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Title

PV Power Forecasting using two of the most effective techniques.

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Abstract

Accurate forecasting of photovoltaic energy production from renewable resources is crucial for economic reasons. In this report we discuss the use of both Machine learning forecasting techniques SVM and ANNs techniques.

We compare between the two methods to predict the output of the PV output power, the data used consist of samples covering different weather conditions and error evaluation indexes RMSE MAE are used to determine the most efficient technique.

SVM Technique is implemented by three different equations: Linear, Quadratic and Cubic equations, the performance results shows a slight differences between the first two **MAE (9.2816% 9.9556%)**, **RMSE (12.562% 12.59%)** respectively while the last model outperforms its predecessors **MAE (8.7952%) RMSE (11.432 %).**

The second technique which is implemented by MLPs and Elman shows ever better performances and efficiency than previous models with error indexes **RMSE (6.79% 4.75%)**, **MAE (0.21720%, 0.112%)**, the Elman RNN is more accurate than the Multi-Layer Perceptron and sows better results on good weather conditions wile bot models sow unstable performance is much less suitable conditions.

The results of this report is to identify the best forecasting technique to be used in further esearch.

Acknowledgments

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Abbreviations	*Definitions*
RES	Renewable Energy Resources
NWP	Numerical Weather prediction
LCOE	Leveled Cost of Electricity
C & I	Residential and Commercial
DNO	Distribution Network Operators
TSO	Transmission System Operators
SVM	Support Vector Machine
ANN	Artificial Neural Network
RNN	Recurrent Neural Network
FFNN	Fast Forward Neural Network

MLP	Multi-Layer Perceptron
MA	Moving Average
AR	Auto-Regression
ARMA	Auto-Regressive Moving Average
ARIMA	Auto Regressive Integrated-Moving Average
NWP	Numerical Weather Prediction
MLR	Multi-Layer Regression
NMAE	Numerical Mean Average Error
MAE	Mean Average Error
RMSE	
PHANN	Root Mean Square Error
NARX	Physical hybrid Artificial Neural Network
GA	Nonlinear Auto-Regressive wit Exogenous inputs
PSO	Genetic algorithm
GSO	Particle Swarm Optimization
EBP	Genetical Swarm Optimization
ADF	Error Back Propagation

PACF	Augmented Dickey Fuller
RF	Partial Auto Correlation Function
LMS	Random Forrest
AFC	Linear Management System
AIC	Auto Correlation Function
AICc	Akaike Information Criterion
BIC	Corrected Akaike Information Criterion
SSE	Bayesian Information Criterion
SVR	Residual Sum of Squares
ERBF	Support Vector Regression
TDL	Exponential Radial Basis Function
	Tapped Delay Line

GENERAL INTRODUCTION

The world's electricity consumption is growing exponentially as a consequence of world population growth and increasing per capita demand, 5 years ago a study has shown that the global energy investment is in continuous decline, as evidence has shown comparable with respect to the previous years, mainly due to lower production of coal, hydroelectric, and nuclear power. All the while Photovoltaic (PV) systems became the fastest-growing renewable technology in the last decade with the largest investment [3]. The electricity produced by renewable energy sources (RES) especially by PV systems is constantly increasing worldwide thanks both to government policies and technological advancements. Europe has seen some of the fastest growth rates in recent years, and the production of renewable energy, especially photovoltaic power generation, has increased significantly. Due to the intermittent nature of the solar irradiance, the need for development of accurate forecasting techniques are essential in order to optimize the operation of these systems. The term "solar forecasting" is used in two senses; it stands for both solar irradiance and solar (mostly photovoltaic) power fore-casting [8]. PV power prediction is calculated based on irradiance prediction data obtained from sky or satellite images or numerical weather prediction (NWP) [2], or directly based on many possible predictors. On a small scale those who operate a residential and commercial industrial (C & I) PV plants specifically those who operate in a socket parity regime ,accurate forecasts enable the generation of power at a leveled cost of electricity (LCOE) that is less than or equal to the price of power from the electricity grid [18]. Furthermore, On the other hand, considering larger-scale plants the managers of utility-scale PV plants use the forecasts to optimally plan the downtime of plants for maintenance purposes. On the other hand, distribution network operators (DNO) and transmission system operators (TSO) also need reliable forecasts to deal with the uncertainty and fluctuations of the distributed photovoltaic generators connected to their networks. Deal with the intermittent nature of photovoltaic systems and avoid the problem of balancing power generation and load demand [11].Many researches focus on providing an accurate forecasting method in order to enhance reliability, and reduce costs by allowing efficient solar energy management. In recent years several power forecasting models related to PV plants have been published. These methods have been divided into many categories, one of which focuses on the forecast range. Common inputs can be historical measurements of power generation and meteorological parameters of a particular facility, including temperature, global horizontal irradiance on PV modules and the cloud cover above the facility. Additionally, forecasted variables from the numerical weather predictions are also considered. These forecasting horizons can be summarized in four categories [1]:

Very short-term: used usually for PV storage and control of electricity market (1 minute–a few minutes).

Short-term: used usually for decision-making problem in the electricity market and power system operation (1 hour–1week).

Medium-term: used usually for maintenance scheduling (1 month–1 year).

Long-term: used for long-term solar power assessment and facility planning (1–10 years)

Another way of classification is based on methods that are used extensively to perform the forecast which can be divided into three: The statistical, physical and hybrid methods The first one, the statistical or time series based method which relies of a large amount of historical data and its operation has no relationship with the type of PV plant or the location of its installation. These methods are characterized by a high degree of complexity, the commonly used ones are the SVMs (Support Vector Machines), ANNs (Artificial Neural Networks) such as MLP (Multi-Layer Perceptron) and regression methods, the last two being the most widely used. (ANNs) with a multilayer perceptron (MLP) architecture are of the most effective, as they solve specific kinds of problems [6], such as: pattern recognition, function approximation, control, and forecasting .ARIMA and ARMA are regression methods that rely on stationary and non-stationary data respectively. Physical methods is used in applications that range from very short to long terms, they use a theoretical simulation model to calculate the output power of a PV system based on its main design parameters. They operate at global scale and require steps of mathematical equations that are based on Numerical Weather Prediction (NWP) .Regarding its accuracy, evidence can be found for both lower and higher performance of the physical modelling compared to statistical methods [10].

Finally, the hybrid method is a combination of previous two techniques and by all studies outperform both previous methods when they are used individually to enhance forecasting calculations they require complex computation [10]. One of the most common hybridizations used is the ANN-NWP. Numerical weather forecasts are used together with the use of historical data of the meteorological variables typically lead to excellent forecasting [15].

Comparing between different methods is challenging as it requires historical data, weather conditions, the location and type of PV installation, for the sole purpose to find the most efficient method to predict the hourly power output as efficiently as possible with reducing cost to minimum levels.

CHAPTER 1

AN OVERVIEW OF

PHOTOVOLTAIC SYSTEMS

1.1 Introduction

Solar energy is one the most vital sources of renewable energy, and since our planet is running out of fossil fuels and many believe it will be scarce by the end of the century, The primary disadvantage of solar power is that it cannot be produced in the absence of sunlight .nonetheless the sun the source that will permit to ensure future for energy consumption. And PV systems are the tool that enables humanity to harvest this energy.

Photovoltaic systems are crucial in our daily lives, they transform solar energy into electricity by means of solar panels, therefore they are vital in our energy consumption, they help reduce the cost of energy consumption and also reduce environment damage exponentially.

In this chapter we will discuss the history of PV systems, their characteristics, their different parameters and how they operate.

1.2 A Brief History of PV

In 1839 Alexandre Edmond Becquerel observed the photovoltaic (PV) effect via an electrode in a conductive solution exposed to light [27]. It is instructive to look at the history of PV cells [28]. Since that time because there are lessons to be learned that can provide guidance for the future development of PV cells.

1.2.1 The Discovery Years

This 182 year history can be divided into six time periods beginning with the discovery years from 1839 to 1904. Table 1.1 gives the most significant events during this first period. In 1877, Adams and Day observed the PV effect in solidified selenium [29] and in 1904, Hallwachs made a semiconductor-junction solar cell with copper and copper oxide. However, this period was just a discovery period without any real understanding of the science behind the operation of these first PV devices.

1.2.2 Theoretical Foundation

A theoretical foundation for PV device operation and potential improvements was formulated in the second phase of the history of PV in the period from 1905 to 1950. Key events in this period were Einstein's photon theory [30], the adaptation of the Czochralski crystal growth method for single crystal silicon and germanium growth [31] and the development of band theory for high purity single crystal semiconductors [32,33]. The PV cell theory developed emphasized the importance of high purity single crystal semiconductors for high efficiency solar cells.

1.2.3 The First Single Crystal Silicon Solar Cell

The events between 1950 and 1959 That lead to the practical silicon single-crystal PV device were the Bell Lab's announcement of the Silicon solar cell [34] in 1954 with the Pearson, Chapin, and Fuller patent in 1957 for the 8 % efficient Silicon solar cell [35]. The foundation was now laid for the development of a variety of markets for PV.

1.3 Construction of Solar Cell

1.3.1 Materials and Construction

Materials used for PV Cell Thin layer of silicon is used on most of the solar cell which forms an electric field when sun light strikes on the cell. Types of silicon used in PV cell are:

- Single crystalline semiconductor
- Crystalline semiconductor

. In recent day advanced semiconductor materials are used for PV cells are

- Metallic element compound (GaAs).
- Cd chemical compound (CdTe).

1.3.1 Principle of Operation:

The Photovoltaic cell is a semiconductor device that converts light into electrical energy. The voltage induces by the PV cell depends on the intensity of light incident on it. The name Photovoltaic is because of their voltage producing capability .The electrons of the semiconductor material are joined together by the covalent bond. The electromagnetic radiations are made of small energy particles called photons. When the photons are incident on the semiconductor material, then the electrons become energized and starts emitting. The energized electrons are known as the Photoelectrons. And the phenomenon of emission of electrons is known as the photoelectric effect. The working of the Photovoltaic cell depends on the photoelectric effect.

1.3.2 Construction

The figure below shows the constructions of the silicon photovoltaic cell. The upper surface of the cell is made of the thin layer of the p-type material so that the light can easily enter into the material. The metal rings are placed around p-type and n-type material which acts as their positive and negative output terminals respectively.

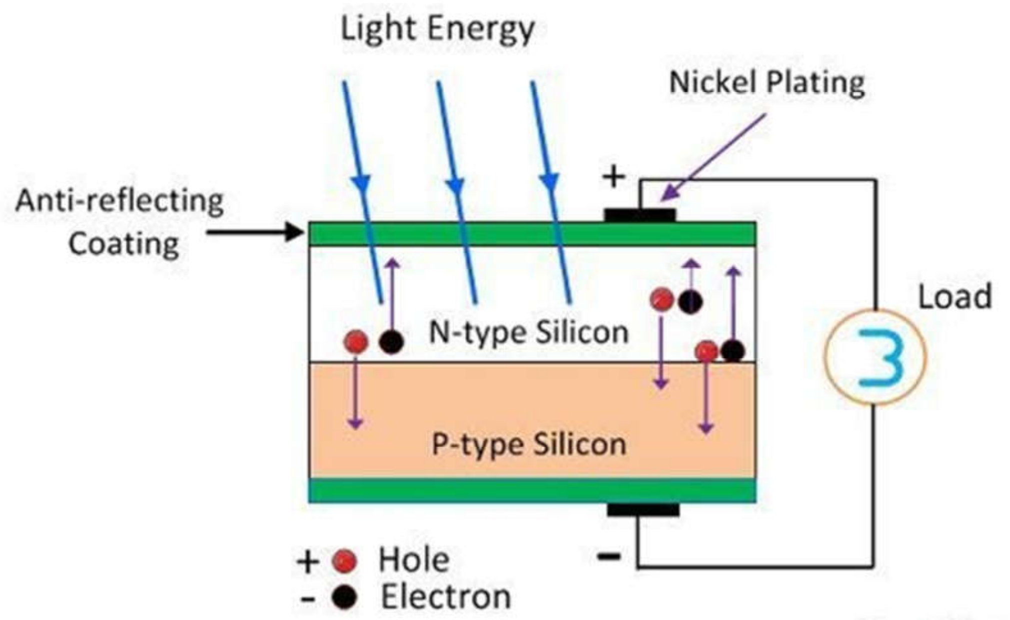

Figure 1.1 the constructions of the silicon photovoltaic cell.

The multi-crystalline or mono-crystalline semiconductor material make the single unit of the PV cell. The mono-crystal cell is cut from the volume of the semiconductor material. The multi-cells are obtained from the material which has many sides. The output voltage and current obtained from the single unit of the cell is very less. **The magnitude of the output voltage is 0.6v, and that of the current is 0.8v.** The different combinations of cells are used for increasing the output efficiency. There are three possible ways of combining the PV cells.

1.4 Combinations of Solar Cells

1.4.1 Solar Panel

A solar cell is the most basic element in a photovoltaic system. Cells are too small to do much work. They only produce about 0.5 V, and usually the system requires 12V or more to charge batteries or run motors. A typical module is a group of PV cells connected in a certain combination. The key purpose of encapsulating a set of electrically connected solar cells, is to protect them and their interconnecting wires from the typically harsh environment in which they are used. Usually commercial modules consist of 36 or 72 cells. For high voltage requirements, modules are connected in series; but for high current requirements, they are connected in parallel. High power requirements need connections in series and in parallel. Such a combination of modules is called a PV array [38].

The solar module is constructed by connecting the single solar cells. And the combination of the solar modules together is known as the solar panel.

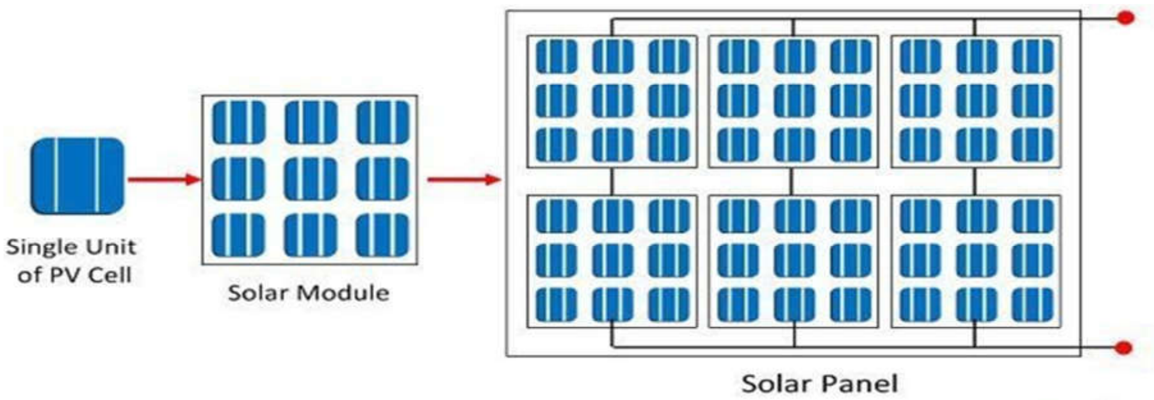

Figure 1.2 PV Solar Module.

1.4.2 Series Combination of PV Cells

If more than two cells are connected in series with each other, then the output current of the cell remains same, and their input voltage becomes doubles. The graph below shows the output characteristic of the PV cells when connected in series.

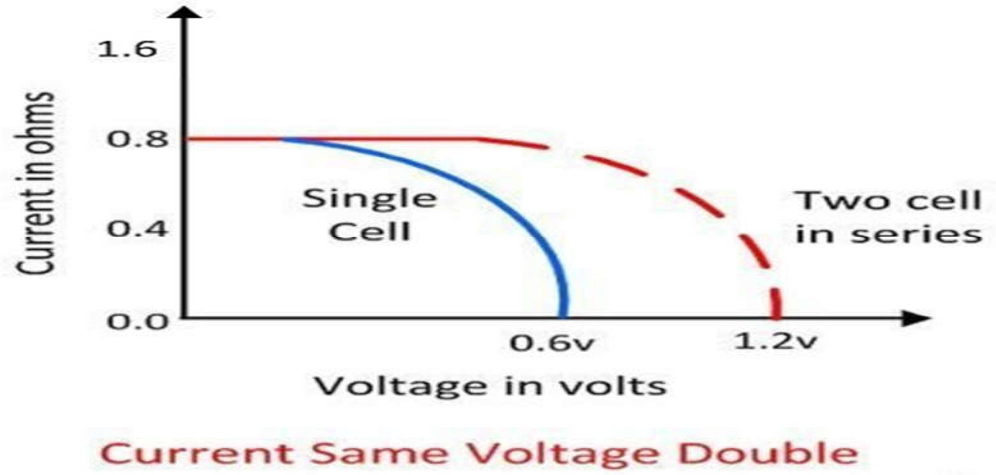

Figure 1.3 Series combination of PV Cell

1.4.3 Parallel Combination of PV Cells

In the parallel combination of the cells, the voltage remains same, and the magnitude of current becomes double. The characteristic curve of the parallel combination of cells is represented below.

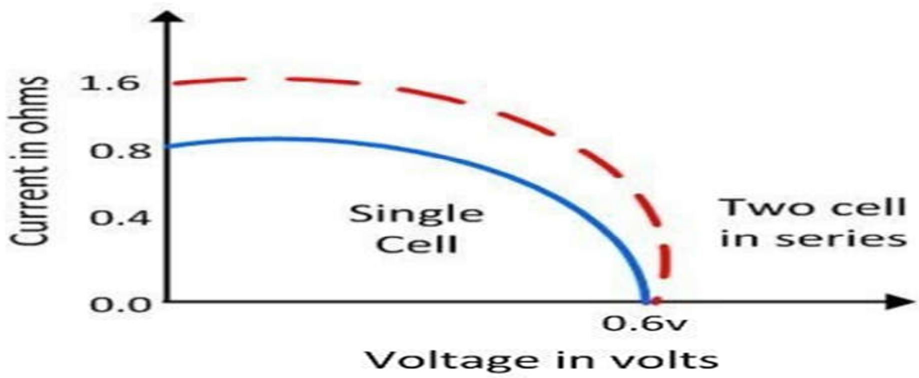

Figure 1.4 Parallel combination of PV Cell.

1.4.4 Series-Parallel Combination

In the series-parallel combination of cells the magnitude of both the voltage and current increases. Thereby, the solar panels are made by using the series-parallel combination of the cells.

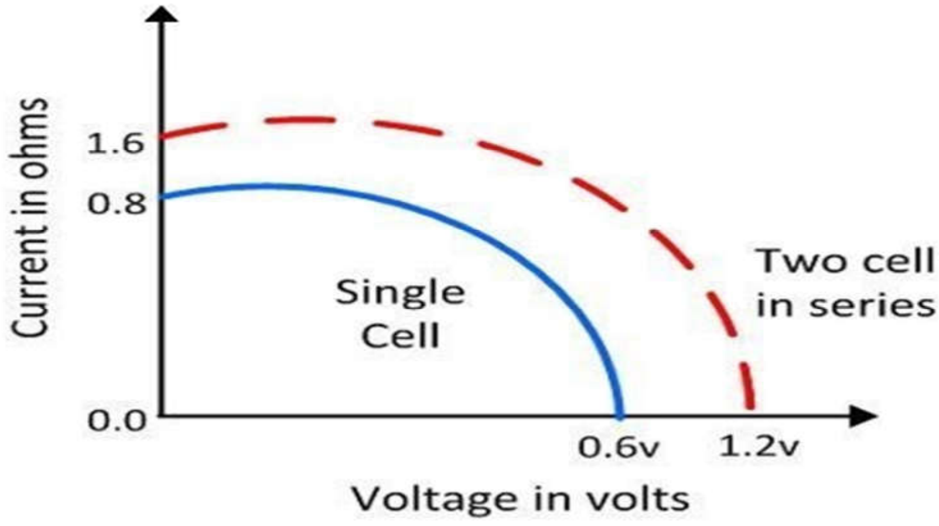

Figure 1.5 Parallel-Series combination of PV Cell.

