MODELING OF SOLAR RADIATION POTENTIAL IN LIBYA BY USING AN ARTIFICIAL NEURAL NETWORK MODEL

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES

OF

NEAR EAST UNIVERSITY

By

HOURIA KHALIFA ALMEJRAB

In Partial Fulfillment of the Requirements for the Degree of Master of Science

in

Electrical & Electronic Engineering

NICOSIA, 2018

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I hereby declare that all information in this dissertation has been obtained and presented in accordance with academic rules and ethical conducts. I also declare that, as required by these rules and conducts, I have fully cited and referenced all material and results that are not original to this work.

Name, last name: Houria Almejrab

Signature:

Date:

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First of all thanks to Almighty ALLAH, who made me capable to achieve this milestone in my life.

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To my Husband and Family…

ABSTRACT

Recently, neural networks have shown a great use in prediction engineering tasks. Different types of neural networks have been used to predict the performance of engineering systems. Feedforward neural networks and radial basis function network showed good accuracies in prediction tasks in areas such as solar radiation predictions. Thus, in this work we employed two neural networks models for the prediction of daily solar radiation in different cities in Libya. A feedforward neural network that uses backpropagation algorithm (BPNN) and radial basis function network (RBFN) are both used in this research for prediction the daily solar radiation of different cities in Libya.

The models are trained on geographical and meteorological data of 25 cities in Libya, collected for a period of 6 years. The data include different parameters such as Latitude, Longitude, month etc… Models are trained on different learning parameters as an attempt to find the best network parameters for such a prediction task. Experimentally, both networks are tested on data that were not used in the training and the results showed that both networks perform differently when tested. Finally, it was seen that the radial basis function network outperforms the backpropagation neural network with 91% and 93.15%, respectively.

***Keywords*:** Artificial neural network; Solar radiation; Backpropagation; Radial basis function network; Libya

ÖZET

Son zamanlarda, sinir ağları tahmin mühendisliği görevlerinde büyük bir kullanım göstermiştir. Mühendislik sistemlerinin performansını öngörmek için farklı sinir ağları türleri kullanılmıştır. Besleme sinir ağları ve adial tabanda fonksiyon ağı, güneş radyasyon tahminleri gibi alanlarda tahmin görevlerinde iyi doğruluk gösterdi. Böylece, bu çalışmada, Libya'daki farklı şehirlerde günlük güneş radyasyonunun tahmini için iki sinir ağları modeli kullandık. Bu araştırmada, Libya'daki farklı şehirlerin günlük güneş radyasyonunu tahmin etmek için, geri yayılım algoritması (BPNN) ve adial taban fonksiyon ağı (RBFN) kullanan bir ileriye besleme sinir ağı kullanılmıştır.

Modeller, Libya'daki 25 ilin coğrafi ve meteorolojik verileri üzerine eğitim almış ve 6 yıllık bir adi için toplanmıştır. Veriler, Enlem, Boylam, ay vb. Gibi farklı parametreleri içerir. Modeller, böyle bir tahmini görev için en iyi ağ parametrelerini bulma çabası olarak farklı öğrenme parametrelerinde eğitilir. Deneysel olarak, her iki şebeke de eğitimde kullanılmayan veriler üzerinde test edildi ve sonuçlar, her iki şebekenin de test edildiğinde farklı performans gösterdiğini gösterdi. Son olarak, adial temel fonksiyon ağının sırt yayılımı sinir ağını sırasıyla 91% ve 93.15% ile üstün performanslı olarak gördüğü görüldü.

Anahtar Kelimeler: Yapay Sinir Ağları; Güneş Radyasyonu; Geri Yayılım; Radyal Temel Fonksiyon Ağı; Libya

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ANN	Artificial Neural Network
BPNN	Back Propagation Neural Network
RBFN	Radial Basis Function Network
MSE	Mean Squared Error
AL	Artificial Intelligence
MLP	Multilayer Perceptron
DSR	Daily solar radiation
PV	Photovoltaic

CHAPTER 1

INTRODUCTION

1.1 Introduction

Neural Networks have been used in several complex tasks such as data mining, optical character recognition, decision support systems, prediction, regression, image compression, encryption and decryption systems, face and voice recognition (Duffie & Beckman, 2013; Alam et al., 2006; Al-Alawi & Al-Hinai, 1998; Elminir et al., 2007; Hontoria et al., 2002; Mehrotra et al., 1997).

The capability of artificial neural networks to use and combine simple learning rules to master different complex tasks is very motivating, and has sufficed on lots of challenging prediction problems.

Solar radiation can be seen as the radiation of the sun which they fall on the surface of the Earth. This energy is accessible for some applications, for example, expanding temperature of water or moving electrons in a photovoltaic cell. Also, it supplies energy to regular procedures like photosynthesis. Solar energy is secure, clean, and accessible on the Earth consistently. Its safe and clean applications are essential to the world, particularly during an era of petroleum derivative high expenses and the basic circumstance of the climate coming about because of non-renewable energy source applications. Solar radiation information gives data on what amount is the Sun potential at an area on the Earth amid a particular day and age. These information are vital for planning measuring solar energy frameworks. Because of the high cost and establishment troubles of estimation, this information are not generally accessible. Subsequently, there is a request to create elective methods for anticipating this information. A solar radiation database is vital piece of an energy effectiveness approach (Duffie & Beckman, 2013).

As of late, ANNs have been utilized as a part of solar radiation demonstrating for areas at various scopes and with various atmospheres utilizing ANN (Alam et al., 2006; Sozen et al.,2005). In these works, the authors utilized the feedback propagation neural network, while better ANN networks might be more exact in anticipating solar radiation.

Notwithstanding, solar expectation techniques that have been produced for Malaysia are found in (Chuah & Lee, 1982; Sopian & Othman, 1992).

In(Chuah & Lee, 1982). the solar radiation information for three areas were considered without utilizing any forecast calculations. In (Sopian & Othman, 1992) a calculation was produced for foreseeing the month to month solar radiation in view of the slightest squares direct relapse examination utilizing information from eight areas. To give an exhaustive database to the solar energy potential in Malaysia, an ANN show is proposed to permit forecast of hourly solar radiation levels.

The fundamental goal of the study is to explore the ANN approach for solar radiation forecast with a specific end goal to create precise models for anticipating hourly solar radiation for Kuala Lumpur in light of the quantity of sunshine hours, day, month, temperature, moistness, and area arranges.

This thesis aims to build an intelligent regression system that uses examples of different countries with their daily solar radiation per country. These examples are used to train the neural networks to have the capability to predict the solar radiation of unseen data based on the knowledge that was acquired during the training phase.

During this phase, part of the data cases is used for training both networks BPNN and RBFN to predict the solar radiation. Back propagation neural network and Radial basis function network analysis methodology are employed at this stage and so on. Data was divided using Cross-validation for training, validating and testing the networks.

1.2 Project Description

This project is to predict the daily solar radiation in different regions in Libya using an intelligent classifier such as backpropagation neural network and radial basis function network. Both networks were trained on past geographical and meteorological of 25 cities in Libya. The data was collected from the NASA geo-satellite database website (Duffie & Beckman, 2013). The data is taken for a period of 6 years (from 2010 to 2015). The selected data set include both geographical parameters (latitude, month, longitude, altitude) and meteorological (mean sunshine duration, mean temperature, relative humidity and solar radiation) parameters. After training the network are expected to have a prediction capability of the daily solar radiation of some unseen cities.

1.3 Aims of Thesis

Prediction is such a challenging task for a neural network. Different types of networks may have different performance accuracy and efficiency in prediction. Thus, in this study we aim to study the performance of two different networks which use different learning algorithms in the prediction of solar daily radiation in one city in Libya. The networks are both trained on same data to show the one that reaches a lower error and higher prediction rate. The performances of both network is compared in terms of accuracy, number of iterations, and mean square error reached.

1.4 Thesis Overview

The thesis contains five chapters:

Chapter 1 introduces the proposed work, its aims, description, and significance of the work. The solar radiation is explained here in addition to the use of artificial intelligence tools network in predicting the solar radiation.

Chapter 2 discusses the related literatures that were conducted by some researchers on the prediction of solar radiation in different countries and cities; using different types of machine learning.

Chapter 3 presents a detailed explanation of artificial neural networks where backpropagation and radial basis function networks are both explained in details.

Chapter 4 discusses the learning and training of the networks. In this chapter the networks are simulated and the performances results are shown in terms of figures, curves and also tables. Different networks models are simulated in this chapter and their results are presented.

Chapter 5 is the last chapter of the thesis and it includes the testing of the system where networks are tested using different data. In this chapter, accuracies and errors are shown and compared between networks.

Chapter 6 this chapter contains the conclusion of the whole presented thesis.

CHAPTER 2

LITERATURE REVIEW: SOLAR RADIATION PREDICTION USING NEURAL NETWORKS

This chapter is a detailed review of the related literatures that have been conducted for the prediction of solar daily radiation. It shows the use of different intelligent systems for the same purpose. Moreover, it presents how researchers use those types of intelligent networks such as backpropagation and radial basis function networks in different areas and countries, for the accurate prediction and also estimation of the daily solar radiation.in this chapter, different related works are discussed and analyzed

2.1 Introduction

The solar radiation is a vital parameter for solar energy inquires, however, isn't accessible for a large portion of the locales because of non-availability of solar radiation measuring gear at the meteorological stations. Along these lines, it is fundamental to foresee solar radiation for an area utilizing a few climatic factors. These factors are daylight length, most extreme surrounding temperature, relative moistness, scope, "longitude", "day of the year", "day by day clear sky worldwide radiation", add up to overcast cover, temperature, clearness file, elevation, months, normal temperature, normal darkness, normal breeze speed, barometrical weight, reference clearness list, mean diffuse radiation, mean shaft radiation, month, extraterrestrial radiation, dissipation and soil temperature. The daylight term is effortlessly accessible and measured at the majority of the destinations so it is by and large utilized for demonstrating of solar radiation (Ahmed & Tiwari, 2010; Bakirci, 2009). The data about solar radiation, solar energy system models, site particular data, and productions, is given in the stock arranged by Myers for NREL (Myers, 2009). A few creators have created exact models for solar radiation prediction (Wong &Chow, 2001; Coskon et al., 2011). The prediction is observed to be precise with quality measured data (Myers, 2005; Muneer et al., 2007). It is assessed with mean supreme rate error (MAPE) i.e. MAPEr10% implies high prediction exactness, 10%rMAPEr20% means a great prediction, 20%rMAPEr50% means a sensible prediction, MAPEZ50% implies wrong anticipating (Lewis, 1982). The principal target of this investigation is to survey Artificial

Neural Network (ANN) based procedures keeping in mind the end goal to distinguish appropriate strategies accessible in the writing and to recognize inquire about holes.

