MULTI-REGION ARTIFICIAL INTELLIGENCE BASED ENSEMBLE MODELING OF DAILY GLOBAL SOLAR RADIATION

A THESIS SUBMITTED TO THE

GRADUATE SCHOOL OF APPLIED SCIENCES

OF

NEAR EAST UNIVERSITY

By
ALA TAHSEEN MOHSIN

In Partial Fulfillment of the Requirements for the Degree of Master of Science
in
Civil Engineering

NICOSIA, 2018

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Ala Tahseen MOHSIN: MULTI-REGION ARTIFICIAL INTELLIGENCE BASED ENSEMBLE MODELING OF DAILY GLOBAL SOLAR RADIATION

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 Civil Engineering

Examining Committee in Charge:

Prof. Dr. Hüseyin GÖKÇEKUŞ	Committee Chairman, Dean of Civil and Environmental Engineering, NEU
Assoc. Prof. Dr. Gözen ELKIRAN	Supervisor, Civil Engineering Department NEU
Prof. Dr. Vahid NOURANI	Co-Supervisor, Civil Engineering Department NEU, University of Tabriz, Iran.
Assist. Prof. Dr. Pinar AKPINAR	Committee Member, Civil Engineering Department, NEU
Assist. Prof. Dr. Boran ŞEKEROĞLU	Committee Member, Information System, NEU

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To my parents and fiancé…

ABSTRACT

In this study, two Artificial Intelligence (AI) based models including Artificial Neural Network (ANN), Adaptive Neuro-fuzzy Inference Systems (ANFIS), three temperature-based empirical models including Meza and Varas (M-V), Hargreaves and Samani (H-S), Chen (CH) and conventional Multi-Linear Regression (MLR) models were employed for multi-region daily global solar radiation estimation for Iraq. To determine the dominant parameters, to ensure appropriate selection of input variables, sensitivity analysis was conducted. Finally, two ensemble approaches, Neural Average Ensemble and Simple Average Ensemble, were applied to improve the performance of the single models. For this purpose, daily meteorological data of maximum temperature (T_{max}), minimum temperature (T_{min}), mean temperature (T_{mean}), relative humidity (R_H), and wind speed (U_2) were obtained from January 2006 to December 2016 from four major cities in Iraq representing, North, West, South, and East regions. Two global statistics of Root Mean Square Error (RMSE) and Determination Coefficients (DC) were employed for performance evaluation of the models. The results revealed that temperatures (T_{max}, T_{mean}, T_{min}) and relative humidity are the dominant parameters, temperature-based empirical models and MLR model could be employed to achieve the valuable results, AI based models are superior in performance to other models, also promising improvement in daily global solar radiation modeling could be achieved by model ensemble. The results of this study affirmed that the provided ensemble approaches can increase the performance of single models up to 19.19%, 7.59%, and 16.81% for training, validation, and testing respectively.

Keywords**:** Artificial Intelligence; Adaptive Neuro-fuzzy Inference System; Iraq; Single Models; Ensemble Approaches

ÖZET

Bu çalışmada, Irakta çoklu bölge günlük küresel güneş ışığı tahmini için, Yapay Sinir Ağları (YSA), Uyarlamalı Nöro-Bulanık Çıkarım Sistemleri (ANFIS) olmak üzere İki Yapay Zeka (AI) temelli model, sıcaklığa dayalı üç empirik model; Meza ve Varas (M-V), Hargreaves ve Samani (H-S), Chen (CH) , ve konvansiyonel Çok Doğrusal Regresyon (MLR) modeli kullanılmıştır. Girdilerin uygun seçimini sağlamak için, dominant parametreleri belirlemek adına duyarlılık analizi yapılmıştır. Son olarak, tekil modellerin performansını geliştirmek için iki topluluk (ensemble) yaklaşımı uygulanmıştır. Bu amaçla, maksimum sıcaklık (Tmax), minimum sıcaklık (Tmin), ortalama sıcaklık (Tmean), bağıl nem (R_H) ve rüzgar hızının (U_2) günlük meteorolojik verileri Ocak 2006 ile Aralık 2016 arasında Irak'taki dört büyük bölgeyi temsil edecek şekilde; Kuzey, Batı, Güney ve Doğu bölgeleri olarak seçilmiştir. Modellerin performans değerlendirmesi için Kök Ortalama Kare Hatası (RMSE) ve determinasyon Katsayıları (DC) olmak üzere iki küresel istatistik kullanılmıştır. Sonuçlar, çalışma amacına ulaşmak için sıcaklıkların (Tmax, Tmean, Tmin) ve bağıl nemin baskın parametreler olduğunu, sıcaklık tabanlı ampirik modellerin ve MLR modelinin makul sonuçlar elde etmek için kullanılabileceğini göstermiştir. AI tabanlı modeller, diğer modellere göre performans açısından üstünlük göstermiştir, ayrıca günlük küresel güneş radyasyonu modellemesinde umut verici bir iyileşme topluluk modeleri tarafından gerçekleştirilmiştir. Bu çalışmanın sonuçlarından, topluluk modellerin kullanımını tekli model kullanımına oranlar 19.19%,7,59%, and 16,81% kadar daha iyi sonuçlar elde edilmiştir.

Anahtar Kelimeler: Yapay Zeka; Uyarlamalı Nöro-Bulanık Çıkarım Sistemi; Irak; Tek Modeller; Topluluk Yaklaşımları

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CHAPTER 1

INTRODUCTION

1.1. Solar Radiation

Solar radiation is a fundamental input in renewable energy application, hydrology, meteorology, and climatology. It is the amount of radiant light and heat that reaches the earth's surface (Budyko, 1969). The solar radiation can be used for many applications such as increasing the water temperature and creating electricity using photovoltaic cells. Also the solar radiation is a very essential component for performing the photosynthesis in the green plants and for the evapotranspiration process. However, it is required for illumination and heating of the buildings and many other domestic uses. The solar radiation is considered one of the most preferred renewable power since it is free, available in many regions and it doesn't produce any pollutant (Dorvlo et al., 2002).

Since the 19th century, the household's fossil fuel consumption has rapidly increased, this led to higher rates of pollution, more health risks, and badly affected climate. In the past 25 years, the world witnessed a remarkable development in the green and alternative energy techniques. Many people think that it is critically required (Katiyar and Pandy, 2013). One of the most essential types of the green energy is the Solar Energy. Solar radiation can be measured in many ways, such as Direct Solar Radiation at normal incidence, Global Solar Radiation, Direct Solar Radiation on a horizontal surface, Reflected Solar Radiation, Diffuse Solar Radiation, Upward Longwave Radiation, Downward Longwave Radiation and others (Mani, 2008). For measuring the direct solar radiation, many devices are used such as the Pyrheliometer, the Pyrometer and the Photoelectric Sunshine Reader (Guide, 2006). But the values of global solar radiation are considered as the most necessary values for solar energy uses (Behrang et al., 2010).

Many parameters are being utilized as inputs for predicting the global solar radiations, such as the astronomical parameters, the geographical parameters, the geometrical parameters, the physical parameters and the meteorological parameters (Almorox, 2011). The meteorological factors are widely used for estimating solar radiation in different weather conditions, these include: hours of sunshine, humidity, max/min/mean temperatures, bright sun hours, pressure, average of sea levels, water perception and others (Trabea and Shaltout, 2000). In the absence of global solar radiation long-term data in many areas, the conventional empirical models, as well as recently used soft computing techniques are developed as two methods for prediction and estimation of global solar radiation (Sharifi et al., 2016).

The empirical formula provides a simple explicit formula for solar radiation estimation. Four categories of empirical (i.e. meteorological) models are defined based on the cloud, temperature, sunshine, and other meteorological parameters (Besharat et al., 2013). A simple Angstrom-Prescott equation that estimates global solar radiation using sunshine hours is the most widely applied empirical models (Zhao et al., 2013). Despite it is confirmed better performance in the calibration of sunshine-based models for solar radiation estimations (Li et al., 2013a, 2013b), lack or insufficiency of sunshine records, results in the inapplicability of Angstrom approach (Tymvios et al., 2005).

Therefore, developing temperature-based model is quite essential as air temperature being the most obtainable variable. The primary advantage of temperature–based empirical models are only air temperature data is employed in the solar radiation estimation, thus, implementation requires less experience and time. Moreover, preferable tool solar radiation is for the calibrated temperature-based models due to readily availability of air temperature data. Minimum and maximum temperature difference (ΔT) is the major parameter that affects the precision and accuracy of the temperature based models. Predictive accuracy improves with a larger temperature difference (ΔT), implying that where a larger range of temperature values is available, there are more applicable temperature depended models (Besharat et al., 2013).

Apart from Artificial intelligence (AI) techniques for long-term data prediction of solar radiation, the models (AI models) are capable of coping with missing and random data, whereas regression models performance is negatively affected by the presence of outliers (Assi et al., 2013).

Where empirical models prediction are not sufficient to provide persistent success due to uncertainty (Mohanty et al., 2016). The AI models are splendid tools that provide solutions to real-world problems (Yacef et al., 2012). AI techniques in more recent time including Artificial Neural Network (ANN), Multilayer Perceptron Neural Network (MLP), Genetic programing (GP), Radial Basis Function Network (RBFN), Support Vector Machine (SVM), Gene Expression Program (GEP), Recurrent Neural Network (RNN), hybrid networks, and Adaptive Neuro-Fuzzy Inference system (ANFIS) have been applied for forecasting and modeling of solar radiation (Yadav and Chandel, 2014; Mellit, 2007; Mohanty et al., 2016; Kalogirou, 2001).

Among all models, Artificial Neural Networks (ANNs) is an effective way of prediction, function approximation and modeling of complex problems. Good efficiency more especially when the parameters are non-linear in nature is the major advantage of the application of ANN over empirical models (Debnath et al., 2000). ANN became very popular among researchers (Chow et al., 2002; Sozen et al., 2004), and that is due to its flexibility in various fields of engineering, hydrology, medicine, meteorology, neurology, psychology, economics, mathematics (Cam, 2005; Mohandes et al., 2004). ANN includes simple elements known as neurons. These neurons receive inputs and change the internal states accordingly (Russell and Norvig, 2016). Using ANN technique, complicated cases can be figured out since it is trained to pass the limits of the conventional approaches (Cam et al., 2005).

ANFIS as another type of AI approach has been also employed for the estimation of solar radiation by some researchers. ANFIS is a hybrid intelligent system which incorporates both ANN learning power and fuzzy logic knowledge representation. Therefore, most advantages that ANFIS has been its adaptability and computational efficiency (Mohammadi et al. 2015). In this technique, the experts merged the basics of both neural network and fuzzy logic. One of the most functional systems used in ANFIS is a Surgeon system of modeling. That is due to its compatibility and computability (Takagi and Surgeno, 1985). ANFIS is composed of five layers; the input, fuzzification, rule, normalization, and defuzzification. Another statistical approach is MLR (Multi -Linear

Regression) which is widely used for modeling relationships between dependent and independent variables to have a linear relation (Abdullahi et al., 2017).

Though the mentioned AI based black box models (e.g. ANN, ANFIS, and MLR) may provide reasonable and reliable results, it is obvious that for a given set of data, the performance of one intelligent technique may surpass another, and when different sets of data use the results may entirely be opposite. In order to benefit from the advantages of all the intelligent techniques and also not to lose generality, a recently unveiled modeling approach called ensemble model provides better predictive performance by utilizing the single output of each intelligent technique with certain priority level assigned to each with the help of an arbitrator, provides the output (Kiran and Ravi, 2008). In ensemble model, the individual constituents obtained as output from each applied technique is used as an input to the model which based on the design of the arbitrator, is processed to give overall output (Kiran and Ravi, 2008). Some techniques of ensemble nature for problems prediction with continuous variable dependent comprised of linear ensemble, such as Stack regression (Breiman, 1996), Simple average (Benediktsson et al., 1997), Weighted average, and Nonlinear ensemble, such as neural-network-based (Yu et al., 2005). According to Kiran and Ravi (2008), there are two ensemble methods: (i) Linear Ensemble method; which includes linear ensemble by simple averaging, linear ensemble by weighted averaging, and linear ensemble by weighted median. (ii) Nonlinear ensemble method; ANN is trained to obtain an ensemble output.

1.2. Problem Statement

In many developing countries, the availability of solar radiation measurements is low, that is because of the high cost of the equipment and the complication of the technical procedure (Assi and Jama, 2010). The Middle East is considered one of the rich regions in solar energy in the world, but this energy is not invested in a proper way due to the limited number of solar radiation measurement stations (Kadouri, 2012). Setting the solar radiation stations at each area is not available everywhere since it is a costly process, so the necessity of creating methods of predicting the solar radiation became critical and many models were built and improved to estimate the global solar radiation (Meenal et al., 2016). Due to climate change and increase in water demands as a result of increase in the world population, arid and semi-arid regions are facing shortage of water (such as Iraq which has mostly arid land). To this effect, estimation of solar radiation is important for the determination of evapotranspiration which in turn helps in predicting irrigation water requirements for agricultural production (Goyal, 2004; Zhang, 2018).

1.3. Objectives of the Study

The objectives of this study are to:

I. Determine the suitability and acceptability of temperature-based empirical models for the prediction of daily global solar radiation in Iraq.
II. Determine the most dominant parameter through sensitivity analysis of inputs on output.
III. Apply AI-based (ANN and ANFIS) and MLR models to predict daily global solar radiation in Iraq and compare their performances.
IV. Develop two multi-region ensemble models to ascertain the superiority and the level of increase in predictive performance that can be reached over single models.

1.4. Hypothesis

The hypotheses are;

- Temperature-based empirical models which utilize only maximum and minimum temperatures cannot give satisfactory results.
- Being majority of Iraq is arid, temperature will be the most influential parameter in estimating solar radiation.
- Owing to their performance in solving complex problems, AI-based models will provide better performance than MLR model.
- Being developed by combining the outputs of many models, results by ensemble modeling will be superior to those obtained by single models.

1.5. Significance of the Study

In the realm of solar radiation estimation, up-to-date inspection of the published articles suggested that:

- This will be the first study that employs at least two AI models to estimate solar radiation in Iraq.
- This will be the first study to utilize different empirical and AI models for the prediction of solar radiation in Iraq.
- This will be the first study in the world to perform multi-regions ensemble modeling using 3 empirical models, 2 AI models and an MLR model to predict daily global solar radiation.

