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PERFORMANCE EVALUATION AND CLASSIFICATION OF SOLAR CELLS EFFICIENCY ACCORDING TO AREA USING NEURAL NETWORKS

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This thesis was defended successfully on **18/06/2016** and approved by:

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Dedication

As well as everything that I do, I would be honored to dedicate this work to my parents, the two persons that gave the values and tools necessary to accomplish my tasks. My parents support me on every step I make. Many thanks for my sisters, wife, and brothers.

Also I would like to dedicate my work for my Palestinian people: Individuals, and organization that may benefit from it.

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Abstract

The prediction of the output power of PV power system in a given place has always been an important factor in planning the installation of PV power system, and guiding electrical companies to control, manage and distribute the energy to their electricity networks properly. The production of the electricity sector in Palestine using PV power system is a promising sector; the aim of this research is to propose two models that are used to predict the future output power values of solar cells, which provides individuals and companies with predicted future information, and thus they can organize their activities in the electricity sector. Firstly; we aim creating a model capable of connecting time, place, and the PV power system output relations between randomly distributed PV power systems. The proposed model analyzes collected data from units through solar cells distributed in different places in Palestine. Multi-layer Feed-Forward with Back propagation Neural Networks (MFFNNBP) is used to predict the power output of the solar cells in different places in Palestine. The model depends on predicting the future production of the power output of PV power system depending on the real power output of the previous values. The data used in this thesis depends on data collection of one day, month, and year. Secondly; we propose an Enhanced Radial Basis Function Neural Networks (RBFNN) model that depends on the standard RBF existing in Matlab (*newrb*). This enhancement on *newrb* depends on the use of intelligent algorithms like K-means Clustering, K-Nearest Neighbor (K-NN,) and Singular Value Decomposition (SVD), to optimize the centers c, radii r, and weights w of the RBFNN, which replace the mathematical calculation used to find these parameters in *newrb*. This enhanced model is applied to predict the solar cells energy production in Palestine using already installed PV power system in Jericho. Solar irradiance and daily temperature used as an input training data set for the proposed model, with the real output power of (2015) as the training supervisor. The model is applied to predict the output power within one month and one year. Finally, a traditional power output equation was optimized to calculate the solar energy depending on the daily irradiance and temperature with an acceptable accuracy. The experimental results show that the enhanced model performs more precisely in prediction than the Multilayer Perceptron Neural Network (MLPNN) algorithm, with low Mean Square Error (MSE) of relatively few neurons on the hidden layer (RBF). The proposed models conduct a systematic process, which predicts the power output of PV power system in selected area. The enhanced RBF model is more precise that MLP and traditional RBF models with low RMSE with relatively few neurons in the hidden layer, and so we can determine the suitable place for an installation of solar cell panel in different areas of Palestine.

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Terminology Index:

1.	ANN	Artificial neural network.
2.	MLP	Multi-layer Perceptron.
3.	MLPFFNN	Multi-layer Perceptron Feed Forward Neural Network.
4.	MFFNNBP	Multi-layer Perceptron Feed Forward backpropagation Neural Network.
5.	rbf	Radial Basis Function.
6.	rbfnn	Radial Basis Function neural network.
7.	Newrb	Matlab function implements the rbfnn.
8.	RMSE	Root Mean Square Error.
9.	SVM	Support Vector Machine.
10.	K-NN	K- Nearest Neighbor algorithm.

ملخص

تعد الطاقة الشمسية من أهم مصادر الطاقة الطبيعية والصديقة للبيئة، حيث يمكن تحويل الطاقة الشمسية إلى عدة أشكال منها الطاقة الكهربائية، والتي يمكن توليدها من خلايا خاصة تقوم بتجميع الإشعاع الشمسي وتحويله إلى طاقة كهربائية والتي تسمى بالخلايا الضوئية، كما أن للتنبؤ بكميات الطاقة التي يمكن توليدها في أماكن مختلفة أهمية كبيرة في عملية التخطيط لإنشاء حقول الطاقة الشمسية من اجل توليد الطاقة الكهربائية, وكذلك تحديد كميات الكهرباء اللازمة في كل يوم لأي منطقة يوجد بها قاعدة للخلايا الشمسية.

تكمن فائدة التنبؤ هذه بتوفير المال والجهد، حيث يمكن من خلالها تقسيم المناطق حسب كمية الإنتاج المتوقعة، وهذا ما قمنا به في هذه الدراسة، حيث تم استخدام بعض الخلايا المتواجدة في فلسطين والموزعة بشكل عشوائي دون دراسة تخطيطية مسبقة ، وتم استخدام بيانات هذه الخلايا المتواجدة في ثلاثة مناطق هي أريحا، جنين، ورام الله من اجل إجراء عملية التنبؤ التي تمت على ثلاثة مراحل باستخدام طرق الذكاء الاصطناعي وتحديداً الشبكات العصبية.

المرحلة الأولى وهي التنبؤ بكميات الإنتاج ليوم، ولشهر، ولسنة كاملة من إنتاج الطاقة اعتماداً على كميات الطاقة المتوفرة من المناطق المذكورة والتي تم توليدها وتسجيل كمياتها باستخدام أنظمة الرصد الخاصة، باستخدام الشبكات العصبية الذكية المسماة (Multilayer Perceptron)، في المرحلة الثانية تمت دراسة المؤثرات البيئية على إنتاج الطاقة باستخدام الخلايا الشمسية وهي درجة الحرارة اليومية، وكميات الإشعاع .الشمسي ، وتمت هذه العملية باستخدام نوع آخر من أنواع الشبكات العصبية الاصطناعية و التي تسمى (radial basis function neural networks) ، لما لهذا النوع من كفاءة في عمليات التنبؤ بالوظائف المرتبطة بالزمن (Time Series) ، حيث تم تطوير إحدى الخوارزميات بإضافة خوارزميات ذكية (K-Means, K-NN, SVD) من اجل تحسين الأداء في عملية التنبؤ، أما في الجزء الثالث فقد تم اشتقاق معادلة تمكننا من حساب كميات الطاقة اعتماداً على درجة الحرارة والإشعاع الشمسي فقط، حيث تم تحديد الثوابت والظروف المعيارية الخاصة بمنطقة فلسطين من اجل إجراء الحسابات. وقد أثبتت التجارب العملية التي قمنا بها كفاءة هذه المعادلة في الحساب بمقارنتها مع نتائج حقيقية مسجلة مسبقاُ، كما انه تم أيضا إثبات كفاءة الأنظمة المقترحة من اجل عمليات التنبؤ من خلال العديد من التجارب. بالإضافة لذلك بالاعتماد على المعلومات المتوفرة من موقع رصد عالمي، قمنا بعمل تصنيف للمناطق حسب قدرتها على إنتاج الطاقة الشمسية.

Chapter 1
Introduction

Chapter 1- Introduction

1.1 Introduction

Society begins searching for other energy resources with more awareness of their responsibility to the environment. Renewable energy experiences a huge expansion, which raises many challenges to the scientific and technical community [1]. Renewable energy is a clean and inexhaustible energy, and its technology is developing rapidly [1]. Palestine is considered a suitable place where the solar irradiance is very good to produce energy from solar cells [2]. This country does not have natural resources, the majority of the energy sector are imported from the state of Israeli occupation. With the technological development nowadays, we need electricity in all fields of life, so we must utilize the solar energy. In recent years, solar cells have been increasingly used to produce the energy in Palestine, however, one of its shortcomings is the unpredictability of their production, since they depend on climatic variables of each moment [2]. Currently, distribution companies are responsible for managing and selling the energy to their networks. Palestine has witnessed an increasing number of solar parks. The current Palestinian society aims at reducing electrical energy dependence, a better use of resources and greater awareness of the environment. There have been many initiatives in Palestine by the directives of support measures, renewable energy, establishing growth targets for renewable technologies in order to get more energy production come from these resources [2].

1.2 Solar Energy

Solar energy is the energy produced by thermonuclear reactions continuously on the surface of the sun, this energy spreads out in the universe with different energy forms such as light, heat, x-ray, and ultraviolet. These forms of energy constitute the solar spectrum. The solar energy is a vital factor of life on the earth [3]. Solar spectrum hits the earth with half of its energy level because of the atmospheric shield and the reflection of the energy of the earth's surface and this energy can be used in different fields like agriculture, heating, cooking, and electricity production [3, 4]. One of the major solar energy usages is producing electricity. This process that can be achieved mainly in two methods; thermal solar energy which depends on heating fluids in pipe network with running turbines to produce electricity, and photovoltaic solar energy, which uses photovoltaic phenomenon to produce electricity directly from the sunlight [5, 6].

The electromagnetic waves are classified by the electromagnetic spectrum. These waves are organized according to their respective wavelengths. Where they consist both of light energy and heat energy, the heat from the sun does not reach the earth as we are 94.5 million miles away from the sun only the light energy reaches us. In fact, the light energy provides us with all the heat required [7]. The solar light spectrum is illustrated in figure1:

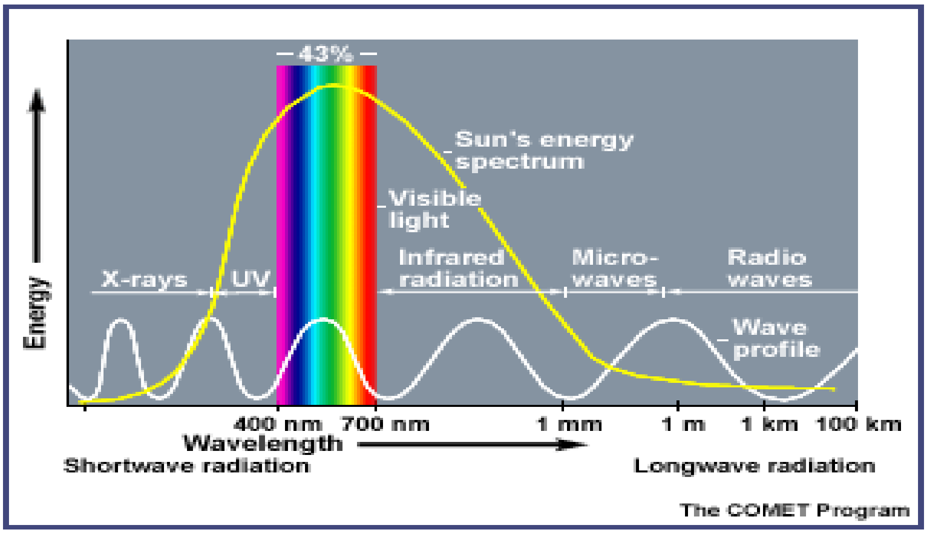

Figure. 1: The Spectrum of Solar Light [8].

As shown in figure 1.1, the spectrum of solar light at the earth's surface is mostly spread across the visible and near-infrared ranges with a small part in the ultraviolet region. The amount of solar energy reaches the earth is reduced to nearly half of its original energy, as a result of many factors like reflection by the atmosphere and clouds, and absorption of the energy by the earth surface, the atmosphere and the oceans, figure 2 illustrates the amount of solar energy hit the earth.

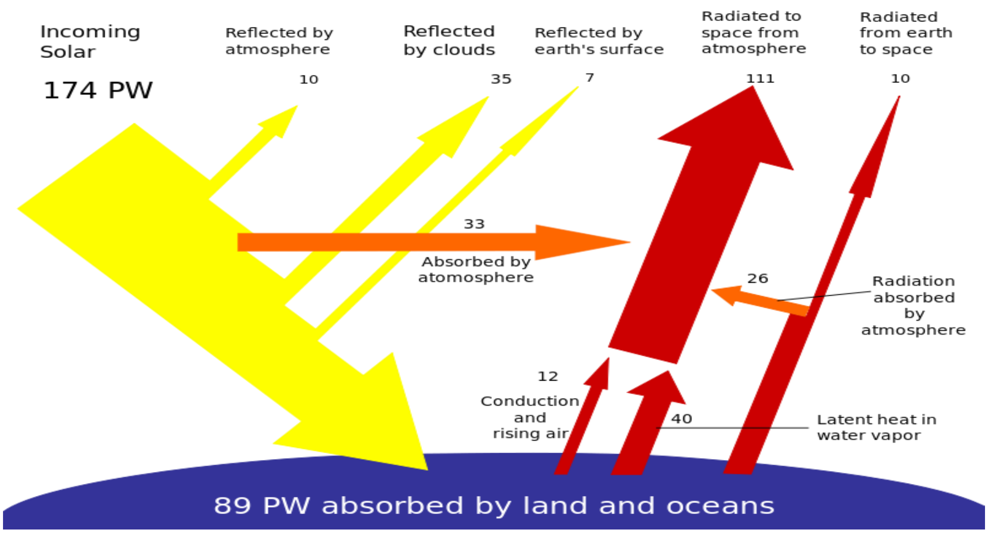

Figure. 2: Solar Energy Hits the Earth [8].

1.3 Electricity Production Using Solar Cells

One of the major solar energy usages is producing electricity, the process that can be performed mainly in two methods:

a) Thermal solar energy: heating fluids in pipes network running turbines to produce electricity.

b) Photovoltaic solar energy: using the photovoltaic phenomenon to produce electricity directly from the sunlight, since we are concerned with this method we explain it more below.

1.4 Photovoltaic Electricity

Converting light into voltage is performed using a solar cell as illustrated in figure 3. The solar cell panel is the unit responsible for collecting solar radiations and transforms it into electricity, the solar cell panel is an array of solar cells that come in two major types, silicon (mono crystalline and poly crystalline) and organic cells according to the manufacturing material.

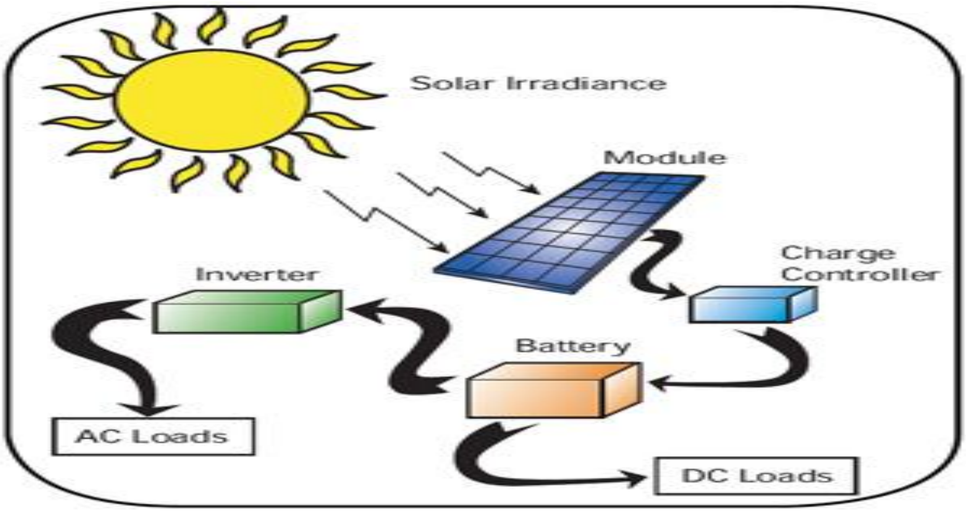

Figure. 3: Photovoltaic Module [9].

2.1 Components of Photovoltaic Module

As shown in figure 3 the module is constructed of Photovoltaic (PV) cell to convert light incident on a material into electrical energy. PV cell materials are composed of silicon and other semiconductor materials. The incident light excites the electrons in the semiconductor, which in turn increases the semiconductor conductivity and produces a direct current (DC) flow [9]. A basic photovoltaic standalone system consists of four components:

- **Solar Panel**: which is the responsible module of converting light to electricity, solar panel is an array of several solar cells (photovoltaic cells), and the arrays can be formed by connecting them in parallel or serial connection depending on the required energy. According to their manufacturing material, solar cells can be classified three types:

  - ✓ **Mono-Si**: is a continuous Crystal Lattice of entire sample, this type is the most efficient , and the most performative on bad weather conditions (i.e. high temperature, high humidity and low irradiation), however , it’s expensive, and needs a large amount of silicon, moreover , it needs more energy for its manufacturing.
  - ✓ Poly-Si: composed of a number of different crystals, fused together to make a single cell, and have a non-uniform texture due to visible crystal grain present due to manufacturing process, this type has a good efficiency (14 to 16 %), and it is effective cost module, but this type as the Mono-Si require large amount of silicon and high energy to produce.

- ✓ Thin Film Cell: thin film is a type of polymer solar cell that uses organic electronics, it performs better especially under conditions of higher relative humidity, higher temperatures, and lower irradiances, but it is the least efficient among both Mono-SI, and Poly–SI (6 to 12%), and takes up more space for same output compared to other types [9,10].

- **The battery:** is used to store the collected energy for later on use.
- **Regulator:** is used to ensure that the power supplied is that at right voltage to charge the batteries.
- **The load:** refers to the electrical devices like lamps, TV, etc.

The sun is considered one of the most promising sources of energy, it is a powerhouse, because this technology is utilizing solar energy , it has been growing up in the market where photovoltaic technology is more impacted , which directly converts solar energy into electricity [6-11]. Table 1 present a comparison between solar cell manufacturing materials.

Table1 Comparison of Mono-Si,, Poly-Si, and Thin Film Panels [10,11].

Thin Film Panels	Poly-Si Panels	Mono-Si Panels
1. Least efficient with max. The efficiency of 12%.	1. Less efficient with efficiency of 16% (max.)	1. Most efficient with max. The efficiency of 21%.
2. Manufactured by depositing 1 or more layers of PV material on the substrate.	2. Manufactured by fusing different crystals of Si.	2. Manufactured from single Si crystal.
3. Performs well at high temperatures.	3. Performs well at moderately high temperature.	3. Performs well at standard temperature.
4. Requires large area for a given power.	4. Requires less area for a given power.	4. Requires least area for a given power.
4. Low amount of Si used hence, low embodied energy.	5. A Large amount of Si hence, high Embodied energy.	5. A Large amount of Si hence, high embodied energy.
5. Performance less affected by low-sunlight conditions.	6. Performance degrades in low-sunlight conditions.	6. Performance degrades in low-sunlight conditions.

7. Cost/watt 0.67 USD	7. Cost/watt 1.418 USD	7. Cost/watt: 1.589 USD
8. First Solar (USA)	8. Suntech (China)	8. Largest Manufacturer: Sun power (USA)

1.5 Solar Energy in Palestine

In recent years, the solar cells have an unprecedented deployment. The total energy supply from solar cells in Palestine in the year 2007 is amounted to 1402 kwh, this amount increased rapidly, but there is no a clear value of the energy supply from solar cells nowadays. The indigenous production constitutes 19% of total primary energy supply while the remaining quantity imported from the state of Israeli occupation, where the share of the Palestinian citizen of the electricity for annual usage is the least in comparison with nearby countries, which is limited to 583Kwh in 2000. The consumption increases rapidly, therefore, the supplied amount whether produced or supplied should be increased as well [12]. One novel idea is to satisfy this growing need is to use the alternative energy source like solar cell energy in cooperation with the traditional electricity source, this idea is applied in Palestine by local electricity provider and other providers in a limited and random distribution zones. Solar cell power in Palestine is a natural wealth, which must be explored; the electric distribution companies receive the electricity in its electrical network from two resources; the direct electrical lines from the state of Israeli occupation and the solar cell panels installed in some areas in Palestine. These companies have no plans or estimation process, to decide the demand and the production of solar cells in such place, so solar cell output power prediction in such place will help the company to plan and manipulate the electricity in this area, which produces stability in electrical connection. For many years, they have tried to learn how to predict future events, so that, they can take preventive action. Weather conditions are one of the future events, which directly or indirectly affect us every day, especially in electricity consumption. Therefore, they have developed methods of climate prediction, supported by different models to predict solar cell output power using mathematical prediction systems [3].

1.6 PV power system Efficiency

Most recent researches have concentrated on increasing the efficiency of the PV power production from different sides; some of the researchers attempted to improve the efficiency by designing new manufacturing materials and adding new compounds, whereas others attempted to study the side effects of the climate conditions on the energy production, or to improve the short-circuit current and the open-circuit voltage using deferent methods that study the operational environment of the PV power system using many techniques like artificial neural networks. [13, 19, 20].

1.6.1 **Efficiency Improvement Based on Design Material**

Recent reports indicated high power conversion efficiency up to 10.39% for the double-junction cell, and a record as high as11.83% was obtained for the triple-junction cell made of solution-deposited polymers [13]. In another report, it based solar energy converters displayed a power efficiency of 25.6% that corresponds to an open-circuit voltage of 0.74V, short-circuit current of 41.8 mA/cm2 with filling factor of 82.7% [14]. In addition, Nano-structured solar cells are shown to exhibit a maximum efficiency of ∼42% under AM 1.5 solar illumination [15]. In [16] solar cell with maximum short circuit current density of 39.7 mA/cm2, an open circuit voltage of 394 mV and a fill factor of 66.4%, was achieved using Cu2ZnSnSe4 solar cells with an absorber layer fabricated by salinization of sputtered Cu, Zn and Cu10Sn90multilayers, where an enhancement of ~ 20mv of the open-circuit voltage of the solar cells was a result of implementation of transparent front contact in Cu(In,Ga)Se2 (CIGS) solar cells using Hydrogenated indium oxide (IOH) [17]. Another improvement on the maximum short circuit current was proposed by Siyu Guo et al. In [18] by optimizing cell spacing of the standard full-size cell module and a halved-cell module to provide 3.08% more current (9.08 vs. 9.36 A) leading to 1.46% higher fill factor (75.5 vs. 76.6%).

