RAINFALL PREDICTION USING MACHINE LEARNING TECHNIQUES

A THESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCES

OF

NEAR EAST UNIVERSITY

By

ZANYAR RZGAR AHMED

In Partial Fulfillment of the Requirements for

the Degree of Master of Science

in

COMPUTER ENGINEERING

NICOSIA, 2018

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Approval of Director of Graduate School of Applied Sciences

Prof. Dr. Nadire Cavus

We certify this thesis is satisfactory for the award of the degree of Master of Science in Computer Engineering

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

Name, Last name: Zanyar Rzgar Ahmed

Signature:

Date:

To my parents...

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ABSTRACT

This study seeks a distinctive and efficient machine learning system for the prediction of rainfall. The study experimented with different parameters of the rainfall from Erbil, Nicosia and Famagusta in order to assess the efficiency and durability of the model. The neuro-fuzzy and neural networks model is focused on this study. The learning of data is completed using hybrid and backpropagation network algorithm. The rainfall parameters in this study are collected, trained and tested to achieve the sustainable results through ANFIS and ANN models. The monthly rainfall predictions obtained after training and testing are then compared with actual data to ensure the accuracy of the model. The results of this study outline that the model is successful in predicting the monthly rainfall data with the particular parameters. The training and testing of data through neuro-fuzzy model helped in not only minimizing the errors up to RMSE of 0.011, 0.015 and 0.025, but also maximizing the reliability and durability of the predicted data. The results of the study highlight that the ANFIS model is most suitable among the artificial networks for the rainfall prediction. The outcome data with ANFIS system presented maximum accuracy with minimum error through the comparison between the actual data and predicted outcome data.

Keywords: machine learning; neuro-fuzzy; neural networks; parameters; rainfall prediction

ÖZET

Bu çalışma, yağış tahmininde ayırt edici ve etkili bir makine öğrenimi sistemi istemektedir. Çalışma, modelin etkinliğini ve dayanıklılığını değerlendirmek için Erbil, Lefkoşa ve Mağusa'ndan gelen yağışların farklı parametreleri ile deney yapmıştır. Nöron bulanık ve sinir ağları modeli bu çalışmaya odaklanmıştır. Verilerin öğrenilmesi melez ve geri yayılım ağ algoritması kullanılarak tamamlanmıştır. Bu çalışmadaki yağış parametreleri ANFIS ve ANN modelleri ile sürdürülebilir sonuçların elde edilmesi için toplanmış, eğitilmiş ve test edilmiştir. Daha sonra, eğitim ve testten sonra elde edilen aylık yağış tahminleri, modelin doğruluğunu sağlamak için gerçek verilerle karşılaştırılır. Bu çalışmanın sonuçları, modelin aylık yağış verilerini belirli parametrelerle tahmin etmede başarılı olduğunu göstermektedir. Nöronal bulanık model aracılığıyla verilerin eğitimi ve test edilmesi, yalnızca 0.011, 0.015 ve 0.025 RMSE hatalarını en aza indirmenin yanı sıra tahmin edilen verilerin güvenilirliğini ve dayanıklılığını en üst düzeye çıkarmada yardımcı oldu. Çalışmanın sonuçları, yağış tahmini için yapay ağlar arasında ANFIS modelinin en uygun olduğunu göstermektedir. ANFIS sistemi ile elde edilen sonuç verileri, gerçek verilerle tahmin edilen sonuç verileri arasındaki karşılaştırma yoluyla minimum hata ile maksimum doğruluğa sahiptir.

Anahtar Kelimeler: makine öğrenimi; Nöro-bulanık; nöral ağlar; parametreler; yağış tahmini

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LIST OF ABBREVIATIONS

AI: Artificial intelligence

ANFIS: Adaptive neuro-fuzzy inference system

ANN: Artificial neural network

ARMA: Auto-regressive moving average

BPNN: Back-Propagation Neural Networks

CBPN: Cascade-forward back propagation neural network

DMSP: Defense Metrological Satellite Program

DTDNN: Distributed time delay neural network

GEP: Gene expression programming

GPCP: Global perception climatology project

MSE: Mean Square Error

NARX: Nonlinear autoregressive exogenous model

NWP: Numerical weather prediction

PR: Precipitation radar

RMSE: Root-mean-square error

SPSS: Statistical Package for the Social Sciences

SSMI: Special Sensor Microwave Imager

TRMM: Tropical Rainfall Measuring Mission

CHAPTER 1

INTRODUCTION

Rainfall play important role in forming of fauna and flora of natural life. It is not just significant for the human beings but also for animals, plants and all living things. It plays a significant role in agriculture and farming and undoubtedly; water is one of the most natural resources on earth. The changing climatic conditions and the increasing greenhouse emissions have made it difficult for the human beings and the planet earth to experience the necessary amount of rainfall that is required to satisfy the human needs and its uninterrupted use in everyday life. Therefore, it has become significant to analyze the changing patterns of the rainfall and try to predict the rain not just for the human needs but also to predict for natural disasters that could cause by the unexpected heavy rainfalls. To be more specific and aware of the devastating climatic changing and stay updated; predicting rainfall has been the focus of computer scientist and engineers.

This study is focusing on predicting rainfall using Neuro-Fuzzy and Artificial Neural Network. The rainfall prediction will not just assist in analyzing the changing patterns of rainfall but it will also help in organizing the precautionary measures in case of disaster and its management. The rainfall prediction would also assist in planning the policies and strategies to deal with the increasing global issue of ozone depletion. The changing patterns of rainfall are associated much with the global warming; that is increasing of the earth's temperature due to increased Chlorofluorocarbons emitting from the refrigerators, air conditioners, deodorants and printers etc. that are the significant part of everyday life. The increasing temperature is actually affecting the climate considerably (Sivakumar, 2006). Similarly, the rainfall prediction and weather updates not only help in managing the macro level problems like flood and agricultural issues because of poor or extreme rainfall (Lima & Guedes, 2015). The rainfall prediction could also contribute to the well-being and comfort of the people by keeping them informed by tracking the rainfall patterns and predicting the rainfall by Neuro-Fuzzy and Artificial Neural Network. The rainfall predictions help the people to deal with hot and humid weather. The technological development in the modern world has expanded the space for innovation and revolution. Although the issues concerned are probably associated with these technological advancements but one needs to consider the range of possibilities and opportunities that this technological evolution has opened to the human beings.

In addition, the inappropriate or poor rainfall prediction is also one of the reasons that are problematic in the water reserve management. The precise and correct rainfall prediction can not only contribute to the effective and efficient utilization of this natural resource but it can also help in managing the projects and plans for power generation. For this purpose, it is very important to design and operate on a system that would assist in accurate prediction and easy access to the users. Artificial Neural Network for rainfall prediction is one of the most suitable and reliable systems for the rainfall prediction that has already benefited the operators for rainfall prediction (Shaikh & Sawlani, 2017). ANN has the ability to access input information and process it for a useful output. ANN does not need a previous knowledge of the processing of information that gives it an advantage over other data processing systems (Darji, Dabhi, & Prajapati, 2015). The rainfall prediction will also integrate adaptive Neuro-Fuzzy with ANN for an increased accuracy and enhanced quality of the predicted output. To analyze the performance of these algorithms; co-relation coefficient will be a key indicator in this study. ANN is the most competent and effective tool for prediction of rainfall that actually contributes to the most accurate forecasting (MuttalebAlhashimi, 2014). The Neuro-Fuzzy is also one of the effective algorithms used for data analysis for the classification. It assigns categories and allocates cases to similar groups/categories. So, each time a data is analyzed; it assigns that data to the most suitable or most similar category it belongs to. This helps in making the regression and allows the user to make a prediction for the similar sets of data or information received each time (Li, Kwon, Sun, Lall, & Kao, 2009).

However, rainfall prediction with ANN using backpropagation and hidden layer approach integrated with Neuro-Fuzzy is intended to produce precise and more accurate forecasts. The predictions could be utilized for a maximum range of purposes and thus can play a vital role in minimizing the issues associated with water reserves, agricultural problems with changing climatic conditions and flood management. The appropriate utility and implication of the estimated outcomes could also support the policy and development of strategies about resource management and control with a variety of techniques and approaches that will actually impact the human life in many ways.

1.1 Aim of the Study

The aim of the study is the prediction of the rainfall using historical monthly data based on artificial intelligence methodologies such as Neuro-Fuzzy and artificial neural network. The extraction procedures/algorithms will produce the output by classification of the data according to the categories using Neuro-Fuzzy. The similar data will be grouped for the accurate and precise information that will predict rainfall more correctly and with perfect figures. The accurate and exact predictions will help in developing the more appropriate strategies for agriculture and water reserves and will also be informed about the flood to implement precautionary measures. The data for the rainfall prediction is collected from Metrology Department of Erbil, Nicosia and Famagusta. This is the monthly data with all parameters of rainfall including wind speed, direction, air pressure, humidity and temperature. The aim of the proposed study is too effective and efficient in predicting the rainfall with accuracy and precision.

1.2 Significance of Study

Rainfall prediction is significant not only on the micro but also on the macro level. The study is of significance with respect to its vital contribution in the field of agriculture, water reserve management, flood prediction and management with an intention to ease the people by keeping them updated with the weather and rainfall prediction. It is also important to be utilized by the agricultural industries for keeping their crops safe and ensure the production of seasonal fruits and vegetables by updated rainfall prediction. The study will also be significant for the flood management authorities as more precise and accurate prediction for heavy monsoon rains will keep the authorities alert and focused for an upcoming event that of which the destruction could be minimized by taking precautionary measures. The rainfall prediction will impressively help in dealing with the increasing issue of water resource management; as water is a scarce resource and it needs to get saved for the benefit of human beings themselves. Also, it will help the people to manage and plan their social activities accordingly.

1.3 Limitations of the Study

i. The data sample is limited to monthly statistics only and does not provide the daily output predictions.
ii. The climatic change and the global warming effect may impact the accuracy of the expected output
iii. The locations for the data processing used in this study are geographically different and distanced that could also impact the correlation efficient that will measure the performance of the ANFIS and ANN in this research.
iv. The system discussed in this particular study will operate with Matlab software (R2017).

1.4 Problem Statement

The accurate and precise rainfall prediction is still lacking which could assist in diverse fields like agriculture, water reservation and flood prediction. The issue is to formulate the calculations for the rainfall prediction that would be based on the previous findings and similarities and will give the output predictions that are reliable and appropriate. The imprecise and inaccurate predictions are not only the waste of time but also the loss of resources and lead to inefficient management of crisis like poor agriculture, poor water reserves and poor management of floods. Therefore, the need is not to formulate only the rainfall predicting system but also a system that is more accurate and precise as compared to the existing rainfall predictors.

1.5 Methodology

Spiral model of programming by creating a V0 and test it for feedback from the test sample. It will retrieve the possible alterations to create the next Version of the algorithm. The test will be by stimulating the neural network to retrieve results by archiving.

1.6 The Study region and data

The metrological data including humidity, air pressure, wind speed, wind direction and temperature will be analyzed for three cities. Erbil in the North of Iraq and it has tall mountains and experiences heavy rain every year. Although, it has very nominal humidity; the data collected for Erbil has some appreciated predicted outcomes. Second is the capital of TRNC that is Nicosia and the third city includes Famagusta that is a seashore city in TRNC. The data is collected for 2012-2017 and it is collected on the monthly basis to predict the rainfall outcomes.

1.7 Overview of the Study

The thesis is designed as follows:

Chapter 1 is an introduction to the topic of the thesis. Chapter 1 outlines the overview of the study, discusses the aims and significance of this study.

Chapter 2 reviewed the existing literature and highlighted the previous research on the proposed thesis.

Chapter 3 is highlighting the general overview to the rainfall prediction and presents the explanation of the rainfall prediction in the field of agriculture, water reservation and flood prediction. It also grants information for the methods and approaches for the accurate prediction in depth.

Chapter 4 is focused on the explanation of the artificial neural system with the ANFIS and several modelling techniques like NARX algorithms are discussed in details.

Chapter 5 is an explanation of the stimulation of the data and presents the pre-processing and correlation between the input and output. The application of ANN and ANFIS is also discussed in detail.

Chapter 6 is the demonstration of results and discussions of the study. It also discusses root-mean-square error to evaluate the best findings for analyzing the accurate rainfall prediction.

CHAPTER 2

LITERATURE REVIEW

Rainfall prediction is not an easy job especially when expecting the accurate and precise digits for predicting the rain. The rainfall prediction is commonly used to protect the agriculture and production of seasonal fruits and vegetables and to sustain their production and quality in relation to the amount of rain required by them (Lima & Guedes, 2015).The rainfall prediction uses several networks and algorithms and obtains the data to be given to the agriculture and production departments. The rainfall prediction is necessary and mandatory especially in the areas where there is heavy rainfall and it's more often expected (Amoo & Dzwairo, 2016). There are huge economies like those of Asia like India and China that that earn a large proportion of their revenue from agriculture and for these economies; rainfall prediction is actually very important (Darji, Dabhi, & Prajapati, 2015).

The rainfall forecasting is prevailing as a popular research in the scientific areas in the modern world of technology and innovation; as it has a huge impact on just the human life but the economies and the living beings as a whole. Rainfall prediction with several Neural Networks has been analyzed previously and the researchers are still trying hard to achieve the more perfect and accurate results in the field of rainfall prediction (Biswas, et al., 2016). The prediction of seasonal rainfall on monthly basis by using the surface data to form annual prediction is also essential for the agricultural activities and therefore the production and supervision of the agriculture and crops. It could be done by recognizing the variations in the supply of moisture in the air. The case of African region illustrates that how this succeeded and how West Africa advantaged from the rainfall prediction in managing their agricultural activities (Omotosho, Balogun, & Ogunjobi, 2000).

