ALI JEMA
SHABAN

FORECASTING OF MONTHLY AVERAGE
GLOBAL SOLAR RADIATION IN LIBYA

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A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES OF NEAR EAST UNIVERSITY

By
ALI JEMA SHABAN

In Partial Fulfilment of the Requirements for the Degree of Master of Science in Electrical and Electronic Engineering

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire ÇAVUŞ

We certify this thesis is satisfactory for the award of the degree of Masters of Science in Electrical and Electronics Engineering

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

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To my parents…

ABSTRACT

Adequate information on global solar radiation with relevant meteorological parameters at any a location, is necessary for planning, designing, and prediction of the efficiency and performance of solar energy applications. Measurements of global solar radiation in developing countries is very difficult and not readily available. This is because of the cost of equipment and their maintenance. Libya as one of the developing countries is facing challenges in global solar radiation measurements and recording. The only alternative is to develop computational models the exploit the relationships between various meteorological parameters to estimate the global solar radiation. In this thesis, two forecasting models are developed based on artificial intelligence (AI) for the forecasting of monthly average global solar radiation in Libya. The first model is using artificial neural network (ANN) and the second is based on adaptive neuro fuzzy inference system (ANFIS). Meteorological data for the period of January 1995 to December 2010 for three important cities of Libya (Tripoli, Sebha, Misurata), is collected from Libyan National Meteorological Centre Climate and Climate Change. The data consist of the monthly average sun shine hours, rainfall, max. temperature, wind speed, mean evaporation, and relative humidity. Data pre-processing is performed, this include data normalization and sensitivity analysis. The models are simulated in Matlab software and the prediction performances of the models are evaluated using MSE, RMSE and DC. The result indicated that both the ANN and ANFIS can be relied upon for the prediction of the global solar radiation in these cities. However, ANFIS models expressed more robustness to parameter variation and outperform ANN in all the three cities.

Keywords: Global solar radiation; Libya; ANN; ANFIS; DC; MSE; RMSE; Matlab Software

ÖZET

Herhangi bir yer üzerindeki küresel güneş radyasyonu hakkında meteorolojik parametrelerle ilgili yeterli bilgi; güneş enerjisi uygulamalarının verimlilik ve performansını planlamak, tasarlamak ve tahmini için gereklidir. Gelişmekte olan ülkelerde küresel güneş radyasyonu ölçümleri çok zor olup hazır değildirler. Bunun nedeni ekipman ve bakım maliyetidir. Gelişmekte olan ülkelerden biri olarak Libya, küresel güneş radyasyonu ölçümleri ile kayıt edilmesinde zorluklarla karşı karşıya bulunmaktadır. Tek alternatif, küresel güneş radyasyonunu tahmin etmek için, çeşitli meteorolojik parametreler arasındaki ilişkilerden yararlanan hesaplamalı modeller geliştirmektir. Bu tezde, Libya'daki aylık ortalama küresel güneş radyasyonunu tahmin etmek için yapay zekâya (AI) dayalı iki tahmin modeli geliştirilmiştir. İlk model, Yapay Sinir Ağı (ANN) kullanmakta, ikincisi ise uyarlanabilir Nöro-Belirsiz Sonuç Çıkarım Sistemi’ne(ANFIS) dayanmaktadır. Libya Ulusal Meteoroloji Merkezi İklim ve İklim Değişikliği'nden, üç önemli Libya kenti (Trablus, Sebha, Misurata) için Ocak 1995 - Aralık 2010 dönemine ait meteorolojik veriler toplanmıştır. Veriler; aylık ortalama Güneşli Saatler (SSH), Maksimum Sıcaklık (Tmax), Rüzgar Hızı (WS), Yağış Miktarı (RF), Nispi Nem (RH) ve Ortalama Buharlaşma (MEV) değerlerinden oluşmaktadır. Veri ön işleme gerçekleştirilmekte ve bu, veri normalizasyonu ile duyarlılık analizini içermektedir. Modeller, Matlab Yazılımında simüle edilmiş ve modellerin tahmin performansları, Belirleme Katsayısı (DC), Ortalama Karekök Hatası (RMSE) ve Ortalama Kareler Hatası (MSE) kullanılarak değerlendirilmiştir. Sonuçlar, bu şehirlerdeki küresel güneş radyasyonu tahmininde hem ANN’a hem de ANFIS'e bağlı olunabileceğini göstermiştir. Bununla birlikte, ANFIS modelleri, üç şehirde de, parametre değişkenliğine daha fazla dayanıklılık göstermişler ve ANN 'den daha üstün olduklarını belli etmişlerdir.

Anahtar Kelimeler: Küresel Güneş Radyasyonu; Libya; ANN; ANFIS; DC; MSE; RMSE; Matlab Yazılım

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LIST OF ABBREVIATIONS

ARMA: Autoregressive Moving Average

ARX: Autoregressive Exogenous

ANN: Artificial Neural Network

ANFIS: Adaptive Neuro-Fuzzy Inference System

GSR: Global Solar Radiation

SSH: Sunshine Hour

Tmax: Maximum Temperature

WS: Wind Speed

RF: Rainfall

RH: Relative Humidity

MEV: Mean Evaporation

DC: Determination Coefficient

MSE: Mean Square Error

RMSE: Root Mean Square Error

CHAPTER 1

INTRODUCTION

1.1 Overview

Recently, the need for clean renewable energy sources is exponentially increasing because of the many advantages and benefits derived from such energy sources. Solar energy is among the most widely used source of energy because of its abundance and relative ease in harnessing it. Global solar radiation is defined as the total amount of solar energy received on the earth’s surface (Muhammad et al., 2018). Sufficient information about the available solar radiation at a particular location on earth is used to study, plan and design solar energy applications. In addition, such information are used for prediction of the efficiency of installed solar devices (Abuain, 1992).

The location of Libya is such important geographic position with wonderful climate. Libya is covering a wide range of land with sahara from the north reaching to Mediterranean Sea from the south. Libyan atmosphere, particularly at beach front district, is transcendently dictated by substantial air convection flows because of generally high temperature gradient existing close to waterfront belt. Such location is commonly moist and calm with some precipitation, for the most part over the period of October-February months, while the inland region has a run of the mill desert (Naser, 2011).

Specifically, Libya stretches over a latitude of $19-33^o\ North$ and $9-25^o\ E$, longitude as depicted in figure 1.1, and its $10\ and\ 700\ m$ height above sea level. In terms of solar energy potentiality, Libyan position is favoured to receive abundant solar radiation. However, its solar energy potentials are yet underutilized. The annual average daily global solar radiation (GSR) is ranging from $5.0\ kWh/m^2$ to $7.0\ kWh/m^2$. Recently, an overview of the available global solar radiation for Libya has been presented in (Abuain, 1992). Nevertheless, so many details are still unavailable and the utilization of solar energy still remain a highly challenging task in Libya. survey of the global radiation has been made, and no data is available about its diffuse component. Figure 1.1 also shows different areas of Libya with their corresponding amount of solar radiation indicated by colour density.

Solar radiation measurement systems are usually arranged to measure the amount of global solar radiation available on the land surface (even surface). And therefore, hourly record and daily data are saved, from which monthly average and annual average may be estimated. In addition, data available at inclined locations can be figured out from measured data on even surface. Pyranometer is the most commonly used instrument to measure global solar radiation. Procurement of the pyranometer instrument, its maintenance cost together with calibration of the instrument made the forecasting of global solar radiation a quite difficult and challenging task (Bannani, Sharif, & Ben-Khalifa, 2006).

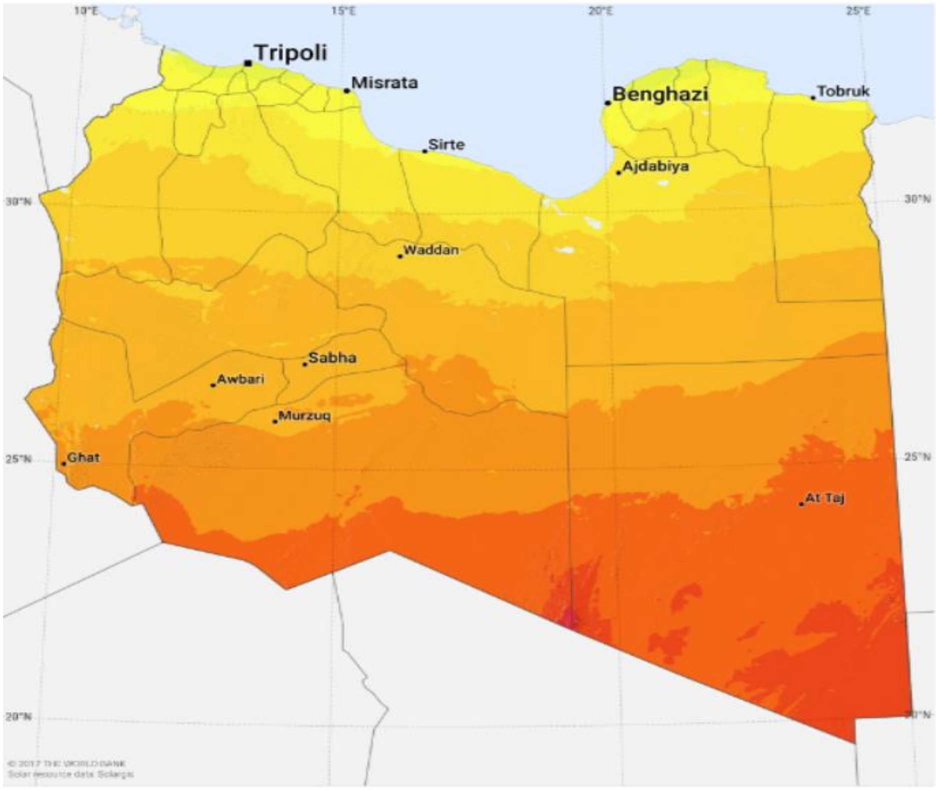


Figure 1.1: Global Solar Radiation in Libya (Abuain, 1992)

In developing economy nations, the circumstance in regards to solar radiation recording is poor, with just a couple of special cases. The current situation in Libya is that, just couple of areas have recorded worldwide solar radiation on the even surface for a long time (1995-2010). Thusly, one needs to rely upon the different exact connections between meteorological parameters such as; sun shine hours, temperature, wind speed, rainfall, relative humidity and mean evaporation to forecast the global solar radiation.