Hence at the successful completion of this study, a lot of issues concerning solar radiation in Iraq in particular and in the world at large could be solved, including possibility of using temperature-based models to predict solar radiation in Iraq, the best model to apply in Iraq to achieve better prediction, the performance of ensemble model with few and many inputs.

CHAPTER 2
LITERATURE REVIEW

2.1. Previous Studies for Iraq

Due to the importance of global solar radiations especially in the developing countries where measuring equipments are scarce owing to cost and technology limitation, some studies were conducted to predict solar radiation in Iraq which include:

Jadallah et al. (2012) studied the behavior of diffused, extraterrestrial, and beam radiation. The results indicated a good correlation between predicted and measured radiance.

Hameed et al. (2017) developed two mathematical models (Isotropic and Isotropiz) used Matlab for solar radiation hourly allocation. Under the various sky status (clear, semi cloudy and cloudy). The results showed that value of radiation was very small in both morning and night, but from 9 till 15, the value of global radiation showed a peak also this studied showed that the angle of surface inclination affects the radiation value.

For forecasting the daily average of the global solar radiation on a horizontal level by the term of sunlight, the Al-Ghezi, (2017) used a mathematical linear relationship promoted from "Angstrom relation". The study was applied on Baghdad and the results indicated that the largest value of radiation is in June while the smallest is in December.

With limited meteorological data, Al-Naimi et al. (2014) applied ANN to predict global solar radiation in Baghdad, Iraq. RMSE and $R^2$are the two statistical indicators applied to determine the performance of the model. The results showed ANN can be used successfully to estimate solar radiation in Baghdad as good agreement was established between ANN predicted and measured values.

Al-Jumaily et al. (2012) estimated under clear sky condition an hourly global solar radiation in Iraq using simple model and compared the obtained results with measured values from several Iraq's locations using Meteosat satellite data and local stations from Baghdad city. The results revealed that for all Iraq's location, measured and calculated value agreements were fairly good.

Al-Riahi and Al-Kayssi (1998) examine and studied some radiation and climatology aspects which have significant values to the utilization of solar energy. The obtained results revealed that the daily global solar radiation annual mean and its spectral in Baghdad varies with the months.

Al-Hamdani et al. (1989) studied clearness index, diffuse fraction and fractional sunshine duration in Baghdad using data collected between 1985-1986 at Fudhaliyah to determine their daily correlation. Comparison was made with page's correlation which showed a good agreement between clearness index and diffuse fraction for monthly average.

Al-Riahi et al. (1990) used data from 1984-1987 obtained from experimental station to measure diffuse and global solar radiation in Baghdad, Iraq. Obtained results showed a quite low cloudy days percentage frequency on the basis of yearly average. Variation of clearness monthly average index was witnessed also between September and December.

Ahmad et al. (1983) applied a number of correlations to predict solar radiation in Iraq using relative humidity, dry bulb temperature, and sunshine duration. Sunshine duration correlative gave the most accurate estimate. Correlation constants representing Iraq's three climate regions for three stations were also determined. Finally, yearly and monthly solar radiation maps were drawn from all over Iraq using sunshine duration data.

Al-Salihi et al. (2010) used Mosul, Baghdad, and Rutba data representing different Iraq's weather condition for the global solar radiation prediction. The correlation coefficient values vary from Rutba station 89% to Baghdad station 97% and 0.035-0.063 error estimation. Finally, concluded that reasonable predictions were achieved by the global solar radiation presented models.

2.2. Empirical and Conventional Models

The empirical formula provides a simple explicit formula for solar radiation estimation. Four meteorological (empirical) classifications of models are defined based on cloud, temperature, sunshine, and other meteorological parameters (Besharat et al., 2013). To study global solar radiation effective prediction method, the statistical analysis shall be dependent on the measurement comparison of daily and the calculated solar radiation. (Yorukoglu, 2006).

Angstrom (1924), developed a linear regression model to predict the solar radiation, the study was conducted in Malawi, this study utilized variables such as hours of sunshine data collected at six (6) different meteorological stations.

In the Almorox and Hontoria (2004) article, the global solar radiation was predicted by utilizing sunshine, relative duration data collected from the meteorological measuring station located in Turkey/Nide to produce many equations. These equations were based on the linear regression functions of Angstrom-Prescot (the original is the modified ones). To validate the output of the equations, comparisons were made with the measured data regarding the standard statistical tests (RMSE, Mean Absolute Percentage Error MAPE and determination coefficient), the study proved these models using only sunshine duration data can be utilized for the global solar radiation prediction. Furthermore, the results showed that the linear models gave more accurate estimation values than the other one.

Both authors Muneer and Gul (2000), recommended that the models using meteorological parameters as input can be utilized well for global solar radiation estimation. Sunshine data and the cloud cover data were combined to develop the estimation model. The combined models were effective in estimating the global solar radiation during the overclouded conditions. While the model which was based on the sunshine fraction only gave better results in the partly-clear or clear sky weather.

To predict a horizontal surface's global solar radiation data Muzathik et al. (2011), used sunshine data as input for the estimation models designed based on the Angstrom-Prescott model, and the measured values collected from Kuala Terengganu station were utilized to calculate the values of monthly mean. The study strongly recommended using the proposed model to simulate the global solar radiation in Terengganu state regions.

Glover and McCulloch (1958) study demonstrated the empirical relationship between sunshine hours and solar radiation.

Rehman (1999) applied average daily rates of global solar radiation in addition to the sunshine hours data located in (41) regions in Saudi Arabia to predict the values at other areas where the values were not measured. The results of this developed estimation model were validated by comparing them to the values resulted from other models designed under different conditions (meteorological and geographical), and that comparison was performed by utilizing standard statistical tests, including ”RMSE”, “MBE”, ”MPE” and “MAPE” tests. The results indicated that the model gives the best prediction of global solar radiation.

Sunshine data were utilized to predict solar radiation through Angstrom- Prescot model when the effectiveness of the model is being studied, statistical parameters such as R^2, MBE, RMSE, MPE, MAPE, and MABE are being used in dependence on the ratio of daily solar and extraterrestrial radiations.

A simple Angstrom-Prescott equation that estimates global solar radiation employing sunshine hours is the most widely applied empirical models (Zhao et al., 2013). Despite its confirmed better approximation in the sunshine-based models calibration for solar radiation estimations (Li et al., 2013a, 2013b), lack or insufficiency of sunshine records, results in the inapplicability of Angstrom approach (Tymvios et al., 2005).

Therefore, developing temperature-based model is quite essential as air temperature being the most obtainable variable. The fundamental significance of temperature–based empirical models is only air temperature data is employed in the solar radiation estimation, thus, implementation requires less experience and time. Moreover, the preferable tool for solar radiation estimation is the calibrated temperature-based models due to readily availability of air temperature data. Minimum and maximum temperature difference (ΔT) is the major parameter that affects the precision and accuracy of the models based on temperature. Predictive accuracy improves with a larger temperature difference (ΔT), implying that where a larger range of temperature values are available, there are more applicable temperature depended models (Besharat et al., 2013).

A number of temperature-based empirical models have been developed in the past for daily global solar radiation estimation (Hassan et al., 2016; Besharat et al., 2013). Daily total extraterrestrial radiation R_a is usually involved in the relationships (Almorox et al., 2011).

In this study, the models selection and evaluations were done in view of the advantages of the models such as availability of temperature data, simplicity, extensiveness of use and higher performance reported.

For solar radiation estimation Hargreaves and Samani (1982) introduced a simple equation using maximum and minimum temperatures only.

Meza and Varas (2000) provided an equation using single coefficient (b) and temperature diffrerence (ΔT) to estimate solar radiation.

Chen et al. (2004) used daily air temperature difference and logarithmic relationship between extraterrestrial radiation (R_a) and solar radiation (R_s) to develop an equation for solar radiation.

For modeling daily solar radiation, Ayodele et al. (2015) applied modification to Angstrom-Prescott for Ibadan, Nigeria using temperature-based model. The data used were daily average temperatures (maximum and minimum), and global solar radiation. The obtained results revealed that quadratic temperature model provided the best predictive performance.
Almorox et al. (2011) introduced a new model by simulating several existing models to investigate the performance of temperature-based models for global solar radiation in Madrid, Spain. The results showed that the new model developed performed accurately in the prediction.

Sharifi et al. (2016) performed a study which compared 5 temperature-based empirical models and artificial intelligence models concluded that provided the empirical parameters are adjusted correctly, temperature-based model's performance would be reasonable.

Ibeh et al. (2012) estimated based on climate parameters including cloudiness, relative humidity, sunshine duration and maximum temperature estimated global solar radiation in monthly bases fo for Warri, Nigeria from the years 1991 to 2007 by using angstrom and MLP ANN models . statistical analysis have been taken such as MPE, RMSE and MBE.To compare the performance of ANN models and Angstrom-Prescott model. The compared results showed the superiority of ANN model over Angstrom–Prescott empirical model.

Almorox and Hontoria (2004) used measured temperature data for many locations in Madrid, Spain for global solar radiation estimation. By developing and calibrating several models (third degree, quadratic, exponential functions and logarithmic) in the conclusion of the study results showed that empirical models have performed well in every location, if the parameters are correctly combined.

2.3. Artificial Neural Networks (ANNs)

ANNs are an effective way of prediction, modeling of complex and function approximation problems. Good efficiency more specifically when the parameters involved are non-linear in nature is the major advantage of the application of ANN over empirical models (Debnath et al., 2000). ANN and Physical method are important for the calculations related to solar energy models. Construction of the solar radiation data base is required in agricultural, environmental, and other applications for solar energy estimation (Senkal and Kuleli, 2009). Within the last 10 years ANN has affected researchers from different fields of learning including researches in Hydrology, Financial market simulation, Agriculture, Engineering and even in the medical field (Coulibaly, 2003).

Where empirical models prediction are not sufficient to provide persistent success owing to uncertainty (Mohanty et al., 2016), the fantastic AI techniques are splendid tools that provide solutions to real world problems (Yacef et al., 2012). AI-techniques in past recent time including ANN, RBFN, MLP, GP, SVM, GEP, RNN, hybrid networks, and Adaptive Neuro-Fuzzy Inference system (ANFIS) have been applied for forecasting and modeling solar radiation (Yadav and Chandel, 2014; Mellit, 2008; Mohanty et al., 2016; Kalogirou, 2001).

To overcome the conventional approaches limitations ANN is trained to solve complex problems (Mohandes, 2004). In other words, corresponding output values and input data are needed for the training and testing of a neural network (Cam, 2005).

Assi et al. (2013) applied radial and multilayer perceptron neural networks to predict global solar radiation in Al-Ain, and Abu Dhabi, and Dubai using different input combinations. The results revealed that the generalization ability of ANN makes it capable of providing accurate predictions.

Benghanem et al. (2009) applied ANN for the modeling and daily global solar radiation. The obtained results implied that ANN can be used sucessfully to estimate solar radiation.

Lam et al. (2008) developed ANN for the prediction of daily global solar radiation for fourty cities in China which covered the major sub-zones and thermal climate zone using measured sunshine duration. The results revealed that global solar radiotion can be successfully be estimated by the the application of ANN.

Bulut and Büyükalaca (2007) studied a set models for daily global solar radiation prediction. The trigonometric function was the basis of this model. For validating the model 68 regions were tested in Turkey utilizing the measured data collected through 10 years duration. The results indicated that the proposed model showed good agreement with the long term measured data. Also, it was recommended that the model can be well used to design the energy system and for global solar radiation prediction in any area in Turkey.

Sahin et al. (2013), in their research for daily global solar radiation prediction a comparison between multi linear regression (MLR) and ANN. The data were taken in Turkey from 73 different regions. The input parameters utilized in the study were (latitude, Land surface temperature, altitude, longitude and month). The results depicted that ANN performed well better than multi linear MLR for global solar radiation prediction.

Rao et al. (2012) applied ANN for global solar radiation prediction employing meteorological parameters including relative humidity, temperature, month and date of the year, the best combination used as input parameters were date, month, and temperature.

Joseph and Lam (2008) developed ANN models for prediction of daily global solar radiation by employing 40 cities measured sunshine duration in china.

Moreno et al. (2011) performed a comparative study using Kernel Ridge Regression (KRR), ANN and Bristow-Campbell BC) based on minimum and maximum air temperature for daily global solar irradiation mapping over spain.

Mohandes (1998) performed global solar radiation estimation using ANN approaches where the radiation data where collected from (41) stations (data gathered from 31 regions were utilized for training the model while the remain 10 were utilized for testing).The results showed the validity of the suggested model to be used in the locative modeling of the global solar radiation.

Jianyuan (2017) study compares and analysed the details of the two prediction models. The results showed similar performances between sunshine duration fraction and ANN models in predicting daily global radiation on montly average bases, while the estimation techniques are needed to study atmospheric attenuation on shorter time intervals and the mechanisms for solar radiation.

Senkal (2009) applied ANN to estimates solar radition in 12 stations of Turkey using data from August to December 1997. The data were devided into 9 and 3 stations for training and testing, respectively. Geographical and meteorological data including altitude, month, longitude, mean beam radiation, latitude etc. were utilized as inputs to the network. Also, C3 D data Meteosat-6 were used over the cities where visible. The results were obtained and presented.

Premalatha and Valanarasu (2012) used ANN Gradient descent back propagation with adaptive learning for solar radiation estimation in India. In the study daily average data such as (maximum and minimum ambient temperature, minimum relative humidity were used as inputs. The results revealed that ANN performed well in predictions of global solar radiation (GSR) for the study region with available minimum ambient temperature.

Ahmed and Adam (2013) estimated average monthly,daily global solar radiation (GSR) applying ANN in Qena, north Eygpt. The results indicated a good correlation between predicted and measured (observed) global solar radiation values.

Kumar et al. (2013) unvailed a new regression model based on Angstrom-Prescott Model to estimate daily global solar radiation (GSR) in monthly average bases in North India. In the study neural fitting tool (nftool) of the neural network was used.as a result artificial neural network (ANN) performed best correlation between predicted and observed global solar radiation values.

Al-Alawi and Al-Hinai (1998) applied ANN based model to predict global radiation (GR) in northern Oman. The study analysed the correlation between global radiation (GR) and climatological parameters. The results showed the superiority of the ANN based model which provided good accuaracy between observed and predicted data.