1.6.2 Efficiency Improvement Based on Prediction of the climate conditions Using Artificial Neural Networks:

Another recent attractive field of study is the prediction and classification of the solar cell energy production using artificial neural networks (ANNs), which perform in an efficient way in this field. In [19] the author used ANNs control algorithms applied to the solar energy prediction. They proposed an algorithm detects the ideal operation point for photovoltaic and thermal panels by studying the (PV/T) model behavior considering irradiation and ambient temperature. Another related study was made to decide the highest time horizon for generating solar energy prediction by Ercan Izgi et al [20]. They used small solar power system application to study and predict the time horizon by dividing the study period of time into short term [5min] in medium term in April, and [3 min] for short term, [40 min] for medium term in August. During April and August, RMSE between the measured value and testing value changed between 33-55 in April and 37-63 in August, ANN algorithm used to predict the electricity generated during 30-300 minutes. The external weather conditions that affect the solar energy generation were studied by Esteban Velilla and others in [21], they used two modules of solar cells [mono-crystalline (55w) and organic solar module (12.4w), the factors monitored by this study are the temperatures, relative humidity, and irradiance, that are used as inputs for an ANNs algorithm, which were developed by the team to train, validate and test the electric power generated. The result obtained for solar energy produced using organic solar module was better than mono-crystalline module in the extreme conditions of (high temperature, high humidity, and lower irradiance). Electricity sector in Palestine was studied by Ayman Abu AlKher in [10] and others, the study was divided into two parts, one part is concerned with studying the current situation of electricity production, consumption, and transmission. The second part is a comparison between Palestine and other neighboring countries, to highlight the electricity consumption gap, and it used a mathematical and economic model to predict the relation between electricity consumption and economic growth. Solar radiation forecasting study which was made by Bader M. Alluhaidah and others in [22] explained the most effective variables that are used in the solar forecasting process as inputs to ANNs, the case study was made in Saudi Arabia. The simple structure offers better results in terms of error between actual and predicted solar radiation values. A method for modeling and prediction of PV-generated power [23] has been developed by Amin Mohammed Sabrian et al, this method uses two kinds of ANNs, general regression neural network (GRNN) and feed-forward back propagation (FFBP). In the modeling process, he used four inputs for both ANNs (max temperature, min temperature, mean temperature, and irradiance) with the power as an output. The data were collected through 5 years from 2006 to 2010 period, it was split into two parts, first 3 years data used for training and 2 years data used for testing, the result in both methods has given good results, where FFBP had better performance than GRNNs.

1.7 External Factors That Reduce the Solar Panel Output Power

Solar PV-output that strongly depends on sunlight intensity and is affected by external conditions is another solar cell efficiency that should be taken into consideration such as, temperature; which has an inversely proportional to the output of solar panel while the temperature increases the output decreases. The solar cell efficiency reduces due to temperature effects approximate to 89% [24] of power production. Solar irradiance; which is basically the light intensity, has an important effect on power production process, as the irradiance increases, output power also does. On the other side, some factors have an indirect effect like dust which covers the surface of the module and hence irradiance is reduced, this will cause the irradiance effect, the dust and dirt reduce the efficiency to about 93% [25]. In general, a lot of researches have been developed for this purpose, but the majority of them, adopted statistical methods as well as historical analysis to get results for the collected energy, without using prediction and classification models to create a solar energy map, that shows the best regions and gives advice for people who are interested in the field of energy.

1.8 Solar Energy Data Collection Methods

One common method for data collection is using a special data acquisition system based on wireless sensor network, this method of data collection uses the wireless sensor network connected by Wi-Fi or Wi-Max technologies, to achieve a reliable connection between far sensor nodes [26]. The other useful method is using the local electricity providers, where they have very useful projects for solar cells energy. They provided us with a very sufficient amount of data that we can use as a starting point in our prediction and classification model, we get solar cells values from Al Ojah village in the East, Al-Zababdeh village in the north, and Ramallah city in the middle of Palestine. Another way of collecting earlier data is the using data in the website "Solar GIS", which is a website which is integrated with satellites, Google maps and other measurement tools, to measure and estimate the atmospheric variables such as temperature, humidity, and solar irradiation which are the main factors that affect the solar energy production all over the world. One of the main problems faced while collecting the data is the limited number of available solar panels especially those which are provided with measurement tools, another problem is data recording problems, while some panels give good and stable reading , other give discrete readings. One more issue, the solar panels are not available in all cities of Palestine, which reduces the classification facilities when we try to classify regions according to the power output.

The general objective of the proposed model is to develop a system based on Neural Networks (ANNs), which can predict the short-term values of an output power of solar cells over days, months and one year. This model aims at assisting companies to plan, manage and forecast the suitable time and place for the energy production from solar cells [19-24, 30]. The data used in this model for the process of learning was taken for one year (one value in each 5 minutes) from different locations in Palestine, which allow a possible approximating value of the total power acquired by solar cells on one hand. And, it analyzes the behavior of the time series that finds the value of solar cells in one year for different cities of Palestine on the other.

1.9 Models Used in Time Series Prediction

Time series prediction is one of the most important aspects for the practical usage of scientific and engineering knowledge, it has been used by many researchers in various disciplines, including physical science, daily temperature, control systems, engineering processes, bioengineering, environmental systems, business, management [27]. Real life problems are often characterized by a large number of variables, parameters, and interactions, resulting in highly complex non-linear dynamics, and in chaotic or random behavior.

Several mathematical models have been designed for the treatment of time series prediction as auto-regressive moving-average models (ARMA) [28], which are used very often and based on it as implicit system linearity that generates the trajectory of variables. A time series is a set of values that can be considered as observations taken from a certain system over time; which are generated by dynamic systems found in the real world applications. While statistical models can be used as ARIMA for predicting a series of this type, the use of a neural networks models are attractive to be a model, which in the case of predictions multivariate can yield better results than ARIMA [28]. The problem of time series prediction consists of predicting the next value of a series known up to a specific time, using the recognized past values of the series. Basically, time series prediction can be considered as a modeling problem. The first step is establishing a mapping between I/O. Usually, the mapping is nonlinear. After such a mapping is set up, future values are predicted based on past and current observations [27].

1.9.1 **Statistical Methods:**

Time series prediction based are historical sample data that describe the whole data using mathematical methods. Most widely used statistical time series prediction techniques are regression model, auto-regressive moving-average models (ARMA), and artificial intelligence-based models, the first and second models are statistical prediction models. [28]

- **Auto regressive moving average (ARMA) model:** in this model, the time series is assumed to be stationary and follows the normal distribution. ARMA is one of the most commonly used hydrologic times series prediction and optimization, where it performs efficiently in short-term time series. Many literature reviews of such models proposed for the modeling of time series were reported in [28, 29].

- **Simple Moving Average;** in this model, we specify a period of time and apply smoothing for past data by arithmetically averaging and projecting forward in time. This model has poor forecasting results in most cases [30, 31].
- **Geometric Moving Average:** the geometric moving average smooth past data by geometrically averaging over a specified period and projecting forward in time. This is normally considered a smoothing algorithm and has poor forecasting results in most cases [32].
- **Triangular Moving Average:** it is like the simple moving average, but with a weighted moving average that forms a triangular shape. The projection technique is normally considered as a smoothing algorithm and has poor forecasting results in most cases [32].

- **Parabolic Moving Average:** prediction and smoothing with weighted moving average that has weights with a parabolic shape. It is the same as simple moving averages projection technique. This is normally considered as a smoothing algorithm and has poor forecasting results in most cases [33].

1.9.2 Artificial Intelligence Models

AI techniques are capable of analyzing and predicting long-term time series and large-scale data, like supported vector machines, artificial neural networks, neuro- fuzzy system etc. [34]

- **The Support Vector Machines (SVMs) technique:** Is one of the widely used machine learning techniques that can be used for time series forecasting and classification designed by Vapnik and his co-workers designed SVM at the AT & T Bell laboratories in 1995. Unlike the other traditional stochastic or neural network methods ,SVM method has a good property that it is always unique and globally optimal, moreover , SVM has an amazing property in that the quality and complexity of the solution can be independently controlled, irrespective of the dimension of - 11 - the input space [35] , However , SVMs has a major disadvantage in that it is hardly used especially when the training size is large, it requires an enormous amount of computation which increases the time complexity of the solution [36].

- Artificial Neural Networks (ANNs): ANNs are based on an understanding of the brain and nervous system to perform behaviors, it play an important role in time series prediction [37-45], most widely used ANNs are the Multi-layer perceptron neural networks and Radial basis functions neural networks, which will be explained both later on in chapter 2.

  HL Chen concluded in his paper AI methods are powerful tools to model the discharge time series that can give good prediction performance than traditional time series approaches. The results indicate that the best performance can be obtained by ANFIS [37].

- **Neuro-fuzzy systems:** Neuro-fuzzy system has joined the capabilities of the neural networks with the fuzzy inference system, where neural network is used as approximation techniques to find the parameters of the neuro system [37], this hybrid system is applied to study many fields. In [38] the team used the neuro-fuzzy system for short time series prediction of water level in two different river reaches in Germany, while Dixon used this system to predict ground water vulnerability in a spatial context by integrating neuro-fuzzy system with GIS system. From these researches we can conclude that neuro-fuzzy systems are efficient time series predictors.

In order to facilitate the modeling process team of [39] used neuro-fuzzy system model to predict solar cell short-circuit current and open-circuit voltage, followed by coordinate translation of a measured current-voltage response for a newly installed solar cells, or solar cells with few historical measured data, considering a range of expected operating conditions.

In this thesis two types of neural networks have been used for time series prediction of power output produced by solar cell panel as a special case in Palestine. Multilayer feed-forward with back propagation neural networks (MFFNNBP) and Enhanced learning method for Radial Basis function neural networks (RBFNNs) are used to predict the power output of the solar cell panels depending on the previous real power output data and on the delay temperature and radiation.

1.10 **Summary**:

In this chapter we presented an overview about the importance of the solar energy that is used for producing electricity for daily usages, we also explored the solar cell types and efficiency improvement techniques, by the next stage of this chapter we studied the environmental effects on the solar cell efficiency, and the techniques used for that purpose.

Then we showed the importance of the time series prediction process especially the solar energy production time series and the method used for this task, where there is a big difference, between statistical methods and the artificial intelligence methods, moreover, we showed how researches had proved the high performance of artificial intelligence methods especially artificial neural networks over the statistical methods.

At the end of this chapter another important point of time series prediction steps that is data collection and preprocessing step, where real data has been collected form few already installed solar panels data in three deferent regions in Palestine.

Chapter 2
ARTIFICIAL NEURAL NETWORK

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2.1 Introduction to Artificial Neural Networks (ANN):

Neural networks appeared in the sixties as a model for the functioning of the human brain. They are trying to solve complex problems by simple and organized learning using a series of mathematical structures called neurons. These organized neurons form more complex structure called the neural network. This structure is capable of solving problems in different areas of knowledge such as math, engineering, communications, function approximation, and predictions. For many years, it has tried to learn how to predict future events so that they can take preventive action [40]. ANN comes in one of two learning methods: supervised or unsupervised. In one hand supervised ANNs depend on the available input data which will be processed using special activation functions, summed using a linear function to find the final output. The current output of the ANN will be compared with the desired output for the purpose of training the ANNs by updating the weights in each epoch, which produce decreasing in approximation error. Artificial neurons are elements with an internal state that changes depending on the signals it receives, such neurons also have a transition function, which allows them to change the level of activation signals received from neurons, whether connected or from the outside [41]. On the other hand unsupervised learning method has no guide in learning process, i.e. the output of the neural network will not be compared with a target output, and here learning process depends on the commonly shared feature between input data items [40].

The weather conditions, affect directly or indirectly every day. Therefore, methods have been developed climate prediction supported by artificial neural networks and other numerical methods. Neural networks were used for weather prediction taking into account the meteorological data such as temperature, relative humidity, cloud cover and radiation. Different models were used in predicting the solar cells output power from the use of mathematical equations or neural networks conducted to determine the daily, monthly and yearly average output power produced by solar cells using a multilayer neural network with Back propagation algorithm [24, 25].

The general objective of using ANNs models in this thesis is to develop a system, which can predict the short-term values of an output power of solar cells over days, months and one year, which aims to help companies in planning, managing and forecasting the appropriate time and place for the energy production from PV power system. The data used for the process of learning in this models was taken for one year (one value in each 5 minutes) from different locations in Palestine, which allow a possible approximating value of the total power acquired by solar cells. On the other hand, it analyzes the behavior of the time series that determines the value of solar cells in one year for different cities of Palestine [43].

2.2 Structure of Artificial Neural Network

ANNs have a basic structure consisting of a set of entries that are connected to set of neurons in the hidden layer (at least one neuron) and a set of output signals that are connected either to the input of another hidden layer or to the output layer to form the neural network. This structure is known as a single neuron, single layer or multi-layer ANN [40, 41] as shown in Figure 4. This type of structure has an input layer which consists of input patterns. The connections in the hidden layer which are weighted connections between the input layer and the hidden layer, processing units called neurons receive the input data from the input layer and processing it depends on the activation function. Finally the output layer that is used to calculate the output of the ANN that are capable of learning from input/output data to predict future value. Knowledge of this value can be performed in a time step, which is obtained from samples available at time *t*, and it can generate a value for time *t + 1*. It is also possible to predict multiple time steps, which involve taking other values known as the predicted values to generate new future value. Neural networks play an important good role in time series prediction.

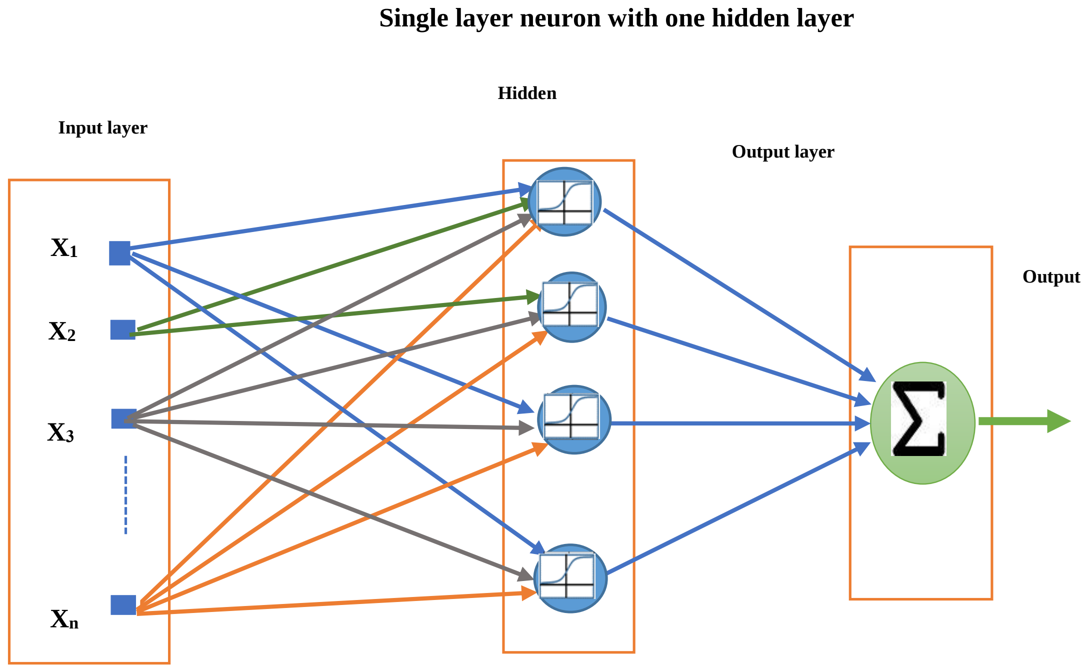

Figure. 4 Basic Single – Layer Artificial Neural Network

The main steps for the basic neural network start by the collection of data to be used in training, validation, and testing. Preprocessing of the data which is an important stage that increases the performance of the neural network, and reduces the number of processors (neurons) is required. This will lead to reduce the number of neurons, and give best curve fitting. Initialization of the neural network starts by assigning values for the input weights, this process is made most likely randomly, or using certain algorithms according to the problem. In the neural network training process, the activation function is applied to find out the relation between the inputs and the outputs, and then updating the weights using specified learning algorithms with a number of training data in order to get the best results. To check the validation of the neural network in this model we use another set of data called validation data. Finally, the generalization process tests the neural network for random and different data set [38, 40]. The PV power system output prediction using silicon cells is affected by several factors like solar irradiation, climate, temperature, relative humidity, dusty weather, cell direction, and the efficiency lose by the time [6]. In our proposed model we will use historical values of the solar cell output power recorded for a period of time (one year), the output values are recorded in (5 min) time horizon, this output power is generated and recorded from the target output of the ANN.

2.3 Types of Artificial Neural Networks

Many types of ANNs were invented for different applications or for optimizing the earlier solutions (training algorithms), from these types the single layer perceptron neural network, multi-layer perceptron neural network, radial basis functions neural network, and many more. The suitable type is selected according to the problem under consideration, there are many types of ANNs presented as a following: Single Neuron

This type is basically formed of one artificial neuron which receives one or more weighted inputs and sums them to produce an output where the sum is passed through a non-linear function known as an activation function or transfer function. The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions, piecewise linear functions, or step functions [38, 40, and 41].

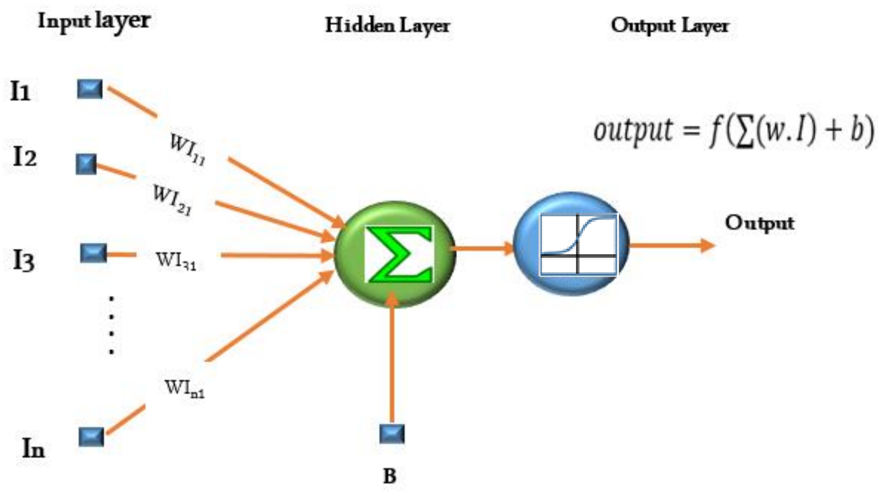

Figure 5. Single Neuron ANN

Figure 5, illustrates the single neuron ANN, where we have *n* inputs (*I*), provided with weights for each, summed and passed to the transfer function to provide the actual output of the neural network, and then this output is compared with objective output in supervised learning model to optimize the error [40].

a. Single Layer Neural Network

Single layer neural network (SLNN) is a neural network which consists of one hidden layer, where this hidden layer may be one-neuron or multi-neurons as shown in figure 6. Each input of the input layer (x_1, $x_{2,..}$ x_n) is connected to all or some of the neurons (n_1, $n_{2,\dots}$,n_n) each is multiplied by its weight (w_1,$w_{2,}\dots w_n$) and then the activation function is applied in each neuron to find the neuron output.

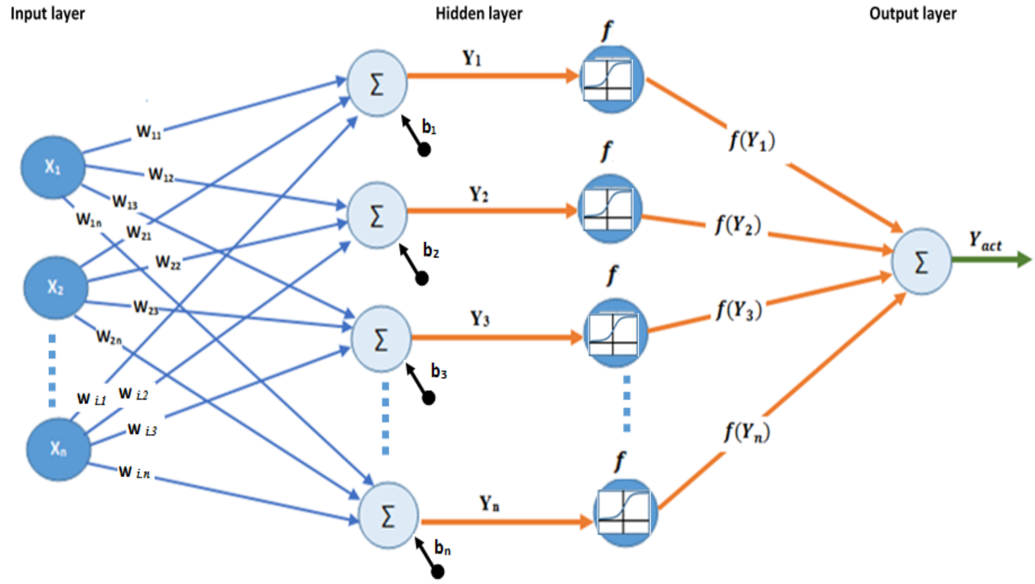

Figure 6. Single layer neural network (SLNN) [24].

b. Multi-layer Perceptron Neural Networks (MLPNNs)

Single layer perceptron with one hidden layer neurons was unable to solve complex problems, therefore, we need more complex and powerful neural network structure which consists of many hidden layers to convert non-linearly separable problems into other domains where they became linear separable.

