T.R.
VAN YUZUNCU YIL UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES
DEPARTMENT OF EGINEERING

ESTIMATION OF METEOROLOGICAL PARAMETERS BY ANFIS METHOD: THE CASE OF KIRKUK STATION, IRAQ

M.Sc. THESIS

PREPARED BY: PINAR BAKHTIYAR ABDULKAREEM SALIHI
SUPERVISOR: Asst. Prof. Dr. NADIRE UCLER

VAN-2020

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ACCEPTANCE and APPROVAL PAGE

This thesis entitled "Estimation of Meteorological Parameters By Anfis Method: The Case of Kirkuk Station, Iraq" presented by Pinar Bakhtiyar Abdulkareem Salihi under supervision of Assist. Prof. Dr. Nadire ÜÇLER in the Department of Civil Engineering has been accepted as a M. Sc. thesis according to Legislations of Graduate Higher Education on 21/07/2020 with unanimity of votes members of jury.

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Member: Assist. Prof. Dr. Nadire ÜÇLER Signature:

This thesis has been approved by the committee of The Institute of Natural and Applied Science on ..……../........../…..….. with decision number ....

Signature

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Director of Institute

THESIS STATEMENT

All information presented in the thesis obtained in the frame of ethical behavior and academic rules. In addition, all kinds of information that does not belong to me have been cited appropriately in the thesis prepared by the thesis writing rules.

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SALIHI, Pinar Bakhtiyar Abdulkareem

ABSTRACT

ESTIMATION OF METEOROLOGICAL PARAMETERS BY ANFIS METHOD: THE CASE OF KIRKUK STATION, IRAQ

SALIHI, Pinar Bakhtiyar Abdulkareem
M.Sc. Thesis, Civil Engineering Department
Supervisor: Asst. Prof. Nadire ÜÇLER

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The exploration and understanding of complex weather patterns to reliably forecast various climatic conditions has been an important part of the scientific process examinations globally. In this study, Adaptive Neuro Fuzzy Inference System (ANFIS) is used to create models to predict some of the most important climatic parameters. Relative humidity, pressure, temperature, and solar radiation parameters have been predicted by depending on the input variables which include daily and hourly data of temperature (℃), wind speed (m/sec), dew point (℃), relative humidity (%), solar radiation (watt/m^2) and pressure (hpa). The models set with data observed in Kirkuk station in Iraq, were tested with data of Mardin and Sanliurfa stations in Turkey. 2014-2017 and 2018 datasets were used as training and checking purposes, respectively. Moreover, the results of normalized and un-normalized dataset and ANFIS and Regression Analysis were compared. The models are evaluated by using root mean square error (RMSE), mean absolute error (MAE), and determination coefficient (R^2). According to the results, ANFIS has much better performance than regression analysis for the estimation of daily normalized data, that had lower error values and higher R^2. Among all the parameters, the temperature parameter achieved the best performance using relative humidity and dew point as input variables. The results of humidity and temperature parameters have shown that these models showed a performance at Mardin and Sanliurfa stations at a similar level with Kirkuk station. If it aimed to predict in case of the lack of better models to use, these models can be used to get an idea about the parameters.

Keywords: ANFIS, Prediction, Pressure, Relative humidity, Solar radiation, Temperature.

ÖZET

METEOROLOJİK PARAMETRELERİN ANFİS YÖNTEMİYLE TAHMİNİ: IRAK KERKÜK İSTASYONU ÖRNEĞİ

SALİHİ, Pınar Bakhtiyar Abdulkareem
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Çeşitli iklim koşullarını güvenilir bir şekilde tahmin etmek için karmaşık hava modellerinin araştırılması ve anlaşılması, küresel olarak bilimsel süreç sınavlarının önemli bir parçası olmuştur. Bu çalışmada, en önemli iklim parametrelerini tahmin etmek için modeller oluşturmak üzere üyelik işlevleriyle kural tabanlı bir model elde etmek için çok daha yararlı olan Adaptif Nöro Bulanık Çıkarım Sistemi (ANFIS) kullanılmıştır. Bağıl nem, basınç, sıcaklık ve güneş radyasyonu parametreleri, günlük ve saatlik sıcaklık (°C), rüzgar hızı (m/s), çiğ noktası (°C), bağıl nem (%), güneş radyasyonu (watt/m2) ve basınç (hpa) verilerini içeren giriş değişkenlerine bağlı olarak tahmin edilmiştir. Irak'taki Kerkük istasyonunda gözlemlenen verilerle kurulan modeller, Türkiye'deki Mardin ve Şanlıurfa istasyonlarına ait verilerle test edilmiştir. 2014-2017 ve 2018 veri setleri sırasıyla eğitim ve kontrol amacıyla kullanılmıştır. Ayrıca, normalize edilmiş ve normalleştirilmemiş veri kümesinin ve ANFIS ve Regresyon Analizinin sonuçları karşılaştırılmıştır. Modeller, kök ortalama kare hatası (KOKH), ortalama mutlak hata (OMH) ve determinasyon katsayısı (R^2) kullanılarak değerlendirilmiştir. Sonuçlara göre ANFIS, saatlik normalleştirilmemiş verilere göre daha düşük hata değerlerine ve daha yüksek R^2'ye sahip olan günlük normalize edilmiş verilerin tahmini için Regresyon Analizinden çok daha iyi bir performansa sahiptir. Dört parametrenin arasında, sıcaklık parametresi modeli, giriş değişkenleri olarak bağıl nem ve çiğ noktasını kullanarak en iyi performansı elde etmiştir. Nem ve sıcaklık parametrelerinin sonuçları, bu modellerin Mardin ve Şanlıurfa istasyonlarında Kerkük istasyonuna benzer bir performans sergilediğini göstermiştir.

Anahtar kelimeler: ANFIS, Tahmin, Rölatif nem, Basınç, Solar radyasyon, Sıcaklık.

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Pinar Bakhtiyar SALIHI

TABLE OF CONTENTS

Pages

Pages

LIST OF TABLES

Table **Pages**

Table **Pages**

LIST OF FIGUERS

Figure **Pages**

Figure **Pages**

SYMBOLS AND ABBREVIATIONS

Some symbols and abbreviations used in this study are presented below, along with descriptions.

Symbols	**Description**
Dp	Dew point
E	East
$\mathbf{f_{i(observed)}}$	Observed values
$\mathbf{f_{i(predicted)}}$	Predicted valued
H	Relative humidity
hpa	Hectopascal
N	North
P	Pressure
$\boldsymbol{p_i, q_i, r_i}$	Consecutive criteria
Sr	Solar radiation
T	Temperature
$\boldsymbol{W_i}$	Force of fire of rules
Ws	Wind speed
X	Expected value
Y	Observed value
%	Percentage
$\boldsymbol{C^{\circ}}$	Centigrade
$\boldsymbol{\mu}$	Mu (membership function)
$\prod$	Multiplication
$\sum$	Summation

Abbreviations	**Description**
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
GP	Grid Partition
MAE	Mean Absolute Error
MLP	Multi-Layer Precipitation
MLR	Multiple Linear Regression
MNLR	Multiple Nonlinear Regression
MSE	Mean Square Error
RMSE	Root Mean Square Error
$\boldsymbol{R^2}$	Coefficient of Determination
$\boldsymbol{SC}$	Sub-Clustering
WNN	Wavelet Neural Network

1. INTRODUCTION

Throughout time immemorial, the desire to explore mysterious facets of various phenomena has consumed human minds. Other than being a matter of fascination, forecasting is valued to be a foundation for the invaluable planning for the forthcoming case. Early in its career, and as a religious term, prediction was unnecessarily planned to ways of accessing human against painful disasters and is regarded with a research resource for a wide range of uses and a multitude of purposes (Agboola et al., 2013). This is clear that forecasting practices have substantial role to play in daily life of human.

Every day the climate estimation shows us how the condition of the weather would be like in the next day. Simply put, current weather assumptions shall involve temperature, relative humidity, clouds, rainfall, atmospheric, pressure, wind speed, dew point and visibility. Such criteria apply to different weather conditions, such as calm, fog, rainy, rainstorm, rain and thunderstorm (Awan and Awais, 2009). We may avoid tremendous damage by anticipating the arrival of hurricanes or typhoons. Normally, we foresee a lot of things in our everyday lives, including the economy, the stock market, population rise, weather, etc. It could be difficult to make a prediction of 100% accuracy, however humans will do their duty to decrease prediction errors or increase the speed of the forecasting cycle.

Many academics have suggested many different methods or models to overcome the forecasting problems (Chen and Hwang, 2000). Weather forecasting systems are one of the most complicated formula frameworks that the machine needs to dissolve. A massive volume of data arriving from satellite systems, radar systems and sensors all over the world, sends information in a day that it will be used to forecast the climate condition around the world over the next few hours and days. Weather predictions estimate the next 24, 48 and 72 hours for large areas (Pasero and Moniaci, 2004). Climate predictions offer important detail on potential environmental conditions.

There are different methods are used in weather forecasting, through straight forward observation of the sky to extremely sophisticated simulated mathematical models (Tektas, 2010). The application of sophisticated methods for predicting and measuring natural phenomena such as relative humidity, temperature, pressure etc. is an up-to-date major issue. Among all these approaches was the Fuzzy Logic system that was founded as a scientific solution but has been used in a variety of areas, such as engineering, computer sciences, medicine, and meteorology it has been used to construct prediction models using known databases. As is recognized, the basic concept of the system is followed by a methodology for the construction of fuzzy structures closer to the essence of human thinking instead of abstract and complicated logical statements. Many researchs based on fuzzy logic approaches for hydrological prediction such as Zeki Sen, which used fuzzy logic for estimating runoff coefficient and rainfall estimation and recommending it for the future studies.

In general, two of the artificial intelligence methods that have quickly achieved popularity as a new technology ANNs and neuro-fuzzy systems are a challenge in computational technology (Tabari et al., 2012). The purpose and impact relationship is more clearly illustrated by ANFIS system that is created by the hybridization ANN and Fuzzy Inference method optimized for input-output sample sets. Therefore, it is offered, with the guidance of ANFIS and expert advice, to model the correct connection between the factors that influence the incidents investigated (Kisi and Tombul, 2013).

Artificial intelligence approaches are becoming extremely important to researchers in hydrology and water resource management over time (Sudheer et al., 2002) and many experiments have been performed applying Fuzzy Logic in hydrology and water supply management. (Firat and Gungor, 2006). The framework ANFIS is becoming a common research method due to its capability to analyze spatial and spectral relevant information within the transmission (Kayda and Kumar, 2015). ANFIS was used to examine non-linear processes and to approximate the interaction between input and output in models comprising of different variables. So many hydrological research experiments have been worked out by using ANFIS (Khodaie et al., 2013). Typically, environmental reports shall contain temperature, relative humidity, solar radiation, precipitation, atmospheric pressure, wind speed, and dew point. These criteria apply to different weather conditions, such as calm, fog, clouds, snowstorms, rainfall, and storm. In addition to forecasting a weather phenomenon, a map of weather variables for weather conditions needs to be established.

This research is focused on the creation of a fuzzy rule-based chart of climate and event parameters, which are classified into four separate predictive models which are temperature, relative humidity, solar radiation, and pressure. These kinds of variables can be described as environmental or climatic conditions. The adverse impacts of climate change on civil engineering systems is obvious. Major factors such as higher wind and snow weights and secondary effects such as erosion and corrosion. Changes in the form of loading on buildings induced by increasing sea levels or variations in temperature across cross-sections. Civil engineers, however, need to respond to emerging developments and continue to address these issues at each stage of planning and development.

In hydrology, there is a big effect of temperature, relative humidity, solar radiation and pressure, and this effect could be obvious on evaporation which is a very important hydrology character for saving the water resources. Evaporation is the transition of water molecules from a liquid state into a gaseous form, hydrologists also realize that evaporation is the total rate of movement of water vapor molecules from the evaporation layers to the air. The evaporation factor is strongly influenced by climatic conditions, such as temperature, solar radiation, wind, pressure, and humidity, except the fact of the conditions on which evaporation happens (Ward and Robinson, 1990).

Solar radiation is the higher heat energy supply. To encourage sustainable types of energy capital, the forecasting of worldwide solar irradiance is crucial in understanding the effectiveness of solar energy resources as available and clean energy track and analyze solar energy locations (Ghimire et al., 2019). The ability to carry vapor away from the evaporative surface depends on the wind speed and pressure over the atmosphere and the same level of humidity in the air above it (Chow et al., 1988). Solar radiation is primary information in many areas. For this purpose, it is very important to understand how this all differs in the same time-period in several applications, for example, earth's atmosphere energy density research, heating energy study of building structures, planning of activities of renewable energy sources, environmental science, agricultural sciences as well as some environmental assessment analyzation (Mellit and Pavan, 2010). Solar radiation, the earth's primary source of energy influences the atmosphere and climate of the planet (Soliman, 2010). Water in the sea melts under solar radiation, and waves of water vapor float above land. Water evaporates from the surface, either dry surface or soil covered by plants, even from trees, highly susceptible surfaces such as roofs and paths, open channels and running streams. The rate of evaporation varies with the color and reflection features of the ground and it would be specific for areas directly related to or shaded by solar radiation. (Wilson et al., 1969).

The relative humidity is the measure of the real to the saturated vapor pressure and it is thus a combination of the amount of moisture in a given area to the quantity that the room might hold if it were saturated (Soliman, 2010). The relative humidity of the atmosphere is yet another aspect influencing evaporation. If the temperature of the air increases, the capacity to contain more water vapor reduces and the speed of evaporation. Replacing the thermal gradient of saturated air with similarly high humidity air does not reduce the evaporation speed, this will only happen if the arriving air is drier than anything that has been displaced. (Wilson et al., 1969).

Another element that has a slight effect on evaporation is air pressure. The amount of evaporation depends on the variation in vapor pressure on the top of the water and in the air (Raghunath, 2006). The pressure is defined as the force on a unit of area. The air around the globe and the composition of the atmosphere has a weight, and therefore has a pressure that affects our bodies. This pressure is known as air pressure, i.e. pressure from the atmosphere. It is scientifically defined as the weight of the air column located on a certain area of the earth, which extends from the surface of the earth to the end of the atmosphere. Here is the importance of atmospheric pressure in the climate, it is count as the main cause of horizontal movement (wind) of all kinds, as well as vertical movement (up and down). Between the top of the earth and the peak hydrosphere. Determines the speed and intensity of winds and their directions according to the pressure gradient and its equal lines, whether they are close or far apart. Irregular pressure change causes whether it is a dynamic change or a thermal change, in the first case upward and downward currents occur causing the presence of high and low-pressure areas, and in the second case a thermal change and the transmission of air masses with properties different from the ones that are different in their density, humidity, and temperature. It caused atmospheric changes in weather as it passed over any region and multiple ritual phenomena such as rain, lightning, thunder, hail, snow, and temperature change occurred. Atmospheric altitudes cause a thermal coup in the upper atmosphere.

Effective weather prediction has a range of significant uses in industry, agriculture, and the atmosphere. Temperature is a major climate parameter that affects electrical load power generating power stations in many regions of the world, as a result, prediction temperature changes are the main characteristic in load forecasting systems (Abdel-Aal, 2004). Information on atmospheric temperature change can also be used to predict soil surface temperature (George, 2001). In agricultural production, hourly atmospheric temperature estimates for illness safety systems and disease control strategies can be used to forecast conditions that are satisfactory for the development of disease in plants and the planning of proper action, including such splattering of sensitive insecticides (Kim et al., 2002).

Different construction materials and buildings react and behave differently in the same climatic conditions. For example, an increase/decrease in relative humidity will cause what is termed movement. This is a seasonal or even daily change in dimensions of a porous material due to a change in the relative humidity of the air. Humidity and precipitation on unprotected steel will lead to corrosion. A galvanic cell is formed on the steel surface with the water drops on the steel surface acting as an electrolyte. Parts of the steel become anodes and cathodes and corrosion of the steel occurs. Lack of moisture can have a dramatic effect on the building materials. Also, the amount of solar radiation varies from one place to another, according to degrees of width and terrain in terms of height and direction of the slope of its slopes. Therefore, it is found a difference in the design of buildings to fit the nature of solar radiation in each region. Also, the amount of solar radiation varies from season to season due to the difference in the angle of the sun's rise that ranges between 90-0 degrees, as well as an effect on the temperature and lighting inside the house. This information also has great importance for designing the houses, buildings, roads, and how to choose the materials, and these reasons push us to search about these parameters and finding the future conditions of the weather.

This study further compared the results of the fuzzy system with the results of the regression analysis. For this purpose, hourly and daily data of Kirkuk has been collected and processed to find out the difference of the accuracy between hourly and daily data and get less error.

Moreover, these data (daily and hourly) have been normalized to investigate the effect of normalization on the error values and which one could get less error. The data presented in this paper divides into four models, which the first one is predicting relative humidity based on several climatological variables, for example, temperature (T), wind speed (W_S), pressure (P) and solar radiation (Sr) with the units centigrade, m/sec, bar and watt/m^2 respectively, the second model has pressure as output depending on four different inputs like T, H, W_S and dew point (D_P), and their units are centigrade, %, m/sec and centigrade respectively, the third model is solar radiation that has been predicted depending on these parameters T, H, W_S and P with centigrade, %, m/sec, and bar as their units respectively and the last model is predicting temperature using two input parameters which are relative humidity and dew point, and their units are % and centigrade respectively.

The last and most important part of this study is comparing the result of Kirkuk city with data of two other Turkish cities which are Mardin and Sanliurfa, that have similar climate features with Kirkuk. The main objective of this comparison is to verify whether the model that is being created based on other city data can be used for other cities with similar climatic conditions. It is not easy to create models for each city, sometimes it is very difficult to obtain specific city data due to policy interference or the economic aspect or the lack of provision of the equipment and tools required to observe the weather condition. If good results are obtained, this will facilitate a lot of researches, it can be used old models that have been done for other cities and depending on it to estimate the meteorological data for a city with a similar climate.