A Multilayer perceptron type of ANN was trained to estimate daily global solar radiation (GSR) in a semi-arid environment as a function of air temperature (minimum and maximum) only. The results indicate that ANN performed well in comparison to Hargreaves and Samani (HS) empirical equation (Rahimikhoob, 2010).

Hasni et al. (2012) tested the performance of ANN technique for the estimation of global solar radiation (GSR) in Western Algeria. In the study the input parameters of (relative humidity and air temperature) were employed as input combination. The result showed that the employed artificial neural network perform well for global solar radiation prediction (GSR).

Lu et al. (2011) suggested a simple algorithm with ANN model to investigate the non-linear physical interpretation in between ground measurement of GSR and MTSAT measurement in china. In the study a three layered feed forward neural network (FFNN) was trained. The obtained results showed the simple algorithm model built with artificial neural network (ANN) is capable of performing good and accurate estimation of global solar radiation (GSR) better than geostationary satellite data in terms of both time and space.

Linares-Rodríguez et al. (2011) predicted daily synthetic global solar radiation by applying ANN. In their study, four meteorological parameters were used as input (skin temperature, total column water vapor, total column ozone, total cloud cover) that are taken from satellite data (ERA-Interim reanalysis) in Andalusia (Spain). The results indicated the ability to generalize this approach to invisible data and its ability to generate accurate predictions and estimations.

Ouammi et al. (2012) estimated annual and monthly global solar radiation (GSR) by using artificial neural network (ANN) in Morocco. In their study a three layered, back propagation type of artificial neural network (ANN) was used and the data are taken from

from the new Satellite Application Facility on Climate Monitoring (CM-SAF)-PVGIS database.the normalized input parameters were (latitude, longitude, elevation) and solar radiation (SRD) as a target. Results indicated that application of artificial neural network (ANN) technique could be used by investigators and engineers to give valuable information to consult in planning of new solar plants, design and sites selection.

Sivamadhavi and Selvaraj (2012) predicted monthly mean daily global solar radiation in India by using a back propagation based, MLFF. In the study, geographical, meteorological, solar and climatological variables of three separate regions were used as input parameters. The results indicated that the developed ANN model are capable of performing well for global solar radiation estimation (GSR) in the regions where there is no available data of measured solar radiation.

Yildiz et al. (2013) developed and compared two models for global solar radiation (GSR) prediction in Turkey by using logistic sigmoid transfer function and Scale conjugate gradient learning algorithms network. In this study the input parameters used for the first model (M1) were (longitude, latitude, month, altitude, surface temperature and meteorological land) and the input parameters used for the second model (M2) (altitude, longitude, altitude, satellite land, surface temperature and month). The results were reliable to predict global solar radiation (GSR).

Kadirgama et al. (2014) developed a quick propagation algorithm of ANN. To predict global solar radiation (GSR). In their study physical interpretation were discussed for wind speed, temperature, humidity, wind chill, pressure. The results implied that applying ANN model inspire the researchers to plan and design solar radiation.

Angela et al. (2011) developed a single parameter model with FFNN in Kampala to predict global solar radiation by using sunshine hours. The study indicate that predicting global solar radiation in the region where the data station are not available could be estimated by using single parameter.

Sanusi et al. (2013) developed an ANN model to predict daily global solar radiation (GSR) in Sokoto. In the stud, air temperature, mean daily data for sunshine hours and relative humidity data, with day and month number of three years data were used as the input parameters. The results indicated that application of artificial neural network (ANN) give a good accuracy in forcasting global solar radiation in different regions having similar climatic factor.

Yacef et al. (2012) predicted daily global solar radiation in Saudi Arabia by using artificial intelligence techniques. The study compares the results obtained from the classical Neural Network (NN), Bayesian Neural Network (BNN) and empirical approaches. In their study, relative humidity, air temperature, sunshine duration and extraterrestrial radiation were used as inputs to the network. The results depicted that the superiority of Bayesian Neural Network (BNN) over the other classical NN and empirical models.

Lazzús et al. (2011) developed an ANN model for hourly global solar radiation estimate in La Serena, Chile. In the study meteorological parameters of soil temperature air temperature, wind speed, and relative humidity were used. The comparison of the obtained results were made between the observed data and predicted data obtained from other available models that are reviewed in literature. The results indicated that neural network (NN) performed well in estimating hourly global solar radiation with good accuracy. MLP were trained to predict daily global solar radiation (GSR). In the study air temperature data were used as input combination in regions were the environment is semi-arid. Comparison between artificial neural network and the Hargreaves and Samani (HS) empirical equations were performed. The results of the study depicted that artificial neural network (ANN) technique performed well in comparison to other empirical models.

Rahimikhoob (2010) used air temperature data and ANN to predict global solar radiation in a semi-arid environment. The results a promising performance by ANN.

Koca et al. (2011) predicted GSR by developing an ANN model. In their study meteorological data which were taken from the meteorological station loctaed in Turkey were used. The study aim was to discuss the physical interpretation among the input parameters. The result of the study demonstrate that combination of input parameters plays an important role in prediction of GSR.

Senkal (2009) trained different ANN algorithms such as Scale conjugate gradient (SCG), Resilient propagation (RP), logistic sigmoid transfer function and learning algorithms. Geographical and meteorological data were taken from twelve (12) station in different regions of Turkey. The parameters used as input involved (longitude, latitude, altitude, month, mean beam radiation and mean diffuse radiation). The obtained results were reliable enough for forcasting solar radiation.

Ozgoren et al. (2012) generated a multi nonlinear based ANN model for prediction of daily (GSR) in Turkey. The meteorological data were taken from (31) different stations. The input parameters were longitude, atitude, month, altitude, monthly minimum atmospheric temperature, mean atmospheric temperature, maximum atmospheric temperature, relative humidity, soil temperature, rainfall, wind speed, vapor pressure, atmospheric pressure, sunshine duration and cloudiness). The study compares the real values with predicted values that are obtained by training ANN. The result of the study showed ANN performed well in prediction of solar irradiance.

Tymvios et al. (2005) Used two techniques to develop and test complex models. In one of the technique Angestrom linear model was developed, by using sunshine hours while in the second technique an ANN model generated based on climatological variables and sunshine hours. The results were compared to both techniques, ANN technique performed well in estimating solar radiation in regions where there is missing measurement of sunshine hours.

2.4. Adaptive Neuro-fuzzy Inference System (ANFIS)

ANFIS is a type of Artificial Intelligence (AI) approaches employed for the estimation of solar radiation by some researchers. ANFIS is a hybrid intelligent system which incorporates both ANNS learning power and fuzzy logic knowledge. Therefore, most advantage that ANFIS has is its adaptibility and computational efficiency. (Mohammadi et al., 2015).

ANFIS has been known to be used as a predictor (estimator) tool through out the world, real functions can be expressed by ANFIS. ANFIS are capable of dealing with complex nonlinear problems and uncertainty in a smart way (Parmar and Bhardwaj, 2015).

Based on sunshine and air temperature data Mellit et al. (2007) modeled global solar radiation using ANFIS technique in Algeria. Using air temperature, precipitation, wind speed and extraterrestrial radiation.

Moghddamnia et al. (2009) compared different non linear models including ANFIS for daily global solar radiation estimation in Bruce catchment, UK.

Mohanty (2014) predicted global solar radiation for monthly mean bases using ANFIS-based model in Bhubaneswar, India. The ANFIS results were compared with that of others Intelligent techniques and Angstrom-Prescott model.

Mohanty et al. (2015) performed a comparative study of ANFIS, MLP,and RBF in 3 locations of India for monthly mean global solar radiation prediction.

Piri and Kisi (2015) predicted global solar radiation in Iran's two cities based on relative humidity, sunshine hour and air temperature as input parameters using ANFIS and some more techniques.

Mohammadi et al. (2015) investigated the potential of ANFIS in predicting horizontal global solar radiation for Tabass, Iran.

In the study of Olatomiwa et al. (2015), a comparison was made between experimental technique and soft computing methods, meteorological data were used for the prediction of global solar radiation in Iseyin, Nigeria. The input parameters were mean monthly minimum temperature (T_{min}), mean monthly maximum temperature (T_{max}) and mean monthly sunshine duration. In their study RMSE as performance criteria was employed. The obtained results of ANFIS were compared with the measured experimental results to demonstrate the superiority of ANFIS model in prediction of global solar radiation.

In their study Salisu et al. (2017), the global solar radiation was estimated using Neuro-Fuzzy Inference System (ANFIS). This technique was applied on a horizontal surface using meteorological parameters during the period from 2002 to 2012 in Nigeria. The estimated values were validated against the values resulted from previous models, the study showed that the proposed ANFIS model gave an accurate estimated results with

(RMSE) equals to 0.8093 MJ/m^2 and R^2 during the training stage and the value of (RMSE) equalls to the1.6954 MJ/m^2 and R^2 equals to 0.73632 MJ/m^2 during the testing stage.

Salisu (2017), designed an ANFIS based model to predict the monthly average of global solar radiation. The input variables were the monthly mean minimum temperature, the relative humidity and maximum temperature. Those variables were collected from the agency of meteorological measurement in Nigeria. The resulted values of the proposed model shows a good agreement with the measured values with a RMSE value of 0.91315 MJ/m^2 and with R value of 0.91264 MJ/m^2 of training phase.

Mohanty (2014) conducted a study in Bhubaneswar for the purpose of estimating the monthly global solar radiation using ANFIS based model on a horizontal surface. In the study the input variables were the sunshine hours, the relative humidity, the temperature and the sky cleared in the duration between 2000 and 2004. The model predicted outputs were compared with the values calculated utilizing "Angstrom Equation" in addition to some other techniques such as Neural Network and SVM.

CHAPTER 3
MATERIALS AND METHOD

3.1. Study Area and Data

Iraq is located in the western Asia (historically named: Mesopotamia) with an area of 437,072 km^2 and population of about 37.2 Millions in 2016. Iraq is bordered to six countries including; Turkey, Iran, Jordan, Syria, the Saudi Arabia and Kuwait. The latitudes of Iraq are between 29°5’ and 37°22’ N and the longitudes are 38°45’ and 48°45’ E (Sarlak and Agha, 2017). Figure 3.1 shows the regions of the study.

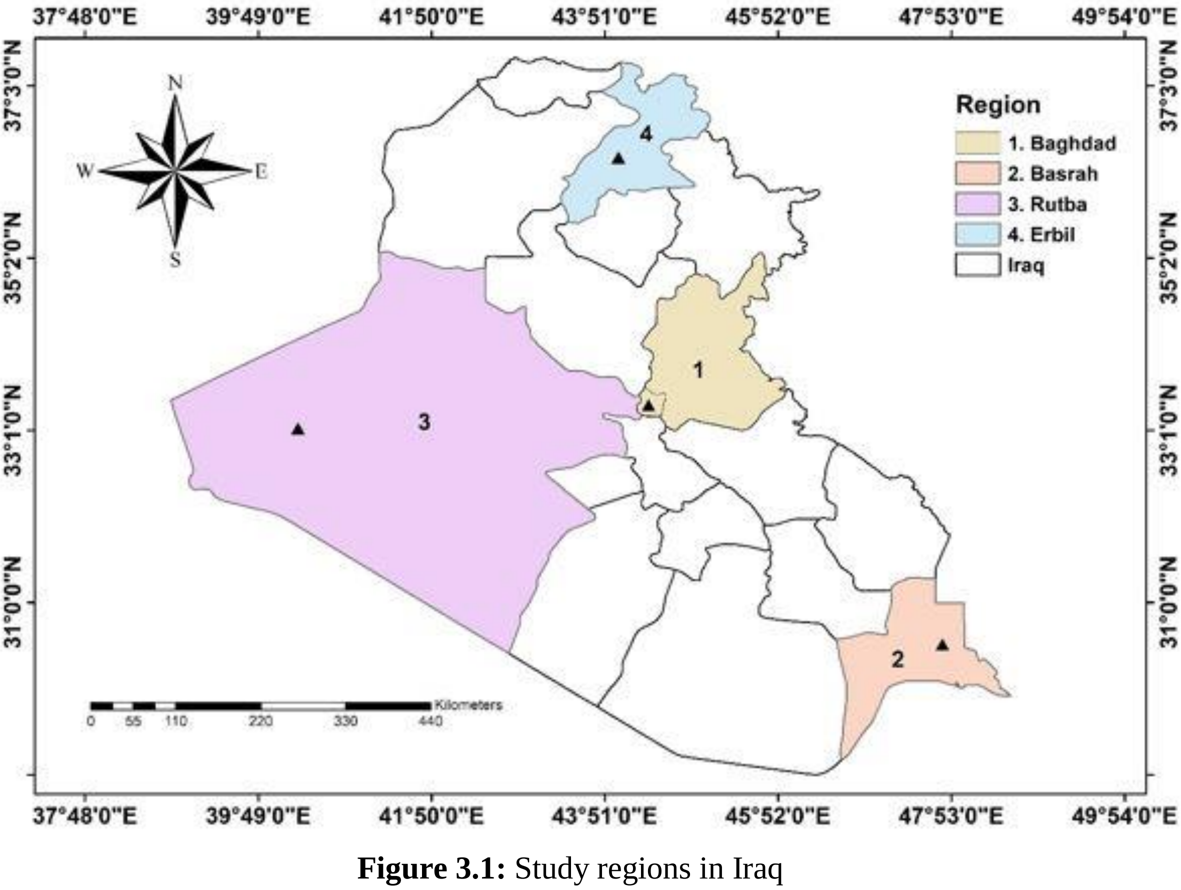

Figure 3.1: Study regions in Iraq

The climate of Iraq is considered to be very hot and dry in summer time, then it changes to be cold in winter due to its location. Iraq is also severely affected by the subtropical high pressure. According to Sarlak et al. (2017), about 97% of Iraq’s areas are covered by arid and semi-arid climate. Using Lang 1920 aridity index between the period 1998-2011, majority of the country's regions are arid (including Basra, Rutbah, and Baghdad) while semi-arid is found in the far North of Erbil.

In this study a total of 4018 daily meteorological data (2006-2016) from four stations (Basra, Rutbah, Baghdad and Erbil) each representing a specific region were collected from National Aeronautics and Space Administration (NASA) (https://power.larc.nasa.gov) including, Solar radiation (MJ/m^2/day), minimum temperature (T_{min}), maximum temperature (T_{max}), mean temperature (T_{mean}) (2m above the surface of the earth in ^{0}C), Wind speed (at 10m which was converted to 2m above the earth surface in m/s), Relative humidity (R_H) (at 2m high in %). The data were divided into 60% (2412) for training, 20% (803) for validation and the remaining 20% for testing. Table 3.1 also shows the geographical locations of the study regions and the statistics of the data used in this study.