1.5 Equivalent circuit of Solar Cell and its Equation

To understand the electronic behavior of a solar cell, it is useful to create a model which is electrically equivalent, and is based on discrete electrical components whose behavior is well known. An ideal solar cell may be modelled by a current source in parallel with a diode; in practice no solar cell is ideal, so a shunt resistance and a series resistance component are added to the model. The resulting equivalent circuit of a solar cell is shown below. Also shown, is the schematic representation of a solar cell for use in circuit diagrams.

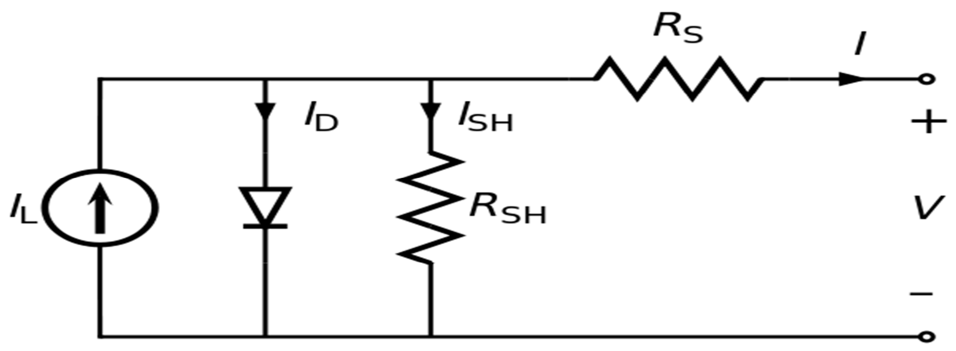

Figure 1.6 The Equivalent Circuit of a Solar Cell.

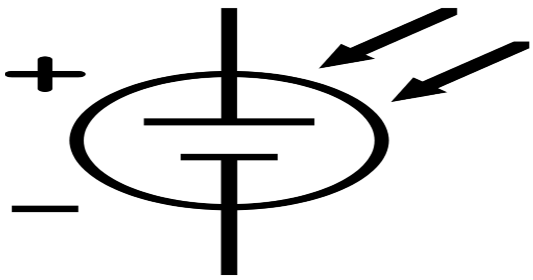

Figure 1.7 The Schematic Symbol of a Solar Cell.

1.5.2 Characteristic equation

From the equivalent circuit it is evident that the current produced by the solar cell is equal to that produced by the current source, minus that which flows through the diode, minus that which flows through the shunt resistor:

$$I=I_L - I_D - I_{SH} \qquad (1.1)$$

Where:

- I = output current (Ampere)
- I_L = photo-generated current (Ampere)
- I_D = diode current (Ampere)
- I_{SH} = shunt current (Ampere).

The current through these elements is governed by the voltage across them:

$$V_j = V + I.Rs \qquad (1.2)$$

Where:

- V_j = voltage across both diode and resistor RSH (Volt)
- V = voltage across the output terminals (Volt)
- I = output current (Ampere)
- Rs = series resistance (Ω).

By the Shockley diode equation, the current diverted through the diode is:

$$I_D = I_0 e^{\frac{qVj}{nkT}} - 1 \qquad (1.3)$$

Where:

- I_0 = reverse saturation current (ampere)
- n = diode ideality factor (1 for an ideal diode)
- q = elementary charge
- k = Boltzmann's constant
- T = absolute temperature
- At 25°C, $\frac{kT}{q} \approx 0.0259$ volt.

By Ohm's law, the current diverted through the shunt resistor is:

$$I_{SH} = \frac{V_j}{R_{SH}} \qquad (1.4)$$

Where:

- R_{SH} = shunt resistance (Ω).

Substituting these into the first equation produces the characteristic equation of a solar cell, which relates solar cell parameters to the output current and voltage: 13xxx

$$I = I_L - I_0 e^{\frac{q(V+I.R_S)}{nkT}} - \frac{V+I.R_S}{R_{SH}} \qquad (1.5)$$

1.6 Solar Cell Parameters and their effect

The main parameters that are used to characterize the performance of solar cells are the series and parallel resistances, temperature and the fill factor FF.

1.6.1 Effect of Parallel Resistance

The parallel resistance or the shunt resistance used in our model lead to a significant power loses, due to manufacturing defects. Low shunt resistance causes power losses in PV cells by providing an alternate current path for the light-generated current. This diversion decreases the amount of current that passes through the PV cell junction, this phenomenon is illustrated by the equation 1.2. It also, reduces the voltage generated by the solar cell. The impact of the parallel resistance is particularly noticed at low light levels, because the light-generated current will be smaller. The loss of this current to the shunt therefore has a larger impact. Moreover, the effect of the shunt resistance is more serious at lower voltages where the effective resistance of the solar cell is higher. [39]

1.6.2 Effect of Series Resistance

The series resistance of our model will lead to a movement of current through the emitter and base of the solar cell, besides it will create a contact resistance between the metal Chapter One: Photovoltaic System Principles 14 contact and the silicon. The series resistance will also cause the resistance of the top and rear metal contacts. The series resistance does not affect the solar cell at the open circuit voltage and is considered to be zero because the current flow through the solar cell. In the other hand the series resistance affect the I-V curve near the short circuit current and it also decreases the fill factor. [39]

1.6.3 Effect of Temperature

Sun's radiations are composed of light and heat. Temperature has no effect on the amount of solar energy that reaches the PV panel. However, it reduces the amount of energy converted into electrical energy. When temperature increases the band gap of the semiconductor material will be reduced, this will also have an impact on the semiconductor parameters. The decrease in the band gap plus the increasing temperature will increase the energy of the electrons. So, less energy is required in order to take them from a lower energy state to a higher energy state. The decrease in the potential difference between the excited electrons and the electrons at rest will produce a slightly smaller amount of power. In a solar cell, the parameter most affected by an increase in temperature is the open.

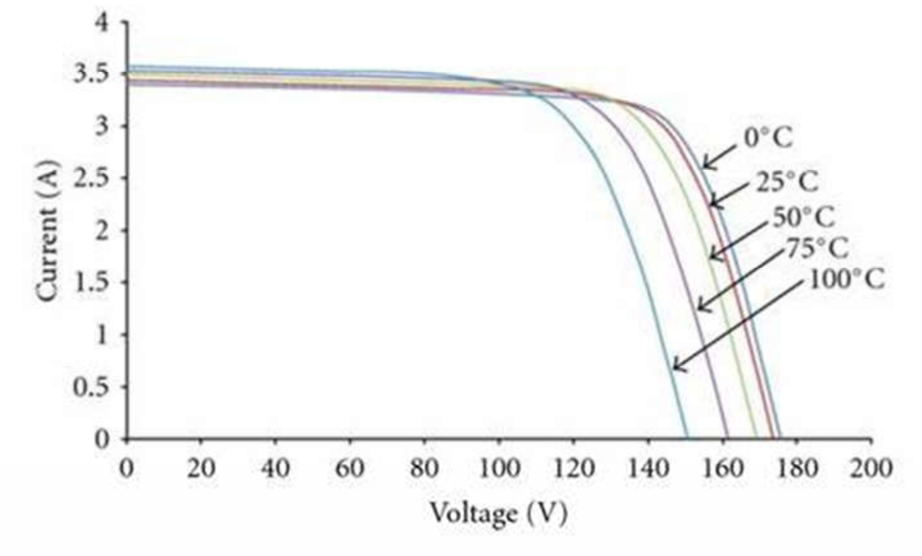

Figure 1.8 Effect of the temperature on the I-V curve [8]

1.6.4 Fill Factor

The short-circuit current and the open-circuit voltage are the maximum current and voltage that can be obtained respectively from a photovoltaic cell. However, at both of these operating points, the power generated by the solar cell is equal to zero. The "fill factor", abbreviated "FF", is a parameter used to express the maximum power produced by a solar cell in terms of Voc and Isc, The FF is defined as the ratio of the maximum power from the solar cell to the product of Voc and Isc.Its equation can be defined as:

$$FF = \frac{P_{max}}{P_T} = \frac{I_{mp}V_{mp}}{I_{sc}V_{op}} \quad (1.6)$$

The fill factor is directly affected by the values of the cell's series, shunt resistances and diodes losses. Increasing the parallel resistance (Rp) and decreasing the series resistance (Rs) lead to a higher fill factor, thus resulting in greater efficiency, and bringing the cell's output power closer to its theoretical maximum. The reason for which the fill factor is calculated by comparing the maximum power to the theoretical power (PT) that would be output at both the open circuit voltage and short circuit current together.

1.6.5 Efficiency

The efficiency is the most commonly used parameter to compare the performance of different solar cells. Efficiency is defined as the ratio of the output power, Pout, from the solar cell, compared to the solar power input, Pin, into the PV cell. Pout can be taken as Pmax since the PV cell can operate up to its maximum power. Pin is considered as the product of the irradiance of the incident light with the surface area of the solar cell. [40] In addition to reflecting the performance of the solar cell itself, the efficiency depends on the spectrum and intensity of the incident sunlight and the temperature of the solar cell. Therefore, conditions under which efficiency is measured must be carefully controlled in order to compare the performance of one device to another. This is done under STC conditions. The efficiency is computed using the following equation:

$$n = \frac{V_{oc}.I_{oc.FF}}{P_{in}} \quad (1.7)$$

1.7 Advantages and Disadvantages of PV Solar Cell

1.7.1 Advantages of Photovoltaic Cells

- **Environmental Sustainability:** Photovoltaic cells generate clean and green energy as no harmful gases such as Co_x, NO_x..etc are emitted. Also, they produce no noise pollution which makes them ideal for application in residential areas.
- **Economically Viable:** Operation and maintenance cost of cells are very low. The cost of solar panel incurred is only the initial cost i.e., purchase and installation.
- **Accessible:** Solar panels are easy to set up and can be made accessible in remote locations or sparsely inhabited areas at a lesser cost as compared to conventional transmission lines. They are easy to install without any interference to the residential lifestyle.
- **Renewable:** Energy is free and abundant in nature.
- **Cost:** Solar panels have no mechanically moving parts except in some highly advanced sunlight tracking mechanical bases. Consequently, the solar panel price for maintenance and repair is negligible.

1.7.2 Disadvantages of Photovoltaic Cells

- The efficiency of solar panels is low compared to other renewable sources of energy.
- Energy from the sun is intermittent and unpredictable and can only be harnessed in the presence of sunlight. Also, the power generated gets reduced during cloudy weather.
- Long-range transmission of solar energy is inefficient and difficult to carry. The current produced is DC in nature and the conversion of DC current to AC current involves the use of additional equipment such as inverters.

- Photovoltaic panels are fragile and can be damaged relatively easily. Additional insurance costs are required to ensure a safeguard to the investments.

CHAPTER 2

GENERALITIES AND METHODS OVERVIEW

[1] Energy generation from wind and solar power plants have become more important over the years due to the ability to match other sources such as fossil fuel in the electricity market but with the ability to reduce the cost of generation which leads to the reliance on forecasting their production even more than society has used to. Some challenges have a raised however, as their output over a short time period remains uncertain. Therefore, several methods to apply the forecasting have been applied in such research to maximize the production and minimize the chance of making errors and mistakes, thus two techniques have been studied:

The machine Non-Learning methods that are based on regression techniques such as Auto-regressive Integrated Moving Averages (ARIMA) and Multiple Linear Regression (MLR) [2], rely on historical data and Numerical Weather Prediction (NWP) [3] without the need of the location of plants. The persistence models are also used, while the Learning Methods mainly Artificial Intelligence (AI) models require the use of algorithms to establish complex relationships between the input and the output.

Several error indicators have been applied to measure the most effective of the techniques to find the margin between the forecasted solar power output and its actual value.

The evaluated test have been carried out between Sep 2013 and May 2014, and the results [1] have shown that the ANN models performs better than the other models and produces more accurate weather forecasts, and with it more accurate power production forecasts due to more compiled data being used in the training process, it has also been concluded that by removing night hours and providing clear sky hour inputs the ANN model’s performance can be improved.

[4]Energy production on Europe has been increasingly reliant on renewable sources as it has seen over a 5% ascent in recent years [4], therefore the electricity market has developed a trading stock for the day-ahead prices of the generated power output and the need for efficient forecasting techniques has climaxed.

This study focus on the hybrid Artificial Neural Networks (ANNs) and their parameters for prediction calculations. These parameters [5] include inputs and outputs as well as the number of layers and neurons used during the training process.

A historical amount of hourly output power of one year for a PV plant has been used, alongside the weather forecast for the next 24hrs and other data such as temperate and wind, clear sky solar irradiance is added to the network to apply a hybrid model

365 blocks are set in the network each repressing day and divided into 3 sets: 70% of data assigned to training set, 15% for validation and the rest for testing.

The normalized mean error NMAE% is evaluated to predict the most suitable method.

Results have shown that training a single hidden layer network is more suitable for the proposed method of PHANN [6] then that of multiple hidden layer networks as they minimize the NMAE% and a set of 10 trails and their averaged produced better forecasting results.

[7] Photovoltaic grid-systems (PV) are becoming more instrumental as a source for renewable energy for market consumption. Therefore it is crucial to develop and study forecasting techniques for the power production to help increase the important of such networks

This work focuses on studying a nonlinear autoregressive neural network system with exogenous inputs called NARX [8], and compare its performance with that of the persistence model.

In this paper the author has discussed the use of the MLP and Lavenberg-Marquardt algorithm [9] in network training to maximize the efficiency of output, data preprocessing is encouraged for better result, with data over fitting as well. Error evaluation indexes to compare between the predicted value and actual value are used to choose the most appropriate model.

Sets of data compiled from 1st to 31st of July 2012 from 5 different neighboring PV plants from Utrecht, Netherlands with addition to ambient temperature and solar radiation as well meteorological data and information about each plant were provided. These sets were divided into 3 ones to train our network: training, validation and testing

6 different cases were studied to find the most efficient model [7], and Narx has shown significant improvement in forecasting production over the persistence model.

[10] In recent years, A qualitative leap occurred in the field of pv power plant, this qualitative development is due to many reasons, one of them is the forecasting techniques to predict the energy power in such specific places, weather conditions and historical data.

Moreover, considering that the use of grid pv power plant were highly increased the forecasting method becoming more important , thus this will lead us to one fact which is developing this methods to have less error prediction and high efficiency performance . In this last years the most developed models are the hybrid one. In this part we are related to one of the most effective hybrid which is a combination between the specific Algorithms with ANN in order to speed up the convergence and reduce the error and get a better predictive power of ANNs.

The development of the hybrid models allows us to combine the best properties of the needed algorithms. The two algorithms used in this research are Genetic algorithm (GA) and particle swarm optimization (PSO) [11]. The reason of the combination between the two algorithms is that PSO have faster convergence and GA finds better solutions. This combination allows the authors to develop a new hybrid strategy called Genetical swarm optimization (GSO) which have the best characteristics of the two previous algorithms.

The developed algorithm is used for the learning process of the ANN, the weight values of the ANN were changed after using this new algorithm and the errors of the prediction were minimized

As result, this model allows an accurate prediction in comparison with the standard one (EBP) and shows better performance in the sunny days.

[12]In this part, we will focus on a short-term Statistical strategy called Autoregressive Moving Average (ARMA). This technique used to predict the power of a pv system upon 24 h ahead.

This research were done in on a horizontal surface in order to evaluate the energy production from photovoltaic solar source. As we know Sahara is the best solar energy source with 3000 hours of sunshine per year and an average of global irradiation about 5.8 kWh / m2 / day. That is why we have chosen Dakar, Senegal as a reference to collect our necessary data to predict the power energy of the pv system for the next 24 hours. The collection of data were taken from October 2016 to September 2017. The reason to choose this model of forecasting (ARMA) is because its robustness and applicability on several sites in the world on different forecast horizons [7, 28, 9, 10, 11].

This method is concentrate on finding an optimal fit parameters p and q for better representation of solar radiation, this solar radiation data has been taken from CIFRES station. This strategy based on observation and can be used to forecast time series. In 1938 wold propose to decompose the time series into components referred to as deterministic component and stochastic one. The deterministic one can be computed using physical and mathematical laws. in other hand the stochastic shows some difficult to be computed, so he proposed a linear random process model composed of an autoregressive process noticed by AR and a moving average one noticed by MA (AR process fits a time series through a linear function of its past values while the MA process smooth fluctuations around a mean of a time series). So they use R software to perform this analysis and to verify non-stationary of the solar radiation. However, in order to determine p and q orders of the ARMA (p, q) the autocorrelation and partial autocorrelation functions are used.

After computing and analyzing some error indexes we finally define the performance of this approach regarding its reliability of planning and managing photovoltaic solar power plants in Senegal and surrounding.

[13] In our days, with the technological advancements the source of the renewable energies got a huge attention, the photovoltaic (PV) based solar energy is the most promising one. The scientist tried to develop more efficient models and method of forecasting to make the best use of it.

One of this approaches called Autoregressive Integrated Moving Average (ARIMA). The reason behind the use of this model is the simplicity of implementation and use of the famous Box-Jenkins methodology. This method is mainly based on stationary time series data. However There are two different variations of ARIMA models: non-seasonal and seasonal. If there is seasonality in the time series data, then seasonal ARIMA model is used. Otherwise, the non-seasonal ARIMA model is used for the general cases.

After checking the stationary and the seasonality using Augmented Dickey Fuller (ADF) , the partial auto correlation function (PACF)and auto correlation function (ACF) plots of the time series, the selection of the optimum ARIMA model (based on some criteria and information) is necessary before starting to forecast .

A collection of a daily data were taken from solar plant located in the rooftop of the Group Nire building in Reese Research Center for a hole year (6 th November, 2017 - 5 th November, 2018) used in the forecasting process using this technique .

The result shows that the seasonal model outperforms the non-seasonal one in terms of all the information criteria, this was determined using the error indexes of the different type of the ARIMA model. In other hand, the accuracy of the developed model can be further increased, which is subject to future research.

[14]Previous research has proved that renewable energy sources, especially solar energy which can be to satisfy global demand and protect the nature from the pollution. The influence of the performance of the energy predicting tools become

very important. The accurate forecasting of solar energy resources is highly needed for the optimum utilization of these resources. Different machine learning models have been applied to forecast solar energy resources. In this part we will propose one type of the machine learning called support vector machine SVM for one-hour ahead forecasting of solar output .SVM is specially used due to its high capability to solving non-linear problems, even when trained with small datasets. It can be used both for classification and regression tasks where the regression version being called Support Vector Regression (SVR). Random forest (RF) is a combinatorial classifier and can be used for regression as well. The main idea of RF is constructing several decision trees at training time and ensembles the results generated from individual trees. RF is based on a decision tree using a random selection of attributes for each node of the decision tree. To find more about the quality of performance of this models to forecast the output power of pv system, an experiment were done in southern Taiwan. The available weather condition data is collected from 2017/1/1 00:00 hour to 2018/4/30 23:00 and the available PV solar invertor data is collected between 2015/1/1 06:00 hour to 2018/4/30 18:00 hour from 22 different PV solar invertors. The forecasting results shows that RF outperforms SVM in term of prediction results, the recommendations presented and implementations proposed were based on statistical tests in a specific region only. It is recommended to test a particular wind and solar energy model in different geographical regions with different overall pattern to compare results for a better accuracy.