2. LITERATURE REVIEW

Jacquin and Shamseldin, (2006), investigated the evolution of Takagi Sugeno fuzzy inference technologies to rainfall-runoff forecasting. The outcomes of the research showed that fuzzy inference systems are an appropriate solution to the traditional one technique for modeling the non-linear relationship among rainfall and runoff.

Firat and Gungor (2006), focused on the ANFIS methodologies to demonstrate the efficacy and flexibility of the ANFIS, the Great Mender River, situated to the west of Turkey and the most essential water supply of the Great Menders river basin was picked as the study areas. The analysis revealed that the ANFIS can be successfully applied as well as provided rising accuracy and reliability for estimating the flow of the river.

Mellit et al. (2007), introduced a new approach to forecast and model total solar radiation information from the average sunshine period and air temperature using ANFIS. Despite that, the uncertain verification data set provided a very effective prediction with MRE not surpassing 1% between measured and expected data and the coefficient of correlation achieved for the validation data set is 98%

Aldrian and Djamil (2008), explored the use of multivariable ANFIS to forecast daily rainfall using many surface climate conditions as predictor variables. It was found that relative humidity was the strongest indicator of stable results. ANFIS achievement was receptive to severity and scale distinctions between indicators, thus implying the introduction of a turning and scaling variable or functions.

Yarar et al. (2008), estimated level changes in Beysehir in Turkey using ANFIS and ANN. While all model's results were reliable, the minimum MSE value (0.0057) and the maximum R^2 value (0.7930) was obtained with the ANFIS model, followed by the three-layered ANN1. Also, Buyukyildiz et al. 2014 compared ANFIS with other methods on lake level prediction.

Tektas (2010), offered a comparison project of numerical and neuro-fuzzy network models for prediction of the most important weather parameters, temperature, wind speed, and pressure of Göztepe, İstanbul, Turkey. Based on the experimental results, the most appropriate model and network configuration were calculated based on the forecast efficiency, consistency, and efficacy. Efficiency analyses of models ANFIS and Auto-Regressive Integrated Moving Average (ARIMA) revealed that ANFIS gave the best results.

Kumar (2012), tried to model the correlation among maximum and minimum temperature dataset of Dehradun, India based on ANFIS. This article aimed to build up a forecast model and to validate its ability and provide weekly temperature datasets. Visual evaluation depended on a statistical distinction between the actual and the expected values and a quantitative appraisal of the results of the model suggested that ANFIS would be used successfully for a minimum weekly temperature prediction.

Sumithira and Kumar, (2012), used the ANFIS to predict monthly global solar radiation in India. The analysis aimed to check the effectiveness of ANFIS and different computational intelligence models as seen in the research for the evaluation of solar radiation. The test results indicated that the ANFIS-based forecast was stronger than other models and then further demonstrates its predictability for any geographic location with changing climates.

Rahman et al. (2013), used ARIMA and ANFIS models for predicting the future weather in Dhaka, Bangladesh. Ten years of hydrological parameters (from the year 2000 to 2009), consisting of maximum temperature, minimum temperature, relative humidity, and air pressure were used in this study. Experimental findings indicated that ARIMA had better efficiency relative to ANFIS.

Khodaie et al. (2013), used the ANNs and ANFIS for monthly minimum, maximum, and mean temperature forecasts that have been created at the Tehran Synoptic Station, Iran. Results have shown that ANNs were better than ANFIS to forecast temperature changes.

Kisi and Shiri (2013), evaluated the abilities of ANFIS and ANNs in estimating a long-term temperature of the air per month values at 30 different meteorological stations of Iran. Monthly data from 20 meteorological stations have been applied for training and ten stations have been used as testing. Predictions of the ANFIS and ANN models concerning one another were compared. In general, the ANN models showed improvement than the ANFIS model during the testing period.

Rezaeianzadeh et al. (2014), compared ANN, ANFIS, Multiple Linear Regression (MLR), and Multiple Nonlinear Regression (MNLR) for predicting full daily discharge at the source of the Khosrow Shirin drainage area, situated at the region of Fars in Iran. The findings revealed that precipitation weighted as input to ANNs and MNLR and the Sensory dispersed rainfall data to ANFIS and MLR contributed to more reliable forecasts.

Varzandeh et al. (2014), measured solar irradiation and wind velocity sequence by two main categories of artificial intelligence algorithms called the neural wavelet network (WNN) and ANFIS. The data used by the prediction method was derived from a weather station in Tehran, Iran. The results indicated that the structural rigidity of both wind velocity projection and solar irradiation algorithms and the superior power of WNN to ANFIS for forecasting of solar irradiation and wind velocities.

Karthika and Deka, (2015), proposed to estimate air temperature using the new hybridized (wavelet-ANFIS) technique. The wavelet data were taken as input for the ANFIS. A comparison of the hybridized wavelet-ANFIS method was done. The hybridized wavelet-ANFIS method (Gauss membership) indicated the coefficient of determination (R^2) is 0.95 and the RMSE is 0.74 which was higher than the individual tests.

Mohammadi et al. (2016), used ANFIS to define the most essential of all parameters to forecast of average daily dew point temperature, using eight daily parameters. Seven years of daily analysis of data from two Iranian cities situated in the northern and southern northern regions of Iran. Comparative analysis among the ANFIS method projections depending on chosen inputs and different computational intelligence technologies prove that ANFIS could have better performance to estimate the temperature of the daily dew point. There are other studies which applied ANFIS to this parameter to create a prediction model (Kisi et al. 2013, Baghban et al. 2015)

Ozturk et al. (2017), purposed to predict evaporation based on the ANFIS using three different separate meteorological data. In this particular example, daily information is used from the Guzelyurt weather station in Northern Cyprus. The measurements calculated should contain observations of temperature, relative humidity, and atmospheric pressure. Data from 2005 to 2014 has used. Then, the fuzzy derived result was matched to the actual weather available data. The R^2 is received as 0.74, this is a statistically essential element. Also, some other studies investigated the efficiency of ANFIS on the prediction of evaporation (Moghaddamnia et al. 2009, Shiri et al. 2011, Eslamian and Amiri, 2011, Kisi and Tombul 2013, Goyal et al. 2014,)

Zhu et al. (2019), used four types of artificial intelligence, which include Multilayer Perceptron Neural Network and ANFIS. The outcomes suggested artificial intelligence could be used efficiently for the modeling of river water temperatures.

Setyaningrum and Swarinata (2020), used ANFIS in this research to forecast three environmental factors, namely air temperature, air humidity, and wind speed as a predictor. The records used were climate forecasts from the West Jakarta area in January, February, March, July, August, and September of 2012. ANFIS for the weather forecast, the overall accuracy was 100 percent, because each one was capable of predicting the quality value of bracket 0 (rain) and bracket 1 (not rain) the same as with the qualitative approach and from complete tests 183 and 180 as preparation. Overall, this can be indicated that the use of the ANFIS for climate modeling is 100 percent accurate.

The ANFIS model was also used to create prediction models for different parameters such as evapotranspiration (Kisi, 2013, Baba et al. 2013), rainfall (Agboola et al. 2013, Sharifi et al. 2013, Hashim et al. 2016), rainfall-runoff (Remesan et al. 2008), groundwater level (Sreekanth et al. 2011, Alipour et al. 2014), wind speed (Perez et al. 2012, Maroufpoor et al. 2019), water usage (Altunkaynak et al. 2005), soil variable (Kashi et al. 2014).

3. METHODOLOGY

3.1. Case Study

In this study, 5 years climate data of dew point (Dp), solar radiation (Sr), relative humidity (H), temperature (T), wind speed (W) and pressure (P) which their units centigrade, watt/m^2, %, C°, m/sec, mm, and bar respectively have been used. Five years of data sample considered (2014-2018) were collected, that have been recorded by a meteorological station in Kirkuk city (see figure 3.1). The data of (2014-2017) have been used as training data and the data of 2018 used to be checking data. These data were divided into three individual groups that each one of them contains different inputs and outputs.

Kirkuk has two meteorological stations, one of them belongs to a weather forecast commission, that records the meteorological data, and this station is located in the southwest of the city. Kirkuk climate is generally characterized by hot summers and average rain in the winters, the area receives an average annual rainfall of 361.3 mm which occurs during the monsoon period (October to May). The city is located at 35.4666° N latitude and 44.3799° E longitude and it is situated at elevation 346 meters above sea level in north-central of Iraq with a 9,679 km^2area of the city. It has two main rivers Sirwan river located 45 km in the west part of the city and the Khasa river separate the city into two parts.

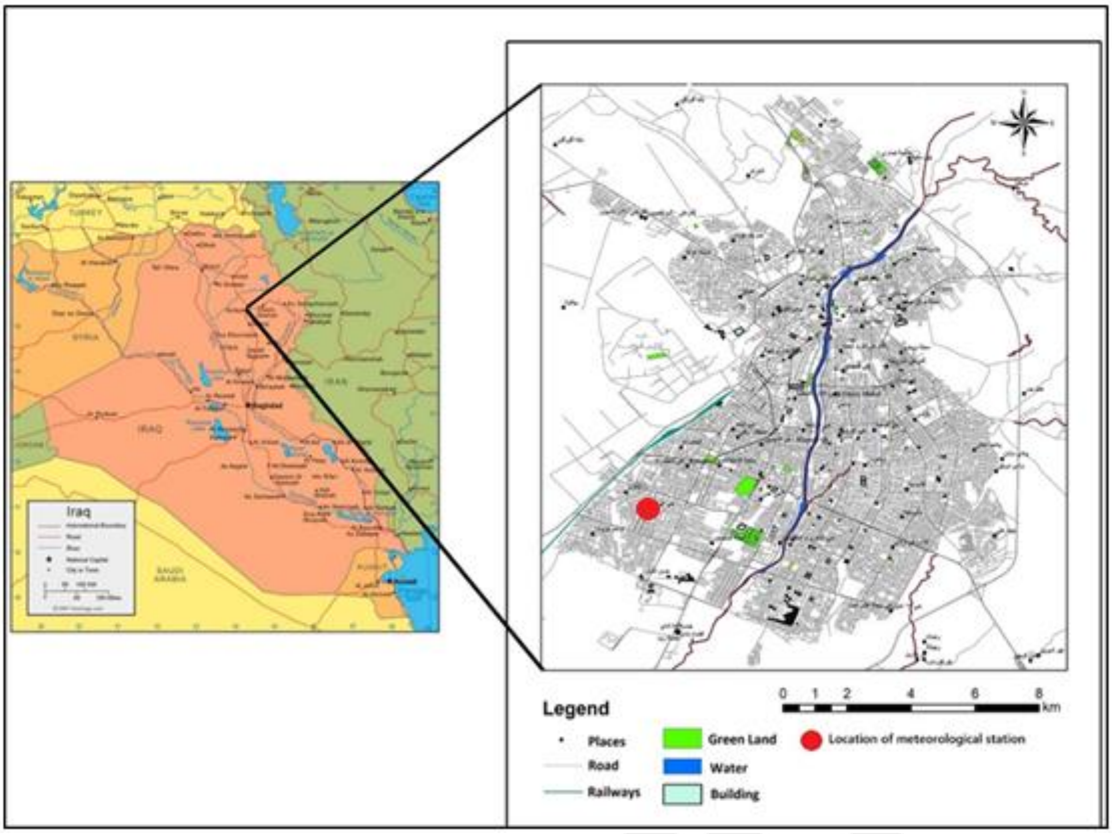

Figure 3.1. The location of Kirkuk station.

The results were compared with the data of Mardin and Sanliurfa city in Turkey, which have similar features with Kirkuk city. Mardin is located in the southwestern part of the country 37°18'47.12"N, 40°44'36.85"E and 1,083 m above the sea level with an area of 8,891 km^2. The city gets more precipitation than the lower regions with hot summers with cold winters. The average rainfall is about 641.4 mm per year. Sanliurfa city is in the southeast part of the country, the area of the city is 18,584 km^2. Its coordinates are $37°10'01''$ N latitude and $38°47'38''$ E longitude and it lies on 543m above sea level the weather here is normal, usually temperate. The precipitation in Sanlıurfa comes mainly in the winter, with very little rain in the summer. The rainfall here is around 477 mm per year. The following figure shows Turkey's map with the location of Mardin and Sanliurfa city.

Figure 3.2. The location of Mardin and Sanliurfa stations.

Some statistical data of parameters are listed in the following tables. The tables show the mean, minimum and maximum values of parameters, standard deviation, skewness, and correlations. The tables consist of the data of Kirkuk, Mardin, and Sanliurfa for the years 2014-2017 and 2018 separately. The following table shows the statistical parameters and the features of the hourly dataset of 2014-2017 of Kirkuk city (see table 3.1).

In the below table, the best value of correlation is between temperature and relative humidity 0.862, which means that they have a stronger linear relationship comparing with the other values of correlation coefficients. Pressure has the lowest skewness value -0.042 and it can be called fairly symmetrical. These values discovered that the best performance of the model belongs to the inputs that include pressure and relative humidity. Wind speed has the highest value of skewness 1.837 which is highly skewed.

Table 3.1. The hourly statistical parameters of the climatic data of Kirkuk (2014-2017)

Station: Kirkuk (2014-2017)							
Data	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	
Model 1							Correlation with relative humidity
Relative Humidity	%	40.75	4	99	24.20	0.605	1
Temperature	C°	24.04	-1.7	49.3	11.24	0.119	-0.862
Pressure	hpa	760.299	745.1	776.1	6.49	-0.042	0.687
Solar radiation	Watt/m^2	178.675	0	917	244.55	1.129	-0.383
Wind speed	m/s	0.676	0	6.7	0.81	1.837	-0.151
Model 2							Correlation with Solar radiation
Solar Radiation	Watt/m^2	178.657	0	917	244.55	1.129	1
Temperature	C°	24.04	-1.7	49.3	11.24	0.119	0.443
Relative Humidity	%	40.75	4	99	24.20	0.605	-0.383
Pressure	hpa	760.299	745.1	776.1	6.49	-0.042	-0.19
Wind speed	m/s	0.676	0	6.7	0.81	1.837	0.242
Model 3							Correlation with pressure
Pressure	hpa	760.299	745.1	776.1	6.49	-0.042	1
Temperature	C°	24.04	-1.7	49.3	11.24	0.119	-0.859
Dew point	Centigrade	6.687	-26.9	20.4	4.26	-1.022	-0.362
Relative humidity	%	40.75	4	99	24.20	0.605	0.687
Wind speed	m/s	0.767	0	6.7	0.81	1.837	-0.196
Model 4							Correlation with temperature
Relative humidity	%	40.75	4	99	24.20	0.605	-0.862
Dew point	Centigrade	6.687	-26.9	20.4	4.26	-1.022	0.309

The following table is showing the statistical parameters of each variable for the dataset of 2018 for Kirkuk city (see table 3.2).

Table 3.2. The hourly statistical parameters of the climatic data of Kirkuk (2018)

Station: Kirkuk (2018)							
Data	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	
							Correlation with relative humidity
Relative Humidity	%	37.436	8	97	20.59	0.961	1
Temperature	C°	27.059	4.6	49.7	9.84	-0.188	-0.836
Pressure	hpa	757.971	746.3	773	5.86	0.172	0.546
Solar radiation	Watt/m^2	194.488	0	880	259.36	1.06	-0.371
Wind speed	m/s	0.895	0	5.8	0.81	1.391	-0.124
							Correlation with Solar radiation
Solar Radiation	Watt/m^2	194.488	0	880	259.36	1.06	1
Temperature	C°	27.059	4.6	49.7	9.84	-0.188	0.486
Relative Humidity	%	37.463	8	97	20.59	0.961	-0.371
Pressure	hpa	757.971	746.3	773	5.86	0.172	-0.196
Wind speed	m/s	0.895	0	5.8	0.81	1.391	0.231
							Correlation with pressure
Pressure	hpa	757.971	746.3	773	5.86	0.172	1
Temperature	C°	27.059	4.6	49.7	9.84	-0.188	-0.796
Dew point	Centigrade	8.901	-9.6	19.2	4.11	-0.746	-0.48
Relative humidity	%	37.436	8	97	20.59	0.961	0.546
Wind speed	m/s	0.895	0	5.8	0.81	1.391	-0.086
							Correlation with temperature
Relative humidity	%	37.436	8	97	20.59	0.961	-0.836
Dew point	Centigrade	8.901	-9.6	19.2	4.11	-0.746	0.393

Among the data of 2018 of Kirkuk city, the best linear relationship is between temperature and relative humidity -0.836, however, pressure has the least skewness that is 0.172, and they are the most effective inputs in the models. Wind speed has the closest standard deviation to its mean and its 0.81, which is the best result of standard deviation among the dataset because the larger the standard deviation the more variance in the results.

-0.196 is the least correlation coefficient between pressure and solar radiation and wind speed has a high skewed 1.391.

While there is a lack of Mardin and Sanliurfa's parameters the correlation has been calculated only with temperature, pressure and relative humidity, the highest correlation value is between temperature and relative humidity which is -0.798 and pressure has the least skewness which is 0.127 of the hourly dataset of 2018 for Mardin city (see table 3.3).

Table 3.3. The hourly statistical parameters of the climatic data of Mardin (2018)

Station: Mardin (2018)									
Parameters	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	Correlation with		
							H	P	T
Temperature	C°	19.971	-0.2	39.2	9.258	-0.202	-0.798	-0.409	1
Relative humidity	%	42.745	8	100	22.369	0.893	1	0.076	-0.798
Wind speed	m/s	3.062	0	9.9	1.755	0.856	-0.02	-0.007	-0.072
Pressure	hpa	895.59	883	908.5	4.566	0.127	0.076	1	-0.409
Dew point	C°	4.545	-4.9	7.4	4.762	-0.444	0.023	-0.448	0.483

Sanliurfa city data gives a weak positive linear relationship by giving 0.105 as a correlation coefficient between relative humidity and dew point, the temperature has the least skewness -0.126, it indicates as fairly symmetrical. The highest value of the standard deviation is 21.799 the result of relative humidity. The highest correlation value is -0.798 and its the relationship between relative humidity and temperature. These parameters could give possible results according to their features (see table 3.4).