Table 3.1: Descriptive statistics and geographical locations for the study regions

					Training				Validation				Testing			
Region	**Location**	**Coordinates**	**Parameter**	**Unit**	**Min**	**Max**	**Mean**	**standard deviation**	**Min**	**Max**	**Mean**	**standard deviation**	**Min**	**Max**	**Mean**	**standard deviation**
Baghdad	Latitude	33°31' N	R_S	$MJ/m^2/day$	0.4	33	19.6	7.06	2	29.7	19	6.91	0.9	29.6	18.3	7.08
			T_{max}	^0C	6.6	54	33	11.43	8.3	51	33	10.57	7.6	51.6	31.8	11.12
	Longitude	44°36' E	T_{min}	^0C	-3.7	36.4	18.9	9.85	-2.6	34.4	18.2	9.06	-4	33.6	16.9	9.65
			Wind	m/s	0.7	8.9	3.3	1.42	0	72.2	0.7	3.95	0.8	6.8	3.3	1.04
	Altitude	34 m	T_{mean}	^0C	2.8	44.6	25.5	10.78	3.7	42.2	25.1	10	2.6	42.1	23.9	10.61
			R_H	%	6	90	26.9	15.37	9.1	86	33.9	18.57	8.2	88.2	34	18.44
Erbil	Latitude	36°21' N	R_S	$MJ/m^2/day$	0.5	32.4	18.3	8.28	0.9	30.9	18.1	8.15	0.6	30.7	16.6	8.45
			T_{max}	^0C	-1.2	49	25.6	12.23	0	45.7	26	11.61	-0.7	45.4	24	11.82
	Longitude	44°01' E	T_{min}	^0C	-11.8	31.4	13	9.73	-10.8	28.3	12.8	9.12	-8.6	28.5	11.2	9.41
			Wind	m/s	0.8	8.9	2.9	1.16	1	10.1	2.8	1.01	1.1	8.6	2.7	0.9
	Altitude	390 m	T_{mean}	^0C	-6.6	39.5	18.8	11.05	-5.8	36.2	19	10.39	-5.4	36.4	17.3	10.68
			R_H	%	5.2	100	36.8	20.37	9.3	100	44	23.18	8.6	98.7	48	24.41
Basra	Latitude	30°51' N	R_S	$MJ/m^2/day$	1	33	20.4	6.75	1.9	29.4	19.9	6.59	0.8	29.2	19	6.51
			T_{max}	^0C	10.4	54.2	35	11.25	11.1	51.5	34.3	10.62	7.7	52.1	33.1	10.93
	Longitude	47°78' E	T_{min}	^0C	-2.1	38.2	20.4	9.4	-1.5	35.5	20.4	9.07	-1.9	36.2	19.1	9.57
			Wind	m/s	0.6	11	3.7	1.71	1.1	10.4	4.5	1.84	1.1	10	4.3	1.74
	Altitude	5 m	T_{mean}	^0C	3.9	45.3	27.2	10.35	4.8	42.8	27	9.97	4	43.8	25.8	10.45
			R_H	%	5.6	93.3	27.2	16.33	6.7	87.2	31.2	20.23	7.6	91.8	30.7	18.51
Rutba	Latitude	33°04' N	R_S	$MJ/m^2/day$	0.7	33.1	20.4	7.45	1.7	30.9	20.4	7.21	1.2	31.1	19.4	7.46
			T_{max}	^0C	2.7	48.6	27.9	10.76	3.7	43.5	27.7	9.58	3.5	45	26.5	10.26
	Longitude	40°28' E	T_{min}	^0C	-4.7	30.7	13.9	8.8	-5.2	26.9	13.5	7.89	-5.9	31.6	12.3	8.62
			Wind	m/s	0.6	9.4	3.5	1.5	1	9.6	4.1	1.4	-21	14	3.2	4.59
	Altitude	619 m	T_{mean}	^0C	-0.9	38.6	20.5	9.93	0.5	34.9	20.2	8.95	-2	37.8	18.9	9.68
			R_H	%	7.1	94.9	33.9	17.1	9.8	91.4	39.3	18.72	11.8	92.8	40.8	20.08

Due to the vulnerability of the study regions to arid and semi-arid climate conditions, it is expected to have high temperature. As shown in Table 3.1, all the regions have T_{max} greater than 45^0C with T_{mean} as high as 36.4^0C in the training, validation, and test data sets, respectively. The wind speed (U_2) is low at some points in the regions, but owing to desertification in the regions, U_2 rises as high as 10m/s. R_H ,being the ratio of the water vapor partial pressure to equilibrium water vapor pressure ratio at a given temperature, is rising at high temperature. U_2 has a lowest deviation from the mean of the data in which its standard deviation is as low as 0.9 m/s. According to the Table 3.1 for different regions, different parameters are dominant parameters for modeling of solar radiation and the best model for each region may be a bit different from the other regions.

3.2. Proposed Methodology

In this study, FFNN, ANFIS and MLR approaches are applied to calculate the solar radiation as stage 1. The inputs of those models are T_{max} , T_{min} , U_2, T_{mean} , R_H collected from NASA. Later on, the solar radiation values are calculated by ensemble approaches (stage 2). The inputs are the solar radiation resulted from the artificial intelligent techniques. Both neural ensembling and simple average are conducted in this stage. The resulted solar radiation of the two stages are then compared with together. Finally all models ensemble is performed at stage 3. Again the neural ensembling and simple average are conducted and in this way the solar radiation of black box and empirical models are used as inputs. The resulted solar radiation of this stage are finally compared with the results obtained at stage 1. Conclusions can be made upon the comparison.

The general procedure of how this study was conducted is illustrated in Figure 3.2.

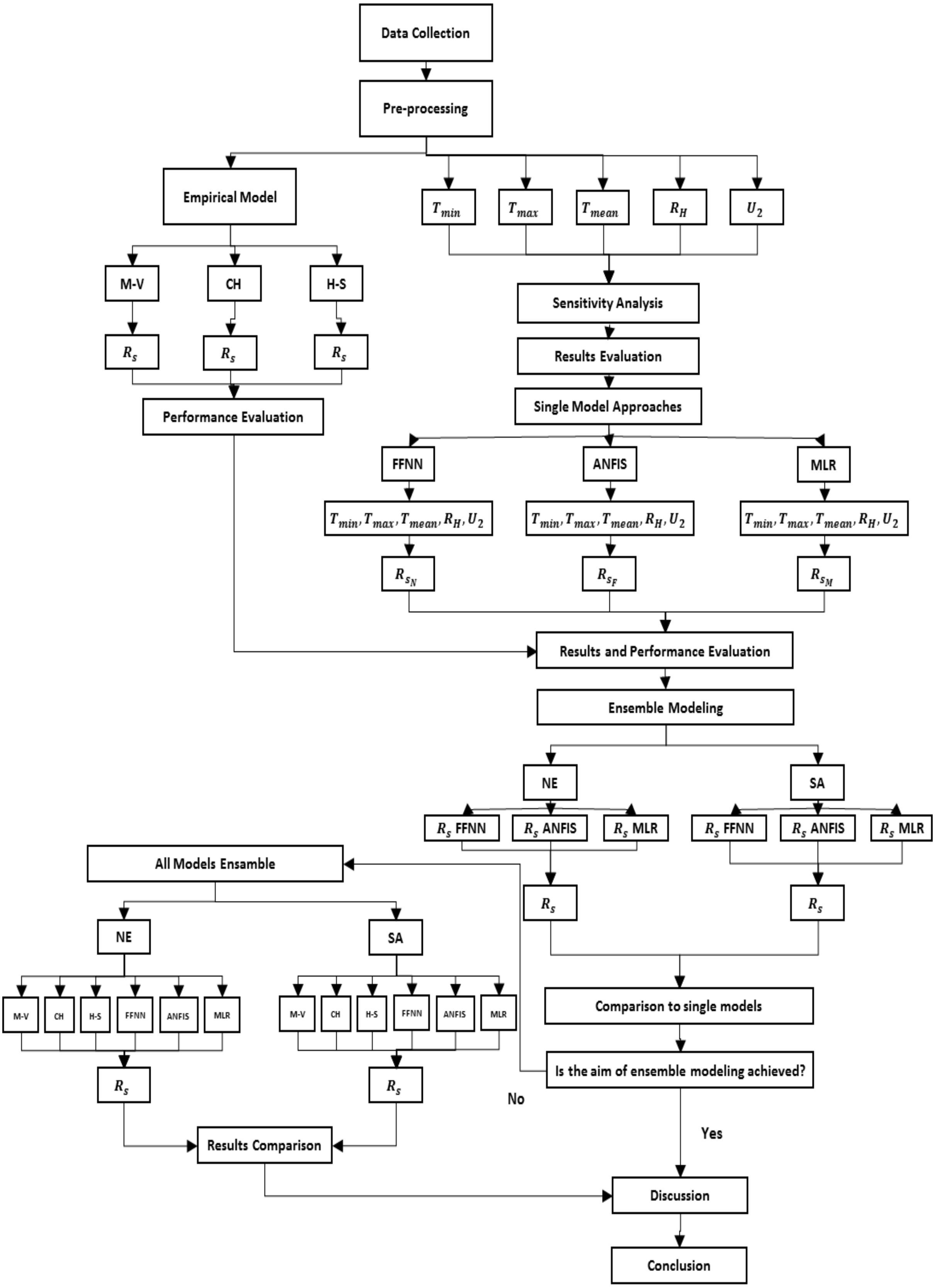

Figure 3.2: Schematic diagram of the proposed methodology

3.3. Empirical Models

A number of temperature-based empirical models have been developed in the past to estimate daily global solar radiation (Hassan et al., 2016; Besharat et al., 2013). Daily total extraterrestrial radiation R_a is usually involved in the relationships (Almorox et al., 2011). In this study, the models selection and evaluation were based on the advantages of the models such as availability of temperature data, simplicity, extensiveness of use and higher reported performance.

The temperature-based Empirical Equations utilized in this study are presented in Table 3.2. The coefficients of the mentioned models were derived by regression analyses.

Table 3.2: Employed temperature based Empirical Equations

Equation	Abbreviation	Parameters	Source
$R_s = 0.75.(1 - \exp(-b.\Delta T^2)).R_a$	M-V	b	Meza and Varas (2000)
$R_s = (a ln(T_{max} - T_{min}) + b) \times R_a$	CH	a, b	Chen et al. (2004)
$R_s = a(T_{max} - T_{min})^{0.5} \times R_a$	H-S	a	Hargreaves and Samani (1982)

Hargreaves and Samani (1982) introduced a simple Equation to estimate Solar radiation using maximum and minimum temperatures only. Meza and Varas (2000) provided an Equation using single coefficient (b) and temperature difference (ΔT) to estimate Solar radiation. Chen et al. (2004) developed an Equation using daily air temperature difference and logarithmic relationship between solar radiation (R_s) and R_a. The calculation of R_a is given by Equation 3.1.

R_a=37.6$d_r(\omega_s sin\varphi sin\delta + cos\varphi cos\delta \ sin\omega_s)$ (3.1) where

d_r = 1+0.33cos$\left[\frac{2\pi}{365} J\right]$ (3.2) and

$\delta = 0.4093 sin\left[\frac{2\pi}{365} J - 1.39\right]$ (3.3)

J is Julian day of the year (from 1 to 365/366), δ is solar declination angle (rad), φ shows latitude (rad), ω_s is sunset hour angle (rad) and d_r is the relative distance between the sun and the earth.

3.4. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is a numerical approach that is based on simulating the operational performance of the biological neural networks. Learning stage is an essential part of the ANN data processing in which the structure is changing according to the internal /external data stream. This technique is used for treating the huge amount of noisy, nonlinear and dynamic data. The structure of ANN consists of nodes which are processing elements that possess unique characteristics like nonlinearity, learning, tolerance and other data processing abilities. ANN technique has got many advantage points; ANN possess nonlinear basic properties and several inputs can be entered to the process which may be used for time-space modeling. Furthermore, ANN is considered to be an efficient method for virtual modeling of nonlinear relations to a high level of accuracy (Nourani et al., 2011).

For solving most of engineering problems, Feed Forwarded Neural Network (FFNN) with Back Propagation (BP) learning algorithm is being utilized (Hornik et al., 1989). In the FFNN method, the proceeding layer is totally interrelated by weights to the other processing layers (neurons). The learning phase here is achieved through the BP algorithm. The aim of using the BP algorithm is to calculate optimum weights which lead to produce an output vector that can be very close to the values of the target according to a chosen accuracy. Figure 3.3 illustrates the layered FFNN structure (Nourani et al., 2011).

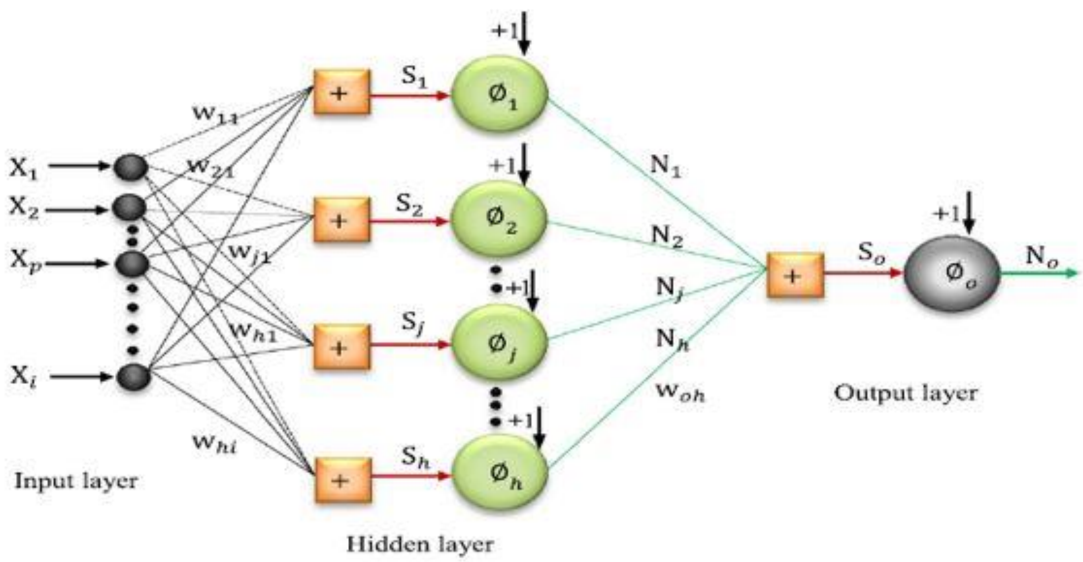

Figure 3.3: A three layered FFNN structure (Nourani and Fard, 2012)

The following formula describes the output value of a three layered FFNN (Nourani et al., 2012):

$$\hat{y}_k = f_0[\sum_{j=1}^{M_N} W_{kj}.f_h(\widehat{\sum_{i=1}^{N_N}} W_{ji}.x_i + W_{jo}) + W_{ko}] \tag{3.4}$$

W_{ji} is a weight in the hidden layer relating the ith neuron of the "Input Layer" by the jth neuron located in the hidden layer, $W_{jo}$is the jth hidden layer neuron's bias, f_h is the hidden neuron's activation function, W_{kj} is the weight located in the output layer that interrelates the kth neuron of the output layer with the jth neuron in the hidden layer, W_{ko} is the kth output layer neuron's bias, f_0 is the output neuron' s activation function, x_i is the input layer's i^{th} input variable, $\hat{y}_k$ is the computed output variable, y is the observed output variable, N_N is the number of input layer's neurons, M_N is the number of hidden layer's neurons.