For instant forecasting techniques based on empirical connections between global solar radiation and sunshine duration have been suggested so far by many authors (ABUAIN, 1992; Bannani et al., 2006; Jakhrani, Samo, Ragai, Rigit, & Kamboh, 2013; Naser, 2011). But generally speaking, these models use only average sunshine hours to make the prediction and only eight years data were available, which restrict the efficiency of this models.

Furthermore, Literature studies indicated that several models ranging from intelligent models to regression models were developed. Regression models such as ARMA and ARX belong to a family of linear models, commonly used in forecasting due to the capability of dealing with large data samples and may yield a better forecasting, but produce poor forecasting for few samples of data (Muhammed et al., 2018).

Intelligent models such as neural network and Fuzzy logic are versatile, accurate and effective in handling noisy/few samples data. However, choice of structure, trapping in local minima and selecting of membership function are the limitations of intelligent models. A combination of neural network and fuzzy logic yielded a neuro fuzzy which overcomes the limitations of the individual method. ANFIS belongs to a class of hybrid neuro fuzzy and has received universal acceptability since evolution. ANFIS has an effective capability for nonlinear mapping. Intelligent models such as neural network and Fuzzy logic are versatile, accurate and effective in handling few samples data. But the former lacks the capability of handling uncertainties in the data while the later has no learning capability.

In order to address the shortcomings of both the classical and intelligent prediction models when used individually, in this thesis hybrid network of ANFIS-based models of prediction of solar radiation in Libya is proposed. Further comparison is made with ANN-based models of same areas to ascertain the robustness and superiority of ANFIS-based models for prediction.

1.2 Thesis Objectives

To develop a robust Intelligent Models using Artificial Neural Network (ANN) and ANFIS for the forecasting of global solar radiation in Libya. For this purpose, following objectives are made and will be accomplished in order to achieve the pre-set aim;

i. Data pre-processing including sensitivity and normalization
ii. Training and testing of ANN model
iii. Training and testing of ANFIS Model
iv. Compare the performance of the two models

1.3 Methodology

The development is based on meteorological data collected from Libyan national Meteorological Centre Climate and Climate Change during a 16-yrs, period 1995-2010. The data consist of the monthly mean of wind speed (WS), sun shine hour (SSH), solar radiation (GSR), relative humidity (RH), max. temperature ($Tmax$) and mean evaporation (MEV) for three stations namely; “Misurata”, “Sebha” and “Tripoli”. The simulation is conducted using a PC CORE i5 with Matlab software.

The performance accuracy of the models is evaluated using mean squared error (MSE), root mean squared error ($RMSE$) and determination coefficient (DC).

1.4 Significance

In Libya, the functioning of instruments in the network of solar radiation measurements should be improved as soon as possible. However, such future improvement will not satisfy the current demand for insulation data because the existing network is too sparse. If new stations are established, it will take several years before a reliable radiation climate can be achieved. This is due to the great natural variability of solar radiation from year to year. As a temporary measure, the existing database should be improved by utilizing climate variables that are closely correlated with solar radiation such as sunshine duration and cloudiness. Regression techniques have successfully related global solar radiation to sunshine duration.

Some of the existing methods lack versatility due to some set back that are rule based system and system specific even though they are fast. With recent advances in soft computing learning techniques, Artificial Neural Network (ANN) based and Adaptive neuro fuzzy Inference (ANFIS) system technique for contingency screening and ranking will be a good option. Furthermore, by using the hybrid of ANN and fuzzy (ANFIS) a more reliable system would be obtained.

The design is limited to only three stations i.e. Tripoli airport with latitude of 12.40°N, longitude of 13.09°E and elevation of 80m, Sebha with latitude of 27.01°N, longitude of 14.26°E and elevation of 440m, and Misurata with latitude of 32.19°N, longitude of 15.03°E and elevation of 32m However these models could be used reliably for the forecasting in other stations.

1.5 Thesis Organization

The thesis composed of four chapters. Chapter one gives an insightful background of the studies including the problem description, objectives, significance and limitations. In chapter two, concise review on the published work for forecasting of solar radiation in Libya is discussed along with related information. Chapter three introduced the methodology employed, it also discusses the design process, performance analysis, results and discussions. Conclusion and recommendation is given in chapter four.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter an overview on global solar radiation is discussed, this include the main advantages of solar radiation, measurement techniques and applications. Also discussed in the chapter are the empirical models used for solar radiation estimation. The chapter also provided a brief review on artificial intelligent based techniques for solar radiation estimation. Finally, the chapter look at present situation of solar radiation measurement and estimation in Libya.

2.2 Overview on Global Solar Radiation

Nowadays, renewable energy systems have dominated and replaces other energy sources due to its economic and environmental importance. Many researches in the literature have suggested that solar energy is one of the most suitable of all the renewable energy sources. Such energy source has no potential environmental dangers, it is unlimited (inexhaustible) and clean, hence its suitable for a lot of applications.

Due to the fact that solar radiation depends on geographical locations, the design and implementation of solar energy based systems requires a reliable, extensive and qualitative knowledge and analysis of solar radiations, in order to achieved an optimized system (Boland, Huang, & Ridley, 2013; Bortolini, Gamberi, Graziani, Manzini, & Mora, 2013; Mohammadi & Khorasanizadeh, 2015; Yao, Li, Wang, Jiang, & Hu, 2014).

In fact, this days, solar energy based technology and power systems may be considered as appropriate substitute for conventional energy dependant systems, so as to provide and maintain sustainability of energy all over the globe (Bakirci, 2012; Dincer, 2000; Kaygusuz, 2002).

However, notwithstanding extensive endeavours to utilize the solar energy by means of different technological advancements, various governments just as business companies up until these days, its potential is essentially unexploited yet.

In general, to get the values of solar radiation at a particular location special measuring instruments are set up in that location. Pyrheliometer as shown in Figure 2.1 and pyranometer shown in Figure 2.2 are among the most popular solar radiation sensors. When we used pyranometer on the flat surface, it takes record of “hemispherical solar radiation”, referred to as “global horizontal irradiance”. Meaning, it measures both the direct and diffuse radiation falling on a horizontal flat surface. On the other hand, pyrheliometer is used to measure only the direct solar beam. By using these instruments as shown in Figure 2.3 solar radiation data can be collected and made available in different time scales ranging from hourly, daily, monthly daily mean and annual average.

Figure 2.1: Pyrheliometer (Hukseflux, 2019)

(a) Thermopile-type pyranometer (b) Hand held digital pyrometer

Figure 2.2: Pyrometer (Poling, 2015)

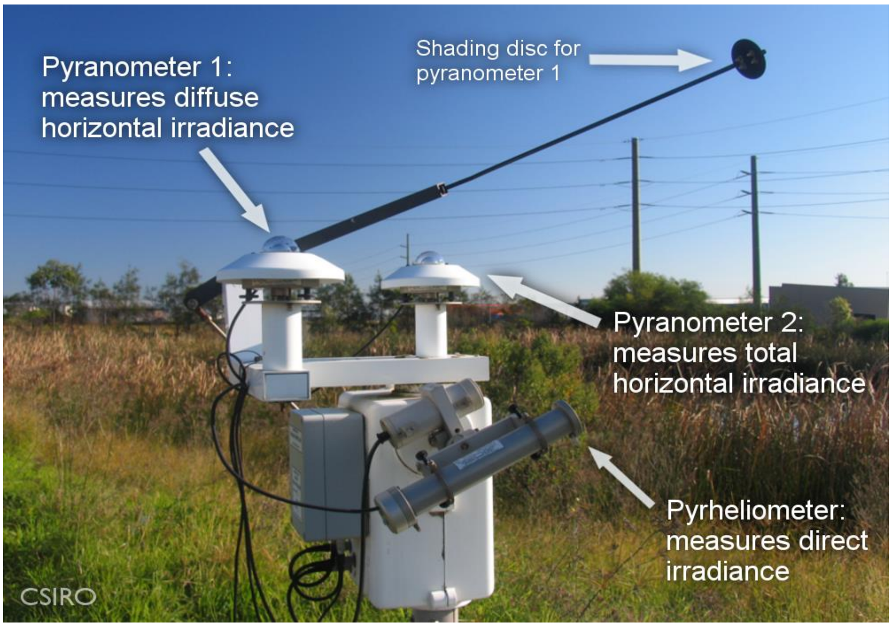


Figure 2.3: Solar Radiation Measurement Site (Poling, 2015)

Nevertheless, the cost of such instruments couple with a number of obstacles such as calibration, maintenance, paucity as well as fiscal issues the solar radiation data are not easily accessible, particularly for stations in developing countries and isolated regions. As a matter of fact, the availability of solar radiation recording stations especially the diffuse part is still insufficient despite the recent attempt globally to build more stations for solar radiation measurement. Consequently, forecasting techniques are relied on by developing countries to obtain the solar radiation.

2.3 Empirical Models for Prediction of Global Solar Radiation

As mentioned in section 2.3, basic requirement for designing and implementing solar energy-based systems an accurate information about diffuse solar radiation is necessary. However, such information is rare in majority of places across the world. For over six decades, to get the solar radiation data empirical models are widely used, by using these models reasonable estimation of solar radiation is obtained. To achieved these various parameters have been used and various functional forms utilized. This section will provide a brief overview of the major solar radiation estimation models proposed in the literature.

Empirical methods provide direct and relatively easy to apply formulae for the estimation. In (Yorukoglu & Celik, 2006) four models are proposed based on meteorological (empirical) data. The models are classified based on cloud, sun shine hour, temperature and related meteorological data (Besharat, Dehghan, & Faghih, 2013). The study suggested that for global solar radiation effective prediction method, statistical analysis should be carried on the measured data.

Similarly in (Angstrom, 1924)(Nnaegbo Okonkwo, 2014), linear regression model are established for some stations in Malawi. However, the study uses just sun shine hour duration data which obtained from six separates stations along different regions of the country.