Table 3.4. The hourly statistical parameters of the climatic data of Sanliurfa (2018)

Station: Sanliurfa (2018)									
Parameters	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	Correlation with		
							H	P	T
Temperature	C°	22.292	2.3	43	9.432	-0.126	-0.769	-0.581	1
Relative humidity	%	45.02	9	98	21.799	0.637	1	0.203	-0.769
Wind speed	m/s	1.451	0	5.5	0.839	0.903	-0.349	-0.381	0.38
Pressure	hap	947.61	933.7	964.2	5.578	0.224	0.203	1	-0.581
Dew point	C°	7.533	-10.2	22.7	5.443	-0.206	0.105	-0.571	0.496

If the hourly data of the three cities compared, Kirkuk data of (2013-2014) has better features, it may affect on having reasonable results. Among the daily dataset of Kirkuk relative humidity and temperature have the most influential correlation coefficient -0.871 which makes temperature the most effective parameter in that model. A fairly symmetrical skewness is temperature and it is 0.031. It's noticed that temperature, solar radiation, and wind speed are the most efficient input parameters while wind speed has the smallest difference between standard deviation and its mean (see table 3.5).

Despite the similarities in the characteristics of the three cities, there are some differences between their features. It's noticed that the daily data of Kirkuk city has the strongest linear correlation which is -0.854 between pressure and temperature, and it may positively affect the results of the model. It's discovered that Kirkuk's average daily data can give better results than hourly data because taking average or numerical means to give one a general estimation of the typical values in the range such that the estimates of all values are more or less the same. The average is a good measure of the dataset when a dataset contains values that are relatively evenly spread with no exceptionally high or low values (see table 3.6).

Table 3.5. The daily statistical parameters of the climatic data of Kirkuk (2014-2017)

Station: Kirkuk(2014-2017)							
Data	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	
							Correlation with Relative humidity
Relative Humidity	%	41.253	8.875	97.083	22.54	0.515	1
Temperature	C°	23.824	1.647	43.308	10.58	0.031	-0.871
Pressure	hpa	760.385	746.212	775.045	6.42	-0.056	0.728
Solar radiation	Watt/m^2	171.038	0	382.4	74.77	-0.132	-0.733
Wind speed	m/s	0.636	0	4.708	0.53	2.222	-0.189
							Correlation with Solar radiation
Solar Radiation	Watt/m^2	171.038	0	382.4	74.77	-0.132	1
Temperature	C°	23.824	1.647	43.308	10.57	0.031	0.739
Relative Humidity	%	41.253	8.875	97.083	22.54	0.515	-0.733
Pressure	hpa	760.385	746.212	775.045	6.42	-0.056	-0.675
Wind speed	m/s	0.636	0	4.708	0.53	2.222	0.141
							Correlation with pressure
Pressure	hpa	760.385	746.212	775.045	6.42	-0.056	1
Temperature	C°	23.824	1.647	43.308	10.58	0.031	-0.906
Dew point	Centigrade	6.666	-21.962	17.808	3.96	-1.186	-0.401
Relative humidity	%	41.253	8.857	97.983	22.54	0.515	0.728
Wind speed	m/s	0.636	0	4.708	0.53	2.222	-0.302
							Correlation with temperature
Relative humidity	%	41.253	8.857	97.983	22.54	0.515	-0.871
Dew point	Centigrade	6.666	-21.962	17.808	3.96	-1.186	0.354

Table 3.6. The daily statistical parameters of the climatic data of Kirkuk (2018)

Station: Kirkuk (2018)							
Data	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	
							Correlation with Relative humidity
Relative Humidity	%	38.266	11.958	92.146	19.58	0.887	1
Temperature	C°	26.726	8.512	43.062	9.23	-0.356	-0.848
Pressure	hpa	758.076	747.237	771.862	5.81	0.136	0.606
Solar radiation	Watt/m^2	187.331	14.458	308.521	77.12	-0.413	-0.687
Wind speed	m/s	0.855	0	2.545	0.49	0.991	-0.183
							Correlation with Solar radiation
Solar Radiation	Watt/m^2	187.331	14.458	308.521	77.12	-0.413	1
Temperature	C°	26.726	8.512	43.062	9.23	-0.356	0.791
Relative Humidity	%	38.266	11.958	92.146	19.58	0.887	-0.687
Pressure	hpa	758.076	747.237	771.862	5.81	0.136	-0.714
Wind speed	m/s	0.855	0	2.545	0.49	0.991	0.04
							Correlation with pressure
Pressure	hpa	758.076	747.237	771.862	5.81	0.136	1
Temperature	C°	26.726	8.512	43.062	9.23	-0.356	-0.854
Dew point	Centigrade	8.887	-5.883	17.4	3.84	-0.842	-0.525
Relative humidity	%	38.266	11.958	92.146	19.58	0.887	0.606
Wind speed	m/s	0.855	0	2.545	0.49	0.991	-0.147
							Correlation with temperature
Relative humidity	%	38.266	11.958	92.146	19.58	0.887	-0.849
Dew point	Centigrade	8.887	-5.883	17.4	3.84	-0.842	0.427

According to the specification of Mardin daily dataset, it's found out that there is not a big difference between hourly and daily dataset, the lowest correlation value is 0.08 which is very close to the results of Mardin hourly data and the biggest difference between the mean and standard deviation is in pressure parameter and it may have a bad effect on the results (see table 3.7).

Table 3.7. The daily statistical parameters of the climatic data of Mardin (2018)

Station: Mardin (2018)							
Data	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	
							Correlation with Relative humidity
Relative Humidity	%	43.556	12.416	95.541	21.484	0.833	1
Temperature	C°	19.73	2.454	35.216	8.854	-0.249	-0.807
Pressure	hpa	895.83	886.16	907.37	4.606	0.193	0.08
Wind speed	m/s	3.131	1	8.6	1.179	1.104	0.01
							Correlation with pressure
Pressure	hpa	895.83	886.16	907.37	4.606	0.193	1
Temperature	C°	19.73	2.454	35.216	8.854	-0.249	-0.43
Dew point	C°	4.635	-7.629	12.987	4.439	-0.541	-0.518
Relative humidity	%	43.556	12.416	95.541	21.484	0.833	0.08
Wind speed	m/s	3.131	1	8.6	1.179	1.104	-0.006
							Correlation with temperature
Relative humidity	%	43.556	12.416	95.541	21.484	0.833	-0.807
Dew point	C°	4.635	-7.629	12.987	4.439	0.833	0.492

Same as Mardin, Sanliurfa daily dataset has almost the same results as hourly data there is not an obvious difference between the two perform of the datasets (see table 3.8).

Table 3.8. The daily statistical parameters of the climatic data of Sanliurfa (2018)

Station: Sanliurfa (2018)									
Parameters	Units	X_{mean}	X_{min}	X_{max}	Standard Deviation	Skewness	Correlation with H	P	T
Temperature	C°	22.093	5.575	34.861	8.544	-0.305	-0.754	-0.62	1
Humidity	%	45.671	18.21	96.166	18.967	0.805	1	0.204	-0.754
Wind speed	m/s	1.433	0.3	3.5	0.533	0.633	-0.481	-0.545	0.546
Pressure	hpa	947.87	935.204	962.22	5.607	0.268	0.204	1	-0.623
Dew point	C°	7.556	19.487	-7.179	5.072	-0.327	0.046	-0.621	0.594

3.2. Fuzzy Logic

In existing approaches, the parameters have real number value systems, the relations are expressed in terms of arithmetic operations and the outputs have silky fundamental features. In Fuzzy Logic, values of variables are represented in colloquial language and the relationship is described in terms of IF-THEN rules and the outputs also are blurry subgroups that can be made smooth using fuzzification strategies. First, the smooth values of the function factors are fuzzified to be represented in linguistic words. Fuzzification is a procedure for measuring the grade of membership that valuation has to a particular fuzzy set. This is evaluated by measuring the membership degree of the fuzzy value system (Center and Verma, 1998). In fact, Fuzzy Logic provides an inference system that makes for sufficient human reasoning skills (Safar et al., 2019).

The source of Fuzzy Logic method dates back to 1965 since the invention of the fuzzy-set theory has been applied by Lotfi Zadeh (1965), and various implementations have also been made in electronics, industry and many other fields. This is a subset of Boolean logic that has been expanded to deal with the idea of partial truth – true values between ‘‘completely true’’ and ‘‘completely false’’, and provides a simple structure for mapping the input domain to the output domain. (Goyal et al., 2014).

The basic principle in Fuzzy Logic is the distribution of partial ownership of some object to various subsets of the linear combination rather than just belonging absolutely to a single group. Partial relating to a series can be characterized numerically by a membership function that supposes values between 0 and 1 inclusive (Sen, 1998). The most popular methods for designing structures with fuzzy laws are those suggested by Mamdani and Assilian (1975) and Takagi and Sugeno methods (1985). The two techniques are close in many ways, the major difference is that the Takagi-Sugeno output membership functions are either linear or stable while the Mamdani membership functions are semantic. (Atiaa and Abdul-Qader, 2011).

3.2.1. Adaptive neuro fuzzy inference system

Neural networks (NNs) have also seemed to have a strong capacity to describe the relationship between input-output parameters. Also, it is often possible to build a framework that computes a function with precise precision (Agarwal et al., 2013). The adaptive network-based fuzzy inference system (ANFIS) that was proposed by Roger Jang (1993) is one of the systems that most widely used among fuzzy inference systems. ANFIS (Jang 1993) returns a Takagi–Sugeno FIS and has a network of five layers of feed forwards. The first hidden layer is used for fuzzification of the input variables and in the second hidden layer, T-norm operators are used to defining the preceding part of the rule.

The third hidden layer normalizes the strength of the rule and the fourth hidden layer follows where the relevant rule parameters are calculated. The output layer measures all the inputs as the number of all incoming signals. ANFIS uses the learning of backpropagation to test hypothesis parameters (to know about membership function parameters) and the least square estimation to evaluate the correct parameters. There are two sections of a method of learning: In the first step, the patterns of input are propagated and optimal consequent parameters are determined by the least mean square method, although the parameters of the assumptions are believed to be defined for the current period through the training set. Within the second section, the patterns are transmitted. During this epoch, backpropagation is used to change the parameters of the assumptions, although the related parameters remain fixed (Sreekanth et al., 2011).

This system is a fuzzy Sugeno network configuration. Usually, this form of the model is built and put within the context of a neural network model to facilitate adaptation. (Figure 3.3) displays an ANFIS framework of two inputs, one output, and two input rules. This system has two inputs x and y and one output, where its rule is:

If x is A_1 and y is B_1 then $f = p_1x + q_1y + r_1$ (3.1)

If x is A_2 and y is B_2 then $f = p_2x + q_2y + r_2$ (3.2)

A_i and B_i are fuzzy sets, f is the output of the fuzzy area defined by the fuzzy rule. p_i, $q_i$and r_i layout criteria that are determined during the training phase. (Figure 3.3) indicates that each node in this layer is a fuzzy set and the output of any node in this layer belongs to the membership level of the input variable in this fuzzy set. Within this layer, the form parameters decide the structure of the fuzzy set membership function. (Rezaeianzadeh et al., 2014). Then a linear regression model developed using the training data to compare with the performance of ANFIS models. Linear regression has been used between the observed (Y) and the expected (X) values of the different models. (Eslamian and Amiri, 2011) as follows:

$$Y = p_x + q \tag{3.3}$$

ANFIS has five layers and each layer contains several node functions and node features. Nodes are classified into two groups: adaptive nodes and fixed nodes. The layers are defined as follows:

Layer 1: The nodes that exist in this layer are adaptive.

$$Q_{i.1=}\mu A_i(x) \tag{3.4}$$

$$Q_{i.1=}\mu B_i(x) \tag{3.5}$$

Layer 2: The nodes are set and represented by a circle and identified by $\prod$. while W_i denotes the force of fire of the rules. The output is determined on the basis, of this formula:

$$Q_{2.i} = w_i = \mu A_i(y)\pi B_i(y) \quad with\ i = 1.2 \tag{3.6}$$

Layer 3: All nodes are set and represented by a circle called N. The name of the output of this layer is normalized firing strength. The output is determined by the i-th firing strength of the rule by summing up all of them.

$$Q_{3.i} = w^{-}{}_{i} = \frac{w_i}{w_1+w_2} \ \ with\ \ i = 1.2 \tag{3.7}$$

Layer 4: The nodes are adaptive nodes which are shown as follows:
Consecutive criteria are p_i, q_i, r_i.

$$Q_{4.i} = w^{-}{}_{i} f_i = w^{-}{}_{i}(p_i x + q_i y + r_i) \tag{3.8}$$

Layer 5: The last layer in which the node is single and marked by $\sum$ and seen by the circle (Varzandeh et al., 2014).

$$Q_{5.i} = \sum_i w^{-}{}_{i} f_i = \frac{\sum_i w_i f_i}{\sum w_i} \tag{3.9}$$

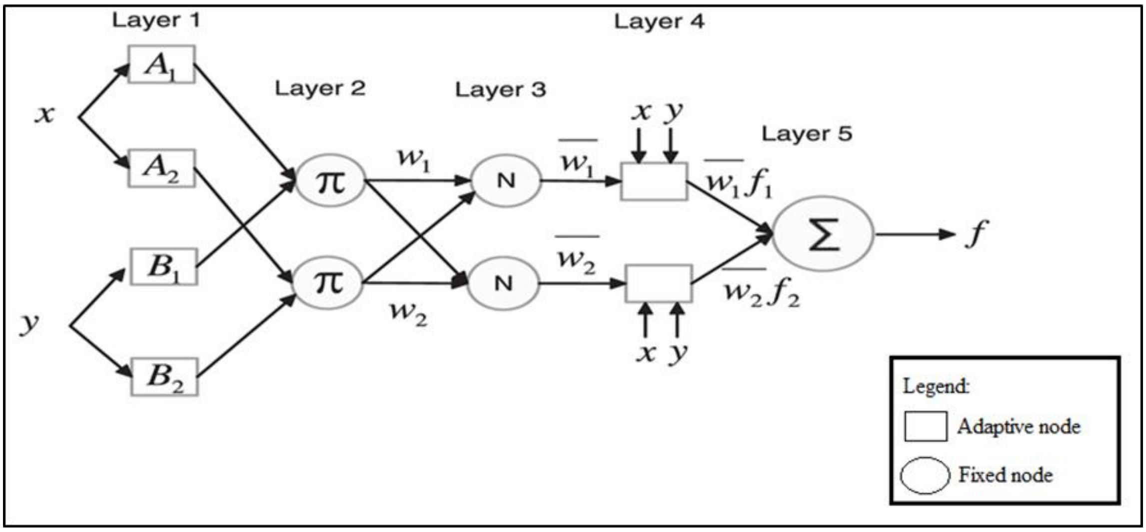

Figure 3.3. ANFIS structure with two inputs, one output, and two rules.

3.3 Regression Analysis

Different methods of weather prediction and predictive analysis have been established over the last decades. In all these frameworks, regression models are still commonly used for evaluating events in the future or values. In general, post-processing methodologies are also used to work on improving the management of errors in simulation results (Sahai et al., 2000). Some of the main issues of mathematical analysis are to consider an acceptable relation between both the dependent variables and the series of regression coefficients (Tabari et al., 2011). Regression analysis is widely used to explain the mathematical relationship between the dependent variables and one or more response variables (Tabari et al., 2010). The suggested framework can predict the climatic conditions for a major location employing regionally recorded information. The data is analyzed to acquire certain statistical measures to derive hidden data from the time series (Paras and Mathur, 2012). The common formula of regression of Y depended on X is:

$$Y= \alpha + \beta X+e \tag{3.10}$$

This method is termed as the linear regression statistical model. As a unique case, form Y= a + β X is known as the deterministic model (Agarwal, 1991).

The function for a linear equation, i.e., straight-line, in the form:

$$Y = \beta_\circ + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{3.11}$$

Where Y is the dependent variable, $\beta_{\circ}$,.., β_n are the equation parameters for the linear relation, and X_1,... , $X_n$are the independent variables for this system (Ozbayoglu and Ozbayoglu, 2006).

The coefficient of determination, R^2, describes the degree to which the variance of the predictor variables Y is represented by the independent variable X. It is obtained as:

$$R^2 = \frac{varience\ explained}{total\ varience} \tag{3.12}$$

A high R^2 indicates that there is a linear correlation among the two parameters If R^2 = 1, this means the optimal relationship between the two variables.

Nonlinear regression is a type of regression analysis in which experimental results are represented by a function that is a nonlinear combination of model parameters and relies on one or more response variables (Bilgili, 2010). Unlike conventional MLR, which is limited to evaluating linear models, MNLR can approximate models with conditional correlations between selected variables (Marofi et al., 2011).

4. RESULT AND DISCUSSION

Equation (4.1) was used to normalize data before the procedure was implemented. Normalization is a database architecture methodology that arranges data in a manner that reduces data consistency and dependency. Normalization splits greater data into smaller data and connects them to relationships. Normalization aims to remove redundant data and to verify the data is processed logically and comparing the result of the un-normalized data to discover how much does the normalization effect on reducing the error value of the program. Here, X_{norm}, X_{min} and X_{max} signify the normalized, minimum, and maximum values of the data set, respectively.

$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{4.1}$$

Various variations of meteorological variables were used as inputs of the ANFIS model to analyze the magnitude of each parameter's impact on the prediction of relative humidity, pressure, temperature, and solar radiation. As assessment criteria, root mean square errors (RMSE), mean absolute relative error (MAE) and, determination coefficient (R^2) statistics were chosen.

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_{i(observed)}-f_{i(predicted)}\right)^2} \tag{4.2}$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|f_{i\ (observed)} - f_{i\ (predicted)}\right| \tag{4.3}$$

$$R^2=\frac{(f_i observed - f_i predicted)^2}{(f_{i\ observed} - average\ of\ dataset)^2} \tag{4.4}$$

Where;$f_{i(observed)}$, and $f_{i(predicted)}$ predicted symbolizes the number of data, observed, an average of observed, predicted and average of predicted values, respectively. To achieve the minimum error and max R^2 values between observed and predicted values ideal model parameters were chosen. Sugeno type was used to set the ANFIS model. The input membership functions were ‘gaussmf’ and the output membership functions were ‘linear’, defuzzification method was ‘wtaver’, generate fis type was ‘subtractive clustering’ method and optimization method was ‘Hybrid Optimization Method’.