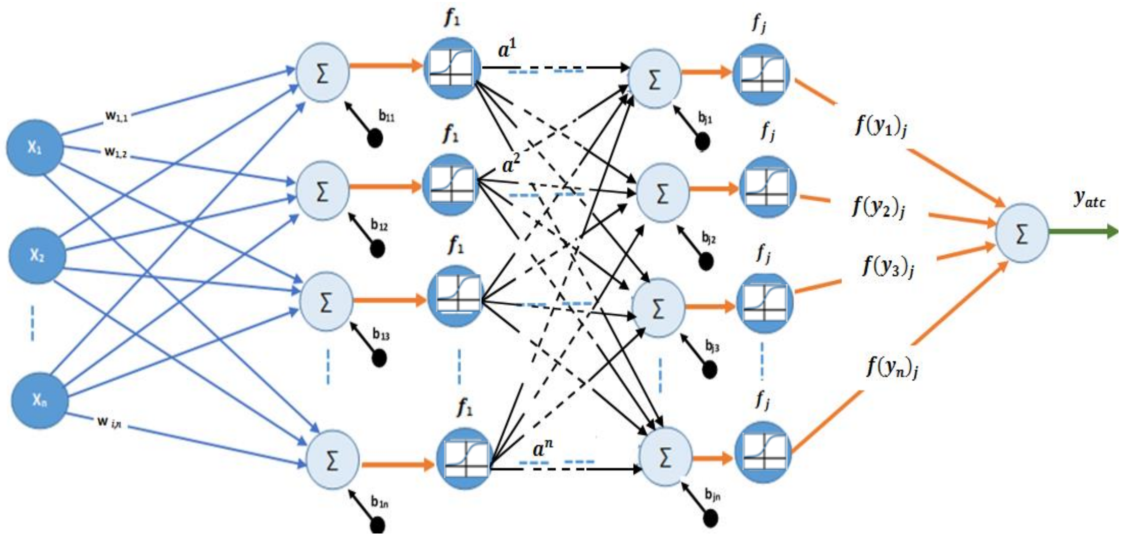

Figure 7. Multi-layer Perceptron NNs [24].

As shown in figure 7, the multilayer perceptron NNs consists of an input layer, an output layer and usually one or more hidden layers. This architecture is employed for modeling a nonlinear system. It has an input layer of neurons, hidden layers, each hidden layer contains neurons and one neuron in the only output layer. The sigmoid activation function, S (.) is usually used in MLPNNs [24]. In MLPNN the output of a layer will be an input for the next layer passing from the input layer to the output layer, the equations used for this procedure are as follows:

$$a^1 = f^1\left(\sum_{i=1}^{n} x_i . w^{i,1} + b^1\right) \qquad 2.1$$

$$a^2 = f^2\left(\sum_{i=1}^{n} x_i . w^{i,2} + b^2\right) \qquad 2.2$$

$$a^n = f^n\left(\sum_{i=1}^{n} x_i . w^{i,n} + b^n\right) \qquad 2.3$$

$$y_{act} = \sum_{i=1}^{n} f(y_i)_j \qquad 2.4$$

Where, X = input vector, W = weight matrix, b = bias vector, and a = layer output vector. The updating of the weights can be calculated by minimizing the output cost function, which may be calculated using different equations. In this work, we will use the Root Mean Square Error (RMSE) equation as a measure of the performance of the model in prediction. This RMSE is calculated using the following expression:

$$E_{sse} = \frac{1}{2} \sum_{j=1}^{n} \sum \left(Target_j - Output_j^{(N)p}{}_j\right)^2 \qquad 2.5$$

To find the weight update we use the gradient decent algorithm that is calculated using the following expression:

$$\Delta w_{jk}^{n} = -\mu \frac{dE(w_{jk}^{n})}{dw_{jk}} \qquad 2.6$$

Where μ is the learning rate (normally between 0 and 1), and final output depends on all earlier layers output, weights, and the algorithm of learning [25].

c. Radial basis function Neural Networks (RBFNNs)

The basic information about artificial neural networks (ANNs) is widely considered in literature [43-47]. The basic structure of the ANNs with n inputs and m weights that passed to the hidden layer, then the current output compared with the objective output to read just the weights and train the network, the output is a prediction, classification, or function approximation, the hidden layer may be a single layer or multilayer to get more accurate results, depending on the complexity of the problem under consideration. Literature data concerning the NNs is used in prediction of time series, and function approximation, like RBFNNs, MLPNN, Generalized Regression Neural Networks (GRNNs), as in this thesis, we will use Enhanced RBFNNs which is an efficient function approximating and time series predictor. RBFNNs is a type of NNs which uses an activation function in the hidden layer is radially symmetrical where their response decreases or increases monotonically with distance from a central point, where the key parameters are the center point [45]. The type constructed of three layers: input layer, hidden layer, and output layer. The input layer sends the information to the hidden layer. The hidden layer which has RBFs is activated depending on Gaussian activation function which depends on two parameter centers, radii, which determine the structure behavior of the RBFNNs. The output layer calculates the linear sum of values of the hidden neuron multiplied by the third parameter of the RBFNN, which is the weight [41]. Figure 8 shows the architecture of RBFNN that including three layers.

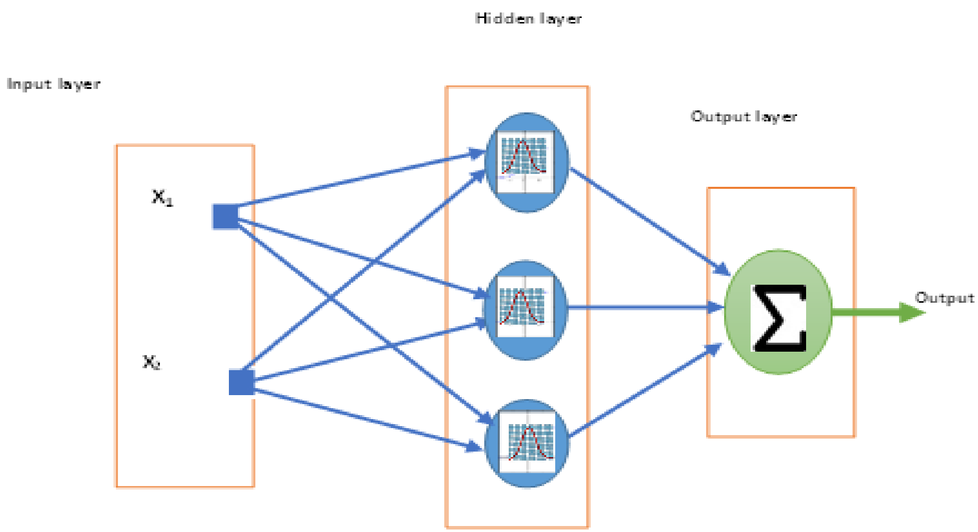

Figure 8. RBFNN Architecture.

Typical radial basis function is the Gaussian function, which is given by the following, the equation:

$$f(x) = \exp\left(\frac{-(x-c)^2}{r^2}\right) \qquad 2.7$$

Where c is the center point, r is the radii of the Gaussian function, and x is any certain input data point [29, 30]. RBFNN is employed for classification and regression, curve fitting, and exact interpolation, where the output function must pass through all data points, it also performs the exact interpolation by providing N basis functions one for each data point given by the equation $\phi\|x-x^p\|$ where ϕ (.) is a non-linear function, and the p_{th} function that depends on the Euclidean distance $\|x-x^p\|$ between x and xp. The final output of the network is given by the following expression [40]:

$$f(x) = \sum_{p=1}^{N} \|x - x^p\| \qquad 2.8$$

When using the Gaussian activation function eq. (2.6) the output then takes the form:

$$f(x) = \sum_{p=1}^{N} W_p \Phi_p(x) = \sum_{p=1}^{N} W_p exp_p \left(-\frac{\|x - x^p\|^2}{\sigma^2} \right) \qquad 2.9$$

The general training process is to update the weight of each input in the following steps [38, 45].

Selecting the number of RBF ϕ as matrix: The selection process has two methods random selection which may cause bad fitting results, or using one of the learning algorithms to give the least number of radial basis functions from the number of data points. The center of the basis function may be determined either in random way which causes risky distribution of the centers, or using learning algorithm like K-mean clustering.

Using suitable value of σ when using Gaussian activation function, while too small σ which causes narrow peaks and too large σ that causes wide peaks, the best σ is given by the following expression:

$$\sigma = 2d_{avg} \qquad 2.10$$

Where d is the average distance.

The weight matrix *w*, is updated using the Micchelli's Theorem for linear equation to find the weight matrix, which depends on *xi, i = 1... N* a set of distinct points in R^d, the N-by-N interpolation matrix, whose j_{ith} element is $\varphi_{ji} = \varphi(\|xi - xj\|)$, is non-singular as in the following equation:

$$W\ D^{-1} = F \qquad 2.11$$

In Micchelli's theorem the error function used is presented as in the following expression [38, 45, and 47]:

$$E = \sum_p \sum_k^N \left(t_k^p - y_k(x^p)\right)^2 = \sum_p \sum_k^N \left(t_k^p - \sum_{j=0}^M W_{kj}\ \Phi_j(x^p), \mu, \sigma_j\right)^2 \quad (2.12)$$

Where the weights w is updated using $\Delta w_{jk} = -ή_w \frac{dE}{dw_{jk}}$, the center c update depends on $\Delta\mu_{ij} = -ή_\mu \frac{dE}{d\mu_{ij}}$ and the radii r update by$\Delta\sigma_j = -ή_\sigma \frac{dE}{d\sigma_j}$.

This type of NNs called RBFNN is used for time series prediction of the solar cell panel output to get the future output power, depending on the climate conditions, and the use of factors that influence the solar energy production most (i.e. temperature, irradiance), with real data collected from already employed solar panels in Palestine to guide the training of the RBFNN.

2.4 Proposed Models

The prediction of the output power of solar cell energy is performed by applying two types of artificial neural networks, that are widely used in such cases in order to decide the best prediction model, where in this thesis we produce two prediction models : the first is for energy prediction based on the recorded output power of solar cell energy panel using multi-layer perceptron neural networks with back propagations learning algorithm (MLPNNBP) model, and the second part uses the daily temperature and daily solar irradiance as inputs of the training and testing an enhanced radial basis function neural network model. See appendix A- sample training data set.

2.4.1 **Proposed MLPNN Solar Energy Prediction Depending on the Previews Output**

In order to design the proposed ANN, we must identify the problem area and the factors that affect or determine the problem, it's known that the time series prediction is one of the most complex of the real world application, and it's also well known that the ANN has a good property of solving such complex problems. The training process is the mapping process between the input/output data of the NN when the input patterns provided to the NN with initial weights, the output of the NN are given by the following expression: [40]

$$y_i = f(\sum_{j=1}^{m} w_{ij} x_j + b_i) \qquad 2.13$$

Where W_{ij} is the weights connection, and X_j are the value of the i^{th} inputs for a simple of the NN, b_i is the NN bias, m is the number of neurons and f is the activation function. The general criterion of approximation which is used to determine the improvement of the prediction process is the error result, which compares the actual output of the NN with the desired output in the learning process, this error is basically calculated using the following expression [34, 38]:

$$Er = y_{id} - y_{ia} \qquad 2.14$$

Where y_{id} is the desired value of the output for each i^{th} element and y_{ia} is the actual value of the i^{th} element, normally this criterion is used as a termination condition to stop the prediction process. Here, we use the root mean square error which is presented by the following expression:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{id} - y_{ia})^2}{n}} \leq \theta \qquad 2.15$$

Where n is the number of the input data, and Θ is the threshold value of the prediction process. The training process continues to adjust the weights until the error criteria are satisfied, the weights updated is performed by the equation 4:

$$\Delta w_{i+1} = \alpha.\ RMSE.\ x_i \qquad 2.16$$

Where α is the learning rate.

One advantage of the multilayer perceptron neural networks (MLPNN), is that it can predict any time series function if a configuration and an adequate number of neurons in the hidden layers are available. The MLPNN is an excellent time series prediction, although it is impossible to find a single configuration for each application. The learning process of the MLPNN with back propagation algorithm is not fixed to any application; a successful method is to try different settings until you get the desired response. The choice of training patterns is performed depending on the explicit needs of the prediction, which will appear on the output and the quality of information available. Any changes in the patterns of training require different training parameters of the NN, but the training process remains the same [28, 34, and 38].

2.4.2 **Proposed MLPNN Model Methodology**

Developing a methodology to establish prediction is a relationship as accurately and precisely as possible. The values of future solar cell energy output require the knowing of the previous solar cell energy output, these values are used as input to the model, $x_t = F(x_t, \ldots, x_{t-tw}) + \varepsilon_t$, where x_t is the forecasting forward steps with respect to time t, F is the modeling function between the previous and future values, ε_t is the modeling error.

Predicting of solar energy output can be performed using different techniques as; prediction by numerical models, prediction by statistical methods, time series prediction based on the application of statistical techniques linear and nonlinear, and prediction coefficient cloud cover from satellite images. Obtaining a final prediction model of solar energy output based on the time series prediction using NNs. Predicting the energy output of solar cell using only numerical models has a high bias and a high mean square error, which depends on the distribution function of the radiance data from the station (at positions predominantly clear sky conditions with errors are smaller). For this reason, we used Multilayer feed- forward with backpropagation neural networks (MFFNNBP) and data of different months, each month presents one season of the year.

Multilayer feed-forward with backpropagation neural networks (MFFNNBP) is an MLPNN that passes the inputs and the weights from one layer to the next one through the feed forward process and then it performs the weights update to be back-propagated to the previous layers in order to recalculate the weights.[34] Our proposed ANN architecture has three parts, one for producing solar energy prediction depending on previous real output measured along one year "2015" from three main solar panels located in Ain-Mousbah – Ramallah, Al-Oja – Jerico, and Al-Zababdeh- Jenin. These three energy collection points provide the power output within 5,10,30,60 minute’s horizon of one month or one-year time horizon, then the data was processed according to the following process shown in figure 9.

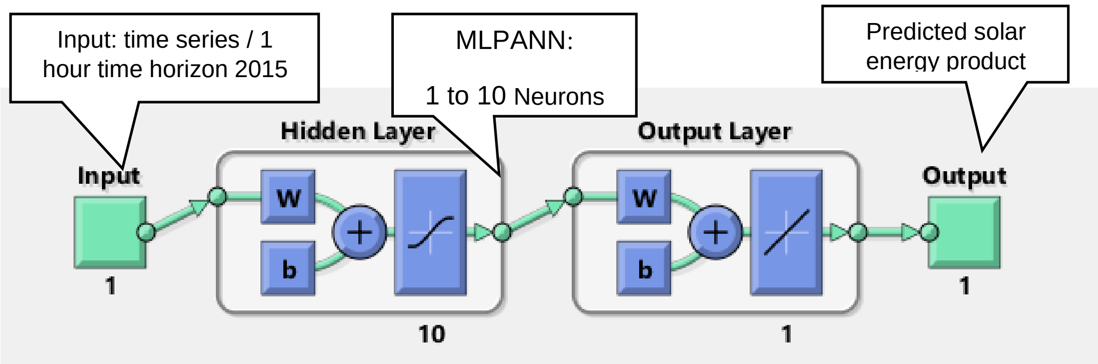

Figure 9. Proposed Solar Energy Prediction ANN.

The sigmoid activation function, f^1 is used [23]. In MLPNN, the output of a layer will be an input for the next layer passing from the input layer to the output layer; the equations used for this procedure are illustrated as follows:

$$output = f^2(\sum_{j=1}^{n} out_1 . w_{jk}) \qquad 2.17$$

Where the output of the first hidden layer *out₁*, which calculated using the following expression:

$$out_1 = f^1(\sum_{j=1}^{n} in_i . w_{ij}) \qquad 2.18$$

Where f^1 and f^2 are the activation functions for output layer and hidden layer, which calculated as in the following expressions:

$$f^1 = \frac{1}{1 + e^{-x}} \qquad 2.19$$

$$f^2 = x \qquad 2.20$$

Where, x = input vector. Depending on equations above, the weights are updated use as the following expression:

$$\Delta w_{jk}^{n} = -\mu \frac{dE(w_{jk}^{n})}{d\,w_{jk}} \qquad 2.21$$

Where µ is the learning rate (normally between 0 and 1). The final output depends on all earlier layer's output, weights, and the algorithm of learning used [34]. Using data collected from previously mentioned solar panels, this data was preprocessed to reduce the noise from the input signal, this process increases the performance of the ANN and reduces the prediction error, using Matlab function called smooth function, then takes the signal and filters the noise by using average filter smooth data, then replacing each data point with the average of the neighboring data points defined within the span. This process is equivalent to low-pass filtering with the response of the smoothing given by the next difference equation [32]:

$$ys\left(i\right)=12N+1\left(y\left(i+N\right)+y\left(i+N-1\right)+...+y\left(i-N\right)\right) \qquad 2.22$$

Where y_s (i) is the smoothed value for the i^{th} data point, N is the number of neighboring data points on either side of y_s (i), and *2N+1* is the span.

The backpropagation process calculates the gradient decent error between the desired and the predicted output considering the new weights each time, this gradient is almost always used in a simple stochastic gradient descent algorithm to find the weights that minimize the error. Different algorithms are used for training the feed forward with backpropagation neural networks, which train the NN and reduce the error values by adjusting and updating the weights and the biases of the connections that form the neural network, two kinds of training algorithms are available to slow convergence according to steepest descent methods with better generalization, and fast convergence according to newton's method, but these methods are complex because of the complex matrix calculations [34]. In our thesis, we use one of the fast convergence algorithms, which is the Levenberg Marquardt Algorithm (LM) training algorithms [49], implemented by Matlab 8.2.7, and we use it in two steps; one is the training of time series using the time as input and the power generated by solar energy points as output, and the second step is to train the data produced by the factors that affect the energy production along the time.

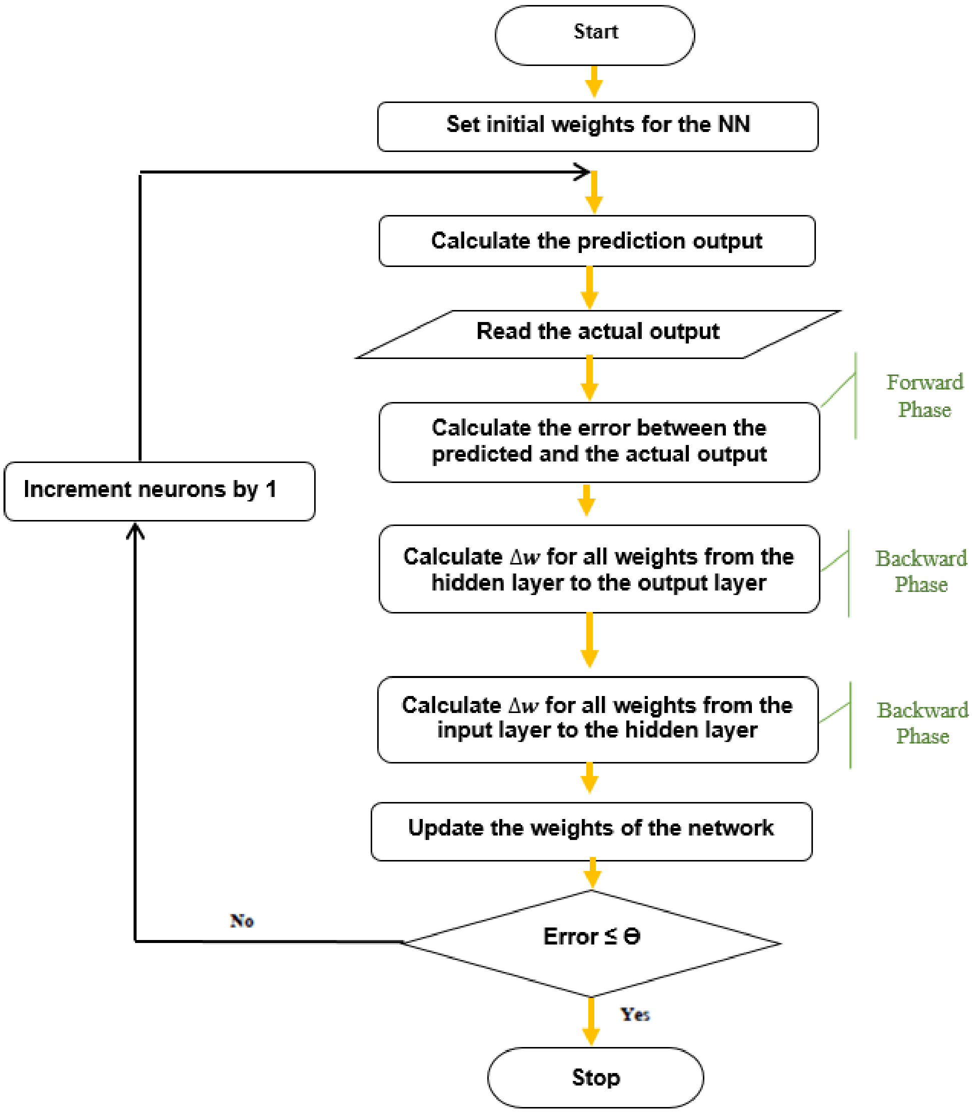

Figure 10. Flow chart of MLPFFNN

Figure 10 illustrates the proposed MLPNN model that uses the Levenberg-Marquardt Algorithm (LM) training algorithms, adapted for the solar energy prediction process based on the output power only. See appendix A-1

- **Levenberg Marquardt Algorithm (LM)**: LM Is used to solve non-linear least squares problems. These minimization problems arise especially in least squares curve fitting LM is a training technique that is used for non-linear real-valued functions [38, and 47] in an iterative manner that aims to locate the minimum function $F(x)$, denoted as the sum of squares of nonlinear functions, expressed by the equation: [50]

$$F(x) = \frac{1}{2}\sum_{i=1}^{m}[f_i(x)]^2. \qquad 2.23$$

This technique became a standard for nonlinear least square functions, and performs well for real world problems, as the LM technique combine the Gaussian Newton algorithm (GNA) and the steepest decent to ensure the fast and accurate training method avoiding the local minimum and convergence problems [49, 450] Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as

$$H = J^{T}J \qquad 2.24$$

And the gradient can be computed as

$$g = J^{T}e \qquad 2.25$$

Where **J** is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and **e** is a vector of network errors. The

Jacobian matrix can be computed through a standard backpropagation that is much less complex than computing the Hessian matrix [51].

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$w_{i+1} = w_i - [J^T j + \mu I]^{-1} J^T e \qquad 2.26$$

Where I the identity matrix and μ is non-negative real number when μ value is zero, this will be Newton's method, using the approximate Hessian matrix. When μ *value* is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm. Application results of this model are shown on next chapter.