Similarly, the short-term streamflow forecasting for the rainfall is also reliable and bias-free. But they are not much effective in predicting the flood and post-processing of rainfall prediction. An approach called raw numerical weather prediction (NWP) was introduced in 2013, where the approach focused on the Bayesian joint probability model to formulate prediction data. The approach formed forecast possibility distributions for each location and it had prediction time for it; collaborative forecasts correlated with space and time was produced in the Southern part of Australia (Khan, Sharma, Mehrotra, Schepen, & Wang, 2015). This approach focused on Schake shuffle to produce the forecast by the forecast possibility distributions (Robertson, Shrestha, & Wang, 2013).

Furthermore, the short-term streamflow forecasting could also be used through the artificial neural networks as researched by Zealand, Burn and Simonovic in 1999. The study conducted outlined that ANNs ability to forecast for short-term stream flow and outlined some of the issues that the approach encountered with ANNs (Kumarasiri & Sonnadara, 2006). Although, ANNs with short-term stream flow can calculate and present complex and nonlinear relationship between input and output with an ability to outline the interface effect as well but has issues in processing some input data with certain type and number. The ANNs also encountered difficulty with dimensions of the hidden layers. This research outcome was represented by the data of Winnipeg River system in Ontario, Canada using the quarter monthly data. The outcomes of the study were encouraging with AANs performed quite well for the four prediction lead-times. The RMSE for the test data of 8 years outlined variation from 5cms to 12.1cms in a forecast from four-time step to two-time step ahead respectively (Zealand, Burn, & Simonovic, 1999).

Also, the recent decade highlighted the significance of artificial intelligence and it has gained attention in water resource management and engineering as well. ANNs, ANFIS and GP are the driving simulations of AI and they are advantaged over other systems and approaches because of being more reliable and competitive. The adaptive neuro-fuzzy inference system (ANFIS) for time series and ANN for predicting streamflow in Apalachicola River, the United States with that of other neural network techniques like hybrid (Mittal, Chowdhury, Roy, Bhatia, & Srivastav, 2012); when compared to wavelet-gene expression' programming approach outlined the following results; ARMA model predicting accurate results for 1 day ahead time whereas, ANFIS forecasted the results for 2 days ahead time. The results from AI using ANFIS were more accurate and could predict 2 days ahead of time data rather than GEP and ANN (Nayak, Mahapatra, & Mishra, 2013). But for the 3 days forward data; ANN performed better than other models. For the monthly data; ANN, ANFIS and GEP outperformed as compared to ARMA models in the first part of the study (Karimi, Shiri, Kisi, & Shiri, 2016).

Water as is one of the most useful resources of the earth. There is no human and living thing on earth that can survive without water. As, this precious resource is running out because of the increasing temperature of the earth and the unexpected and unappreciated climatic conditions due to global warming. (Mittal, Chowdhury, Roy, Bhatia, & Srivastav, 2012). In addition, the comparison among different neural models revealed that Non-linear autoregressive exogenous networks (NARX) and back propagation neural BPN) performed better than distributed time delay neural network (DTDNN) cascade-forward back propagation neural network (CBPN) in outlining more accurate and precise results for rainfall prediction (Devi, Arulmozhivarman, Venkatesh, & Agarwal, 2016). In comparison, statistical forecasting methodology can also be used for the rainfall prediction that outlines by using two different approaches like traditional linear regression and polynomial-based nonparametric; where nonparametric method outlined more competing results. Both the approaches could predict the 1-3 monthly rainfall forecasting data that could actually impact water resource planning and controlling (Singhrattna, Rajagopalan, Clark, & Kumar, 2005). The periodic and episodic rainfall data for the south-west peninsula of England has also exposed that atmospheric characteristics are key players of outlining the monthly and seasonal forecast (Mcgregor & Phillips, 2003).

The rainfall prediction is also emphasized for its significance for the prediction of flood and consequently takes the precautionary measure to save the people from devastating destructions that a flood can cause (Hoai, Udo, & Mano, 2011). There are studies that outlined the significance of rainfall prediction in forecasting flood on the regions where there is heavy rain every year. The areas with high risk for flood are the vulnerable areas that need the rainfall forecasting not just to save a human life but to safe agriculture, water reservation and livestock (Fang & Zhongda, 2015).

In comparison, the significance of rainfall prediction is also important for areas with high probability for the drought. The areas with high drought seasons are also vulnerable to high risk in terms of agriculture and livestock with an extreme threat to human life as a whole; the study conducted for Sakae River basin of Thailand (Wichitarapongsakun, Sarin, Klomjek, & Chuenchooklin, 2016). The artificial neural network model for rainfall prediction of 1to 6 hour ahead time is studied for Bangkok, Thailand by Hung, Babel, Weesakul, and Tripathi in 2008. The study outlined that within artificial neural networks, using six models utilizing rainfall parameters like humidity, air pressure, wind direction and wind speed can give more accurate and precise prediction when previous forecasting data is also used with these parameters as an input as well (Hung, Babel, Weesakul, & Tripathi, 2009).

Nevertheless, land sliding is another natural hazard that could be caused due to heavy rainfall. The rainfall prediction could assist in combating the devastation caused by land sliding. The rainfall prediction for the areas vulnerable to land sliding is an essential part of artificial intelligence within engineering and management fields (Schmidt, Turek, Clark, Uddstrom, & Dymond, 2008). The metrological and hydrological centres are struggling hard to produce the more competitive and precise rainfall prediction in order to overcome these issues that the rainfall can cause and their efforts have marked quite an improvement in the rainfall prediction and forecasting data for many models using the neural networks. The prediction for extreme rainfalls is useful for not just the metrological departments in sharing in time alerts but also for the hydrological departments in order to form better safety measures for example the flood prediction in Australia (White, Franks, & McEvy, 2015).

The rainfall prediction systems are much popular with artificial neural networks and the rainfall prediction departments like the metrology and hydrology engineering with management (Abhishek, Kumar, Ranjan, & Kumar, 2012). The rainfall prediction using the neural network aims at predicting more efficient and more accurate results and precise predictions for a more useful and reliable output that could be used by the management and engineering departments in designing the plans and policies that will not only increase efficiency but it will also enhance the management systems from a quality data produced by using the Artificial Neural Networks. The study conducted with the different networks highlighted different results by operating within same training functions and outlined that back propagation neural network is capable of obtaining more precise predictions. Also, that increased neurons can decrease errors (MSE) (Sharma & Nijhawan, 2015). Neural networks have proved capability for the rainfall prediction and in obtaining accuracy with precision among the other networks with other modelling techniques (Narvekar & Fargose, 2015).

CHAPTER 3

RAINFALL

3.1 Introduction to rainfall

Rainfall is one the most significant atmospheric occurrence that is not only useful for the environment itself but for all the living beings on the earth. It affects everything directly or indirectly and because it is one of the most important natural phenomena; it is also important for the human beings to ponder on the precipitation changes with the change in climate (Alpers & Melsheimer, 2004). The rainfall has a significant impact on the universal gauge of atmospheric circulation and it affects the local weather conditions as well. The rainfall helps in balancing the increasing temperature and in the survival of the human beings (Trenberth, 2011). The increasing temperature of the world is associated with the global warming and the water is one of the scarce and most useful resources which in the result of this increasing temperature are evaporating from the reserves. Rainfall is also compensation to all these reserves and it is necessary for the agriculture and its production as well. The phenomenon of rainfall differs with the difference in latitude and longitude. The rainfall phenomenon also differs with the difference of regions, planes, mountainous and plateaus (Alpers & Melsheimer, 2004).

Rainfall occurs as stratiform or convective rain; the high latitude areas experience stratiform rain which is quite a dominant form of the rain. These areas include the tropical and subtropical and they experience 50% to 80% of stratiform rain precipitation (Alpers & Melsheimer, 2004). It is important to measure the distribution of the rainfall on the global level and for that currently the remote satellite sensing techniques are assisting in measuring the distribution of the rain on the global level. Special Sensor Microwave Imager (SSM/I) onboard with the US Defense Metrological Satellite Program (DMSP) are used for gathering the information about the rainfall with other space-borne instruments like microwave instrument , flying aboard the US –Japanese Tropical Rainfall Measuring Mission (TRMM) and precipitation radar (PR) that operate on different frequencies and are assisting in the data collection and in getting the footprints accurately (Alpers & Melsheimer, 2004).

However, the precipitation of the rainfall is not constant and it changes every year. The rainfall is actually the evaporated water from the earth surface because of high temperature or heat that goes up and then comes down in the form of rain or snow (Alpers & Melsheimer, 2004). The rainfall is the most significant phenomenon has always been associated with the increasing demands of mankind. The human beings on the earth cannot live without water and there is no way that they can also prude it artificially. It is one of those precious resources that cannot be artificially produced and thus it is the focus of the most studies and researches going on in the world. the scientists and the engineers are collaborating researchers to find out the best and most effective way of measuring the rainfall and predicting the rainfall to compensate for the extreme water use around the globe and to be sufficient for the increasing demands in terms of agriculture, water reserves and in order to be safe and sound from the natural disasters like the flood and land sliding. There is a need to focus on the efficient use of the water and to make the accurate predictions about the rainfall so that the time and the resource could be saved (Trenberth, 2011).

Similarly, the frequency, intensity and the amount of precipitation are changing with the changing temperatures and the effect of heat on the environment is also causing the changes in the precipitation levels (Kumar, Yang, Goddard, & Schubert, 2004). The rainfall can vary from the tropical storms to a thunderstorm, orographic rainfall and cyclones. The changing precipitation levels are observed by the Global Precipitation Climatology Project (GPCP) and presented the global changes in precipitation by the changing lands and the time period to impact it (Gu, Adler, Huffman, & Curtis, 2007). The rainfall affects the surface gravity waves in the upper water layer by generating turbulence and enhancing the roughness on the sea surface (Nystuen, 1990). The rainfall causes the notable changes to the environment and does not only assist in the everyday demands but also in cleaning the environment for the human beings. The air after the rainfall is fresh and clean and the pollution caused by the human beings is also controlled by the rainfall. The distribution and the amount of rainfall differ from region to region and area to area; therefore, with some precipitation in the different area it can also cause floods, tsunamis and land sliding. Therefore; the prediction of the rainfall and the forecasting of the precipitation is quite a significant field on which the scientists and the researchers are exploring ways to accommodate this natural phenomenon and to manage the resource in a more appropriate and useful manner to multiply the human life.

3.2 Types of rain

3.2.1 Conventional precipitation

The significant and the most dominant form of the rainfall is the convectional rainfall. It is experienced in the high latitude areas like the tropical and the subtropical. It is usually observed with lightning and thunderstorm. The conventional rainfall is a type of rainfall that is affected by the mountains and the mountainous regions; as it is the most dominant form of rainfall and it depends on the latitude (Collier, 2003). The formation of the conventional rainfall occurs when the air on the surface of the earth gets intense by the heat of the sun. The hot air is lighter than the cool air so it evaporates from the earth surface and forms clouds in the atmosphere. The further rise in the water vapours and gradually these vapours move upward direction towards the area of converging air and forms thick and heavy clouds. The heavy and unstable clouds rise further and the instability of these clouds then compel them to fall on the surface of the earth again in the form of conventional rain (Selase, Agyimpomaa, Selasi, & Hakii, Precipitation and Rainfall Types with Their Characteristic Features, 2015).

The conventional form of rainfall is observed mostly in West Africa and it is always followed by a thunderstorm and heavy lightening because of the heavy and unstable clouds rising upward in the atmosphere with converging air (Blyth, Bennett, & Collier, 2015). The figure 2 below shows the instability of the heavy clouds of convectional rainfall.

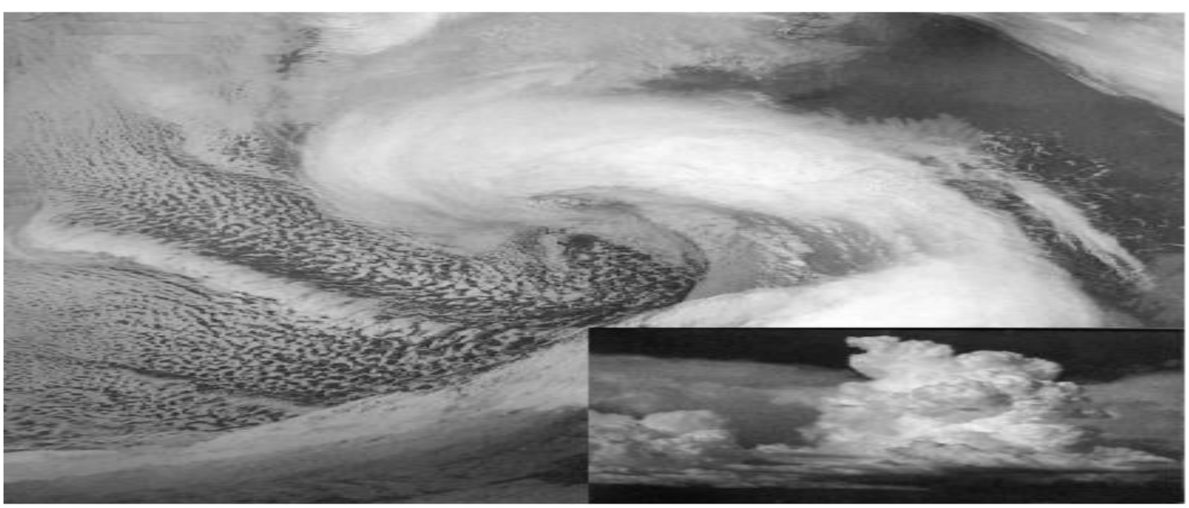


Figure 3.1: Heavy and unstable clouds of conventional rainfall (Collier, 2003).