ANFIS model has been built many times with different inputs each time to find the best effect of each parameter.

The first model is predicting pressure by using 15 different inputs which are:

- (T), (H),(W_S), (Dp),
- (T and H), (T and Ws), (T and Dp), (H and Ws), (H and Dp), (Ws and Dp),
- (T, H and Dp), (T, Dp and Ws), (T, H and Ws), (H, Ws and Dp) and
- (T, H, Ws and Dp) respectively.

The second model is forecasting relative humidity depending on 15 various inputs that include:

- (T), (P), (Sr), (Ws),
- (T and P), (T and Sr), (T and Ws), (P and Sr), (P and Ws), (Sr and Ws),
- (T, P and Sr), (T, P and Ws), (T, Sr, Ws), (P, Sr and Ws) and
- (T, P, Sr and Ws) respectively.

The third model predicts solar radiation based on 15 diverse parameters as inputs:

- (T), (H), (Ws), (P),
- (T and H), (T and Ws), (T and P), (H and Ws), (H and P), (Ws and P),
- (T, H and Ws), (T, H and P), (T, Ws and P), (H, Ws and P),
- (T, H, Ws and P) respectively.

The last model predicts temperature based on 3 different input:

- (H), (Dp),
- (H and Dp) respectively

ANFIS has been applied for each of these models on daily and hourly data plus normalized and un-normalized data. However, the regression equation exercised on a daily and hourly, normalized, and un-normalized data set for each model.

Four different parameters are defined to be the output of four models, which are (relative humidity, pressure, temperature, and solar radiation). These model's inputs have chosen according to the correlation between the parameters. These four models were evaluated depending on ANFIS and regression analysis, to find out which one will be having the best performance. This is the main comparison in this study, in another hand, all data converted to normalized data to reduce the dependency and make them more accurate, so the second comparison is between normalized and un-normalized data, using the same four models. Average daily and hourly data of (2014-2017) used for training, and daily and hourly data of 2018 of Kirkuk, Mardin, and Sanliurfa were for checking. These comparisons were done by calculating RMSE, MAE and R^2 .

4.1. The Results of Pressure Model

4.1.1. The results of anfis model

Table 4.1 represents RMSE, MAE and R^2statistics for the hourly pressure model. According to the results, while normalized data had higher R^2 and lower error values than un-normalized data for pressure model depending on T, H, and Ws as inputs.

Table 4.1. RMSE, MAE and R^2statistics of hourly pressure model

Output: Pressure	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	3.644	3.015	0.613	3.541	2.905	0.635
H	4.964	4.135	0.283	4.629	3.818	0.376
Ws	6.119	4.942	-0.089	5.908	4.820	-0.015
Dp	5.236	4.296	0.202	5.158	4.305	0.226
T, H	3.439	2.825	0.655	3.377	2.835	0.668
T, Ws	3.615	2.991	0.619	3.537	2.899	0.636
T, Dp	3.434	2.816	0.656	3.374	2.749	0.668
H, Ws	4.886	4.052	0.305	4.551	3.713	0.397
H, Dp	3.491	2.864	0.645	3.389	2.771	0.665
Ws, Dp	5.154	4.249	0.227	5.133	4.303	0.233
T, H, and Dp	3.436	2.816	0.656	3.388	2.760	0.666
T, Dp and Ws	3.391	2.780	0.665	3.355	2.742	0.672
T, H and Ws	3.397	2.775	0.664	3.343	2.720	0.674
H, Dp and Ws	3.451	2.823	0.653	3.371	2.744	0.669
T, H, Ws and Dp	3.401	2.781	0.663	3.364	2.742	0.670

Figure 4.1 shows the scattering chart of the ANFIS model of hourly normalized data of pressure model for three inputs which had the highest R^2 value.

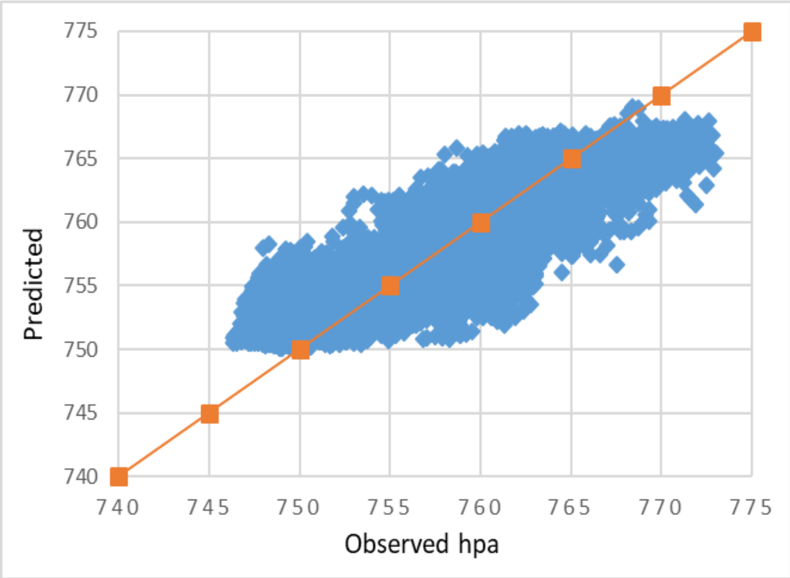

Figure 4.1. The scattering of ANFIS of hourly normalized pressure model for three inputs.

Table 4.2 shows the results of the daily pressure model. Here it is obvious that average daily data had a better performance than hourly data, which used three inputs (T, Ws and Dp) got the highest value of R^2(0.789) among all the inputs and models. For the models that settled with one input and two inputs, best results were obtained with (T) and (T and Dp) respectively.

Table 4.2. RMSE, MAE and R^2statistics of daily pressure model

Output: Pressure	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	2.986	2.453	0.735	2.937	2.407	0.744
H	4.564	3.835	0.383	4.169	3.445	0.485
Ws	6.640	4.629	0.058	5.556	4.591	0.085
Dp	5.011	4.127	0.256	4.941	4.149	0.277
T, H	2.731	2.238	0.779	2.745	2.235	0.776
T, Ws	2.959	2.384	0.741	3.001	2.397	0.746
T, Dp	2.720	2.215	0.781	2.693	2.186	0.785
H, Ws	4.212	3.466	0.474	3.971	3.168	0.533
H, Dp	2.834	2.334	0.762	2.818	2.329	0.764
Ws, Dp	4.734	3.986	0.336	4.800	4.073	0.317
T, H, and Dp	2.742	2.236	0.777	2.736	2.229	0.778
T, Dp and Ws	2.691	2.132	0.789	2.779	2.218	0.771
T, H and Ws	2.755	2.215	0.775	2.801	2.235	0.767
H, Dp and Ws	2.776	2.229	0.771	2.848	2.272	0.759
T, H, Ws and Dp	2.775	2.193	0.778	2.790	2.203	0.769

According to the table 4.2, the result of pressure model had higher error values and lower R^2 than reults of (Tektas, 2010).

Figure 4.2 shows the result of the ANFIS model of daily un-normalized data of pressure model for three inputs which had the highest R^2 value.

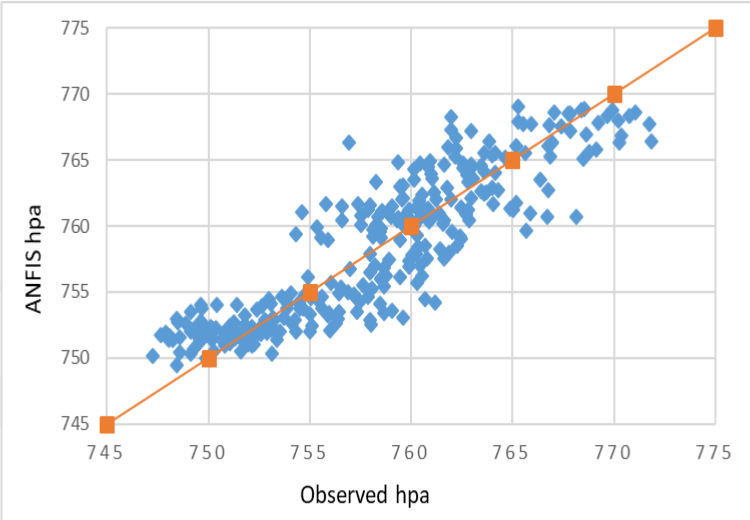

Figure 4.2. The scattering of ANFIS of daily un-normalized pressure model for three inputs.

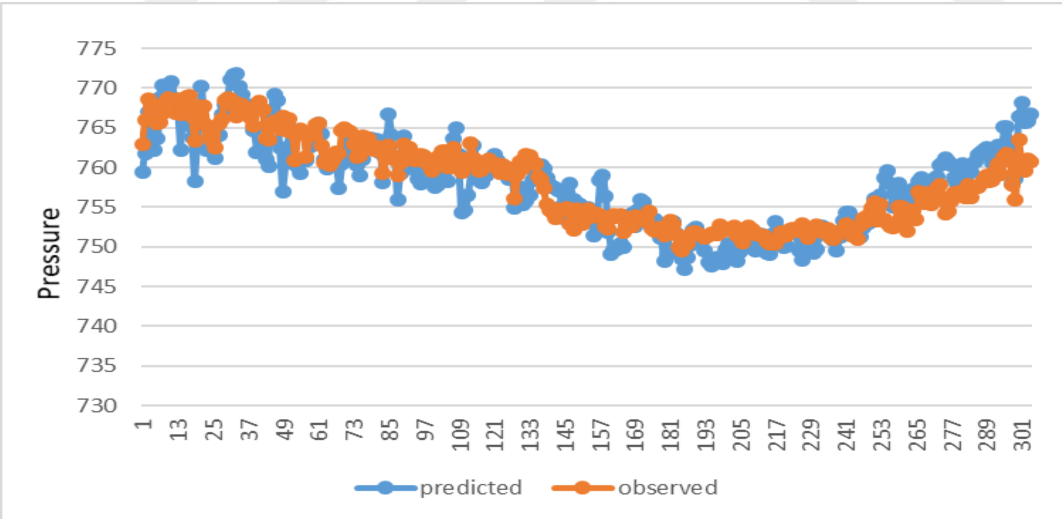

Figure 4.3. The observed and predicted data of the ANFIS method for the daily normalized pressure model.

4.1.2. The Results of Regression Analysis

Table 4.3 shows RMSE, MAE and R^2 statistics of regression analysis for each input of the pressure model created using hourly data. The pressure model had a better performance using the hourly normalized dataset, RMSE, MAE and R^2 were 3.432, 2.796, and 0.657 respectively, using T, H, and Dp as input variables. Those models based on one and two models, (T) and (T, H) had the best results.

Table 4.3. RMSE, MAE and R^2 statistics of regression of hourly pressure model

Output: Pressure	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	3.650	2.998	0.612	3.58	2.922	0.627
H	5.160	4.286	0.225	4.923	4.081	0.294
Ws	6.216	5.016	-0.123	5.977	4.868	-0.039
Dp	5.288	4.336	0.186	5.227	4.353	0.205
T, H	3.488	2.851	0.646	3.443	2.801	0.655
T, Ws	3.658	3.001	0.611	3.597	2.931	0.623
T, Dp	3.467	2.837	0.650	3.452	2.818	0.653
H, Ws	5.136	4.246	0.232	4.919	4.054	0.296
H, Dp	3.726	3.058	0.596	3.775	3.119	0.585
Ws, Dp	5.276	4.342	0.190	5.231	4.381	0.205
T, H, and Dp	3.462	2.831	0.651	3.432	2.796	0.657
T, Dp and Ws	3.481	2.845	0.647	3.474	2.831	0.648
T, H and Ws	3.498	2.856	0.643	3.467	2.815	0.650
H, Dp and Ws	3.764	3.085	0.587	3.819	3.147	0.575
T, H, Ws and Dp	3.473	2.836	0.649	3.453	2.808	0.653

Figure 4.4 is describing the scatter of observed and predicted variables for the pressure model depending on three inputs.

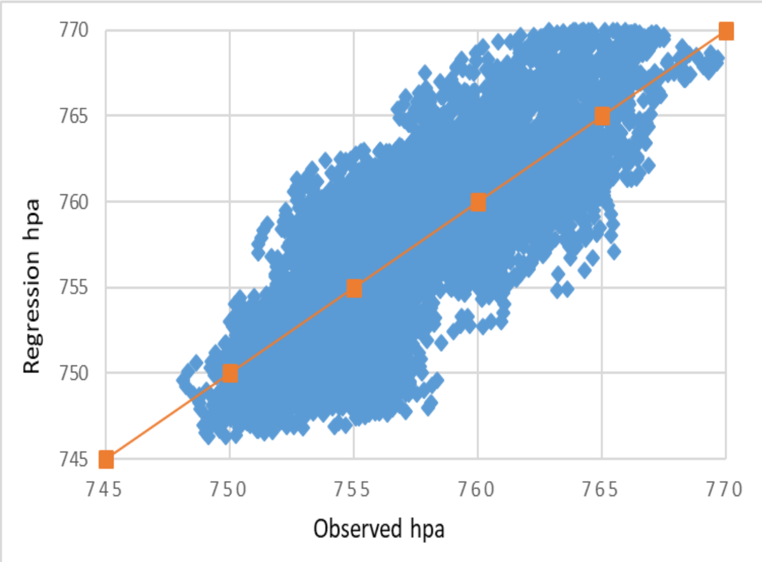

Figure 4.4. The scattering of regression analysis of hourly normalized pressure model for three inputs.

The fulfillment of daily data was better than hourly data depending on two inputs. The evaluation was like RMSE=2.834, MAE= 2.344 and R^2= 0.762 (see table 4.4).

Table 4.4. RMSE, MAE and R^2 statistics of regression analysis of daily pressure model

Output: Pressure	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	3.105	2.585	0.714	3.087	2.559	0.717
H	4.950	4.098	0.274	4.680	3.899	0.351
Ws	6.018	4.861	-0.072	5.815	4.761	-0.002
Dp	5.103	4.359	0.228	5.031	4.242	0.251
T, H	2.834	2.344	0.762	2.876	2.372	0.754
T, Ws	3.131	2.551	0.709	3.163	2.576	0.703
T, Dp	2.927	2.428	0.746	2.977	2.462	0.737
H, Ws	4.881	4.006	0.294	4.675	3.835	0.352
H, Dp	3.316	2.754	0.674	3.426	2.846	0.652
Ws, Dp	5.009	4.226	0.257	5.055	4.343	0.243
T, H, and Dp	2.850	2.360	0.759	2.864	2.365	0.757
T, Dp and Ws	2.972	2.411	0.738	3.071	2.499	0.721
T, H and Ws	2.864	2.316	0.757	2.961	2.392	0.740
H, Dp and Ws	3.423	2.814	0.653	3.557	2.918	0.625
T, H, Ws and Dp	2.862	2.322	0.757	2.938	2.374	0.744

The following figures show the results regression analysis of the scattering of daily un-normalized pressure model (see figure 4.5).

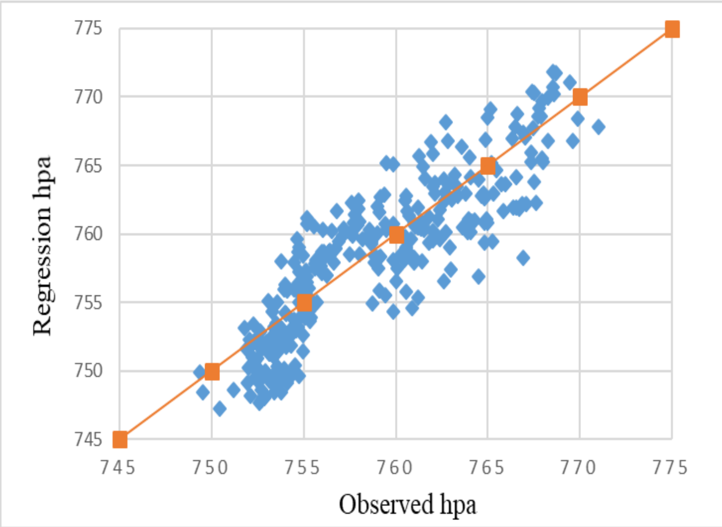

Figure 4.5. The scattering of regression analysis of daily un-normalized pressure model for two inputs.

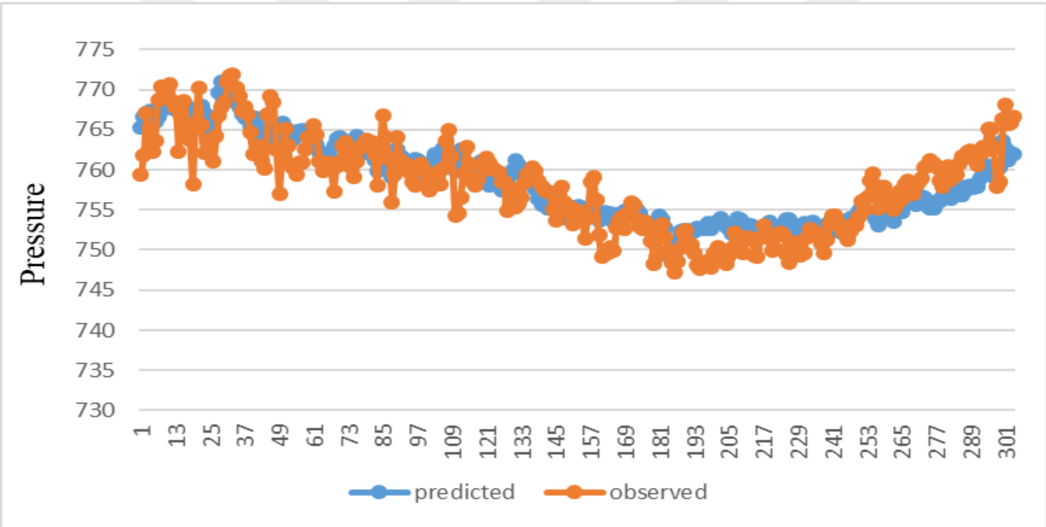

Figure 4.6. The observed and predicted data of regression method for daily un-normalized pressure model.