[15]It is essential to apply power production forecasting techniques for PV Power plants for the benefit of maximizing profit and reducing cost in. This research represents the Physical Model technique.

This method is solely based on the parameters of the specified PV plant without reliance on historical data, its inputs are Numeral Weather Prediction (NWP) data provided from a nearby plant with 1-year 15min resolution sets and its output is the forecasted power for the next 24 hours.

16 PV plants from Hungary were used in this study, and 32000 model chains combined of separation and transposition models, reflection, PV cell temperature and performance, shading and finally the inverter model. Are verified for observation of the forecasting performance. To the compare the results of performance of the plants six main factors were considered , 3 of which are error evaluation indexes MAE%,MBE% and RMSE% in addition to persistence and climatology-persistence skill scores and variation ratio, several results and conclusions can be made :

Physical models do not provide the most accurate prediction, we can observe the difference between the best and worst models have showed parity in error calculations thus selection the most efficient one is of high important as it can reduce cost in the electricity market, 6 of those plants situated in The Great Hungarian plants have shown lower error predictions compared to the remaining ones.

It is encouraged by the authors to peruse further research in terms of providing more weather forecasting data, as well as acquire more access to PV plant production to help obtain better results and power forecasts.

[16] The development of smart grid networks is crucial to forecasting renewable energy production specifically solar energy, for this case it is crucial to rely on computational intelligence to maximize and optimize our predictions, therefore a hybrid physical ensemble is developed as the prediction technique

The authors have compiled a series of data from Rockhamption, Australia spanning for a six year period

The proposed Hybrid Model in this research is mainly based on regression algorithms, 10 were selected and tested individually using a set of historical data in which 70% were used for network training and 30% for testing, the trials have shown that MLP,LMS and SVM techniques are the best choices respectively for a better and more accurate prediction and have the lowest prediction error, then the previous algorithms are trained in the network with feature selection separately, with error indicators analysis and then they would be integrated in a non-linear regression algorithm that severs the optimization of management of the smart grid .the tests are carried out for the prediction of the next 6 hours of ensemble generation.

[17]Power reduction forecasting is crucial for the electricity market to go forward renewable energy especially the solar one.

In this research we compare between the two of the most effective models to apply a precise forecast.

The first method called the statistical method which is based on ANN networking, its input is the previously acquired historical data that is trained through a process, also worth noting the data is preferable pre-processed. Its output is the predicted hourly power for the next day.

While the second method called the hybrid physical method (PHANN) is a combination between the first one and the physical to overcome both their defenses its training process is more complex as well as the fact is also relies on the parameters and the location of the plant

Results have shown after evaluating error indexes that there is no evident conclusion on which method outperforms the other, as for sunny days the hybrid shows more accurate results but the ANN-based one shows more stable and performance while for cloudy days the Hybrid shows more error prediction percentage and while for the ANN-based method shows higher error efficiency as well it is still more consistent.

[18] Forecasting Photovoltaic output energy is necessary for power plants to maximize energy production with the lowest cost. For this purpose a certain technique is used to predict the hourly output of the next 24 hours of the power generated. This paper focuses on the statistical method based on the Fast Forward Neural Network that is based on the back-propagation algorithm.

Researchers have focused on obtaining the historical meteorological weather data from a nearby weather service center in Milano, Italy as inputs and classify them into an array of 8 columns and 4192 rows.3 models were studied to investigate the error of the trained network, each network has been subjected into 100 trails to predict the hourly output for the month of June 2016. The first case uses 1 hidden layer while the other 2 uses two hidden layers and for each case the numbers of neurons is increased for each network training session.

The report has found that the average of these 3 configurations is better and more efficient on forecasting the output power than to rely on each one of them individually.

CHAPTER 3

METHODS PRESENTATION

3.1 Introduction

In fact, the demand for energy and global energy consumption in various fields are higher than ever before. In addition to the increasing demand for energy, oil and other fossil resources have become scarce on the earth. Environmentalists, socialists and economics Home supports climate. Agreements and the use of clean energy as solutions to replicate global energy demand, profitability and environmental impact like common problems caused by global warming[19]. The two main issues associated with the high penetration rate of photovoltaic systems are variability and uncertainty; forecasting. The second problem, uncertainty and its solution: the prediction of photovoltaic energy [13]. In recent years, the application of photoelectric prediction methods has become an active research field. An important issue in the development and management of grid-connected photovoltaic (PV) systems is the ability to predict energy production from different perspectives. A forecasting method for forecasting solar energy production with expected accuracy. Choosing a suitable forecast period and/or spatial scope and a suitable forecasting method are crucial in the forecasting process. These methods are divided into three important methods: physical methods, statistical methods, and hybrid methods. Overall, comparing forecasting methods is challenging because of the many factors that affect performance and vary from situation to situation: availability of historical and forecast data, time range and resolution, climatic conditions, geographic location and statistical techniques, appropriate preprocessing Data (nighttime samples, when power generation is not available) is also important to achieve good performance and reduce computational costs [16]. The information available in the literature provides some information about the characteristics of different methods, but the results are qualitative rather than quantitative. Some recent comments [14, 16] contain a comparative analysis of the works of different authors, including statistical errors. However, due to the different conditions and indicators of each job, from a quantitative point of view, this comparison is not important [20].

3.2 Forecasting Methods Classification

3.2.1 Based On Time Horizon

Photovoltaic forecasting modeling is related to choosing a suitable time range and forecast resolution, so the time range is defined as the time between present and future forecasts, and can span a short period of time, considering from a few seconds to a few minutes, here There are also "now cast" and "intra hour" below, the time range is 0 to 6 hours, short-term or one day in advance, taking into account up to 24 hours, medium-term from a few hours to a few hours to several days to several months of long time. Generally speaking, any prediction made using any technology must have a goal, that is, a decision must be made when the final result is in the hands of the decision maker. Therefore, the model is related to the different options used or has different inputs for development. In the case of solar power generation in a facility, general inputs can be facility-specific historical power generation measurements and meteorological parameters, including temperature, global level lighting in photovoltaic panels, and cloud cover. About installation. The weather forecast is also taken into account. These forecast ranges can be divided into four categories [7]:

- **Very short-term horizon**, used usually for PV storage and control of electricity market with granularity from few seconds up to few minutes.
- **Short-term horizon**, used usually for decision-making problem in the electricity market and power system operation with granularity from few hours up to 48 hours.
- **Medium-term horizon**, used usually for maintenance scheduling with granularity from few hours up to 72 hours.
- **Long-term horizon**, used for long-term solar power assessment and facility planning with granularity from few months up to few years

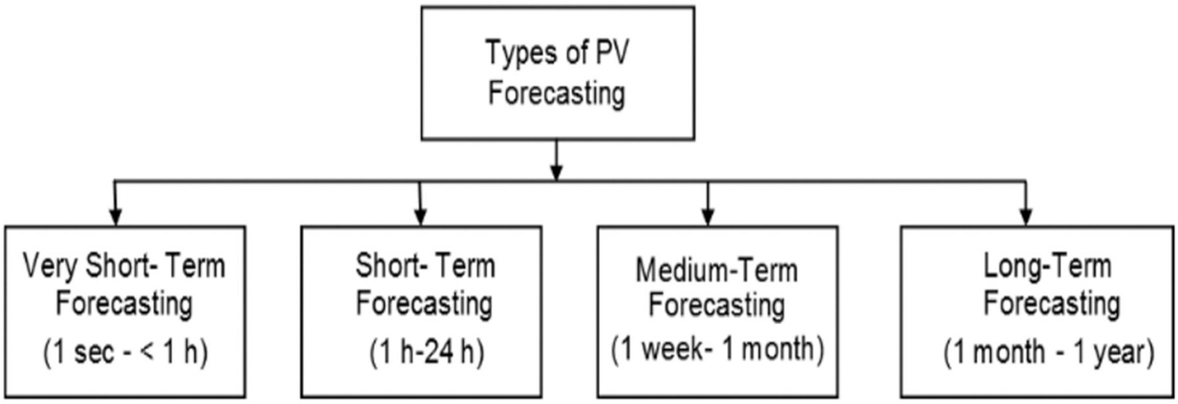

Figure 3.1 classification of pv forecasting methods based on time horizon.

3.2.2 Based On the Method Used To Perform the Forecast

These methods are divided into three important methods: first, physical methods based on photovoltaic energy models, second, statistical methods based on artificial intelligence and machine learning processes, and third, hybrid methods. Based on technology from the same method or a combination of technologies from other methods.

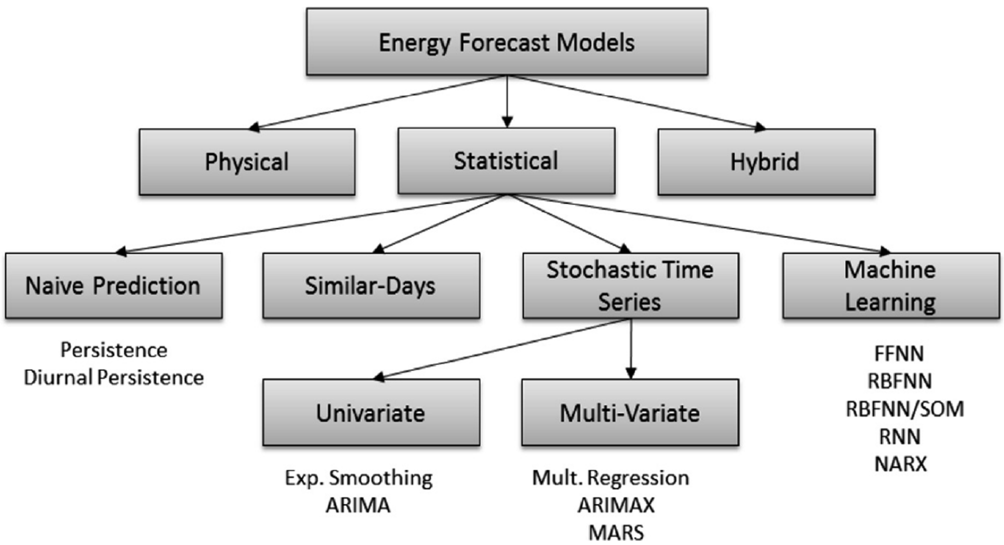

Figure 3.2 Classification of pv forecasting methods based on the three families.

3.2.2.1 Statistical Methods

Statistical methods follow a data-driven model. The main process of this method is usually based on extracting relationships from past data to predict the future performance of photovoltaic power plants. By applying optimization algorithms for optimization and organization, these optimization algorithms select the input data that will provide the best results and find a balance between load and accuracy [4]. Literature analysis shows that statistical methods are common and usually provide better results than statistical predictors. Regression and ANN models [1] are the most commonly used.

3.2.2.2 Physical Methods

Physical modeling is a general method for calculating expected energy production based on numerical weather forecast data. This method is only based on the basic design parameters of the photovoltaic system and does not require any historical data. Therefore, this is a useful method. For owners of photovoltaic systems, they have all the necessary information contained in the system planning documents. The physical method uses theoretical simulation models to calculate the output power of the photovoltaic system according to the most important design parameters [15]. The calculation step is defined as a separate simulation of emission and transposition, and the significance of the inverter model is the least important. Absolute error and quadratic error are two contradictory indicators, because a more detailed model gives the lowest MAE, while a simpler model gives the lowest RMSE [15]. The wind speed forecast has little effect on the forecast of photovoltaic power generation.

3.2.2.3 Hybrid Prediction Method

In order to successfully study the best model, reliable methods are needed to combine different regression algorithms [2], sets, test models, etc., to improve prediction accuracy [7]. The term "hybrid" here is associated with the three main local predictors, which are based on the most frequently chosen heterogeneous regression algorithm [2] and the global predictor. The performance of hybrid models depends on the performance of individual models, and these models must be specifically designed for specific plants and locations. However, in general, the weakness of hybrid forecasting methods is that they are not effective under unstable weather conditions [9].

3.3 Most Effective Techniques Used In Photovoltaic Forecasting

3.3.1 Artificial Neural Network ANNs

The ANN is a simple biological analogy of the brain. They are implemented in common applications with different AI methods, such as under control. Using applied mathematics, back propagation algorithms help train RNA to recognize similar patterns. The number of neurons is divided into different layers and receives information from all neurons in the previous layer [4]. Each neuron performs a simple non-linear operation, and learning is limited due to the number of neurons and the connections between them [20]. If historical data is available, artificial neural networks can provide forecasts for different generations of wind and solar energy. Available again. The performance of ANN depends on its training level and the quality of the data used. the number of layers depends on several factors and the type of problem to be solved [20]. Several models have been proposed to determine the best network [21], but these methods are not applicable to all research fields. In fact, the success of a network depends to a large extent on the experience of the creator [22], and many attempts must be made to obtain satisfactory results. In addition, the computational load also imposes some restrictions. The more complex the network, the more time (hours) required to process the **data.**

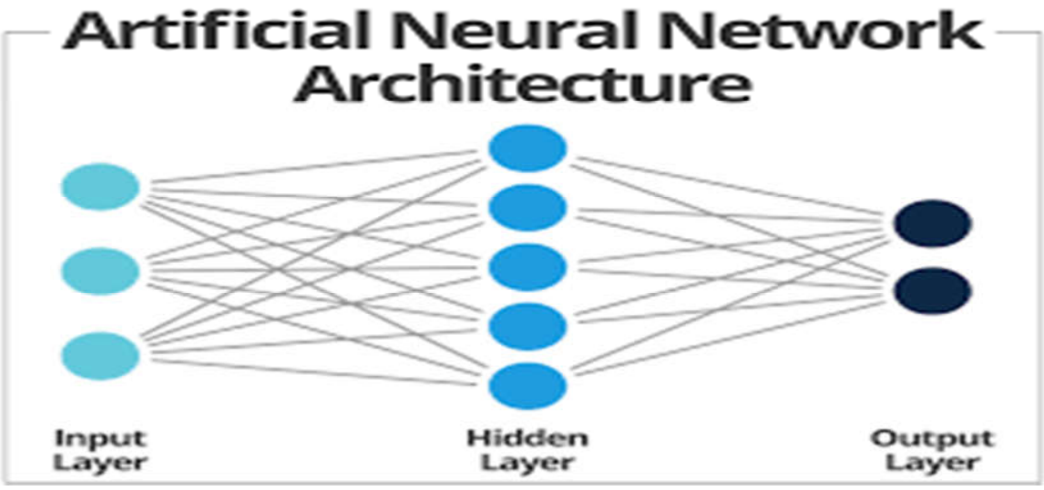

Figure 3.3 classification of pv forecasting methods based on the three families.

3.3.1.1 Mathematical Representation of ANNs

3.3.1.1.1 Transfer function

Transfer function or activation function controls the amplitude of the output of the neuron and is based on the neurons reactions to the input values and depends on the level of activity of the neurons (activation state). This premise is founded on the biological model, where every neuron is, at all times, somewhat active. Essentially, neurons are activated when the network input exceeds the uniquely maximum gradient assigned value of the activation function, known as threshold. Accordingly, near the threshold value the activation function has a rather sensitive reaction[7]. The activation function is dependent of the previous activation state of the neuron and the external input and is defined as:

$$\boldsymbol{a_j(t) = f_{at}(net_j(t), a_j(t-1), \emptyset_j)} \qquad \textbf{(3.1)}$$

This equation demonstrates how the network input, previous activation state $\boldsymbol{a}_{\mathrm{j}}(\boldsymbol{t-1})$ and the influence of the threshold $\boldsymbol{\theta}_{\mathrm{j}}$, is transformed into new activation state $\boldsymbol{a}_{\mathrm{j}}(\boldsymbol{t-1})$.

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, $\boldsymbol{\gamma} = \frac{\mathbf{1}}{(\mathbf{1}+\boldsymbol{e}^{-\boldsymbol{x}})}$ takes the input with any value between plus and minus infinity and maps the output to the range values (0, 1). The hyperbolic tangent:

$\mathbf{tanh}(\boldsymbol{x}) = \frac{\boldsymbol{e}^{\boldsymbol{x}}-\boldsymbol{e}^{-\boldsymbol{x}}}{\boldsymbol{e}^{\boldsymbol{x}}+\boldsymbol{e}^{-\boldsymbol{x}}}$ also takes the input with any value between plus and minus infinity and squashes 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 preprocesses the input data, for example, by normalizing the data. Another relevant function is the linear function $\boldsymbol{\mathcal{F}}(\mathbf{x}) = \mathbf{x}$, where the inputs and outputs range from minus infinity to plus infinity, which it is generally used in the output layer of the network[7].

3.3.1.1.2 The Back propagation Algorithm

Back propagation is the essence of neural network training. It is a method of adjusting the weights of neural networks based on the error rate obtained in the previous epoch (iteration). Correctly adjusting the weights can reduce the number of errors and make the model more reliable by increasing its generalization. Back propagation in neural networks is a short form of "error back propagation". This is the standard method for training artificial neural networks. This process helps to calculate the gradient of the loss function with respect to all weights in the network. The neural network back propagation algorithm uses the chain rule to calculate the gradient of the weight loss function. Effectively calculate one level at a time, rather than directly. Calculate the gradient, but do not specify how to use the gradient. Summarize the calculations in the incremental rule. [23]

Consider the following Back propagation neural network example diagram to understand:

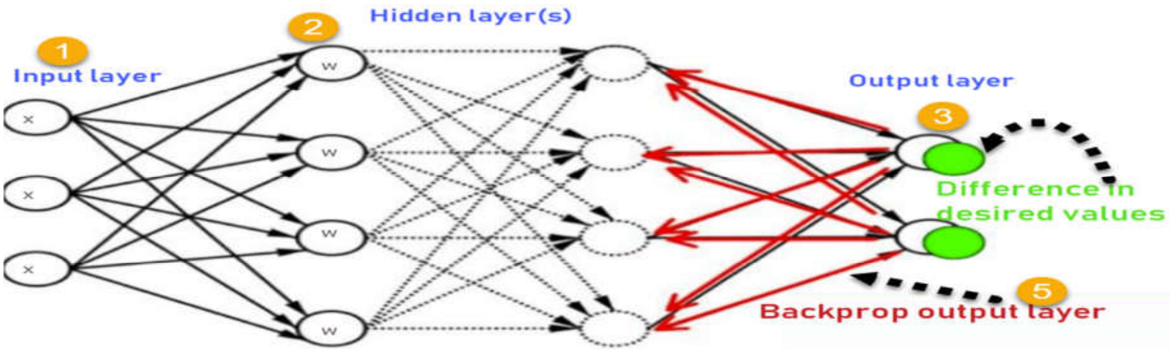

Figure 3.4 example of how back propagation neural network works.

Explanation:

1. Inputs X, arrive through the pre-connected path
2. Input is modeled using real weights W. The weights are usually randomly selected.
3. Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
4. Calculate the error in the outputs

$Error_B$= Actual Output – Desired Output

5. Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased.

Keep repeating the process until the desired output is achieved [23].