2.2 Artificial Neural Network Techniques for Solar Radiation Prediction: A Review

ANN is an area in artificial intelligence (AI) which fills in as a magnificent instrument for investigation as it is equipped to explain non-linear function estimation, data arranging, pattern discovery, streamlining, bunching and recreation. These are called "discovery" demonstrating strategies to complete non-linear mapping. Its design mainly includes the input layer, hidden layer, output layer, association of weight and inclination, function activator and center combination. Its activity is divided into two phases: get a comment (training) and circularization (review). The weights of the training network and trends are used to create the objective result by reducing the error function.

The networks are provided through a learning account and configured by ages that constitute a complete cycle of all training data in the network. Learning methods are divided into administration, without supervision, support and evolutionary learning. Structured learning depends on the total oscillation between the actual network outputs and the preferred output. The weights and assumptions are changed by organizing the group training pattern and the results of the faults between the preferred output and the resulting network output. Subsequent learning continues when the regulator closes the input system circuit where error is the science of criticism. The error score is visualized by the mean square error (m). Small and micro-enterprises dissolve after all ages and learning takes place when small and micro-enterprises are limited.

It has been shown that the strategies are elective techniques for traditional systems and are used as part of various solar applications. Kalogirou (Kalogirou, 2001) considered the use of the network in the application of systems of sustainable energy sources Melit et al (Melit et al., 2009) Thay carried out research on the estimation of photovoltaic systems, and Melit & Kalgirou (Melit & Kalgirou, 2008) evaluated it for photovoltaic applications. It has many applications to demonstrate, predict and measure from month to month, day to day and solar radiation every hour and are reported in the public services section.

2.2.1 Global solar radiation prediction

The accessibility of worldwide solar radiation on the ground surface is a standout amongst the most imperative elements for functioning of a solar energy system. Subsequently, this segment manages the use of ANN systems in prediction of worldwide solar radiation utilizing distinctive meteorological and topographical factors (Alawi & Hanai) .

Alawi and Hinai (Alawi & Hanai, 1998) connected multilayer feedforward network, named as back propagation(BP) training calculation to foresee worldwide radiation for Seeb areas.

Ouammi et al. (Ouammi et al., 2012) created ANN demonstrate for assessing month to month solar irradiation of 41 Moroccan locales. The authors used a data time frame between “1998 to 2010” and as inputs of the networks they used standardized estimations of “longitude”, “latitude” and “height”. The anticipated solar irradiation fluctuates from 5030 to 6230 W h/m2/day.

Lazzús et al. (Lazzús et al., 2001) utilized ANN show with “wind speed”, “relative stickiness”, “air temperature” and “soil temperature” as inputs to appraise hourly worldwide solar radiation for La Serena in Chile. It is discovered that R2 is 94%, demonstrating solid relationship between hourly worldwide solar radiation and meteorological data.

Azeez (Azeez, 2011) connected nourish forward back spread Neural Network to assess month to month average worldwide solar irradiation on a flat surface for Gusau in Nigeria. The outcomes have demonstrated great understanding between the assessed and measured estimations of worldwide solar irradiation.

Linares-Rodríguez et al. (Linares-Rodríguez et al., 2011) connected ANN for anticipating solar radiation in Spain in view of latitude, longitude, day of the year, day by day clear sky worldwide radiation, add up to overcast cover, skin temperature, add up to segment water vapor and aggregate section ozone as inputs. The RMSE between ANN anticipated and measured esteems are observed to be 13.52% (for training stations) to 14.20% (for testing stations). The 9 year measured data from 83 metrological stations is utilized for display approval in Andalusia (Spain). The approach can be utilized to produce day by day worldwide solar radiation for areas where meteorological data is accessible.

The ANN estimation is observed to be remove subordinate and can't be extrapolated if just a couple of meteorological stations are utilized for training or these stations don't cover the whole zone of study. In this manner, for precise prediction of solar radiation for locales situated at more noteworthy separations data from an expansive number of stations covering the district must be utilized and furthermore, the solar maps could be created with a sensible accuracy for the area of intrigue.

Koca et al. (Koca et al., 2011) built up an ANN based model for estimation of solar radiation for seven urban areas in Mediterranean district of Anatolia, Turkey. Six distinct mixes are utilized as input parameters to locate the best ANN design for estimation. It is demonstrated that the quantity of input parameters influences R2 esteem in estimation of solar radiation.

Also, Voyant et al. (Voyant et al., 2011) considered the impact of the factors of exogenous meteorology in the prediction of day by day solar radiation. Because of exogenous factors standardized root mean square blunder (RMSE) is observed as 0.5%, 1% for Corsica Island, France and expansion of the endogenous and also exogenous factors diminishes nRMSE by 1% hence enhancing prediction accuracy.

$$H = K_T H_O$$

$$H_D = (0.9505 + 0.91634\, K_T \quad 4.851\, K_T^2 + 3.2353\, K_T^3)\, H \qquad (2.1)$$

The MAPE in estimating global, diffuse radiation are 7.96%, 9.8% respectively for cities of Kuala Lumpur, Alor, Setar, Johor Bahru, Kuching and Ipoh in Malaysia. The mean absolute percentage error (MAPE) measures the accuracy of estimated solar radiation value and is defined by following relation:

$$\left(\frac{1}{n}\sum_{i-1}^{n}\left|\frac{SR_{i(estimated)} - SR_{i(measured)}}{SR_{i(measured)}}\right|\right) \times 100 \qquad (2.2)$$

where SRi(estimated) is estimated solar radiation, SRi(estimated) is measured solar radiation and n is the number of data points.

Elminir et al. (Elminir et al., 2007) proposed ANN model based on determination and pattern selection techniques to predict diffuse fraction (KD) in hourly and daily scale. The global solar radiation and other meteorological parameters, like long-wave atmospheric emission, air temperature, relative humidity and atmospheric pressure are taken as input parameters to ANN model and KD as output parameter.

Elminir et al.(Elminir et al., 2005) used multilayer feed forward network for predicting infrared, ultraviolet, global solar radiation at Helwan, university Aswan monitoring stations. The input data of network are wind direction, wind speed, ambient temperature, relative humidity, cloudiness and water vapor. The RMSE are found to be 5.02%, 7.46% and 3.97% for infrared, ultraviolet and global solar radiation respectively.

Kutucu and Almryad (Kutucu & Almryad, 2016) studied about feed-forward, back-propagation networks are developed to predict the mean monthly global solar radiation in Libya and provided the ANN model with the best performance.

2.3 Daily Solar Radiation Prediction

The daily solar radiation (DSR) is a standout amongst the most vital parameters in solar energy applications particularly to size of independent solar photovoltaic (PV) systems. The inaccuracy and absence of measured DSR data prompts high cost of a PV system. The DSR prediction has been given by various specialists (Bulut & Büyükalaca, 2007; Elminir et al., 2007; Erbs et al., 1982).

Bulut and Büyükalaca (Bulut & Büyükalaca, 2007) have utilized trigonometric function for assessing the daily worldwide radiation at 68 areas in Turkey. This model has day of the year as one autonomous parameter. Solar radiation data of 10 years are utilized for training and testing the model. The estimations are in great concurrence with both the deliberate data and the data accessible in the writing.

Elminir et al. (Elminir et al., 2007) assessed hourly and daily estimations of the diffuse division (KD) utilizing ANN in Egypt. The network joins inputs as the worldwide solar radiation, long-wave barometrical outflow, air temperature, relative moistness and environmental strain to foresee hourly KD. For daily KD, ANN has three inputs i.e. daily estimation of the worldwide radiation, extraterrestrial irradiation and sunshine division. The standard error (SE) in assessing hourly KD utilizing ANN in Erbs et al. demonstrate are 4.2%, 5.6% individually.

The Gopinathan and Soler (Gopinathan & Soler, 1995) demonstrate evaluates daily KD with SE extend 4.84– 17.76% while in ANN display SE fluctuates from 2.51% to 5.96% indicating better accuracy of ANN show.

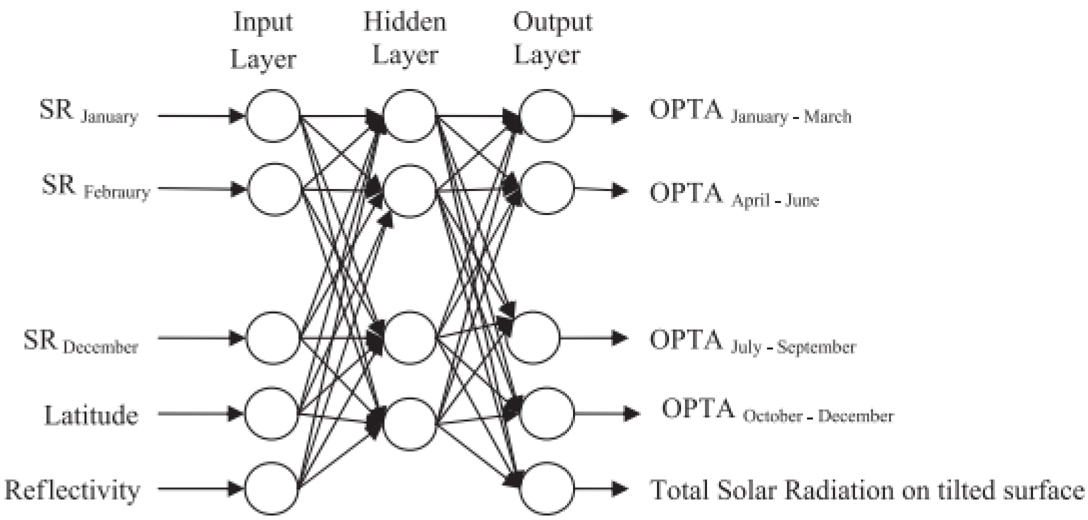

Figure 2.1: ANN architecture to predict solar radiation on tilted surface (Mellit et al.,2010)

Moustris et al. (Moustris et al., 2008) utilized MLP in view of hourly data of air temperature, relative dampness, sunshine duration, mists octals and latitude to make missing mean, most extreme and least worldwide and diffuse solar irradiance hourly data for Greek areas. The connection coefficient esteems are measurably noteworthy at 99% certainty level (ρo0.01). Along these lines, hourly worldwide and diffuse mean hourly solar irradiance esteems anticipated by ANN are in great concurrence with genuine estimations.