4.2. The Results of Relative Humidity Model

4.2.1. The results of anfis model

Table 4.5 represents the result of daily data of the relative humidity model. It showed that the best result could be getting by using un-normalized T, P, and Ws as inputs because these parameters had the best correlation with relative humidity, RMSE, MAE and R^2 were 9.455, 6.551, and 0.766 respectively. As well as the models that depended on one and two inputs, (T) and (T, P) had the best results.

Table 4.5. RMSE, MAE and R^2statistics of daily relative humidity model

Output: Relative humidity	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	10.804	7.631	0.695	10.525	7.292	0.711
P	15.936	11.533	0.337	15.567	11.164	0.367
Sr	14.752	11.106	0.432	14.422	11.004	0.457
Ws	18.535	15.711	0.103	18.865	16.045	0.071
T, P	9.852	6.931	0.746	9.631	6.573	0.757
T, Sr	10.991	7.758	0.684	10.531	7.240	0.711
T, Ws	10.984	7.611	0.685	10.526	7.178	0.711
P, Sr	14.520	10.977	0.229	13.934	10.187	0.493
P, Ws	16.171	11.692	0.317	15.487	11.278	0.374
Sr, Ws	14.441	10.770	0.455	14.163	10.723	0.476
T, P and Sr	9.966	7.199	0.741	9.789	6.725	0.749
T, P and Ws	9.455	6.551	0.766	9.479	6.430	0.765
T, Sr and Ws	10.528	7.539	0.711	10.884	7.528	0.691
P, Sr and Ws	14.509	10.717	0.451	15.875	11.329	0.342
T, P, Sr and Ws	10.023	7.031	0.737	9.745	6.737	0.752

The results of Table 4.5 shows that humidity model had higher value of R^2, RMSE and MAE values than the result of (Rahman et al., 2013)

Figure 4.7 shows the result of the ANFIS model of daily un-normalized relative humidity model for three inputs which had the highest R^2 value.

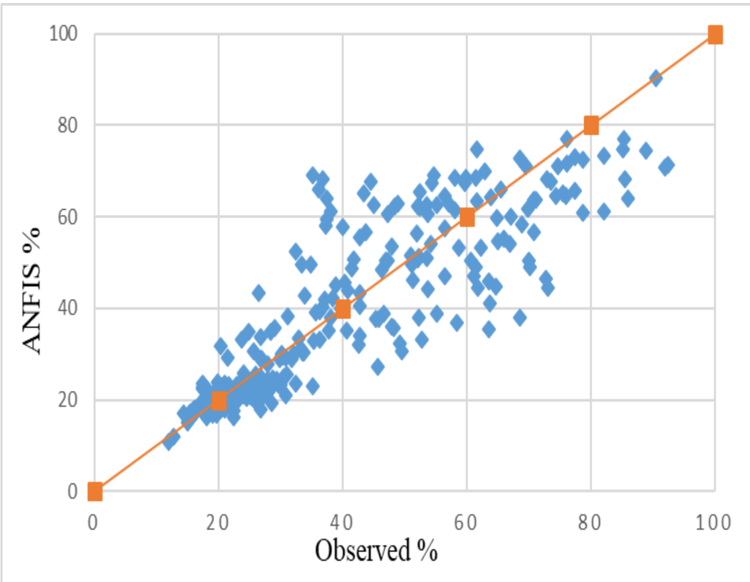

Figure 4.7. The scattering of ANFIS of daily un-normalized relative humidity model for three inputs.

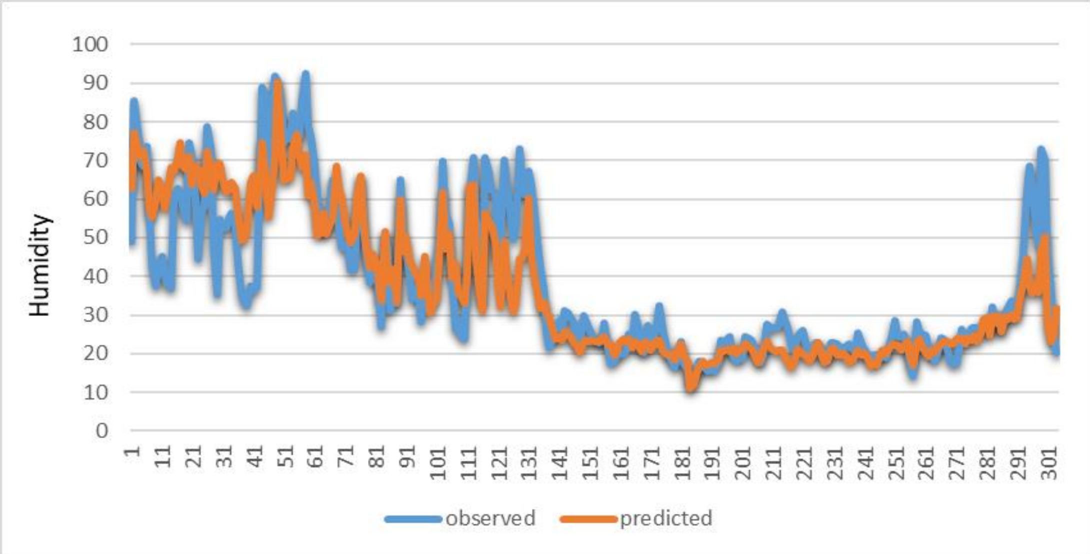

Figure 4.8. The observed and predicted data of the ANFIS method for daily un-normalized humidity model.

Table 4.6 shows that hourly data got the best results depending on normalized T, P, Sr, and Ws as inputs. RMSE, MAE, and R^2 were 10.185, 7.025, and 0.755 respectively. The daily data of the relative humidity model had better results than hourly data, this means that the central tendency of a dataset may have better performance than a single data. (T) and (T, P) got the best results as one and two input models.

Table 4.6. RMSE, MAE and R^2statistics of hourly relative humidity model

Output: Relative humidity	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	11.664	8.289	0.679	11.237	7.771	0.702
P	17.437	12.885	0.282	17.084	12.760	0.311
Sr	19.421	16.184	0.110	19.665	16.665	0.087
Ws	20.587	17.392	0.0001	20.844	17.916	-0.025
T, P	10.691	7.565	0.730	10.326	7.175	0.748
T, Sr	11.565	8.214	0.684	11.123	7.710	0.708
T, Ws	11.569	8.248	0.684	11.164	7.758	0.705
P, Sr	16.379	12.078	0.367	16.012	11.837	0.395
P, Ws	17.314	12.761	0.292	17.154	11.558	0.291
Sr, Ws	19.291	16.019	0.122	19.471	16.409	0.105
T, P and Sr	10.763	7.612	0.726	10.328	7.132	0.748
T, P and Ws	10.597	7.486	0.735	10.277	7.139	0.751
T, Sr and Ws	11.456	8.144	0.690	11.111	7.726	0.708
P, Sr and Ws	16.324	12.073	0.371	15.951	11.836	0.399
T, P, Sr and Ws	10.563	7.512	0.736	10.185	7.025	0.755

Figure 4.9 shows the scattering chart of the ANFIS model of hourly normalized relative humidity model for four inputs which had the highest R^2 value.

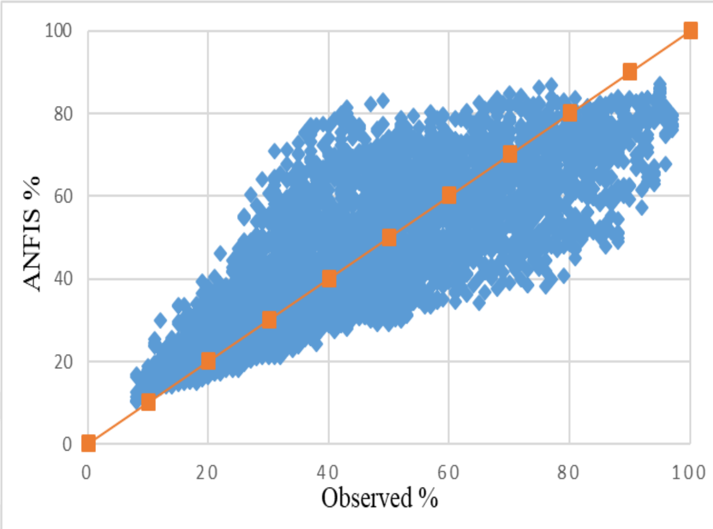

Figure 4.9. The scattering of ANFIS of hourly normalized relative humidity model for four inputs.

4.2.2. The results of regression analysis

Table 4.7 shows that the model created using T, P, and Ws as inputs have the best achievement for relative humidity parameter, and normalized data had better accuracy of error values.

Table 4.7. RMSE, MAE and R^2 statistics of regression analysis of daily relative humidity model

Output: Relative humidity	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	10.638	7.719	0.704	10.534	7.376	0.710
P	20.047	17.044	-0.048	15.810	11.867	0.347
Sr	14.664	11.404	0.438	14.36	11.155	0.461
Ws	19.289	16.593	0.029	19.313	16.701	0.026
T, P	9.514	6.846	0.763	9.526	6.752	0.763
T, Sr	10.943	8.4103	0.687	10.683	7.821	0.702
T, Ws	10.645	7.730	0.704	10.534	7.346	0.710
P, Sr	14.726	11.707	0.434	14.272	11.055	0.468
P, Ws	16.198	12.279	0.315	15.881	11.968	0.341
Sr, Ws	14.395	11.196	0.459	14.091	10.935	0.481
T, P and Sr	9.737	7.106	0.752	9.546	6.751	0.762
T, P and Ws	9.529	7.006	0.763	9.452	6.753	0.766
T, Sr and Ws	10.940	8.422	0.687	10.675	7.811	0.702
P, Sr and Ws	14.734	11.713	0.433	14.281	11.063	0.467
T, P, Sr and Ws	9.691	7.149	0.754	9.461	6.763	0.766

The results from the Table 4.6 shows that humidity model had much better performance of R2 the result of (Paras and Mathur, 2012)

Figure 4.10 represents the scatter of the best results of the daily normalized relative humidity model using three inputs.

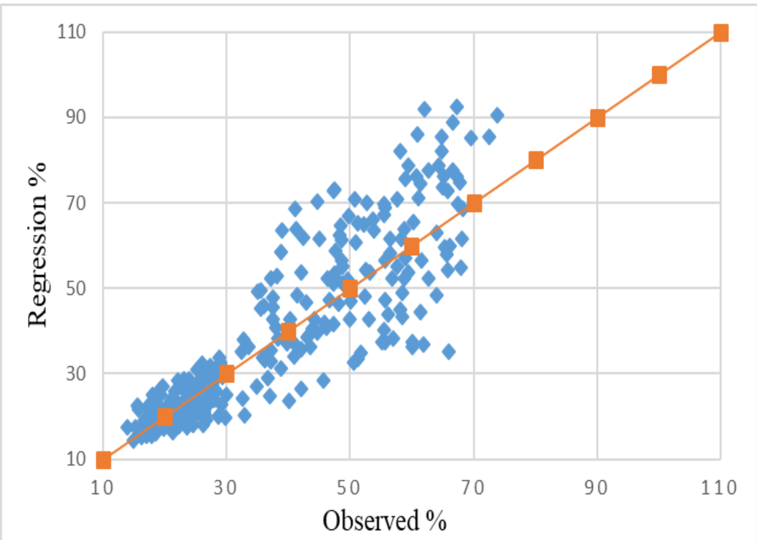

Figure 4.10. The scattering of regression analysis of daily normalized data of relative humidity model for three inputs.

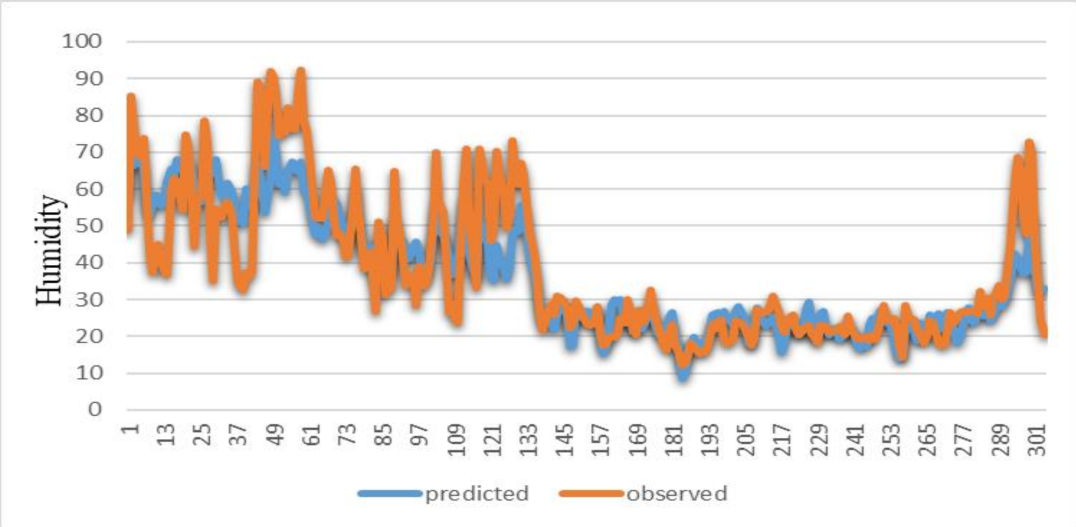

Figure 4.11. The observed and predicted data of the regression method for daily normalized humidity model.

Table 4.8 shows that in an hourly dataset, T, P, Sr, and Ws could get the highest R^2value plus another input set which are T, P, Sr they both have almost the same result.

Table 4.8. RMSE, MAE and R^2 statistics of regression analysis of hourly relative humidity model

Output: Relative humidity	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	11.566	8.580	0.684	11.290	8.219	0.699
P	17.539	13.283	0.274	17.187	13.084	0.303
Sr	19.429	16.188	0.109	20.152	17.621	0.041
Ws	20.587	17.392	0.0001	20.845	17.917	-0.025
T, P	10.961	8.325	0.716	10.784	8.083	0.725
T, Sr	11.569	8.585	0.684	11.292	8.227	0.699
T, Ws	11.562	8.575	0.684	11.291	8.219	0.699
P, Sr	16.745	12.950	0.383	16.339	12.665	0.370
P, Ws	17.513	13.236	0.276	17.154	13.037	0.305
Sr, Ws	30.319	25.966	-0.168	19.592	16.547	0.094
T, P and Sr	10.752	8.032	0.727	10.604	7.769	0.734
T, P and Ws	10.963	8.330	0.716	10.784	8.086	0.725
T, Sr and Ws	11.566	8.584	0.684	11.295	8.232	0.699
P, Sr and Ws	16.786	13.016	0.335	16.395	12.741	0.365
T, P, Sr and Ws	10.752	8.045	0.727	10.591	7.760	0.735

Figure 4.12 is describing the scatter of the hourly relative humidity model of four inputs and calculation of R^2 parameter.

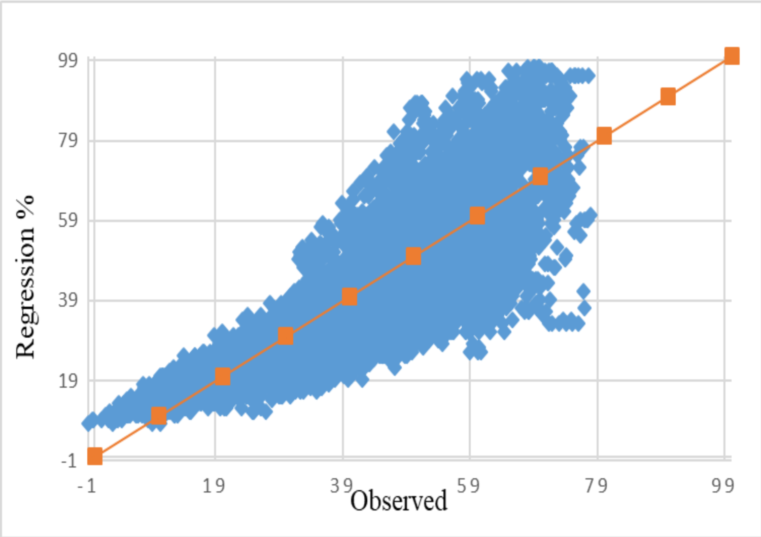

Figure 4.12. The scattering of regression analysis of hourly normalized relative humidity model for four inputs.

4.3. Results of Solar Radiation Model

4.3.1. The results of anfis model

The solar radiation model had the worst results compared with the other three models because of the correlation between the inputs parameters and solar radiation. Table 4.9 is showing that un-normalized hourly data got RMSE, MAE and R^2 as 189.412, 145.923, and 0.466 respectively. Based on these unacceptable results, it can be said that it is not appropriate to apply the ANFIS model to hourly solar radiation data.

Table 4.9. RMSE, MAE and R^2statistics of the hourly solar radiation model

Output: Solar radiation	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	213.969	178.274	0.319	214.813	177.419	0.314
H	233.511	189.994	0.189	234.931	189.133	0.179
Ws	252.352	212.322	0.053	246.841	207.998	0.094
P	254.374	217.300	0.038	254.544	215.094	0.036
T, H	209.606	173.772	0.346	209.155	171.726	0.349
T, Ws	210.819	176.931	0.339	210.774	175.980	0.339
T, P	201.334	150.095	0.397	201.618	149.482	0.395
H, Ws	221.383	182.415	0.271	222.778	182.387	0.262
H, P	235.753	180.542	0.173	237.325	180.101	0.162
Ws, P	241.092	205.193	0.135	240.942	203.115	0.136
T, H and Ws	208.658	174.593	0.352	208.703	173.471	0.352
T, H and P	192.188	147.935	0.451	193.617	147.226	0.442
T, Ws and P	196.390	151.533	0.426	196.707	150.017	0.424
H, Ws and P	222.580	173.264	0.263	223.532	172.897	0.257
T, H, Ws and P	189.412	145.923	0.466	191.438	147.187	0.455

According to these results, Solar radiation had lower R^2 and much higher RMSE values that (Mellit and Pavan, 2010).