3.2.2 Orographic rainfall

The orographic rain is the form of rainfall that is formed by the moist air which usually can be observed above the mountains. The moist air above the mountains is evaporated or lifted upward direction. When the moist air is lifted and rises to a certain level it cools down; the orographic clouds are formed and then condenses and forms the precipitation. The orographic rainfall is formed by the midlatitude lands like the one with large mountains (Gray & Seed, 2006). The orographic rainfall has tiny water drops that are condensed. These small water drops from clouds and then these small clouds come together to form bigger clouds. These clouds also turn into snow over some period of time (Jr., 2012).

The orographic rainfall is observed on the midlatitude mountains with an axis perpendicular to the prevalent wind direction. These directions cause the sharp rainfall transitions and could be observed better with two adjacent ranges of the mountain to circulate the moist air more. The steadier and these are experienced mainly in afternoon of the summers with dynamic thunderstorms. The discrete formation of orographic precipitation is sometimes observed on the small mountains as well (Roe, 2005). Orographic rainfall is due to the uplift of masses of air by the wind (Smith & Evans, 2007).

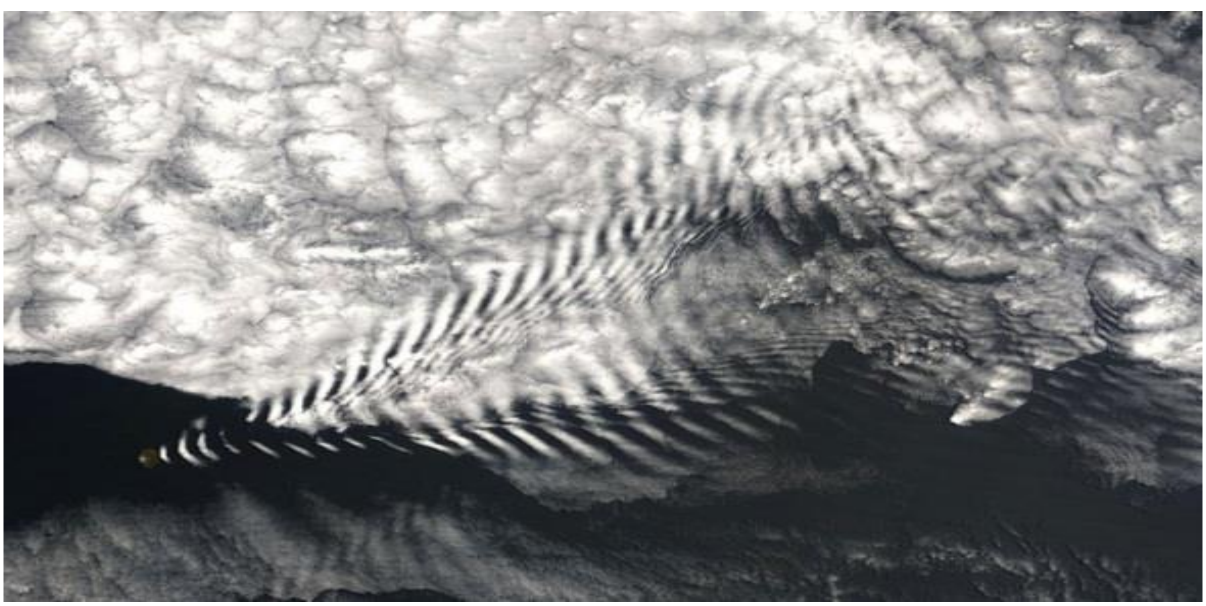


Figure 3.2: Wave cloud formation on Amsterdam Island in the far Southern Indian Ocean (NASA, 2005).

3.2.3 Cyclonic or frontal rainfall

The cyclonic or the frontal rainfall is the last and third type of the rainfall. The cyclonic by name represents the tempesting and occurs when the air masses with distinct characteristics collide with one another. The collision of light air that is warm and the cold air that is heavy occurs; the cold air encourages the warm air because it is lighter to rise. The rising air cools down by forming the water vapours. The condensation process initiates and forms the clouds (Thatcher, Takayabu, Yokoyama, & Pu, 2012).

The formation of clouds become heavy as they meet with other clouds and these heavy clouds become unstable and fall back on the earth as cyclonic rainfall. The cyclonic rainfall is common in Tropical areas with 23% of Degrees North Latitude and South of the equator with the temperate zone latitude of 66% degrees North and South. This is the reason that it is also known as the frontal rainfall (Thatcher, Takayabu, Yokoyama, & Pu, 2012).

The frontal/cyclonic rainfall has a specific period and time when it is more dominant and the precipitation is more rapid and concentrated. The cyclonic/frontal rain may have an extended precipitation that could be extended and keep the weather wet for log days. It is a lognormal type of distribution and its distribution depends on the area of precipitation (Cheng & Qi, 2001).

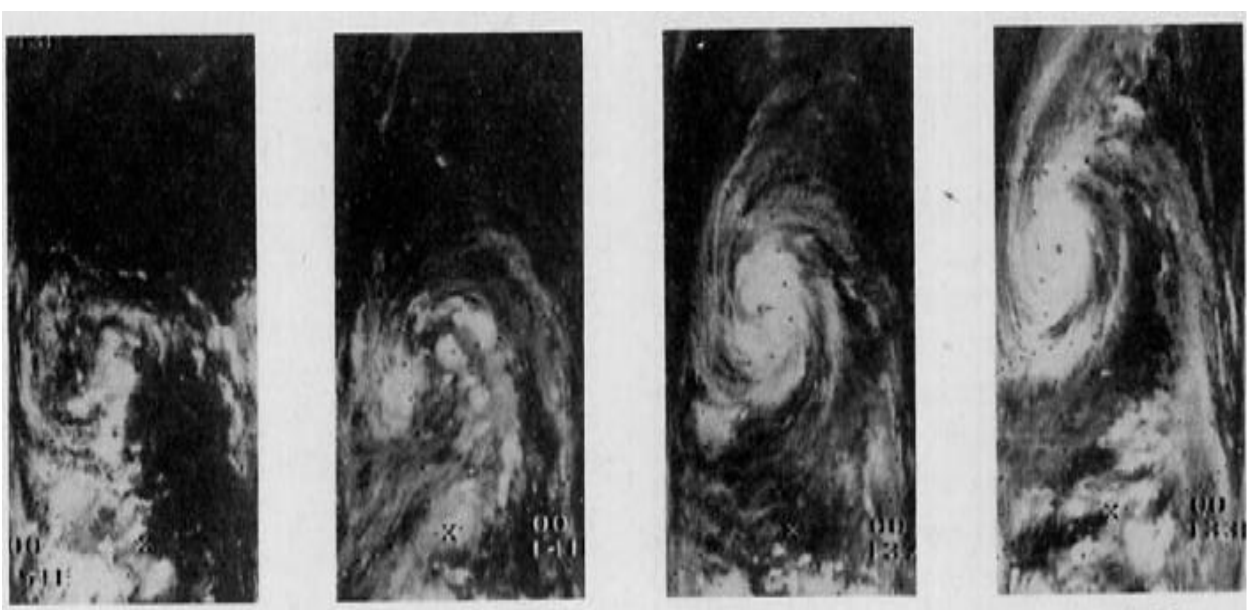


Figure 3.3: Cyclonic rainfall cloud formation (Rodgers & Adler, 1980)

The above figure 3 represents the formation of cyclone rainfall or the frontal rainfall in the tropics and highlights the changing data readout orbit that is increasing with the increase in the cyclonic visibility as shown in the four pictures (Rodgers & Adler, 1980).

3.3 Measurement of rainfall

The rainfall is a natural phenomenon that is measured in mm. The measuring instrument is 203mm in diameter. This is a funnel that gathers the rainfall into a cylinder and has the capacity of measuring u to 25mm of rainfall (Alpers & Melsheimer, 2004). There are two techniques for measuring rainfall as described below:

3.3.1 Ordinary rain Gauge

The ordinary rain gauge measurement is a less effective and less accurate technique of measuring the rainfall. It has been observed that the ordinary gauge is the non-automatic observation and uses a glass to measure the rain at regular intervals. It has a shell, a storage bottle with a storage vessel and a glass for measuring the rain. It is not effective for the heavier and substantial rainfall like the cyclonic/frontal rainfall (Carvalho, Assad, Oliveira, & Pinto, 2014). It uses a rainfall record book to compare and measure the rainfall for a particular period. It is less accurate and the data collected may not be precise (Agnihotri & Panda, 2014). The ordinary method of the rainfall measurement is helping in the local level measurements and those that are less accurate and less precise but this method of rainfall collection is appropriate for the measurement t record for a larger level. The observations performed in the ordinary rainfall are manual so the errors are not minimized.

3.3.2 Self-recording rain Gauge

The conventional self-recording rain gauge is more efficient and more effective in measuring the rain than that of the ordinary gauge for the measurement of rain. The traditional method of recording rain is inefficient and gives inaccurate results as it’s done manually so it can involve human errors (Beard, 1962). The self-recording rain gauge is observed to use simple technique and instruments to produce better measurements in order to have better probability and accuracy. The self-recording gauge consists of a tipping bucket and a lever balance that weighs the rain accordingly. It has a marking pen which marls each certain level recorded with the movement of the bucket and the precipitation for each hour is recorded by the gauge automatically without the support of human beings (Hansen, 1961).

3.3.3 Zonal distribution of rain

The patterns of the rainfall precipitation are not constant; it varies season to season and location to location. There are certain different zones that get more precipitation than few of them getting less precipitation. The precipitation of the rainfall as a mean global distribution studied to be affected by the latitudinal zones, land and sea surfaces and precipitation. The East Asian region precipitation including China, Korea and Japan evaluates that monsoon starts from mid-end of May to the end of July for China and September in case if Korea. It ends by the early August Peninsula and for Japan; it lasts longer from mid-September to end of October. (Qian, Kang, & Lee, 2002).

The Middle Eastern region experiences a severe autumn rainstorm. The countries along the red sea are the most significant to experience this kind of rainfall distribution and the Mediterranean countries are more unstable to these conditions. The experience intense thunderstorms but the weather for summer is more of hot and dry. These countries also experience hailing and may sometime encounter flooding. The North African region is also included within this area and experience the same weather. Both the weathers are extreme; in case of summers and winter being on the cold front (Dayan, Ziv, Margalit, Morin, & Sharon, 2001).

The rainfall distribution in the region of East Africa is also studied as significantly more than that of the amount of rainfall studied. The patterns of zonal distribution are observed to be variable for each season. The rainfall prediction for each day is also changing with the changing trends of rainfall. The zonal distribution of the rainfall is open to seasonal change and the change in the sea level and earth surface due to the movement of plates (Johnson, 1962). The parameter like wind, atmosphere and humidity are also significant in determining these patterns. Air pressure and temperature also affect the zonal distribution of the rainfall annually and monthly. The changing temperature of the earth is also influencing the zonal distribution because it has more chances of being deteriorated. The high precipitation of the rainfall distribution recorded is that of an equatorial zone. Southeast Asia and the middle latitude areas experience the comparatively low amount of rain distribution and the deserts of subtropical regions experience even fewer or extremely insufficient rainfall annually (Adler, Huffman, Bolvin, Curtis, & Nelkin, 2000).

3.4 Regime of rainfall

According to Haurwitz and Austin in 1944; there are six main regimes of the rainfall that are described as:

3.4.1 Equatorial rainfall regime

It is the form of rain that is characterized by experiencing the rainfall throughout the year and in all seasons. This character of rainfall is not outlined by the rainfall in a particular season or in few specific months rather it is characterized by the consistent and continuous rainfall annually. The equatorial rainfall regime is experienced to have heavy rainfall in the month of March and September. The thermal air currents are generated by the heating effect and that contributes to the formation of heavy and unstable clouds resulting in the extreme rainfall within these months of the year. The equatorial regime of the rainfall extends between the zone of 10º N and 10º S latitude. The equatorial rainfall regime is followed by thunderstorm and heavy lighting because of the instability and huge size of the clouds. The rainfall is observed to be in the form of heavy showers but the time duration observed for these types of regimes is quite less as compared to the other regimes. These are the low-pressure belts and relatively high temperatures. Mostly they experience the conventional rainfall because of the heating effect. The distribution of the rainfall throughout the year is equal and uniform. These regions experience heavy rainfall sometimes with hailing and storms during the year (Haurwitz & Austin, 1944).

3.4.2 Tropical rainfall regime

The tropical rainfall regime is characterized by the heavy rainfall not throughout the year but only in the summers. The winters of the tropical areas are usually dry and they are not associated with much rainfall. The summer season not only experiences the heavy rainfall but is comparatively pleasant because of the consistent rainfall. The northern hemisphere and the Eastern hemisphere usually experience the maximum and minimum rainfall during the months of July and December. The tropical regime of the rainfall is under the influence of summer stagnation and thus it can be said that the winters are significantly dry. Therefore, the areas occupying the tropical regime may suffer in the winters but are ready to shine in the summers (Haurwitz & Austin, 1944).

