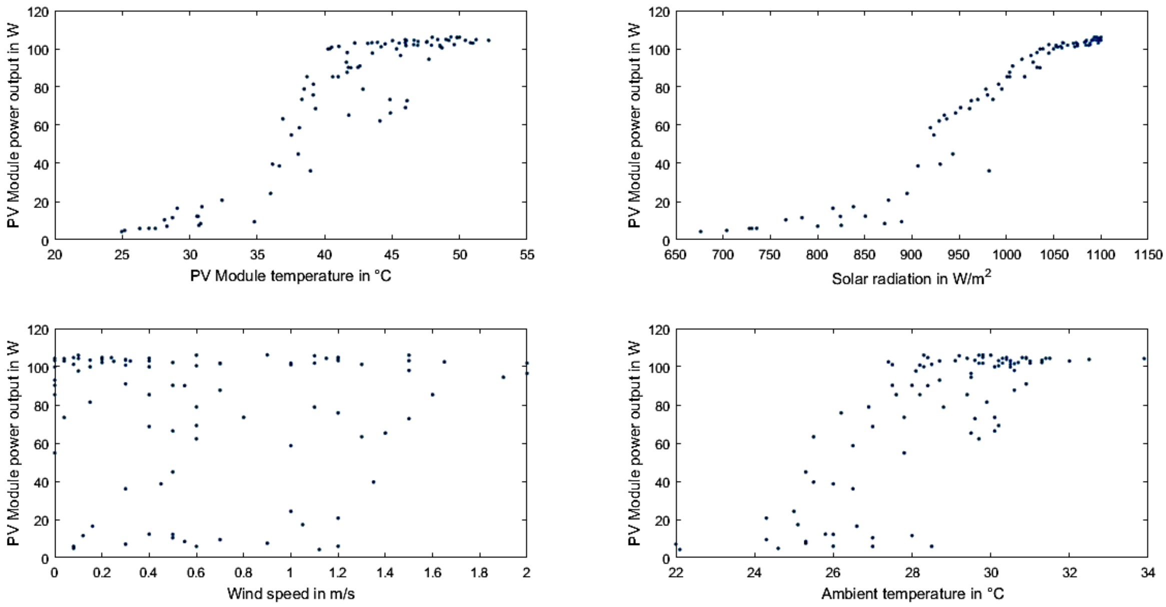


Figure III-10: energy curves in terms of variables (atmospheric temperature, solar radiation intensity, wind speed and solar panel temperature)

By observing the four curves, we obtained random results and values, meaning that there is no relationship between the inputs and the outputs, so we resort to using the artificial neural network because it is considered very accurate in predicting energy.

III.10 Structure and prediction accuracy of an artificial neural network

Based on previously explained criteria as an ideal configuration, the schematic structure of the model can be seen in Figure IV, it was constructed of three hidden layers with12, 9 and 6 neurons in each layer respectively, and the prediction results from the test set are shown in. Figure IV 7 We note that there is a good agreement.

This training (learning) process enables the NN to improve its performance and learn from its environment leading to minimizing the error between the actual output and the desired one, where the training process continues until the difference between actual output and target becomes very small.