Table 4.10 shows that daily normalized data had better achievement than the hourly data in terms of R^2 but error values are still high due to the great values of the solar radiation parameter. The best results of RMSE, MAE and R^2 for un-normalized data was getting by using T and P as inputs, this input set has been taken as the best result of this model because the difference between RMSE and MAE of normalized and un-normalized data was very high this difference is referred to calculating an average of the main dataset, this made the data more appropriate, and it is the value that produces the lowest amount of error from all other values in the data set. The models that depended on one and two inputs, (T) and (T, P) got the best results.

Table 4.10. RMSE, MAE and R^2statistics of the daily solar radiation model

Output: Solar radiation	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	48.887	38.906	0.598	59.198	49.861	0.410
H	55.547	46.551	0.481	67.837	58.079	0.226
Ws	74.649	64.253	0.062	81.383	71.757	-0.113
P	52.256	38.656	0.541	63.345	53.333	0.325
T, H	49.721	40.411	0.584	61.756	51.791	0.358
T, Ws	46.130	36.301	0.642	58.228	49.496	0.429
T, P	44.532	33.778	0.666	57.433	48.073	0.445
H, Ws	54.152	44.185	0.506	64.150	54.956	0.307
H, P	52.035	39.494	0.544	62.431	52.295	0.344
Ws, P	53.139	39.089	0.525	62.992	52.802	0.332
T, H and Ws	58.940	40.010	0.597	60.635	51.607	0.381
T, H and P	51.591	39.100	0.552	61.723	51.065	0.359
T, Ws and P	45.207	34.794	0.656	55.515	46.505	0.481
H, Ws and P	48.631	38.446	0.602	61.289	51.563	0.368
T, H, Ws and P	48.303	37.545	0.607	60.394	51.064	0.386

The Solar radiation model in this study had lower RMSE and R^2 values than (Varzandah et al., 2014).

Figure 4.13 represents the result of the ANFIS model of daily un-normalized solar radiation model for two inputs which had the highest R^2 value.

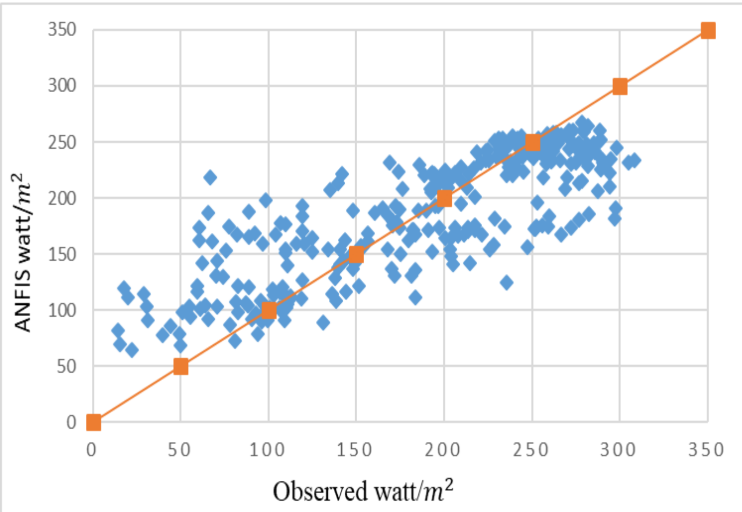

Figure 4.13. The scattering of ANFIS of daily un-normalized solar radiation model for two inputs.

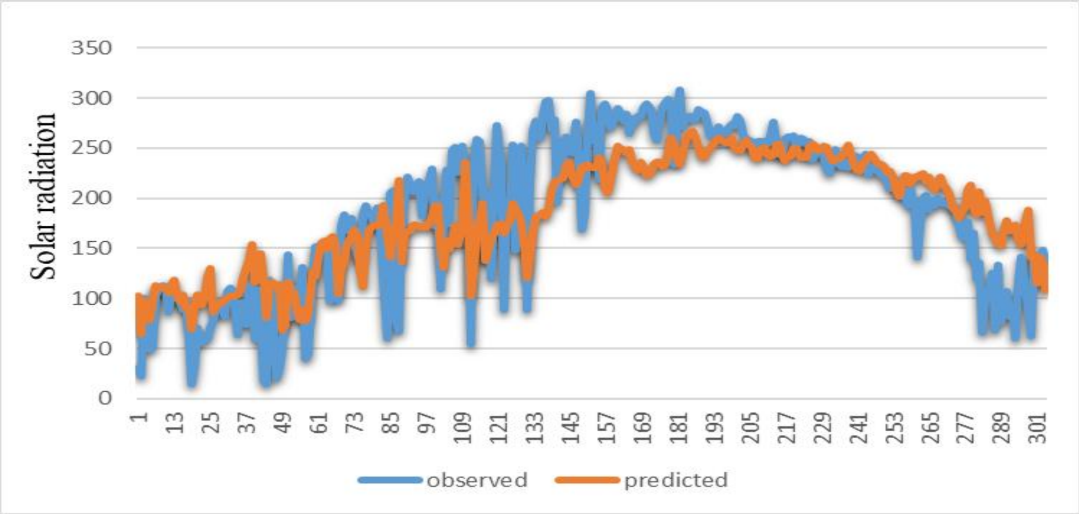

Figure 4.14. The observed and predicted data of the ANFIS method for daily un-normalized solar radiation model.

4.3.2. Results of regression analysis

Solar radiation had the best performance by using T, Ws, and P as input parameters, daily un-normalized dataset achieved RMSE, MAE and R^2 as 48.561, 38.438 and 0.603 respectively (see table 4.11).

Table 4.11. RMSE, MAE and R^2 statistics of regression analysis of daily solar radiation model

Output: Solar radiation	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	48.811	38.709	0.599	60.599	51.138	0.382
H	56.951	47.825	0.454	68.421	59.184	0.212
Ws	78.261	69.215	-0.029	86.025	76.312	-0.244
P	54.794	40.791	0.495	63.698	54.276	0.317
T, H	50.155	41.039	0.576	63.322	53.049	0.346
T, Ws	48.719	38.685	0.601	60.634	51.153	0.381
T, P	48.721	38.535	0.601	60.471	51.028	0.385
H, Ws	56.957	47.825	0.454	68.409	59.182	0.213
H, P	50.237	40.243	0.575	62.152	53.198	0.350
Ws, P	54.410	40.723	0.502	63.881	54.177	0.313
T, H and Ws	50.034	41.006	0.579	55.328	44.484	0.485
T, H and P	49.034	39.842	0.588	61.557	52.456	0.362
T, Ws and P	48.561	38.438	0.603	60.477	51.026	0.384
H, Ws and P	49.691	39.988	0.584	62.179	53.107	0.349
T, H, Ws and P	49.627	39.962	0.585	61.622	52.412	0.361

Figure 4.15 is representing the scattering of the solar radiation model using only three inputs to get the best performance which is showing by the following figure.

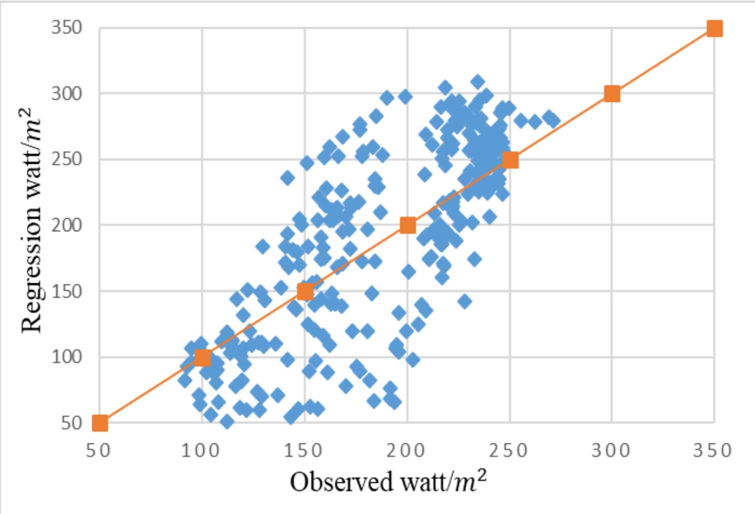

Figure 4.15. The scattering of regression analysis of daily un-normalized solar radiation model for three inputs.

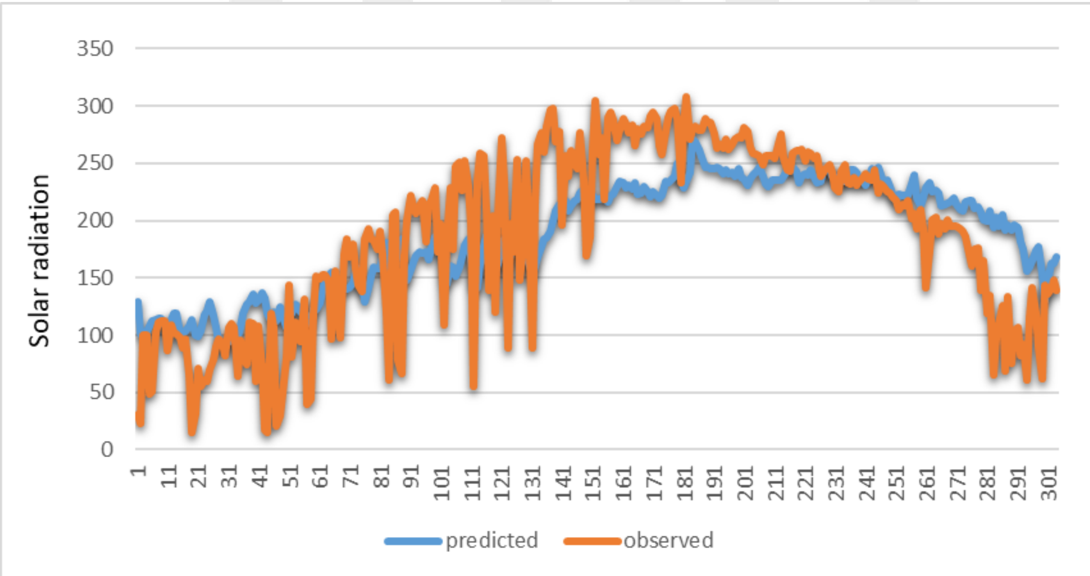

Figure 4.16. The observed and predicted data of regression method for daily un-normalized solar radiation model.

From table 4.12, it is noticed that using four inputs had the best performance ignoring the normalization process of the dataset. The normalized and raw data got alomost the same results in all the statistic parameters RMSE, MAE and R^2, and it explained that the normalization process does not have an obvious effect on the hourly dataset.

Table 4.12. RMSE, MAE and R^2 statistics of regression of hourly solar radiation model

Output: Solar radiation	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
T	229.153	193.441	0.219	229.374	192.117	0.236
H	241.369	201.203	0.133	241.831	199.813	0.138
Ws	252.352	212.322	0.053	252.485	210.303	0.053
P	254.458	217.709	0.038	254.618	215.665	0.037
T, H	229.191	193.439	0.236	229.415	192.121	0.219
T, Ws	226.067	191.984	0.261	225.955	190.424	0.240
T, P	213.671	173.374	0.323	237.471	192.197	0.321
H, Ws	236.664	198.658	0.172	236.786	197.088	0.167
H, P	242.372	200.510	0.129	242.974	198.731	0.126
Ws, P	248.789	213.269	0.083	248.678	211.127	0.079
T, H and Ws	226.132	191.978	0.260	226.039	190.724	0.239
T, H and P	210.435	170.674	0.343	211.172	169.974	0.341
T, Ws and P	210.882	170.644	0.338	211.071	169.649	0.338
H, Ws and P	237.755	196.671	0.159	237.856	196.675	0.159
T, H, Ws and P	207.689	168.008	0.358	207.867	167.067	0.358

4.4. Results of Temperature Model

4.4.1. Results of ANFIS model

During this study and using different inputs and outputs, it was found out that temperature could have the best performance depending on H and Dp as input parameters. Normalized and un-normalized models had acceptable R^2 values but un-normalized data get the lowest error values with RMSE= 0.629 and MAE= 0.727. As one input parameter, relative humidity had better performance than Dp (see table 4.13).

Table 4.13. RMSE, MAE and R^2statistics of the daily dataset of the temperature model

Output: Temperature	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
H	4.596	3.757	0.752	4.369	3.195	0.775
Dp	8.188	7.159	0.219	8.224	7.069	0.205
H and Dp	0.629	0.727	0.993	3.184	2.803	0.881

Temperature model had almost similar result with (Tektas, 2010) of RMSE and R^2 values.

Figure 4.17 represents the scattering chart of the ANFIS model of daily un-normalized temperature model for two inputs which had the highest R^2 value.

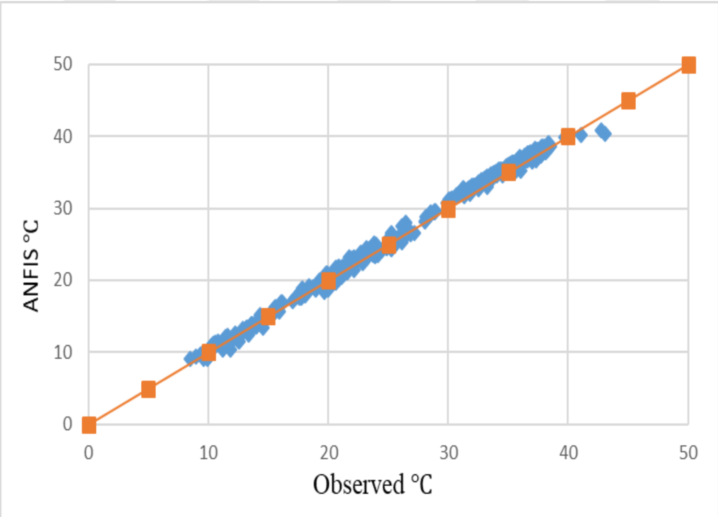

Figure 4.17. The scattering of ANFIS of daily un-normalized temperature model for two inputs.

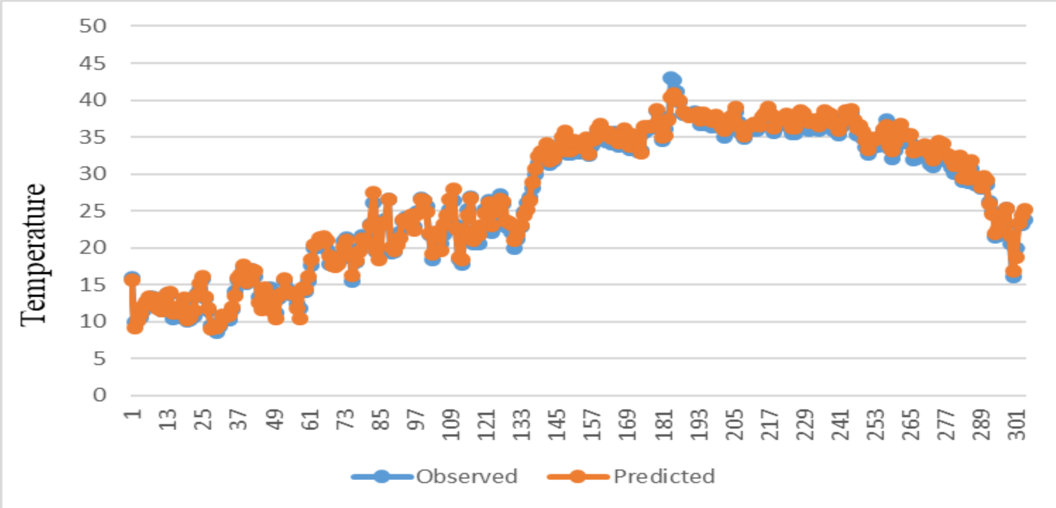

Figure 4.18. The observed and predicted data of the ANFIS method for daily un-normalized temperature model.

Table 4.14 represents that there is not a big difference between R^2 of daily and hourly datasets but according to the other statistics, it was clear that daily data had better performance.

Table 4.14. RMSE, MAE and R^2statistics of the hourly temperature model

Output: Temperature	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
H	5.086	4.224	0.732	17.087	14.831	0.708
Dp	9.022	7.616	0.159	11.463	9.631	-0.356
H and Dp	0.927	0.788	0.991	18.699	16.067	0.843

Figure 4.19 represents the scattering chart of the ANFIS model of the hourly un-normalized temperature model for two inputs which had the highest R^2 value.

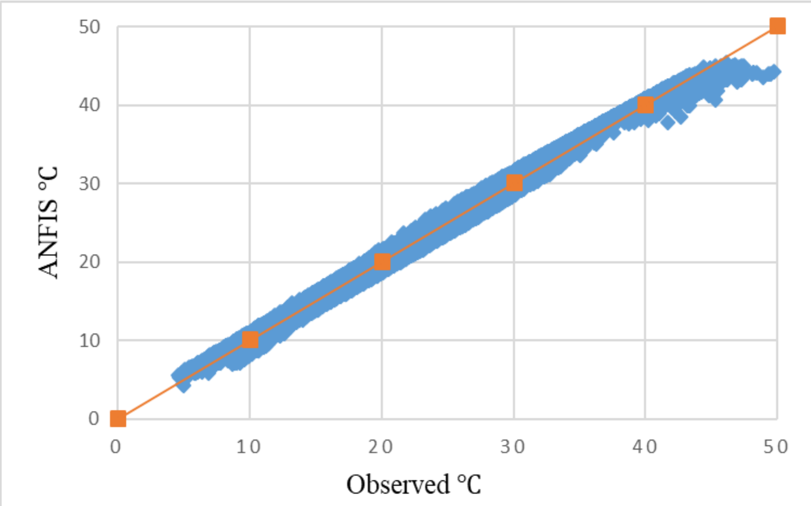

Figure 4.19. The scattering of ANFIS of hourly un-normalized temperature model for two inputs.

4.4.2. Result of regression analysis

In the temperature model, using both inputs had the best performance which was H and Dp, both had the best correlation with the output parameter. Despite that ANFIS had better performance than regression but also regression analysis got good results for the daily dataset of each statistic parameters RMSE, MAE and R^2(see table 4.15).