Also, in ("Models for obtaining daily global solar radiation with measured air temperature data in Madrid (Spain)," 2011) similar models are introduced to forecast global solar radiation in Turkey. Measured data was taken from the station located in Nide/Turkey. A number of equations were established from the well known "Angstrom Prescot linear regression function". However, in addition to sun shine hour duration relative humidity is also used as input. To check the accuracy of the equations obtained, statistical performance measures are used such as "determination coefficient (DC), RMSE and Mean Absolute Percentage Error MAPE". The result of these study indicated that using just sun shine hour duration as input solar radiation can be reliably estimated. It further proved that "Angstrom Prescot linear regression function" provides more accurate result when compared with other LR methods.

Munir et al (Muneer & Gul, 2000) suggested that empirical models based on meteorological data can be efficiently employed for forecasting solar radiation at a particular station. Unlike previous works in this work cloud cover and sun shine hour durations are used as inputs to make the prediction. The advantage of this method is that solar radiation can be estimated even under cloudy sky conditions. in contrast sun shine hour dependant models express better accuracy under clear sky conditions.

In order to forecast solar radiation on a flat surface (Muzathik & Ibrahim, 2011). "Angstrom-Prescott model" is used for the prediction, with sun shine hour duration as input. The data (daily measurement) was collected from "Kuala Terengganu station" from which monthly average was calculated. The performance result indicated that the models can be utilized to estimate monthly, solar radiation at Kuala/Terengganu region.

Rehman et al in their work (Rehman, 1999), develop models to forecast solar radiation in areas where solar radiation measurements are not available by using using available measured solar radiation from other stations. For this modelling sun shine hour duration plus daily hourly average solar radiation data are used as inputs. the data is obtained from forty one (41) locations in Saudi Arabia. Moreover, the developed model is compared with models obtained by other empirical methods. The comparison is based on the statistical test measures; “MPE”, “RMSE”, “MPE”, “MBE” and “MAPE”. In all the cases, the result shows that the model here outperform all others.

As seen from above examples, “Angstrom-Prescott” equation with sun shine our duration data as the only input has been very popular over time in forecasting of solar radiation. This has to do with their simplicity and good approximation capability. Nevertheless, it suffers setbacks when the sun shine data is not enough, and therefore large data record is necessary for high accuracy.

Meanwhile, many researchers have resort to using temperature as the input. Due to the fact that temperature measurements are available and are easy to obtained, models based on temperature (including minimum, maximum and mean) become popular as well. The basic advantage of these empirical strategy is that only temperature data is required which makes their implementation straight forward and faster. In addition, these models give better result when temperature difference (between maximum and minimum, ΔT) is used as inputs. Least and most extreme temperature distinction (ΔT) is the real parameter that influences the exactness and precision of the models dependent on temperature. The accuracy become higher if ΔT is high. Therefore such models are more suitable in areas where there is large temperature difference (Besharat et al., 2013).

Several methods have been proposed using daily temperature measurements to forecast daily solar radiation (Besharat et al., 2013; Hassan, Youssef, Mohamed, Ali, & Hanafy, 2016). The superiority of the models is established by considering factors like simplicity and temperature data accessibility in addition to statistical tests. In (Chen, Ersi, Yang, Lu, & Zhao, 2004), an equation for solar radiation estimation is established.Daily temperature difference temperature difference and logarithmic relation between solar radiation (Rs) and extra terrestrial radiation (Ra) are used as inputs. To model daily global solar radiation, using temperature data (Ayodele, Ogunjuyigbe, & Oyediran, n.d.) employed the modified "Angstrom-Prescott function". Daily-mean temperature data is taken form Ibadan station in Nigeria.

In similar work, temperature data from several stations have been used in Spain, Madrid for forecasting solar radiation. A number of equations from polynomials (quadratic and third order), logarithmic and exponential functions are ("Models for obtaining daily global solar radiation with measured air temperature data in Madrid (Spain)," 2011).

Despite the huge number of researches using empirical methods and several advantages and benefits recorded, these methods are highly constrained. For instant, they are constrained by amount of data. Since majority of these methods are based on linear equation their performance is greatly affected by non-linearity of the solar radiation measurements. Furthermore, huge amount of data is required for accuracy.

2.4 AI Models for Prediction of Global Solar Radiation

Within the last decade or so, Artificial Intelligence (henceforth call AI here) techniques have brought a great change in the area of modelling and computing, especially used for complex function approximations and forecasting, artificial neural networks (henceforth call ANNs here) and adaptive neuro fuzzy inference systems (henceforth call ANFIS here) are most popular among AI methods. ANN success is linked to its learning capability and ability to handle nonlinear systems. ANFIS on other hand integrate the ANN with fuzzy systems and therefore combine the advantages of ANN and advantages of fuzzy systems which include ability to handle uncertainties, and therefore ANFIS are robust models, with these advantages

of AI based models they replace empirical approaches and they are often used more nowadays (Abba, Jasim, & Abdullahi, 2018; Mohammadi, Shamshirband, Wen, Arif, & Petkovic, 2015; "Prediction of air permeability of needle-punched nonwoven fabrics using artificial neural network and empirical models & V R Srinivasamoorth l," 2000).

Many researchers from different areas of studies have being using AI-based models for forecasting, modelling, recognition, function approximations. This include studies in areas of robotics, hydrology, environmental sciences, banking and finance, medicine, agriculture and many more (Coulibaly, 2003). In this section, a number of researches conducted using ANN and ANFIS for estimation of solar radiation are reviewed.

To predict solar radiation in various locations worldwide, ANN models were developed by using sunshine hours duration as input. Radial basic function (RBF) and multilayer perceptron neural networks are used in (Henn, Silva, Praça, Barreto, & Demercil, 2010) to forecast solar radiation in Ain and Abu Dhabi cities of UAE. Also, (Benghanem, Mellit, & Alamri, 2009) used MLP-NN to model daily solar radiation. The result from both models gives a reliable accuracy of predictions.

In their works (Ai & Ai, 1998; Bu, 2007; Lam, Wan, & Yang, 2008) proposed ANN based models to forecast global solar radiation in different locations of world. For instant, in (Lam et al., 2008) prediction model is constructed for about forty towns in China using measured sun shine hour duration data. In (Ai & Ai, 1998) ANN model is used to forecast global solar radiation for the a city located in northern Oman. This work investigated the correlation existing among climatology parameters and solar radiation. Also (Bu, 2007) developed models for a number stations in Turkey. The performance of is evaluated using data from over sixty eight (68) locations. In all the stations ten years prediction is made.

In a similar passion but using relative humidity (RH) and temperature (T) as the only inputs, (Rao, Rani, & Ilango, 2012) and (Hasni, Sehli, Draoui, Bassou, & Amieur, 2012) applied ANN to predict the amount of global solar radiation western Algeria and India. In both works the predictors (T and RH) are used simultaneously. Their performance confirmed that ANN models based on RH and T as only inputs can be used in those areas for the forecasting of solar radiation.

Rodríguez et al. (Linares-Rodríguez, Ruiz-Arias, Pozo-Vázquez, & Tovar-Pescador, 2011) proposed a model based on ANN to forecast synthetic solar radiation. For this purpose, daily data of four (4) meteorology parameters are used as predictors. The input parameters are; total column ozone, cloud cover and water vapor plus temperature. The data is obtained online from a satellite record “ERA-Interim analysis” for Andalusia location in Spain. Both the training as well as testing performances strongly indicate that ANN models have good generalization capability.

Premalatha et al. (Premalatha & Valan Arasu, 2012) uses Gradient decent based back propagation learning approach to forecast solar radiation in some particular areas of India. unlike many previous researches this one used both maximum and minimum temperature in addition to relative humidity as predictors. However, their finding shows that minimum temperature data alone can be used to guessed solar radiation in their study area with high accuracy. Using similar learning method, Rahimikhoob et al applied Multi layer perceptron to predict solar radiation. However, their area of study is semi arid environment and uses only temperature (maximum and minimum) as inputs. when compared with empirical models developed for the same area, their model shows higher robustness and efficiency (Rahimikhoob, 2010).

In a little bit different approach, Yacef et al. (Yacef, Benghanem, & Mellit, 2012) carried out a comparative studies between empirical, classical ANN and Bayesian based Neural Network (BNN) techniques. The developed models are compared to make predictions of global solar radiation in areas of Saudi Arabia. The study combined ambient temperature, sun shine hour duration, radiation and relative humidity as inputs to the system. Although conventional NN shows promising performance yet BNN result is more accurate and more reliable.

Another comparative studies by Sahin et al. (Şahin, Kaya, & Uyar, 2013), compared performance of conventional ANN model with linear regression models to predict global solar radiation on daily basis. For this study measured data is collected from about seventy three stations in Turkey. In this study four inputs parameters are considered namely; air temperature, longitude, altitude, month and latitude. The result as expected favoured the performance of ANN over linear regression approach.

Other similar studies include (Kumar, Aggarwal, & Sharma, 2013; Mellit, Arab, Khorissi, & Salhi, 2007; Moghaddamnia, Gousheh, & Jamshid, 2009; Mohanty, 2014; Salisu et al., 2017) done for multiple locations around the globe including Algeria, North India, Nigeria and UK. In (Mellit et al., 2007) wind speed, precipitation, extra terrestrial radiation and temperature are used as inputs. Also (Salisu et al., 2017) in addition to MLP, RBF and ANFIS models and ANFIS based models outperforms all others.

In their work (Olatomiwa, Mekhilef, Shamshirband, & Petković, 2015), compared ANN, ANFIS against experimental approaches for Isenyin Nigeria. The input parameters were mean monthly minimum temperature, mean monthly maximum temperature and mean monthly sunshine duration. ANFIS outperformed ANN as well.

2.5 Models for Prediction of Global Solar Radiation in Libya

The overview of the general characteristics of "global solar radiation" in Libya is presented (ABUAIN, 1992). This paper uses data collected from 15 stations across different part of Libya, these meteorological data include the solar radiation and sunshine hour duration. The geometrical location of these stations is re-presented here in Table 2.1.

Various techniques for associating month to month normal day by day worldwide radiation with recorded daylight term have been endeavored. It is discovered that some outstanding connection formulae show vast inconsistencies in anticipating the worldwide radiation of Libya. Besides, the Dogniaux-Lemoine relationship condition is observed to be reasonable for the expectation. However only 5 years data is available and only sunshine duration is used.