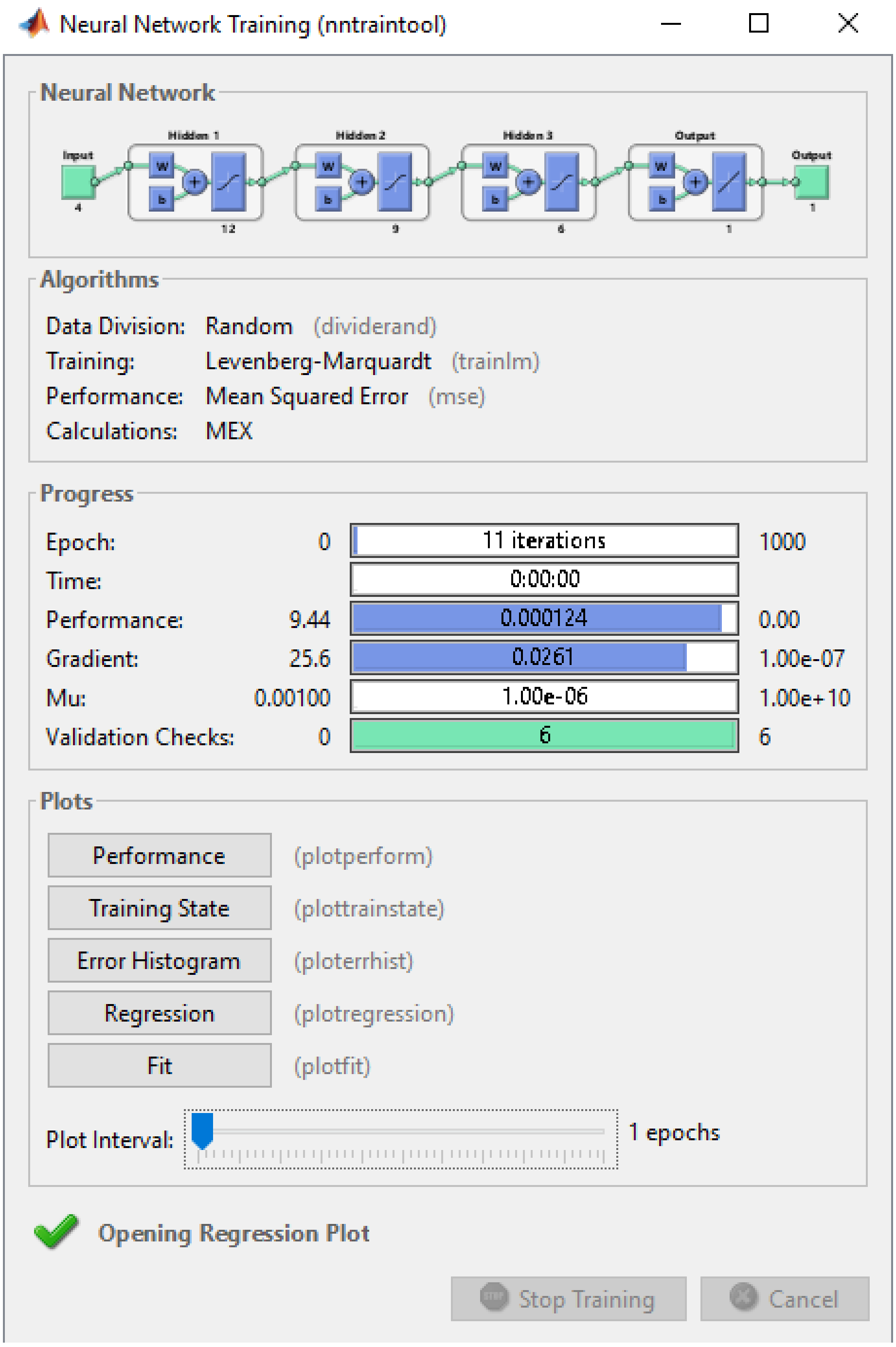


Figure III-11: neural network structure

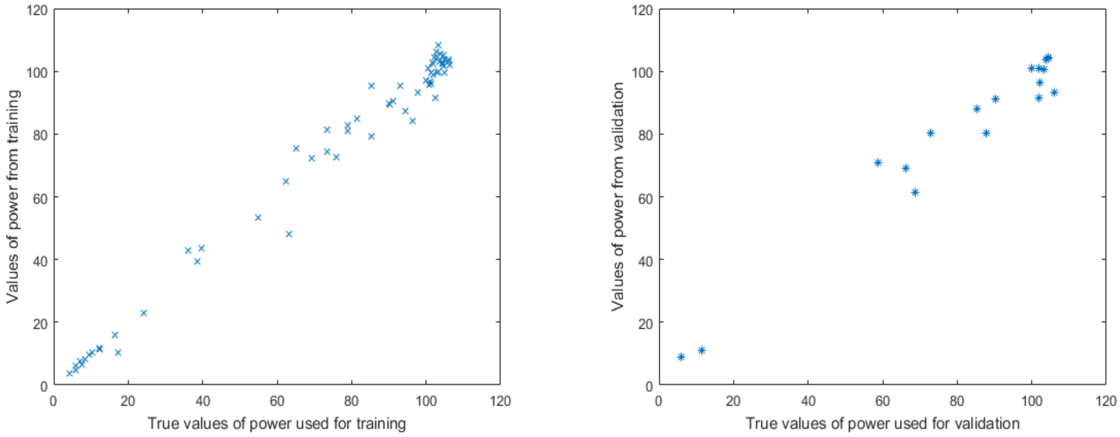


Figure III-12: artificial neural network prediction accuracy

III.11 Effect of the number of hidden layer neurons

Hidden nodes in the hidden layer that enable neural networks to distinguish a component, capture the instance in information and perform