3.3.2 Autoregressive moving average process (ARMA)

In the literature, some authors [24, 25] believe that the autoregressive moving average (ARMA) process seems suitable for adjusting the time series of solar radiation. In addition, the time series can be predicted by the ARMA method. To determine the appropriate random model corresponding to the check variable. When analyzing time series in 1938, Wald suggested to decompose the time series into components called deterministic components (trend and periodic components) and random components [18]. Due to its random nature, the random component cannot be accurately determined from the known physical and mathematical minimums; then it is modeled using random methods. Stochastic process is also called Yule process (unpredictable infinite linear combination process). In 1954, Wald defined a linear model based on a stochastic process, which is composed of the autonomous or regression process observed by AR and the moving average marked by MA [16]. ... The combination of the two processes leads to the ARMA process. The AR process uses linear functions of their past values to compare time series, while the MA process smooth's fluctuations around the average value sequentially.

In addition, the trend component is represented by a weighted average based on past time series values. Elsewhere, the rest consists of strictly random parts of the original time series. noticed by εi. ARMA process is characterized by following equation:

$$\boldsymbol{x_t = \sum_{i=1}^{p} \varphi_i x_{t-1} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}} \qquad \textbf{(3.2)}$$

Φ_i : parameter of Autoregressive process.

θ_j : parameter of the moving average process ($\theta_j = 0$).

ε_j a residual.

3.3.2.1 Application of the ARMA process on the studied site

3.3.2.1.1 Dickey-Fuller test

To check for non-stationary of recorded data, a general function noticed by "adf.test" has been used. The function is applied using the package “tseries" of the R software. Among tests, one can cite the classical Dickey-Fuller test, the augmented Dickey-Fuller test and the Phillips-Perron test. For above tests, the null hypothesis is non-stationary of the time series [15]. In this study, the augmented Dickey-Fuller test is used to verify non-stationary of the solar radiation.

```
        Augmented Dickey-Fuller Test

data:  data.sum.ts.clean
Dickey-Fuller = -1.7941, Lag order = 7, p-value = 0.6639
alternative hypothesis: stationary
```

Figure 3.5 example of Dickey-Fuller test.

3.3.2.1.2 Validation of the ARMA process (p, q)

In the determination p and q orders of the ARMA (p, q) process, the autocorrelation and partial autocorrelation functions can be used. Through above functions, we can select several possible orders p and q. The AIC criterion is used to select the optimal order of p and q. Validation of the process includes an examination of the estimated coefficients and by analyzing the residue, (the estimated residues must follow a white noise process). Indeed, analysis of residual is based on the autocorrelation, Box, and Pierre tests [12, 19]. This test applied to the residual to validate whether residual is "white noise" (zero mean, fixe and uncorrelated variance).We use the Box-Test function of the R software to perform this test. In practice, this function gives a p-value for the applied test. The null hypothesis H0 of white noise is accepted, when the p-value is greater than 5% and is rejected otherwise.

3.3.2.1.3 Information Criterion

We study the specific criteria of the stochastic models such the Akaike's AIC (An information criterion) criterion and the Bayesian one (BIC) to check for optimum orders of the model. Among these criteria, we chose to work with the Akaike criterion. Indeed, this criterion of Akaike or AIC is based on researching optimum parameters p and q [25]. The best of the ARMA models (p, q) is the model that minimizes the statistic determined in priori. This criterion AIC is described as:

$$\boldsymbol{AIC(p,q) = \log \sigma^2 + \frac{2(p+q)}{T}} \quad \textbf{(3.3)}$$

- $\boldsymbol{\sigma^2 = \frac{1}{T}\sum_{t=0}^{N}(\varepsilon_t - \overline{\varepsilon_t})^2}$
- $\boldsymbol{\overline{\varepsilon_t} = 0}$

3.3.2.2 Autoregressive Integrated Moving Average

3.3.2.2.1 General Formulation

The value of a dependent variable is expressed as a linear relationship between past values of the dependent variable and random errors in ARIMA model. However, a time series can only be modeled as an ARIMA process if it is stationary. As strong stationary is somewhat complex to demonstrate [12], in this paper we would assume stationary if the time series is weakly stationary. In general terms, a weakly stationary time series has constant statistical properties, namely mean and variance [25]. Transformation operations like differencing, logging and deflating [19] are performed on a non-stationary time series to make it stationary. There are two different variations of ARIMA models: non-seasonal and seasonal. If there is seasonality in the time series data, then seasonal ARIMA model is used. Otherwise, the non-seasonal ARIMA model is used for the general cases. The non-seasonal ARIMA is modeled in the following way [25]:

$$\hat{y}_t = \boldsymbol{\mu} + \boldsymbol{\phi}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{\phi}_p \boldsymbol{y}_{t-p} - \boldsymbol{\theta}_1 \boldsymbol{e}_{t-1} - \cdots - \boldsymbol{\theta q}\, \boldsymbol{e}_{t-}\boldsymbol{q}' \quad \textit{(3.4)}$$

Where $\hat{y}_t$ is the d'th difference of a non-stationary time series Y. The order of autoregressive lag terms, differencing and moving average lag terms are represented by p,d and q, respectively. The autoregressive and moving average parameters are expressed with $\boldsymbol{\phi}$ and $\boldsymbol{\theta}$ terms, respectively. Finally, $\boldsymbol{\mu}$ is a constant. Depending on the values of p,d and q, an ARIMA process can undertake the form of purely moving average (MA), purely autoregressive (AR) or autoregressive moving average (ARMA) processes. Presence of a periodic pattern in the time series is called seasonality. Seasonality in a time series is expressed by its span, S. For example, monthly solar energy generation has higher values in summer months, so S = 12 in this case.

ARIMA models can be used to forecast seasonal time series data, just like non-seasonal time series data. A multiplicative model, including both the non-seasonal and seasonal fluctuations, is used to represent seasonal ARIMA model.

3.3.2.2.2 Model Parameter Selection

The first step in the modeling process is checking for the stationary of the time series. A rough estimate of stationary can be graphically obtained by plotting the partial auto correlation function (PACF) and auto correlation function (ACF) plots of the time series. ACF measures the correlation of a time series value with other values of the same time series at different lags. PACF also measures the correlation between a value of a time series and another value at different lag.

However, PACF ignores the other values at different lags while calculating the correlation for a particular lag value [25]. If the ACF doesn't display any significant value after a few lags or the PACF contains a sharp cutoff after the initial value [19], then we have a stationary time series on our hand. However, most real life problems are not as straightforward and stationary. After the initial estimation, a more methodical approach, named Augmented Dickey Fuller (ADF) test, is executed to confirm stationary [24], [19], [12]. ADF is also known as unit root test. If there is no unit root of the characteristic equation, then the time series is stationary. Otherwise, the time series in non-stationary. The general equation for testing stationary using the ADF test is as follows:

$$\boldsymbol{\partial Y}_{\mathrm{r}} = \boldsymbol{\mu} + \boldsymbol{\beta t} + \boldsymbol{\rho Y}_{\mathrm{t\text{-}l}} + \boldsymbol{\partial}_{\mathrm{l}}\boldsymbol{Y}_{\mathrm{t\text{-}l}} + \cdots + \boldsymbol{\partial}_{\mathrm{p}}\boldsymbol{Y}_{\mathrm{t-p}} + \boldsymbol{e}_{\mathrm{t}} \qquad \textbf{(3.5)}$$

Here, $\boldsymbol{\beta}$ represents the trend. Moreover, $\boldsymbol{e}_{\mathrm{t}}$ represents a sequence of independent normal random variables of zero mean and unit variance. Then hypothesis is formulated in the following way [25]

$$\boldsymbol{NullHypothesis} : \boldsymbol{H}_{\mathrm{o}} : |\boldsymbol{\rho}| = \mathbf{0}(\boldsymbol{Non-stationarity})$$

$$\boldsymbol{AlternativeHypothesis} : \boldsymbol{H}_{\mathrm{l}} : |\boldsymbol{\rho}| \neq \mathbf{0}(\boldsymbol{Stationarity})$$

Rejection or acceptance of the null hypothesis is dictated by the p-value. A confidence level of 95% is assumed in this work. If $p \geq 0.05$, the time series is non-stationary (null hypothesis is true). Otherwise, the time series is stationary (null hypothesis is rejected).

3.3.2.2.3 Model Selection and Validation

After the initial checking of stationary, differencing operation is performed in case the time series is non-stationary. If the initial time series is stationary, then the order of differencing, d = 0. Differencing would be performed as long as the time series isn't transformed into a stationary one. In this work, other transformation techniques are not studied. After each differencing operation, the stationary can be checked using the ACF and PACF plots or ADF test or both. Finally, the PACF and ACF plots of the derived stationary time series would determine the p and q parameters. p and q generally correspond to significant terms in PACF and ACF plots, respectively. However, they might not always be the optimum model parameters. The seasonal parameters can also be determined from the ACF and PACF plots. The final step before forecasting is selection of the optimum ARIMA model. [26]

The following criteria are commonly used to estimate the goodness of fit for the developed models:

1) Akaike Information Criterion (AIC)

2) Corrected Akaike Information Criterion (AICc)

3) Bayesian Information Criterion (BIC)

4) Residual sum of squares (SSE)

1- **AIC**: The formulation of AIC [25] is as follows:

$$\boldsymbol{AIC = -2\log(maximumlikelihood) + 2K} \quad \textbf{(3.6)}$$

Where **K** is independently adjusted number of parameters.

2- **AICc:** The formulation of AICc [25] is as follows:

$$\boldsymbol{AICc = -2\log(maximumlikelihood) + \frac{n+k}{n-k-2}} \quad \textbf{(3.7)}$$

Where **n** is total number of data points.

3- BIC: The formulation of BIC ([25]) is as follows:

$$\boldsymbol{BIC = -2\log(maximumlikelihood) + \frac{k\log n}{n}} \quad \textbf{(3.8)}$$

Where **k** and **n** are the same as defined in AIC and AICc.

The preferred model is the one that minimizes all these criteria. In this work, AIC and SSE have been used for optimum model selection[14]

3.3.4 Support vector machine models

An SVM is a machine learning algorithm based on statistical learning theory and the principle of structural risk minimization, which was presented firstly by Cortes and Vapnik in 1995 (Cortes and Vapnik, 1995). The network structure of an SVM can be seen in **Fig. 6**.

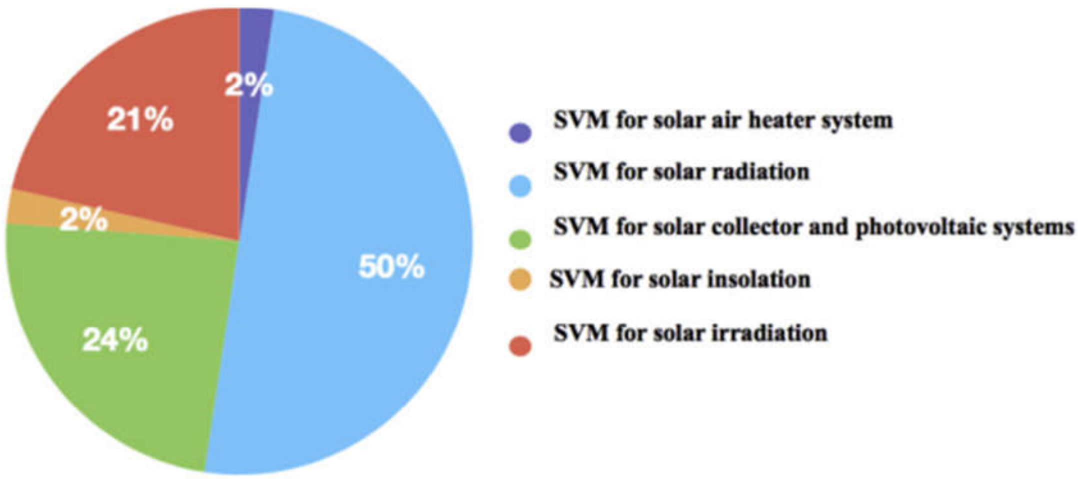

Figure 3.6 The network structure of an SVM.

SVMs have been successfully implemented for various purposes, such as images retrieval (Tao et al., 2006), fault diagnosis (Tian et al., 2015), text detection (Kim et al., 2001) and regression problems (Hemmati-Sarapardeh et al., 2014).

The main idea of this approach is transforming the nonlinear input area to an area with high-dimensional properties to find a hyper-plane via nonlinear mapping. For classification, pattern recognition and analysis of regression, SVMs are mostly implemented and usually outperformed other methodologies such as traditional statistical models that have been developed earlier (Huang et al., 2002; Sung and Mukkamala, 2003).

The SVR, support vector regression, is the SVM utilization for function approximation and regression.

Different basic kernel functions are used in SVM models. The functions can be classified as polynomial (Poly), exponential radial basis function (ERBF), radial basis function (RBF), sigmoid and linear. A training dataset of input-output pairs is considered **as**

$$\boldsymbol{Z} = \{ \boldsymbol{X}_{\mathrm{i}}, \boldsymbol{Y}_{\mathrm{i}} | \boldsymbol{i} = \mathbf{1}, \mathbf{2}, \mathbf{3} \ldots, \boldsymbol{n} \} \qquad \textbf{(3.9)}$$

Where $\boldsymbol{X}_{\mathrm{i}} \boldsymbol{\epsilon} \boldsymbol{R}^{\varphi}$, $\boldsymbol{\varphi}$ is the dimensional input vector, $\boldsymbol{Y}_{\mathrm{i}} \boldsymbol{\epsilon} \boldsymbol{R}$ is the corresponding target value and **n** refers to the training data size. The regression model can be constructed, as shown in the Equation

$$\boldsymbol{Y} = \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{\theta}(\boldsymbol{x}) + \boldsymbol{b} \qquad \textbf{(3.10)}$$

Where $\boldsymbol{\omega}$ is the weight vector, $\boldsymbol{b}$ is the bias term and $\boldsymbol{\theta}(\boldsymbol{x})$ is representative of a nonlinear mapping function, which maps $\boldsymbol{x}$ into higher dimensional feature space. To obtain $\boldsymbol{\omega}$, it is necessary to minimize the following regularized function, which can be formulated as in Equation (2), with the constraint of Equations (3- 5):

$$\boldsymbol{min}\{\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\omega}^{\mathbf{2}} + \boldsymbol{c}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}(\boldsymbol{\xi}_{\mathrm{i}} + \boldsymbol{\xi}_{\mathrm{i}}{}^{(*)})\} \qquad \textbf{\textit{(3.11)}}$$

$$\boldsymbol{Y}_{\mathrm{i}} - \left\{\left(\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{\theta}(\boldsymbol{x}_{\mathrm{i}})\right) + \boldsymbol{b}\right\} \leq \boldsymbol{\psi} + \boldsymbol{\xi}_{\mathrm{i}} \quad , \quad i=1,\ 2,\dots,\ N$$

$$\boldsymbol{\xi}_{\mathrm{i}}, \boldsymbol{\xi}_{\mathrm{i}}{}^{(*)} \geq \mathbf{0} \qquad\qquad \mathbf{,}\ i=1,\ 2,\dots,\ N$$

Where $\boldsymbol{\xi}$ is equivalent to the function approximation accuracy placed on the training data samples, $\boldsymbol{\omega}^{\mathrm{T}}\boldsymbol{\theta}$ and $\boldsymbol{x}_{\mathrm{i}}$ represent the positive slack variables and C is the penalization parameter of the error that is applied to control the trade-off between the regularization term and empirical risk.

Ultimately, the SVR is solved by introducing Lagrange multipliers, $\boldsymbol{\delta}_{\mathrm{i}}$ and $\boldsymbol{\delta}_{\mathrm{i}}$‘, and exploiting the constraints, which has the following form:

$$\boldsymbol{f}(\boldsymbol{x}) = \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}\left(\boldsymbol{\delta}_{\mathrm{i}} - \boldsymbol{\delta}_{\mathrm{i}}{}^{‘}\right)\boldsymbol{K}(\boldsymbol{x}, \boldsymbol{x}_{\mathrm{i}}) + \boldsymbol{b} \qquad \mathbf{(3.12)}$$

Generally, the characteristics of the SVM method can be briefly stated as:

I. Considerably precise and robust,
II. Able to model complex nonlinear decision boundaries,
III. Less prone to over fitting in comparison with other models,

IV. Exhibit a compact description of the learned model,

IV. Potential of implementation in pattern recognition, regression and classification.

3.3.5 Recurrent Neural Networks

Recurrent Neural Networks are similar to Feed-forward neural networks but with no limitations regarding back-loops, that is, the network exhibits cycles (Figure 8). Therefore, information may be transmitted both forward and backwards. Consequently, an internal state of the network is created displaying a dynamic temporal behavior. (Krenker et al., 2011)

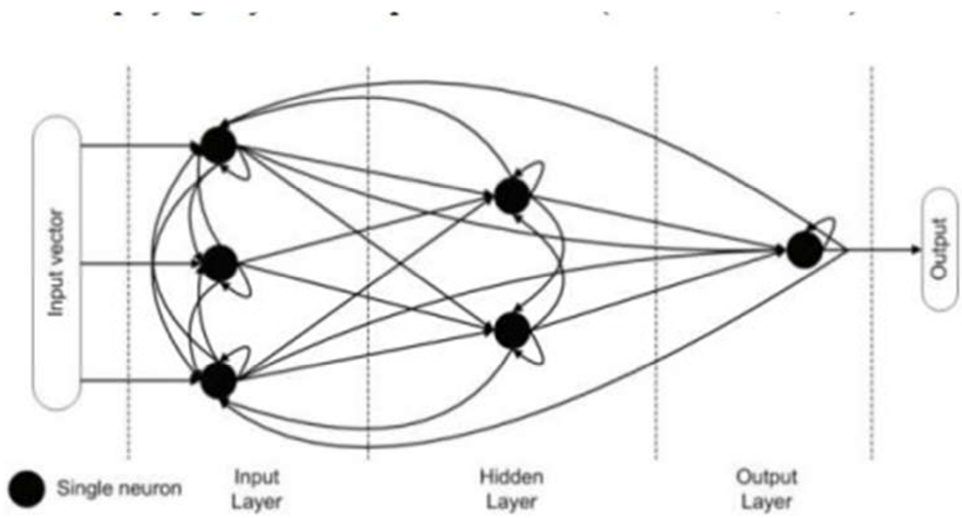

Figure 3.7 Fully recurrent artificial neural network.

Given the fact that the output of a neuron cannot be a function of itself but can be a function of past values, these architectures require *time* to be explicitly taken into consideration. The ordinary framework applied to recurrent networks is the discrete-time system, which is described mathematically by recurrent equations.

These equations are discrete-time equivalents of continuous-time differential equations. Therefore, besides being assigned a parameter as in Feed-forward neural networks, a delay is assigned to each connection of a recurrent neural network (this delay can be made equal to zero). Each delay is a numeric value multiple of an elementary time that is considered as a time unit.

Essentially, a discrete-time recurrent neural network follows a set of non-linear discrete-time recurrent equations, not only through the neurons functions configuration but also through the time delays associated to its connections.

3.3.5.1 Dynamic Driven Recurrent Networks

Most dynamical systems involve an autonomous part and a part governed by external force that usually is difficult to identify or noisy. Forecasting deals with dynamic models whose inputs and outputs are related through differential equations, or, for discrete-time systems, by recurrent equations. Recurrent networks with global feedback will be discussed, which is relevant for the scope of this thesis. For a thoroughly understanding of recurrent networks with local feedback, (Haylin, 1999) is suggested.