Mellit et al. (Mellit et al., 2010) proposed versatile α show for anticipating hourly worldwide, diffuse and coordinate solar irradiance in Saudi Arabia. The relationship coefficient (R) esteem for approval data set is more prominent than 97.0% and the mean inclination blunder (MBE) is under 0.8. The best R estimations of 96.65% and 94.94% are gotten by utilizing sunshine duration and air temperature as input parameters to ANN show.

In other examination, Mellit et al. (Mellit et al., 2005) additionally proposed a half breed display (ANN– MTM) i.e. blend of multi-layer perceptron (MLP) and library of Markov progress networks (MTM) to produce succession of daily worldwide solar radiation data for Algeria. The ANN show consolidates bolster forward network and back proliferation learning calculation. In ANN– MTM mixture demonstrate first square goes about as ANN display for the age of month to month average worldwide solar irradiation data H from the geological directions (latitude, longitude and altitude) of the site. The second square comprise of Markov change networks (MTM) to create daily clearness lists KT esteems from the month to month clearness files KT got by the principal piece, and clearness file data are partitioned by the relating extraterrestrial esteems Ho to get daily worldwide solar radiation data H. The proposed show is contrasted and the conventional models and relationship coefficient running from 90% to 92% is gotten.

Moreover, a neural network that used forward propagation is used by Behrang et al. (Behrang et al., 2010) in addition to the use of radial basis function (RBF) network for demonstrating of daily consumption of GSR in a city in “Dezful”, Iran. The networks utilize six proposed mixes of “Day (Day)”, “daily mean air temperature” (AT), “relative mugginess (RH)”, “sunshine hours (SH)”, “vanishing (E)” and “wind speed (WS)” as inputs factors and daily GSR as output appeared in Figure 2.2 The deliberate data in the vicinity of 2002 and 2005 are utilized for training the networks while the data for 214 days from 2006 are utilized for testing the network.

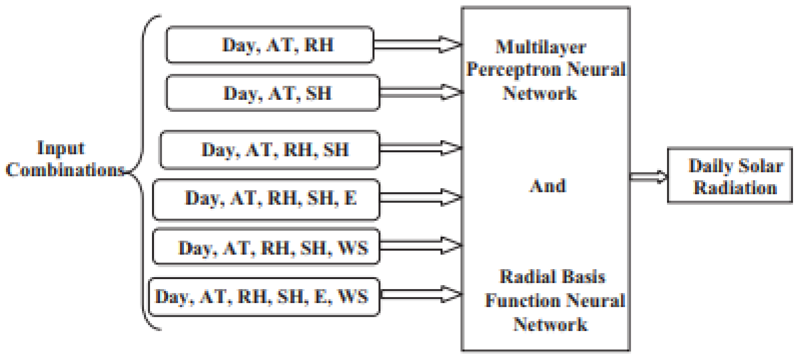

Figure 2.2: Daily solar radiation prediction ANN model (Mellit et al., 2005)

CHAPTER 3

MACHINE LEARNING AND ARTIFICAL NEURAL NETWORKS: AN OVERVIEW

3.1 MACHINE LEARNING

Machine learning aims to develop algorithm-based systems which explore data to discover interesting features and patterns therein without being ‘precisely’ programmed. The process of exploring data is commonly referred to as learning or training. One interesting aspect is that the same algorithm can be successfully used to probe different data with promising results. Generally, many of these algorithms are iterative in nature where the goal is to use previous experience (learning) for producing reliable and repeatable decisions. Machine learning has been applied in diverse areas such as financial services in identifying important patterns in financial data and customer behaviors for fraud risks; in health care as fast diagnostic tools for identifying abnormal patterns in health records or real time assessment patients’ health; in marketing for recommending new purchases based on customers’ buying histories; in transportation for predicting traffic flows based on commuters use pattern, etc (Linares-Rodriguez, 2011). The three basic machine learning methods are supervised learning, unsupervised learning and reinforcement learning.

3.2 ARTIFICIAL NEURAL NETWORKS

Artificial neural systems are structure that originated from the cerebrum of the human brain that is used for reasoning. The structure has been used to deal with troublesome issues in science. The vast majority of the structures of neural systems are like the organic mind in the requirement for preparing before having the capacity to complete a required assignment (Linares-Rodriguez, 2011). Like the standard of the human neuron, neural system processes the aggregate of every one of its data sources.

On the off chance that that aggregate is more than a decided level, the journalist yield would then be able to be enacted. Something else, the yield isn't go to the actuation work. Figure 3.2 illustrates the principal assembly of the neural system where the source of the weight and info on summation of work is shown. The quantity of neuron that is find in a structure can is referred to as the yield work. The equation that is used in the calculation of initial work is precisely explained in (Duffie & Beckman, 2013).

$$TP = \sum X_i W_i \tag{3.1}$$

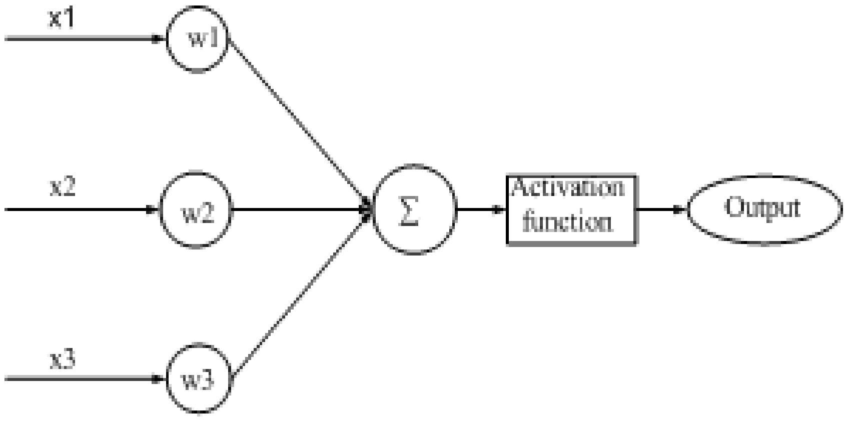

Figure 3.1: Artificial Neural Network's Basic Structure (Linares-Rodriguez, 2011).

3.3 STRUCTURE OF ANN

The ANNs structure contains three angles despite the learning technique. These angles are the layers, weights, and initiation capacities. Every last one of these three sections play an imperative lead in the ANN limit. The three sections or segment works collectively to ensure proper working of the system (Koca et al., 2011).

3.3.1 ANN Layers

The mutual relationship that occurs between the layers of ANN is the major derivative to its creations. The layers interact by sending information between each other using the synaptic weight. The ANN structure can be subdivided into three layers that are listed in the subsequent section below.

1. Input layer: This is the first layers that are found in the neural system of ANN. This layer is major that send information or data to other layers in the neural system. It

can be regarded as a sensor because it doesn't process later but only pass information processed by other layers.

2. Hidden layers: this can be regard as the central bit of the neural system. It involves no less than one of the layers which is the input layer and the neural layer. This layer transmit the data to the output layers. The Hidden layer can be regards as the intermediate layers or as a principal layer because the synaptic weight found in it are reliable (Linares-Rodriguez, 2011).

3. Output layer: This layers is regard as the output layers because its last contact where the result of the neural system are gotten, the output layer got its information that is processed from the Hidden layer.

The figure below shows the neural system and the interactions that occurs between its three layers. The first layer which is the input layers is the source of the data that is passed to the hidden layer and later to the output layer. The yield or result of the neural system is gotten from the output layer.

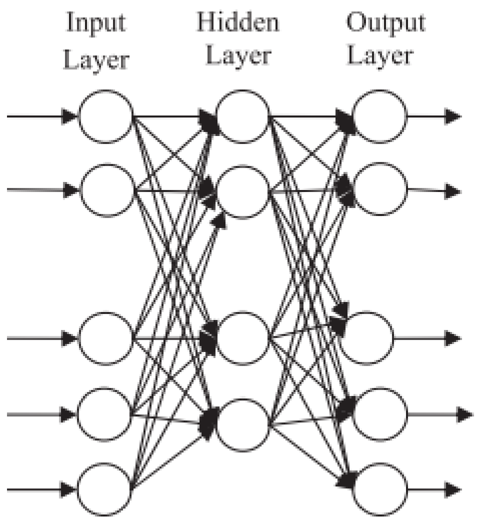

Figure 3.2: Backpropagation neural network (BPNN) (Eluyode & Akomolafe, 2013)

3.3.2 Weights

The ANN weights stands for the network memory in which all information is provided. The weights estimations are invigorated reliably in the midst of the planning of the system until the point when the yield is met. The weights or memory are then secured to be used as a piece of future. The estimations of the weight of ANNs can be regards as the network memory (Linares-Rodriguez, 2011; Khatib et al., 2012).

- **The Activation capacities**

Once the data are enacted from the source and passed across the layers through the synaptic weight, the yield or output is known or gotten by using a trade work. Also, on the other hand in some actuation capacities, the capacity is utilized to decide how much the handled information will partake in developing the aggregate yield of the system.

The neural system are very reliable in determining whether the neuron can adequate transmit its self to the associated layers or not and this made the initiation capacity to be very critical (Khatib et al., 2012).

- **Linear initiation functions or slope**

In this sort of the enactment work, the yield is fluctuating straightly when the input is close to nothing. When the input value is massive, the preeminent yield is limited by 1 as showed up in figure 3.3. The limit of this exchange work is described by:

$$O(TP) = \begin{cases} -1 & TP \leq -1 \\ TP & -1 \leq TP \leq 1 \\ 1 & 1 \leq TP \end{cases} \tag{3.2}$$

- **Threshold function (Hard activation function)**

The limit yield is zero if the summed input isn't as much as certain estimation of edge, and 1 if the summed input is more significant than edge. The yield can be located between zero and one. The limits yield can be enacted and be deactivate as found in the Figure 3.4 below. The activation function of the hard limits is illustrate by:

- **Sigmoid function**

This function can run in the vicinity of 0 and 1, however sometimes its better to run its within -1 and 1. The most perceived sigmoid limits are the logarithmic sigmoid and hyperbolic digression.

The above listed functions are the most utilized as a part of the back proliferation since they are differentiable. The recipes of these two capacities notwithstanding the bends are displayed in figure 3.4. The incline of the bends can be changed in light of the purposeits to be utilized for (Khatib et al., 2012).