nonlinear convolutional mapping between information and production factors. The software allows us to get the best results for hidden neurons. The following Figure IV 8 shows the regression coefficient of hidden neurons which is approximately 1.

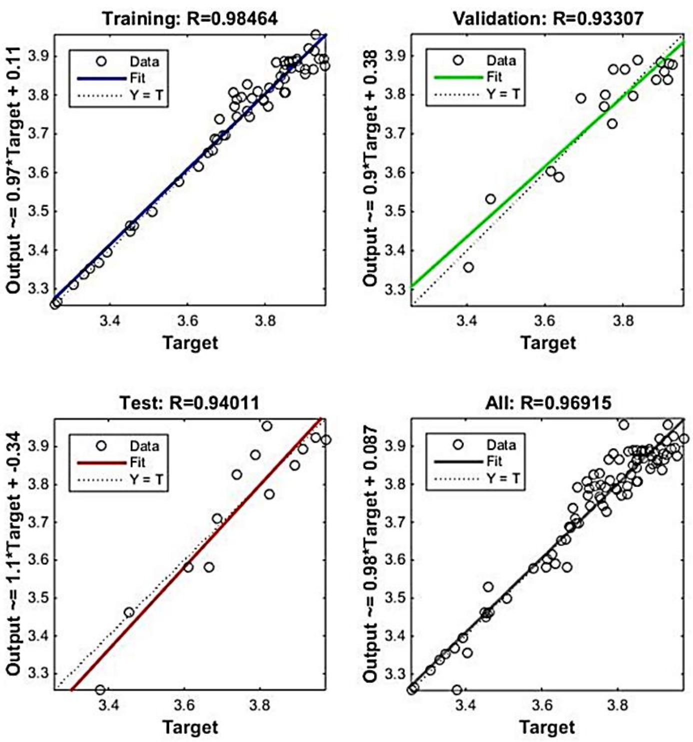


Figure III-13: regression coefficient for dye synthesized solar cell for the hidden neuron