In this study, Levenberg-Marquardt (LM) training algorithm was selected due to its ability to converge quickly. Also Tangent Sigmoid (Tansig) transfer function was used for the hidden and output layers. Additionally, the epoch number and hidden layer neurons were determined by the process of trial and error.

3.5. Adaptive Neuro-fuzzy Inference System (ANFIS)

Neuro-fuzzy simulation points to the techniques of applying different learning algorithm to fuzzy modeling in the neural network literature or fuzzy inference system (FIS). A distinctive approach in the development of neuro-fuzzy is ANFIS which was first introduced by Jang (1993) and utilize the learning algorithm of NN.

Every fuzzy system is comprised of three main parts; fuzzy data base, fuzzifier, and defuzzifier (Nourani et al., 2015; Nourani and Komasi, 2013). Inference engine and fuzzy rule base are the two main parts of fuzzy data base. Fuzzy rule base involves rules that are related to fuzzy propositions as illustrated by Jang et al. (1997). Consequently, fuzzy inference applied operation analysis. Many fuzzy inference engine can be employed to achieve this goal, in which Mamdani and Sugeno are the two most famous ones.

As a universal approximator, ANFIS is capable of compacting set of accuracy to any degree for any real continuous function. The ANFIS general structure is given in Figure 3.4 which consists of (a) if-then rule Sugeno model which involves the mechanism of input vector (x, y) and obtain an output function f; (b) The ANFIS equivalent structure is shown. As seen in Figure 3.4b, it is considered that the ANFIS has x and y inputs, and f output. Using the Sugeno first order fuzzy model with two fuzzy if-then rules as Aqil et al. (2007):

Rule (1): If μ(x) is A_1 and μ(y) is B_1; the $f_1 = p_1x + q_1y + r_1$

Rule (2): If μ(x) is A_2 and μ(y) is B_2; the $f_2 = p_2x + q_2y + r_2$

In which, A_1 and A_2 are inputs Membership Functions (MFs) of , B_1 and B_2 are inputs (MFs) of y, respectively. The output function parameters are p_1, q_1, r_1, and p_2, q_2, r_2. The functions of each ANFIS layer are as follows:

Layer 1: An input variable membership grades are produced in this layer by each node. The i^{th} node output in k layer is donated as Q_i^k. Assuming MF as generalized bell function (gbellmf), the output (Q_i^1) can be obtained by:

$$Q_i^1 = \mu_{A_i}(x) = \frac{1}{1+((x-c_i)/a_i))^{2b_i}} \quad (3.5)$$

Where a_i, b_i, c_i are called premise parameters which are adaptable variables.

Layer 2: In this layer, each node multiplies the incoming signals:

$$Q_i^2 = w_i = \mu_{A_i}(x).\mu_{B_i}(y)\ i = 1, 2, ... \quad (3.6)$$

Layer 3: In this layer, the normalized firing strength is calculated by the ith node:

$$Q_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} i = 1, 2 \quad (3.7)$$

Layer 4: In this layer, the contribution given to the model output by the ith rule is calculated by node i:

$$Q_i^4 = \bar{w}_i(p_ix + p_iy + r_i) = \bar{w}_i f_i \quad (3.8)$$

Where, p_i, q_i, r_i are the perimeter parameters, $\bar{w}_i$ is the layer 3 output.

Layer 5: In this layer, the overall ANFIS output is calculated by single node.

$$Q_i^5 = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{3.9}$$

The ANFIS learning algorithm is a hybrid algorithm and is a combination of least-squares and gradient descent method (Aqil et al., 2007). The optimization parameters are a_i, b_i, c_i which are the premise parameters, while, p_i, q_i, r_i are the consequent parameters. In the hybrid learning approach toward forward pass, until layer (4), the node output go forward and the least-square technique identify the consequent parameter. The error signals propagate backward, in the backward pass and the gradient descent updates the premise parameters (Nourani and Komasi, 2013). Figure 3.4 shows the structure of ANFIS.

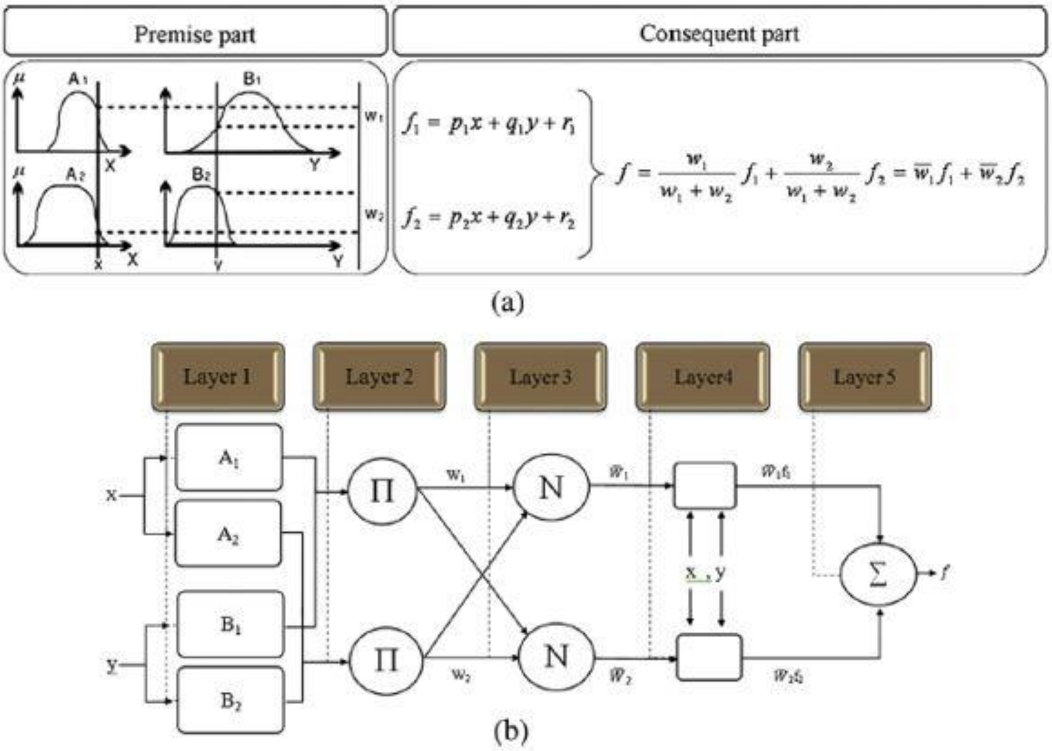

Figure 3.4: Structure of (a) first order Sugeno type FIS (b) equivalent ANFIS (Nourani et al.
2017a)

3.6. Multi-Linear Regression

Multi-linear regression (MLR) is a famous method of mathematical modeling to create a linear relationship between one or more independent variables and dependent variable. In general, the dependent variable y, and n regressor variables may be related (Parmar and Bhardwaj, 2015). The model is defined with n regressor as the Equation (3.10):

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_ix_i \qquad (3.10)$$

Where x_i is the value of the i^{th} predictor, b_0 is the regression constant, and b_i is the coefficient of the i^{th} predictor.

3.7. Sensitivity Analysis

In order to determine the most effective input parameter for the estimation of daily global solar radiation in Iraq, sensitivity has to be investigated. A three-layer FFNN is the type of Multi-Layer Perceptron (MLP) that utilizes BP algorithm while training. In this study, the FFNN is employed to investigate the influence of each in depended variable on the depended variable (Nourani and Fard, 2012).

3.8. Ensemble Technique

For a given set of data, it is obvious that performance of one technique may surpass another, and when different sets of data are used, the results may entirely be opposite. In order to benefit from the advantages of all the single techniques and also not to lose generality, an ensemble technique is develop which utilizes the single output of each technique with certain priority level assigned to each with the help of an arbitrator, provides the output (Kiran and Ravi, 2008). In ensemble technique, the individual constituents obtained as output from each applied technique is used as an input to the model which based on the design of the arbitrator, is processed to give overall output (Kiran and Ravi, 2008). Some techniques of ensemble nature for problems prediction with continuous variable dependent comprised of linear ensemble, such as Stack regression (Breiman, 1996), Weighted average (Perrone and Cooper, 1995), Simple average (Benediktsson et al., 1997); and Nonlinear ensemble, such as neural-network-based (Yu et al., 2005). According to Kiran and Ravi (2008), there are two ensemble methods: (i) Linear Ensemble method; which includes linear ensemble by simple averaging, linear ensemble by weighted averaging, and linear ensemble by weighted median and (ii) Nonlinear ensemble method; e.g. ANN is trained as a non-linear kernel to obtain an ensemble output.

The ensemble modeling in this study was conducted via a linear (simple averaging) and non-linear (FFNN) ensemble methods.

Simple linear averaging is done as:

$$\bar{f}(t) = \frac{1}{N}\sum_{i=1}^{N} f_i(t) \tag{3.11}$$

Where $\bar{f}(t)$ is output of simple ensemble technique, $f_i(t)$ is the output of i^{th} single model (here outputs of FFNN, ANFIS, and MLR) and N is the number of single models (here, N=3).

Figure 3.5 shows the general procedure employed for ensemble modeling.

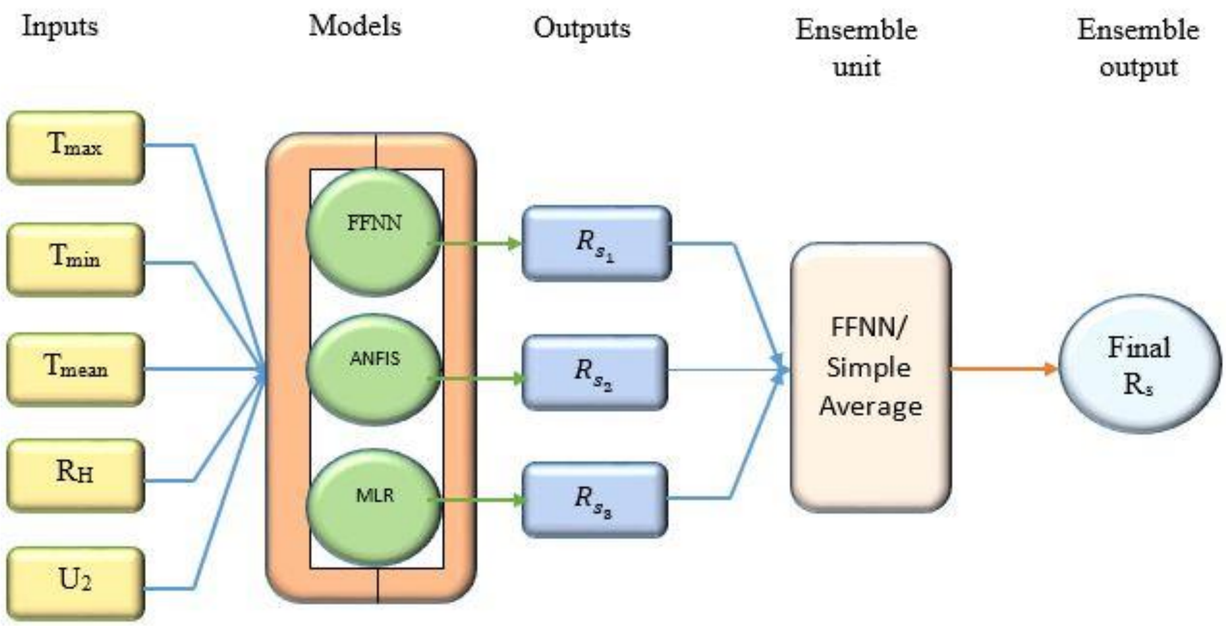

Figure 3.5: General ensemble procedure

While in the non-linear method, the outputs obtained by models (FFNN, ANFIS and MLR) are integrated together as inputs to create a new model and train via FFNN technique to produce the ensemble output.

Although linear models such as MLR sometimes couldn't provide accurate results based on their limitations to handle nonstationary and non-linearity, these models are still used because, a) linear models are low-cost and simple, and the superposition principle can be applied in such linear models, b) the noise (or error) included in the used data (or employed computational scheme) increases linearly in a linear model, but such a noise (or error) may non-linearly be magnified over further time/space steps. Hence, by combining MLR and AI models, complex structures in the data may be detected more accurately (Sharghi et al. 2018).

3.9. Data Normalization and Performance Evaluation

To ensure equal attention is given to all inputs and output, and to eliminate their dimensions, the data used in this study were scaled between 0 and 1. There are two main advantages of data normalization before the application of AI models. The first is the avoidance of using attributes in bigger numeric ranges that overshadow those in smaller numeric ranges. The second is to avoid numerical difficulties in the calculation.

Therefore, the data used in this study were normalized as the following:

$$E_n = \frac{E_i - E_{min}}{E_{max} - E_{min}} \quad i = 1, 2, \ldots, n \tag{3.12}$$

Where E_n, E_i, E_{min}, E_{max} represent the normalized values, actual values, minimum values, and maximum values, respectively.