3.4.3 Monsoon rainfall regime

The monsoon rainfall regime is characterized as the zone 4 that is also under the stagnation of the summer season. The rainfall experienced in this regime is characterized as only in summers but slightly less as compared to that of tropical. The winters are also extremely dry as that of the tropical because this regime is at the sub-tropical high-pressure belt. The maximum rainfall is experienced in the month of July that is known to be the monsoon season and continues to the end of August. There are not much heavy showers of the rainfall and the thunderstorm and the lightning is also merely observed but the light shower continues for almost 2 months day to day and time to time. This regime is associated with the monsoon winds; as the monsoon winds start to blow; like the phenomenon experienced on the orographic rainfall; the wind elevates the water vapours and condenses them to form clouds and then into rainfall shower (Haurwitz & Austin, 1944). The winds observed to move the water vapours in the upward direction are also associated with the formation of the cyclonic rainfall as described above. The air of different masses collides with one another and initiates the condensation process. The lighter air that is warm air collides with the heavy cold air to form the clouds and thunderstorms or lightening effects could be observed for the monsoon regime of the rainfall.

3.4.4 Mediterranean rainfall regime

The Mediterranean rainfall regime experiences the driest weather. For example: the weather conditions of Nicosia and Famagusta. The weather of these cities are extremely dry not only in winters but also in summers. The regime is associated with the sub-tropical high-pressure belt for the whole year. Although, the winters are cold and rainy they last for only 2 months that of January and February and the summer season is extremely hot and dry. They experience the comparatively heavy rainfall in the winter season opposite to the above-mentioned regime sand but dryness prevails throughout. The summers despite being very hot for the Mediterranean are still dry and hardly the rainfall is experienced. The city of Nicosia and Famagusta are also following this belt ad experience exactly the same weather as observed from the data collected from the metrological department. The Mediterranean rainfall regime is defined as zone 4 by Haurwitz and Austin, as extremely dry (Haurwitz & Austin, 1944).

3.4.5 Continental rainfall regime

Similarly, the continental rainfall regime experiences the heavy rainfall in summers due to the convection. The high temperature forces the water to evaporate in the form of water vapors from the water surface and form clouds. The summer season continuously experiences the convection and the rainfall is experienced throughout the summer season opposite to that of the winter season formation of the clouds. Because the summer season experiences the heavy rainfall therefore, the winter season is usually dry it experiences only few slight showers of the precipitation. The weather conditions for such a regime is neither very dry nor are they rainy. The weather is moderate and the extreme seasons are not experienced. The high precipitation within the continental regime could experience the cyclonic rainfall and conventional rainfall as the precipitation depends upon the temperature. The high temperature will impact the precipitation and the formation of the clouds for heavy showers of the rainfall (Haurwitz & Austin, 1944).

3.4.6 Maritime rainfall regime

The maritime regime is characterized by the mid-latitudes and along the western margins of the continent. The maritime regimes experience the rainfall in winter season and the summer is not very dry but due to the high precipitation in the winter season; the maritime regimes experience usually the dry summers. These regimes also experience the cyclonic rainfalls with several intervals and the process of rainfall continues throughout the year. There is no season in these regimes that is extremely dry or experiences no rainfall. These regimes also experience the winter monsoons despite of the summer monsoon winds and are expected to observe with the monsoon showers in the winters rather than that of the summers. The maritime air is conveyed to the cost through the dominant westerly (Haurwitz & Austin, 1944).

CHAPTER 4

MACHINE LEARNING TECHNOLOGIES

4.1 Introduction to machine learning

Machine learning is associated with the study of the algorithms that enhance the efficiency of the machines/computers automatically through the training and testing of the machine/computers with certainly different variables. The machine learning is among the most favourable and fastest growing areas of computer technology. The computers work efficiently with different algorithms and functions. The machine learning is the training the computer with certainly different algorithms to experience the machine in automatic smart data processing. The machine learning enhances the efficiency and accuracy of the data processing and is used in a wide range of fields. The machine learning is developed with effectual algorithms that utilize a certain set of tools and functions to solve the complex and huge data. The machine learning is assisting in the diverse field; these are normally artificial intelligence applications that are used for recognition and prediction like that of computer engineering and medical fields. The machine learning is popular among the modern computer technology and has many benefits. Machine learning develops some rules for the input data as discussed in the hybrid model that helps the machine to process the similar case each tie efficiently. It works on the prediction, and it is more important to understand that how variables the inputs into are moved into vectors. The machine learning has minimized the manual jobs for the people that also could have the space for errors and inaccuracy (Smola & Vishwanathan, 2008)

4.1.1 Artificial neural networks

The artificial neural network is a computer networking system that can perform huge and intelligent tasks. It is a parallel and distributed processing system that can accomplish most complex tasks of recognition, prediction and detection without increasing the complexity of the problem. The artificial neural network has one input layer and one output layer between which are the hidden layers that process data. Each layer by processing the data forwards the result to the next hidden layer and finally the output layer obtains the result after the data processing. The artificial neural network is one the most popular machines of artificial intelligence that are used almost in every field nowadays. It uses certain different models for processing data like feed-forward back propagation, NARX model with different functions for each model. These are dynamic machines capable of solving complex to everyday problems and made the human life easy (Yegnanarayana, 2009).

4.1.1.2 Neurons

The artificial neural network performs these complex and huge tasks through the neurons that are fed into the layers and process the data just like the human brain. Neurons operate in the human brain to perform all the tasks and so are the artificial neural network does. The neural network is non-linear functions. The neurons in the neural network are first trained with the old data in order to get the new and predicted data.

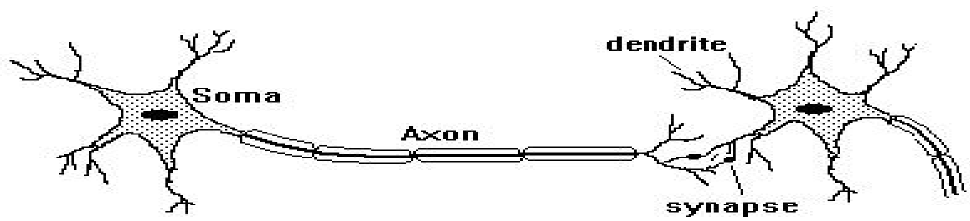


Figure 4.1: Neuron scheme (Skorpil & Stastny, 2006)

After the training, testing is carried out to check the different results with different data and to obtain the comparison by feeding the system with a different number of neurons. The number of neurons fed to the system is varying and depends on the data and processing complexity. Therefore, the architectures may differ from one another depending on input/output complexity and the layers in the system (Demuth, Beale, Jess, & Hagan, 2014).

4.1.1.3 Structure of ANN

The architecture of the ANN has three layers with a large number of neurons, the neurons are called the units and they are arranged in a sequence of layers.

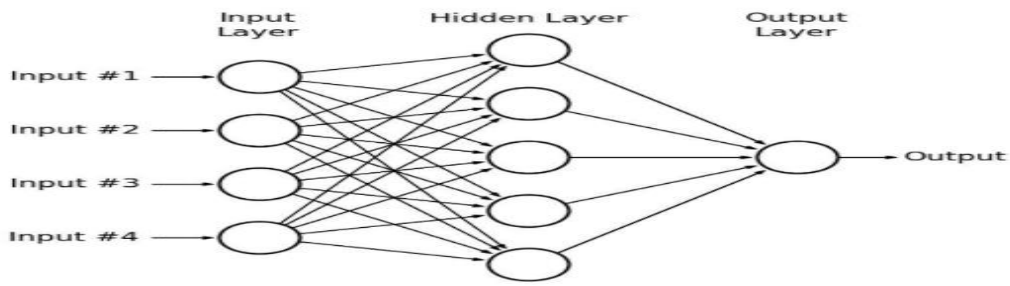


Figure 4.2: Structure of ANN (Ahn, 2017)

INPUT LAYER is the first layer of the ANN structure is the input layer that takes the input for processing.

HIDDEN LAYER is the second layer that process the data transferred from the input layer for processing through neurons and, the weights are updated continuously for precision and validity of the output

OUTPUT LAYER is the third and the last layer through which the results are obtained from the, as shown in figure 4.2 above.

4.1.1.4 Weights

The weights in the ANN architecture are the memory storage that stores the information and data to get the desired results. The weight during the training, testing and validation are modified at every step so that the accuracy of the output is achieved; also, they store data for the future operations.

4.1.1.5 Feedforward neural network

The feed-forward neural network has multilayers for the processing of elements. Each layer processes the input data that it receives and forward the results obtained to the next layer. For this processing, each layer operates independently to generate the resulting that is forwarded to the next layer. The result obtained through processing of each layer is ultimately obtained from the output layer. Between input and output layer; there are hidden layers. The elements that process the input data work like the neurons in the human brain, these are called artificial neurons. The neurons in the layers send messages or information to other neurons through a channel called connections.

4.1.1.6 Backpropagation algorithm

The feed forward back propagation is used to detect the error and consequently highlight the performance of the network using the certain inputs, number of neurons and to check the validity and accuracy of the output obtained. In the back-propagation model by the ANN; weights are decrypted and adjusted in the neural network. The system performs several cycles of backpropagation with the input data to get the desired output (Y.H.Zweiri, J.F.Whidborne, & L.D.Seneviratne, 2002). The backpropagation a very simple yet efficient algorithm, it consists of N processing elements with functions of input and output as below.

$$\mathbf{y = G(x, W)} \tag{4.1}$$

In this equation, x is the input vector, y is the output vector and W is the propagation error weight matrix, the later matrix is shown by equation 4.2.

$$\mathbf{W} = (\boldsymbol{w_1}^{\mathrm{T}}, \boldsymbol{w_2}^{\mathrm{T}}, ..., \boldsymbol{w_N^T})^{\mathrm{T}} \tag{4.2}$$

In equation 2,w_1,w_2, ..., w_N are the individual vectors given by in equation 4.3 below.

$$\boldsymbol{w_i} = \begin{bmatrix} w_{i1} \\ w_{i2} \\ \vdots \\ w_{in} \end{bmatrix}, \qquad i = 1, 2, .., N. \tag{4.3}$$

4.1.1.7 Nonlinear autoregressive exogenous model (NARX)

The NARX is the model that is found from Autoregressive with Exogenous Input model. The NARX is a nonlinear and recurrent dynamic model. It is a feedback neural network which is efficient in obtaining the output results that are accurate and precise. It is suitable for modelling nonlinear systems like the artificial neural network. The NARX is best for learning with gradient algorithm. The gradient descent is obtained accurately with NARX. The below equation 4.4 illustrates the algebraic expression of NARX.

$$y(t+1) = f\,[y(t),\ldots,x(t-d_y+1);\ u(t-k),\ u(t-k-1),\ldots,\ u(t-k-d_u+1)] \qquad \textbf{(4.4)}$$

The NARX equation in the vector form can be written as below equation 4.5.

$$y(t+1) = f\,[\mathbf{y}(t);\ \boldsymbol{u}(t)] \qquad \textbf{(4.5)}$$

The NARX models are used popularly for the identification and recognition tasks. The predictions are and forecasts could also be made efficiently by using the NARX models. They operate under certain different functions and are autoregressive. This model uses feedback connections (that are neurons sending the information to other neurons) in the several layers of the network for enhanced accuracy. It is based on ARX model that is linear and used to predict the time series commonly (Khamis, Nabilah, & Abdullah, 2014).

4.1.2. Adaptive Neuro-Fuzzy Inference System

The ANFIs is an efficient machine learning and artificial intelligence network that is sometimes advantaged over the neural networks. The ANFIS aims at reducing the complexity of the operation and simplify it to get the desired results and output. It also uses the neurons for processing the data, the neurons work as nodes. The neuro-fuzzy system introduces a set of rules for each operation that also stores the data and information for the future operations. The rules introduced depend on the inputs and outputs. It has a domain knowledge which is commonly practised for obtaining the outputs. The concepts of adaptive networking are used with certain techniques to process the desired output. The output depends on the updating parameters and their collection. The node is the processing unit of the neuro-fuzzy. The ANFIS drives the rule for the different optimization techniques (Wahyuni, Mahmudy, & Iriany, 2017).

4.1.2.1 ANFIS architecture

The below figure 4.3 illustrate the ANFIS architecture for two inputs with five layers. The ANFIS makes rules while processing the data that are used for accurate and precise results.