Considering the typical design of the multilayer networks previously shown, applying the global feedback can take a variety of arrangements. Global feedback can either be in a form of output neuron to the input layer or from the hidden neuron to the input layer. Other architectural layouts for recurrent networks exist, for instance, for multilayer networks with more than one hidden layer; however, those are not relevant for the current work and will not be discussed in detail.

Pertinent to this work is the discussion of recurrent networks used as input-output mapping networks. Basically, in this situation, an external input is applied and the recurrent network has a temporary response. Consequently, the recurrent network is considered as dynamically driven recurrent network. This characteristic enables recurrent networks to acquire state representations, which are fundamental for applications such as nonlinear predictions and modelling. In section 2.7, the recent use of neural networks for forecasting purposes is thoroughly discussed.

3.3.5.2 Input-Output Recurrent Model

The input-Output recurrent model, with a design that follows the typical multilayer perceptron, is illustrated in Figure 9. One can notice that the model has a single input that is applied to a tapped-delay-line (TDL) memory of q elements. A delay line tap extracts a signal output from somewhere within the delay line and usually sums with other taps to form an output signal. Moreover, via another TDL memory with q units, the single output is also fed back to the input. Thus, the contents from both TDL memories are fed to the input layer of the multilayer perceptron.

In Figure 9, u(n) denotes the present value of the model input and y(n + 1) corresponds to the value of the model output. Accordingly, one may understand that the output is one time unit ahead of the input. Hence, the present and past values of the input, which are exogenous inputs generated from outside the network, and delayed values of the output, on which the model output is regressed, are the data window of the signal vector applied to the input layer.

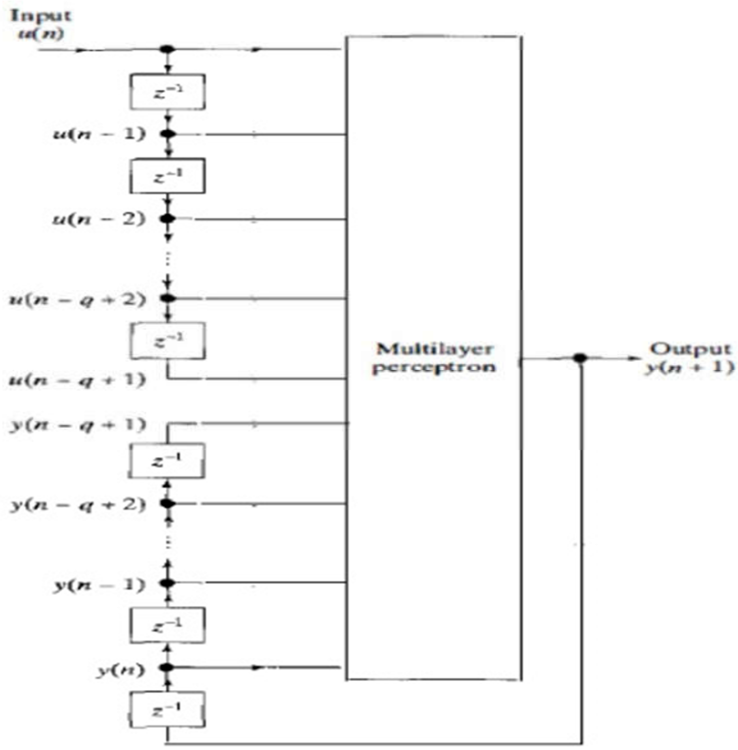

Figure 3.8 Nonlinear autoregressive with exogenous inputs (NARX) model.

$$\mathbf{(n + 1) = F(y(n), \dots , y(n - q + 1), u(n), \dots , u(n - q + 1))} \qquad (3.12)$$

Equation 11 demonstrates the dynamic behavior of the NARX model, where F is a nonlinear function of its arguments. The two delay line memories in the model are generally different, albeit they can.

CHAPTER 4

METHODOLOGY AND DATA GATHERNIG

CHAPTER 4 : METHODLOGY AND DATA GATHERING

4.1 Introduction

According to the weather parameters, a scaling approach for smaller off-grid systems that provides an accurate forecast of the PV output based on data collected from sensors is developed. The proposed methodology is based on sensor implementation in RES operation and big data technologies are considered for data processing and analytics.

4.2 Data Gathering

In the present work the data used to carry the investigation are referred to the ENG36P150W Photovoltaic module is used in the implementation maximum power of 150 KW, located in the institute of electronics and Electrical Engineering University of boumerdés. The panels are installed in the car parking. The PV system consists of fore northeast oriented subfields with an azimuth angle of 10°.

Figure 4.1 The PV array site.

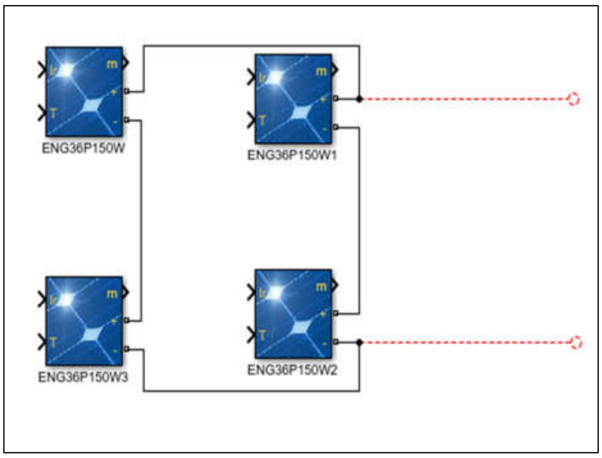

Figure 4.2 The connection of the PV Modules.

Table 1 ENG36P150W characteristics under STC.59

P_{max}	150W
V_{oc}	23.06
I_{sc}	9.30
V_{mpp}	17.68
I_{mpp}	8.49
$NOCT$	45
$T.C.V_{oc}$[1]	-0.32%
$T.C.I_{sc}$[2]	0.05%
T.C.P_{max}[3]	-0.45%

In order to monitor the main parameters of PV plant, an integrated data acquisition system is configured to measure the solar irradiation on tilted planes, ambient temperature and output power. Generally, the input for prediction methods can consist of different parameters, called forecasting factors, which compound an input vector. In the present work the input vector is given by each five minute measurement of ambient temperature, solar irradiance on tilted of array. The monitored data are related to the historical data from eight non-successive different days. In order to implement the forecasting models, the collected data were divided in two sets: the training data set included 70% of the time series data and the 30% remaining of data represented the validation and the testing data.

[1] Temperature coefficient of V_{oc} (%/deg.C).
[2] Temperature coefficient of I_{sc} (%/deg.C).
[3] Temperature coefficient of P_{max}(%/deg.C).

4.3 Methodology

The process of applying ML on any dataset to predict unknown output values consists of three general phases: Pre-processing of data to extract features, training the prediction models and observing validation accuracy on training dataset and evaluation of the pre-trained model for the test dataset. Firstly, the dataset was prepared and checked for any missing outliers and erroneous data values. We have used the collection of the data selected (Temperature and Irradiance), to train and test the model. In this study, 978 instances were used 684 for training, 147 for validation, whereas 147 instances were used for testing. In the prediction phase, data with known output response values were used for training several ML algorithms using Regression Learner from Statistical and Machine Learning Toolbox and Neural Network toolbox of Matlab. The two most used ML approaches for forecasting power plant output of 5 minute ahead of time are used in this work. The models used are ANNs and SVM. The detailed work of simulation and parameter is shown in Sections 5.2 and 5.3.

4.2.1 Support Vector Machines

Support Vector Machines Support vector machines are statistics learning tools widely used in classification problems [22]. SVM is a linear model for classifications and regressions problems. It can solve linear and nonlinear problems and is very suitable for many practical tasks. The idea behind SVM is simple: the algorithm creates a line or hyper plane, dividing the data into several categories. Figure SVMs separation of classes.

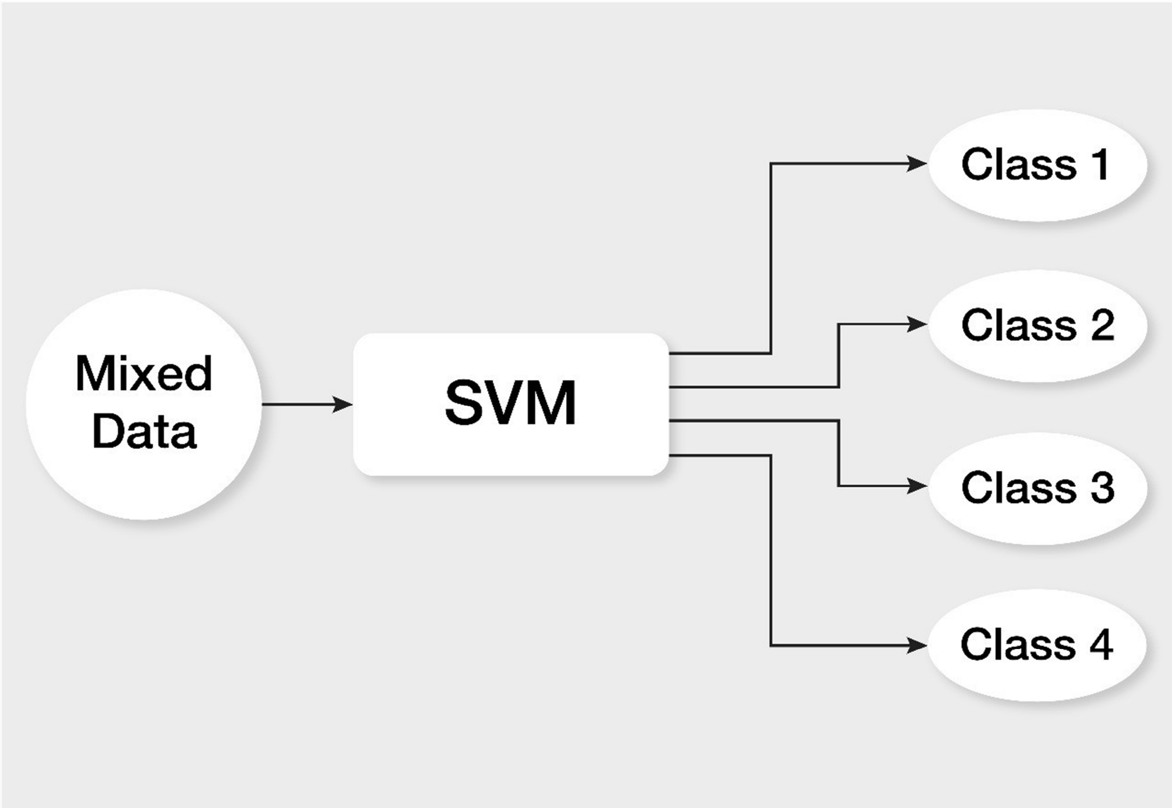

Figure 4.3 SVMs separation of classes.

As a first approximation, SVM finds the dividing line (or hyper plane) between the two types of data. SVM is an algorithm that takes data as input and generates a line, separating these classes when possible.

In our research we have chosen three most effective model of SVMs (linear, quadratic and cubic) to compare the result of the prediction of the three of them and having a clear idea of the most effective one.

The objective of the SVM algorithm is to find a hyper plane that, to the best degree possible, separates data points of one class from those of another class. “Best” is defined as the hyper plane with the largest margin between the two classes, represented by plus versus minus in the figure below. Margin means the maximal width of the slab parallel to the hyper plane that has no interior data points. Only for linearly separable problems can the algorithm find such a hyper plane, for most practical problems the algorithm maximizes the soft margin allowing a small number of misclassifications.

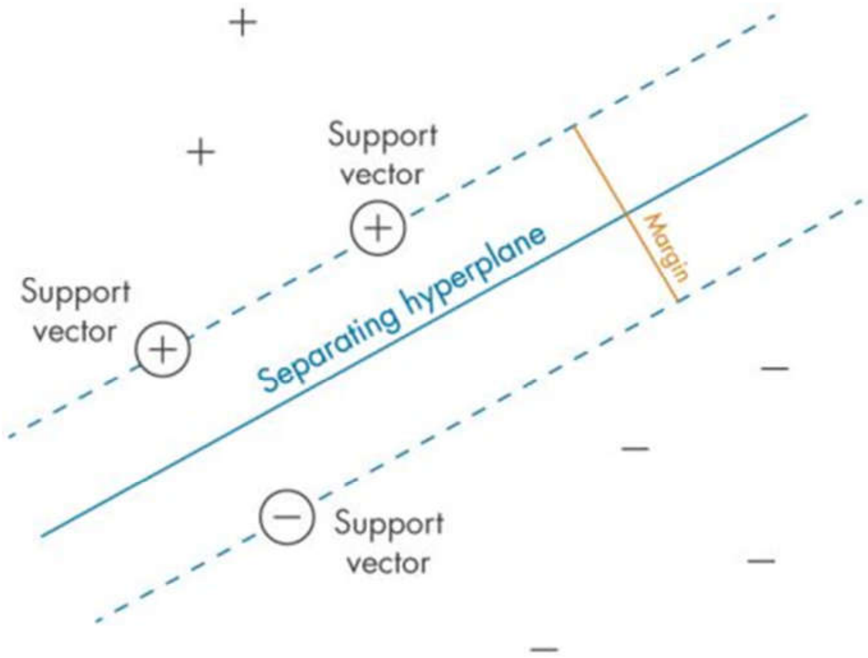

Figure 4.4 Defining the "margin" between classes.

4.2.2 Artificial Neural Networks

A neural network is heuristically developed from the human brain's learning processes on recognizing visualized objects. Similar to neurons in a biological brain, ANN is operated on many different artificial neurons. The structure is a network model that connects the input layer, hidden layer, and output layer. These layers are constructed using neural nodes. You don't need to make assumptions about model inputs or outputs.

The user only needs to define the structure of the model, such as the number of hidden layers, the number of neurons in each layer, and the corresponding learning algorithm. The input of a neuron can be an external stimulus or the direct output of another neuron.

In this study, **feed-forward neural networks (FFNN)** and **Elman RNN** for a single layer and are used. The performance of FFNN depends strongly on the parameter settings. For this study, FFNN is modeled as 1 hidden layer with more than 10 neurons, 1 output neuron (the prediction of power production), and 2 input neurons .A simplified diagram of the FFNN is shown in Figure bellow:

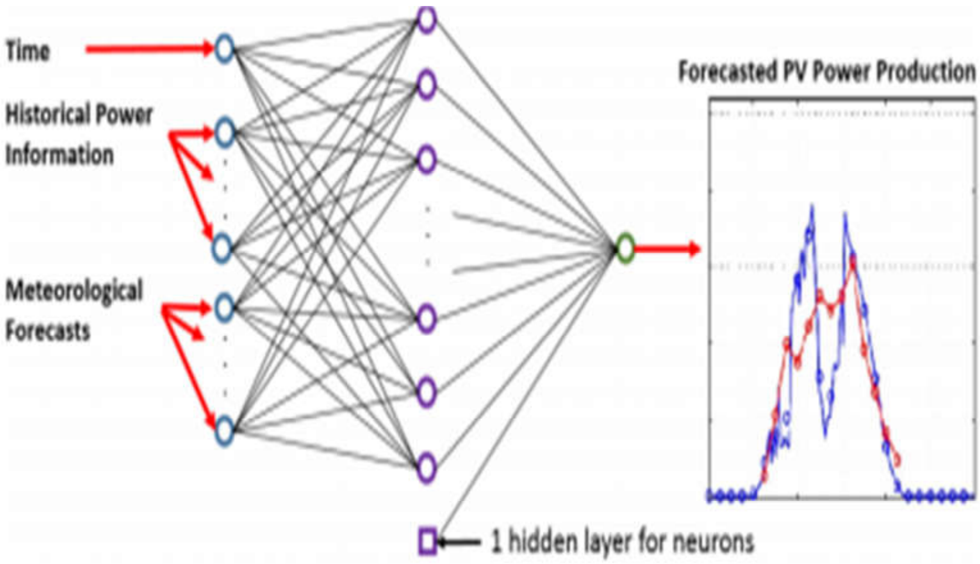

Figure 4.5 Artificial feed-forward neural network (FFNN) structure.

For Elman RNN the structure is shown bellow :

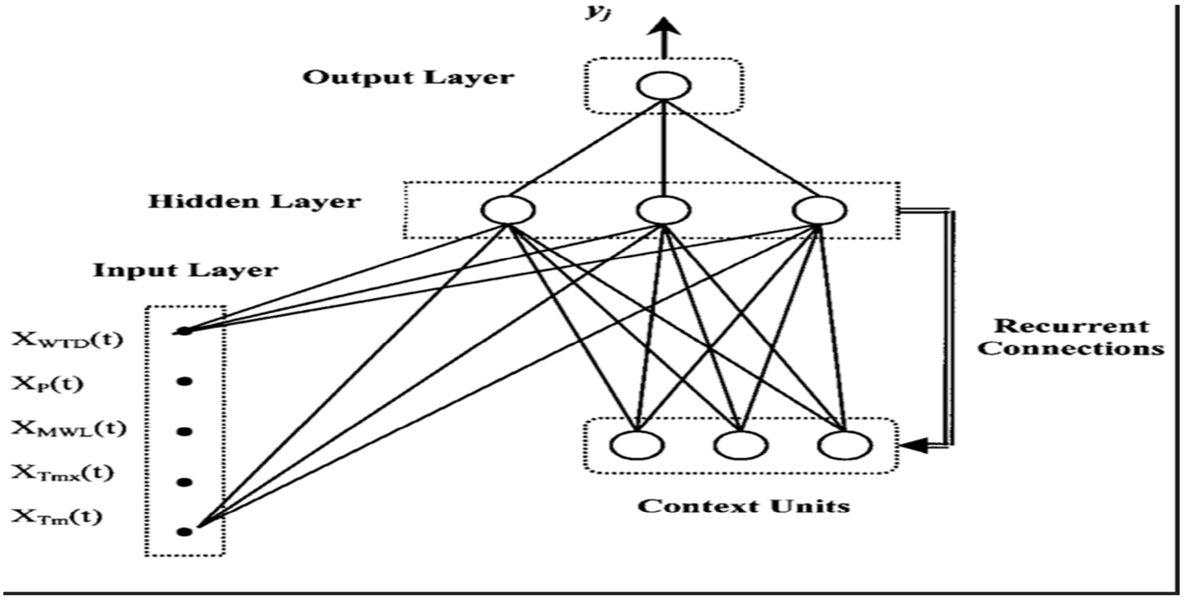

Figure 4.6 Elman RNN structure.

4.4 Performance Matrixes

The performances of the methods described in the previous section are evaluated by several error calculations. For test samples during night hours, i.e. when solar irradiance is not available, there are no needs to evaluate the system performances. Forecast accuracy is mainly evaluated using the following common statistical metrics:

- Mean square error (MSE)

$$MSE = \frac{1}{n}\sum(y - \hat{y})^2 \qquad (4.1)$$

- Mean absolute error (MAE)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \qquad (4.2)$$

- Root mean square error (RMSE)

$$\boldsymbol{RMSE} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{N}}(\boldsymbol{y}_{\mathrm{i}} - \hat{\mathrm{y}}_{\mathrm{i}})^{\mathbf{2}}} \qquad \textbf{(4.3)}$$

Where $\boldsymbol{y}_{\mathrm{i}}$ is the measured power output, $\hat{\mathrm{y}}_{\mathrm{i}}$ is the forecasting for $_{\mathrm{i}}$, and **N** represents the number of data points which the forecast errors are calculated. MAE provides a view of how close the forecasts are to the measurements in absolute scale. RMSE, amplifies and severely punishes large errors by using the square form. The last one Although these performance metrics are popular and considered the standard performance measures, limitations with MAE, MSE and RMSE are that the relative sizes of the reported errors are not obvious. It is hard to tell whether they are big or small when comparing to different series of data in different scales.