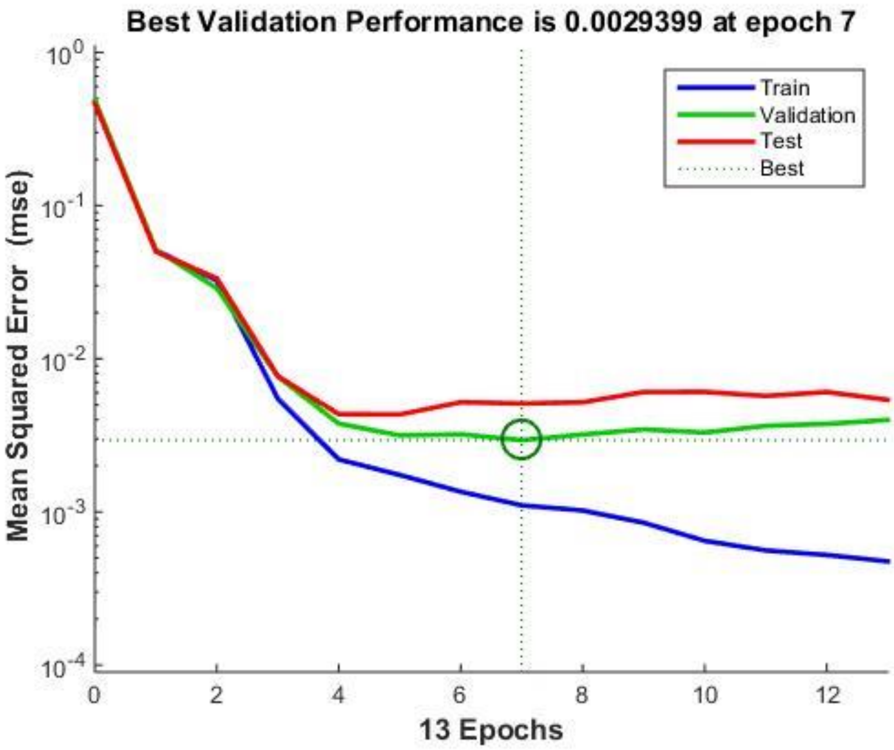


Figure III-14: the best performance of ANN model

Best Mean Square Error, MSE performance for this model it is 0.0029399 at ERA 13. However, the MSE value of the error it is still considered to be of immense value, meaning the differences between the output of the target and the ANN is higher. Stop training Standard is when validation stops decreasing at some point 1.3

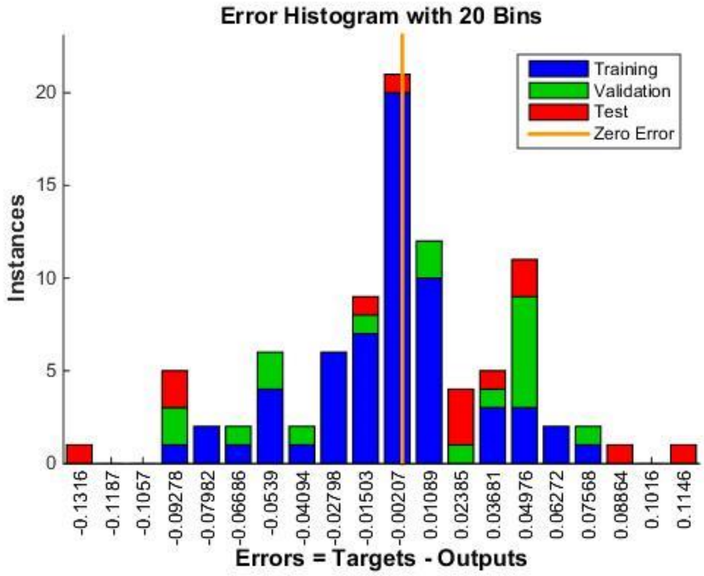


Figure III-15: error histogram with 20 bins

Error histogram is the histogram of the errors between target values and predicted values after training a feedforward neural network. As these error values indicates how predicted values are differing from the target values, hence these can be negative.

Bins are the number of vertical bars you are observing on the graph. The total error range is divided into 20 smaller bins here.

Y-axis represents the number of samples from your dataset, which lies in a particular bin. For example, at the mid of your plot, you have a bin corresponding to the error of -0.00207 and the height of that bin for training dataset lies below but near to 15 and validation and test dataset lies between 15 and 20. It means that many samples samples from you different datasets have an error lies in that following range.

Zero error line corresponding to the zero error value on the error axis (i.e. X-axis). In this case zero error point falls under the bin with centre-0.00207.