These rules also help to operate the future data for maximum efficiency (Wahyuni, Mahmudy, & Iriany, 2017). The architecture has five layers as described below:

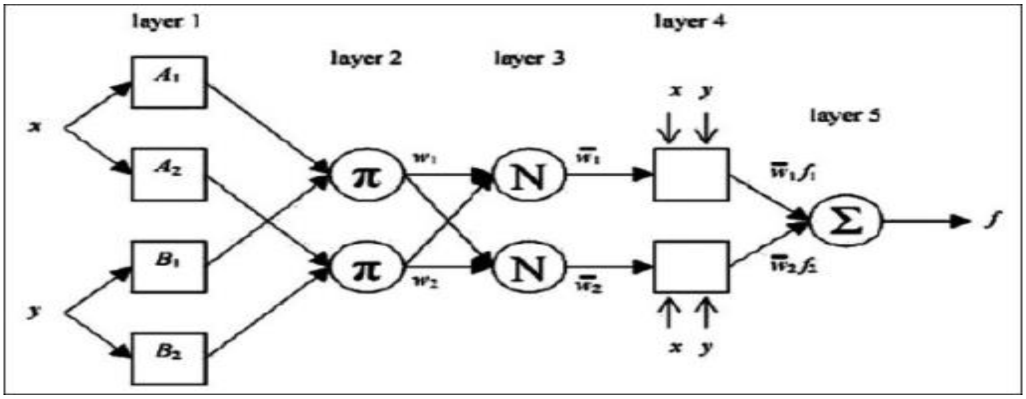


Figure 4.3: ANFIS architecture

LAYER 1 (MEMBERSHIP FUNCTION**)**

The first layer has nodes and each node *i* in this layer is an adaptive node to node to function, as outlined in the equation 4.6 below.

$$O_{1,i} = \mu A_i(x), \quad for\ i = 1, 2\ and$$
$$O_{1,i} = \mu B_{i-2}(y), \ for\ i = 3, 4 \tag{4.6}$$

In the above equation 1, x and y are the inputs at node *i*, *Ai and Bi* are the linguistics label. The $O1_i$ and $O1_i$ -2 are the membership functions of *Ai* and *Bi*. The member ship function is based on the linear equation curve that specifies the maximum value as 1 and minimum value as 0. The membership function *A* has parameters as shown in equation 4.7 below.

$$\mu Ai\ (x) = \begin{cases} 0; & x \le ai\ or\ x \ge c \\ \frac{x-ai}{bi-ai}; & ai \le x \le bi \\ \frac{bi-x}{ci-bi}; & bi \le x \le ci \end{cases} \tag{4.7}$$

LAYER 2 (RULES LAYER)

The layer 2 in the architecture has fixed node. The output obtained through this layer is the product of all the inputs that are fed into this layer. To calculate the output through this layer, following equation 4.8 can be used.

$$O_{2,i} = wi = \ Ai(x) \,.\ Bi(y) \quad where\ i = 1, 2 \tag{4.8}$$

LAYER 3 (NORMALIZED FIRING STRENGTH)

Similar to the layer 2, each node in this layer is also fixed. In this layer, normalized firing strength is the ratio of the output *i* on the preceding layer to the whole output of the preceding layer. It is represented in equation 4.9 below.

$$O_{3,i} = \overline{w}i = \frac{wi}{\sum_{i=1}^{16} wi} \quad where\ i = 1, 2, \dots, 4 \tag{4.9}$$

LAYER 4 (DEFUZZIFICATION)

In this layer, *i* is a node to node adaptive function. The weight obtained from layer 3 and the parameters to two inputs are obtained by linear regression function of order 1, as shown in equation 4.10 below.

$$O_{4,i} = \overline{w}ifi = \ \overline{w}i(p_i x + q_i y + \ r_i\,) \tag{4.10}$$

LAYER 5 (ADDITION)

The last layer 5 gathers all the inputs obtained from each layer and adds them up for the final result. The sum function is outlined in the equation 4.11 below.

$$O_{5,i} = \ \sum_i \overline{w}ifi = \frac{\sum_i wifi}{\sum_i wi} \tag{4.11}$$

4.1.2.2 Hybrid learning algorithm

In the ANFIS architecture there are five layers. The first and the fourth layer contain the parameters that can be updated time to time. But the first layer is nonlinear while the fourth is linear. Therefore, both the parameters need to be updated through the learning method which is capable of training linear and nonlinear simultaneously, hybrid system is the one introduced in 1993 by Jang, that train both layers at the same time (Faulina & Suhartono, 2013). The ANFIS network is trained through Hybrid learning algorithm. It uses descent gradient to denote the errors by forward pass and backward pass in order to train layer 1 and layer 4 at the same time. The error can be measured by the equation 4.12 below.

$$E_p = \sum_{m=1}^{\#(L)} (T_{m,p} - O_{m,p}^L)^2 \tag{4.12}$$

$T_{m,p}$ is the *m*th component of the *p*th target

$O^L_{m,p}$ is the *m*th component the actual output vector

The overall error is as follows,

$$E = \sum_{p=1}^{P} E_p \tag{4.13}$$

CHAPTER 5

SIMULATION

5.1 Data processing

In this study, we are considering the prediction of rainfall. The main purpose and aim of the study are to utilize the machine learning for predicting the rainfall with accuracy and precision. Therefore, the study includes and examines the source data in the pre-processing phase and utilizes this data in the stimulation or processing phase further to predict the output that is forecasting effectively and efficiently. For this purpose, statistical data of Erbil, Nicosia and Famagusta is collected from the metrological departments. The data collected from the metrological departments is monthly, as this study will also focus on the monthly rainfall prediction. The data includes the significant parameters of the rainfall. Temperature, wind direction, wind speed, air pressure and humidity are considered. Each parameter of the rainfall is analyzed separately for Erbil, Nicosia and Famagusta. The statistical data studied and examined in this study will be used as input for processing the output as rainfall prediction. The data processing is done through machine learning techniques and different neural networks like ANFIS and NARX and Back-Propagation models.

1. ERBIL

Erbil is located in the north of Iraq. It has a total land area of 438 320 km2 with a population of 28.8 million. Its latitude is 36.191113 and longitude is 44.009167. It is a mountainous region and experience snowfall in winter season with temperature on average of 6℃ in urban and in the mountainous ranges about -10℃ (MuttalebAlhashimi, 2014).

There are four seasons experienced in the north of Iraq and the winters are extremely cold. There is heavy rainfall which continues for a long span of time and only a few months of the year have very less or no rainfall. The weather of north Iraq has variations and the metrological departments measure the parameters like humidity, air pressure, wind direction and wind speed for predicting the rainfall daily, monthly or annual data.

Besides, the region of northern Iraq is rich in agricultural activities and production of agricultural products associated with the need of rainfall prediction for effective and efficient supply and production of agricultural products (Gibson, 2012). The irrigation system in north Iraq also needs to focus on the reservation of water as it is a scares resource and being the agricultural economy; it is also significant for this region to utilize water more effectively and efficiently (Frenken, 2009). This also makes it significant for the study to analyze the weather forecasting for this region.

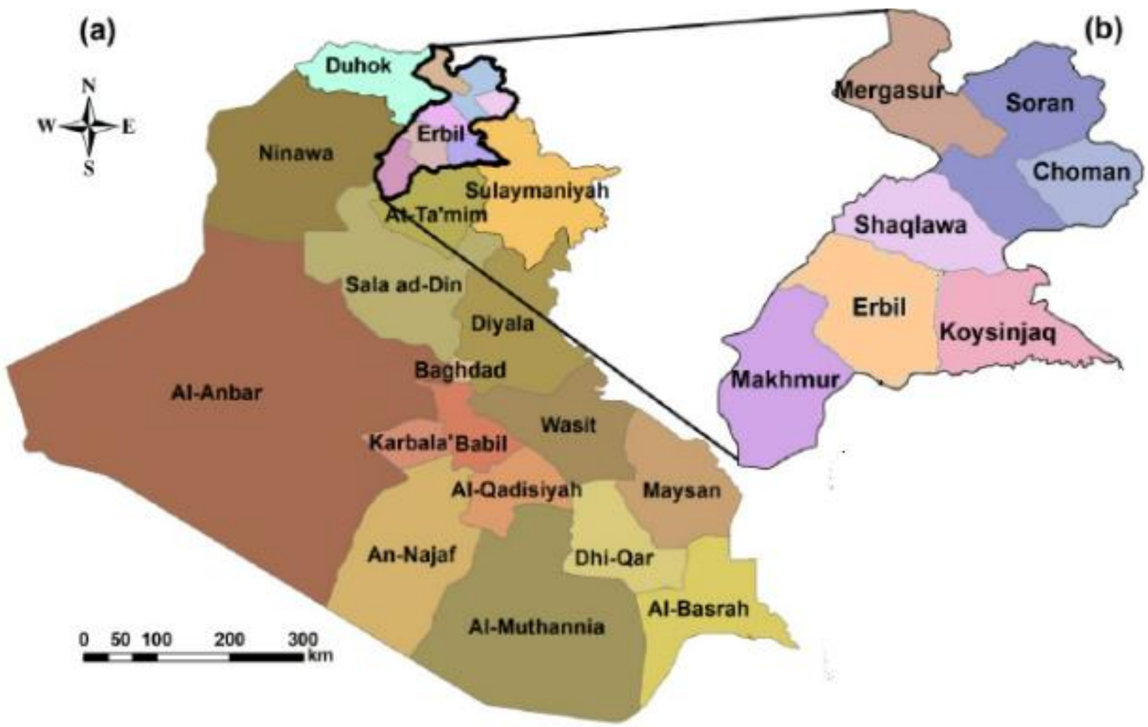


Figure 5.1: Map of Iraq; (a) Erbil (b) focus area of this study (north Iraq) (Zakaria, Al-Ansari, Mustafa, & Knutsson, 2013).

2. NICOSIA

Nicosia is the capital city of North Cyprus. It has a total population 61,378 according to the census of 2011. It has a total area of 3,355-kilometer square. The weather conditions of Nicosia are extreme for summers and winters. The winters normally experience cold with mostly rain. The latitude of Nicosia is 34^0 and 36^0 North and longitude of 32^0 and 35^0 East (SPO, 2014). It experiences 60% of the annual rainfall from December to February. The weather in Nicosia is usually very dry and humidity is experienced to be 56% (bbc).

Nicosia is an Urban/metropolitan city and occupies huge area; as it is the biggest cities in North Cyprus. The city has a metrological department that predicts the rainfall to sustain the everyday life and avoid the natural disasters. The rainfall parameters for the city of Nicosia are studied in this particular research to evaluate the output prediction as that of Erbil in Iraq.

3. FAMAGUSTA

Famagusta is the seashore city of Northern Cyprus. It is located on the east coast of Northern Cyprus. The city f Famagusta is not very huge like that of Nicosia but it has many beaches and has a total population 46,900 according to the survey of 2015. The area of Famagusta consists of $35^{0}7'13.94''$ of North and $33^{0}56'20.18''$ of the East. The humidity in Famagusta is observed to be (Akingbaso, 2014). The rainfall parameter data is collected for Famagusta as an input of this study to evaluate the output for precision and accuracy.

Figure 5.2: Map of Northern Cyprus; showing Nicosia and Famagusta (Akingbaso, 2014).

5.1.1 Data Pre-Processing for Erbil

The monthly rainfall data from 2012-2017 for Erbil, is collected from the metrological department to outline the trends and variations that are being observed within this time period and to highlight the rain cycles for each that will effective for prediction.

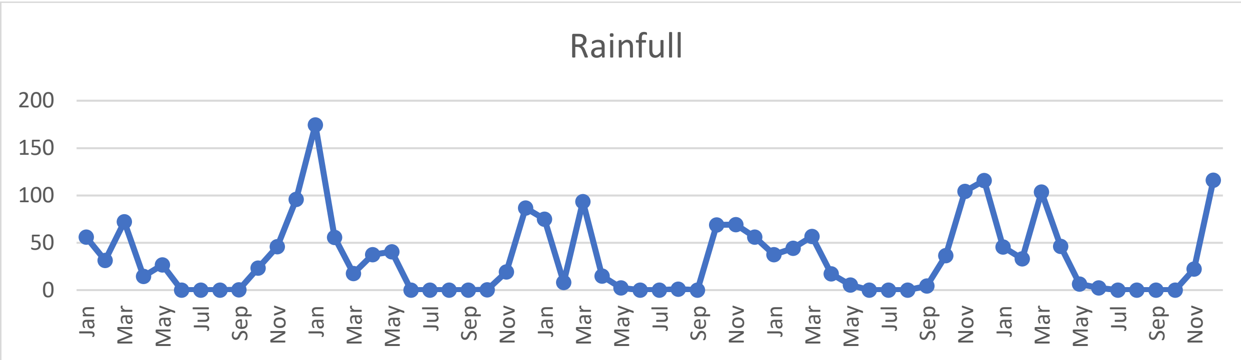


Figure 5.3: Trends in the distribution of rainfall for Erbil

The figure 5.3 above is a graph showing the rainfall distribution of each month for Erbil. The graph outlines that the cycle of the rainfall is varying for each year but the rain circle is constant as observed. Each rain circle starts from November and ends in May that shows the winter season in Erbil is very cold and rainy. Also, by the graph; it is prominent that distribution of rainfall in winter season is high. Similarly, the high distribution of rain in winters indicates that the summer season is comparatively dry with almost 0 mm rain as shown by the data. Therefore, the weather of Erbil in summers is hot and dry. Furthermore, the data outline that for each year, Erbil experienced showers for 7 months (Nov-May) continuously as significant amount of rainfall is observed that is almost 180-185 mm, indicating that 5 months of the years are extremely dry with no precipitation at all.