Table 2.1: Geometrical locations of 15 Libyan stations studied in (ABUAIN, 1992)

No.	Station	Latitude	Longitude	Elevation(m)
1	Benina	$32^0 06' N$	$20^0 16' E$	**130**
2	Ejdabia	$30^0 43' N$	$20^0 10' E$	**5**
3	Elgariat	$30^0 23' N$	$13^0 35' E$	**500**
4	Ghadames	$30^0 08' N$	$09^0 30' E$	**326**
5	Hun	$29^0 08' N$	$15^0 57' E$	**260**
6	Jaghbub	$29^0 45' N$	$24^0 32' E$	**2**
7	Jalu	$29^0 02' N$	$21^0 34' E$	**61**
8	Kufra	$24^0 13' N$	$23^0 18' E$	**381**
9	Nalut	$31^0 52' N$	$10^0 59' E$	**619**
10	Nassir	$31^0 51' N$	$23^0 55' E$	**155**
11	Sebha	$27^0 01' N$	$14^0 26' E$	**440**
12	Shahat	$32^0 49' N$	$21^0 51' E$	**621**
13	Sirte	$31^0 12' N$	$16^0 35' E$	**20**
14	Tobruk	$32^0 05' N$	$23^0 55' E$	**50**
15	Tripoli	$32^0 54' N$	$13^0 11' E$	**80**

The correlation formulae used include; Sabbag-Sayigh correlation formula given in equation (2.1), Garg and Garg relation given in equation (2.4), Hay's formula equation (2.6) and the Dogniaux-Lemoine correlation equation (2.8).

$$H = 0.01163 \left[1.53kexp\theta(\frac{S}{Z} - \frac{h^{\frac{1}{3}}}{100} - \frac{1}{T_{max}}) \right] \qquad (2.1)$$

Where

$$k = [\beta_i + W_{ij}cos\theta]x100, \qquad (2.2)$$

$$\beta_i = 0.2/(1 + 0.1\ x\ \ \pi\theta/180). \qquad (2.3)$$

And

S = observed monthly average daily sunshine hours (hr)

Z = computed monthly average day duration (hr)

θ =latitude

$h = monthly - mean\ relative\ humidity$ (%)

$T_{max} = monthly - mean\ max.temperature$ (℃)

$$H = H_o \left(0.44 + \frac{0.40S}{Z} - 0.005W\right) \qquad (2.4)$$

Where

$$W = R(4.7923 + 0.364T + 0.005T^2 + 0.0003T^3), \qquad (2.5)$$

R is the relative humidity and

T is temperature.

$$\frac{H}{H_o} = \frac{[0.1572+0.5566(S/Z')]}{1-0.2[0.25(S/Z')+0.6(1-S/Z')]} \qquad (2.6)$$

Where

$$Z' = \frac{arc\ cos[(\cos 85 - \sin \gamma sin\delta)/cos\gamma cos\delta]}{7.5}. \tag{2.7}$$

$$\frac{H}{H_o} = \left(0.00506\frac{s}{Z} - 0.00313\right)\gamma + 0.32029\frac{S}{Z} + 0.037022 \tag{2.8}$$

In another article (Bannani et al., 2006), regression approach is used to estimate the monthly mean solar radiation. For this purpose, data is collected from eleven stations. In this paper also monthly average sunshine hours duration is used as predictor. Famous Angstrom correlation equation (2.9) is used due to its simplicity and accuracy. Because of the limited data (only eight years duration) only one regression equation was obtained for each station. Meanwhile, the limitation in the available data and the fact that it's a linear model constraint the accuracy of the model. Furthermore, their results indicated that only ten from the total eleven work very well.

$$H = H_o(a + b\,\bar{n}/N) \tag{2.9}$$

Where:

$$H_o = \frac{24I_{SC}}{\pi}[1 + 0.033\cos(360\,\bar{n}/N)]x\left[cos\emptyset cos\delta sin\omega_s + \frac{\pi\omega_s}{180}sin\delta sin\emptyset\right] \tag{2.10}$$

$$\omega_s = cos^{-1}\emptyset[-tan\emptyset tan\delta] \tag{2.11}$$

$$\delta = 23.45\ sin\left[360(284 + \bar{d})/365\right] \tag{2.12}$$

$H = monthly - mean\ of\ daily\ solar\ radiation\ (kWh/m^2)$

$H_o = monthly - mean\ of\ daily\ solar\ radiation\ on\ flat\ surface\ (kWh/m^2)$

$\bar{n} = average\ daily\ bright\ sun\ shine\ hour$

$N = mean\ daily\ sun\ shine\ hour$

$a\ and\ b$ are regression coefficient

$I_{SC} = solar\ constant\ given\ as$ 1.367 kWm^{-2},

ω_s = sunset hour angle,

δ = declination in degrees,

$\bar{d} = mean\ ith\ day\ of\ month$

$\emptyset = latitude$

In his paper (Naser, 2011) Naser, study prediction models for diffuse solar radiation, similarly, by considering average monthly data obtained from sixteen (16) stations using correlations. Sunshine hour duration is also been used for the prediction. Measured data was taken over the period of 1981 to 1987. Table 2.2 illustrated the geographical specifications of the meteorological stations under studied.

Table 2.2: Geographical locations of the stations studied by (Naser, 2011)

Station	Latitude(N)	Longitude(E)	Elevation(m)
Sirte	$31^0 20'$	$16^0 35'$	**025**
Sebha	$27^0 02'$	$14^0 26'$	**437**
Tripoli	$32^0 50'$	$13^0 11'$	**030**
Tripoli airport	$32^0 54'$	$13^0 50'$	**185**
Elgariat	$30^0 38'$	$13^0 35'$	**505**
Ghadames	$30^0 13'$	$09^0 30'$	**331**
Ghat	$24^0 95'$	$10^0 10'$	**699**
Nasser	$31^0 87'$	$23^0 55'$	**156**
Hun	$29^0 13'$	$15^0 57'$	**265**
Ejdabia	$30^0 72'$	$20^0 10'$	**011**
Jaghbub	$29^0 82'$	$24^0 32'$	**003**
Jalo	$29^0 03'$	$21^0 34'$	**065**
Kufra	$24^0 22'$	$23^0 18'$	**408**
Nalut	$31^0 87'$	$10^0 59'$	**626**
Shahat	$32^0 82'$	$21^0 51'$	**626**
Benina	$32^0 10'$	$20^0 09'$	**039**

Data dependent correlation formulae of Iqbal, Rabi, are used for the estimation. Iqbal uses a linear equation, as a function of bright sunshine hours, given as:

$$\frac{\bar{H}_d}{\bar{H}} = 1.00 - 1.13\bar{K}_T \qquad (2.13)$$

Similarly, Rabi presented

$$\frac{\bar{H}_d}{\bar{H}} = 0.775 + 0.00606(\omega_s - 90) - [0.505 + 0.00455(\omega_s - 90)]\cos(115\bar{K}_T - 103) \qquad (2.14)$$

Where

ω_s = sunset hour angle in degrees with

$\omega_s \approx 90^o$ between "August-October and February-April"

$\omega_s \approx 100^o$ between "May to July", and

$\omega_s \approx 80^o$ between "November to January".

Iqbal also introduced and used the correlation based equation using diffuse solar radiation and bright sun shine hours, using data from Canadian stations.

$$\frac{\bar{H}_d}{\bar{H}} = 0.791 - 0.635\left(\frac{\bar{S}}{\bar{S}_o}\right) \qquad (2.15)$$

Where

$$\bar{S}_o = \left(\frac{2}{15}\right)\omega_s, \qquad (2.16)$$

$\bar{S}$ = represent the monthly-mean of daily bright sun shine hours,

$\bar{S}_o$ = represent the monthly mean of daily max. sun shine hours.

Mean bias error is used to obtained accuracy for long, it therefore provides a genuine assessment of predicted and measured data. When MBE is zero, it indicated a perfect model. When compared the performance of various correlation based models, Igbal's model has the best performance.

Recently, researches have been conducted on selected cities to explore in deep the future of solar energy in that area, specifically in Tripoli. In this context Elmabrouk (Elmabrouk, 2017) The main estimate a number of solar radiation components in Tripoli by collecting measured data from Libyan meteorological organization. These data are used for forecasting of diffuse, reflected and direct solar radiation.

Modified Angstrom equation (2.9) is used for the prediction of the average monthly average global solar radiation on a horizontal surface.

$$\frac{\bar{H}_d}{\bar{H}} = a + b\left(\frac{\bar{S}}{\bar{S}_o}\right) \qquad (2.17)$$

Where

$$a = -0.110 + 0.235cos\theta + 0.323\left(\frac{\bar{S}}{\bar{S}_o}\right) \qquad (2.18)$$

And

$$b = 1.449 - 0.553cos\theta - 0.694\left(\frac{\bar{S}}{\bar{S}_o}\right). \qquad (2.19)$$

The performance of the model was established using "root mean squared error (RMSE) mean bias error (MBE) and mean percentage error (MPE)", whose equations are shown in (2.20), (2.21) and (2.22) respectively.

$$MBE = \sum_{i=1}^{N} \frac{(H_m - H_S)}{N} \qquad (2.20)$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(H_m - H_S)^2}{N}} \qquad (2.21)$$

$$MPE = \left[\frac{(H_m - H_{cal})/H_m}{N}\right] x100 \qquad (2.22)$$

Figure 2.4 shows the comparison made between predicted values and the measured data collected from NASA website. From this figure it is observed that the prediction model performs better around the summer season and relatively ok around the winter. Hence application of this model is limited to summer season. In addition the model is based on satellite estimated data which makes it not preferable.