2.4.3 **Proposed RBFNN Model Based on the Climate Conditions**

In order to study the climate factors that affect the output efficiency of the solar cell panels in Palestine as an interested example, we have collected real data form a solar cell panel located in Jericho city, where this location has special geographical challenges, where Jericho is located at an altitude below sea level of 273m, and the average annual temperature is 24^{o} C, with an average annual humidity of approximately 49.3% [52]. This data is a collection of temperature, solar irradiance, and the output power of an installed solar cell panel for the year 2015. Training process divided into two parts (for a one month, and study for one year), using *newrb* Matlab function has been used for training the RBFNN, with small enhancement achieved by using K-means clustering algorithm for clustering process (choosing centers), and K nearest neighbor algorithm (*K-nn*) to optimize the radii of the RBFNN, and Singular Value Decomposition algorithm (*SVD*) for weight *w* update we can produce very efficient prediction process compares with MLPNN. *Newrb* function creates a RBFNN used for function approximation, where new neuron is being added to achieve the determined error or to achieve the best fit, in general and depending to *newrb* used in Matlab, this model function has the form of:

S1: *Initialize the model parameters as: Net = newrb (P, T, goal, spread, MN, DF);*

P: R-by-Q matrix of Q input vectors.

T: S-by-Q matrix of Q target class vectors.

Goal: Mean squared error goal (default = 0.0)

Spread: Spread of radial basis functions (default =1.0)

MN: Maximum number of neurons (default is Q)

DF: Number of neurons to add (default =25).

S2: Use mathematical calculation depends on the values of the above parameters to train the system.

S3: Does the training process meet the Goal.

If yes → stop and return the RBFNN Architecture.
Else return to S2.

In the returned Architecture and values of RBFNN, the *newrb* depends on spread value; too large a spread means a lot of neurons are required to fit a fast-changing function, and too small a spread means many neurons are required to fit a smooth function, and the RBFNN might not generalize well [53].

2.4.4 **Proposed RBF Model Methodology**

The enhancement of *newrb* depends on replacing the mathematical calculation used in *newrb* by more efficient algorithms to optimize the RBFNN parameters (centers *c*, radii *r*, and weights *w*). To optimize the center's position we use K-means clustering algorithm [53], which is an iterative algorithm, in each iteration new cluster centers are computed, and each data point is re-assigned to its nearest center [53, and 54]. This algorithm is one of the simplest unsupervised learning algorithms that are used to solve clustering problems. It starts with initialization of points called centers and then it calculates the distance between one of these centers and other points to classify a given data set through a certain number of clusters (assume *k* clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in an intelligent way because of different location causes different result, and then it takes each point related to a given data set and associates it to the nearest centroid [53, 54]. The algorithm minimizes the squared error function that is the distance between points and centers:

$$E = \sum_{j=1}^{k} \sum_{i=1}^{k} \left\| x_i^{(j)} - c_j \right\|^2 \qquad 2.27$$

Where $\left\| x_i^{(j)} - c_j \right\|^2$ is a selected distance between a data point $x_i^{(j)}$ and the cluster center c_j, is an indicator of the distance of the *k* data points from their respective cluster centers, the K-means pseudo code is shown as the following [54-56]:

Let $X = \{x_1, x_2, x_3, \ldots\ldots, x_n\}$ be the set of data points and $V = \{v_1, v_2, \ldots\ldots, v_c\}$ be the set of centers.

1. *Determine the number of clusters K.*
2. *Randomly select c cluster centers.*
3. *Compute distance between each point in the data space and cluster centers.*
4. *Assign the data point to the closer cluster center.*
5. *Recalculate the new cluster center using:*

$$v_i = \frac{\sum_{j=1}^{p_i} x_i}{p_i} \qquad 2.28$$

Where p_i represents the number of data points in i^{th} cluster.

6. *Recalculate the distance between each data point and new obtained cluster centers.*
7. *If no data point was reassigned then stop, otherwise repeat from step 3.*

To optimize the radii r of the RBFNN, K nearest neighbor algorithm (*K-nn*) is used. An enhancement of the Original *K-nn* algorithm since it ignores the relationship between the neighboring points [58, and 59]. In our model, the *K-nn* algorithm is employed to initialize the radii *r* of the radial basis functions to get a more precise value of the *rbf*. The singular value decomposition (SVD) is also defined as a technique that is used to determine and sort the dimensions in which data points show the most data variation, or it can be used to transform data from relative data points to irrelative points to detect the relationship between them, another usage of SVD is to find the best approximation of the original data points using fewer dimensions which is done by detecting the most variation of that data. Mathematically SVD can be expressed for given a symmetric matrix *M*, we can find a set of diagonal vectors v_i, where Mv_i is a scalar multiple of v_i, that satisfies the equation [60]:

$$Mv_i = \lambda_i . v_i \qquad 2.29$$

Where λ_i is a scalar. In our enhanced RBFNN model (enhanced *Newrb*), we have used SVD technique to get the best prediction of the solar energy depending on the climate conditions. To optimize the weights of each RBF, we use Singular Value Decomposition (SVD), SVD is a powerful and useful matrix decomposition which has been used in many fields such as data analysis, reducing dimension transformations of images, data compression, and signal processing and pattern analysis [61]. If $A \in R^{mxn}$, there exist orthogonal matrices $S \in R^{mxm}$ and $H \in R^{nxn}$ such that:

$$S^T A\ H = diag(\sigma_1,...,\sigma_p) \qquad 2.30$$

Where p is the minimum of *(m, n)*, σ are the singular values of A. The use of SVD technique to calculate the optimal weights *w* of the RBFN depends on using matrix notation described in the following reducing expression:

$$\vec{Y} = \vec{w}\ \Phi \qquad 2.31$$

Where Y is the real output of RBFN, *w* is the weights vector, and *Φ* is the Gaussian activation function matrix. Using the next following expression:

$$A = H\ diag(\frac{1}{k})\ S^T \qquad 2.32$$

Where $k = diag(\sigma_1,...,\sigma_p)$, by replacing Φ in equation 11 using equation 12, the weights vector is calculated as in equation 13:

$$\vec{w} = \left[H\ diag(\frac{1}{k})\ S^T \right] \vec{y} \qquad 2.33$$

The use of the singular value decomposition provides a solution for any system equations, and can reduce the error in the output of the network, it can also be used to remove any basis function whose associated singular value had a small amount or the approximation error would not be affected [61]. The general approximation criterion which was used to determines the improvement of the prediction is the error result, which compares the actual output of the NN with the desired output in learning process, this error are basically calculated using the following expression:

$$Er = t_i - y_i \qquad 2.34$$

Where t_i is the desired value of the output for each ith element and y_i is the actual value of the ith element, normally this criterion use as termination condition to stop the prediction process. Here we use the root mean square error which presented by the following expression:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(t_{id} - y_{ia})^2}{n}} \leq \theta \qquad 2.35$$

Where n is the number of the input data, and ϴ is the threshold value of the prediction process.

Radial basis function neural network prediction and approximation models were applied in many application in real world and revealed with excited results, in [42] rbf was used in modeling the process of solar-array and maximum power-point prediction, while in [44] radial basis functions model was applied for estimating monthly mean daily solar radiation, another application Al Shamisi et al [45] used radial basis function neural network in Predicting Global Solar Radiation in Al Ain City-UAE.

Benghanem et al [46] used radial basis function network-based prediction of global solar radiation data: application for sizing of a stand-alone photovoltaic system at Al-Madinah, Saudi Arabia, from these researches we conclude that radial basis function neural network is efficient for time series applications.

As we notice from the flowchart (figure 11) this model is fed by the climate parameters (temperature, and solar irradiance) as inputs, the real panel power as the learning target, maximum number of neurons, and the minimum MSE error target, then newrb creates a rbf neural network which has weights initialized by SVD algorithm [61], the initial selection of the centers is performed by the K-mean clustering algorithm to get rid of random center selection risks, the Gaussian function radius is determined using KNN, the learning process continued by finding the vector with the greatest error, then this vector is used as weights for a new radial basis function, that are updated using the SVD algorithm in order to minimize the error, in the case where the error has reached it’s limit the learning process stopped, moreover , a new radial basis function is added and the weight adjustment is restarted until the error values is achieved or the predetermined number of neurons is reached.

The new model is applied to predict solar energy production in Jericho which has special climate conditions and geographical location where it’s very striking point of research. The model is applied to predict one month and one year production, and to study the effect of temperature and solar irradiance in the production process using real dataset as in appendix A-2, this application method and results are presented in the next chapter.

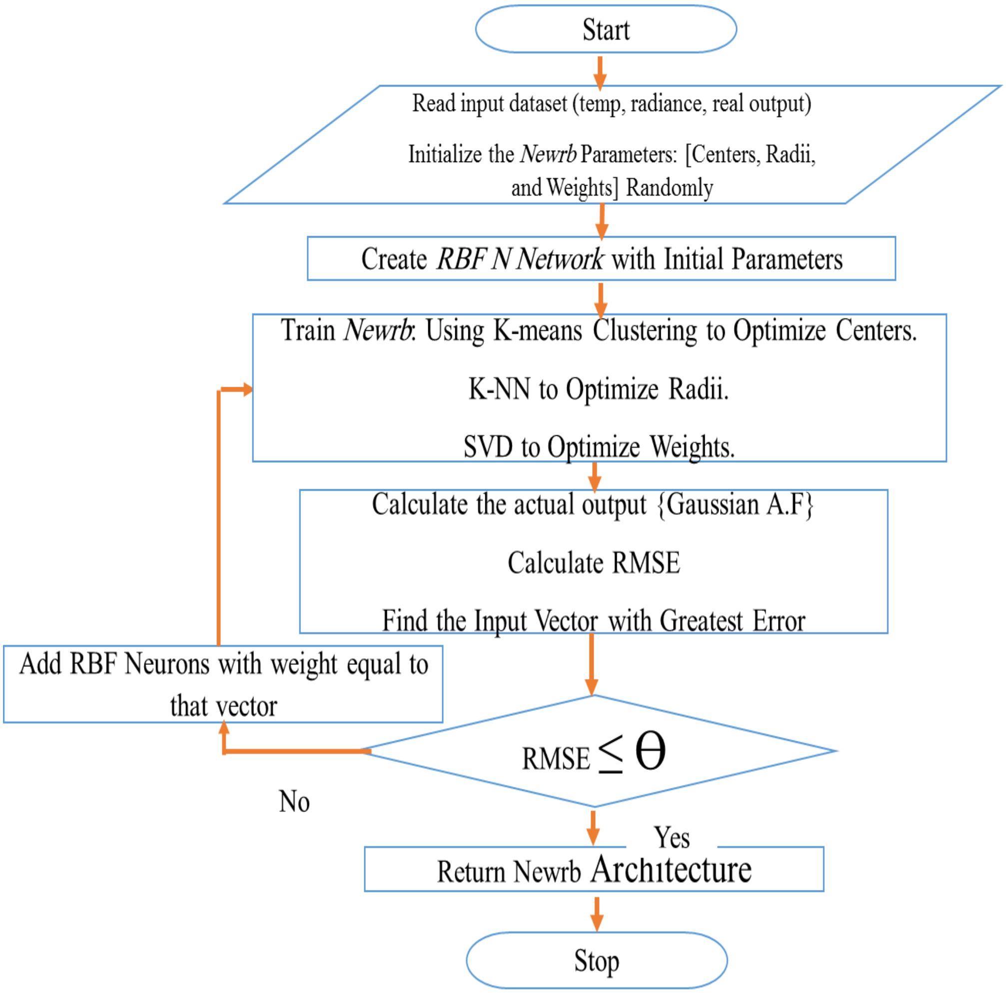

Figure 11 -Proposed RBFNN Model.

2.5 Theoretical calculation of Solar Energy

To proof that the collected data from the installed PV power system output is compatible with the theoretical calculation of the power output of the solar cell. In module structure, the mathematical model of the single-diode model without resistances can be expressed as [62]: $P_{solar} = I_{pv} \times V_{oc}$.

In the case of the standard solar panel of length 1 m we have $V_{c_0}^{c} = 160\,V$. *After substitution of constants parameters* $(C_2 = 0.03, C_3 = -2.3, and\ T_0 = 25^{o}C)$ *we get [40, 62]:*

1- $I_{pv} = (\frac{G}{1kw/m^2}) \times 0.8.$ *2.31*

Where Ipv =I_L*-* I_{SC}*,* I_L*: light current, Isc: short circuit*

2- $V_{oc} = 160 - 2.3\big((T_a + 0.03G) - 25\,\big)$ 2.32.

$where\ T_a\ \ the\ ambient\ temperature\ and\ G\ is\ the\ irradiance$

3- *So the solar Power* $P_{solar} = I_{pv} \times V_{oc}.$ *2.33*

The power can be calculated as the product of the current and the voltage, to get the maximum power point of a solar cell we need in one hand the short circuit current ($I_{s.c}$) which is the current produced connecting battery terminals directly to each other, where the voltage is zero, and on the other hand we need the open circuit voltage ($V_{o.c}$) which is the voltage resulted in an open circuit conditions.

I_{pv}*: cell output current.*

I_L*: is the current of light.*

I_{sc}*: short circuit current.*

I_0*: PV cell reverse saturation current (A)*

$\propto$*: Ideality or completion factor.*

K: Boltzmann's constant (J/°K)(1.38X10^{-23}*).*

M_v*: voltage factor.*

Np: number of parallel strings.

Ns: number of series strings

q: electron in charge (C) (-1.602 X 10^{-23})

R_s: series resistance of PV cell (Ω).

T: PV Junction temperature (^oK).

V_{MP}: PV cell voltage corresponding to maximum power (P).

$V_{O.C:}$ Open circuit voltage.

T_a: The ambient temperature

G: is the irradiance.

$$I_{PV} = I_l - I_d \qquad 2.36$$

$$I_{PV} = N_P I_S - N_P I_0 \left[e^{\frac{qV_{PV}}{\propto kT}} - 1 \right]. \qquad 2.37$$

Since $\mathrm{e}^{\frac{\mathrm{qV_{PV}}}{\propto \mathrm{kT}}} \gg 1 \rightarrow \mathrm{I_s} \approx 10^{-10}$ We get

$$I_d = I_s \left(e^{\frac{qV_{PV}}{\propto kT}} \right), \ where \ \propto = 1 \qquad 2.38$$

Where $\frac{\mathrm{q.v}}{\mathrm{kT}} = 38.5 \times (0.5)$ so $\mathrm{I_{dark}} \approx 0.$

$$I_s = A \times A^{**} \times T^2 \times e^{q\emptyset/KT}$$

T: Temperature = 300K. A: area of the cell

area of 2.5 cm × 2.5cm × 4 cells = $25\mathrm{cm}^2$

$$A^{**} = 120 \times 0.5\ , where\ m^* = \ 0.5 \times 9.1 \times 10^{-31} \frac{\mathrm{A}}{\mathrm{cm^2K^2}}$$

A^{**} *is the effective mass for Si, and* $\emptyset = 0.7$ *is the barrier hight.* [62]

$$\frac{q\emptyset}{KT} = 38.6 \times 0.7 \; too\ much\ less\ than\ 1\ this\ will\ lead\ to I_d \approx 10^{-10} \approx 0$$

$$I_{sc}(C_0) = \frac{G}{G_0} . I_l(G_0). \qquad 2.39$$

Where $I_l(G_0) = 200mA$. When $G_0 = 1\frac{kw}{m^2}$

$\rightarrow$ $I_l(G_0)$. for a panel with area of $2.5\ cm \times 2.5cm \times 4$ cells

$= 25cm^2$ $\rightarrow$ experimentally 200mA for 1 m^2 we have 0.8 A

$$P = I_l . V_{oc} .. where\ V_{oc} = G.T. \qquad 2.40$$

$$I_l = I_{sc} - I_s\left(e^{\frac{qV}{kT}} - 1\right) = I_{sc} \qquad 2.41$$

$$I_{sc}(G) = \frac{G}{G_0} I_l(\,G_0). \qquad 2.42$$

$G_0 = 1\ {}^{kw}/_{m^2}$ at 1.30 AM (maximum irradiance), $I_1(G_0)$ in case of 1 m^2

$$power = I_{cell} V_{cell} \qquad 2.43$$

$P_{Max} = I_m V_m = FF. I_{sc} V_{oc}$ where FF is the quality of the solar cell

T_{oc} is the cell temperature at open circuit.

$$Ambient\ temerature\ at\ 20\ {}^0C\ at\ 1{:}30\ AM\ irradiance\ is\ 0.8\ \frac{kw}{m^2}.$$

$$and\ wind\ speed \frac{1m}{s} \rightarrow T_{cell} = T_a + \left(\frac{T_{oc} - 20}{1x0.8}\right) G . T_a\ is\ ambient\ temperature.$$

$$I_{PV} = I_1 - AAT_c^2\ \left(e^{\frac{q}{kT}(V - V_0)} - 1\right)$$

$$I_l = \left(\frac{G}{G_0}\right) I_{sc}(G_0) .. since\ G_0 = \frac{1kw}{m^2}$$

$$T_{cell} = T_a + \left(\frac{T_{oc} - 20}{1kw}\right) G.$$

On the other hand, the open circuit voltage can then be found from the relation

$$qV_{oc} = E_g - \left(\frac{\sigma p^2 + \sigma_r}{2kT}\right) .. where\ \sigma_r = 0.3mV/k$$

While $P = I_{sc} \times V_{O.C}$ *, we need to compute* $V_{O.C}$ *with respect to temperature.*

$$V_{oc} = V_{c_0}^c + C_3(T^c - T_0^c)$$

$$T^c = T_a + C_2 G$$

$$T^c : operating\ temperature\ of\ the\ cell$$

$C_2 = \frac{T_0^c - T_a}{G_0} = 0.03\frac{m^2}{w} \rightarrow T_0^c = T_a + 0.03G.$ [62]

$$C_3 = -2.3\frac{mv}{c}. [62]$$

$$V_{oc} = V_{c_0}^c - 2.3\big((T_a + 0.03G) - T_0^c\big). where\ T_0^c\ \ the\ room\ temperature = 25^0 C.$$

As an evaluation of the power solar panel energy formula, we calculate the power for July 2015 depending on the solar irradiance and the temperature. Figure 12 illustrates the difference between real recorded solar power for July 2015, and the calculated power values depending on the temperature and the solar irradiance, it is clear that the data collected form the solar cell energy panel equals the theoretical power output of the solar cell energy panel, the behavior of the time series curves of the output power for Jericho in July, and for Jenin for both August and *February* were approximately the same in the two different methods.

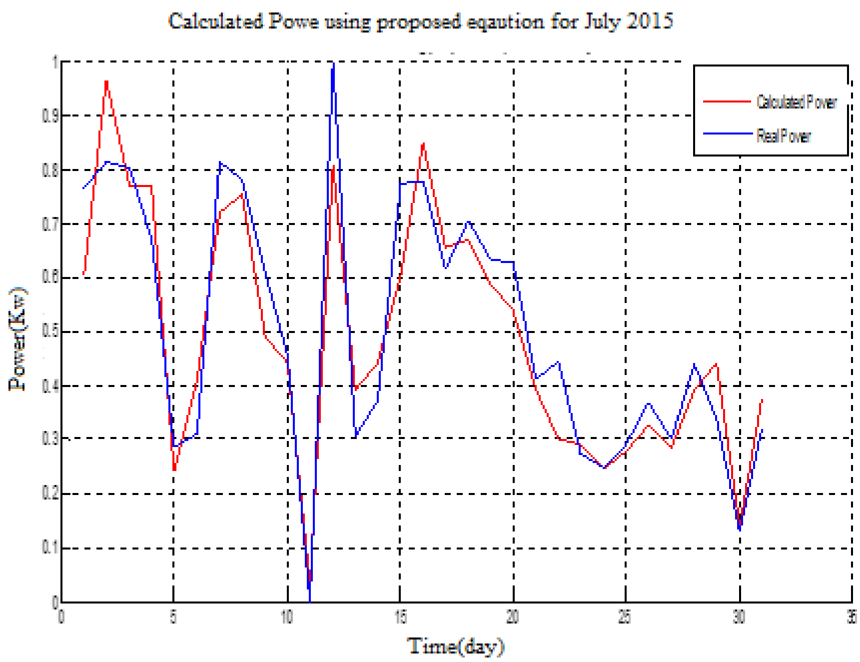

Figure 12. Solar Panel Power calculated for Jericho in July 2015

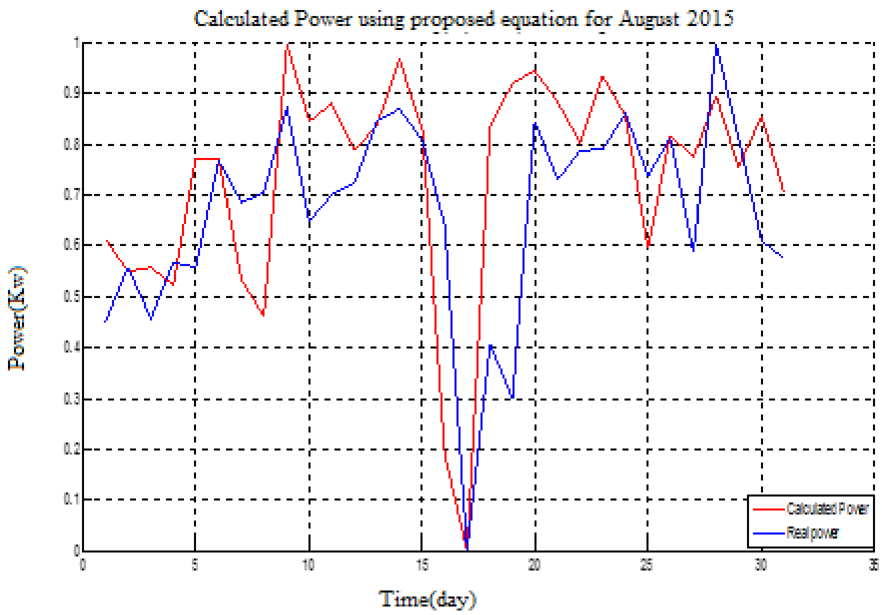

Figure 13. Solar Panel Power calculated for Jenin in August 2015

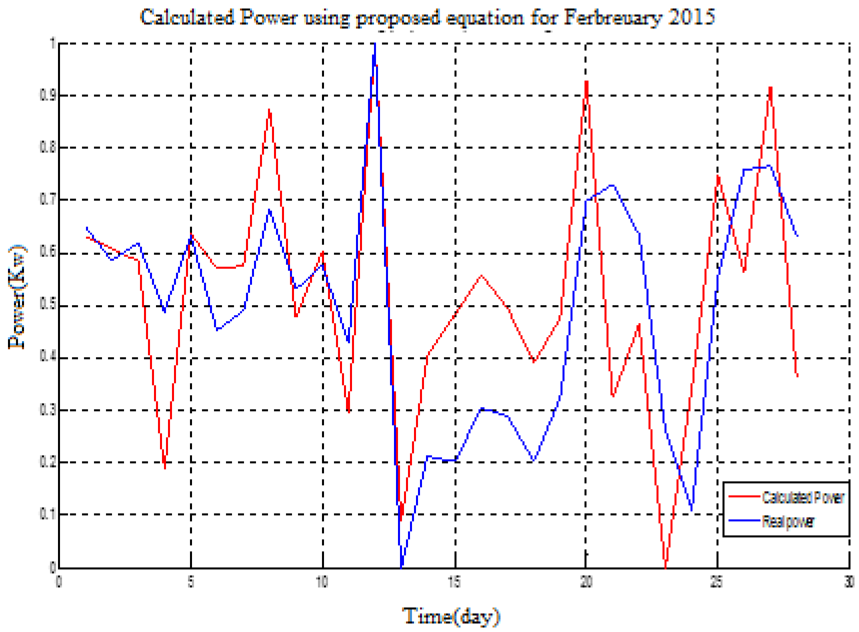

Figure 14 . Solar Panel Power calculated for Jenin in February 2015

From figures (12,13, and 14) we notice the low deference between real output of the solar panel and the calculated solar power using the derived equation, so we can use this equation to find the loss of the real solar power data to apply the proposed models for wide area in Palestine if we have the accurate climate information.