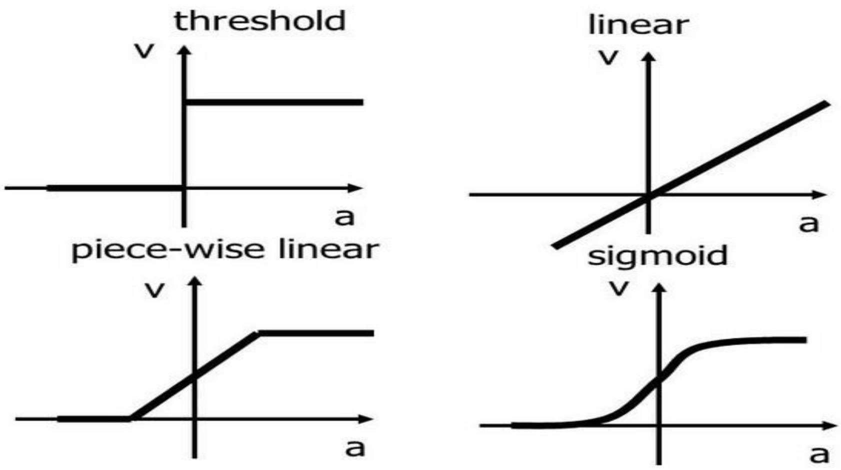

Figure 3.3: Types of activation functions (Sathyam & Abraham, 2013)

In the process of calculating the back-induction, the log-sig and tan-sig capacities are utilized (Yadav & Chandel, 2012). This two function listed above can also be used separately. The log-sigmoid auxilliary is given as:

$$\frac{d}{dt}o(\theta) = o(\theta) * (1 - o(\theta)) \tag{3.3}$$

3.4 CLASSIFICATION OF ANNS

ANNs are sometimes described using different approach such as; information, limits and preparatory system. The transmission of data in the ANNs system started from the input later to the hidden layer and later to the yield or output layer. On the aspect of functions, neural system can dedicated to varieties of assignment and can be accomplished with it. This functions can subdivided into four major classes:

- Classification: This is when enquiry is passed out but done using a known arrangement.
- Association: This is creating interaction or relationship between articles to achieved a more outline program.
- Optimization: This is when the action is to established a better response to an issue or case.
- Organization: The ANNs attributes is needed to factored out using the preparation method.

3.4.1 ANN's Training Methods

The main purpose of preparing a system is in order to achieved a wanted result or yields (Elminir et al., 2007; Bulut & Bűyűkalaca, 2007). The two fundamental learning method which comprises of the; coordinated and the unsupervised learning method are utilized in order to enlighten the systems,

- Verified learning method

The ANNs values are gotten from the input information. The system at that point refreshes its weights as indicated by a characterized calculation govern until the point that it unites to a base mistake or achieves a most extreme number of emphases. An imperative case of the directed learning technique is the mistake back engendering strategy.

- Unsupervised learning

In this technique, the input information is given to the system which thusly alters its weights as per characterized conditions.

3.5 BACKPROPAGATION ALGORITHM

The Back propagation neural network algorithm is executed utilizing an encourage forward network, back spread updating process, and lastly supervised learning topology. This method of neural network algorithm was developed in the late 1980s. Back propagation is a multipurpose in the field of recognition algorithm. Even though this algorithm is a very efficient and accurate model it has a major constrained which time is consuming. Back propagation network when given a certain amount of elements to simulate can produce a certain level of correctness (Elminir et al., 2007).

Back propagation since its creation has a simple attribute thus making it a legacy algorithm by maintaining its initial attributes till today. The first layer is the input layer in which the initial weights are being inputed, next is the activation function layer in which the weights are processed before the last layer which is the output layer for the weights to be presented. Lastly is the error layer in which the weights are update in the input layer before the network is run again for another iteration until a minimal level of error is achieved which can be neglected.

The said process above is repeated until a certain level of error achieved which is to a bare minimal then the network can be said as learned network. The Figure 3.5 shows the artificial neural network layer with error back propagation.

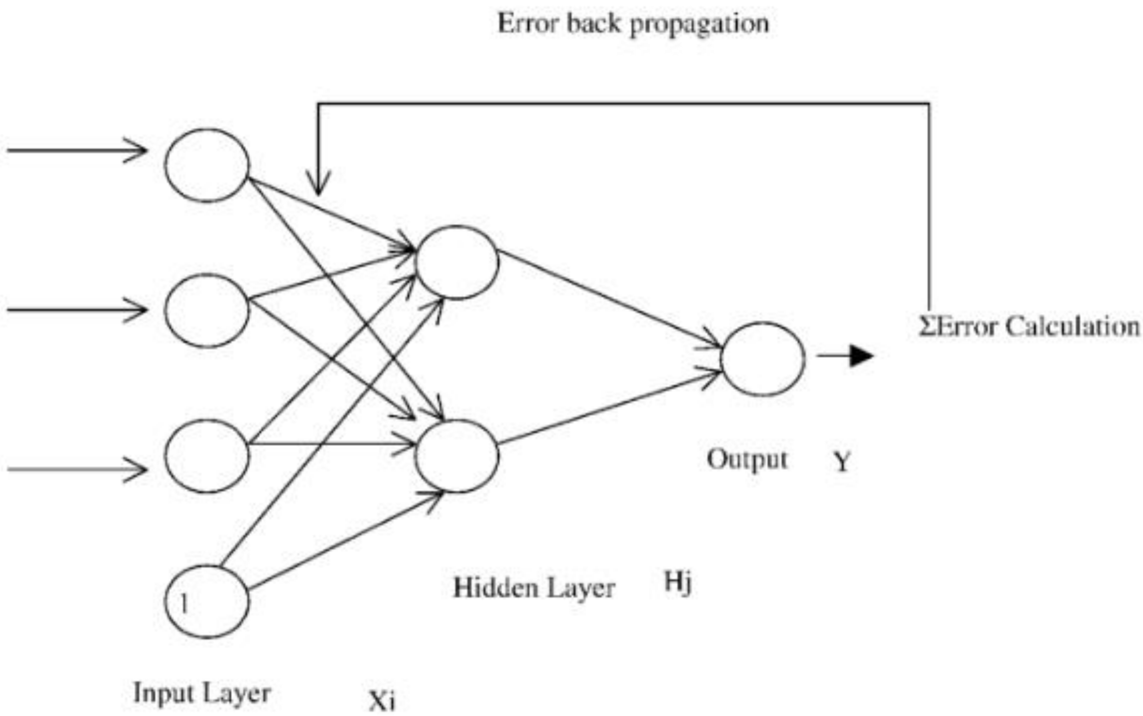

Figure 3.5: The Artificial Neural Network Structure With Error Backpropagation (Elminir et al., 2007).

There exist two basic protocols in the process of back propagation which are learning rate and momentum factor, the first which is the learning rate determines after a test of the network if the network weights shall be updated or not, thus for every iteration the learning rate determine if there should be an update of the weights or not, eventually learning rate should be set to the minimal because a network with a higher learning rate makes the network to memories instead of learning the updates, and lastly is the factor of momentum utilized in organizing the update intensity that the system can do.

3.5.1 Modeling of Backpropagation Algorithms

As an algorithm, back propagation utilizes the error minimization theory coupled with gradient descent to figure and point out errors that are least squared, doing so ensures every iteration done will have gradient error calculated which results to an un hindered delivery of functions.

In most of cases, the tangent or logarithmic sigmoid functions are used. The sigmoid function is defined by (Hontoria et al., 2005).

$$o(x) = \frac{1}{1+e^{-ax}} \tag{3.4}$$

The above equation is the constant, which control the slant, consequently the derived sigmoid is:

$$o^{\backslash}(x) = f(x)(1-f(x)) \tag{3.5}$$

Training of neural network can be categorized into sub divisions as equated below:

1- Feed forward training: used in training as well as testing the network.
2- Error back propagation: categorically used to train the network.

In a feed forward network, output and can be denoted as

$$TP = \sum x_n \omega_n + b_n \tag{3.6}$$

The x_n is the (input data), the w_n is the (weight matrix), while the b_n is the (double values). The total values of each layers is the Tp. The starting function exists as a straight or as a non-direct functions. A typical straight capacity that is broadly conveyed in neural networks is the sigmoid capacity which is characterized in the capacity, another case which is the digression of the sigmoid that is specified by:

$$O(X) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad (3.7)$$

another fact about this function is that it can be continuous and derived also, the derived function can be equated by:

$$o^{\backslash}(x) = 1 - \frac{(e^{x} - e^{-x})^2}{(e^{x} + e^{-x})^2} \qquad (3.8)$$

the consequence of the past activation function is the right aftereffect of the NN, the output is define as the objective which is utilized to deliver the amount of error, the error rate is expressed by the equation underneath, the reason for preparing NN is to decrease the amount of error in the Neural network.

$$E = \sum (T - o)^2 \qquad (3.9)$$

T is the objective output, while E is value of the error functions. Which:

$$\Delta_j = (T_j - o_j) o_j (1 - o_j) \qquad (3.10)$$

the values gotten from the network is defined in the equations and the network becomes updated, the weights are updated using :

$$W_{jk\ new} = W_{jk\ old} + \eta \Delta_j O_k + \alpha(\delta W_{jk\ old}) \qquad (3.11)$$

the hidden layers weights are updated using error update which is given as:

$$\Delta_k = O_k(1 - O_k) \sum w_{jk} \Delta_j \tag{3.12}$$

the new weights would be given by:

$$W_{ki\,new} = W_{ki\,old} + \mu \Delta_k O_i + \alpha(\delta W_{ki\,old}) \tag{3.13}$$

the momentum factor values is known as the αwhich is used in reducing the number of updates and η as the learning rate which is used in updating the weights, after successful network run, a new iteration is done until a desired until it arrives to an acceptable error value (Hontoria et al.; 2005).

3.6 Radial Basis Function Network

A Radial Basis Function Network (RBFN) is a particular kind of neural system. Generally, when people examine neural systems or "Recreated Neural Networks" they are suggesting the Multilayer Perceptron (MLP). Each neuron in a MLP takes the weighted aggregate of its data esteems. That is, every data regard is expanded by a coefficient, and the results are by and large summed together. A lone MLP neuron is a clear straight classifier, however complex non-direct classifiers can be worked by solidifying these neurons into a system (Strumiłło and Kamiński, 2003).

Generally, the RBFN approach is more normal than the MLP. A RBFN performs gathering by estimating the information's closeness to cases from the readiness set. Each RBFN neuron stores a "model", which is just a single of the cases from the arrangement set. When we have to mastermind data, each neuron forms the Euclidean detachment between the data and its model. By and large, if the data all the more about resembles the class A models than the class B models, it is named class A.