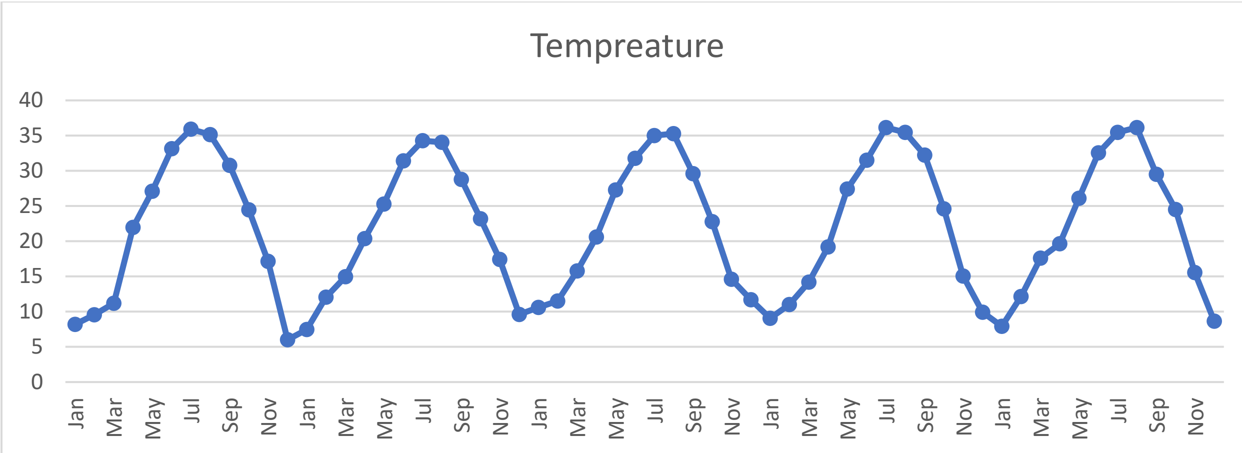


Figure 5.4: Monthly average temperature for Erbil

The above figure 5.4 highlights the average temperature data for Erbil. The graph outlines that the average temperature is not changing for these years and similar patterns are observed with the lowest temperature in January and highest temperature in August. Whereas, in January, the city experiences the high precipitation and it's cold and rainy winters with as low temperature as 5º C but the hot and dry summer with average temperature of 35ºC to 37ºC. The trends in average temperature are constant and the same pattern is observed from 2012-2017.

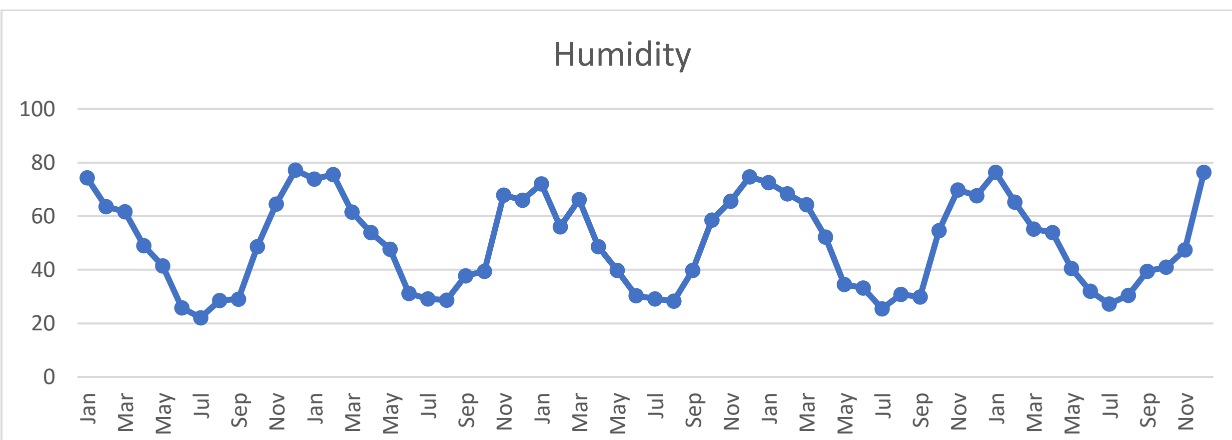


Figure 5.5: Trends in humidity for Erbil

The above figure 5.5 outlines the trends in humidity for Erbil. The data in the humidity graph outlines that highest rate of humidity is observed from the month of January up to May; the rainfall period with low temperature. In comparison, the month of July outlines lowest humidity rate because of no rainfall and extreme temperatures. The weather is extremely dry and hot during this time period of each year as observed from the data. Also, the trends in humidity from 2012-2017 are not varying much.

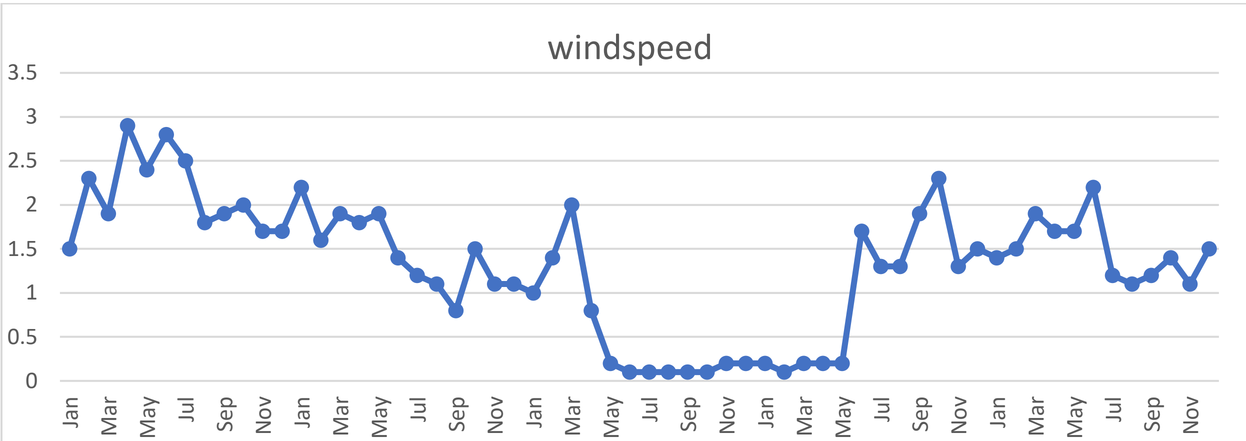


Figure 5.6: Average wind speed for Erbil

The exceeding figure 5.6 shows the average wind speed for Erbil from 2012-2017 which is not varying except for the years 2014 and 2015 when the average wind speed is nearly zero. 2014 and 2015 were extremely hot in summers and almost dry throughout the year with the precipitation for 2014 in February was 8.2 mm only and for February 2015, went to just 44.3 mm. 2014 and 2015 were the drought years that impact the production of agricultural products and the agricultural industry directly. Because of nearly zero wind speed; there was no formation of clouds that affected the rainfall vice versa.

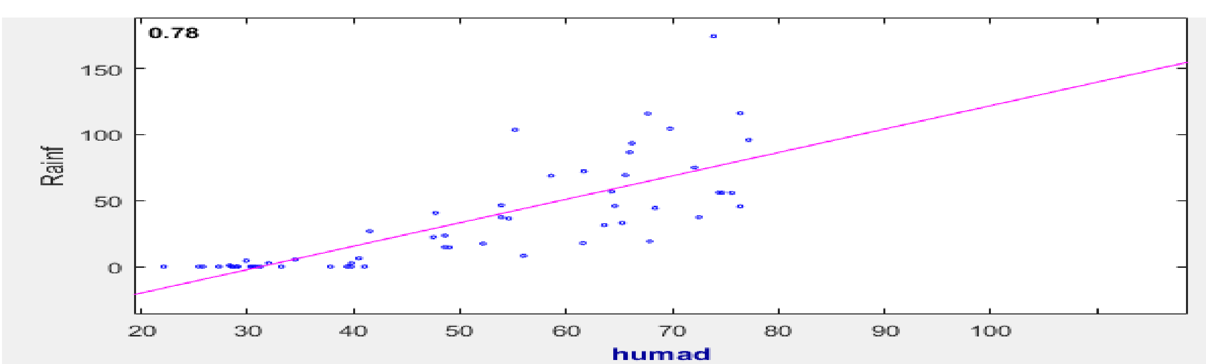


Figure 5.7: Correlation between humidity and rainfall for Erbil

The figure 5.7 above shows the correlation between humidity and rainfall. It is expected that the humidity increases with the increase in the amount of rainfall. For, Erbil the correlation is 0.76 which is quite good. Normally, with high relative humidity; the saturation of vapours into clouds at a certain temperature helps in precipitation. The drier air will less accommodate the formation of clouds and thus lead to low chances for the rain showers.

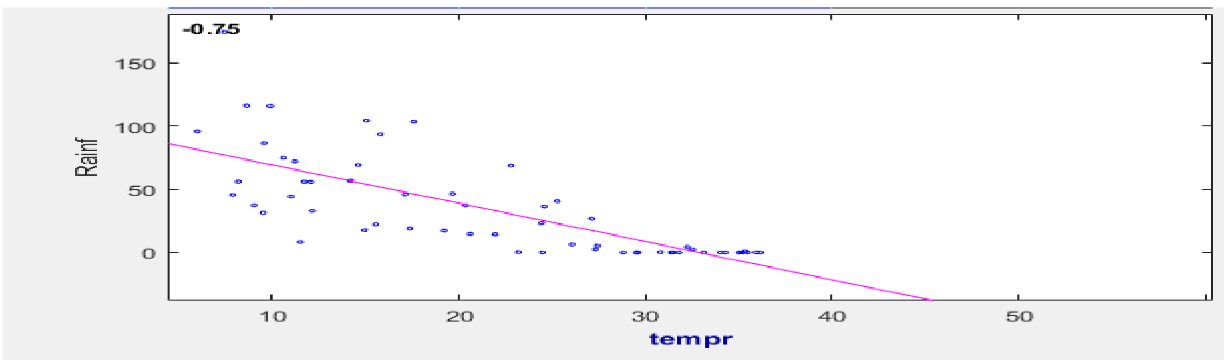


Figure 5.8: Correlation between temperature and rainfall for Erbil.

The figure 5.8 above illustrates that correlation between the temperature and rainfall using the Plot Chart. The correlation between temperature and rainfall is 78.2% as outlined by the data. This correlation is good for the prediction rainfall. As, increased temperature will affect the rainfall consequently low temperature will compensate the precipitation and increase the amount of rainfall.

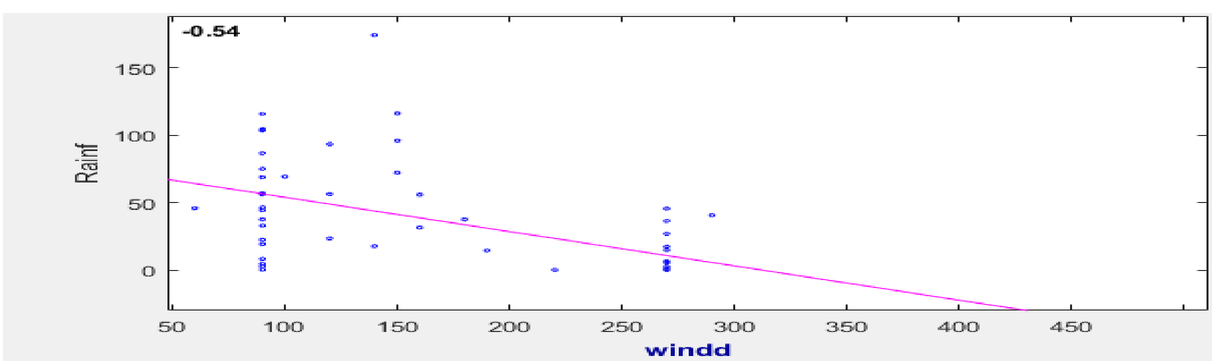


Figure 5.9: Correlation between wind direction and rainfall for Erbil

The above figure 5.9 demonstrates the correlation between the wind direction and rainfall. The correlation between wind direction and rainfall is 54% which is a very relationship.

The correlation data shows that there is an increased precipitation with the particular direction of the wind.

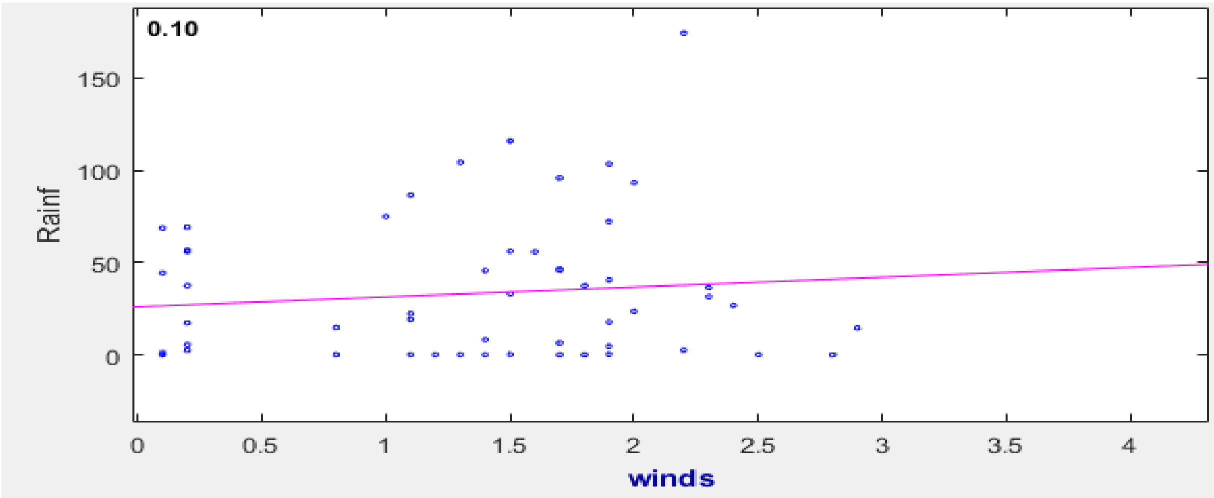


Figure 5.10: Correlation between wind speed and rainfall for Erbil.