Chapter 3

RESULTS AND DISCUSSION

Chapter 3 RESULTS AND DISCUSSION

Preface

This chapter is divided into four main sections, section one explores the MFFNNBP with Levenberg-Marquardt algorithm and checks it's performance for time series applications, the second section shows application of Multi-Layer Perceptron Proposed model for solar energy prediction based on the output, where this model was applied to predict one day, one month, and one year solar energy. The third section shows the experimental result of the radial basis function neural networks (RBFNN) with new proposed intelligent training algorithm model for energy prediction based on the atmospheric condition, these parameters were the daily temperature, and the solar irradiance, that are collected for Jericho area using already installed solar panels, while temperature and irradiance were collected from the Palestinian weather cast. In section four we examine the performance of the previous models with results of derived power equation.

3.1 Introduction

Experiments have been performed to test the proposed prediction model. The models are simulated in MATLAB 8.2.7 under Windows 8 with processor core I5. In this section, different examples are given to verify the procedure of the proposed models. Three different results are presented; One day, one month and one year. The results of the validity of the model in prediction samples of I/O data, compared with real results of the solar cell energy product of the last year in different areas of Palestine. The results are obtained in 5 executions; {# of neurons} the set of neurons used in each MFFNNBP. # of Epochs is the number of the execution cycle of the MFFNNBP. $RMSE_{test}$ is the Root mean squared error of the training. The RBF proposed model results are the number of neurons, RMSE value which is compared with the RMSE of the general MLP model.

3.2 Testing the Levenberg-Marquardt Training Algorithm

In order to check the performance of the Levenberg-Marquardt algorithm we will use different functions of deferent levels of complexity, by increasing the number of neuron in the hidden layer:

3.2.1 First benchmark Example

$Y = \frac{\sin(2\pi x)}{e^x}$ $, where\ x\ is\ in\ the\ interval$ $[0,10]$$with\ step\ value\ of$ 0.01.

A Multi-layer perceptron neural network (figure 16) uses the Levenberg-Marquardt algorithm implemented using Matlab 8.2.7,ANN with one hidden layer number of neurons was obtained by trial and error and data set of 1000 items divided into 70% training data set, 15% for validation, and 15% for testing, the training results to the following table

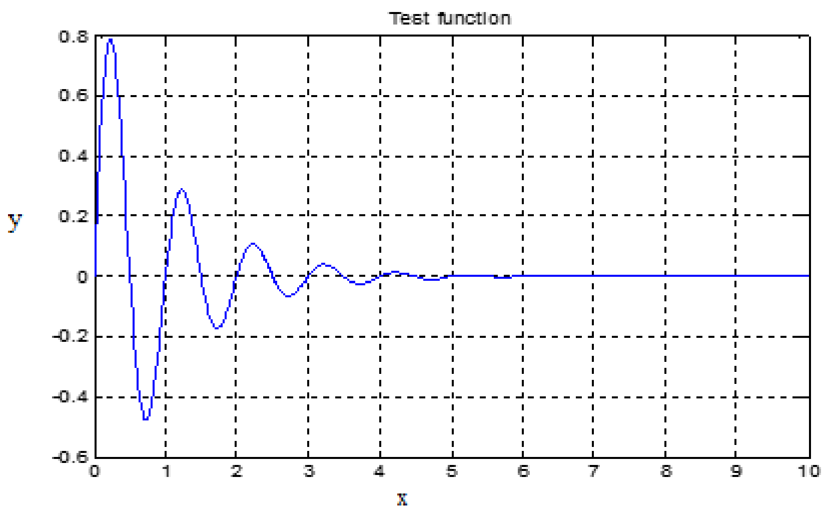

Figure 15. First Example Objective Function

Table 2. LM training results for the function of first example.

(# of neurons)	# of epochs	train	test	validation	RMSE
2	21	0.7	0.15	0.15	0.2813
4	25	0.7	0.15	0.15	0.0172
6	495	0.7	0.15	0.15	4.1767e-09
8	468	0.7	0.15	0.15	1.7854e-09
10	805	0.7	0.15	0.15	5.7079e-10

As we see from the figure as the number of neurons increases we get a better fit for the function, this also shows the best fit was captured when number of neurons was (10), if we increase the number of neurons for more than 10 we will get an over fitting problem, which results in predicted values above the target values of the curve. Where the error column shows the fitting result of the algorithm, as the error decreases we have a better fit, the figure below shows the function fit when 2, 6, and 10 neurons were used.

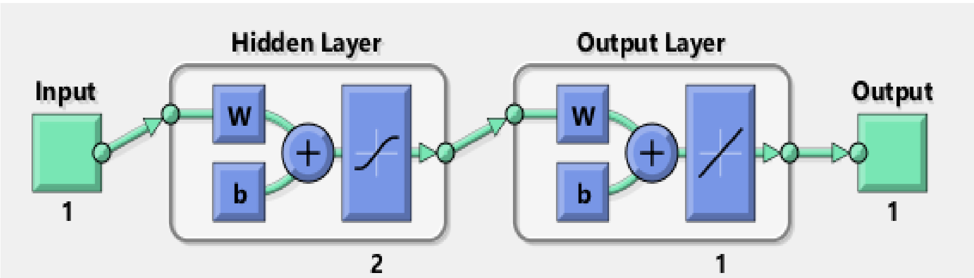

Figure 16. MPLNNBP with 2 Neurons

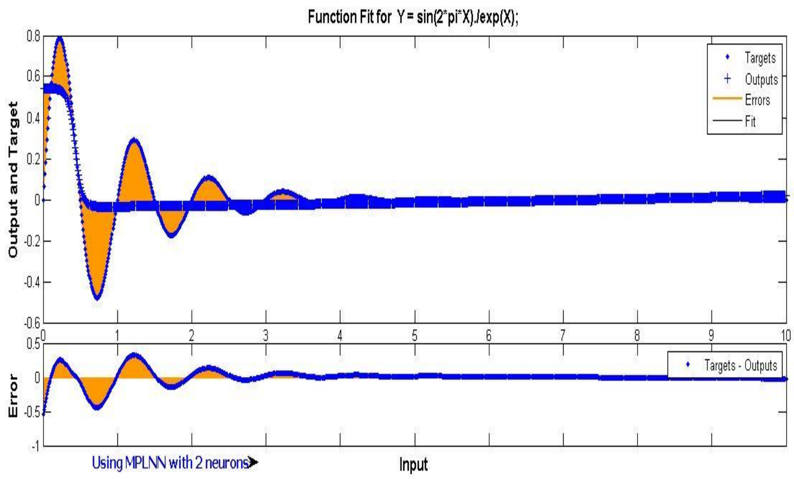

Figure 17. MLPNNBP Result of Using 2 Neurons.

In figure 17 we notice that the function fit couldn't be done using 2 neurons only as the error value is very high (0.2813), in the next test we use 4 neurons and the error still large, when applying 6 neurons there was a good enhancement and the error is relatively decreased as shown in the figure 18.

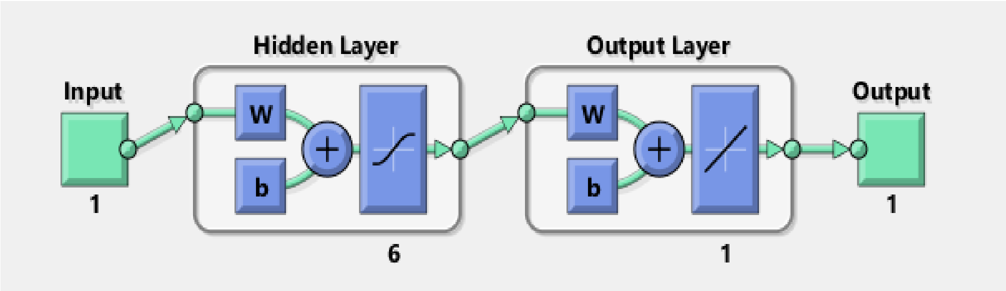

Figure 18. MPLNNBP with 6 Neurons.

The result was as shown in figure 19 where we have a better performance and good enhancement of the fitting process, with error value (4.1767e-09):

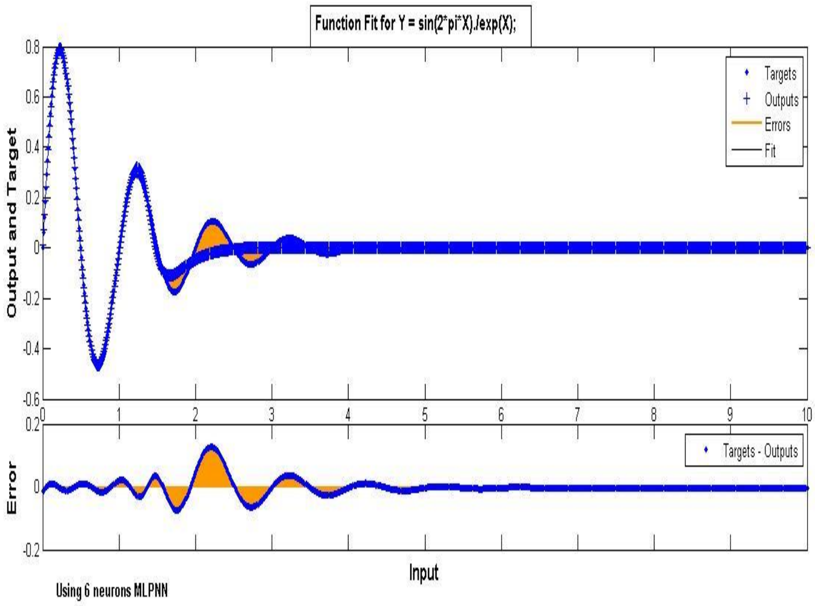

Figure 19. MLPNNBP Result of Using 6 Neurons.

The best fit was performed using 10 neurons MLPNN as shown in the figure 20, and the result is shown in the function fit figure 21.

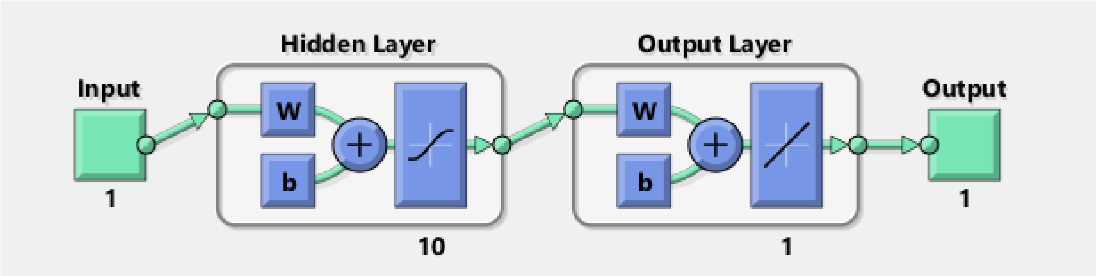

Figure 20. MPLNNBP with 10 neurons for function

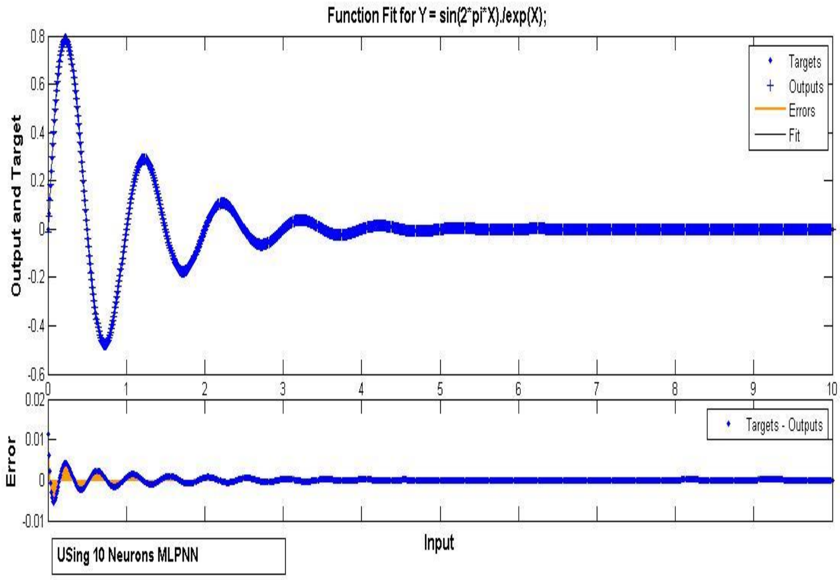

Figure 21. MPLNNBP with 10 Neurons for Function Approximation.

As shown in figure 21 the best fit with very small error (5.7079e-10), with relative few number of neurons proves the high performance of the standard the Levenberg-Marquardt algorithm.

3.2.2 **Second benchmark Example**

The next test of using Levenberg-Marquardt algorithm to fit a very complex time series like nonlinear Mackey-Glass equation time delay differential equation which is a chaotic time series making it an ideal representation of the nonlinear oscillations of many physiological processes, the general form of it is given by the expression:

$$\frac{ds(t)}{dt} = \frac{\mathrm{a.s(t-\tau))}}{1+s^{10}(\mathrm{t-\tau})} - b.s(\mathrm{t}) \qquad (50)$$

Where x (t) is the value of the time series at time t. The time series was constructed with parameter values a = 0.2 and b = 0.1. In this test we set the initial conditions as s (0) = 1.2 and s (t) = 0 when t < 0, with t = 17 to give figure 22. [60]

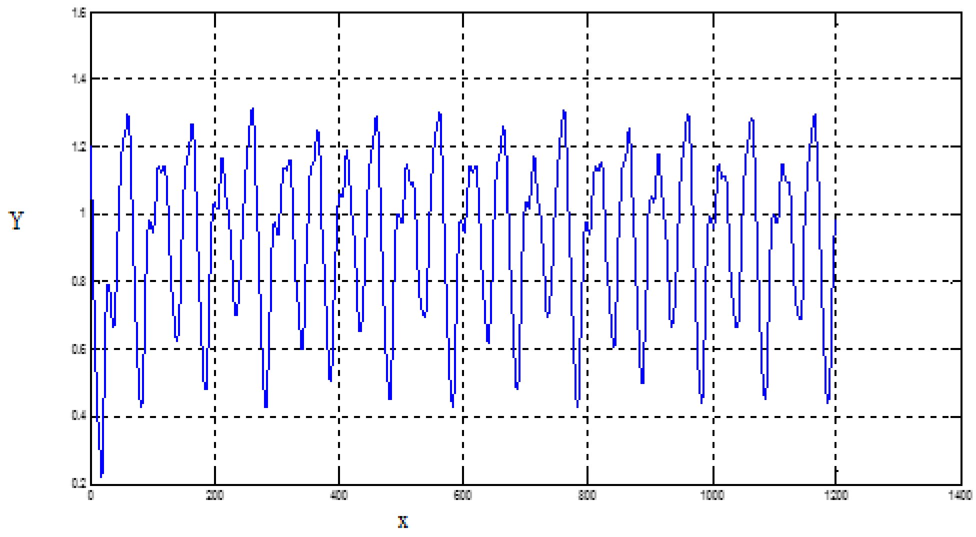

Figure 22. Mackey-Glass equation example function

Time series signal is a very complex challenge for the neural network because large number of curves and noise as many signals of the real world. To predict such signals we need more complex neural network with even multi-layer NN or single layer with large number of neurons. Output test on Levenberg-Marquardt algorithm is started with 10 neurons in the hidden layer and then we increase them by 10 each time till we reach the best fit for such signals.

Table 3. Shows the MPLNN results for 10, 20, 30, 40, 50 neurons.

(# of neurons)	# of epochs	train	test	validation	RMSE
10	26	0.7	0.15	0.15	0.0529
20	101	0.7	0.15	0.15	0.0322

30	133	0.7	0.15	0.15	0.0097
40	216	0.7	0.15	0.15	0.0023
50	109	0.7	0.15	0.15	0.0011

From the table 3 we see that the error was at the minimum of its values when the network was built with 50 neurons, and we notice also that even the function is very complex the target signal, the Levenberg-Marquardt algorithm performs very well with relatively few number of iterations.

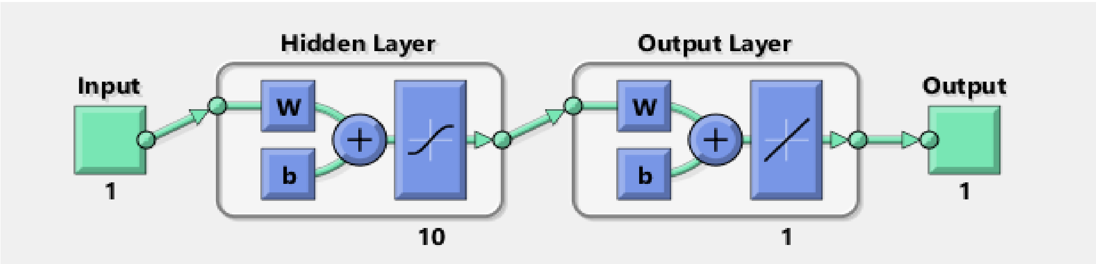

Figure 23. MPLNNBP with 10 neurons Mackey-Glass

According to these results we can conclude that Levenberg-Marquardt algorithm is a powerful training algorithm and has a good performance in time series application, therefore, we decide to use it in our application for PV power system output prediction.

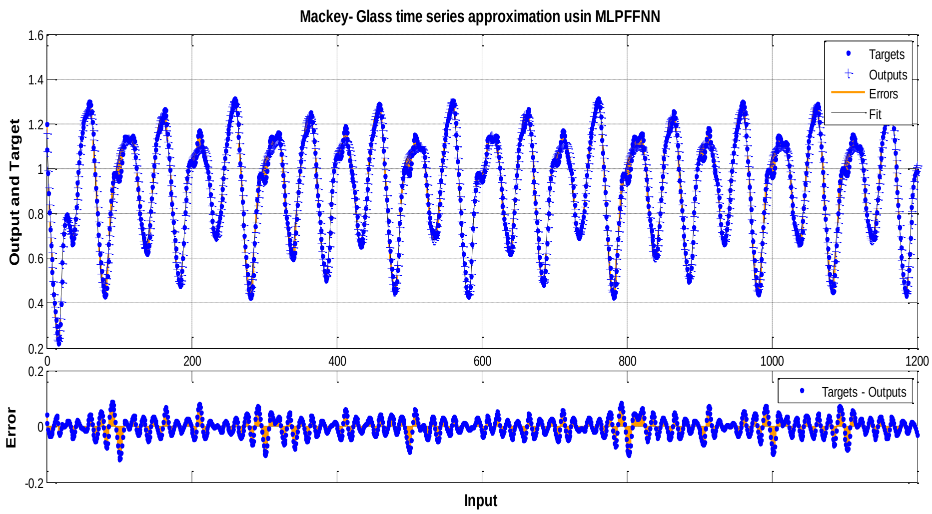

Figure 24- Mackey- Glass time series approximation using MLPFFNN

Figure 24 shows the best fit achieved using MLPFFNN with 50 neurons only.

3.3 Experimental Results of the MLP Prediction Model Based on PV power system Output

A solar panel of silicon cells with dimensions of 1m wide by 2m length connected in parallel and series with other panels to form 5Kwh PV power model installed in different location in Palestine is, where the output data is stored in a special database on the official website of the Green Power company, this website provide many filters for exporting available data for certain time. After taking the privileges from the company we downloaded and preprocessed our data set for ANN training, see appendix A-1 for sample data.