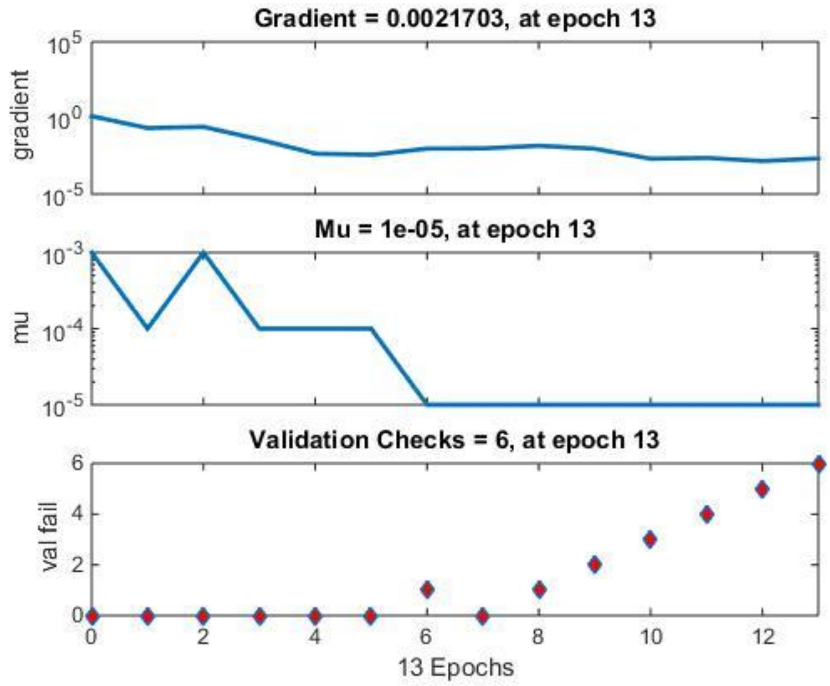


Figure III-16: neural network training state

At epoch 13, gradient = 0.0021703

Mutation = 1e-05

Validation check = 6

Validation check is applicable only to certain algorithm such as Back propagation.