4.5 Conclusion

The analysis of the evolutionary error calculated from the sum of the number of different investors shows the potential of a tiered approach to determine which smaller cash-generating units have the greatest impact on the forecast.

CHAPTER 5

SIMULATION AND DISCUSSION

5.1 Introduction

In this chapter we address the methodology of our techniques, each one has its own parameters to be able to reach the desired forecast.

Matlab toolboxes is used to perform these predictions and error evaluators are relied upon to find out the most suitable method.

5.2 Methodology, Simulation and Results

The wide use of the matlab allows us to perform several tasks by writing codes of function and algorithms or by using the toolboxes which are a collection of functions built on the MATLAB technical computing environment.

Machine learning is a data analytics technique that teaches computers to do what comes naturally to humans and animals .With the rise in big data, machine learning has become a key technique for solving problems in areas.

A MATLAB app is a self-contained MATLAB program with a user interface that automates a task or calculation. All the operations required to complete the task — getting data into the app, performing calculations on the data, and getting results are performed within the app. Apps are included in many MATLAB products.

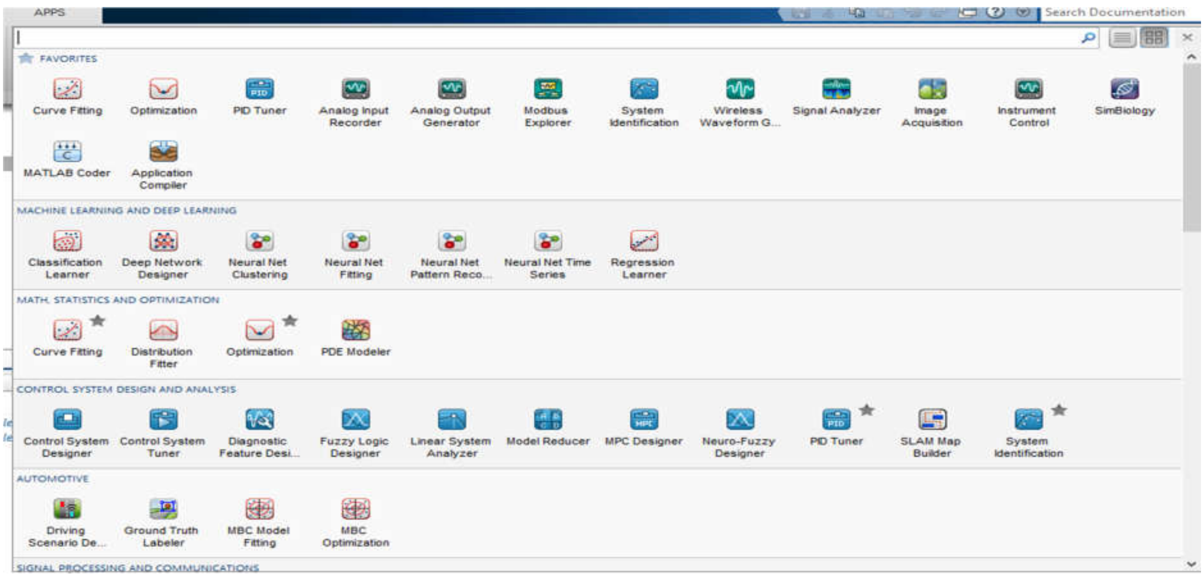

Figure 5.1 Matlab apps.

In our project we have chosen two mainly toolboxes based on machine learning :

The first one is **support vector machine toolbox** is a set of Matlab functions that provide access to basic SVM functionalities such as linear and non-linear separation of data points in an arbitrarily dimensional room

The second toolbox is **nntool** which opens the Network/Data Manager window, which allows you to import, create, use, and export neural networks and data

5.2.1 Support vector machine regression (SVM)

The basic idea for this approach is to classify the data using the **Classification Learner**. Using this app, you can explore supervised machine learning using various classifiers. You can explore your data, select features, specify validation schemes, train models, and assess results. You can perform automated training to search for the best classification model type, including decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbors, naive Bayes, ensemble, and neural network classification.

To select the SVMs classifiers :

OPEN MATLAB → APP → MACHINE LEARNING AND DEEP LEARNING →

REGRESSION LEARNER → SVMs

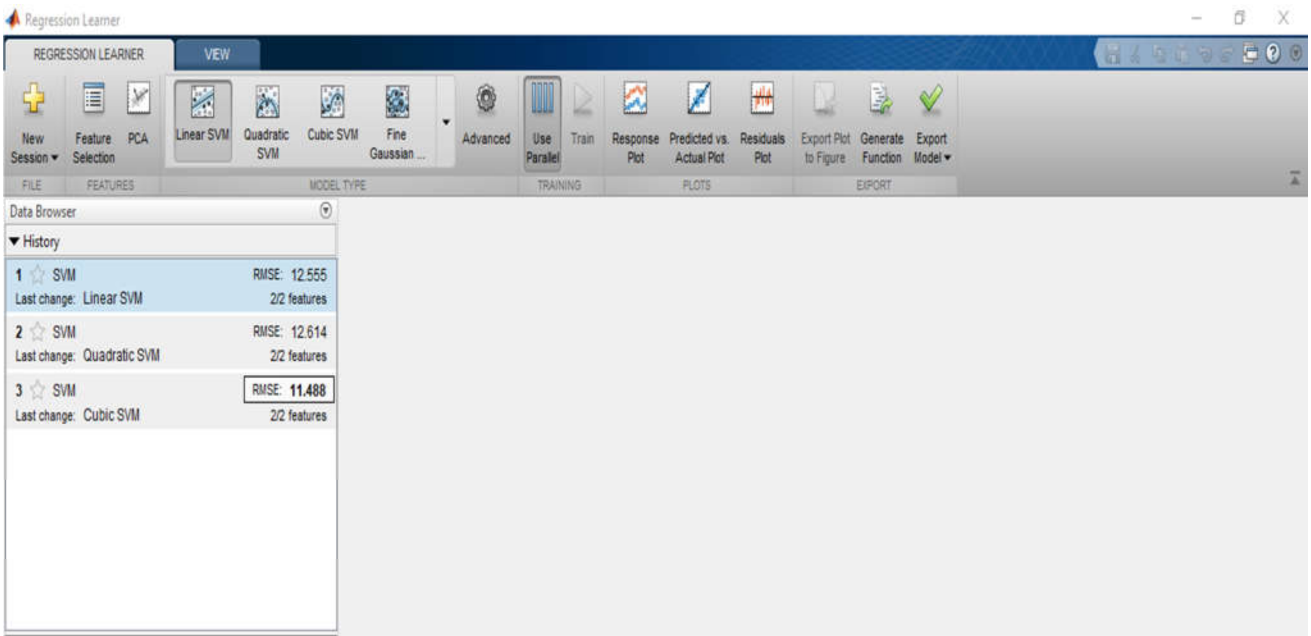

Figure 5.2 Regression learner tool-box.

For using the SVM regression in the PV power forecast, the input data contain temperature and solar irradiance, while the output data are obviously the power generated by the PV panel or array.

So in the regression learner toolbox we have chosen three types based on the hyper plan and we compare them by their performance. They are linear, quadratic and cubic .

5.2.1.1 The Linear Model

In the linear type the hyper-plan line representation is governed by a simple equation like

$$ax + by + c = 0. \qquad (5.1)$$

The target is to optimally determine the coefficients a, b and c so that the hyper-plan delimits the objects as well as possible

We import the data from the matlab work space and we train the model , the result is shown in the following figures :

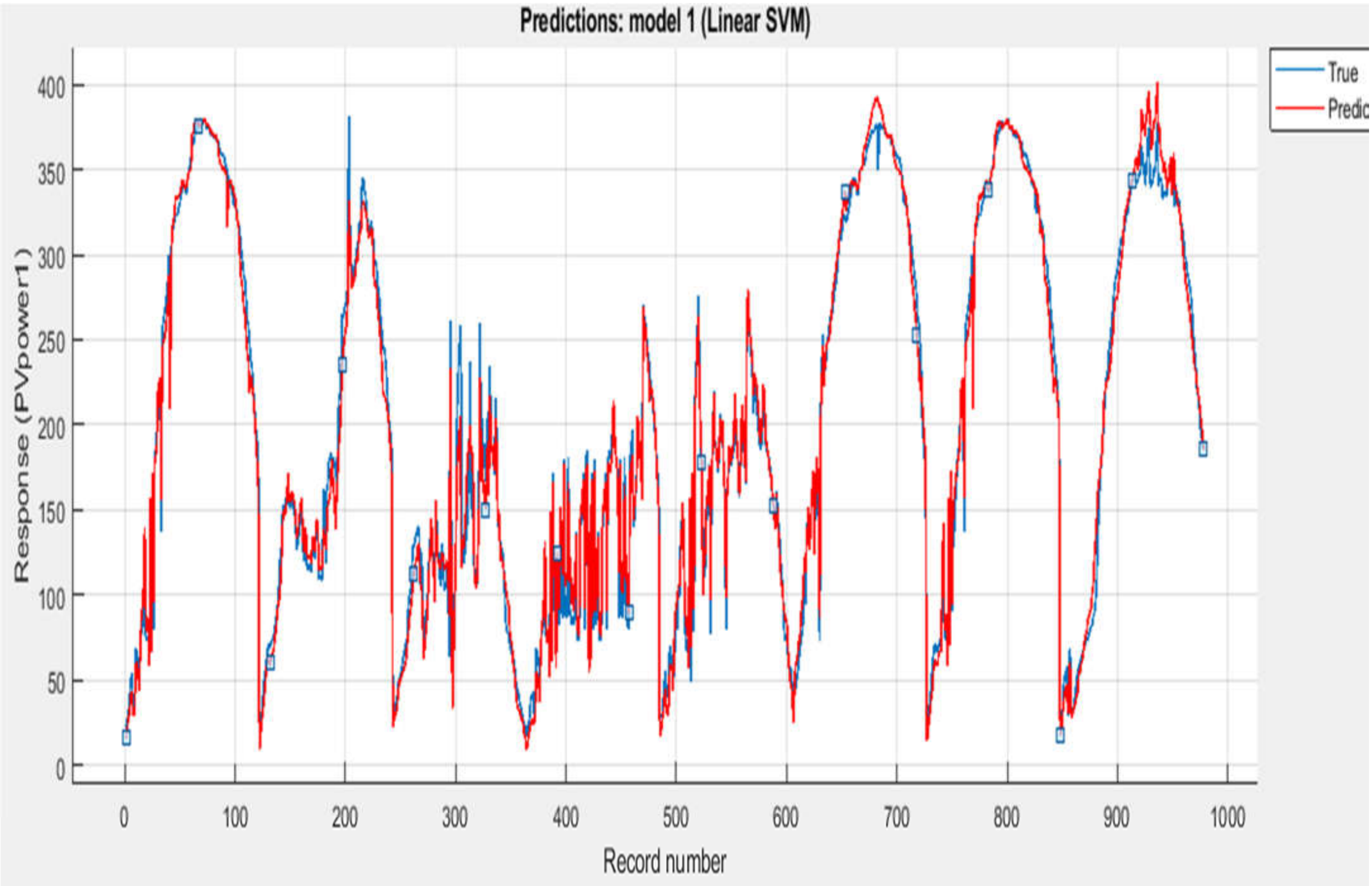

Figure 5.3 Actual vs predicted power using linear SVM.

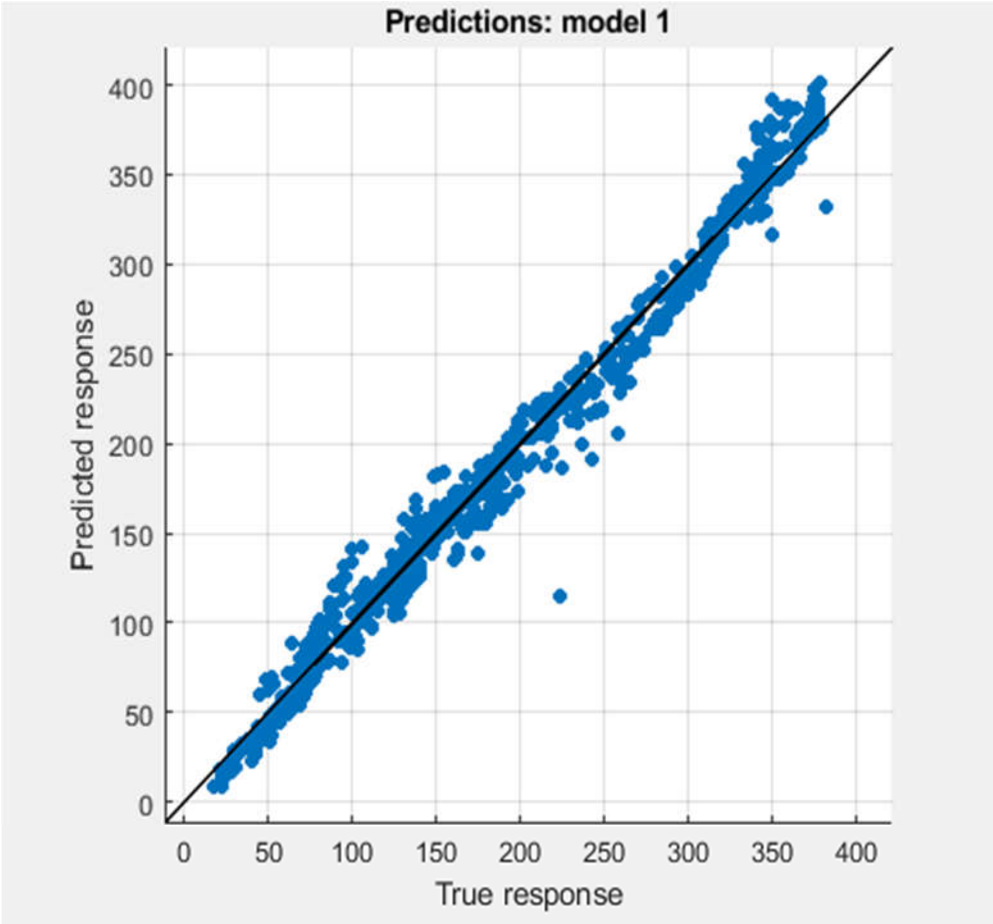

Figure 5.4 Perfect prediction vs observed prediction.

	RMSE	**R-squared**	**MSE**	**MAE**	**Prediction speed**	**Training time**
Linear SVM	12.562	0.99	157.8	9.2816	3100	102.05

Table 2–Prediction model 1 performance.

5.2.1.2 The Quadratic model

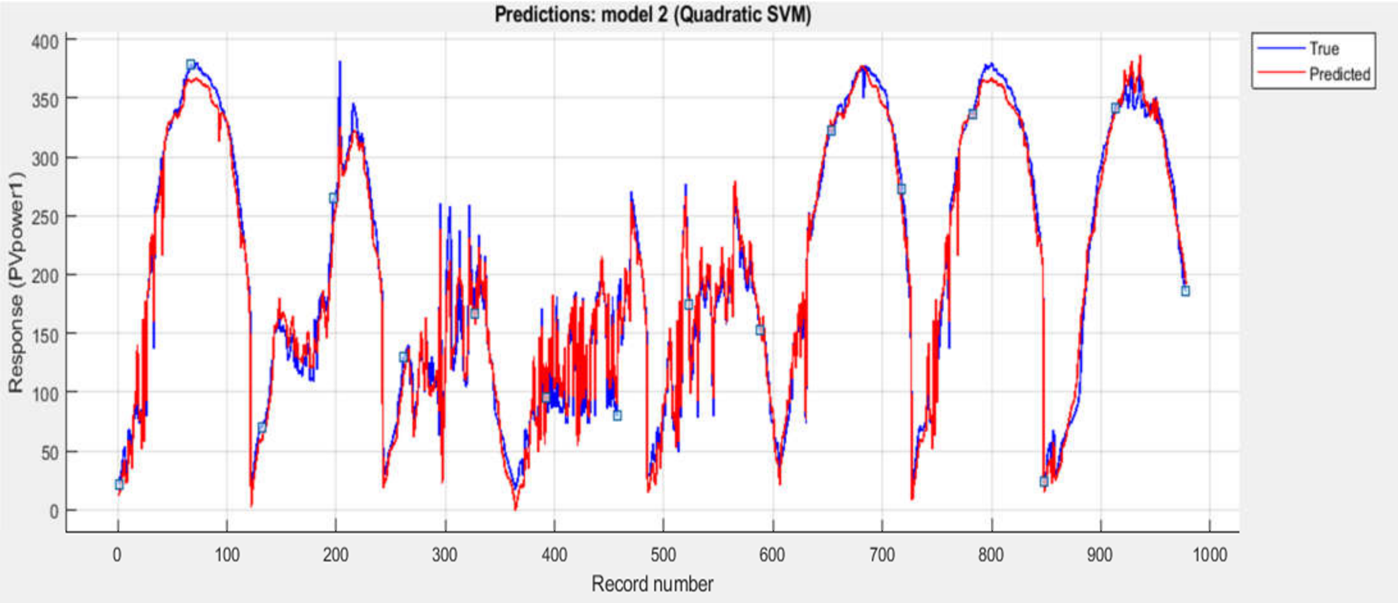

Figure 5.5 Actual vs predicted power using Quadratic SVM.

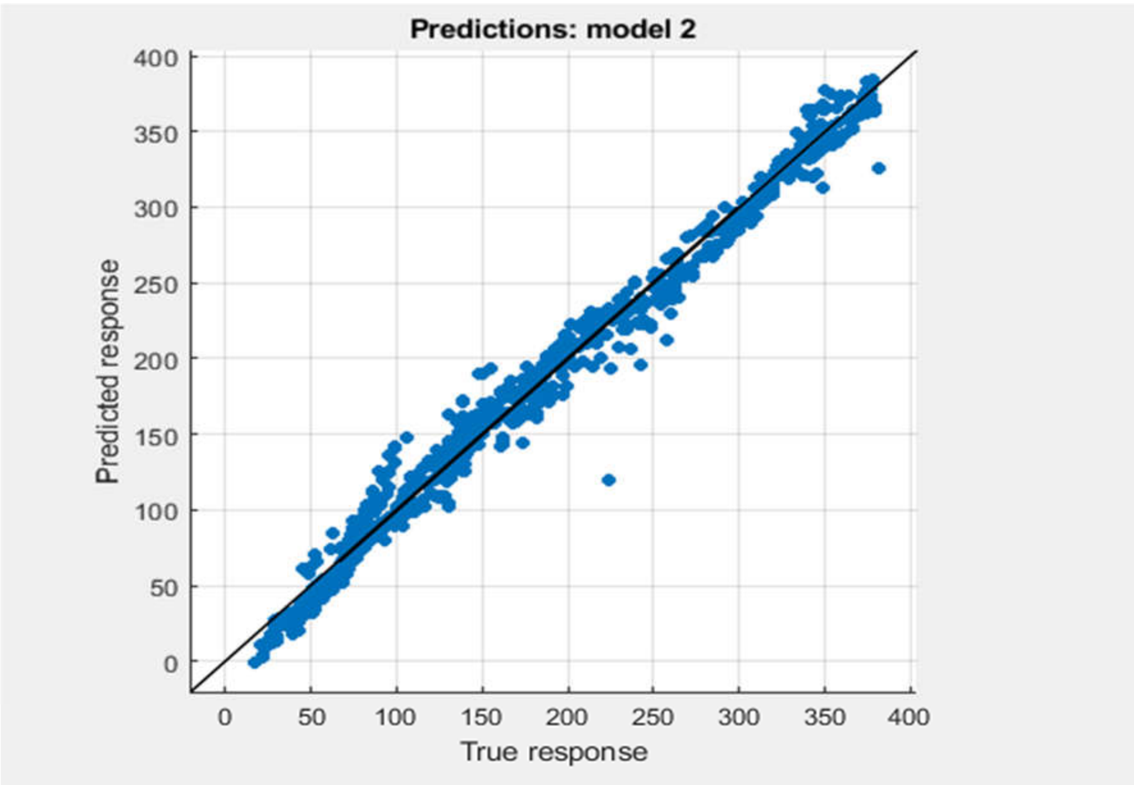

Figure 5.6 Perfect prediction vs observed prediction model 2.