3.3.1 One Day Solar Energy Prediction

For one day prediction, we use data for each hour, which present the mean of all the read values in each 5 minutes. The day (15- May-2015) was selected with good climate conditions, like clear sky, long daytime, high solar irradiance, and medium humidity level. These conditions highly effect the solar energy production. Applying the proposed model for one day of solar prediction produces the following results:

Table 4. Results of Applying Proposed MFFNNBP in One-Day

Neurons	epochs	Train Data	Test Data	RMSE
2	15	70%	15%	0.000566
4	28	70%	15%	0.000666
6	*14*	*70%*	*15%*	*0.00031*
8	9	70%	15%	0.001585
10	8	70%	15%	0.001391

As seen from table 4, MFFNNBP plays a good role in solar prediction for one day, the real output for one day is a curve with some noise that are removed by using a smooth function as shown in figure 25. With one hidden layer of a small number of neurons, the proposed model predicts the future energy produced by the solar cell value in one day. This evaluated to find the RMSE of the MFFNNBP. Table 5 represents the test RMSE. In addition, figure 26 shows that the production process produces a fitting curve, with small values of RMSE.

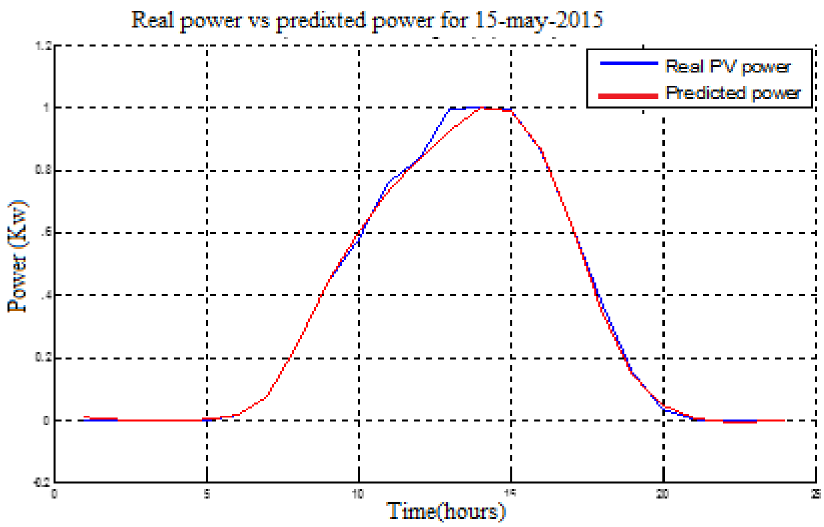

Figure 25. Power Generated for One Day 15-may-2015.

Table 5. Results of Applying Proposed MFFNNBP in One-Day 1 August- 2015

Neurons	epochs	Train Data	Test Data	RMSE
2	19	70%	15%	0.000150
4	*21*	*70%*	*15%*	*0.000005*
6	13	70%	15%	0.000015
8	19	70%	15%	0.000179
10	9	70%	15%	0.000803

As seen from table the best result was achieved using only 4 nerons with RMSE value of (0.000005). In the next step we examine the model for defferent times and locations.

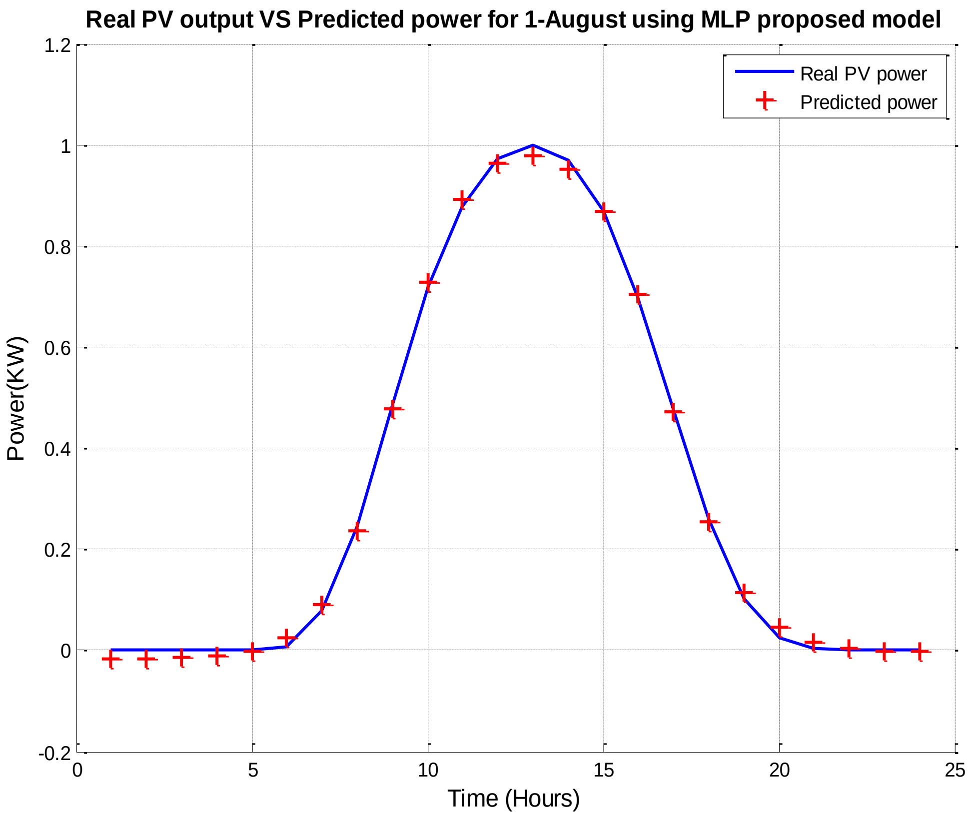

Figure 26. Power Generated for One Day (1 August- 2015- Ramallah).

Table 6. Results of Applying Proposed MFFNNBP in One-Day (5 January- 2015- Jenin)

Neurons	epochs	Train Data	Validate	Test Data	RMSE
2	12	70%	15%	15%	0.00486
4	20	70%	15%	15%	0.0016
6	12	70%	15%	15%	0.00154
8	*30*	*70%*	*15%*	*15%*	*0.000391*
10	15	70%	15%	15%	0.00121

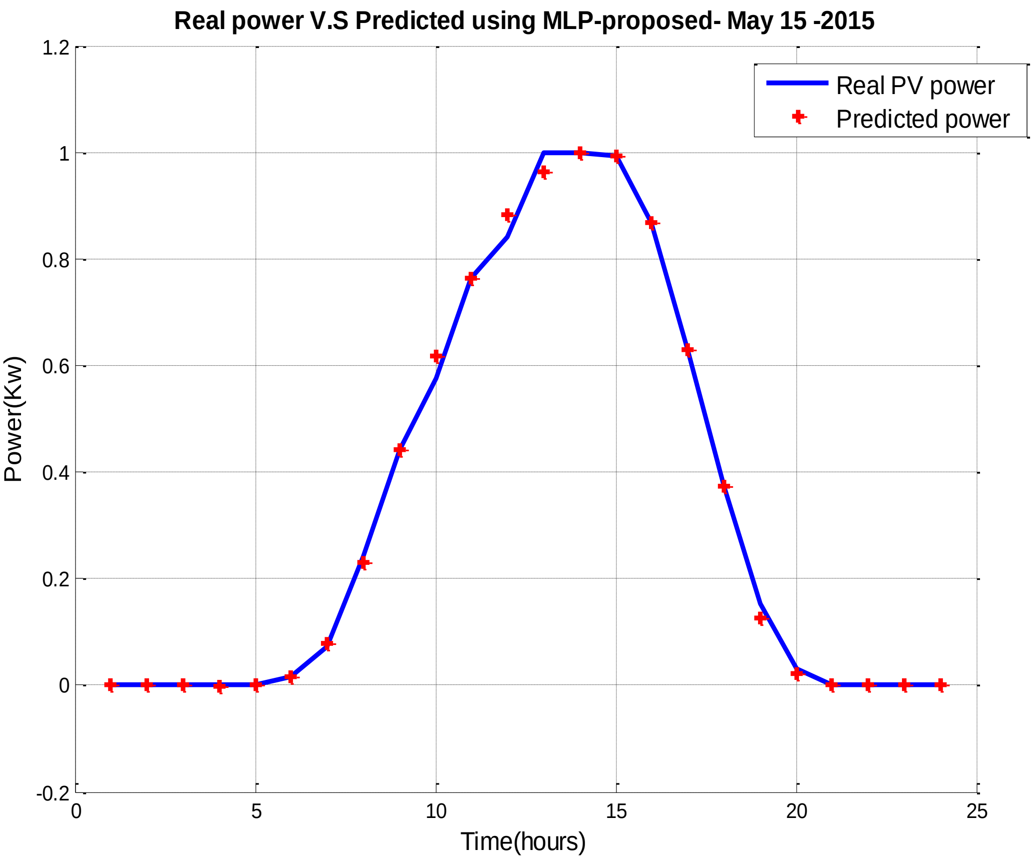

Figure 26. Power Generated for One Day (5 January- 2015- Jenin).

From table 6 the best result was achieved using only 8 nerons with rmse value of (0.000391).

3.3.2 **One Month Prediction**

To prove the process of predictions for the proposed models, we apply the proposed MFFNNBP to predict energy that can be produced in one month as the second part of the study, where July period of time was selected. Data was recorded for ALFARA'A solar panel along the year 2014, and we built the training set for July record. The process was accomplished by taking the mean value of the generated power every 10 days with 10 readings per day that can be illustrated in figure 28. Table 7 shows the results of applying proposed MFFNNBP for the training set which is composed of 30 examples (30 days), the results show that the best prediction result was achieved when hidden layer of 10 neurons was trained to give the following figures. According to the figure 29, the best prediction is achieved with 10 neurons in the hidden layer and 18 epoch. MFFNNBP produce small RMSE in monthly measured.

Table 7. Model Training Results for Energy Prediction for July-2015 in Alfar'ah (One-Month)

(# of Neurons)	Train	Test	Validate	Epochs	$RMSE_{test}$
2	70%	15%	15%	8	0.09164
4	70%	15%	15%	9	0.0728
6	70%	15%	15%	11	0.00044
8	70%	15%	15%	18	0.00041
10	*70%*	*15%*	*15%*	*18*	*0.00024*

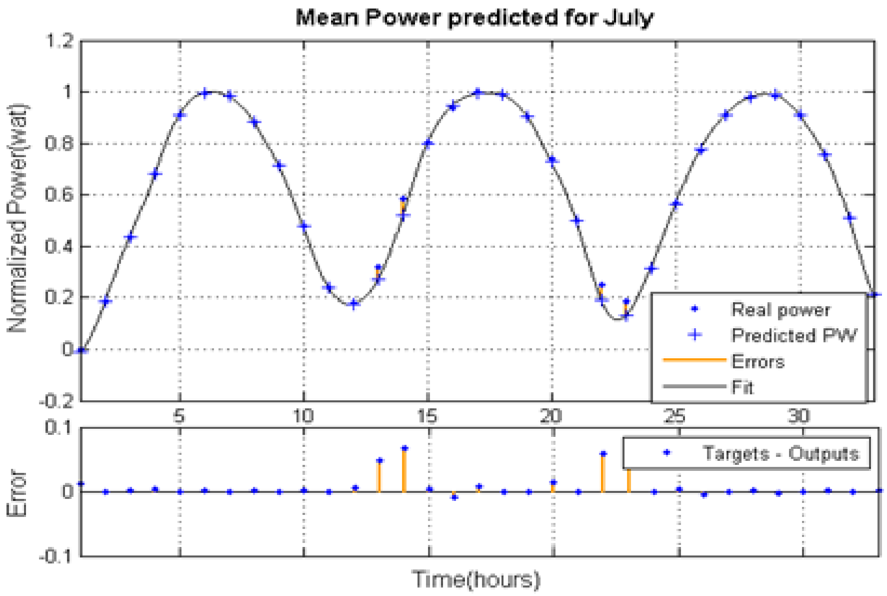

Figure 27. The Best Prediction Result of the Training Process for One-Month

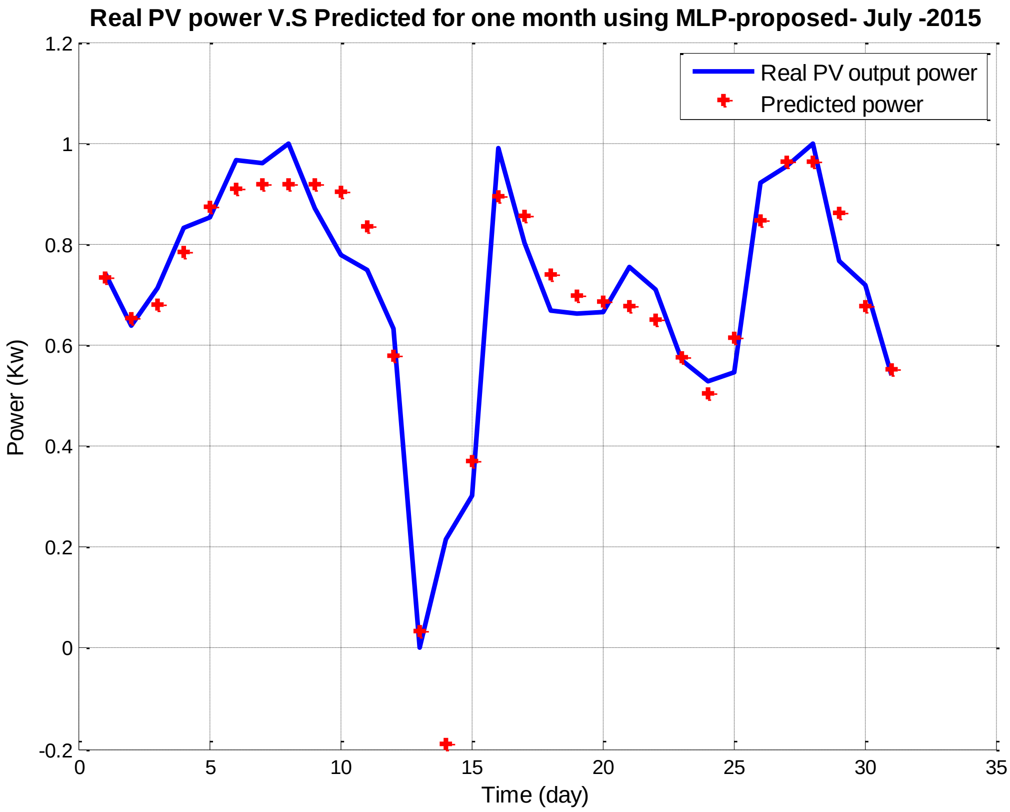

Figure 28. Solar Energy Prediction at July-2015 for Jenin (One-Month)

Table 8.Model Training Results for Energy Prediction for July-2015 in Jenin (One-Month).

Neurons	epochs	Train Data	Test Data	RMSE
2	19	75%	15%	0.045751
4	10	75%	15%	0.028641
6	11	75%	15%	0.015808
8	7	75%	15%	0.028308
10	*11*	*75%*	*15%*	*0.012775*
12	7	75%	15%	0.028377
14	9	75%	15%	0.01673
16	8	75%	15%	0.023226
18	7	75%	15%	0.017446
20	6	75%	15%	0.01758
22	7	75%	15%	0.021156
24	7	75%	15%	0.017826
26	5	75%	15%	0.023349
28	4	75%	15%	0.049362
30	4	75%	15%	0.066278

Table 9. Model Training Results for Energy Prediction for December -2015 in Jenin (One-Month):

Neurons	epochs	Train Data	Test Data	RMSE
2	40	75%	15%	0.070144
4	21	75%	15%	0.012569
6	12	75%	15%	0.031238
8	12	75%	15%	0.014445
10	8	75%	15%	0.012793
12	7	75%	15%	0.019505
14	*12*	*75%*	*15%*	*0.004164*
16	7	75%	15%	0.01021
18	7	75%	15%	0.024368
20	11	75%	15%	0.016052
22	5	75%	15%	0.025713
24	7	75%	15%	0.01649
26	5	75%	15%	0.014491
28	5	75%	15%	0.054254
30	4	75%	15%	0.03105

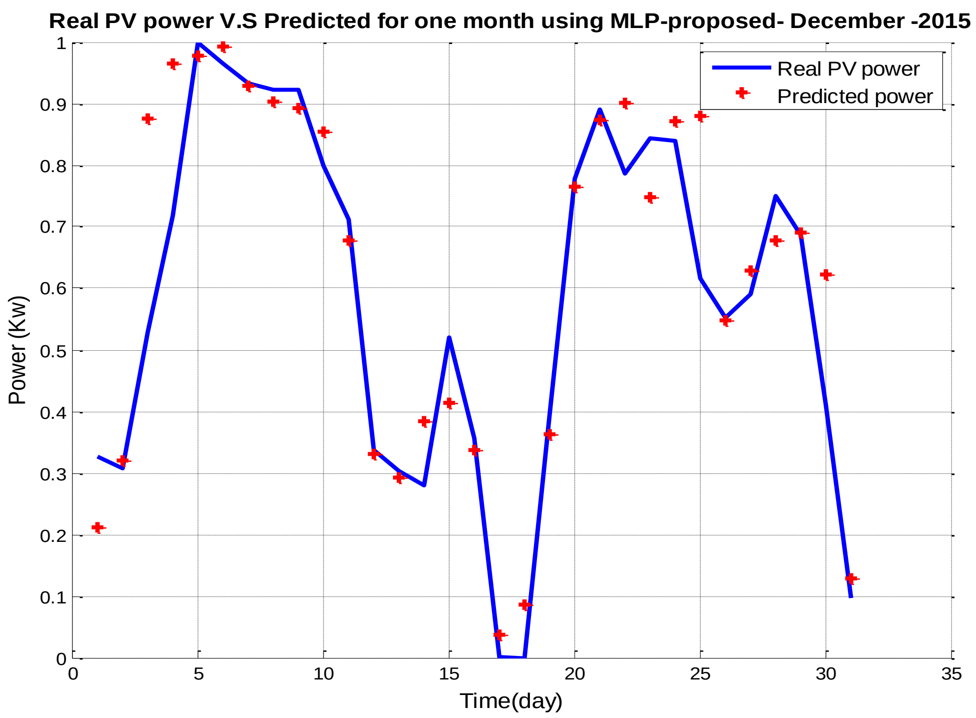

Figure 29. Solar Energy Prediction for December -2015 for Jenin (One-Month*)*.

3.3.3 One Year Prediction

In order to get energy production along one year we need to deal with complex time series, figure 12 below shows the time series signal for one year [1-Jan-2014 to 1-Jan-2015], so we divided the year into four parts representing the four seasons of the year, dealing with each part as the mean value of the produced solar energy. As we see the high complexity of this signal, so we need to process it before we use it as target function to be predicted using the MFFNNBP model. This process started by; dividing the year into four parts, remove the night time where the energy produced goes to zero, reduce the large amount of data as Mean of one month = Mean [mean (1^{st} ,2^{nd} , 3^{rd} days) + mean (14 ,15 , 16 days) + mean (28 ,29 , 30 days), the noise is reduced using smoothing function, normalization of the signal data, and applying the proposed model using several probabilities to get the best prediction results.