To analyze and determine the performance and efficiency of the models proposed, Legates and McCabe (1999) research is endorsed, which stated that Determination Coefficient (DC or Nash-Sutcliffe efficiency criterion) and Root Mean Square Error (RMSE) can sufficiently evaluate prediction model. The Equations for DC and RMSE are given by (Nourani et al. 2015; Nourani et al. 2017b):

$$DC = 1 - \frac{\sum_{i=1}^{N}(R_i - \hat{R}_i)^2}{\sum_{i=1}^{N}(R_i - \bar{R})^2} \tag{3.13}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(R_i - \hat{R}_i)^2}{N}} \tag{3.14}$$

Where N, R_i, $\bar{R}$, and $\hat{R}_i$ are respectively the number of observations, observed data, mean of the observed values, and predicted values. The accuracy of the forecasted values are measured by RMSE, which gives positive value by squaring the errors. As divergence increasingly becomes large between observations and forecasts, the RMSE increases for perfect forecasts from zero through large positive values. DC is between -∞ to 1 and RMSE value close to 0, implies higher efficiency of the modeling (Nourani et al. 2015).

CHAPTER 4

RESULTS AND DISCUSSIONS

Since the proposed methodology contains 3 parts, the results are also provided in 3 sections as (i) Sensitivity analysis focusing on the effect of each variable on solar radiation (ii) Application of 3 empirical models, Artificial Intelligence (AI) based non-linear and linear (MLR) techniques using different combinations of input parameters to estimate daily global solar radiation (iii) Finally, the results of ensemble techniques are presented to appraise the improvement in performance that could be attain over the single models.

4.1. Sensitivity Analysis Results

One of the most important task in any AI based modeling is selection of the most dominant input parameters. To obtain optimum results, the most influential variables should be included in the input layer while unnecessary and less effective variables should be discarded. In view of this, a neural network based-sensitivity analysis was applied in order to identify the key input parameters for the daily global solar radiation modeling over Iraq. The results according to the training, validation and testing of the individual models are given in Figure 4.1 Five parameters were involved in the analysis, including T_{max}, T_{min}, U_2, $R_H, and\ T_{mean}$.

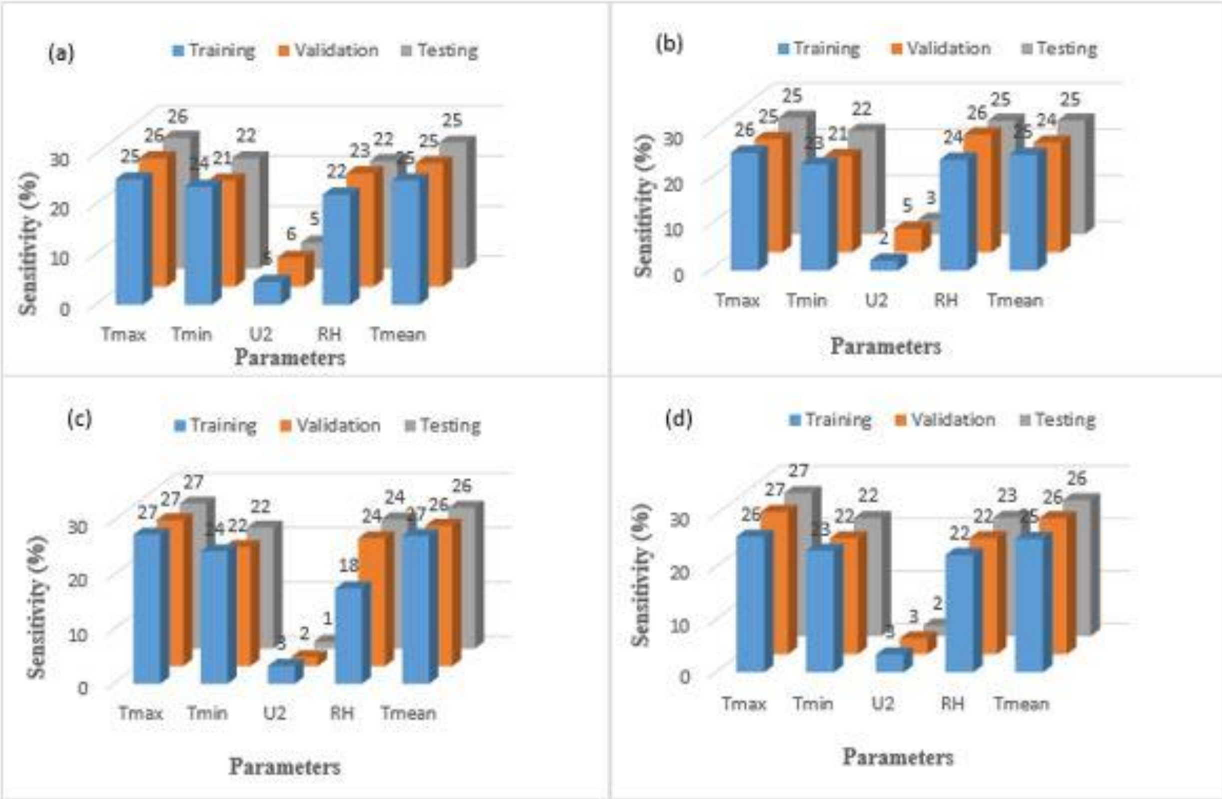

Figure 4.1: Sensitivity analysis results for (a) Baghdad (b) Basra (c) Rutbah (d) Erbil

For all 4 regions, T_{max} has the highest impact on solar radiation followed by T_{mean}, R_H, T_{min}, and lastly U_2 for the training, validation and testing, respectively. The similarity in impacts of the variables could be due to resemblance of climate in the study regions as according to Sarlak and Agha (2017) which used Lang 1920 aridity index to show that majority of Iraq land is arid (including Rutbah, Baghdad and Basra) while in the further north of Iraq it is semi-arid (Erbil included). T_{max} has a direct relationship with solar radiation in all regions, so that with higher temperature, the radiation effect of the sun increases, and hence T_{max} becomes the most dominant parameter.

4.2. Empirical Equations Results

The suitability of employing temperature-based empirical models to estimate daily global solar radiation was accessed in this study using three Empirical Equations. The data collected were calibrated by temperature-based Empirical Equations of Meza and Varas (2000) (M-V), Chen et al., (2004) (CH) and Hargreaves and Samani, (1982).

As seen in Table 4.1, the constants of the models are region-dependent as reported by other researchers as well (Sharifi et al., 2016; Li et al., 2013a, 2013b; Elagib and Mansell, 2000). Table 4.1 also shows similar (though not exact) values of the calibrated coefficients to those suggested by Hargreaves for the interior regions (0.16). The slight difference especially in Erbil could be due to temperature difference upon which the coefficients were derived from one location to another. The performances of all three Empirical Equations in each study region are presented in Table 4.1. It should be noted that the results of the empirical models in this study were compared with those of AI based models as such, in order to have accurate basis for comparison, the former results were divided into training, validation, and testing as the latter.

Table 4.1: Coefficients used in the study and the performance of the empirical equations for the study regions

				Training		Validation		Testing	
Region	**Model**	**Coefficient**		**DC**	**RMSE***	**DC**	**RMSE**	**DC**	**RMSE**
Baghdad	M-V	b	0.0090	0.7991	0.1057	0.7514	0.1058	0.7623	0.0973
	CH	a b	0.1580 0.2921	0.7929	0.1192	0.7542	0.1052	0.6975	0.0988
	H-S	a	0.1660	0.8535	0.1110	0.8099	0.0925	0.7377	0.0831
Basra	M-V	b	0.0064	0.7923	0.1122	0.7622	0.0998	0.7128	0.0921
	CH	a b	0.1720 0.0153	0.7290	0.1211	0.7129	0.1097	0.6659	0.1052
	H-S	a	0.1690	0.7319	0.1207	0.7142	0.1094	0.6678	0.1046
Rutbah	M-V	b	0.0125	0.7609	0.1203	0.7536	0.1104	0.7261	0.1125
	CH	a b	0.1260 0.0210	0.7904	0.1196	0.7928	0.1013	0.7294	0.1053
	H-S	a	0.1620	0.7949	0.1193	0.7956	0.1006	0.7307	0.1042
Erbil	M-V	b	0.0780	0.7961	0.1219	0.8231	0.1073	0.7794	0.1195
	CH	a b	0.1711 0.2110	0.7997	0.1295	0.8125	0.1105	0.7510	0.1184
	H-S	a	0.1880	0.8277	0.1269	0.8320	0.1046	0.7609	0.1098

*Data are normalized, hence RMSE has no unit.

As shown in Table 4.1, the statistical indices of DC and RMSE indicate that all the empirical models developed in this study in all training phases are suitable for estimating daily global solar radiation in Iraq. These results affirmed the conclusion drawn by Sharifi et al., (2016) that provided the model coefficients are well calibrated, temperature-based empirical models are capable of estimating solar radiation with reasonable accuracy.

Based upon the results in Table 4.1, H-S model was found to have better performance (to a maximum DC of 0.8535 and RMSE of 0.1110 in Baghdad region) in training phase, while highest performing models in validation and testing phases were for Erbil region with maximum DC and RMSE of 0.8320, 0.1046, and 0.7794, 0.1195 by H-S and M-V models, respectively. The results clearly show the superiority of H-S model over the rest of the models due to the suitability of the indicators used in this model. Hence, where only temperature data are available to estimate daily global solar radiation, H-S model can be successfully applied.

4.3. Results of the Black Box Models (ANN, ANFIS and MLR)

In this section, the results of two AI based techniques (FFNN and ANFIS) and one conventional technique (MLR) are presented for daily global solar radiation estimation for different regions of Iraq using different input combinations based upon the sensitivity analysis conducted.

Levenberg Marquardt algorithm was used to train the FFNN with single hidden layer and varying number of neurons for daily global solar radiation simulation. The hidden layer optimal node number was determined using trial and error procedure for each region. Accordingly, the number of nodes in the hidden layer that provided the best results were found to be 8, 10, 6, and 12 for Baghdad, Basra, Rutbah, and Erbil, respectively.

ANFIS model which used Sugeno type fuzzy inference algorithm was applied in this study, where the membership function parameters were calibrated by a set of given input-output data via hybrid optimization algorithm. Trial and error procedure was applied for the formulation of the structures of the ANFIS models in order to find the best ANFIS construction. MLR which expresses linearly the relationship between independent and dependent parameters was used in this study as well.

Eight models were developed for each region by each applied technique considering different input combinations as given in Table 4.2.

Table 4.2: Input combinations of the models

Model	Input Parameters	Output Parameter
M1	T_{max} , T_{min}	Rs
M2	U_2 , R_H	Rs
M3	T_{mean} , R_H	Rs
M4	T_{max} , T_{min} , U_2	Rs
M5	T_{max} , T_{min} , T_{mean}	Rs
M6	T_{max} , T_{min} , R_H	Rs
M7	T_{max} , T_{min} , U_2, T_{mean}	Rs
M8	T_{max} , T_{min} , U_2, T_{mean} , R_H	Rs

The results of all the models showed that model 8 (M8) which comprises of 5 inputs provided the best results, this also justified the inclusion of U_2 despite its poor performance in the sensitivity analysis. Therefore, this study is performed on the basis of M8. The results of the single models are given in Table 4.3.

Table 4.3: Comparison of results of the single models

		Training		Validation		Testing	
Region	**Model**	**DC**	**RMSE**	**DC**	**RMSE**	**DC**	**RMSE**
Baghdad	FFNN	0.8110	0.1032	0.8188	0.0903	0.7731	0.0944
	ANFIS	0.8211	0.0987	0.8303	0.0874	0.7925	0.0919
	MLR	0.7698	0.1120	0.7854	0.0983	0.7327	0.1042
Basra	FFNN	0.8145	0.0967	0.8086	0.0895	0.7868	0.0870
	ANFIS	0.8314	0.0919	0.8256	0.0855	0.8077	0.0830
	MLR	0.7941	0.1007	0.7913	0.0935	0.7690	0.0917
Rutbah	FFNN	0.8109	0.1044	0.8024	0.0989	0.7938	0.1000
	ANFIS	0.8373	0.0986	0.8258	0.0929	0.8160	0.0928
	MLR	0.7784	0.1160	0.7773	0.1050	0.7451	0.1083
Erbil	FFNN	0.8237	0.1160	0.8271	0.1061	0.8002	0.1111
	ANFIS	0.8383	0.1092	0.8418	0.1015	0.8230	0.1064
	MLR	0.7925	0.1251	0.7899	0.1170	0.7676	0.1205

It is clear from the results shown in Table 4.3 that ANFIS and FFNN performances are better than MLR. This might be due to their ability to deal with complex non-linear phenomena. The inability of the MLR model to match the results of FFNN and ANFIS models may be owing to one or all of the following reasons:

(i) MLR is based on the Least Square method which models linearly the relationship between independent and dependent variables. As such, its performance could be reduced for problems involving nonlinear characteristics.

(ii) After MLR modeling, some negative values were observed in the simulated results which may not have meaning in the real world problems and may impact negatively on the overall performance.

Figure 4.2 shows the time series and scatter plots of the observed vs. predicted values (via ANFIS) in the testing phase for the best models in the four study regions.