III.12 Prediction of power output using artificial neural network model

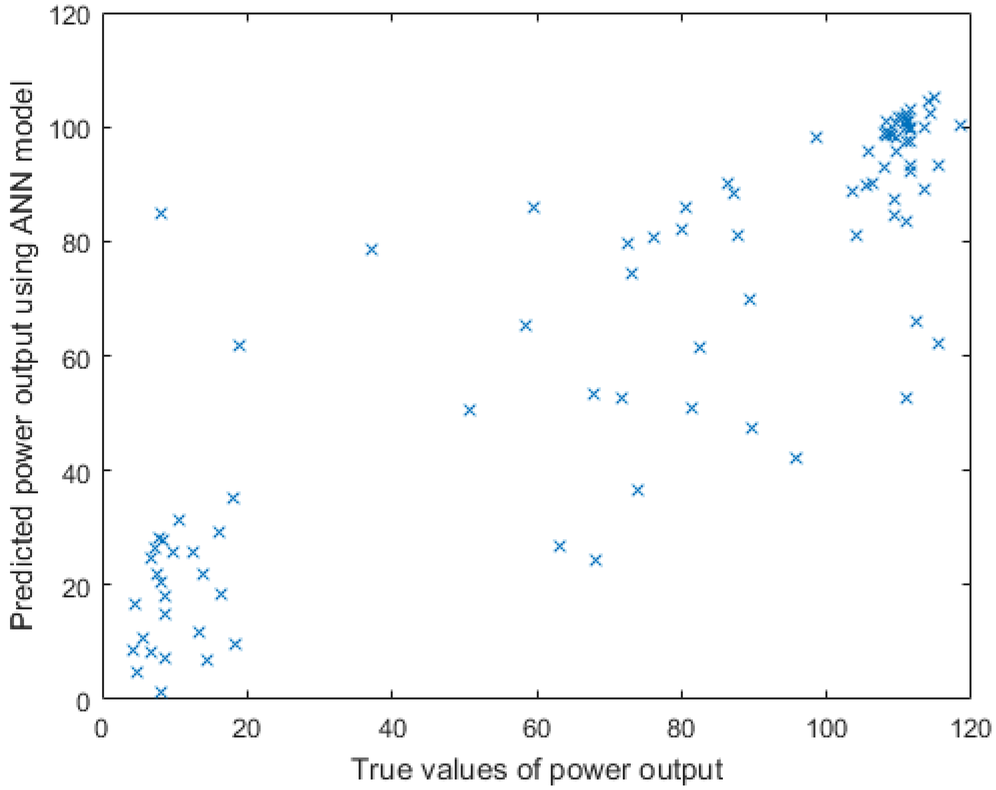


Figure III-17: prediction of power output using an artificial neural network model

The figure above represents a prediction of the power output using the artificial neural network unit in terms of the real values of the power output. We note that there is an agreement and correspondence in power output between the result of the artificial neural network and the photovoltaic cells, with some resulting uncertainties and errors that are due to the experimental errors, materials, and lack of data values.

III.13 Conclusion

In this chapter, we discussed the description of the solar panel and its characteristics, in addition to knowing all the measuring devices, including:

- Multimeter to measure current and tension

- pyr 1307 solar energy meter to measure the intensity of solar radiation

- Air Velocity ANEMOMETR AIR FLOW TO MEASURE WIND SPEED

- BTM-4208SD for Thermometer

A dataset from the PV system was used to train and test the ANN models in MATLAB. The preliminary data from the measurements contained many uncertainties, and therefore a comprehensive review was carried out

The remaining data was divided into subsets that are used for training, validation and testing purposes The ANN model enables prediction with high accuracy and good agreement with the results of the experiment.

GENERAL CONCLUSION

GENERAL CONCLUSION

This study aimed to apply neural network techniques to predict the energy generated by a photovoltaic system. According to the results of the study, it can be concluded that these networks have the ability to successfully carry around out of this task. Other partial conclusions obtained during the study are:

• Neural networks are tools that do not work with exact relationships, such as systems of equations. While that, it works by relating the input values to the output values using the intrinsic nonlinear relationships of Network. Therefore, it is very important that the input and output sample sets that are submitted to the network is well constructed and best represents the system that represents the network model. In addition to, before being sent to the network, this data must be processed by filtering methods, to eliminate defects Conic samples that deviate from the normal behavior of the system, and normalization methods, to avoid saturating the internal functions of the network.

• It is also important that the parameters chosen for the network (tolerance, learning rate, initial values of clamp weights) are correctly selected to allow the mesh to function in the best possible way. Initial guessing the weights is very important to ensure that the net reaches a good end result and does not get stuck at the local minimum points of the error function. Currently, there are several ways to help with this start Choose weights, such as those that use genetic algorithms to ensure that the network starts looking for them the perfect solution in an area that definitely includes the optimum point.

• An alternative to increasing the accuracy of network results for practical applications is frequent training network by updating the dataset with new metrics obtained from acquisition systems. This guarantees it the network remains up to date and it follows the development of the analyzed system. It was a structure using only real dynamometers as input. Future work In order to improve the energy prediction result, some actions that can be done are:

• Auxiliary methods can be applied in future studies to improve prediction accuracy. Among these methods a similar day's algorithm can be mentioned, which creates several training networks, one for each type from the weather condition (sunny, cloudy, partly cloudy day). This kind of method has already been applied successfully in literature. Its disadvantage is that it requires a large number of historical data and thus it can only be applied in longer studies.

• Using local weather data (radiation, temperature, wind) obtained from local measurements.