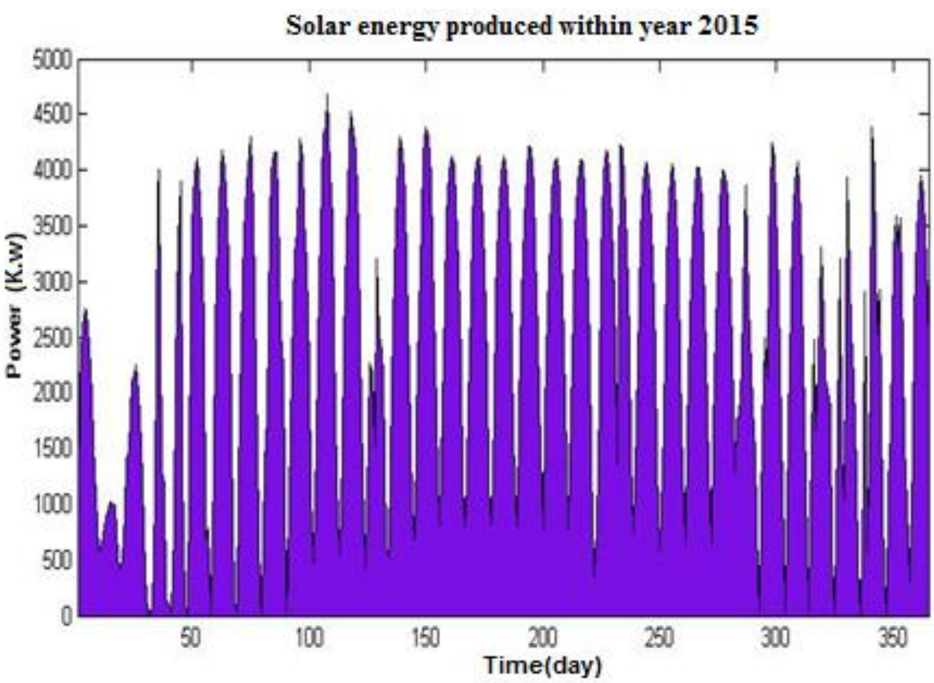

Figure 30. Energy Produced on One-Year

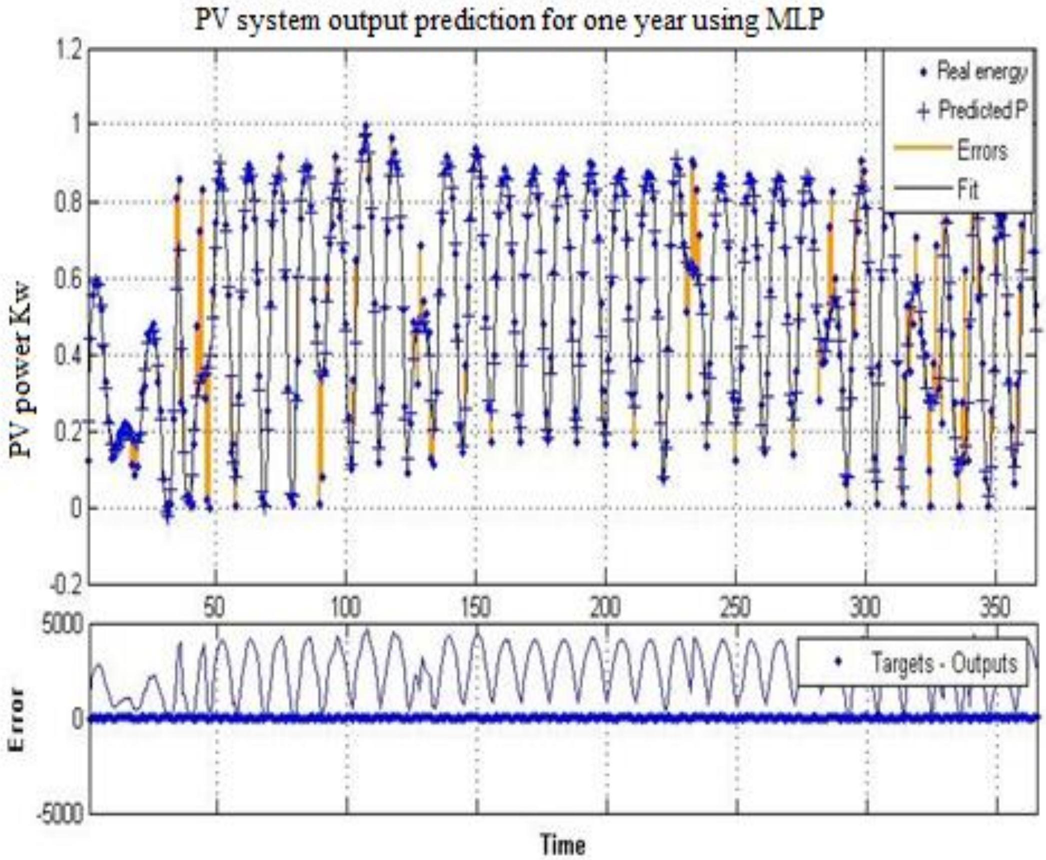

Figure 31. The Best Prediction Result of the Training Process for One-Year

Figure 31 shows the best result for one-year prediction which was achieved when we applied the proposed model with 80 neurons in the hidden layer, and also shows the complexity of one-year time series solar energy prediction. As we see from table 10 the error was at its minimum value with 90 neurons hidden layer is used [0.00564], which is the best error value, while when using more than 90 neurons , the system will produce an over fitting problem. In all tables and approximation curves, we can observe the RMSE of the prediction, which clearly shows that the prediction is closest to the real value, regardless of the loss in the efficiency of the solar cells in energy production decreases by %5 in each year, all with few epochs. The prediction process using the proposed model MFFNNBP was achieved using 80 neurons in the hidden layer, as shown in table 10:

Table 10. Model Training Results for Energy Prediction for One-Year

(# of neurons)	Train	Test	Validate	Epochs	$RMSE_{test}$
20	70%	15%	15%	7	0.070022
30	70%	15%	15%	8	0.067588
40	70%	15%	15%	9	0.064546
50	70%	15%	15%	22	0.039261
60	70%	15%	15%	11	0.035956
70	70%	15%	15%	11	0.01505
80	*70%*	*15%*	*15%*	*10*	*0.008242*
90	70%	15%	15%	12	0.00564
100	70%	15%	15%	12	0.008293

As we can see in the tables and figures, it is possible to observe the correlation values between real solar cell output power and power output obtained from the prediction using the proposed model MFFNNBP, that are measured in the same place. It is clear that we can consider the possibility of including other information as input to the model like, temperature, radiation, and humidity, and the time duration of the sunlight. This may achieve better prediction of solar cell output power. Hence, the idea to predict more deeply the correlation between climatic parameters using ANNs. The use of the MFFNNBP model for prediction of climatic variables becomes a viable solution for the knowledge of these values. Implementing this model for solving a prediction problem is necessary to decide the optimum areas, where the solar cell panels can produce a more efficient power output. The obtained result, which uses the MFFNNBP model for solar energy prediction, different attributes like training algorithm, training data, a region of study will change the values of the prediction result. This result obtained using real output data (previous data) as a measure of the prediction improvement, or prediction of the actual output using some input parameters. Next section we will study the prediction process using the input data parameters that affect the power output of the PV power system like; temperature, and radiation, and the time duration of the sunlight. Furthermore, we will apply the model in two different types of solar cells; mono-crystalline and organic solar module, in the aim to determine the best type for our region.

3.4 Experimental Results of the RBFNN Prediction Model Based on Climate Conditions effects PV power system Output

In this section we apply the proposed model to predict the output of the solar energy panels in two parts on the recorded irradiance, temperature and output power data collected form Jericho Palestine station, A-2 for sample data. Part one is the prediction using proposed RBFNN (enhanced *Newrb*) fed by daily temperature, solar irradiance, that are the most influencing parameters of the solar energy production, and using the real recorded output as the neural network guide, then we applied multi-layer perceptron neural network (MLPNN) model on the same parameters to compare the efficiency of the new model enhanced *Newrb*. To analyze the effectiveness of the proposed model, it's applied to predict the output power for one month and complete year data, using real data and calculated solar power propose special equations then perform forecasting for one month (daily main data, 30 items), and for one year of 340 days for year 2015. The system is simulated in MATLAB 8.2.7 under Windows 8 with processor I5; the experiment was portioned into three parts.

3.4.1 **One Month Prediction**

Applying the proposed RBFNN model with real data concurrently with proposed MLPNN model and traditional RBF model with an error goal of (0.001). Figure 33. Shows the result of applying the proposed model to predict one month PV power system output depending on the daily temperature and solar irradiance as mean value for each day, the approximation finished with an RMSE of 0.00078 with 24 neurons in the hidden layer using proposed model while the MLPNN finished with an error of 0.018546, which verify the performance of the proposed RBF model in prediction time series and solar cell data of one month. As shown, in the figure 33, there is a change in the PV power system output due to variations in cloudiness or radiation.

Table 11. The Result of the RMSE for the Proposed Model and MLPNN

Neurons	RBFNN				MLPNN
	Proposed rbf Model			Traditi-onal rbf	
	RMSE	STD(10times)	Test error		
2	0.11014	0.0099	0.3028	0.0968	0.04843
4	0.01175	0.0015	0.3124	0.0478	0.00640
6	0.00845	7.3269e-04	0.3046	0.0513	0.00680
8	0.00692	1.6092e-04	0.2480	0.0539	0.00652
10	0.00521	4.2655e-05	0.2097	0.0156	0.01522
12	0.00475	1.9031e-04	0.2239	0.0838	0.01508
14	0.00349	2.9618e-04	0.2464	0.0366	0.05604
16	0.00215	1.7708e-04	0.1506	0.1031	0.01402
18	0.00180	1.2986e-05	0.1994	0.0468	0.01966
20	0.00173	9.0663e-06	0.3004	0.0375	0.00649
22	0.00169	2.9337e-06	0.2716	0.0437	0.02453
24	0.00156	9.5460e-07	0.2606	0.0956	0.04092
26	0.00091	1.0650e-04	0.2606	0.0723	0.00846

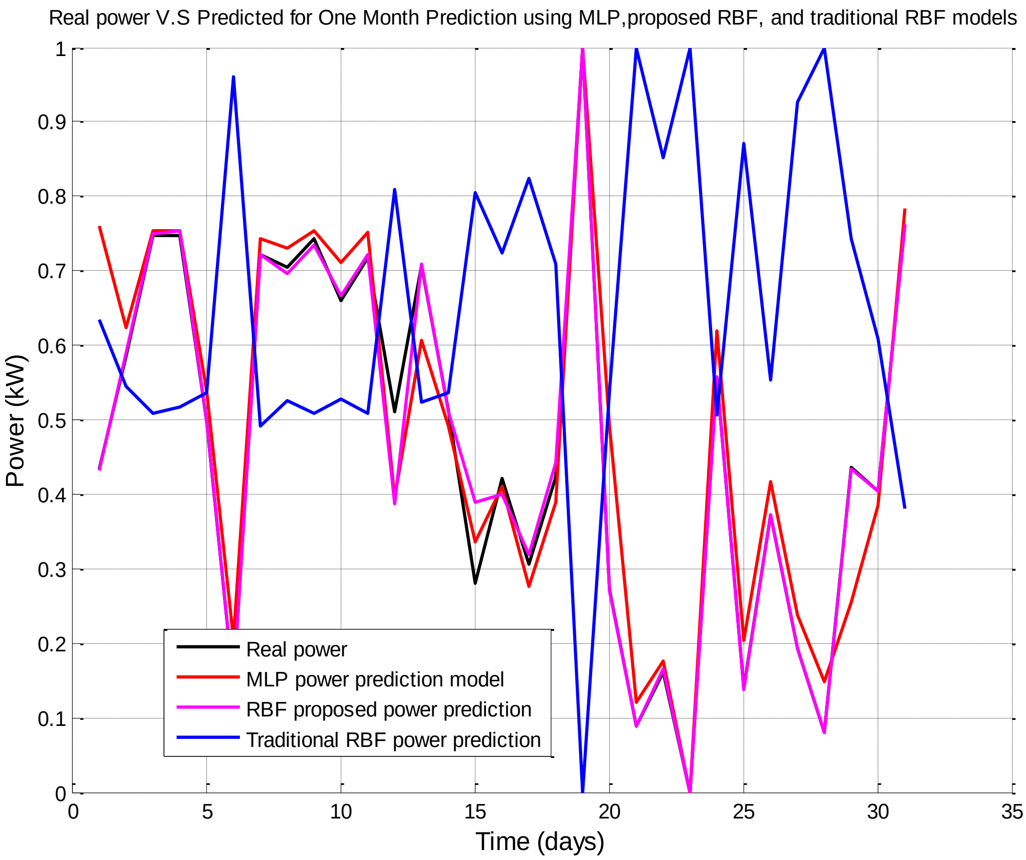

Figure 32. Month Power Prediction Using Proposed RBF Model.

From table 11 we can see that the behavior of out proposed RBF model (bink color) in the prediction process of the nonlinear time series. It is clear that the proposed model converges to the optimum value with less number of RBF (hidden layer neurons) with better prediction error; the proposed approach performs very well in comparison with the MLPNN (red color), and traditional RBF model (blue color). It is improving the prediction performance.

With the proposed model an efficient prediction is obtained, a brief comparison of the two models, the proposed model indicates that using efficient algorithms to optimize parameters of RBFNN is promising.

3.4.2 **One Year Prediction**

To verify the efficiency of the proposed model, one year data is used. This data is collected from the solar cell panel installed in the city Jericho – Palestine. The data of 340 days for year 2015, the medium daily temperature and the medium daily irradiance. In Table 12, and figures 32, 33 we can observe the values of the prediction depend on our proposed model, MLPNN proposed, and traditional RBF model with the same PV power system parameters (radiation and temperature), which are used as input to the two models. The threshold value used for this experiment is error goal =0.002. In the case of one-year prediction and for the complexity of the time series as shown in the Table 12, the minimum RMSE values are not recorded in the last row. But it is clear that the proposed model out performs the MLPNN model. Such complex time series needs very complex models to perform prediction, Table 12 shows the effectiveness of our model in comparison with the MLPNN model, where the model achieved very close RMSE error to the error goal while MLPNN, and traditional RBF so far and needs more neurons to achieve the same result.

Figure 33 shows magnified 60 days (from the year prediction), this shows our proposed model (bink) was the best prediction technique, to clearly see the differences

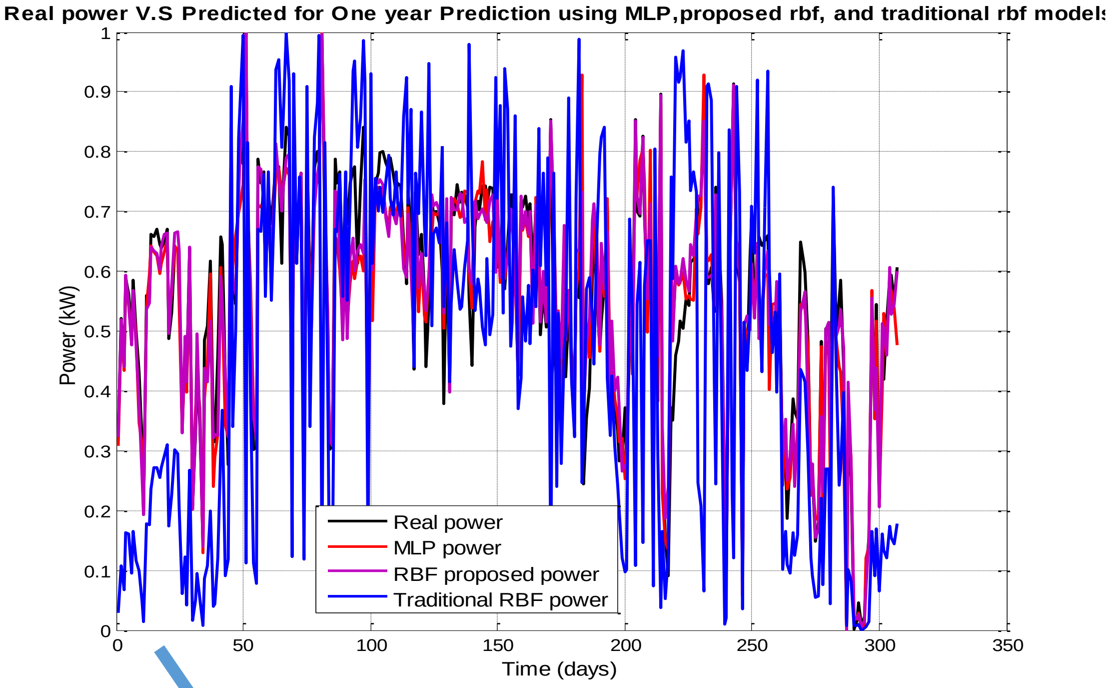

Figure 32. Year Power Prediction Using our Proposed RBF Model compared with MLP and tradional RBF models.

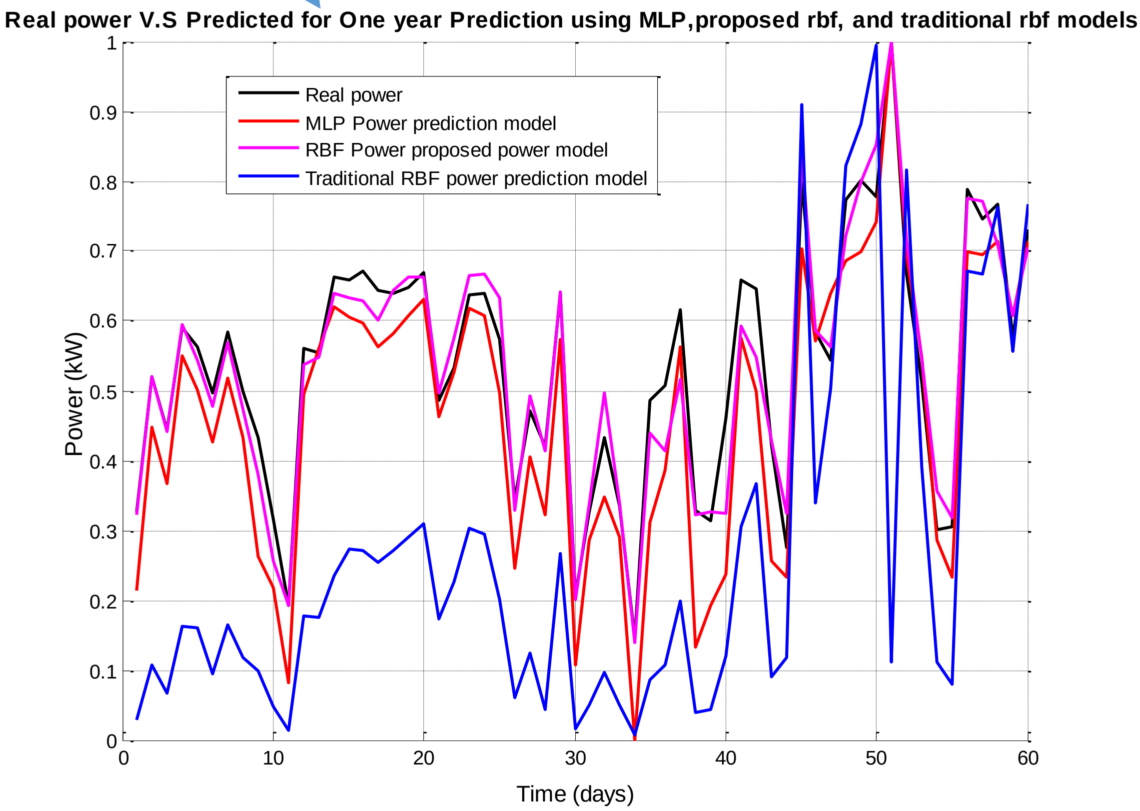

Figure 33- Two Months Prediction using MLPNN, our RBF, and traditional RBF model.

Table 12. The Result of the RMSE for the Proposed Model and MLPNN.

Neurons	Proposed Model RBFNN				MLPNN RMSE
	Proposed rbf Model			Traditional rbf RMSE	
	RMSE	STD(10times)	Test error		
6	0.028142	8.0376e-06	0.1367	0.02	0.015968
11	0.015172	3.2311e-16	0.0981	0.0129	0.017249
16	0.009828	1.0020e-14	0.1110	0.0112	0.014173
21	0.008756	9.9747e-05	0.1087	0.0088	0.030769
26	0.008285	1.8497e-05	0.1141	0.0097	0.014886
31	0.007409	1.0596e-04	0.1133	0.0118	0.014084
36	0.007548	1.4121e-04	0.0980	0.0184	0.015186
41	0.007672	1.4388e-04	0.0931	0.0208	0.01805
46	0.006469	2.7393e-05	0.1100	0.0232	0.026315
51	0.005317	1.9013e-04	0.1086	0.0329	0.015284
56	0.004994	5.7033e-05	0.0914	0.0215	0.016295
61	0.005081	1.1105e-04	0.0862	0.019	0.022558
66	0.004837	3.9976e-05	0.1041	0.0254	0.015536
71	0.004657	9.1827e-05	0.0959	0.0211	0.016094
76	0.005019	2.2366e-04	0.0938	0.0188	0.031676
81	0.004187	2.0268e-06	0.0857	0.0294	0.042582
86	0.004031	1.3588e-05	0.0890	0.0238	0.016009
91	0.003933	3.0227e-06	0.1070	0.0156	0.030073
96	0.003792	1.8053e-05	0.1058	0.0248	0.015654
101	0.003734	6.7442e-06	0.0667	0.0279	0.028633

In Table 12, we can show that the number of RBFs (neurons) in the hidden layer which causes the neural network over fitting. Also, from RMSE values in this table, it can be seen that the lowest error values obtained from the proposed model are much better than MLPNN. Furthermore, as the number of RBFs (neurons) increases slowly one by one in each training iteration, note that lowest number of neurons in the hidden layer decreases the complexity of the system, which means less time of execution. The RMSE values were decreasing with the usage of the proposed model each time the learning operation and calculation were performed, indicating that this has a good ability to learn the behavior of the time series which depends on our case study on two climatic conditions (Temperature and Radiation).

3.5 Prediction Using Theoretical Calculation Formula of the Power Output

To verify the efficiency of the proposed model, we used the power output values produced by theoretical calculation to predict the power output depending on the real data collection as target values. It's clear that the proposed model calculated for one moth (July) using the proposed model with an error goal of (0.002). Then we used the power equation to calculate the power generated for a year depending on the climate data, the table 13 below shows the training of the proposed model with error goal of (0.001).

Table 13. The Result of the RMSE used the Proposed Model Applied on Theoretical Calculation of the Power Output. (Month and Year):

One Month Prediction			**One Year Prediction**	
Neurons	**RMSE**		**Neurons**	**RMSE**
	July	**February**	**Year 2015**	
2	0.000387669	0.000186	**6**	0.028142
3	0.000108555	0.000173	**16**	0.009828
4	0.000085201	0.000108	**26**	0.008285
5	0.000032470	0.000108	**36**	0.007548
6	0.000030911	7.36E-05	**46**	0.006469
7	0.000005900	6.24E-05	**56**	0.004994

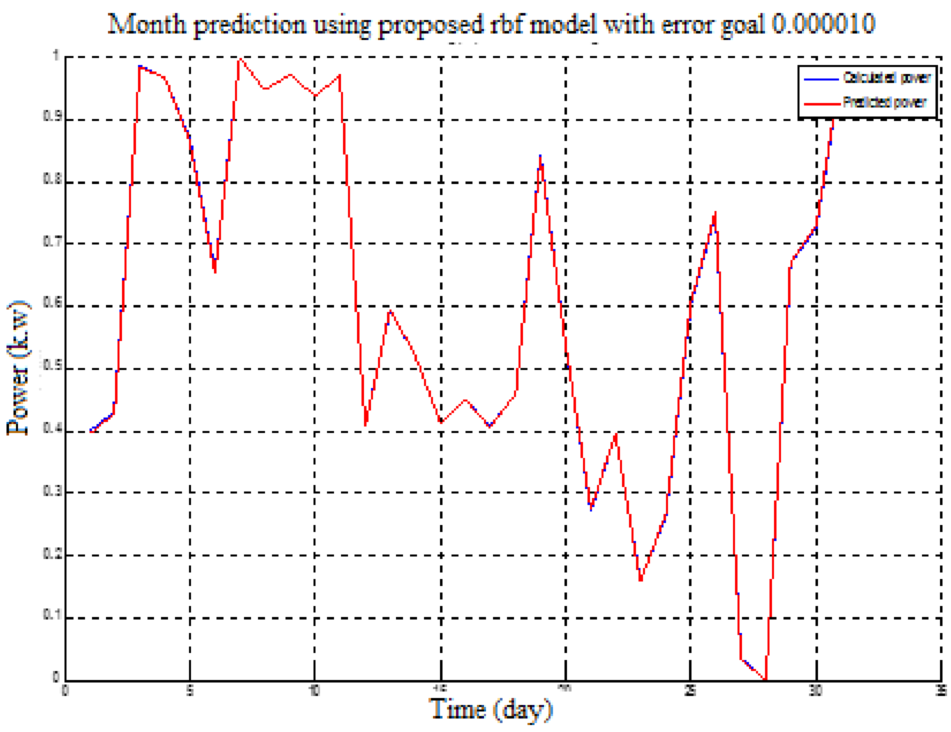

Figure 344. Prediction Result for one month depends on theoretical calculation of the power output using the proposed model.