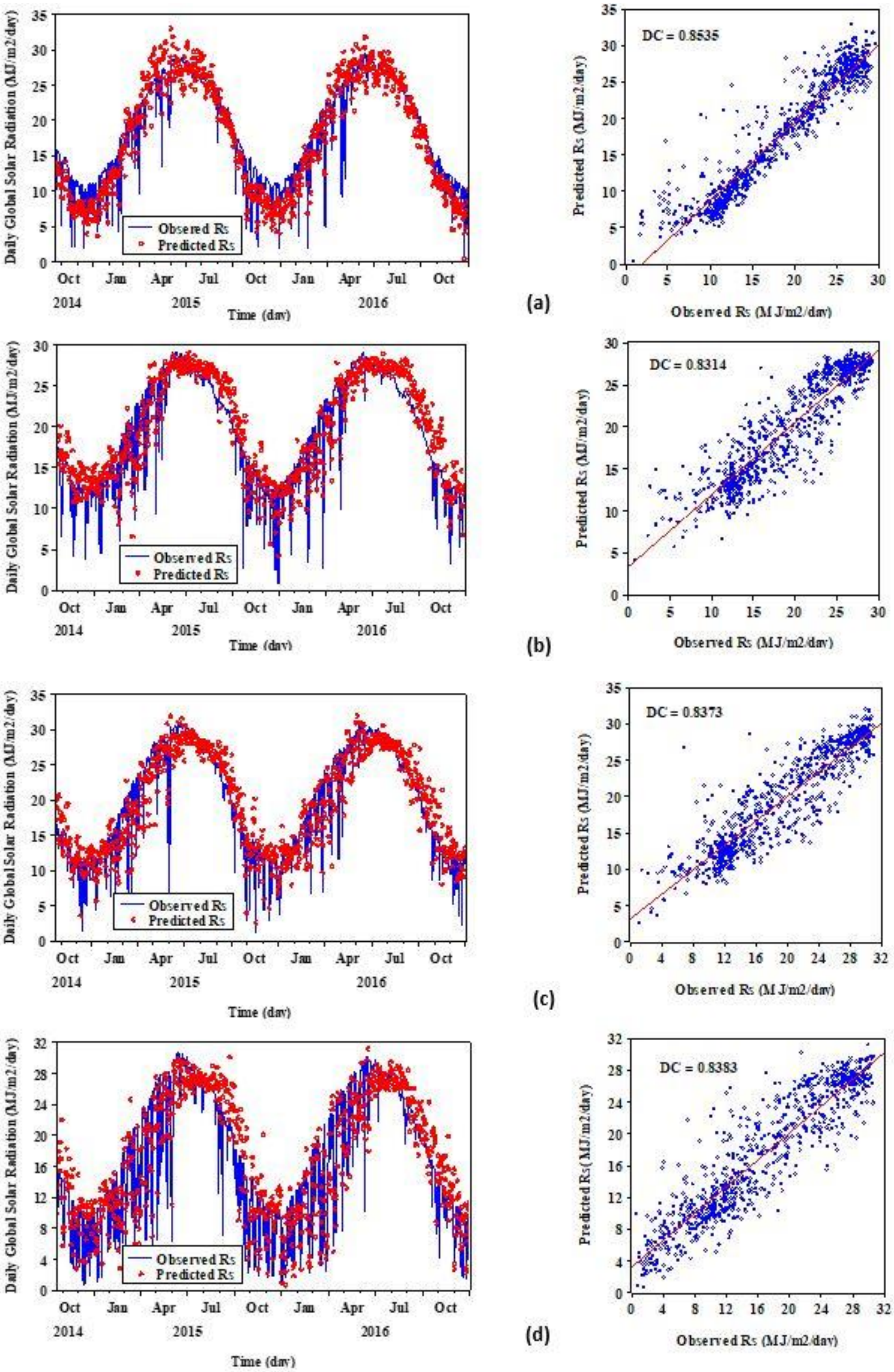

Figure 4.2: Time series and scatter plots for the best model in (a) Baghdad (H-S model) (b)

Basra (ANFIS model) (c) Rutbah (ANFIS model) (d) Erbil (ANFIS model)

Comparing the results of empirical models (Table 4.1), AI based models and MLR (Table 4.3) it can be deduced that AI models are superior in performance than all other models and fluctuations in performance are observed between MLR and empirical models either in training, validation or testing phases. One notable circumstance is the performance of H-S in the testing phase for Erbil region. H-S is found to be the second highest performing model with DC = 0.7609 and RMSE = 0.1098. This shows that for an intense climate region (Hyper-arid, Arid or Semi-arid) empirical models could lead to better performance. However, presence of U_2 could also affect the performance of empirical models, looking into the descriptive statistics (Table 3.1) it could be seen that the Baghdad in testing phase is less windy compared to rest of the regions in which its maximum value is 6.8 m/s. Figure 4.3 shows the general performance of all the models in the study area.

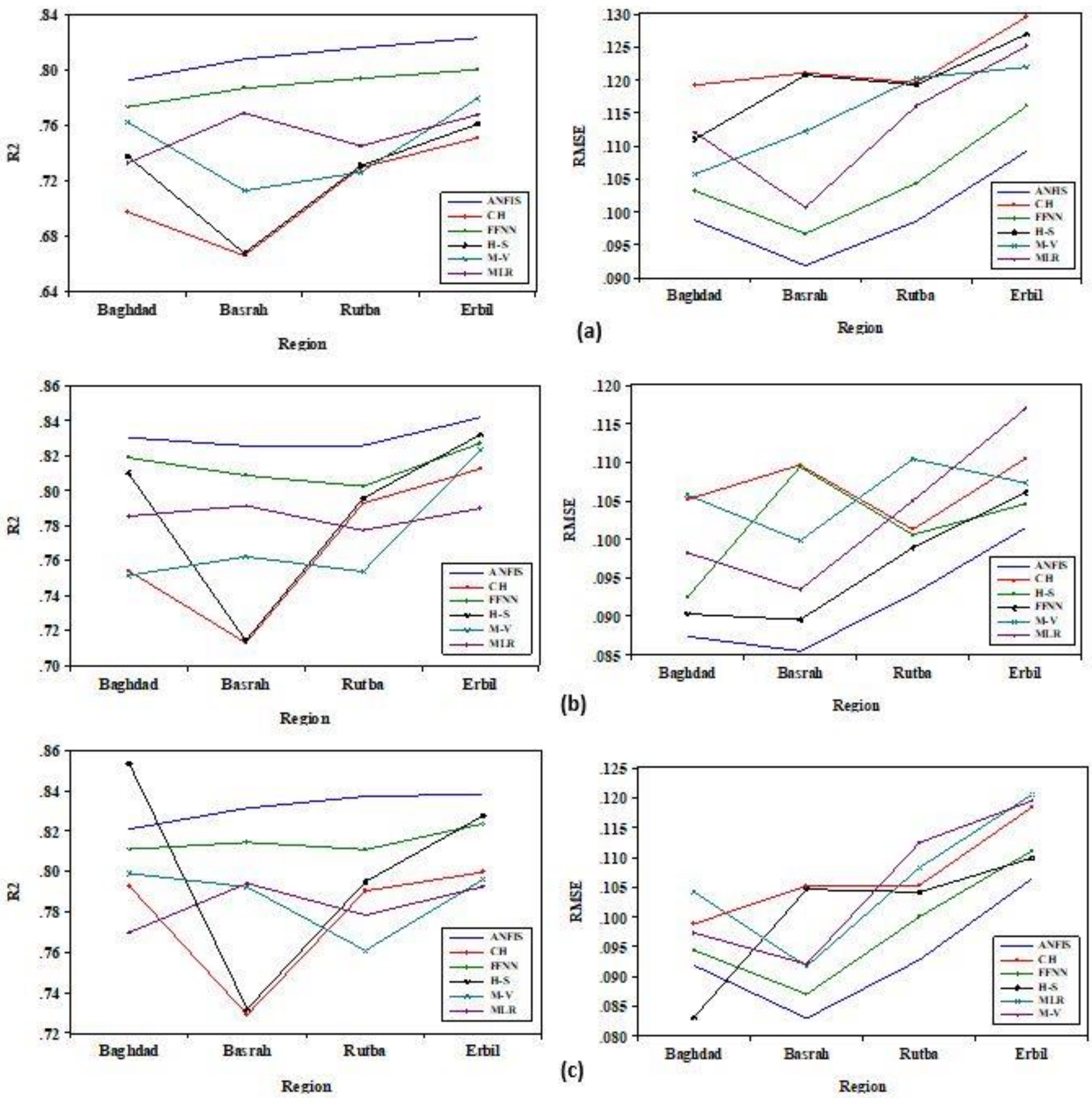

Figure 4.3: Models performance in term of DC and RMSE in phases of (a) training (b) validation (c) testing

Based on the presented results in Figure 4.3, it can be seen that the empirical models are the least in performance for the study regions especially in the training phase. Despite fluctuations in performance, generally MLR performed better than empirical models perhaps due to having more inputs (5 input parameters) than empirical models (with 2 input parameters only) but inferior to AI based models due to its inability to deal with nonlinear features of the phenomenon. Owing to its robustness in dealing with complex processes, FFNN performance is impressive being the second best performing model after

ANFIS. With incorporation of both ANN and Fuzzy concepts, ANFIS predictive performance is exceptional with highest DC and lowest RMSE in almost all regions and phases of the modeling (excluding testing phase in Baghdad). Despite its superiority in performance, the best ANFIS performance is in the verification phase of Erbil with DC = 0.8230 and RMSE = 0.1064. This shows there is room for prediction improvement. At this juncture, combining the outputs of these models may result in an improved prediction over single models. In view of the overall results in Figure 4.3, AI based and MLR models were selected for the ensemble modeling at first stage

As mentioned previously, in the next step, two ensemble techniques were employed to improve the predictive performance by combining the outputs of the single models. The choice of ANN in this study as the non-linear ensemble technique over other AI models was made due to its popularity, compatibility, and above all high reported performance by many ensemble modeling studies, including Yu et al. (2005); Kiran and Ravi (2008); Sharghi et al. (2018); Yamashkin et al. (2018) while other AI models may also be employed.

4.4. Results of Ensemble Techniques

The simple average ensemble modeling was performed as given in Equation 3.11 and the neural ensemble trained in a similar manner to FFNN using Tangent Sigmoid activation functions in both hidden and output layers. Also the BP algorithm was employed, and also, trial-and-error procedure was applied to determine the average epoch and the hidden neuron numbers. The ensemble modeling results for both (simple average and neural ensemble) are presented in Table 4.4.

Table 4.4: Results of the ensemble techniques

		Training		Validation		Testing	
Region	**Model**	**DC**	**RMSE**	**DC**	**RMSE**	**DC**	**RMSE**
Baghdad	SA*	0.8210	0.0990	0.8290	0.0880	0.7930	0.0920
	NE	0.8224	0.0985	0.8291	0.0877	0.7935	0.0915
Basra	SA	0.7740	0.0980	0.7720	0.0980	0.7810	0.0960
	NE	0.7767	0.0982	0.7695	0.0983	0.7801	0.0955
Rutbah	SA	0.8350	0.0980	0.8230	0.0940	0.8200	0.0930
	NE	0.8240	0.1030	0.8171	0.0952	0.7993	0.0965
Erbil	SA	0.8380	0.1080	0.8430	0.1010	0.8250	0.1060
	NE	0.8383	0.1080	0.8431	0.1011	0.8250	0.1064

*SA is simple average, NE neural ensemble. RMSE has no unit as data were normalized.

Table 4.4 depicts that ensemble modeling could improve the accuracy of performance over single models somewhere. The ensemble approaches improved the prediction performance of daily global solar radiation estimated for Baghdad, Erbil, Basra, and Rutbah. The performance improved up to 6%, 4%, 5% for Baghdad, 6%, 5%, 5% for Erbil, 11%, 0%, 1% for Basra, and 7%, 4%, 6% for Rutbah in the training, validation and testing, respectively.

Comparing the results in Tables 4.3 and 4.4, it could be realized that ensemble techniques are far superior to FFNN and MLR models which is reasonable in view of the capability of ensemble techniques in combining the outputs of single models. Also as seen from Table 4.3, ANFIS had a better performance than ensemble techniques in some regions such as Basra (in training, validation and testing), and Erbil (in validation and testing). The superiority of the ANFIS models could be due to the following reasons:

i. ANFIS is a robust nonlinear black box model that was introduced to improve the performance of ANN and fuzzy inference system (FIS). It incorporates both ANN and fuzzy concepts, hence by virtue of its development, it can be said that ANFIS is similar in performance to ensemble techniques as such, depending on the nature of problem and complexity involved, and variable results could be possible between ensemble approaches and ANFIS models.
ii. In regions (such as in Iraq) where the most portion of the land is arid and semi-arid, climate parameters modeling could be tedious due to the extreme variability of the

climate, hence, ensemble approaches may not have much effects on the output of the single models.

iii. Ensemble modeling could be more effective if there are more outputs of the single models. In other words, ensemble modeling of several single models may provide better results than ensemble modeling with few single models (such as 3 single models in case of this study which also one of them is linear model).

iv. Being a nonlinear model, it is expected that neural ensemble technique could provide better results over simple average ensemble technique, but the results were found to be opposite as revealed in Table 4.3. This turn in performance may be because, ANFIS was found to be the best model and simple average ensemble technique has a direct (linear) interaction with the ANFIS model hence, the results of the linear models would be more close to ANFIS than indirect (nonlinear) method.

To tackle and address the above raised issues, second ensemble modeling was conducted employing all the single models (FFNN, ANFIS, MLR, M-V, CH, H-S) outputs as inputs to the ensemble technique. The ensemble results of this strategy are given in Table 4.5.

Table 4.5: Ensemble results employing all single models

		Training		Validation		Testing	
Region	**Model**	**DC**	**RMSE**	**DC**	**RMSE**	**DC**	**RMSE**
Baghdad	SA2	0.9854	0.0903	0.8713	0.0761	0.9793	0.0712
	NE2	0.9892	0.0783	0.9062	0.0650	0.9844	0.0611
Basra	SA2	0.9844	0.0909	0.8442	0.0808	0.9801	0.0742
	NE2	0.9891	0.0763	0.8879	0.0685	0.9860	0.0620
Rutbah	SA2	0.9856	0.0858	0.9001	0.0703	0.9826	0.0746
	NE2	0.9901	0.0720	0.9156	0.0646	0.9877	0.0619
Erbil	SA2	0.9793	0.0926	0.9009	0.0803	0.9773	0.0822
	NE2	0.9791	0.0926	0.9009	0.0803	0.9773	0.0822

SA2 implies second simple average and NE2 implies second neural average

The results in Table 4.5 show an overwhelming increase in predictive performance. Comparing the results with the highest performing model (ANFIS) in Table 4.3, it can be seen that the neural ensemble modeling increased the predictive performance of ANFIS up to 19%, 8%, and 17% for Baghdad region, 18%, 6%, and 16% for Basra region, 17%, 9%, and 15% for Rutbah region, 15%, 6%, and 14% for Erbil region in the training, validation, and testing phases, respectively.

The results depicted in Table 4.5 indicate that the second ensemble strategy which used all single models outputs could address the deficiency of the first ensemble strategy as:

1. The results showed that ensemble modeling with outputs of a few single models increase predictive performance for some single models but does not provide superior performance over the highest performing (ANFIS) model.
2. The effect of ensemble modeling is less with less number of single models especially in hot climate (arid and semi-arid) conditions.
3. The performance of ensemble techniques is increased with increase of inputs.
4. With less ensemble inputs the results are more linear (SA greater than NE) but with increased inputs, the results tend to be more nonlinear (SA less than NE). That could be the reason why simple average ensemble was better than neural ensemble in the first strategy less in the second ensemble modeling.