	RMSE	R-squared	MSE	MAE	Prediction speed	Training time
Linear SVM	12.59	0.99	158.51	9.9556	1800	85.497

Table 3 Prediction model 2 performance.

5.2.1.3 The Cubic model

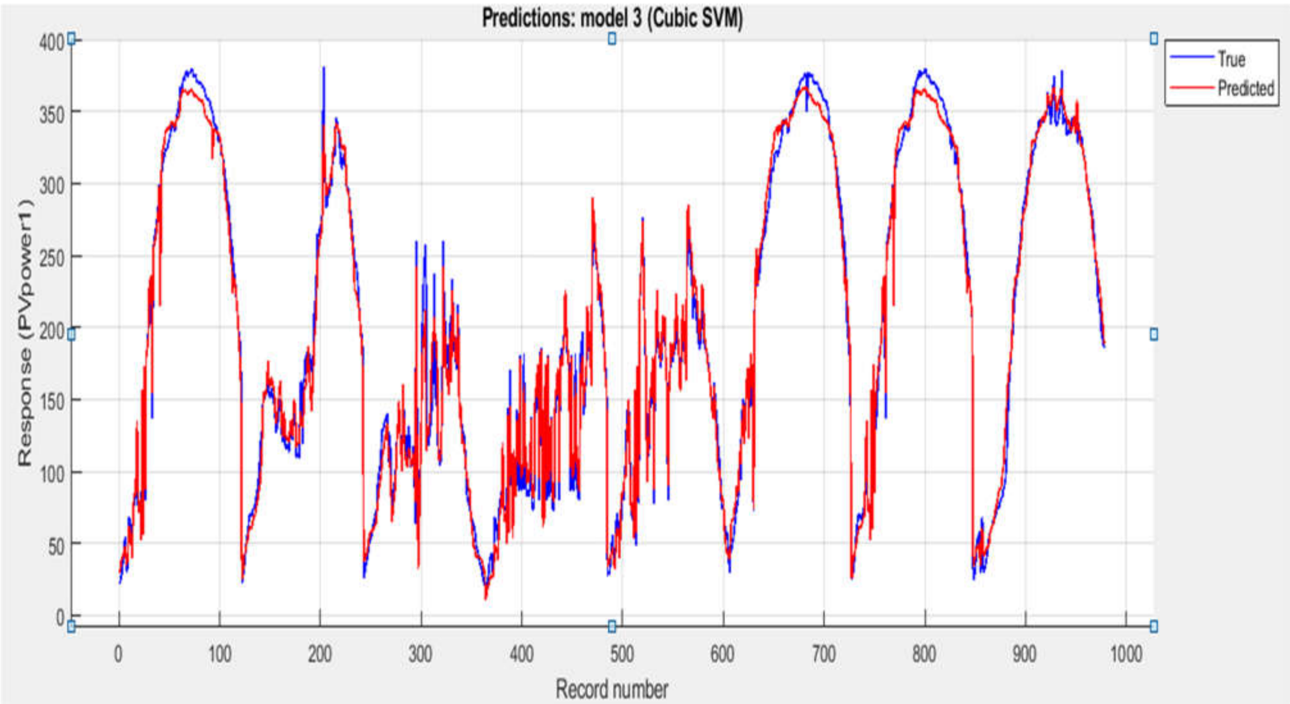

Figure 5.7 Actual vs predicted power using cubic SVM.

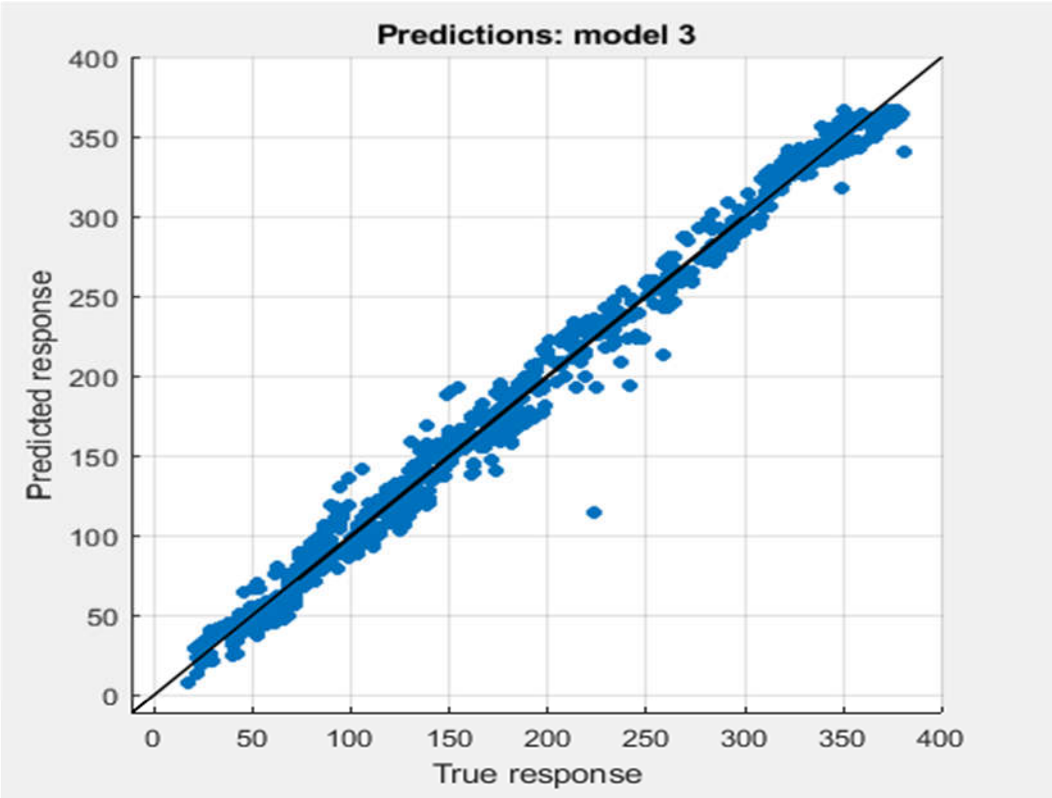

Figure 5.8 Perfect prediction vs observed prediction model 3.

	RMSE	R-squared	MSE	MAE	Prediction speed	Training time
Linear SVM	11.432	0.99	130.69	8.7952	3500	64.95

Table 4 Prediction model 3 performance.

5.2.1.4 Analysis and comparison

To find out the most effective performance of these models, we need to compare the performance result of each model :

	RMSE	R-squared	MSE	MAE	Prediction speed	Training time
Linear SVM	12.562	0.99	157.8	9.2816	3100	102.05
Quadratic SVM	12.59	0.99	158.51	9.9556	1800	85.497
Cubic SVM	11.432	0.99	130.69	8.7952	3500	64.95

Table 5 Performance parameters of the 3 models.

We remark some interesting results, as when it comes to the linear and quadratic based SVM techniques we do not see a big difference in performance as both error predictors MAE and RMSE show close difference with 12.55 and 12.61 respectively with the edge to the first model, however there is major gap in training time and prediction speed as the second model is faster but with a slightly less accurate performance.

Furthermore, it is clear that the Cubic-based SVM outperforms both methods as it shows less MAE AND RMSE error evaluations with low training time and high prediction speed.

The following conclusion can be made that the SVM that relies upon a Cubic type calculations is the most suitable of the three as it is more accurate for forecasting output power with respectable performance time.

5.2.2 Artificial Neural Network

The forecasting accuracy of ANN networks requires multitude of variables, as they are different types of ANNs ,different sets of activation functions, as well as the numbers of layers and neurons used. A set on of inputs including 2 columns and 978 rows of irradiance and temperature are applied.

For this purpose Matlab Toolbox (nntool) is used, the input data are imported as well as the target data which is the desired output power that have in our disposal, then the network is created and divided as : 70% for training, 15% for validation and 15% for testing, the training is carried out multiple times until the best and most accurate model has been created

We open the nntool tool-box using the command “nntool” in the matlab work space

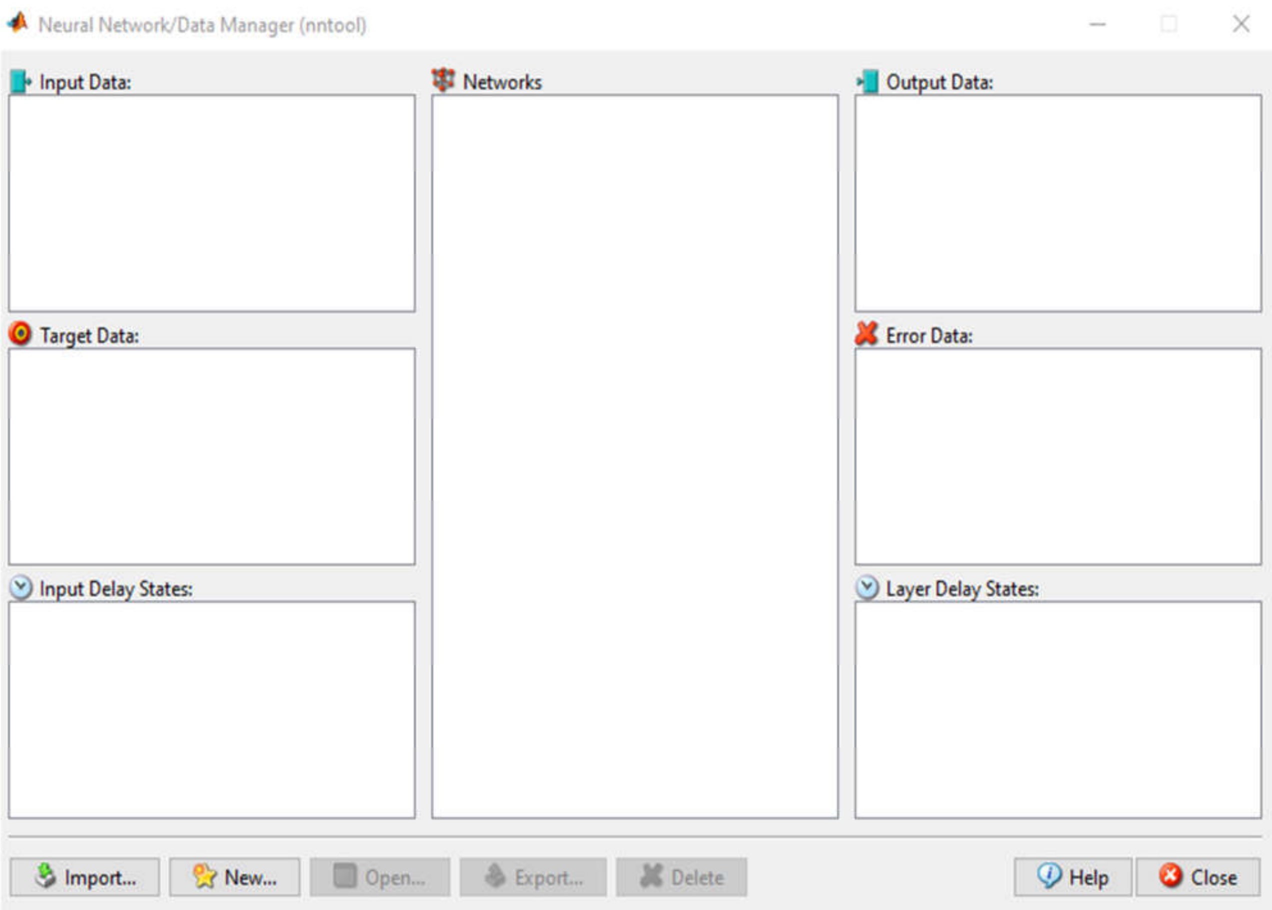

Figure 5.9 nntol tool-box.

We have focused on two main types of ANN architecture:

5.2.2.1 The Multi-Layer Perceptron (MLP)

also called the Feed-Forward Neural Network (FFNN) has all its weights moving forward with no back-movement, the Levenberg-Marquardt algorithm is the most suitable one for training, in which only 2 layers have been used, and 10 neurons chosen. The activation function of neurons is the hyperbolic function and PURLIN for the output layer. This will be represented in the following figure

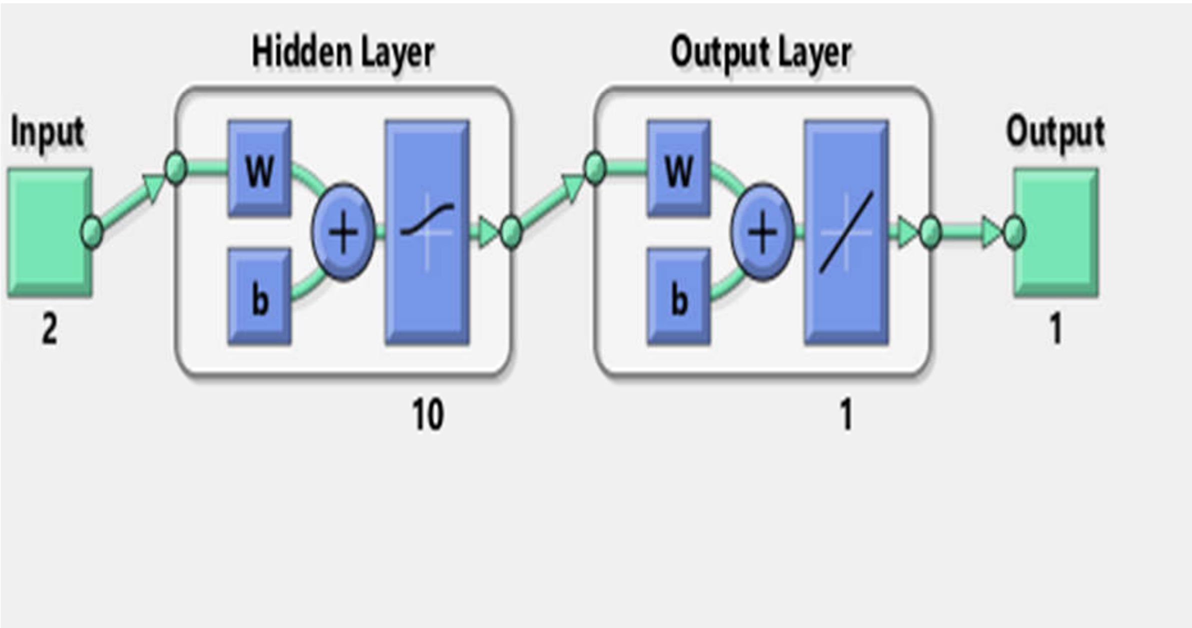

Figure 5.10 Feed-Forward Neural Network (FFNN).

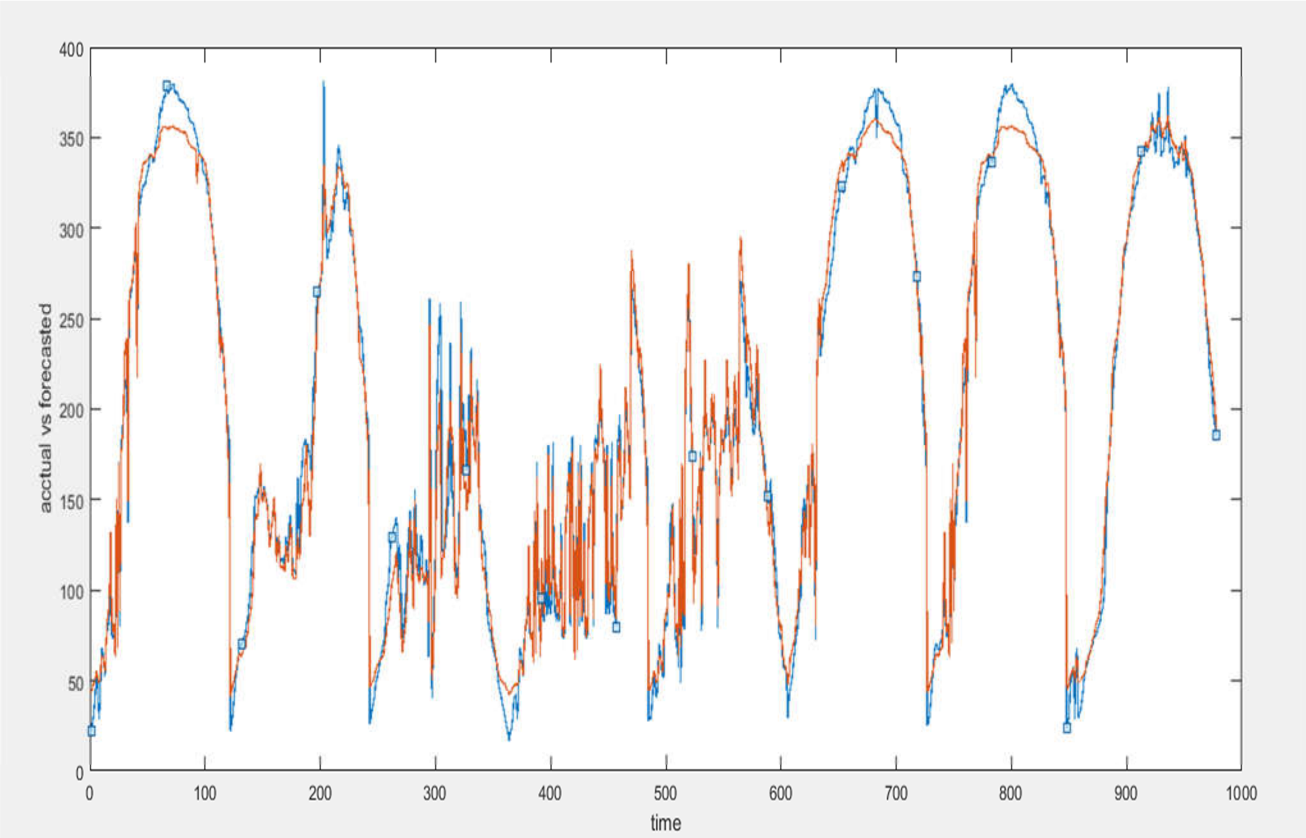

Figure 5.11 Actual vs predicted power using FFNN.