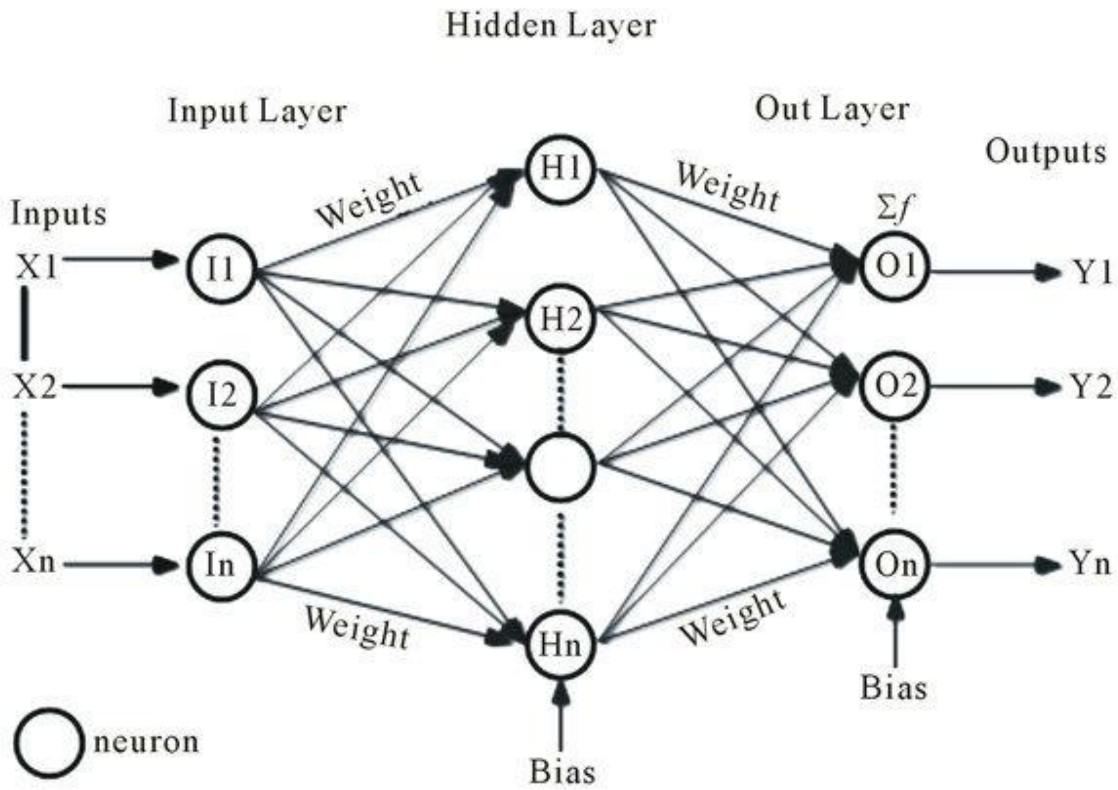

Figure 3.5: RBF Network engineering (Strumiłło and Kamiński, 2003)

The above depiction shows the basic designing of a RBF Network. It includes an input vector, a layer of RBF neurons, and an output layer with one hub for every order or class of data.

- The Input Vector

The input vector is the n-dimensional vector that you are endeavoring to group. The entire input vector has appeared to each of the RBF neurons.

- The RBF Neurons

Each RBF neuron stores a "model" vector which is just a single of the vectors from the planning set. Each RBF neuron takes a gander at the input vector to its model, and outputs a motivator in the region of 0 and 1 which is a measure of closeness. In case the input is equal to the model, at that point the output of that RBF neuron will be 1. As the partition between the input and model builds up, the response tumbles off exponentially towards 0.

The condition of the RBF neuron's response is a ring twist, as sketched out in the system configuration graph (Garg et al., 2013).
The neuron's response regard is moreover called its "activation" regard. The model vector is furthermore as often as possible called the neuron's "center", since it's the motivation at the point of convergence of the ring twist.

- The Output Nodes

The output of the system includes a game plan of hubs, one for every characterization that we are endeavoring to order. Each output hub forms a sort of score for the related order. Frequently, a grouping decision is made by doling out the input to the class with the most shocking score.
The score is handled by taking a weighted aggregate of the sanctioning esteems from each RBF neuron. By weighted total we infer that an output hub relates a weight a motivating force with each of the RBF neurons, and copies the neuron's institution by this weight before adding it to the total response.
Since each output hub is figuring the score for a substitute grouping, each output hub has its own specific plan of weights. The output hub will customarily give a positive weight to the RBF neurons that have a place with its arrangement, and a negative weight to the others.

CHAPTER 4

MATERIALS AND METHODS

This chapter presents the learning phase of all the used models in which it shows the training phase of the system. Moreover, in this chapter a comparison between all the used network models are presented in terms of time, validation and testing accuracies, and mean square error achieved.

4.1 Intelligent Solar Radiation Prediction System: Training Phase

This system is an intelligent regression system that uses examples of different cities with their daily solar radiation per city. These examples are used to train the neural networks to have the capability to predict the solar radiation of unseen data based on the knowledge that was acquired during the training phase.

During this phase, part of the data cases is used for training both networks BPNN and RBFN to predict the solar radiation. Back propagation neural network and Radial basis function network analysis methodology are employed at this stage and so on. Data was divided using Cross-validation for training, validating and testing the networks.

4.1.1 Database Description

In this work, one year solar radiation data of different cities and each of different months are used. The data for the selected location is taken from the NASA geo-satellite database website (Erhan et al., 2010 ;Kutucu & Almryad, 2016). The data are geographical and meteorological of 25 cities in Libya obtained for a period of 6 years (from 2010 to 2015). The selected data set include both geographical parameters (latitude, month, longitude, altitude) and meteorological (mean sunshine duration, mean temperature, relative humidity and solar radiation) parameters.

This report selects eight attributes, inputs; month, latitude, longitude, elevation, mean temperature, relative humidity, mean sunshine duration/h. Table-4.1 shows the listings of the data that are used as inputs for the ANN, networks. Moreover, the last column shows the output attribute which represents the daily solar radiation of each city.

Table 4.1: Input Parameters

Input	Output
Month	Daily solar radiation intensity. (kW h/m2/day)
Latitude	
Longitude	
Elevation	
Mean temperature	
Relative humidity	
Mean sunshine duration\h	

As seen in table 4.1, the database consists of 7 parameters for each different city as inputs such as latitude, month etc...

These input parameters are correspondent to the other solar power variables which help the network to find the real regression values after training it.

For outputs we will have one parameter which represents the Daly solar radiation represented by a decimal value. Upon training the system will be capable of predicting the regression values of different cities that represent the daily solar radiation of them.

Note that the data were normalized before being fed to network so that they fit the network inputs. Tables 4.2&4.3 show a sample of the data before and after normalization, respectively.

Table 4.2: Data before normalization

	Inputs							Output
City	**Month**	**Latitude**	**Longitude**	**Elevation**	**Mean Temperature**	**Relative Humidity**	**sunshine duration/h**	**Daily solar radiation**
Zuara	1	32.88	12.08	3	12.1483871	0.498090323	6.38	3.39806451
Zuara	2	32.88	12.08	3	16.50035714	0.361085714	7.1	4.53821428
Zuara	3	32.88	12.08	3	18.44548387	0.369854839	7.4	5.48967741
Zalta	27	33	11.9	93	14.7006451612903	0.4757903225	7.4	5.4893548

Table 4.3: Some data after normalization

Input	**Values of data after normalization**			
Month	0.000907439	0.001930052	0.002952665	0.003975277
Latitude	0.033508331	0.033508331	0.033508331	0.033508331
Longitude	0.012237987	0.012237987	0.012237987	0.012237987
Elevation	0.002952665	0.002952665	0.002952665	0.002952665
Mean temperature	0.012307921	0.016758301	0.018747412	0.021911903
Relative humidity	0.00039418	0.000254077	0.000263045	0.000326363
Mean sunshine duration\h	0.006409095	0.000254077	0.00745216	0.00827025
Outputs	0.207366	0.38856	0.539767	0.696196

4.2 BPNN Training

4.2.1 Backpropagation learning algorithm

The most common multilayer neural network used is the feedforward network; they work on supervised learning algorithms known as back propagation networks considering how learning is achieved, i.e., errors accumulated at the output layer are propagated back into the network for the adjustment of weights. These networks use the delta learning rule for learning, the only difference being that back propagation algorithm can be extended to update the weights of multilayer networks.

A Backpropagation Neural Network (BPNN) is a type of neural network that relies on feeding back error values accumulated at the output of the network in order to update the weights of interconnections between layers of the network.

It is noted that there is no backward pass of computation of any such except during training. i.e. all links proceed in the forward direction during simulation. Backpropagation algorithm is based on the gradient descent optimization method.

4.2.2 Proposed Backpropagation neural network structure

Back propagation neural systems are vital and valuable in forecast issues; it depends on a directed learning calculation. The fruitful preparing of back propagation systems is for the most part a heuristic procedure (experimentation), with a specific end goal to acquire arrange parameters which deliver great outcomes.

Henceforth, in this work, a few tests were directed with the end goal that altogether vital outcomes can be acquired. The learning parameters changed incorporate, the quantity of hidden neurons, the learning rate, and force rate.

The proposed backpropagation neural network is a feedforward neural network that consists of three layers. The first one consists of 7 neurons; each represents on attribute like month, elevation etc... The second layer is the hidden layer and it consists of 50 neurons that were set by experience to provide a good regression rate and faster training time.

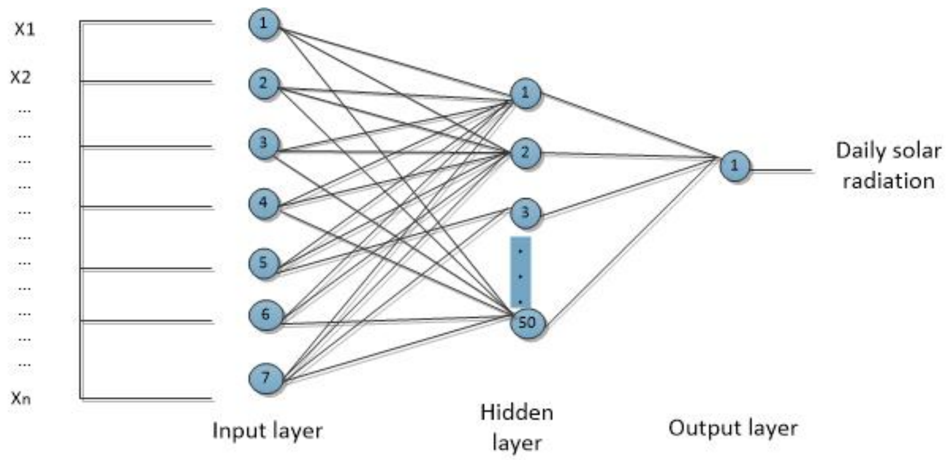

Figure 4.1: Backpropagation Neural Network architecture

Training the system and making it adhere to the wanted results is not an easy task. Indeed several trainings may be required to achieve that and end up with good acceptable results. Therefore, several trials have been done in this project to reduce and reach the minimum mean square error, MSE*;* percentage. The degree of difficulties in such systems can sometimes be misleading since the best training results, minimum MSE, may not always indicate the best performance (testing) of the neural network system.