As depicted in Figure 4.4, there is a wide gap in the performance between single models and second ensemble technique in all three phases of model development, which shows that the ensemble results are more sensitive to the best single model. That is to say, a single model that has extremely poor or good performance may influence the ensemble results in case of few inputs, whereas in the case of 6 inputs, all models have different performance as such, the results will be decided by all the input models. Hence, this showed that with appropriate number of combined outputs of single models and having more heterogeneous inputs for ensemble modeling, ensemble technique could produce better efficiency. Table 4.6 shows the performance of all models for the testing phase. Figure 4.5 shows the scatter plots of the observed vs. predicted solar radiation using second NE strategy.

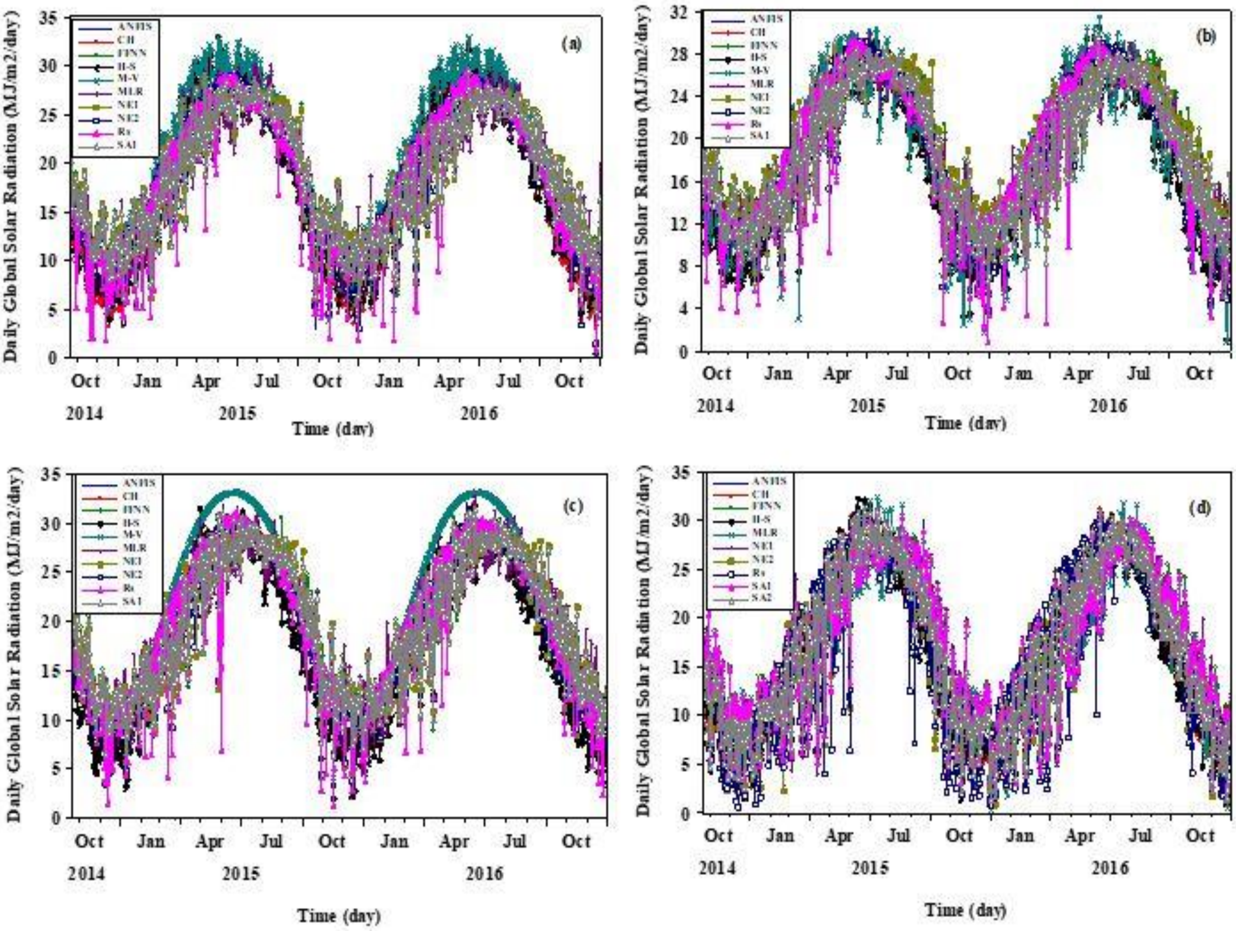

Figure 4.4: Performance of all the models in (a) Baghdad (b) Basra (c) Ruthba (d) Erbil

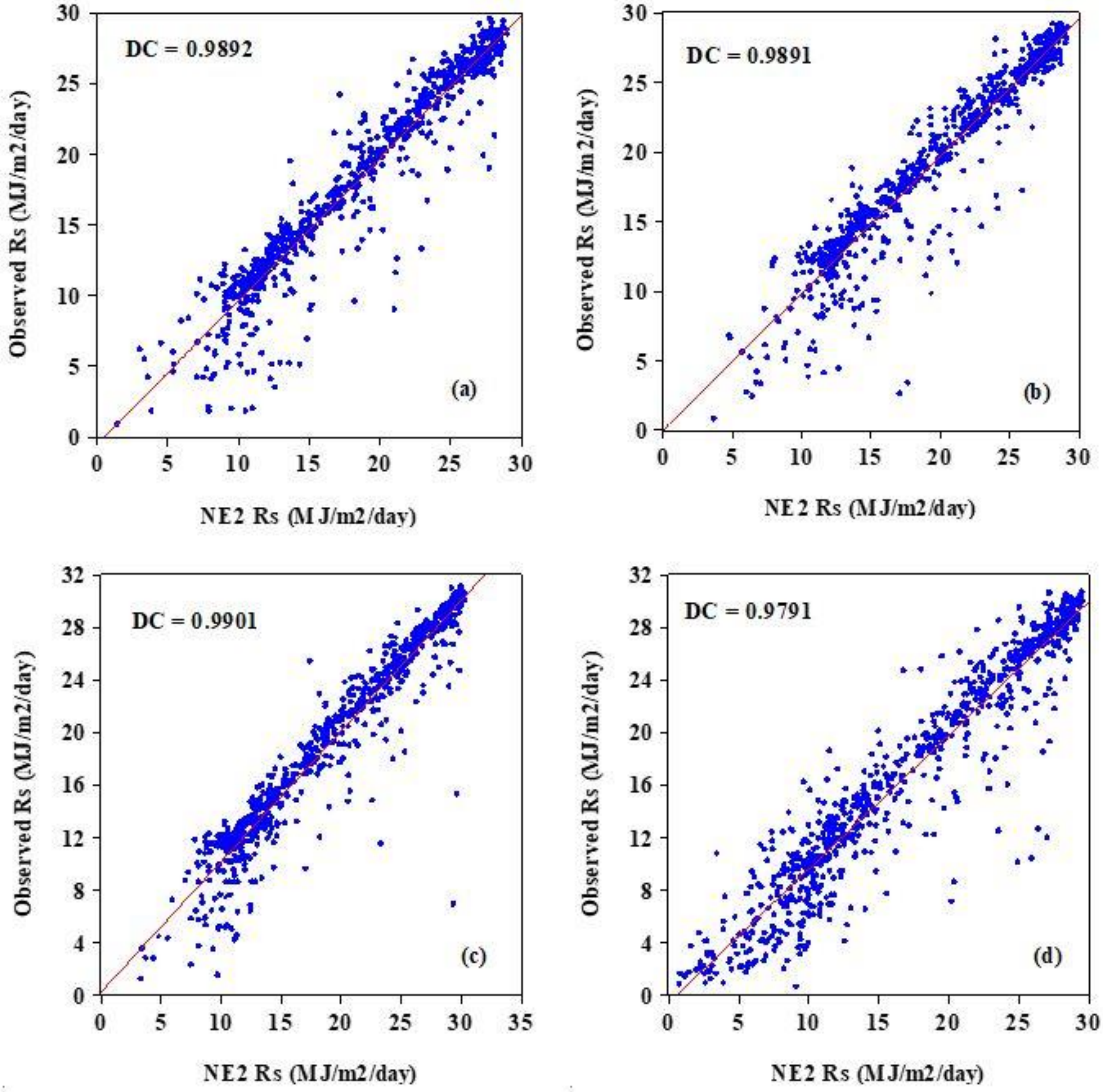

Figure 4.5: Observed vs predicted scatter plots by neural ensemble 2 for (a) Baghdad, (b) Basra, (c) Rutbah, and (d) Erbil

Table 4.6: Overall performance of all models in terms of DC and RMSE for training validation and testing

		Training		Validation		Testing	
Region	**Model**	**DC**	**RMSE**	**DC**	**RMSE**	**DC**	**RMSE**
Baghdad	FFNN	0.811	0.1032	0.8188	0.0903	0.7731	0.0944
	ANFIS	0.8211	0.0987	0.8303	0.0874	0.7925	0.0919
	MLR	0.7698	0.112	0.7854	0.0983	0.7327	0.1042
	M-V	0.7991	0.1057	0.7514	0.1058	0.7623	0.0973
	CH	0.7929	0.1192	0.7542	0.1052	0.6975	0.0988
	H-S	0.8535	0.111	0.8099	0.0925	0.7377	0.0831
Basra	FFNN	0.8145	0.0967	0.8086	0.0895	0.7868	0.087
	ANFIS	0.8314	0.0919	0.8256	0.0855	0.8077	0.083
	MLR	0.7941	0.1007	0.7913	0.0935	0.769	0.0917
	M-V	0.7923	0.1122	0.7622	0.0998	0.7128	0.0921
	CH	0.729	0.1211	0.7129	0.1097	0.6659	0.1052
	H-S	0.7319	0.1207	0.7142	0.1094	0.6678	0.1046
Rutbah	FFNN	0.8109	0.1044	0.8024	0.0989	0.7938	0.1
	ANFIS	0.8373	0.0986	0.8258	0.0929	0.816	0.0928
	MLR	0.7784	0.116	0.7773	0.105	0.7451	0.1083
	M-V	0.7609	0.1203	0.7536	0.1104	0.7261	0.1125
	CH	0.7904	0.1196	0.7928	0.1013	0.7294	0.1053
	H-S	0.7949	0.1193	0.7956	0.1006	0.7307	0.1042
Erbil	FFNN	0.8237	0.116	0.8271	0.1061	0.8002	0.1111
	ANFIS	0.8383	0.1092	0.8418	0.1015	0.823	0.1064
	MLR	0.7925	0.1251	0.7899	0.117	0.7676	0.1205
	M-V	0.7961	0.1219	0.8231	0.1073	0.7794	0.1195
	CH	0.7997	0.1295	0.8125	0.1105	0.751	0.1184
	H-S	0.8277	0.1269	0.832	0.1046	0.7609	0.1098

				Validation		Testing	
Region	**Model**	**DC**	**RMSE**	**DC**	**RMSE**	**DC**	**RMSE**
Baghdad	SA	0.821	0.099	0.829	0.088	0.793	0.092
	NE	0.8224	0.0985	0.8291	0.0877	0.7935	0.0915
	SA2	0.9854	0.0903	0.8713	0.0761	0.9793	0.0712
	NE2	0.9892	0.0783	0.9062	0.065	0.9844	0.0611
Basra	SA	0.774	0.098	0.772	0.098	0.781	0.096
	NE	0.7767	0.0982	0.7695	0.0983	0.7801	0.0955
	SA2	0.9844	0.0909	0.8442	0.0808	0.9801	0.0742
	NE2	0.9891	0.0763	0.8879	0.0685	0.986	0.062
Rutbah	SA	0.835	0.098	0.823	0.094	0.82	0.093
	NE	0.824	0.103	0.8171	0.0952	0.7993	0.0965
	SA2	0.9856	0.0858	0.9001	0.0703	0.9826	0.0746
	NE2	0.9901	0.072	0.9156	0.0646	0.9877	0.0619
Erbil	SA	0.838	0.108	0.843	0.101	0.825	0.106
	NE	0.8383	0.108	0.8431	0.1011	0.825	0.1064
	SA2	0.9793	0.0926	0.9009	0.0803	0.9773	0.0822
	NE2	0.9791	0.0926	0.9009	0.0803	0.9773	0.0822

CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusion

In this study, daily global solar radiation was simulated in four regions in Iraq via 3 empirical models of M-V, CH, H-S, 2 different AI models of FFNN, ANFIS as well as conventional MLR model. Afterwards, simple averaging and neural ensemble techniques which combine the outputs of the single models were employed to improve the performance of the single models. In this way, different models with different input combinations were developed and applied for the modelling.

According to the results, Tmax is the most dominant in the simulation of daily global solar radiation in Iraq. Based on the two statistics of DC and RMSE employed, this study showed that temperature empirical models can provide satisfactory results for the estimation of daily global solar radiation. The results also showed that AI models are superior to MLR model due to the fact that MLR is linear model and as such, the model could not cope with nonlinear properties.

Comparison of the models showed that the ensemble modeling could increase the predictive performance of most of the single models up to 11%, 5%, and 6% for training, validation, and testing, respectively, when 3 single models were employed as the inputs of ensemble modeling.

On the other hand, the results showed significant increase in estimation of daily global solar radiation using 6 outputs of the single models as inputs to the second ensemble strategy up to 19.19%, 7.59%, and 16.81% with the best single model and 20.59%, 11.83%, and 21.24% for the 3 inputs neural ensemble technique (first strategy). In general, the results obtained in this study revealed that ensemble modeling provides promising predictive performance over single models when appropriate number of single models are used.

In view of the obtained results in this study which show more heterogeneous inputs for ensemble technique could lead to better overall results, it can be suggested that for further studies, more AI based models such as Support Vector Machine (SVM) are also applied and their outputs are also included in the ensemble modeling.

5.2. Recommendation

In view of the obtained results in this study, it can be suggested that for further studies, more AI based models such as Support Vector Machine (SVM), Genetic Programing (GP), Genetic expression Programming (GEP), Wavelet, etc. due to their performances in dealing with complex problems.

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