Table 4.15. RMSE, MAE and R^2 statistics of regression of daily temperature model

Output: Temperature	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
H	5.163	4.306	0.686	5.162	3.758	0.687
Dp	8.379	7.496	0.175	13.608	10.253	-0.173
H and Dp	2.109	1.790	0.947	4.009	3.537	0.802

According to R^2 values,temperature model had similar result with (Paras and Mathur, 2012).

Figure 4.20 represents the scattering chart of regression analysis of daily un-normalized temperature model for two inputs which has the highest R^2 value.

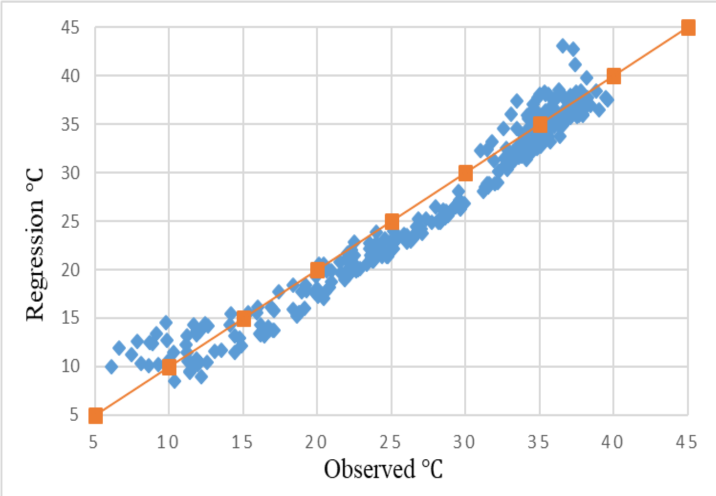

Figure 4.20. The scattering of regression analysis of daily un-normalized temperature model for two inputs.

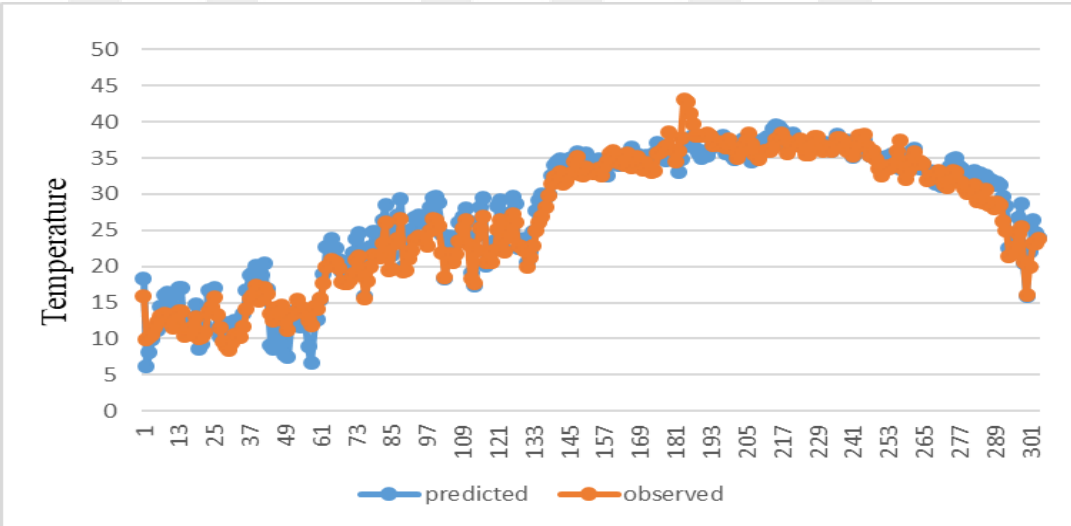

Figure 4.21. The observed and predicted data of the regression method for the un-normalized temperature model.

Table 4.16 shows the result of each input set of temperature model using normalized and un-normalized hourly datasets. RMSE, MAE and R^2 results were 2.762, 2.358, and 0.921, respectively. Using only H and Dp as inputs for the un-normalized dataset.

Table 4.16. RMSE, MAE and R^2 statistics of regression of hourly temperature model

Output: Temperature	Un-normalized			Normalized		
Inputs	RMSE	MAE	R^2	RMSE	MAE	R^2
H	5.654	4.578	0.699	5.636	4.191	0.672
Dp	9.142	7.817	0.137	9.255	7.731	0.115
H and Dp	2.762	2.358	0.921	4.536	4.023	0.787

Figure 4.22 shows the scattering chart of regression analysis for estimation temperature using two inputs.

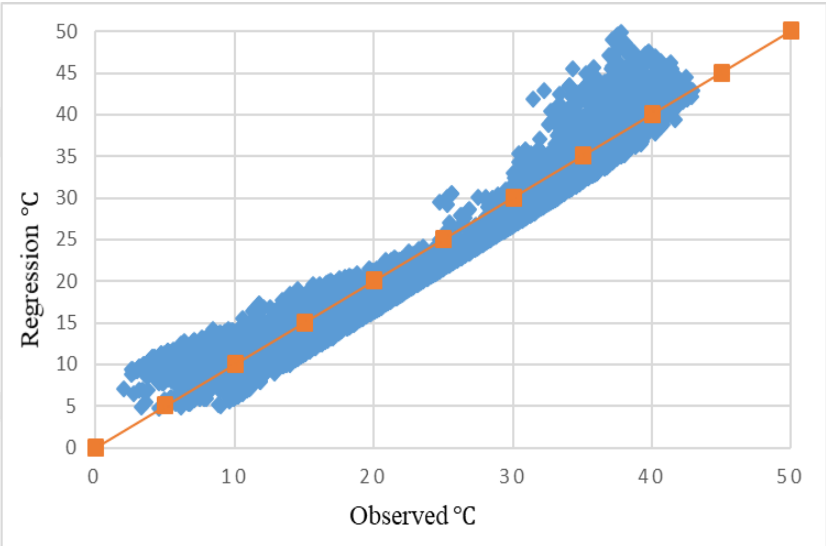

Figure 4.22. The scattering of regression analysis of hourly un-normalized temperature model for two inputs.

4.5. The Results of Mardin and Sanliurfa Data Sets

4.5.1. Result of ANFIS model

One of the main purposes of this study is trying to use data of Mardin and Sanliurfa as checking data to find out if it could give good results. For this reason, best models of the relative humidity and temperature parameters were chosen to check with data that were observed in Mardin and Sanliurfa separately. Table 4.17 shows the results of this checking.

Table 4.17. Results of RMSE, MAE and R^2 statistics of Mardin daily dataset

Type of data	Inputs	Output	RMSE	MAE	$\mathbf{R^2}$
Un-normalized	T, P and Ws	H	15.377	11.749	0.487
Normalized	T, P and Ws	H	14.453	10.783	0.547
Un-normalized	H and Dp	T	7.618	7.324	0.259
Normalized	H and Dp	T	3.468	2.819	0.846

Generally, Mardind daily dataset had much higher MAE and RMSE, and lower value of R^2 than (Kisi and Shiri, 2013).

The relative humidity model had 14.453 as RMSE, 10.783 as MAE and 0.547 as R^2 depending on T, P, and Ws as inputs for daily normalized data, and temperature got 3.468, 2.819 and 0.846 as RMSE, MAE and R^2. Temerature could get lower error and higher R^2 than humidity because of having a good relation with input parameters.

Figure 4.23 shows the result of the temperature model for the daily normalized datasets which had higher value of R^2.

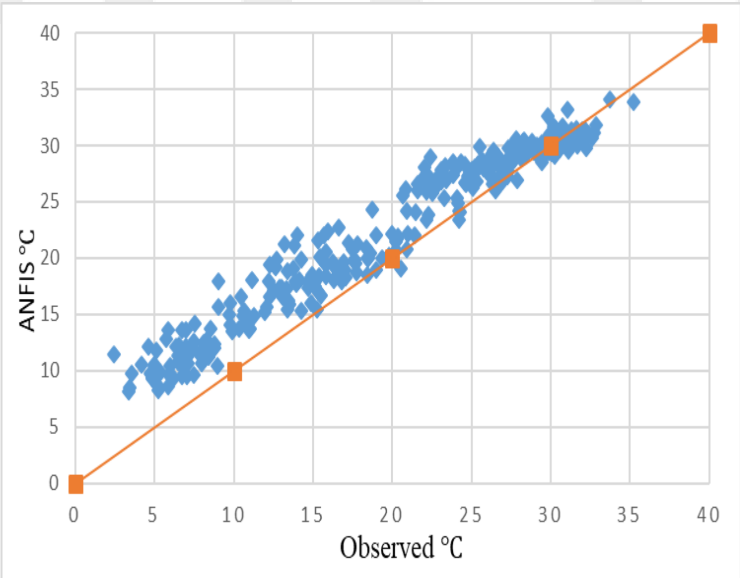

Figure 4.23. The scattering of ANFIS of daily normalized temperature model for two inputs at Mardin station.

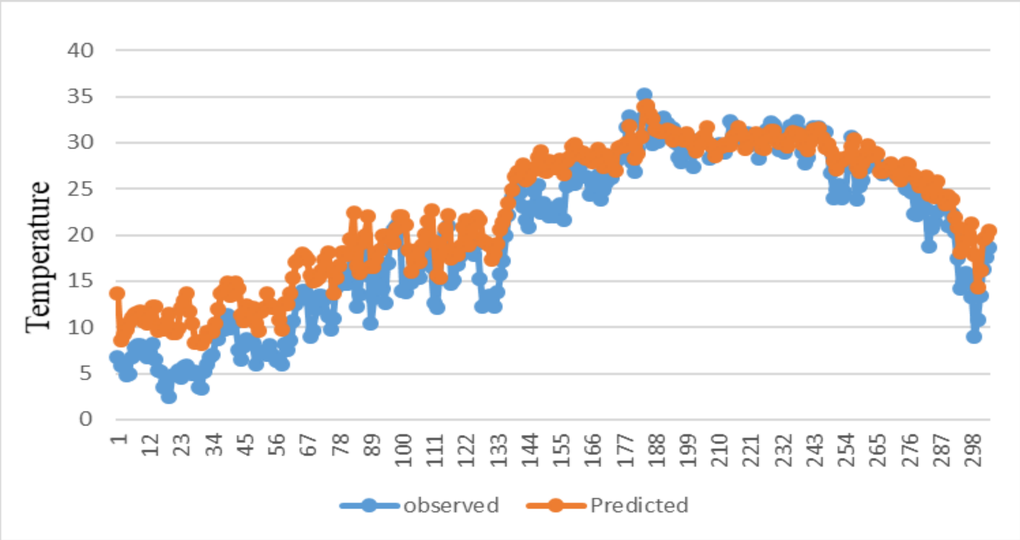

Figure 4.24. The observed and predicted data of the ANFIS method for the temperature model of Mardin station.

For Sanliurfa station, normalized daily data had better performance for the temperature model, which the results were RMSE=3.005, MAE=2.389 and R^2=0.876 (see table 4.18). The result of the following table shows that Mardin had better performance in estimating humidity model, but Sanliurfa had better result for temperature prediction

Table 4.18. Results of RMSE, MAE and R^2 statistics of Sanliurfa daily dataset

Type of data	Inputs	Output	RMSE	MAE	$\mathbf{R^2}$
Un-normalized	T, P and Ws	H	17.244	13.926	0.173
Normalized	T, P and Ws	H	14.290	11.076	0.432
Un-normalized	H and Dp	T	5.548	5.044	0.578
Normalized	H and Dp	T	3.005	2.389	0.876

The following figure shows the result of the temperature model using ANFIS analysis for prediction, depending on the daily normalized dataset (see figure 4.25).

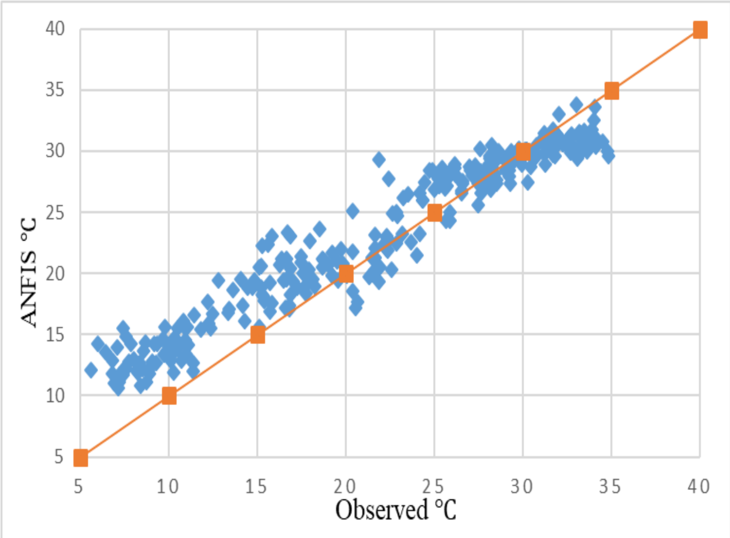

Figure 4.25. The scattering of ANFIS of daily normalized temperature model for two inputs at Sanliurfa station.

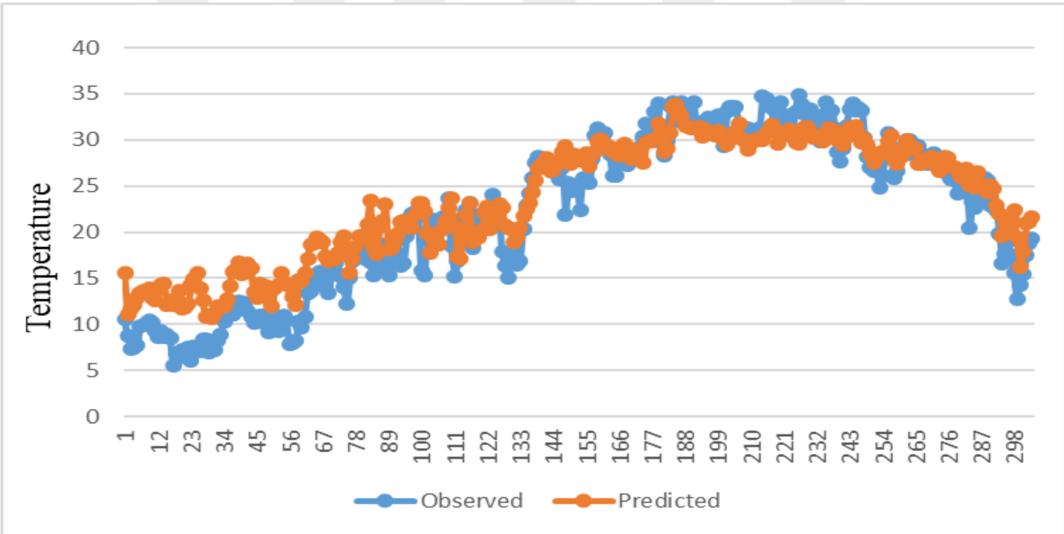

Figure 4.26. The observed and predicted data of the ANFIS method for the temperature model of Sanliurfa station.

4.5.2. Results of regression analysis

Using Mardin and Sanliurfa dataset for getting temperature as output had the best performance. Depending on H and Dp variables for daily normalized data of Mardin city the result of RMSE, MAE and R^2 were like 4.307, 3.635, and 0.763 respectively (see table 4.19).

Table 4.19 Results of RMSE, MAE and R^2 statistics of regression analysis at Mardin daily dataset

Type of data	Inputs	Output	RMSE	MAE	R^2
Un-normalized	T, P and Ws	H	15.444	12.164	0.483
Normalized	T, P and Ws	H	14.586	11.210	0.534
Un-normalized	H and Dp	T	8.319	7.828	0.117
Normalized	H and Dp	T	4.307	3.534	0.763

The next figure is showing the performance of regression analysis for the temperature model of the Mardin dataset using. The temperature model could get the highest value of R^2 and the lowest results of other statistic parameters in comparison with the other model (see figure 4.27).

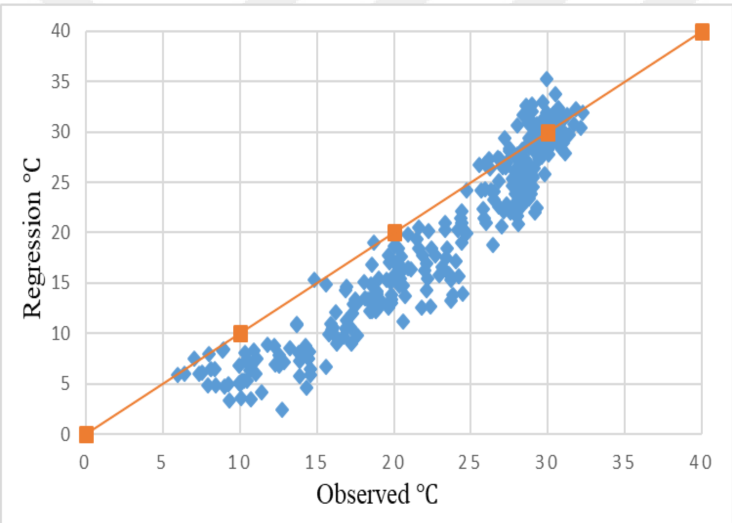

Figure 4.27. The scattering of regression analysis of daily normalized temperature model for two inputs at Mardin station.

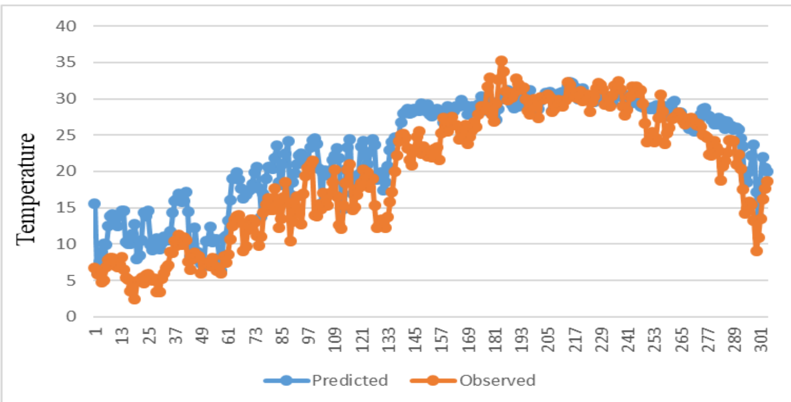

Figure 4.28. The observed and predicted data of the regression method for the humidity model of Mardin station.