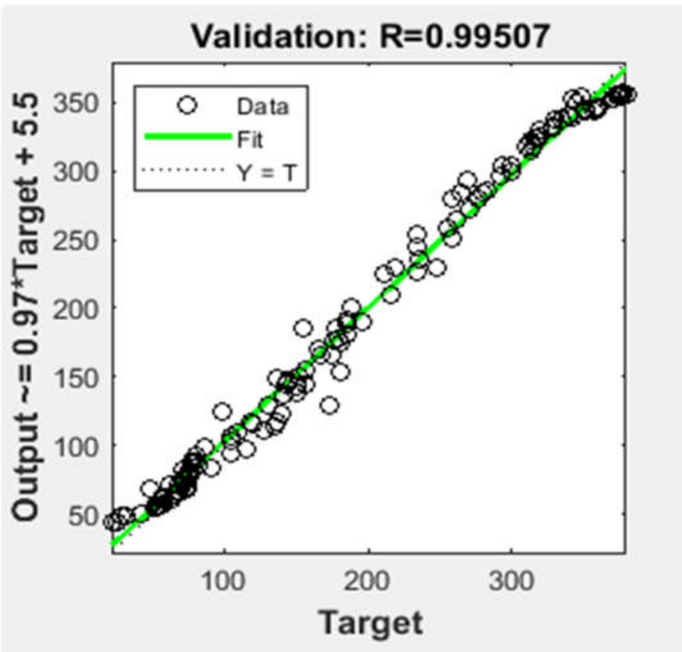

Figure 5.12 Regression plot for FFNN validation.

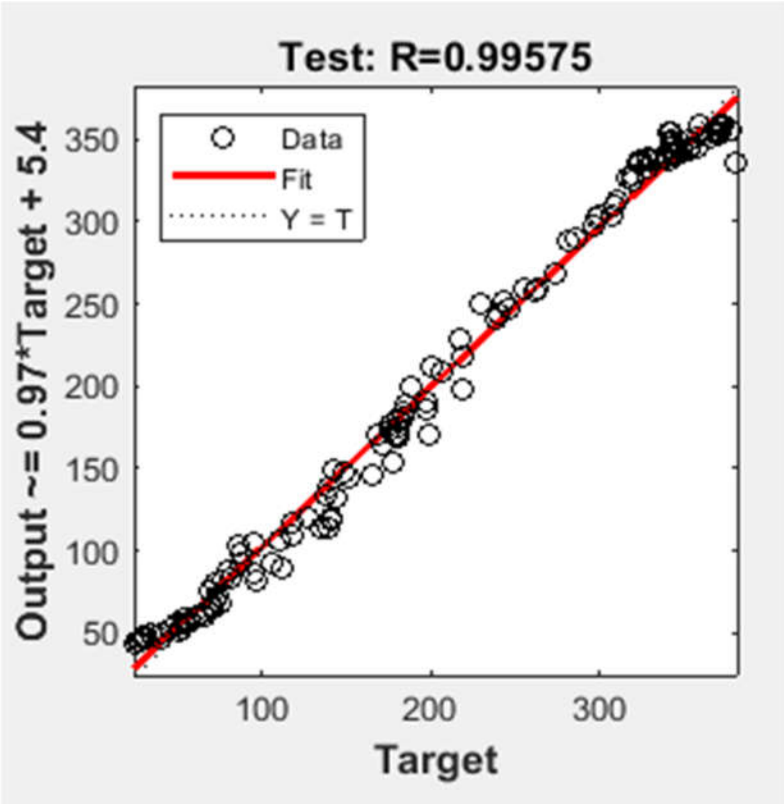

Figure 5.13 Regression plot for FFNN testing.

5.2.2.2 Elman RNN

The recurrent Neural Network has the same number of neurons and same activation functions used as the previous model, however the main difference is that this one is an extension of MLP models and the predicted output relies on the input, it also considers a feedback loop. The same number of data, the same data division subsets in terms of training validation and testing are also considered back propagation algorithm is used for stable and fast prediction.

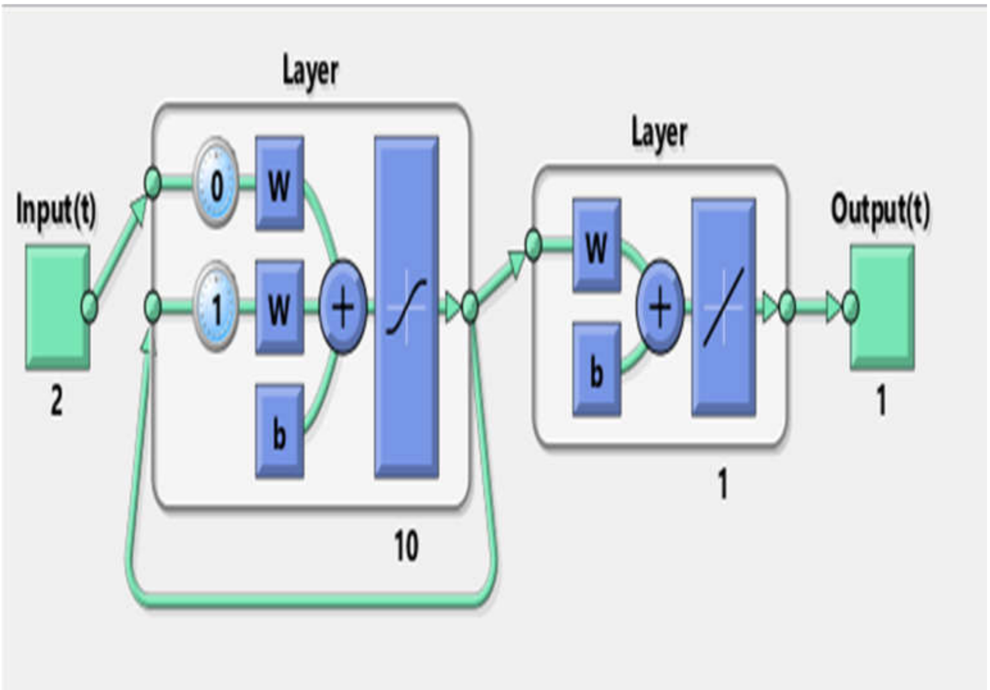

Figure 5.14 Recurrent Neural Network (RNN).

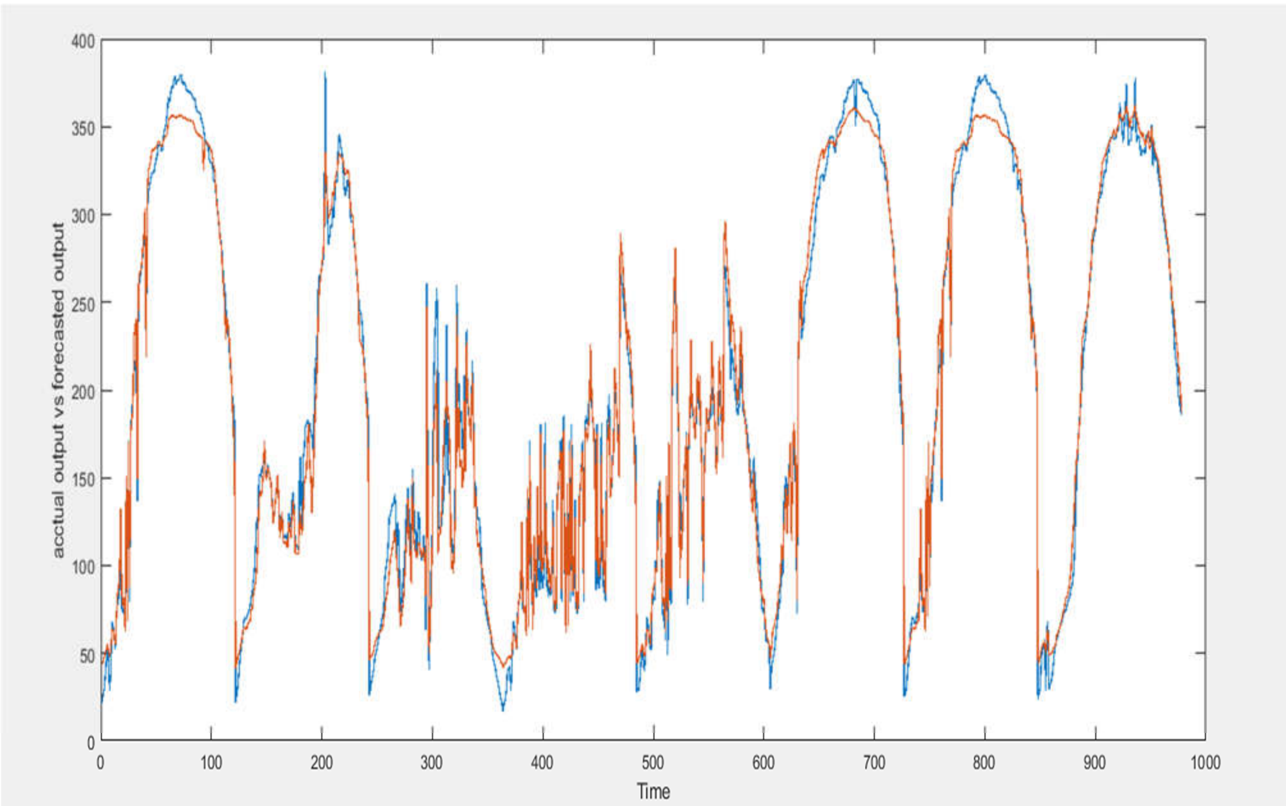

Figure 5.16 Actual vs predicted power using RNN.

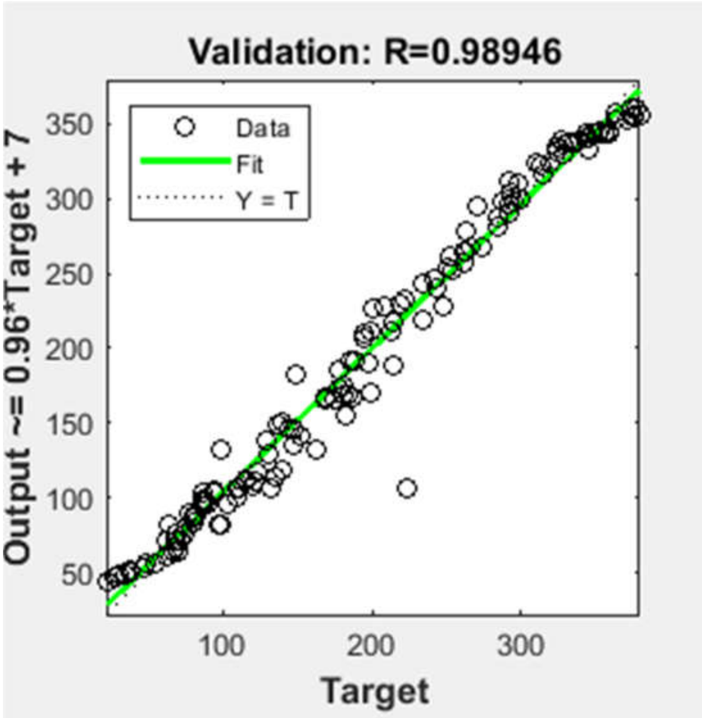

Figure 5.17 Regression plot for RNN validation.

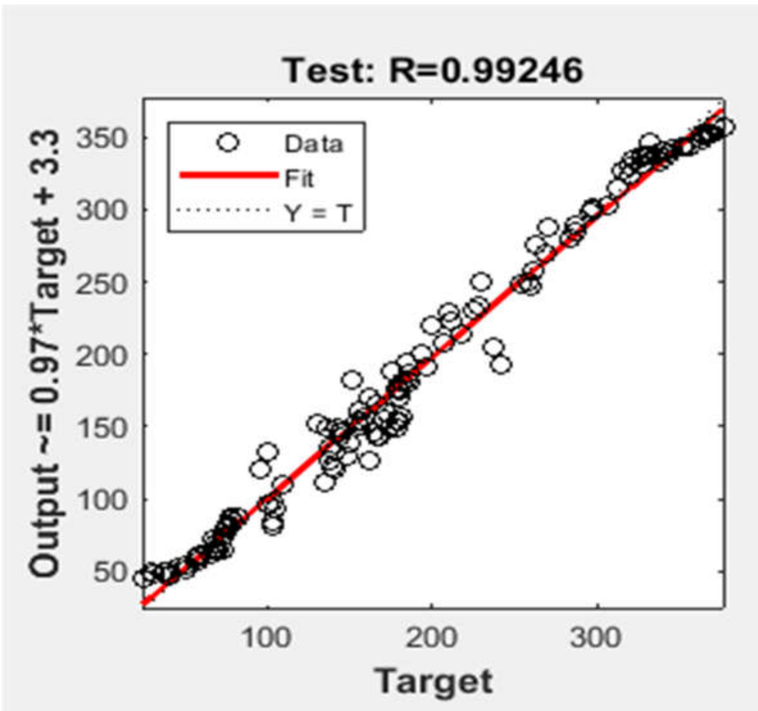

Figure 5.18 Regression plot for RNN testing.

5.2.2.3 Analysis

First, we plot both predicted output powers values vs time and observe the difference in our plots.

We can observe that we have an accurate output power forecasting for both models of ANN and RNN, with no large deviation observed initially from out graphs, RNN yields a near identical output to that of our actual output, while ANN also produces precise forecasting it is less accurate that the Elman RNN

We plot the result of the prediction of the two approaches, mainly to have a clear observation and comparison compared with the actual output

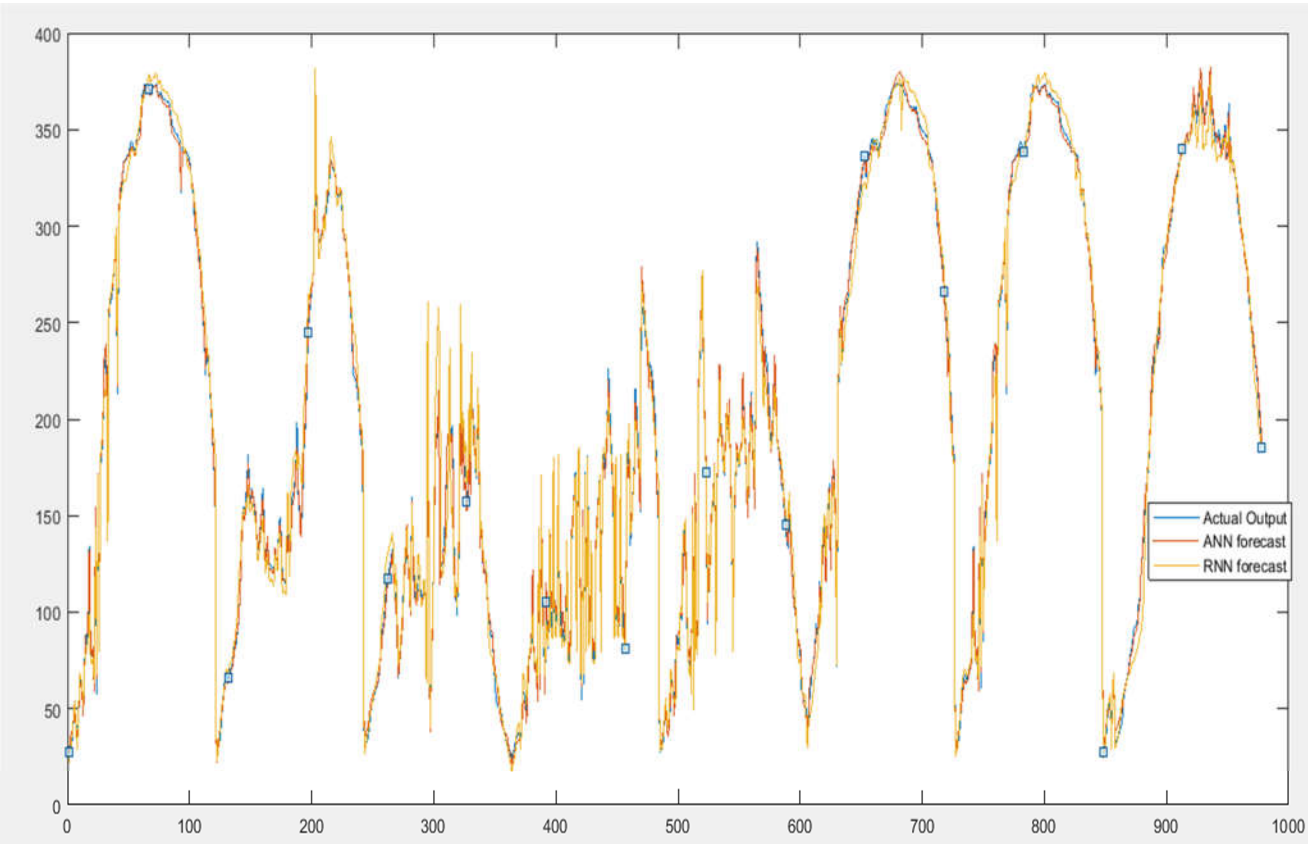

Figure 5.19 Forecasted values vs Actual value.

Comparing between both models of ANN networking can be expressed by error indexes in this table below:

	RMSE	MSE	MAE
FFNN	6.79	46.13	0.2172
RNN	4.75	32.57	0.112

Table 6 Performance parameters of the 2 models.

The table shows that RNN is clearly the most effective method as it shows much better performance in all error indexes RMSE MSE AND MAE, although ANN is very accurate it is not the suitable method for our predictions. It should be noticed training time has not been included in our analysis because it takes a very short time (mili-3seconds) to do the calculations.

5.3 CONCLUSION

We can concluded from our analysis that ANN architecture that use machine learning algorithms and non-linear functions models are much more effective than stochastic linear models SVMs.

And the Elman RNN model has by far outperformed all the previous models and seems the most efficient tool.

However, it should be noted the quality and quantity of data, the selection of parameters are varied and we can explore an infinite number of options, adding to the fact that all we have is data of 8 days so it should not be conclusive, it is advised to use a larger sets of data .

General Conclusion

PV output power forecasting and its different models and techniques allow for better use of renewable energy resources to improve our daily lives economically and to ensure the preservation of our environment.

This report focuses on presenting SVM and ANN methods, a short term analysis has been suggested to find out which of the two methods has the best prediction accuracy.

Error evaluation indexes identify the differences in their performances, while using the Matlab Toolbox we can also calculate the time of operation and the of the models different parameters to eventually reach the best and most efficient one.

The dataset comprises of different weather conditions and solar irradiance and temperature are the inputs that are fed into the Matlab Toolbox to train validate and test it.

The SVM model is a stochastic learning technique that is uses less complex and direct approach to perform the forecasting however it is takes some time and its efficiency depends on which equation is implemented while the ANN is a deep machine learning approach that uses more complex equations and its flexibility especially when it comes to the numbers of neurons and its activation functions gives more maneuverability and the time of operation is much quicker than its predecessor method largely due to the use of a more sophisticated equations.

The results have shown that cubic SVM yields better performance than the two other techniques with use Linear and Quadratic equations but the two ANN models, FFNN and RNN both outperform the stochastic methods in sunny days while the performance of both of them is generally the same and unstable under cloudy or rainy weather conditions.

It should be also noted that the size of the data used and its quality define the accuracy of any technique.

GENERAL CONCLUSION

Its is recommended to use ANN networks in further research as they show better forecasting performance with much more speed.

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