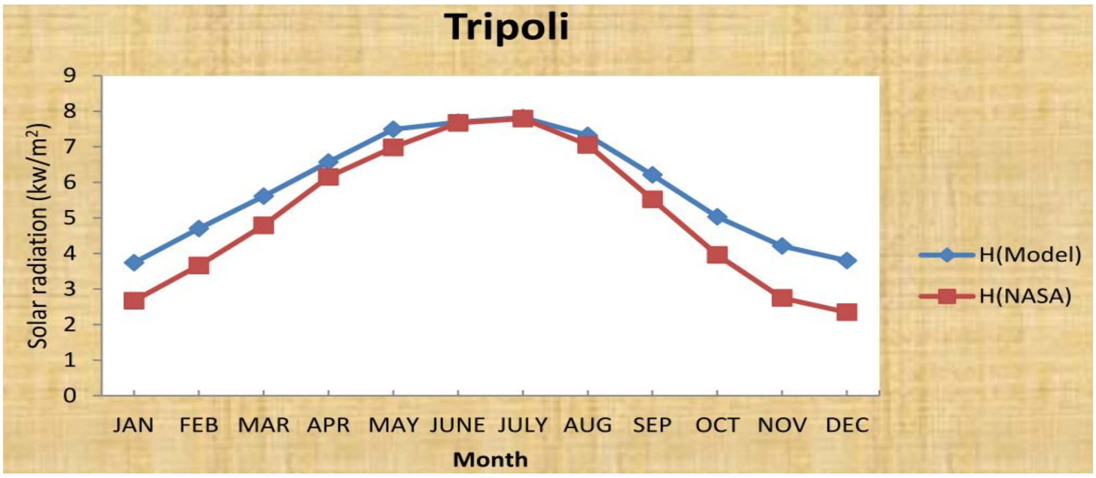


Figure 2.4: Comparison between model predicted result and data from NASA

2.6 Summary

A precise and concise review on global solar radiation, it's measurement methods and estimation techniques are presented in this chapter. The chapter also investigated some of the researches conducted on global solar radiation estimation in Libya.

Solar radiation is one of the most important sources of alternative energy. Global solar radiation is the sum of direct and diffuses incoming solar energy received at the earth's surface. The information on solar energy characteristics and the relevant meteorological parameters at any one location, play an important role for studying, planning and designing solar energy applications. Adequate information regarding the availability of global solar radiation and its components at a particular location is essential to predict the efficiency and performance of solar thermal devices.

The measuring devices used for solar radiation estimations as a rule records worldwide solar energy radiation on the level surface. In developing-economy nations in general and Libya in particular, the circumstance with regards to solar radiation radiation recording is poor, with just a couple of special cases. Acquisition of estimating device, maintenance cost coupled with calibration of the instrument increases the difficulty in measuring and recording of global solar radiation in those places.

In our case, presently few stations have record of global solar radiation. Therefore, the only alternative is to depend on the links between solar-radiation and other meteorological parameters to estimate. Currently, few researchers developed models for the forecasting prediction of solar-radiation for some parts of Libya. But generally, these models use only average sunshine hours to make the prediction and only eight years data were available, which restrict the efficiency of this models. Furthermore, these models empirical and conventional methods, belonging to a family of linear models. These models give poor forecasting for few data samples.

Intelligent models such as neural network and Fuzzy logic are versatile, accurate and effective in handling few samples data. But the former lacks the capability of handling uncertainties in the data while the later has no learning capability. A combination of Artificial Neural Network (ANN) and fuzzy logic yielded neuro-fuzzy which overcomes the limitations of the individual methods. Adaptive Neuro Fuzzy Inference System (ANFIS) has an effective capability for handling noisy/few data samples.

CHAPTER 3

DESIGN METHODDOLOGY AND SIMULATION RESULTS

3.1 Introduction

In this chapter, the general methodology used in this study are explained. General information about the study location are briefly discussed, followed by data collection methods. Basic information about the two modelling techniques; Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference (ANFIS), are presented. Finally, the simulation results are presented and discussed.

3.2 Study Location and Data Collection

In terms of land mass Libya has been rated as the 16th biggest country in the world. Libya is positioned along the cancer obit, it boarded with “Sahara” from the north, and reaches to “Mediterranean Sea” from the south. It is exposed to sun rays throughout the year with long sunshine hours. Libya stretches out from the surmised scope Libya stretches over a latitude of “$19 - 33^o\ North$ and $9 - 25^o\ E$, longitude as depicted in Figure 3.1, and it is “$10\ and\ 700\ m$" height above sea (Abuain, 1992).

The Libyan atmosphere, particularly in the seaside district, is transcendently characterized by the vast air convection flows because of a generally huge temperature slope existing close to the beach front belt. This district is commonly moist and mild with some precipitation, for the most part amid “October-February” months, and the tremendous zone inland has an ordinary desert atmosphere. Therefore, the location is favorably located for high solar insolation. The annual average daily global solar irradiation is between 5.0 kWh/m^2 and 7.0 kWh/m^2. The land area and height above ocean dimension of the three stations directly under examination i.e. Tripoli, Misurata and Sebha are listed in Table 3.1.

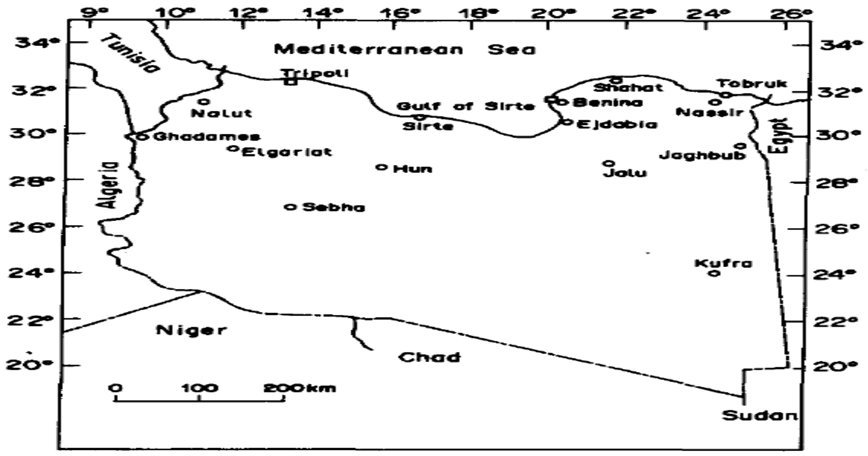


Figure 3.1: Map of Libya (Abuain, 1992)

In this thesis, a meteorological data is collected from Libyan National Meteorological Centre Climate and Climate Change. The data consist of the monthly mean of wind speed (WS), sun shine hour (SSH), solar radiation (GSR), relative humidity (RH), max. temperature $(Tmax)$ and mean evaporation (MEV). A total of 192 data points for a period of 16 years (1995-2010) from these three stations (Tripoli, Sebha and Misurata). From the obtained data 60% (115) is set for training, and 40% (77) for testing.

3.3 Methodology

The major target of this thesis is development of artificial intelligent (AI) based models using "ANN" and ANFIS techniques, the models are to be used to forecast solar-radiation from measured meteorological data. From the data collected, six parameters: $RH, RF, Tmax, WS, SSH\ and\ MEV$ will serve as inputs to the models for predicting the solar radiation GRS. The models are developed by using the famous MATLAB/SIMULINK software.

The overall methodology used I this study is shown in Figure 3.2. In this figure the first stage involves the procedure used for data collection as described in subsection 3.2, this is followed by data pre-processing which include data normalization and sensitivity analysis, to make the data more suitable for the analysis. The processed data is then used for the developments of the models, in developing both ANN and ANFIS the process starts with training and then followed by testing, after testing performance accuracy of the models is evaluated, the training and testing for each model is repeated until a significantly good results are obtained. Afterwards, the final model parameters are saved.

Table 3.1: Geographical location and parameter description of the study area

Region	Location	Coordinates	Parameters	Min	Max	Mean
Tripoli	Latitude	$\mathbf{32^{o}40'N}$	SR ($\frac{kWh}{m^2}$)	2	8.3	5.19
			Tmax (°C)	3.4	40.3	27.45
	Longitude	$\mathbf{13^{o}09'E}$	SSH (hr)	3.2	12.9	8.48
			WS (konts)	3.7	11.8	7.42
	Elevation	$\mathbf{81m}$	RF (mm)	0	173.4	19.29
			RH (%)	39	84	67
			MEV (mm)	2.2	14.1	7.52
Sebha	Latitude	$\mathbf{27^{o}01'N}$	SR ($\frac{kWh}{m^2}$)	2.6	8.2	5.84
			Tmax (°C)	16.8	42.2	31.19
	Longitude	$\mathbf{14^{o}26'E}$	SSH (hr)	5.9	12.7	9.91
			WS (konts)	4.9	14.4	9.93
	Elevation	$\mathbf{432m}$	RF (mm)	0	29	0.81
			RH (%)	16	63	33.69
			MEV (mm)	4.9	24.7	15.09
Misurata	Latitude	$\mathbf{32^{o}19'N}$	SR ($\frac{kWh}{m^2}$)	2.2	8.4	5.48
			Tmax (°C)	16.1	34.4	25.42
	Longitude	$\mathbf{15^{o}03'E}$	SSH (hr)	4.5	12.5	8.80
			WS (konts)	5.4	13.4	9.2
	Elevation	$\mathbf{32m}$	RF (mm)	0	215	22.68
			RH (%)	47	97	70.27
			MEV (mm)	2.9	10.1	5.89

For the purpose of comparison, three models are developed using each technique, i.e. three models based on ANN and three models based on ANFIS, this is based on sensitivity analysis explained in the next subsection, the results of the sensitivity analysis suggested the inputs that have more influence on the solar radiation prediction, based on that three different combinations of input parameters are used to developed the three models for each technique. Finally, performance of the overall models is compared to identify the best among them.