Table 4.20 shows the results of the regression analysis of each model after applying Sanliurfa's dataset. It appears that normalized data had better outcomes. Results of RMSE, MAE and R^2 were 3.653, 2.977 and 0.817, respectively.

Table 4.20. Results of RMSE, MAE and R^2 statistics of regression calculation Sanliurfa daily dataset

Type of data	Inputs	Output	RMSE	MAE	$\mathbf{R^2}$
Un-normalized	T, P and Ws	H	17.220	14.103	0.175
Normalized	T, P and Ws	H	14.304	11.286	0.343
Un-normalized	H and Dp	T	6.245	5.642	0.464
Normalized	H and Dp	T	3.653	2.977	0.817

Figure 4.29 clarifies the performance of regression analysis for estimating temperature, using two input variables of daily normalized data of Sanliurfa station that had higher value of R^2.

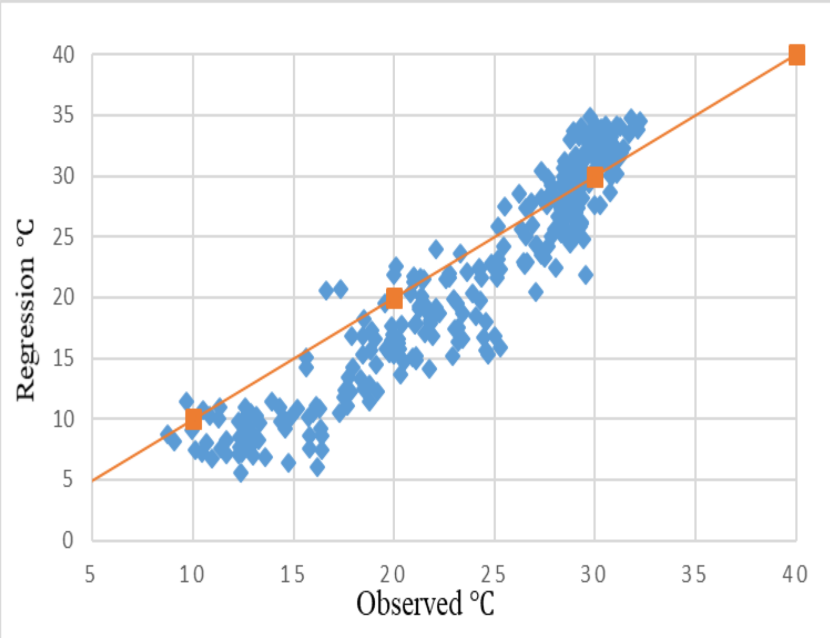

Figure 4.29. The scattering of regression analysis of daily normalized data of temperature model for two inputs at Sanliurfa station.

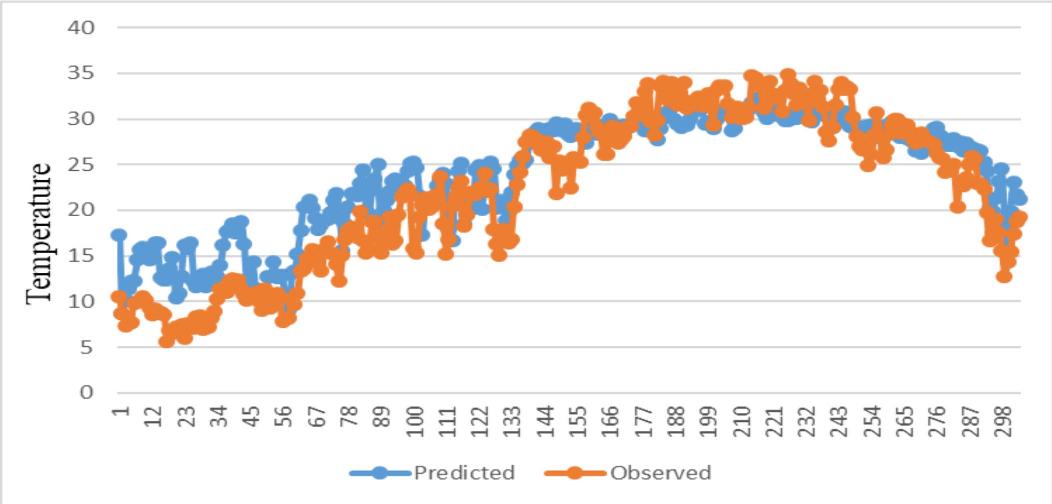

Figure 4.30. The observed and predicted data of the regression method for the temperature model of Mardin station.

Table 4.21 shows the difference between the results of each of daily and hourly data of ANFIS method for raw dataset, and it is obvious that daily data had better performance than hourly and could get more acceptable results.

Table 4.22 shows the difference between the results of each of daily and hourly data of ANFIS method for normalized dataset, and how calculating average of daily data could be having positive affect on the performance.

Table 4.21 Comparison of each parameter of hourly and daily result of ANFIS application for un-normalized dataset

	Hourly result			Daily result		
Parameters	RMSE	MAE	R^2	RMSE	MAE	R^2
Pressure	3.391	2.780	0.665	2.691	2.132	0.789
Relative humidity	10.563	7.512	0.736	9.455	6.551	0.765
Solar radiayion	189.412	145.923	0.466	44.532	33.778	0.666
Temperature	0.927	0.788	0.991	0.629	0.721	0.993

Table 4.22 Comparison of each parameter of hourly and daily result of ANFIS application for normalized dataset

	Hourly result			Daily result		
Parameters	RMSE	MAE	R^2	RMSE	MAE	R^2
Pressure	3.343	2.720	0.674	2.693	2.186	0.785
Relative humidity	10.185	7.025	0.755	9.479	6.430	0.765
Solar radiayion	191.438	147.187	0.455	55.515	46.505	0.481
Temperature	18.699	16.067	0.843	3.184	2.803	0.881

Table 4.23 shows the difference between each of regression analysis and ANFIS application on raw dataset. It is clear that ANFIS had better performance and got more reliable results.

Table 4.23 Comparison of ANFIS and Regression application of daily data result of raw dataset

	ANFIS application			Regression application		
Parameters	RMSE	MAE	R^2	RMSE	MAE	R^2
Pressure	2.691	2.132	0.789	2.834	2.344	0.762
Relative humidity	9.455	6.551	0.765	9.514	6.846	0.763
Solar radiation	44.532	33.778	0.666	48.561	38.438	0.603
Temperature	0.629	0.721	0.993	2.109	1.790	0.947

Table 4.24 explains that ANFIS could get better results using normalized normalized daily dataset. Despite that ANFIS had better performance in all the models, but in the following table regression analysis got higher R^2 and lower RMSE than ANFIS method.

Table 4.24 Comparison of ANFIS and Regression application of daily data result of normalized dataset

	ANFIS application			Regression application		
Parameters	RMSE	MAE	R^2	RMSE	MAE	R^2
Pressure	2.693	2.186	0.785	2.864	2.365	0.757
Relative humidity	9.479	6.430	0.765	9.452	6.753	0.766
Solar radiation	55.515	46.505	0.481	60.471	51.028	0.385
Temperature	3.184	2.803	0.881	4.009	3.537	0.802

5. CONCLUSION

In this study, ANFIS methodology has been used for predicting the most impactful meteorological parameters in hydrology, which include temperature, pressure, solar radiation, and relative humidity. These parameters are observed in Kirkuk that located in the north part of Iraq. Data from 2014 to 2017 used for testing while data of 2018 used for checking purposes. Furthermore, the ANFIS performance was compared with regression analysis to detect the best achievement among these two methodologies. However, the max-min normalization procedure was applied to the dataset to investigate the effect of the normalization on the results of the ANFIS method. Additionally, the results of the models which were set with hourly and daily data were compared to see the impact of the data type on the results of the models. The results of each one of temperature, relative humidity, and pressure model were taken to make a comparison between Mardin and Sanliurfa that both have similar weather conditions with Kirkuk.

The noticeable difference between the results of ANFIS and regression analysis proved that ANFIS had better performance than regression. The results showed that ANFIS could be used effectively to forecast these four parameters and more accurate than regression analysis. However, it was obtained that the calculation of the average daily parameters from the original dataset could affect positively on the results and get much better outcomes than hourly data. The results indicated that the normalization process that applied on both daily and hourly data is the process of organizing a database to reduce redundancy was more proper for all the models to obtain the best results. Moreover, among the four parameters, the temperature had a perfect performance and got the highest value of R^2 and the most acceptable error values of RMSE and MAE, because of having the best correlation between the input and output variables of the model. According to the results of humidity and temperature parameters at Mardin and Sanliurfa stations, the performances of these models are close to the Kirkuk station. Therefore, if it is necessary, these models can be preferred to predicted these parameters.

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GENİŞLETİLMİŞ TÜRKÇE ÖZET
(EXTENDED TURKISH SUMMARY)

METEOROLOJİK PARAMETRELERİN ANFİS YÖNTEMİYLE TAHMİNİ: IRAK KERKÜK İSTASYONU ÖRNEĞİ

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ÖZ

Çeşitli iklim koşullarını güvenilir bir şekilde tahmin etmek için karmaşık hava modellerinin araştırılması ve anlaşılması, küresel olarak bilimsel süreç sınavlarının önemli bir parçası olmuştur. Bu çalışmada, en önemli iklim parametrelerini tahmin etmek için modeller oluşturmak üzere üyelik işlevleriyle kural tabanlı bir model elde etmek için çok daha yararlı olan Adaptif Nöro Bulanık Çıkarım Sistemi (ANFIS) kullanılmıştır. Bağıl nem, basınç, sıcaklık ve güneş radyasyonu parametreleri, günlük ve saatlik sıcaklık (°C), rüzgar hızı (m/s), çiğ noktası (°C), bağıl nem (%), güneş radyasyonu (watt/m2) ve basınç (hpa) verilerini içeren giriş değişkenlerine bağlı olarak tahmin edilmiştir. Irak'taki Kerkük istasyonunda gözlemlenen verilerle kurulan modeller, Türkiye'deki Mardin ve Şanlıurfa istasyonlarına ait verilerle test edilmiştir. 2014-2017 ve 2018 veri setleri sırasıyla eğitim ve kontrol amacıyla kullanılmıştır. Ayrıca, normalize edilmiş ve normalleştirilmemiş veri kümesinin ve ANFIS ve Regresyon Analizinin sonuçları karşılaştırılmıştır. Modeller, kök ortalama kare hatası (KOKH), ortalama mutlak hata (OMH) ve determinasyon katsayısı (R2) kullanılarak değerlendirilmiştir. Sonuçlara göre ANFIS, saatlik normalleştirilmemiş verilere göre daha düşük hata değerlerine ve daha yüksek R2'ye sahip olan günlük normalize edilmiş verilerin tahmini için Regresyon Analizinden çok daha iyi bir performansa sahiptir. Dört parametrenin arasında, sıcaklık parametresi modeli, giriş değişkenleri olarak bağıl nem ve çiğ noktasını kullanarak en iyi performansı elde etmiştir. Nem ve sıcaklık parametrelerinin sonuçları, bu modellerin Mardin ve Şanlıurfa istasyonlarında Kerkük istasyonuna benzer bir performans sergilediğini göstermiştir.

Anahtar kelimeler: ANFIS, tahmin, rölatif nem, basınç, solar radyasyon, sıcaklık

1. GİRİŞ

Pek çok mühendislik alanında, tarımda, kara ve hava yolu trafiğinin planlama, projelendirme ve işletme aşamalarında; sıcaklık, nem, rüzgâr hızı, solar radyasyon, nem vb. meteorolojik verilere ihtiyaç duyulmaktadır. Ancak, gerekli tüm parametrelerle ilgili ölçüm yapabilecek yeterli düzeneğin her bölgede olmaması ya da verilerde yıllar içinde çeşitli sebeplerle düzenli ölçüm yapılamaması gibi sorunlar yaşanabilmektedir. Bu sebeple mevcut verilerden yararlanarak ihtiyaç duyulan veriyi tahmin etmeye yarayacak modeller gereklidir. Son yıllarda araştırmacılar bu konu üzerine yönelmiş ve farklı regresyon modelleri, yapay sinir ağları, bulanık mantık yöntemleri uygulayarak saatlik, günlük, aylık verilere ait modeller geliştirmişlerdir.

Bu çalışmada, ortalama saatlik ve günlük sıcaklık (C°), rölatif nem (%), basınç (hpa) ve solar radyasyon (watt/m^2) parametreleri için en uygun tahmin modeli Uyarlanabilir Sinirsel Bulanık Çıkarım Sistemi (ANFİS) ile oluşturulmuştur. Bu amaçla söz konusu parametrelerle en yüksek korelasyona sahip meteorolojik parametreler girdi olarak seçilmiş ve girdi sayısı her seferinde arttırılarak ve farklı kombinasyonlar denenerek en uygun model elde edilmeye çalışılmıştır.

2. MATERYAL YÖNTEM

Çalışmada Irak Kerkük istasyonuna ait 2014-2017 veri setleri ve 2018 veri seti sırasıyla modelin eğitimi ve test edilmesi amacıyla kullanılmıştır.

Ayrıca, normalizasyon işleminin modele etkisini görmek için, en sık kullanılan normalleştirme yöntemlerden biri olan ve aşağıda formülü verilen maksimum-minimum normalleştirmesi ile hem saatlik hem de günlük veriler normalleştirilmiş ve bu veriler kullanılarak oluşturulan modeller ve ham veri seti kullanılarak oluşturulan modellerin sonuçları karşılaştırılmıştır. Burada, X_{norm}, X_{min} and X_{mak} sırasıyla veri setinin normalleştirilmiş, minimum, and maksimum değerlerini ifade etmektedir.

$$x_{norm} = \frac{x_i - x_{min}}{x_{mak} - x_{min}} \tag{1}$$

ANFİS yaklaşımı ile elde edilen sonuçların başarısını ölçmek için aynı verilere Regresyon Analizi uygulanmış ve elde edilen sonuçlar karşılaştırmalı olarak verilmiştir.

Ek olarak, bir ülkenin verileri kullanılarak oluşturulan modelin başka bir ülkede uygulanabilirliğini araştırmak amacıyla, Irak'ın Kerkük istasyonunda ölçülen verilerle kurulan modeller Türkiye'nin Mardin ve Şanlıurfa istasyonlarına ait 2018 yılı verileriyle test edilmiştir.

Modellerin performansları aşağıda formülleri verilen, kök ortalama kare hata (KOKH), ortalama mutlak hata (OMH) ve determinasyon katsayısı (R^2) kullanılarak değerlendirilmiştir. Burada $f_{igözlenen}$, $f_{itahmin\ edilen}$, sırasıyla gözlenen ve tahmin edilen veriyi ifade etmektedir.

$$\text{KOKH}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_{i(gözlenen)}-f_{i(tahmin\ edilen)}\right)^2} \tag{2}$$

$$\text{OMH}=\frac{1}{n}\sum_{i=1}^{n}\left|f_{i\ (gözlenen)} - f_{i\ (tahmin\ edilen)}\right| \tag{3}$$

$$R^2=\frac{(f_i gözlenen - f_i tahmin\ edilen)^2}{(f_{i\ gözlenen} - veri\ ortalaması)^2} \tag{4}$$

3. SONUÇLAR VE TARTIŞMA

Sonuçlar, ANFİS yönteminin bu dört parametreyi tahmin etmek için etkili bir şekilde kullanılabileceğini ve Regresyon Analizinden daha iyi sonuçlar verdiğini göstermiştir (Tablo 1).

Table 1 Günlük ham veri üzerinde ANFIS ve Regresyon Analizi sonuçları karşılaştırması

	ANFIS			Regresyon Analizi		
Parametre	KOKH	OMH	R^2	KOKH	OMH	R^2
Basınç	2.691	2.132	0.789	2.834	2.344	0.762
Bağıl Nem	9.455	6.551	0.765	9.514	6.846	0.763
Solar Radyasyon	44.532	33.778	0.666	48.561	38.438	0.603
Sıcaklık	0.629	0.721	0.993	2.109	1.790	0.947

Bununla birlikte, ortalama günlük veriler kullanılarak oluşturulan modellerin saatlik veriler kullanılarak elde edilen modellere göre çok daha iyi sonuçlar verdiği görülmüştür (Tablo 2).

Table 2 ANFİS uygulamasında normalleştirilmiş verinin saatlik ve günlük sonuçlarının karşılaştırılması

	Saatlik Sonuçlar			Günlük Sonuçlar		
Parametre	KOKH	OMH	R^2	KOKH	OMH	R^2
Basınç	3.343	2.720	0.674	2.693	2.186	0.785
Bağıl Nem	10.185	7.025	0.755	9.479	6.430	0.765
Solar Radyasyon	191.438	147.187	0.455	55.515	46.505	0.481
Sıcaklık	18.699	16.067	0.843	3.184	2.803	0.881

Sonuçlar birbirine yakın olsa da normalleştirilmiş verilerle kurulan modellerin genellikle ham verilerle kurulan modellere göre daha iyi sonuçlar verdiği belirlenmiştir.

Dört model arasında, en iyi sonuçlar girdi parametreleri ile en yüksek korelasyona sahip olan sıcaklık parametresinde elde edilmiş olup bu durum girdi seçiminin modelde ne derece önemli olduğunun kanıtı niteliğindedir.

Farklı bir veri seti kullanılarak elde edilen modelin ihtiyaç duyulduğunda benzer iklim koşullarına sahip başka bir ülkede kullanılıp kullanılmayaağını araştırmak adına rölatif nem ve sıcaklık parametrelerinde Kerkük istasyonu verileri ile eğitilen model Mardin ve Şanlıurfa istasyonlarının verileri ile test edilmiştir. Sonuçlar tatmin edici olmasa da hata oranlarının Kerkük istasyonu ile aynı seviyede olduğu ve mecbur kalınması halinde modelin fikir vermesi açısından kullanılablanılabiceği sonucuna ulaşılmıştır.

CURRICULUM VITAE

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