To start the training, variable parameters are selected as listed below. This is done as such to indicate whether or not the training results could show up within desired limits. Otherwise, they can be modified by the programmer and have their values changed until reaching acceptable limits. Then an acceptable performance of the neural network is checked for the largest percentage of accuracy rate up to100%.

- Number of hidden neurons
- Momentum rate
- Learning rate
- Number of iterations (epochs)

Note that only 70% of the data was used for training, while 10% are used for validation and 20% for testing.

4.2.1.1 First Training Result (BPNN1)

Initially, the network was set to run 5000 maximum iterations with a learning rate of 0.2, a momentum rate of 0.7, 50 hidden neurons and a minimum mean error of 0.010252. This high number of iterations is done on purpose since our application is critical and has to show high degree of reliability. Figure 4.2 shows the first training result (learning curve) of the system.

In short, figure 4.2 has indicated that the system has kept training itself without any interference on the input data provided by the user until it has reached the lowest value of MSE. Note that the network reached the minimum square error at epoch 94 and in a short time of 6 seconds.

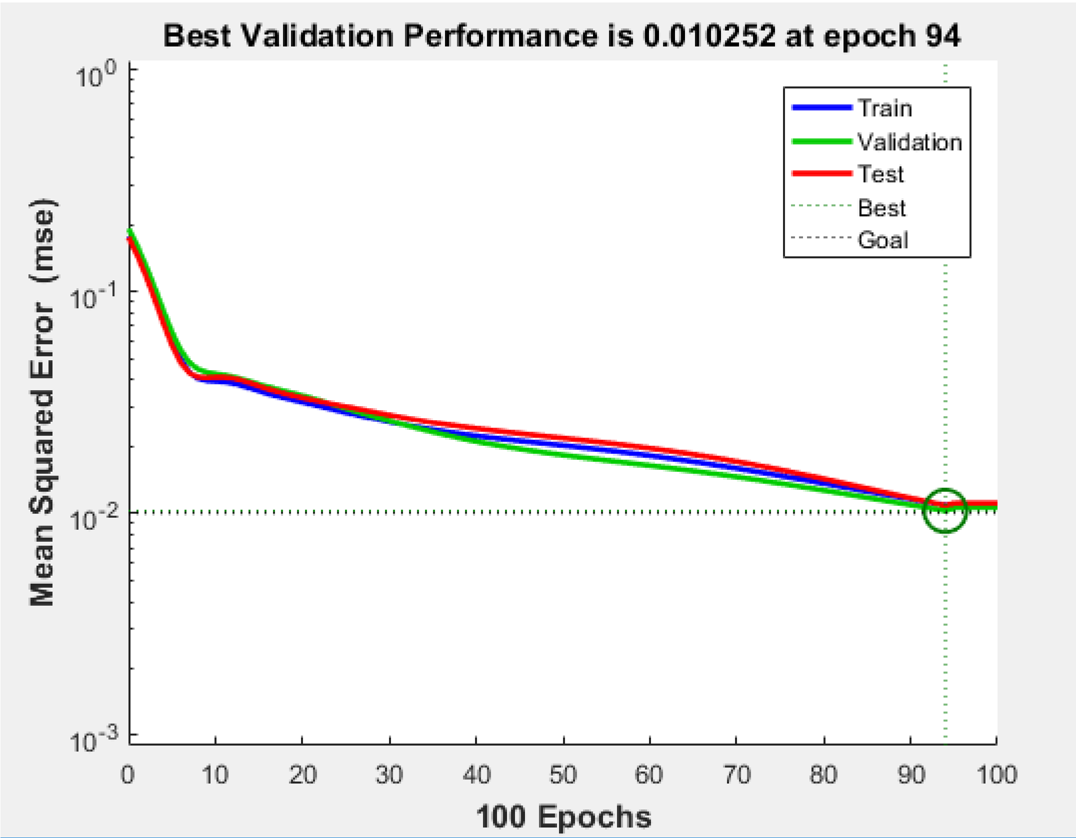

Figure 4.2: Variation of MSE with iteration numbers

To further ensure system stability and accuracy, Regression was computed by the software and drawn as illustrated in Figure 4.3. In measurable displaying, regression examination is a factual procedure for evaluating the connections among factors. It incorporates numerous systems for displaying and dissecting a few factors, when the emphasis is on the connection between a reliant variable and at least one autonomous factors (or 'indicators'). The regression plot as observed is essentially the bend plot of the coveted output (dabbed line) versus the real output. In Figure 4.3, it is commented that the objective and the real output are close which implies that the mistake is limited and the system is very much prepared by demonstrating the preparation proportion at 91%.

The plot shows also the validation and testing curve that achieved 92% and 91% respectively.

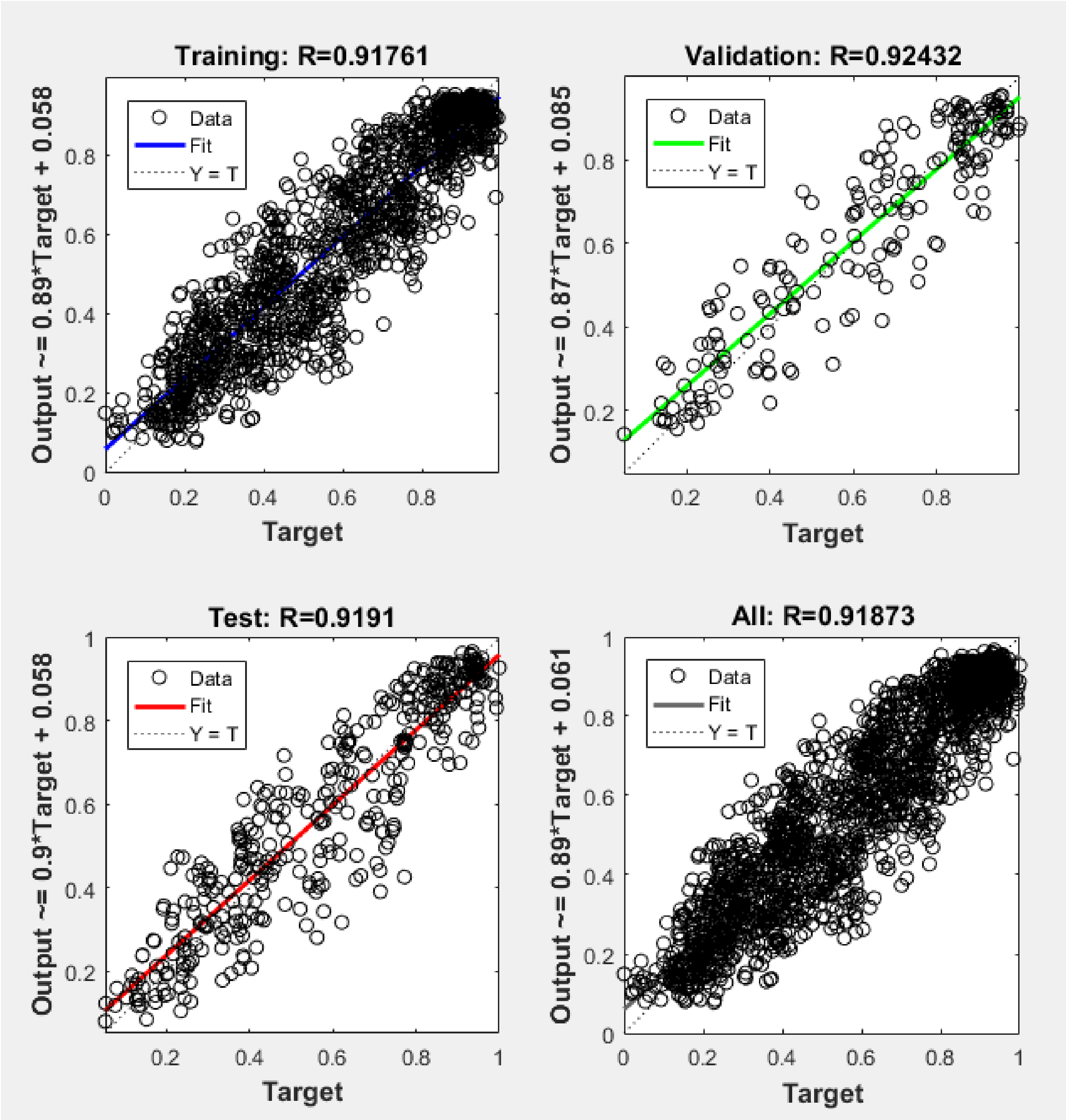

Figure 4.3: Training, validation, and testing results

Having achieved the first training does not mean the conclusion of a satisfying outcome yet. Therefore, additional trials are required in search of better results. So we changed the parameters, already mentioned, again as stipulated next.

4.2.1.2 Second Training Result (BPNN2)

To enhance the results, a second training has been initiated with the following values:

- Number of hidden neurons = 30
- Learning Rate = 0.2
- Momentum rate = 0.7
- Number of iterations = 5000

Figure 4.4 shows the training curve result obtained by using the parameters as set above. Note that the network with the newly set parameters was able to reach a minimum square error of 0.01118 at epoch 138 in 6.389 seconds.