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ABSTRACT

Report title: Power output prediction of a photovoltaic (PV) module using artificial neural network

Master: Electromechanics

Authors: Ben Abdallah Abdelali -Tliba Mohamed El Azouzi - Ben amour Hicham -Selatna Mouad

Keywords: Artificial Neural Network (ANN); photovoltaic (PV) module; prediction; power

Abstract: In present work, a solar power modelling using artificial neural networks (ANN) is presented, for a precise prediction of generated output power of a PV module. Prediction process plays an essential aspect in many sectors of power system like in solar energy sources which is the current topic being discussed. Output power for solar energy system is a tough parameter to be predicted due to the influence of numerous parameters, fluctuations and due to the fact that parameters are dependent on each other which produces the nonlinearity problem. In this study, ambient conditions of PV module temperature, solar radiation, wind speed and ambient temperature are collected and then introduced to an artificial neural network to predict the output power.

Finally, after this study, we concluded that the artificial neural network has a good and accurate prediction ability, despite its difficulty

Résumé

Titre du mémoire: Prédiction de la puissance de sortie d'un module photovoltaïque (PV) à l'aide d'un réseau de neurones artificiels

Master: Electromécanique

Auteurs: Ben Abdallah Abdelali -Tliba Mohamed El Azouzi - Ben amour Hicham -Selatna Mouad

Mots clés: Réseau de neurones artificiels (ANN); module photovoltaïque (PV); prédiction; Puissance

Résumé: Dans le présent travail, une modélisation de l'énergie solaire utilisant des réseaux de neurones artificiels (ANN) est présentée, pour une prédiction précise de la puissance de sortie générée d'un module PV. Le processus de prédiction joue un aspect essentiel dans de nombreux secteurs du système électrique, comme dans les sources d'énergie solaire, qui est le sujet actuellement en discussion. La puissance de sortie du système d'énergie solaire est un paramètre difficile à prédire en raison de l'influence de nombreux paramètres, des fluctuations et du fait que les paramètres dépendent les uns des autres, ce qui produit le problème de non-linéarité. Dans cette étude, les conditions ambiantes de température du module PV, de rayonnement solaire, de vitesse du vent et de température ambiante sont collectées puis introduites dans un réseau de neurones artificiels pour prédire la puissance de sortie.

Enfin, après cette étude, nous avons conclu que le réseau de neurones artificiels a une capacité de prédiction bonne et précise, malgré sa difficulté

ملخص

عنوان المذكرة: توقع خرج الطاقة وحدة كهروضوئية باستخدام شبكة عصبية اصطناعية

ماستر: كهروميكانيك

المألفون: بن عبد الله عبد العالي – طليبة محمد العزوزي – بن عمر هشام – سلاطنة معاذ

كلمات مفتاحية: الشبكة العصبية الاصطناعية– الوحدة الكهروضوئية– التنبؤ – الطاقة

الملخص :في العمل الحالي ، يتم تقديم نمذجة الطاقة الشمسية باستخدام الشبكات العصبية الاصطناعية (ANN) ، من أجل التنبؤ الدقيق للطاقة الناتجة المتولدة من وحدة الكهروضوئية. تلعب عملية التنبؤ جانبًا أساسيًا في العديد من قطاعات نظام الطاقة مثل مصادر الطاقة الشمسية وهو الموضوع الحالي الذي تتم مناقشته. تعد الطاقة الخارجة لنظام الطاقة الشمسية معلمة صعبة يمكن التنبؤ بها بسبب تأثير العديد من المعلمات والتقلبات ونظرًا لحقيقة أن المعلمات تعتمد على بعضها البعض مما ينتج عنه مشكلة غير خطية. في هذه الدراسة ، يتم جمع الظروف المحيطة لدرجة حرارة الوحدة الكهروضوئية والإشعاع الشمسي وسرعة الرياح ودرجة الحرارة المحيطة ثم إدخالها إلى شبكة عصبية اصطناعية للتنبؤ بالطاقة الناتجة.

وفي الاخير بعد هذه الدراسة توصلنا الى انا الشبكة العصبية الاصطناعية لها قدرة جيدة ودقيقة في التنبؤ رغم صعوبتها