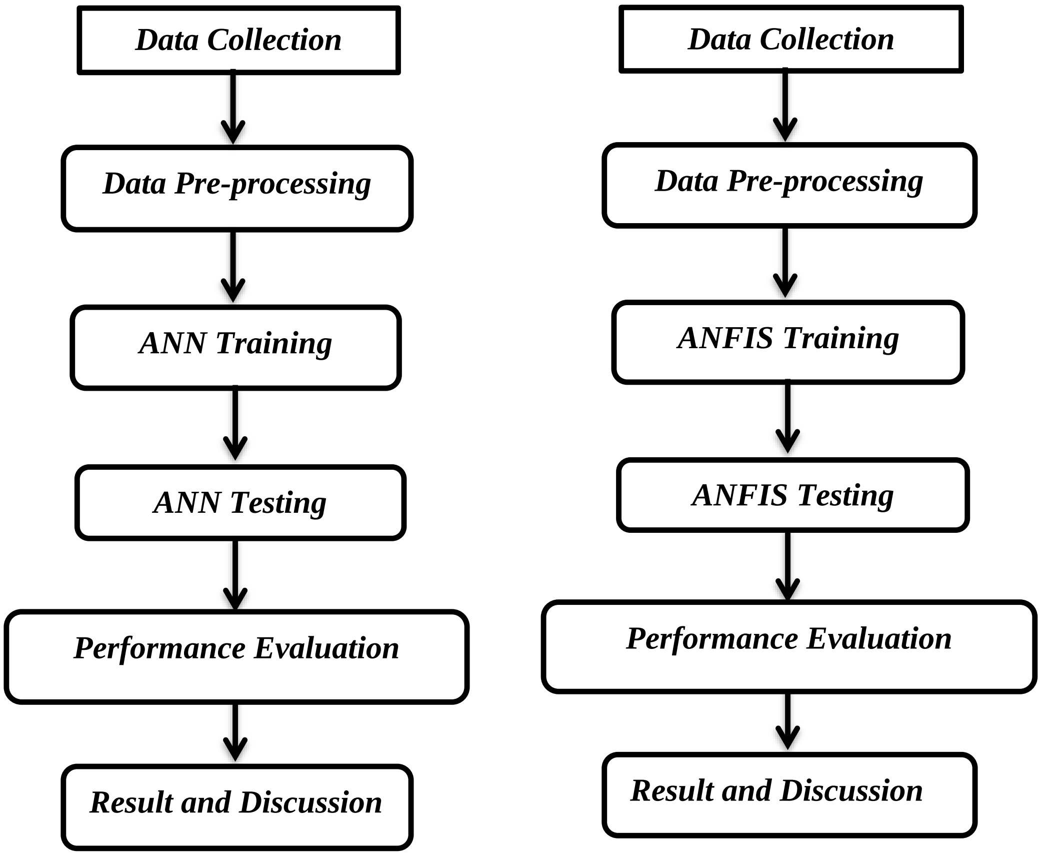


Figure 3.2: Block diagram of Methodology

3.3.1 Data Pre-processing

The design is preceded by data pre-processing which combine data normalization and parameters sensitivity evaluation. In all AI-based modeling design processes it's very important to determine most significant parameters from the data. In order to save time and gain higher accuracy only parameters with highest influence should be incorporated into the development process. Parameters with less influence are discarded. Sensitivity analysis is carried out to determine the input parameters that have most effect on the global solar radiation in Libya. In this work, correlation method is employed similar to the one used in (Nourani & Sayyah Fard, 2012).

Normalization here refers to the process we use to scale the whole data between 0 to 1, to make sure all data instances for both the input and output have equal influence, and make the data dimensionless. Data normalization before applying AI models offers two advantages; it reduces calculation difficulties and avoids using large values which will overshadow those in small ranges. The formula expressed in equation (3.1) is used for the normalization.

$$E_n = \frac{E_i - E_{min}}{E_{max} - E_{min}} \,, \; i = 1, 2, 3, \dots \dots .., n \qquad (3.1)$$

Where En, Ei, $Emin$, $Emax$ represent the normalized values, real qualities, least qualities, and greatest qualities, separately.

3.3.2 ANN Model

ANN is acronym for "Artificial Neural Network" and is defined as "information processing tool, inspired by the biological nervous system, obtained by simulating the operational performance of the biological neural networks" (Abdulkadir, Imam, & Jibril, 2017). Among the development stages learning phase is the most significant stage. In learning stage ANN structure and parameters are adjusted based on the data internal relationship. Due to their learning capability ANN are widely used in many applications such as forecasting, classifications, function approximation and dynamic nonlinear data etc. (Abdulkadir et al., 2017). ANN structure is composed of nodes that serves as processing tools which has special features such as non-linearity, robustness, and many other abilities. They are considered to be an excellent techniques for virtual modelling of complex functions with high accuracy (Nourani, Mousavi, Sadikoglu, & Singh, 2017).

For many applications, "Feed Forwarded Neural Network (FFNN)" are often used along with "Back Propagation (BP) learning" algorithm. In $FFNN$ structure, layers (nodes) are connected to subsequent layers through weighted links. Learning is then perform using BP algorithm. The purpose of employing BP algorithm is to determine the best weights combination that gives an output closer to the target output values based on certain precision. Architectural layout of FFNN is depicted in Figure. 3.3.

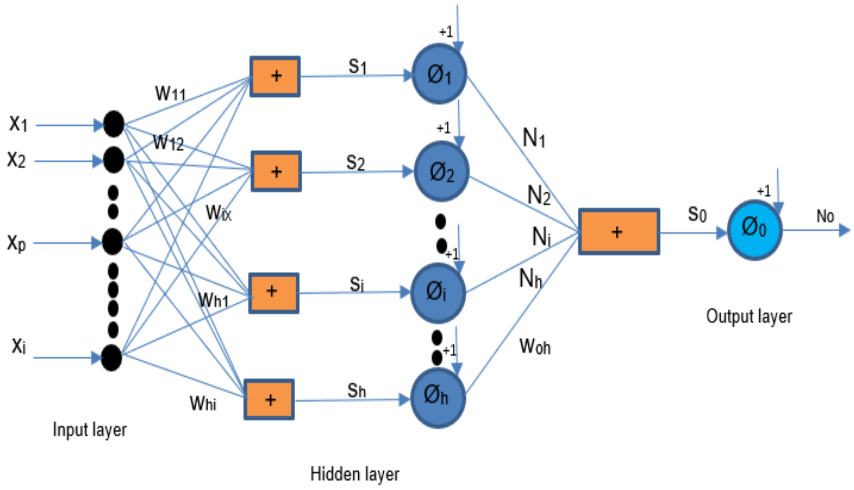


Figure 3.3: A three layered FFNN structure (Nourani et al., 2017)

The output is described by equation (3.2)

$$\hat{y}_k = f_o\left[\sum_{j=1}^{M_N} W_{kj} * f_h\left(\sum_{i=1}^{N_N} W_{ji} * x_i + W_{jo}\right) + W_{ko}\right] \quad (3.2)$$

Where

W_{ji} = weighting factor connecting ith input neuron to jth hidden neuron

W_{jo} =bias of jth hidden neuron

fh = activation function of hidden neuron

W_{kj} = weighting factor connecting jth hidden-neuron to kth output neuron

W_{ko} = bias of kth output neuron

f_o = activation function of output neuron

x_i = ith input variable of input neuron

$\hat{y}_k$ = predicted output

y = actual output

N_N = number of input layer neurons

M_N = number of hidden layer neurons

Developing the network consist of two stages. Learning stage and the prediction stage. During the learning stage also known as training stage, the network is presented with recorded known data consisting of the inputs (parameters to be used for prediction) and the output (parameter to be predicted later). The network processes the data, what's more, realize by contrasting their expectation of the information, with the known genuine record. The blunders from the underlying forecast is sustained back to the system and used to adjust the system's calculation (loads) for the second cycle.

These steps are repeated multiple times, until the predicted output converges to the actual output. In iteration stage the weights are updated. When the learning process is finished, i.e. after the network has learnt the relationship between the inputs and outputs, the knowledge learnt from the data is stored in the weight's values. During the prediction stage also known as testing stage; only inputs are presented to the network for prediction of the output. The number of epochs and neurons in the hidden layer are selected by trial and error.

3.3.3 ANFIS Model

ANFIS has an ability of fast learning, adaptability, effective handling of imprecision and uncertainty. ANFIS structures comprises of five layers as illustrated in Figure 3.4 below. The square nodes are known as adaptive having parameters in them to be updated during learning process, and the circular nodes are fixed. The parameters of ANFIS are updated through supervise learning. The training and testing processes are the same as in ANN.

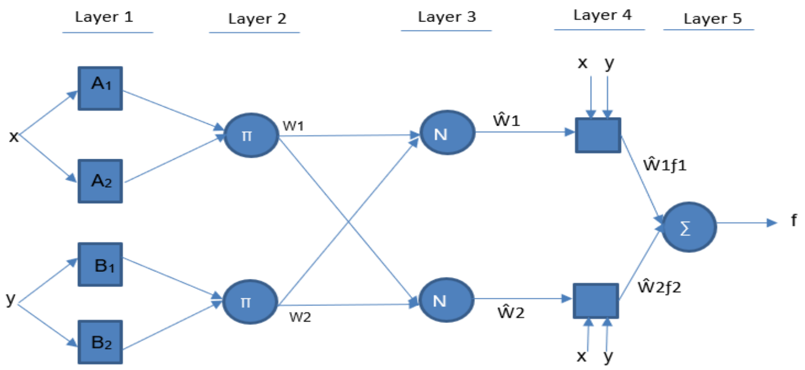


Figure 3.4: ANFIS Structure (Muhammad et al., 2018)

The structure of ANFIS is not unique, two or more layers could be combined together and produce same results. The parameters of ANFIS are updated through supervised learning to reduce the error measure.

The structure of ANFIS is developed using MatLab command "genfis 1" to generate first order "Sugeno Fuzzy Inference System" (FIS). As the framework is realized, ANFIS make use of hybrid learning methods to update parameters of the FIS through learning from the data set to get the target output.

3.3.4 Performance Evaluation

The prediction performance accuracy is calculated using $DC, RMSE\ and$ to established their forecasting efficiency. Many researchers suggested that DC and RMSE are enough to ascertain accuracy prediction models. Equation (3.2), (3.3) and (3.4) presented in (Muhammad et al., 2018; Nourani & Sayyah Fard, 2012) and shown here are used for the calculations.

$$DC = 1 - \frac{\sum_{i=1}^{N}(R_i - \hat{R}_i)^2}{\sum_{i=1}^{N}(R_i - \bar{R}_i)^2} \tag{3.2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \hat{R}_i)^2}{N}} \tag{3.3}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(R_i - \hat{R}_i\right)^2 \tag{3.4}$$

Where $N, R_i, \bar{R}_i$ and $\hat{R}_i$ are the total number of perceptions, watched information, mean of the watched qualities, and anticipated qualities, It is known that DC values between -∞ to 1, and RMSE and MSE values close to 0, implies higher efficiency of the models.

3.4 Simulation Result and Discussion

In this section the simulation results are presented. The results are arranged according to techniques i.e. first ANN result for the three stations are discussed followed by the ANFIS results. And finally, a comparison is made and recommendations are given.

Table 3.2 shows the correlation result for the data collected from Tripoli. From this table we observed that sunshine hour duration has the highest influence on global solar-radiation in Tripoli, followed by mean evaporation, and maximum temperature. Three models were developed for this region by considering three different input combinations from the correlation result. This is shown in Table 3.3.