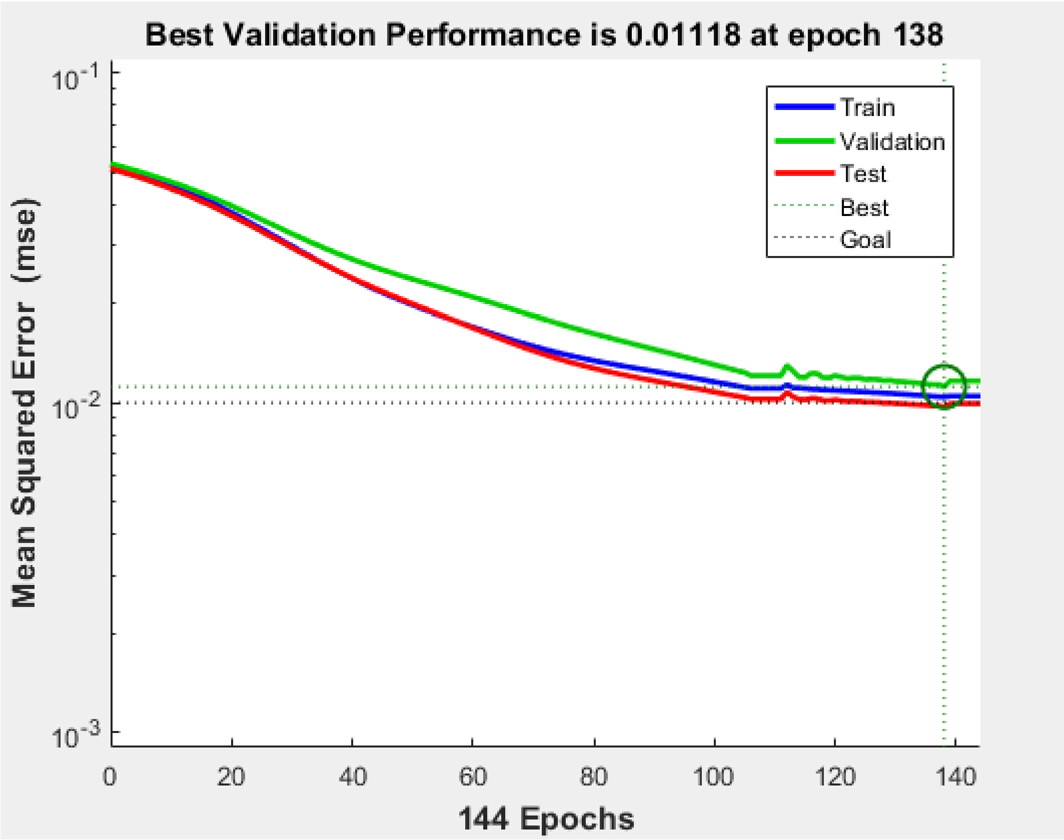

Figure 4.4: Variation of MSE with number of iterations

Figures 4.4 and 4.5 show that the training result is becoming less satisfying with the newly set parameters as it achieved 90.2% as learning ratio, 90.6% validation ratio, and 88.0% as testing ratio. The regression curves for training, validating, and testing are shown in the figure below.

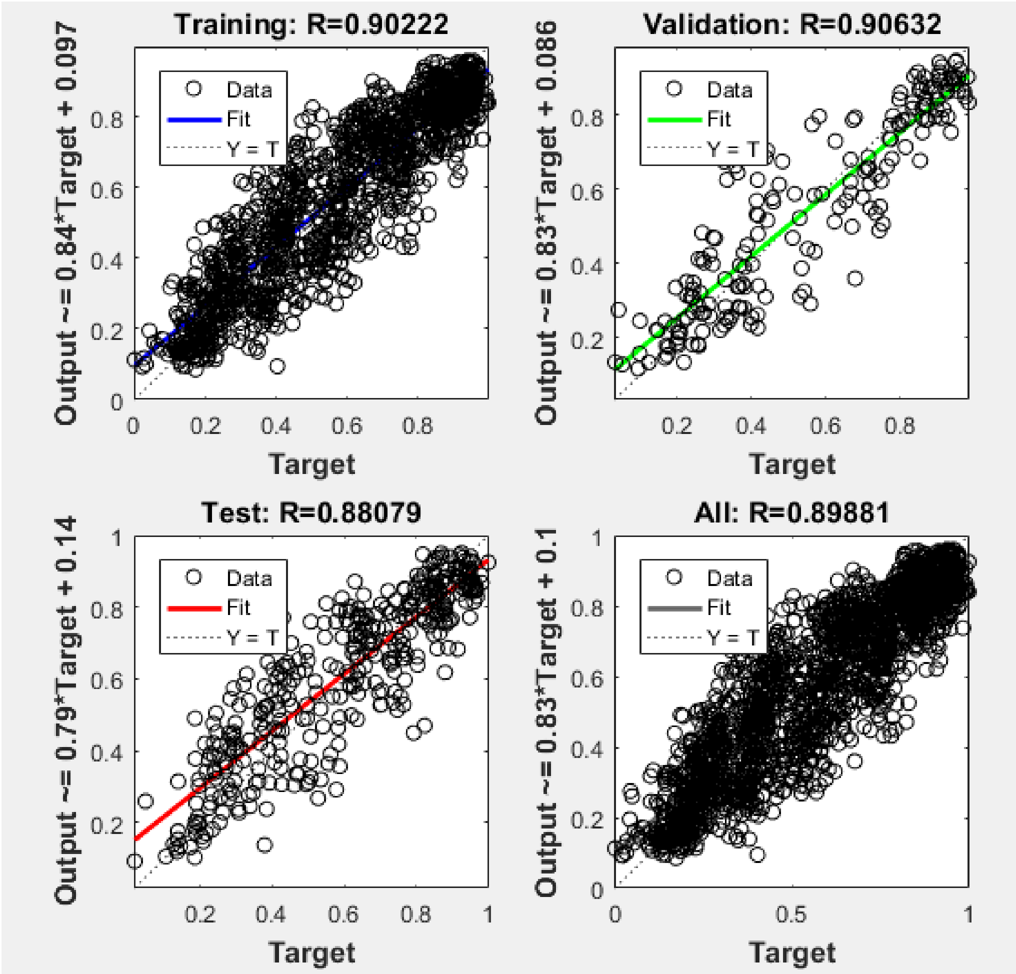

Figure 4.5: Actual Vs. Target Output

4.3 RBFN training and performance

4.3.1 Radial Basis Function network

This type of networks is a feedforward neural network that is trained using for function approximation or regression. However his network can also be used for classification purposes. In this work, radial basis function network is used for the prediction the radiation of solar power in Libya. The details of the employed model are explained below.

4.3.2 RBFN1 Model

Different models of Radial basis network were deployed to find out the best network with the best parameters for performing this regression task. The first model uses 100 iterations, 50 hidden neurons and a spread constant of 1.5. Note that this network was trained on 70% of the data while the rest 30% of data were used for validating and testing the network. As seen in figure below this model of Radial basis function network was able to achieve a good regression ratio of 93.15% in a very short time 5.8s and in a smaller minimum square error (0.0090) that that of the BPNN.

Moreover this network achieved such a good regression rate with a small number of epochs (100) as seen in figure 4.6.

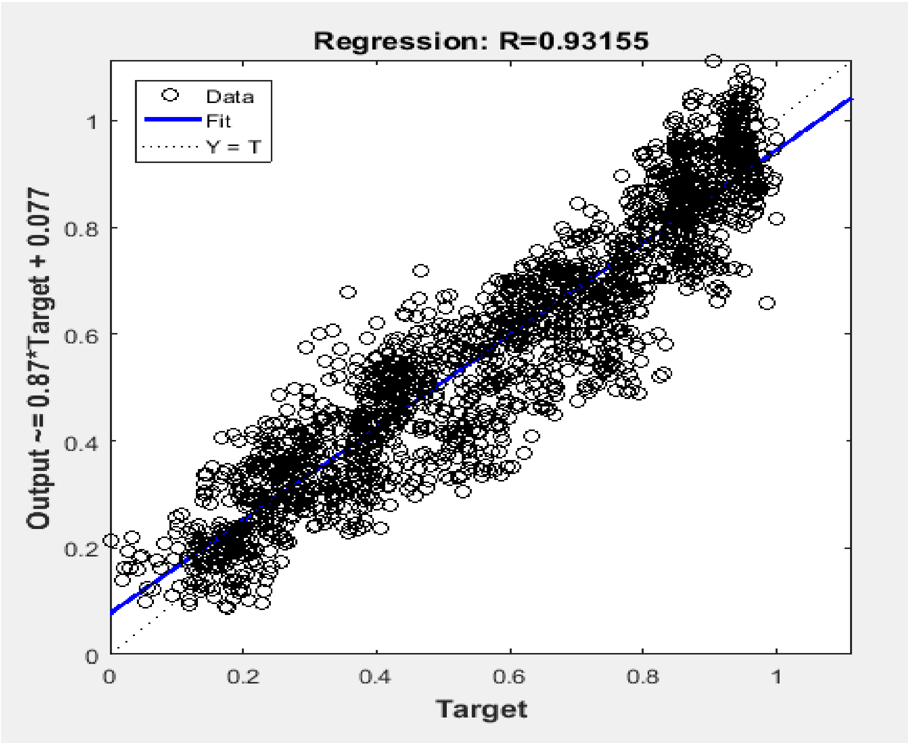

Figure 4.6: Regression plot of RBFN1

4.3.3 RBFN2 Model

A model 2 of radial basis function neural network was deployed of 30 hidden neurons in the hidden layer and with a spread constant of 1.5. In addition, only 100 epochs were set for training this model.

As seen in the figure below, the network with of 30 hidden neurons was able to achieve 93.1% regression rate with 100 epochs and 1.5 spread constant. Note that this model has reached a minimum square error of 0.009 in 7.53s which is more than compared to that of RBFN1 model.

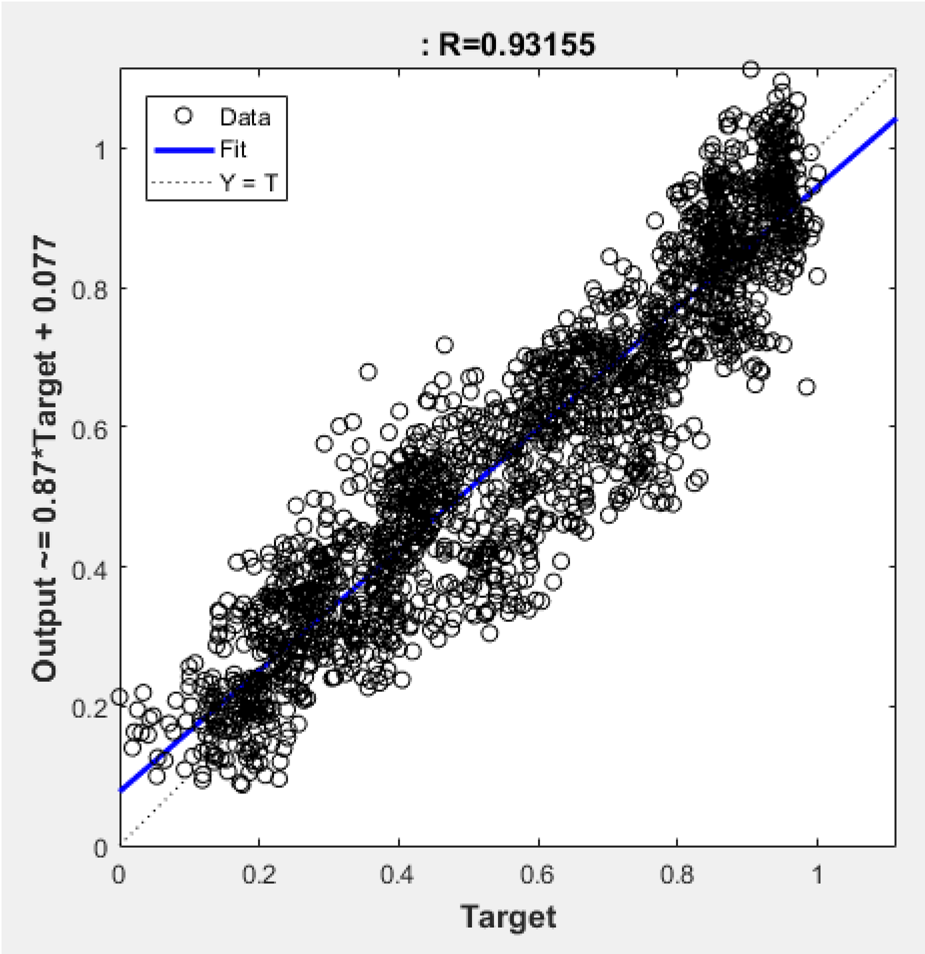

Figure 4.7: Regression plot of RBFN2

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Results Discussion

This solar power radiation regression and predictive system has been tested using MATLAB software and tools. All used networks have been tested on 20% of the available dataset.