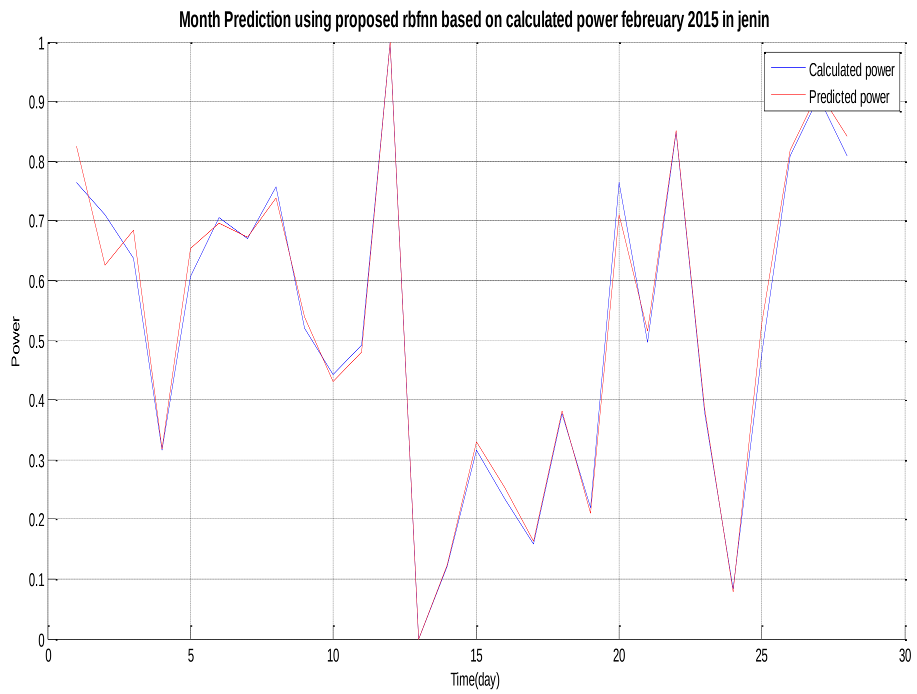

Figure 35. Prediction Result for one month depends on theoretical calculation of the power output using the proposed model for Jenin in ferbruar 2015.

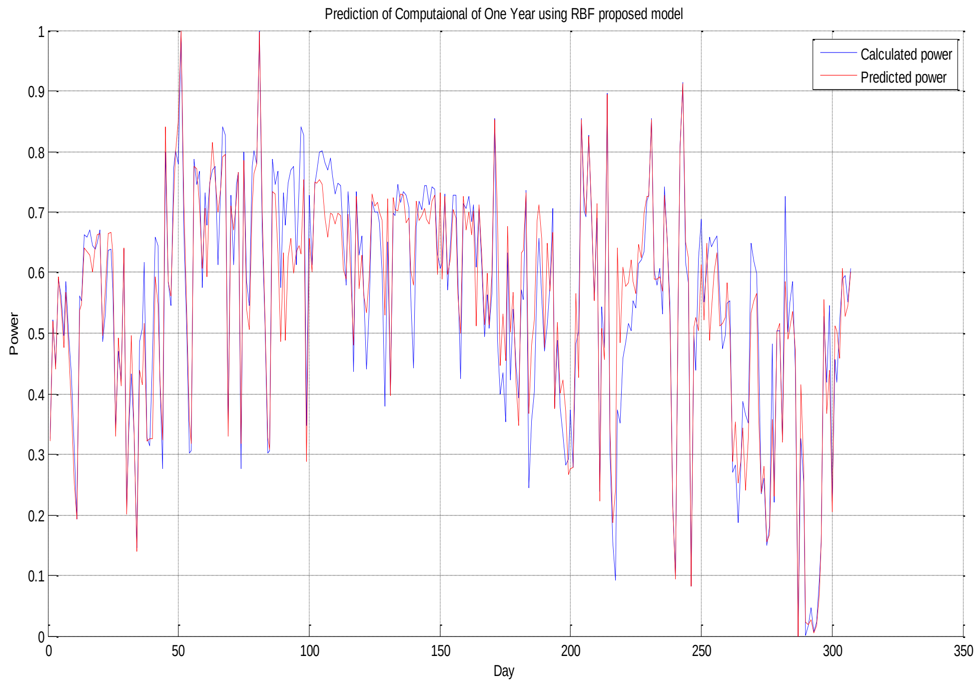

Figure 36. Prediction Result for one year depends on theoretical calculation of the power output using the proposed model for Jerhico.

We notice from figures 34, 35 and 36, the efficiency of the proposed model when applied to calculated power formula, where the original curve of the generated power has less sudden large deviation with the noticeable complexity of this function, the training was stopped with an error of (0.004994), which is a relatively acceptable approximation. Where the error produced by the prediction of one month is about equal to zero.

3.6 Classification

Classification part is done by comparing the output results for generated power within a year in 11 Palestinian cities, where this data collected from the solar GIS website [63], which provides satellite data for many regions all over the world as climate data and solar PV planner tool. The table (14) below shows one year data power per month (average moth). It’s noticeable after averaging the output power for each city along the year that Bethlehem city has the maximum total power, and the next city was Hebron, table (14) , this can be explained as a result of the height of these cities above sea level, with low temperature and high solar irradiance in these areas in comparison with other cities, even we notice that difference between the generated power in all selected cities are very close to each other, which means the validity of all Palestinian cities for solar energy panels installation the selected PV panel power is 1kw for each panel.

Table 14 - shows the monthly average generated power for Palestinian cities in Kw[63]

Month / City	Jenin	Tubas	Jericho	Nablus	Tulkarm	Qalqelia	Salfet	Jerusalem	Bethlehem	Hebron	Ramallah
Jan	106.1	109.4	112.3	106.1	105.7	105.5	107.2	114.1	115.8	112.7	111.5
Feb	106.1	107.6	111.8	105.9	106.1	106.6	106.4	113.7	115.4	112.8	112
Mar	145.8	148.8	150.5	146.7	146.7	145.8	146.1	152.5	154.5	152.2	150.8
Apr	147	148.4	145.9	147.7	147.4	146.9	146.9	152.4	153.3	152.3	152.1
May	167.2	169.1	165.6	170.4	167.7	167.6	169.9	172.6	173.4	173.3	173.1
Jun	168.6	170.5	166.8	171.4	168.4	168.5	171.2	172.6	172.9	172.9	173.1
Jul	172.9	174.9	170.3	175.8	171.5	171.5	175.4	177	177.2	177.5	177.8
Aug	170.2	173	168.4	173.6	167.6	168.5	173.1	176.3	177.1	178.3	176.8
Sep	157.2	160.7	156.9	160.8	155.3	155.7	159.1	164.2	165.7	166.2	164.2
Oct	134.9	136.7	138.4	138.5	134.1	134.5	137.7	144.6	146.6	146.5	144.9
Nov	117	118.6	117.4	117	116	116.2	118.5	123	124.8	124.1	122.7
Dec	99.8	102.7	103.7	100.8	100.1	106.2	102.8	107.2	109.2	107.4	105.8
Average	**141.067**	**143.37**	**142.333**	**142.892**	**140.55**	**141.125**	**142.858**	**147.517**	**148.825**	**148.017**	**147.067**

Table 15- show the most suitable cities to install PV panels.

City	Average Solar Power(Kw)
Bethlehem	148.825
Hebron	148.0166667
Jerusalem	147.5166667
Ramallah	147.0666667
Tubas	143.3666667
Nablus	142.8916667
Salfet	142.8583333
Jericho	142.3333333
Qalqelia	141.125
Jenin	141.0666667
Tulkarm	140.55

Figure (37) illustrates the Palestinian cities classified according to the solar energy production with color gradient for purple to yellow, while purple means the highest energy production level and the yellow color represent the least energy production level.

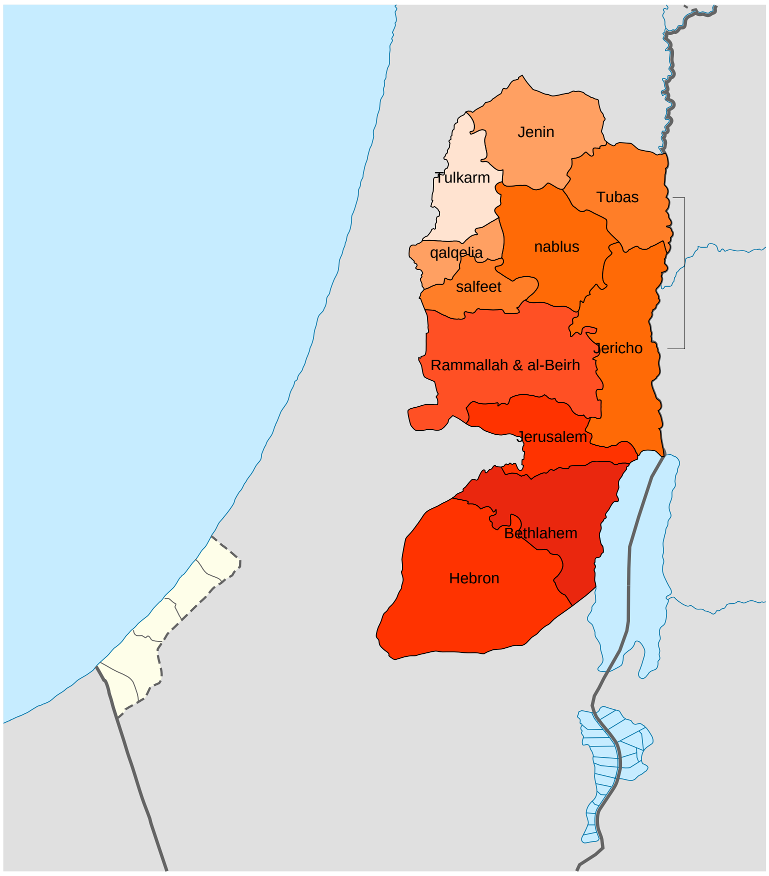

Figure 37- Palestine map classified according to solar energy production

CHAPTER 4

CONCLUSIONS

CHAPTER 4- CONCLUSIONS

4.1 Conclusions

Highly importance of renewal energy especially solar energy innovates researchers to perform studies on solar energy features, mainly efficiency affecters, to enhance the solar cells panel production. In one hand a lot of researches have been made on the design elements that improve the efficiency, and on the other hand, many researches try to predict the effect of climate conditions on the efficiency using different techniques like artificial neural network (ANN). The use of artificial neural networks for predicting the power output of the PV power system depending on the previously collected data or on the climate variables becomes a viable solution for knowledge of the future values, which help the electricity companies to know and plan the distribution of the electricity on Palestinian zones depending on the quantities of the power output of the solar cells parks. The results of this study allow us to conclude that neural networks, in general, are suitable to make a good prediction of daily, monthly and yearly output power of PV power system parks, even using only the recorded power output from previous years or other variables like temperature, and radiation. The results show that when we use a mathematical calculation formula to calculate the output power of solar cells produce values approximately equal the recorded power output from previous years. The data used in this research, are collected from weather stations and PV power system distribution companies.

Using artificial neural networks has an evolutional performance in time series prediction, and function approximation, as we noticed from this thesis where we applied two new models based on the multi-layer perceptron and radial basis function designed for solar energy prediction in Palestine, to help in classifying the best area that provides the higher amount of solar energy. Applying these models enables us to conclude that: In the first part of this thesis we proposed multi-layer perceptron neural networks with back propagation model, which uses the energy produced data from solar panel located in different places in Palestine for the year 2014, to train and test prediction technique that uses multilayer feed forward with back propagation neural networks (MFFNNBP) trained using Levenberg-Marquardt algorithm, the model predicted the solar cells energy production for one day, one month and finally for the whole year with very high accuracy and relatively small number of processing units (neurons) to accomplish this task. The use of MFFNNBP for the prediction of PV power system energy output becomes a viable solution for the knowledge of these future values. In fact, introducing another meteorological system such as radiation, temperature, and sunshine hours and humidity may perform a significant improvement in prediction. From these results, we can predict the PV power system energy output for the next year, and we notice that August was the best month of the PV power system energy production, that is because of the clear sky, relatively intermediate temperature in southern Palestinian cities, and long daytime which gives a long time of solar irradiation to produce energy. By looking at the figures obtained by the model you can perceive that this model predicts the future PV power system energy output accurately.

In the second part of this thesis we proposed a radial basis neural network model to predict the effect of the daily temperature and solar irradiance on the efficiency of producing output power of the solar panel , this model was trained using real data recorded along one year on solar panel installed in Jericho-Palestine, and compared with MLPNN, where the model revealed great results with small root mean square error for one month ,and for complete year prediction while using the MLPNN results used more number of RBFs (neurons) than the proposed model , also in this work we used a traditional power equation adapted for Palestine to calculate the solar power depending on real climate data, then we trained the proposed model with that data to get an exact interpolation for one month and good result for one year prediction results. These proposed models can be very useful in future, not only for owners of small PV power system installations or the managers of PV power system parks but also for the electricity companies in which they know approximately the quantities of the electricity needed every day for any zone, if and only if this zone has a solar cells parks.

Therefore, we can say that the research of this thesis, is to determine, as approximately as possible, the energy which will be generated by the PV power system parks in short term prediction, particularly for any day or any month of the year , or for the whole year. This research will provide us with several advantages and can include the following:

- It will be able to use the predicted values for improving electricity connection for any place and organize it.
- Getting the maximum economic benefit from the sale of solar energy, and exploit the best way at all hours of the day.

Classification process results showed the best area in Palestine to install PV panels even all areas are much closed to each other in energy production process, which means that Palestine is a rich in solar energy.

4.2 Future Work

In fact, we can introduce other meteorological values like solar irradiance, and the clouds duration may represent a significant improvement in the model prediction variables. As a future work we aim to complete the classification process by involving more Palestinian cities, by applying the proposed models, the process that needs more PV power system output data, and climate data to help in the prediction process.

Using the energy consumption data from the local electricity company to help in designing solar panel system that reduces the amount of consumed power in each area.

We suggest also creating wireless sensor network capable to monitor solar energy and climate conditions that affect the solar energy production process in wide area in Palestine.

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Appendix A-:

1. Sample from the training sets for output prediction model based in real output.

PV power system output for one year			
Date	Jenin	Ramallah	Jericho
01-01-201	0	0.51195	0.43531
02-01-201	1.25292	0.41485	0.52412
03-01-201	1.22104	0.4998	0.40761
04-01-201	0.88691	0.29996	0.29356
05-01-201	0.5738	0.83406	0.59704
06-01-201	0.35416	0.36188	0.41509
07-01-201	0.53332	0.05926	0.67178
08-01-201	0.87165	0.2169	0.28693
09-01-201	0	0.06502	0.12984
10-01-201	1.52763	0.02628	0.4208
11-01-201	1.21218	0.59615	0.60645
12-01-201	1.16638	0.29264	1.07147
13-01-201	1.1226	1.03233	1.38787
14-01-201	1.05961	0.73996	0.96707
15-01-201	0.75071	0.33101	0.64204
16-01-201	0.81882	0.21003	0.18558
17-01-201	0.37766	0.3775	0.54719
18-01-201	0.63782	1.00705	0.85908
19-01-201	1.14776	0.70943	0.73546
20-01-201	1.1246	1.02034	0.96926
21-01-201	1.21366	1.0334	0.92434
22-01-201	1.22179	1.05513	0.8192
23-01-201	1.11207	0.99303	0.96122
24-01-201	1.17307	0.9901	0.82408
25-01-201	0.95172	0.72687	0.71696
26-01-201	1.19229	0.57067	0.52986
27-01-201	0.89607	0.40561	0.33282
28-01-201	0.95615	0.52063	0.92201
29-01-201	1.27643	1.4257	0.91122
30-01-201	1.0218	1.0911	1.08524
31-01-201	1.10078	1.12166	1.07838
01-02-201	0.85528	1.09986	1.09873
02-02-201	1.80052	1.07795	1.05653
03-02-201	0.14799	1.1121	1.04687
04-02-201	0.49698	0.93714	1.06284
05-02-201	0.48135	1.20307	1.09715
06-02-201	0.65156	0.90056	0.80372
07-02-201	0.62442	0.97358	0.87761
08-02-201	0.48306	0.57485	1.04378
09-02-201	0.68384	1.09552	1.04833
10-02-201	1.3015	1.17091	0.9428
11-02-201	1.35665	0.84677	0.57472
12-02-201	1.19668	0.88599	0.77864
13-02-201	0.57954	0.6434	0.69601
14-02-201	0.32872	1.03571	1.04764
15-02-201	1.06358	0.49646	0.35731
16-02-201	1.40085	1.06975	0.54895
17-02-201	1.4116	0.70213	0.71864
18-02-201	1.19238	0.66172	0.56147
19-02-201	1.03449	0.44479	0.25793
20-02-201	1.02692	0.37485	0.80229
21-02-201	1.22295	1.05653	0.83741
22-02-201	0.58698	1.08658	1.012

PV power system output for one year with tem and radiacne AL-Ojah -jericho		
Irradiance	Temp	Output power
0.2135	13.05	0.54719
0.005544	17.17	0.85908
0.006241	15.5	0.73546
0.00793	18.77	0.96926
0.137693	18.7	0.92434
0.139441	16.7	0.8192
0.16514	18.82	0.96122
0.166881	17.49	0.82408
0.451835	16.88	0.71696
0.452036	14.47	0.52986
0.523241	11.72	0.33282
0.518725	19.1	0.92201
0.53624	19.04	0.91122
0.540942	20.25	1.08524
0.462326	20.86	1.07838
0.460137	20.85	1.09873
0.51392	20.56	1.05653
0.513213	20.84	1.04687
0.51253	21.12	1.06284
0.511832	21.4	1.09715
0.511152	19.03	0.80372
0.510445	20.09	0.87761
0.509777	21.3	1.04378
0.509144	21.19	1.04833
0.509086	19.6	0.9428
0.508695	15.24	0.57472
0.508411	17.69	0.77864
0.508562	14.12	0.69601
0.508352	20.77	1.04764
0.508139	11.85	0.35731
0.507683	14.59	0.54895
0.507345	16.75	0.71864
0.507334	14.57	0.56147
0.506515	10.84	0.25793
0.506122	16.4	0.80229
0.493064	17.17	0.83741
0.481206	19.58	1.012
0.46919	13.89	0.55059
0.468719	14.2	0.52704
0.46829	17.57	0.7613
0.467873	21.35	1.0793
0.467895	22.13	1.05716
0.476374	16.57	0.70114
0.46793	17.5	0.4663
0.480433	26.11	1.30423
0.48003	21.79	0.9609
0.479623	23.48	0.89678
0.479211	25.66	1.26172
0.479014	25.97	1.30688
0.47861	26.55	1.27091
0.478264	35.76	1.62595
0.477831	25.62	1.09216
0.477496	22.38	0.8439

PV power system output for one month			
Time (July 2015	Jenin Power(kw)	Rammallah Power(kw)	Jericho Power(kw)
01-07-2015	1.30617	1.33824	0.93936
02-07-2015	1.25556	1.31257	1.06038
03-07-2015	1.27551	1.36709	1.19052
04-07-2015	1.36417	1.35769	1.19027
05-07-2015	1.34961	1.33018	0.98956
06-07-2015	1.28995	1.2923	0.70588
07-07-2015	1.45267	1.39082	1.16856
08-07-2015	1.34494	1.3313	1.15634
09-07-2015	1.32001	1.30359	1.18631
10-07-2015	1.35442	1.33484	1.11917
11-07-2015	1.27202	1.34597	1.16582
12-07-2015	1.29587	1.35811	0.99952
13-07-2015	1.26467	1.26905	1.15794
14-07-2015	0.77699	1.26558	1.00194
15-07-2015	1.46373	1.28976	0.81488
16-07-2015	1.33194	1.33782	0.92784
17-07-2015	1.31579	1.28666	0.83691
18-07-2015	1.31799	1.3118	0.92944
19-07-2015	1.22674	1.29508	1.39206
20-07-2015	1.31103	1.29676	0.80806
21-07-2015	1.31921	1.26561	0.66249
22-07-2015	1.29695	1.23924	0.7203
23-07-2015	1.27662	1.2335	0.59108
24-07-2015	1.20968	1.23965	1.037
25-07-2015	1.26489	1.14439	0.70302
26-07-2015	1.28943	1.22877	0.88927
27-07-2015	1.50267	1.20921	0.74621
28-07-2015	1.29088	1.20454	0.65557
29-07-2015	1.32595	1.6511	0.93968
30-07-2015	1.32091	1.26357	0.91418
31-07-2015	1.25295	1.16357	1.20186

PV power system output for one day			
Time (1- Aug- 2015)	Jenin Power(kw)	Rammallah Power(kw)	Jericho Power(kw)
00	0	0	0
01	0	0	0
02	0	0	0
03	0	0	0
04	0	0	0
05	0	0	0
06	0.10767	0.06925	0.08117
07	0.52783	0.76083	0.38308
08	1.47983	1.80633	1.40342
09	2.39675	2.65492	2.42183
10	3.02829	3.223	3.12
11	1.8915	3.50717	3.53842
12	3.79733	3.65817	3.43467
13	3.8115	3.536	3.77108
14	3.58017	3.18783	2.80478
15	3.07883	2.55133	1.94991
16	2.30592	1.72308	0.751
17	1.31417	0.83958	1.151
18	0.41617	0.23708	0.34658
19	0.04125	0.02792	0.02808
20	0	0	0
21	0	0	0
22	0	0	0
23	0	0	0

2. Sample from the training sets for output prediction model based in temperature, radiance, and real output.