Table 3.2: Correlation result in Tripoli

	RF	***MEV***	***RH***	***SSH***	***Tmax***	***WS***	***GRS***
RF	1						
MEV	-0.59797	1					
RH	0.526522	-0.83026	1				
SSH	-0.60812	0.759443	-0.56628	1			
Tmax	-0.5817	0.735419	-0.5912	0.759043	1		
WS	-0.23723	0.509406	-0.42503	0.352075	0.183314	1	
GRS	-0.63046	0.825244	-0.65168	0.945667	0.736125	0.462666	1

Table 3.3: Input combinations of Models in Tripoli

Model	**inputs**	**output**
M1	SSH, MEV, Tmax	GRS
M2	SSH, MEV, Tmax, RH, RF	GRS
M3	SH, MEV, Tmax, RH, RF, WS	GRS

Similarly, the correlation result for Sebha is illustrated in Table 3.4. From this table it can be seen that mean evaporation has the highest influence in this case, followed by maximum temperature and relative humidity. Table 3.5 shows the three models for this region according to the result.

Table 3.4: Correlation result in Sebha

	RF	*MEV*	*RH*	*SSH*	*Tmax*	*WS*	*GRS*
RF	1						
MEV	-0.17154	1					
RH	0.273465	-0.85662	1				
SSH	-0.19412	0.713197	-0.66997	1			
Tmax	-0.18056	0.933875	-0.82494	0.768067	1		
WS	-0.08435	0.690028	-0.61251	0.293371	0.608488	1	
GRS	-0.12755	0.887575	-0.81063	0.798194	0.8612	0.684715	1

Table 3.5: Input combinations of the models in Sebha

Model	**inputs**	**output**
M1	MEV, Tmax, RH	GSR
M2	MEV, Tmax, RH, SSH, WS	GSR
M3	MEV, Tmax, RH, SSH, WS, RF	GSR

The correlation result for Misurata is given in Table 3.6 and the corresponding models are given in Table 3.7. In this case as in Tripoli sunshine hour duration has the highest influence while wind speed has the least.

Table 3.6: Correlation result in Misurata

	RF	*MEV*	*RH*	*SSH*	*Tmax*	*WS*	*GRS*
RF	1						
MEV	-0.2975	1					
RH	-0.05718	-0.44383	1				
SSH	-0.54166	0.291998	0.217265	1			
Tmax	-0.50724	0.450315	0.193368	0.713902	1		
WS	0.195154	0.107732	-0.30731	-0.2599	-0.4534	1	
GRS	-0.59393	0.272132	0.302089	0.834315	0.727478	-0.15385	1

Table 3.7: Input combinations of the models in Misusrata

Model	**inputs**	**output**
M1	SSH,Tmax,RF	Rs
M2	SSH,Tmax,RF, RH, MEV	Rs
M3	SSH, RF, Tmax, RH, MEV, WS	Rs

The performance of the ANN based models are summarized in Table 3.8. From this table it is evident that models ANN-2 with R^2 value 0.932 during the testing stage, ANN-3 with R^2 value 0.890 during the testing stage and ANN-3 with R^2 value 0.794 during the testing stage, have the best performance for Tripoli, Sebha and Misurata regions respectively. However, R^2 values closer to 1 were expected, hence the need for ANFIS to check the possibility of getting better performance.

Similarly, the performance of the ANFIS based models are shown in Table 3.9. from this table it can be seen that models ANFIS-3 with R^2 value 0.97 during the testing stage, ANFIS-3 with R^2 value 0.94 during the testing stage and ANFIS-2 with R^2 value 0.89 during the testing stage, have the best performance for Tripoli, Sebha and Misurata regions respectively.

For the purpose of comparison, the performance of the ANN based models and ANFIS based models are compared and summarized in Table 3.10. From this table, we see that in all the three regions ANFIS based models outperformed the ANN, this is not surprising due to the fact that ANFIS combined the learning capability of ANN and ability of fuzzy inference systems to handle uncertainties, which make it more robust.

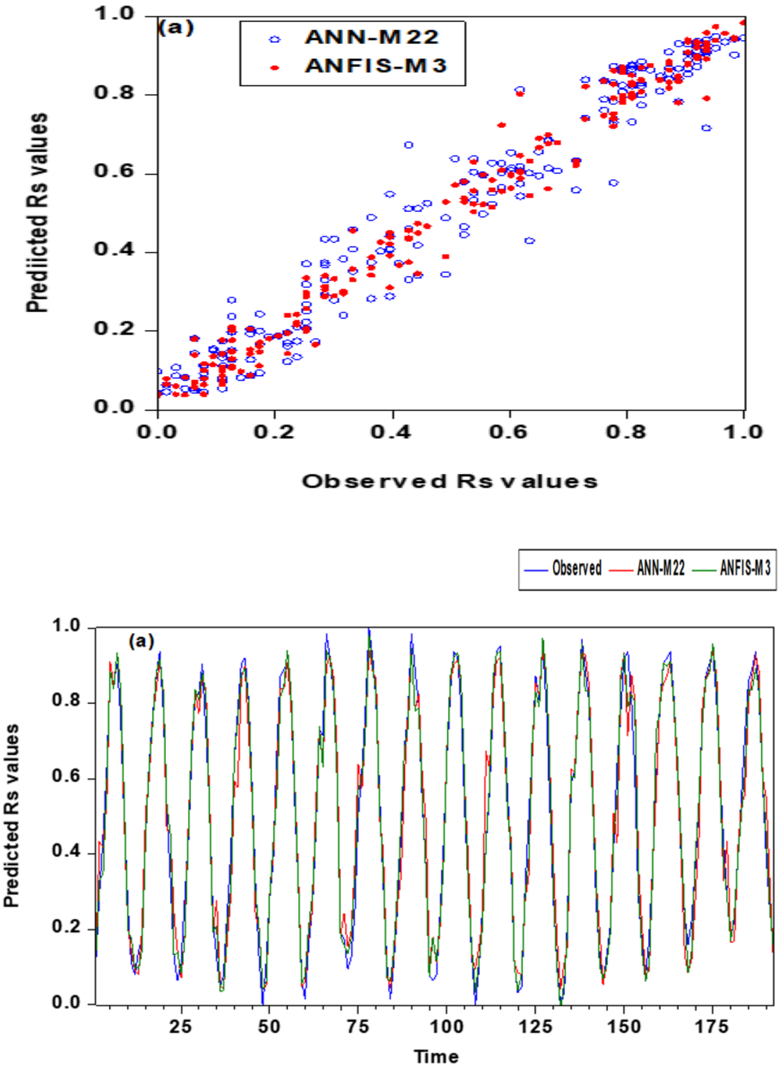
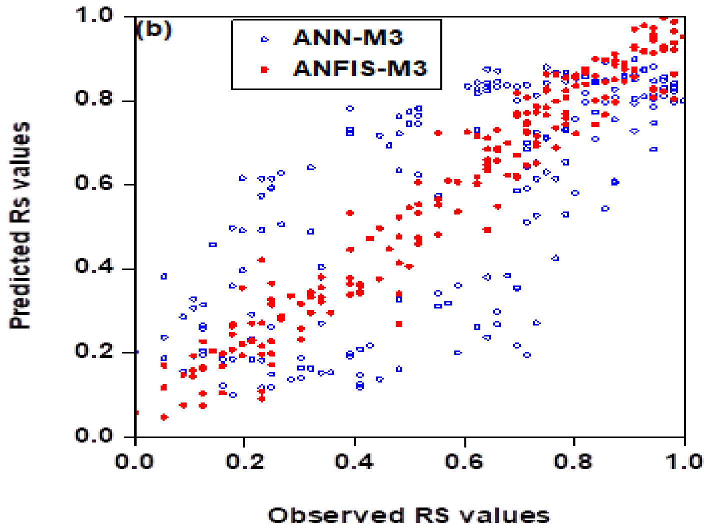


Figure 3.5: Time series and scatter plots for the best model in Tripoli

Furthermore, in the case of Misurata ANFIS-2 model which does not include wind speed in the inputs performs better than ANFIS-3. Figure 3.5, 3.6 and 3.7 show the scatter plots and time series fitting of the measured (observed) data and the model predicted values in the three regions; Tripoli, Sebha and Misurata respectively. From these plots it’s evident that the accuracy of the overall performance is impressive and therefore these models can be reliably used in estimation of global solar radiation in these regions.



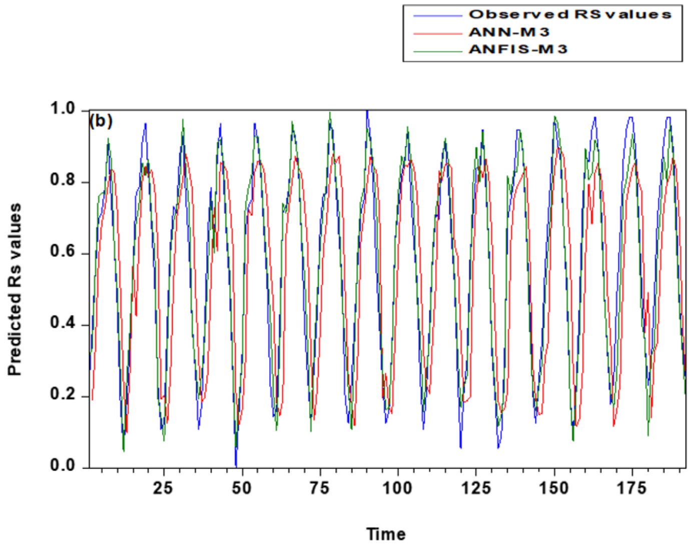
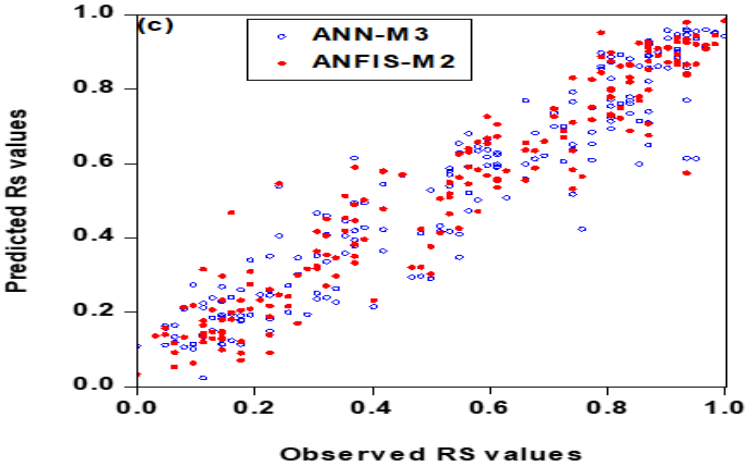