The rate of success of this project lies in the training results of the fed data and software tools; number of hidden neurons, momentum rate, learning rate and last number of iterations (epochs). Selection of Back-propagation methodology has facilitated and supplied the system with a high degree of precision due to its internal architecture and operation; MSE and training performance. None the less, the system could not identify and unable to predict some new unseen inputs. Yet the three training trials and performance results performed during system testing have illustrated clearly the presence of an acceptable outcome one can rely on and continue its improvement.

Table 5.1: Comparison of BPNN1 and BPNN2

Parameter	BPNN1	BPNN2
Number of hidden neurons	50	30
Number of iteration	94	138
Learning rate	0.2	0.2
Momentum rate	0.7	0.7
Training time (seconds)	6	6.389
MSE	0.010252	0.0111
Training ratio (%)	91	90.2
Validation ratio (%)	92	90.6
Testing ratio (%)	91	88.0

For comparison purposes, the parameters of the backpropagation neural network were changed and results were compared correspondingly as seen in Table 5.1. For the first network, 94 iterations and 50 hidden neurons are used when training the network. The regression results were satisfying as the network was capable of getting 91% as testing ratio while 92 and 91% are obtained for training and validating the network respectively. Note that this network reached a 0.010252 minimum square error in a short time of 6 seconds.

On the other hands, it can be noticed that the BPNN2 couldn't achieve such good regression rate achieved by BPNN1. As seen in table 5.1 the BPNN2 reached only 88.0 as testing ratio which is lower than that of BPNN1. This might be due to the change in the network parameters values where 30 hidden neurons used. Note that this network (BPNN2) reached a training rate of 90.2% in 6.29 seconds which is longer that the time taken for the BPNN1 to get 91%.

Furthermore, two Radial basis functions networks were used for testing the networks; each with different set hidden neurons. Note that 20% of the data are used for testing these two networks.

Table 5.2 presents a comparison of the performance of both types of used networks which are the BPNN and RBF networks. It is seen that the RBF network achieved a higher generalization power in terms of accuracy where it achieved 93.1% recognition rate which is higher than that of BPNN. Moreover, it can be seen that the RBFN has achieved this high recognition rate in lesser time and lower number of iterations compared to those of BPNN.

This thesis features an overwhelming assignment in AI, in like manner in data processing. We have demonstrated that neural system (BPNN) backpropagation can be utilized in understanding the grouping/detection of hand motion gestures. The Back Propagation Neural Network that has be thoroughly trained is then utilized as a part of a non-covering inspecting design to 'identify' data that indicate the solar radiations.
The efficiency of the developed system has been tested when the data were used for training it, the system was particularly tested for different data which were unseen before. Furthermore the system is insignificantly affected when there is change in conditions or different data different areas which implies the system is found to be intelligent.

The training phase of this work faced a significant challenge in getting an impressive rate of recognition, which was a result of the data which are fuzzy, which implies the network will have difficulty in learning any difference from the images. To handle the fore mentioned challenge the system was designed to segment images in order to significantly reduce the learning process of the network.

Amongst the issues of the system is the verity of arranging recognition that is hard to be gotten at the initial cycle. Along these lines, the system was set up for a couple of running's until the moment that the mean square mix-up is achieved and an elevated recognition rate is derived. Therefore, the framework must be rechecked and orchestrated twice or thrice prior to testing it with the target of correct weights will be capable while ensuring the realization of basic recognition.

In any case, the arrangement of the neural system learning rate was high during recognition; moreover the network couldn't have generalized new gesture images. This problem is common with back propagation networks, the fact the stage learning rate becomes a memorizing one, thus becoming not intelligent, and this can be prevented by Lessing the total number of iterations used in the neural network.

Table 5.2: Comparison of BPNN1 and RBFN1

Parameters	**BPNN1**	**RBFN1**
Number of neurons in hidden layer	50	50
Iterations number	94	100
Learning rate	0.2	0.3
Momentum rate	0.7	0.6
Mean Square Error reached	0.0124	0.0090
Training time	6.1s	5.8s
Prediction rate	91%	93.15%

5.2 Prediction For Future

Solar radiation is radiant energy emitted by the sun, particularly electromagnetic energy. In future, the temperature may be higher in some areas due to global warming. Thus, increase in temperature and humidity can results in more solar radiation. Therefore, we tested the network on some data that include high temperature and humidity in order to investigate the performance of network in such cases.

For the predictions of future cases, the network is tested on some new data that include 21 months, latitude of 32.88, longitude of 12.08, elevation of 3, mean temperature of 36, humidity of 5, mean sunshine of 15 hours and the results shows that the solar radiation gets high (9.32). This can be due to the high temperature and humidity which may cause more solar radiation.

CHAPTER 6

CONCLUSION

6.1 Conclusion

Neural networks have shown a great efficacy in prediction tasks, in different fields. Thus, there is a need for applying a neural network in the prediction of solar radiation when data are available. This thesis proposed an intelligent system for the daily solar radiation prediction in different Libyan cities. In this thesis, two types of learning systems were employed in order to predict the daily solar radiation. Hence, two neural systems are used for performing this task. A neural network trained using backpropagation algorithm and radial basis function network are both used in this study. Both networks are trained and also tested on same data collected from one database. Upon convergence, the networks were both tested using data which were not seen before. On testing, networks behaved differently and produced different accuracies and prediction rates.

Thus, the networks performances was shown and compared based on different parameters during the training stage. This aims to investigate the parameters that lead to better performance and also find out the network that achieves higher generalization capability with least error and shorter training time.

Overall, the interpretation of this comparison can prove that the radial basis function network achieved a higher prediction rate with less error than that reached by the backpropagation neural network. Moreover, it is concluded that a radial basis function network was capable of reaching iterations.

6.2 Risk Assessments

This project has several difficulties as any other project. The main risk was in collecting the suitable data used in the neural network system. Being able to find ready data on internet is something difficult since we are not able to have access on all the needed data because most of datasets are private to specific research centers and not easy to reach. Fortunately we were able to find the wanted data after several days of research. In addition, one of the difficulties was in the ability of stopping the training correctly when having the minimum square error (MSE) needed. Finally, finding the recognized testing results was also a problem since not every satisfying training result gives a suitable and recognized testing result.

6.3 Recommendations

An improvement of the proposed predication system may be by improving the performance of the neural systems. This can be by the following:

- Using more data for training the network
- Use different algorithms to train and obtain higher performances for comparison purposes.
- Manipulate with the import of data in MATLAB; instead of importing all the parameters you have in training and repeating the same process in testing, import fewer number in training while a bigger number in testing and vice versa to avoid the memorizing of neural network.

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APPENDIX:SOURCE CODE

```
close all

clear all

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%using BPNN....

train_input=xlsread('DataSolar.xlsx', 'sheet3');

target=xlsread('DataSolar.xlsx', 'sheet5');

% CREATING AND INITIATING THE NETWORK

Spread=0.5;

K_i=0;

 basisfunction='gaussian';

 goal=0.01;

 net.divideFcn = 'divideind'; % Divide data using indicies

%net.divideMode = 'sample'; % Divide up every sample

net.divideFcn= 'dividerand'; % divide the data randomly

net.divideParam.trainRatio= 0.7; % we use 70% of the data for training

net.divideParam.valRatio= 0.1; % 30% is for validation

net.divideParam.testRatio= 0.2; % 0% for testing

[net, tr] = newrb(train_input,target,goal,Spread, 10, 100);

%The network is simulated for a new input.

Y = sim(net,train_input)

errors = target-Y;

MSEtst = mse(errors)

RMSEtst = sqrt(MSEtst)
```

% For a list of all performance functions type: help nnperformance

net.performFcn = 'mse'; % Mean squared error

% Choose Plot Functions

% For a list of all plot functions type: help nnplot

net.plotFcns = {'plotperform','plottrainstate','ploterrhist', 'plotregression', 'plotfit'};

figure, ploterrhist(errors)

plotregression(target, Y)

%%

BPNN

close all

clear all

%%%using BPNN....

train_input=xlsread('DataSolar.xlsx', 'sheet3');

train_target=xlsread('DataSolar.xlsx', 'sheet5');

% CREATING AND INITIATING THE NETWORK

net = newff(minmax(train_input),[50 1],{'logsig','logsig'},'traingdx');

% TRAINING THE NETWORK

net.trainParam.goal = 0.01; % Sum-squared error goal.

net.trainParam.lr = 0.2; % Learning Rate.

net.trainParam.epochs =5000;% Maximum number of epochs to train.

net.trainParam.mc = 0.7 % Momentum Factor.

net.divideFcn = 'divideind'; % Divide data using indicies

```
%net.divideMode = 'sample'; % Divide up every sample

net.divideFcn= 'dividerand'; % divide the data randomly

net.divideParam.trainRatio= 0.7; % we use 70% of the data for training

net.divideParam.valRatio= 0.1; % 30% is for validation

net.divideParam.testRatio= 0.2; % 0% for testing

[net,tr] = train(net,train_input,train_target);

ActualOutputs=sim(net, train_input)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

errors = train_target-ActualOutputs;

MSEtst = mse(errors)

RMSEtst = sqrt(MSEtst)

% For a list of all performance functions type: help nnperformance

net.performFcn = 'mse'; % Mean squared error

% Choose Plot Functions

% For a list of all plot functions type: help nnplot

net.plotFcns = {'plotperform','plottrainstate','ploterrhist', 'plotregression', 'plotfit'};

figure, ploterrhist(errors)

% Recalculate Training, Validation and Test Performance
```