The above figure 5.10 highlights the correlation between the wind speed and rainfall. The data reveals that there is only 10% correspondence between the wind speed and rainfall for the Erbil city. As, the wind speed has no prominent role in predicting the rainfall for Erbil; this study will least consider this parameter in rainfall prediction for Erbil. Since, the correlation obtained by Plot Chart represents the least significant of wind speed with rainfall; considering it a noticeable parameter is inappropriate.

Table 5.1: Correlation between input and outputs using SPSS for Erbil

Correlations

		tempreature	humadity	wind direction	windspeed	rainfall	air pressur
tempreature	Pearson Correlation	1	-.960**	.646**	.003	-.750**	.b
	Sig. (2-tailed)		.000	.000	.982	.000	.
	N	60	60	60	60	59	60
humadity	Pearson Correlation	-.960**	1	-.624**	-.040	.782**	.b
	Sig. (2-tailed)	.000		.000	.762	.000	.
	N	60	60	60	60	59	60
wind direction	Pearson Correlation	.646**	-.624**	1	-.048	-.532**	.b
	Sig. (2-tailed)	.000	.000		.717	.000	.
	N	60	60	60	60	59	60
windspeed	Pearson Correlation	.003	-.040	-.048	1	.105	.b
	Sig. (2-tailed)	.982	.762	.717		.430	.
	N	60	60	60	60	59	60
rainfall	Pearson Correlation	-.750**	.782**	-.532**	.105	1	.b
	Sig. (2-tailed)	.000	.000	.000	.430		.
	N	59	59	59	59	59	59
air pressur	Pearson Correlation	.b	.b	.b	.b	.b	.b
	Sig. (2-tailed)	.	.	.	.	.	
	N	60	60	60	60	59	60

**. Correlation is significant at the 0.01 level (2-tailed).

b. Cannot be computed because at least one of the variables is constant.

The above table 5.1 illustrates the correlation between the inputs and outputs using the SPSS software to find the inputs for training the Neural Network. Since, the data for air pressure is not available that is why it is assigned the value of zero. The test results from SPSS demonstrate that the main training inputs for Erbil to predict rainfall are: humidity, temperature and wind direction.

5.1.2 Data Pre-Processing for Nicosia

The monthly rainfall data from 2012-2017 is collected for Nicosia as well. The parameters of the rainfall that are to evaluate in this study are observed with their varying trends and are analyzed for the forecasting.

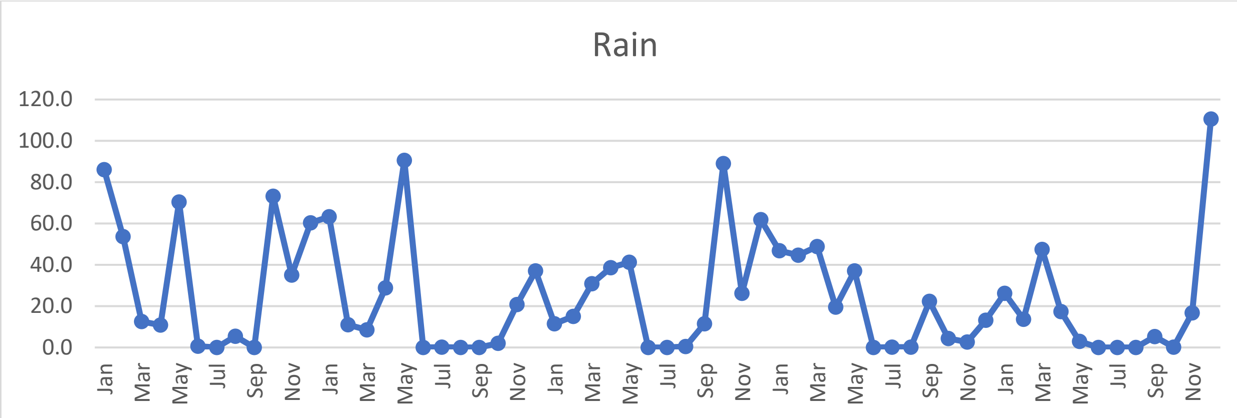


Figure 5.11: Trends in distribution of rainfall for Nicosia

The above figure 5.11 shows the trends in the distribution of rainfall in the past six years for Nicosia. The rainfall data highlights the changing rain cycles in Nicosia whereas, the overall patterns are not varying much. Nicosia in the Northern Cyprus experiences rainfall usually in the month of September to May. However, the data outline that the summers are hot and dry with zero or very little rainfall. The winters are cold and rainy. Nicosia has a long-time period of rain with only 4 months without precipitation. But the overall rain cycle in Nicosia is not constant; sometimes it rains in September until November only.

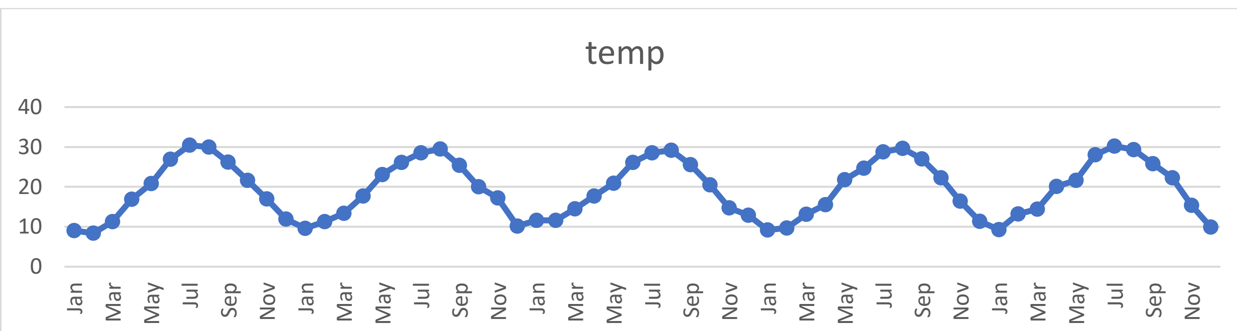


Figure 5.12: Average temperature for Nicosia

The above figure 5.12 illustrates the trends in average temperature for Nicosia. The average temperature as shown in the graph is constant for the last years with lowest observed in February and highest observed in July. There is no variation in the trends of average temperature that would affect the rainfall. Also, the highest temperature goes to 30ºC to 38ºC as observed by the monthly data.

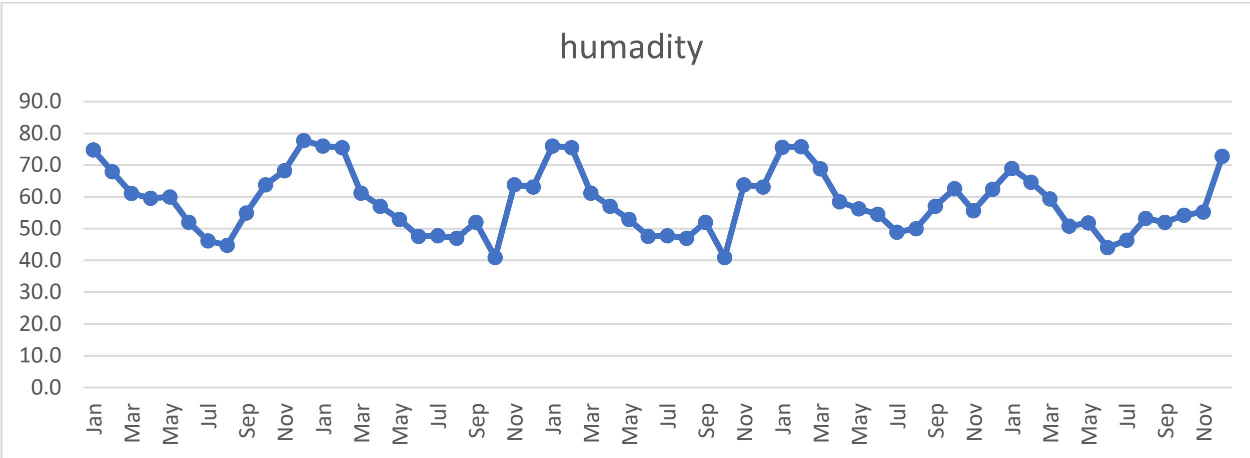


Figure 5.13: Trends in humidity for Nicosia

The above figure 5.13 highlights the trends in the humidity for Nicosia. The graph shows that the highest humidity rate is observed in the month of January whereas, the lowest is observed within the month of July. As discussed above, the rainfall cycle starts in September with high humidity observed within these months to compensate saturation of water vapours and formation of clouds.

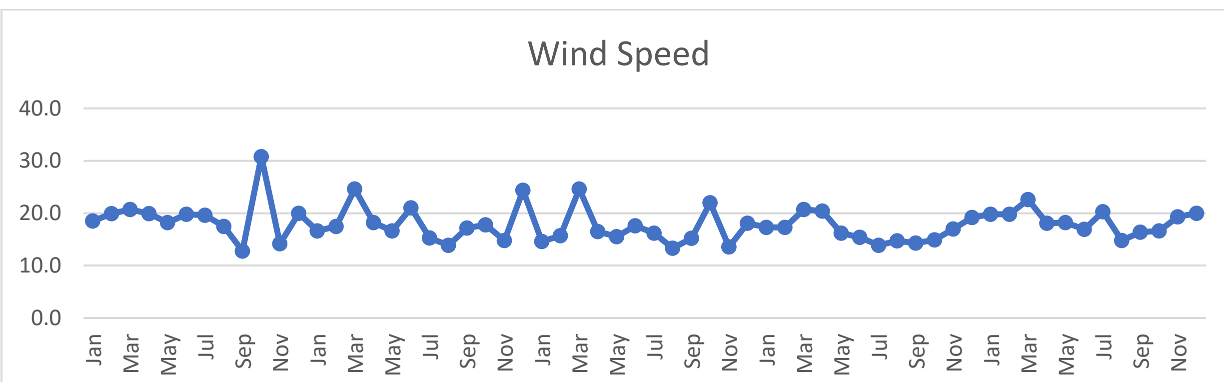


Figure 5.14: Trends in wind speed for Nicosia

The above figure 5.14 demonstrates the changing trends in the wind speed for Nicosia. The wind speed is a significant parameter to observe the rainfall and to make predictions for precipitation.

The wind speed is highest in September when the rainfall starts in Nicosia and is observed as lowest in July when the rainfall ends normally. Although, there are variations in the overall wind speed for these years but the average wind speed cycle is same.

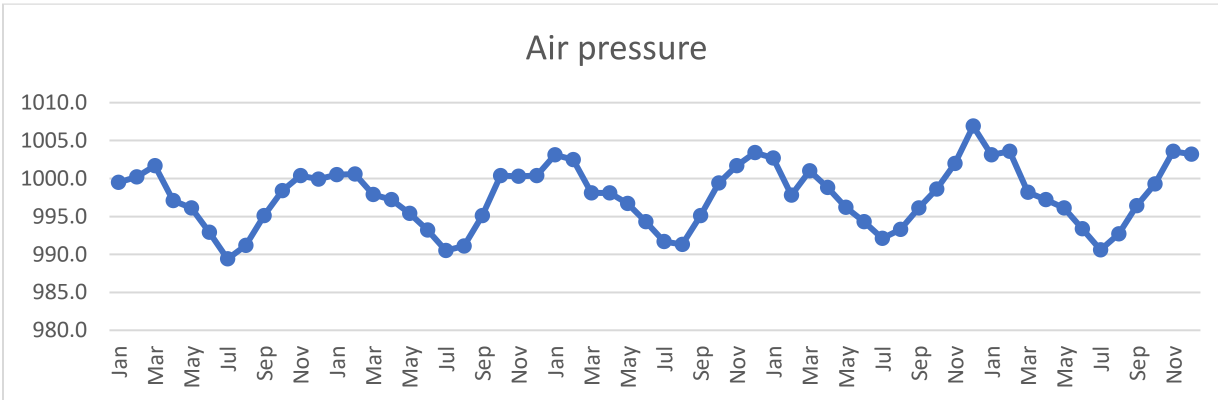


Figure 5.15: Trends in average air pressure for Nicosia

The above figure 5.15 illustrates the trends in the air pressure for Nicosia. The graph presents a constant cycle of the air pressure observed with lowest in July when there is no rainfall and highest in Dec/Jan that is the rainy season. Therefore, air pressure is also an important parameter for predicting rainfall in Nicosia.

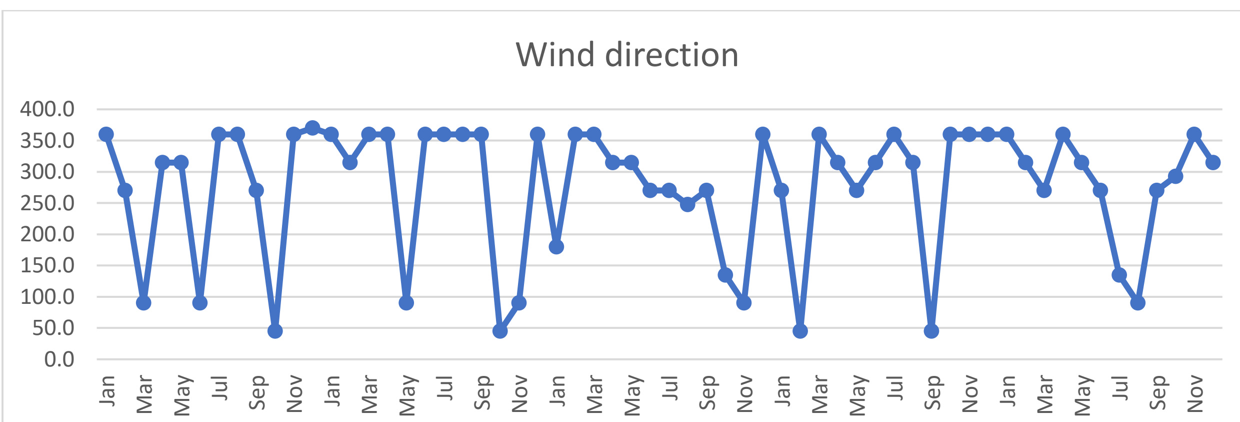


Figure 5.16: Trends in wind direction for Nicosia

The above figure 5.16 demonstrates the trends in the wind direction for Nicosia. The graph shows that the wind direction is in favour of the rainfall and it observed especially in relation to the rainfall season. This means that wind direction plays a significant role in the formation of clouds and precipitation in Nicosia.