Figure 3.6: Time series and scatter plots for the best model in Sebha



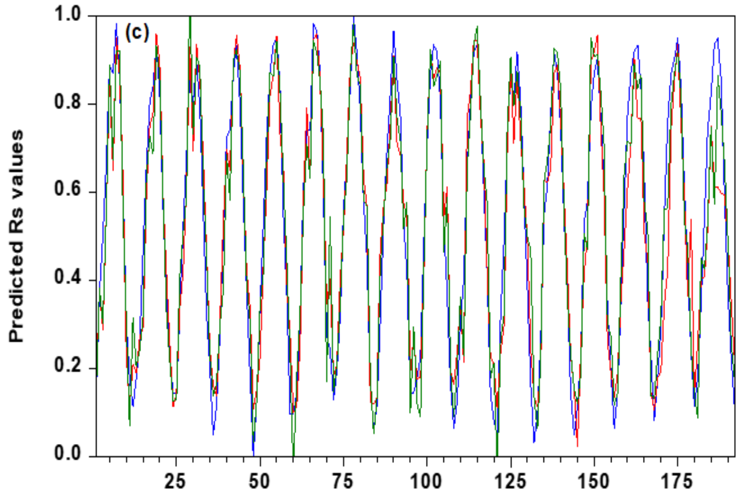


Figure 3.7: Time series and scatter plots for the best model in Misurata

Table 3.8: ANN Models Performance Evaluation

			Training			Testing		
	Regions	**Model**	R^2	**RMSE**	**MSE**	R^2	**RMSE**	**MSE**
		ANN-1	0.9555794971	0.06600567647	0.004356749326	0.8997330949	0.0938271921	0.008803541977
	Tripoli	**ANN-2**	**0.9573137325**	**0.06470437432**	**0.004186656056**	**0.9324902652**	**0.07698978655**	**0.005927427233**
		ANN-3	0.9620861238	0.06098017197	0.003718581374	0.902201681	0.09266497433	0.008586797467
		ANN-1	0.9003249252	0.09011447325	0.008120618289	0.8618389593	0.1191704774	0.01420160269
ANN	Sebha	ANN-2	0.8666021495	0.1042499077	0.01086804326	0.864903207	0.1178415378	0.01388662802
		ANN-3	**0.9076846765**	**0.08672377246**	**0.00752101271**	**0.8895318361**	**0.1065600582**	**0.01135504601**
		ANN-1	0.7549295018	0.1484730913	0.02204425884	0.400662454	0.23686003	0.05610267379
	Misurata	ANN-2	0.917862381	0.08595542438	0.00738833498	0.6582528613	0.1788580456	0.03199020046
		ANN-3	**0.9271933251**	**0.08092595494**	**0.006549010182**	**0.7940509324**	**0.1388468247**	**0.01927844073**

Table 3.9: ANFIS Models Performance Evaluation

			Training			Testing		
	Regions	**Model**	R^2	**RMSE**	**MSE**	R^2	**RMSE**	**MSE**
		ANFIS-1	0.9565903717	0.06525031081	0.004257603061	0.9095157989	0.08913254206	0.007944610054
	Tripoli	ANFIS-2	0.9724810058	0.05195242562	0.002699054528	0.9424608509	0.07107741628	0.005051999105
		ANFIS-3	**0.9811325543**	**0.04301759287**	**0.001850513297**	**0.9665055436**	**0.05422959754**	**0.002940849249**
		ANFIS-1	0.9143661656	0.08352643749	0.00697666576	0.9076243374	0.09744390161	0.009495313961
ANFIS	Sebha	ANFIS-2	0.9289241129	0.07609610146	0.005790616657	0.9162185371	0.0928004006	0.008611914351
		ANFIS-3	**0.9554683365**	**0.06023317038**	**0.003628034814**	**0.9375260863**	**0.08013555298**	**0.006421706851**
		ANFIS-1	0.8919256019	0.09859698774	0.009721365991	0.6961338591	0.1686542122	0.0284442433
	Misurata	**ANFIS-2**	**0.9171943967**	**0.08630423294**	**0.007448420623**	**0.8911620065**	**0.1009360489**	**0.01018808597**
		ANFIS-3	0.6312599	0.1821220033	0.03316842407	0.720701556	0.1616926561	0.02614451505

Table 3.10: Performance Comparison Between ANN and ANFIS

		Training			Testing		
Regions	**Model**	R^2	**RMSE**	**MSE**	R^2	**RMSE**	**MSE**
	ANN-2	**0.9573137325**	**0.06470437432**	**0.004186656056**	**0.9324902652**	**0.07698978655**	**0.005927427233**
Tripoli	**ANFIS-3**	**0.9811325543**	**0.04301759287**	**0.001850513297**	**0.9665055436**	**0.05422959754**	**0.002940849249**
	ANN-3	**0.9076846765**	**0.08672377246**	**0.00752101271**	**0.8895318361**	**0.1065600582**	**0.01135504601**
Sebha	**ANFIS-3**	**0.9554683365**	**0.06023317038**	**0.003628034814**	**0.9375260863**	**0.08013555298**	**0.006421706851**
	ANN-3	**0.9271933251**	**0.08092595494**	**0.006549010182**	**0.7940509324**	**0.1388468247**	**0.01927844073**
Misurata	**ANFIS-2**	**0.9171943967**	**0.08630423294**	**0.007448420623**	**0.8911620065**	**0.1009360489**	**0.01018808597**

CHAPTER 4

CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

Recently, the demand for renewable energy is increasing because of the increase in the need for pollution free energy sources. Solar energy is among the widely used sources of renewable energy. Reliable knowledge about solar energy is measured through the amount of global solar-radiation in a certain area. GSR measurement along with related meteorological information at a given location play a vital role in studying, designing and maintenance of solar energy based applications. Furthermore, this information will make the forecasting of performance and efficiency of solar-thermal equipment.

In Libya like majority of developing countries have problem with GSR measurement, and therefore there is no enough recorded data. Meanwhile, the relationship between GSR and relevant meteorological data is used to forecast the GSR. A number of publications have presented models for prediction of GSR in some parts of Libya. But generally, these models use only average sunshine hours to make the prediction and insufficient data were available, which restrict the efficiency of this models. Furthermore, these models rely on empirical and conventional methods, belonging to a family of linear models. These models give poor forecasting for few data samples. With recent advances in AI techniques, such as "ANN" and "ANFIS" techniques offered alternatives, and have been extensively used for prediction of many parameters in different places in the world.

In this thesis, artificial intelligence based (AI-based) models are introduced. These models are used to forecast solar-radiation in key areas of Libya. "ANN and ANFIS" based models are developed. The simulation is conducted using a PC CORE i5 with Matlab software and the prediction performances of the models are evaluated using "DC, MSE, and RMSE" performance measures.

The modelling is carried out using a meteorological data, collected from Libyan National Meteorological Centre Climate and Climate Change. The data collected is for sixteen years duration from 1995 to 2010, which is the only available global solar radiation measurements in these areas, as of the time of collection. The meteorological parameters are: monthly mean of global solar radiation (GSR), sun shine hours (SSH), maximum temperature (Tmax), rain-fall (RF), wind speed (WS), relative humidity (RH), mean evaporation (MEV). The three stations considered are Tripoli located at $32^{o}40'N$ latitude, $13^{o}09'E$ longitude and $81m$ elevation, Sebha located at $27^{o}01'N$ latitude, $14^{o}26'E$ longitude and $432m$ elevation, and Misurata located at $32^{o}19'N$ latitude, $15^{o}03'E$ longitude and $32m$ elevation.

The data collection is followed by data pre-processing including data normalization and sensitivity analysis. The sensitivity analysis is done by using three layer feed forward neural network, the result indicated that sunshine hour duration (SSH) is the most influential parameter for forecasting of GSR in these areas.

Furthermore, by considering the sensitivity analysis results, three inputs arrangement are used to developed the models as follows: $M1$ with $SSH, MEV\ and\ T_{max}$ as inputs, $M2$ with $SSH, MEV, RH, RF\ \ and\ T_{max}$ as inputs and $M1$ with $SSH, MEV, RH, RF, WS\ \ and\ T_{max}$ as inputs. This mean that we have three ANNs models ANN-1, ANN-2 and ANN-3 for each location, and similarly, we have three ANFIS models for each location ANFIS-1, ANFIS-2 and ANFIS-3. This is to select the optimum inputs combination for the prediction to avoid using redundant information.

In the case of ANNs the testing results indicated that ANN-2 with DC value equal to 0.932 has shown best performance in Tripoli. Whereas, ANN-3 with DC of 0.890 is the best for Sebha and ANN-3 with DC of 0.794 is best for Misurata. However, the performance of ANN-2 in Tripoli is best among all the three.

On the other hand, the performance of the ANFIS based models during the testing phase has shown that ANFIS-3 with DC value 0.97 is the best performance among the three models in Tripoli, while ANFIS-3 with DC value of 0.94 is also the best in case of Sebha and ANFIS-2 with DC value 0.89 is the best for Misurata.

When we compare the performance of the best among the ANNs and ANFIS models for each location we found that ANFIS-3 is the best for Tripoli, ANFIS-3 is the best for Sebha and ANIS-2 is the best for Misurata. This means that for forecasting of GSR in Misurata using our model, the wind speed data is not required. Furthermore, the scatter plots and time series fitting of the measured (observed) data and the model predicted values in the three stations are plotted, and from the graphs it's evident that the accuracy of the overall performance is impressive and therefore these models can be reliably used in estimation of global solar radiation in these regions.

4.2 Recommendation

Possible improvements can be made to further the performance of this models. It is recommended that other AI-based models should also be used such as state vector machine (SVM) which has a number of advantages. To achieve more accuracy the outputs of these individual models can be combine and used for the prediction through ensemble approaches, which demonstrated promising results in other works. Furthermore, accuracy of AI-models can also be enhanced by using large data which may make it possible to use deeplearning approaches.

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