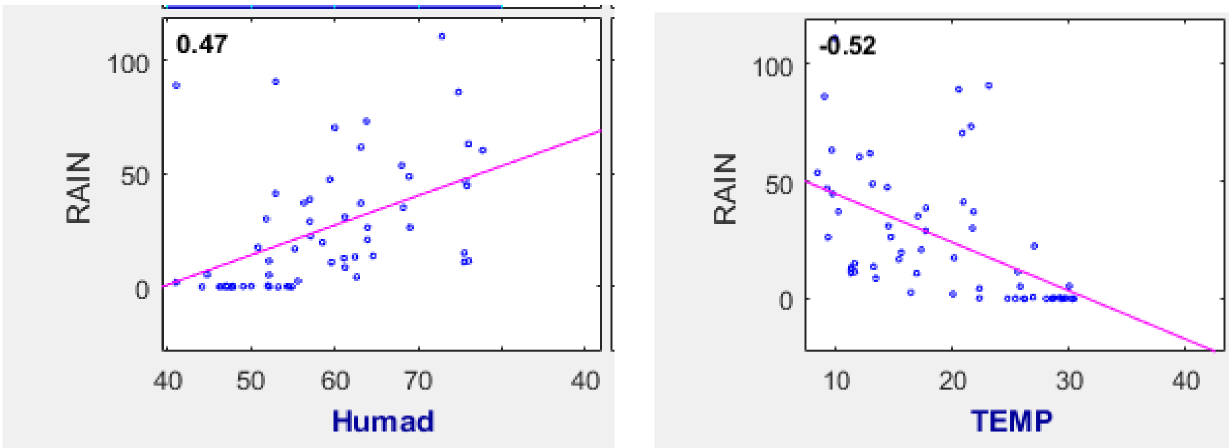


Figure 5.17: Correlation for rainfall with humidity and temperature

The above figures 5.17 illustrate the correlation between rain with humidity and rainfall and with temperature respectively. The rainfall and humidity are observed with a close relation that is 47% and the correlation between rainfall and temperature are also high that is 52%. This means that the humidity and temperature are significant parameters for predicting rainfall in Nicosia.

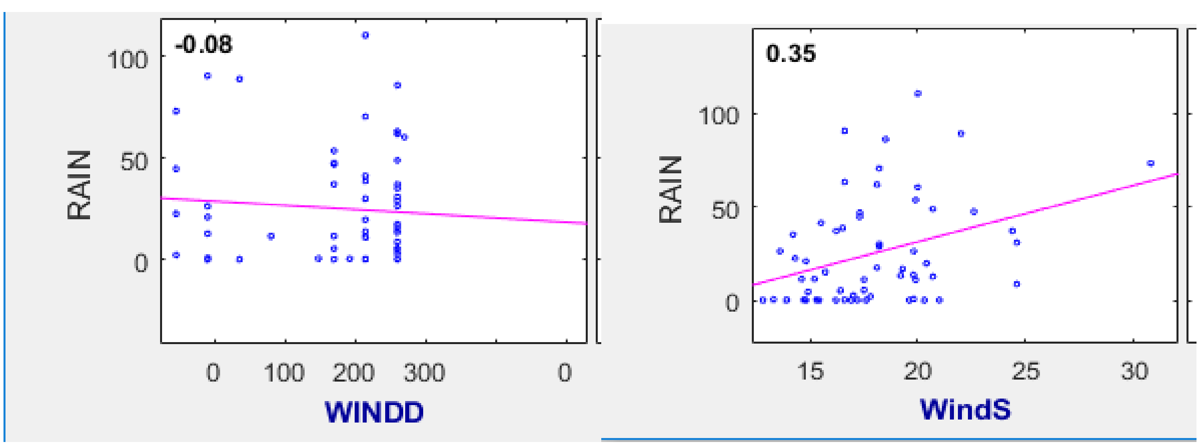


Figure 5.18: Correlation for rainfall with wind direction and rainfall with wind speed

The above figure 5.18 demonstrates the correlation between rainfall with wind direction and rainfall and wind speed. The correlation is studied by using the Plot Chart and illustrates that there is 35.3% correlation between the rainfall and wind speed which does not qualify this parameter as a significant trainer for neural network. For the correlation between wind direction and rainfall is observed to be 7.8% which is important in making rainfall predictions for Nicosia.

Table 5.2: Correlation between input and output using SPSS for Nicosia

Correlations

		temp	air pressur	wind derection	rain	wind	humadity
temp	Pearson Correlation	1	-.879**	-.129	-.524**	-.342**	-.836**
	Sig. (2-tailed)		.000	.327	.000	.008	.000
	N	60	60	60	60	60	60
air pressur	Pearson Correlation	-.879**	1	.053	.413**	.230	.692**
	Sig. (2-tailed)	.000		.686	.001	.077	.000
	N	60	60	60	60	60	60
wind derection	Pearson Correlation	-.129	.053	1	-.078	-.002	.101
	Sig. (2-tailed)	.327	.686		.553	.985	.441
	N	60	60	60	60	60	60
rain	Pearson Correlation	-.524**	.413**	-.078	1	.353**	.469**
	Sig. (2-tailed)	.000	.001	.553		.006	.000
	N	60	60	60	60	60	60
wind	Pearson Correlation	-.342**	.230	-.002	.353**	1	.132
	Sig. (2-tailed)	.008	.077	.985	.006		.314
	N	60	60	60	60	60	60
humadity	Pearson Correlation	-.836**	.692**	.101	.469**	.132	1
	Sig. (2-tailed)	.000	.000	.441	.000	.314	
	N	60	60	60	60	60	60

**. Correlation is significant at the 0.01 level (2-tailed).

The above table 5.2 illustrates the correlation between inputs and outputs using the SPSS software. The correlation is analyzed for all these parameters and the result outlines that for training the Neural Network to make rainfall predictions for Nicosia, temperature, humidity, wind speed, and air pressure are most prominent for accuracy and precision.

5.1.3 Data Pre-Processing for Famagusta

The data for the rainfall parameters are analyzed for Famagusta in this study. The parameters of rainfall are evaluated to be trained for neural-network to make predictions. The data for analysis is gathered from the metrological department and analyzed for the seashore city. As the rainfall parameters have a variance for the seashore city.

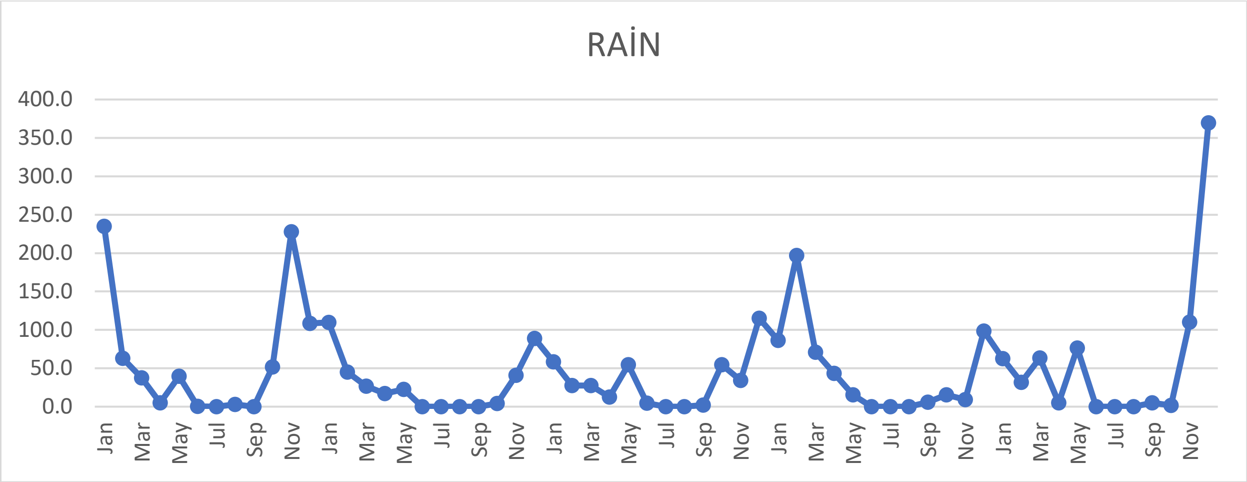


Figure 5.19: Trends in distribution of rainfall in Famagusta

The above figure 5.19 illustrates the trends in the distribution of the rainfall in Famagusta. The graph presents that the rainy season starts from September and ends in May as that of Nicosia. The summer season is normally dry with no precipitation and the winters are usually cold and wet. The data represents that the overall rain cycle is constant but there is variation in the distribution of rainfall year to year.

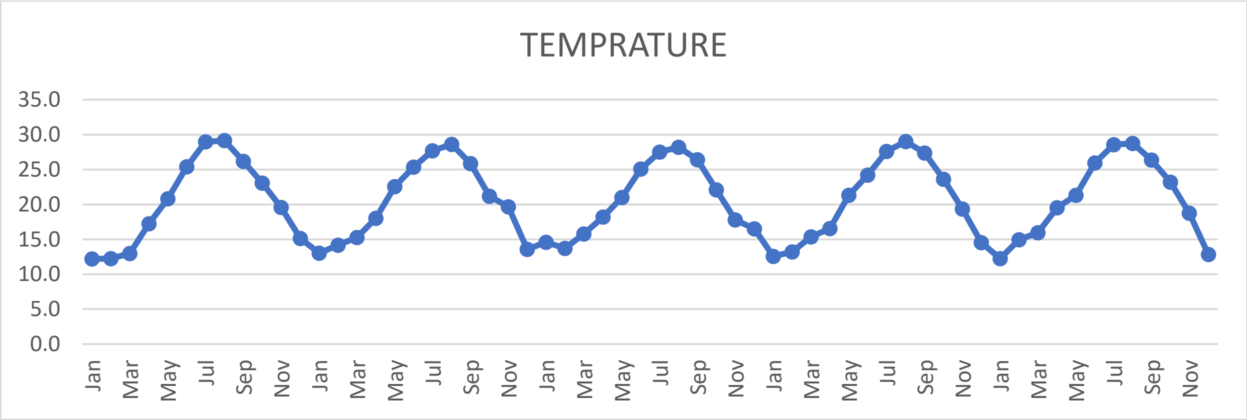


Figure 5.20: Average temperature for Famagusta

The above figure 5.20 shows the trends in average temperature for Famagusta. The data indicates that the lowest temperature is observed in the month of January and highest in the month of July. The overall pattern of the temperature is constant from 2012 to 2017. The temperature affects the rainfall in Famagusta, so this study will consider temperature into account for predicting rainfall in Famagusta.

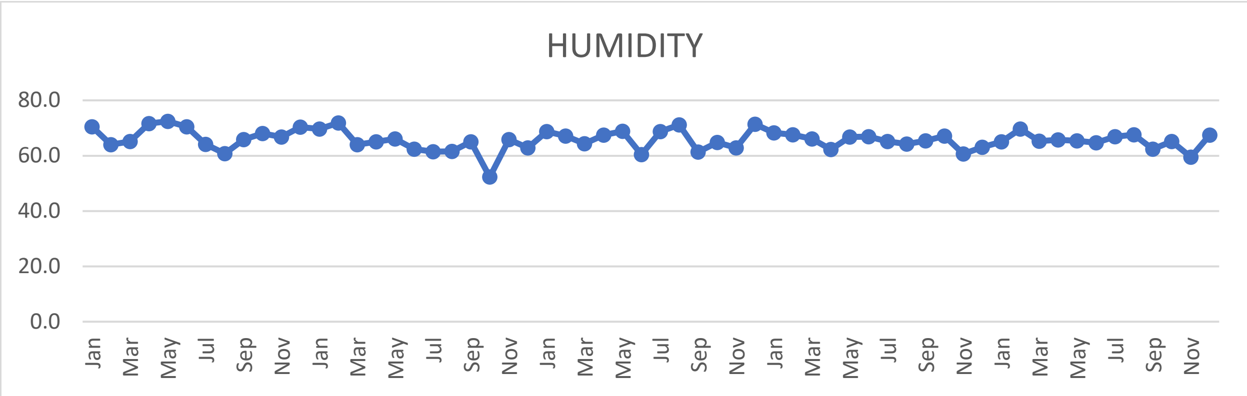


Figure 5.21: Trends in humidity for Famagusta

The above figure 5.21 shows the trends in the humidity for Famagusta. The humidity is observed from the data as high throughout the year. Opposite to other two cities; the high humidity rate throughout the year because Famagusta is a seashore city. Its climate is humid even when it's hot in the summer season. Therefore, for this study humidity is important for making rainfall predictions in Famagusta.

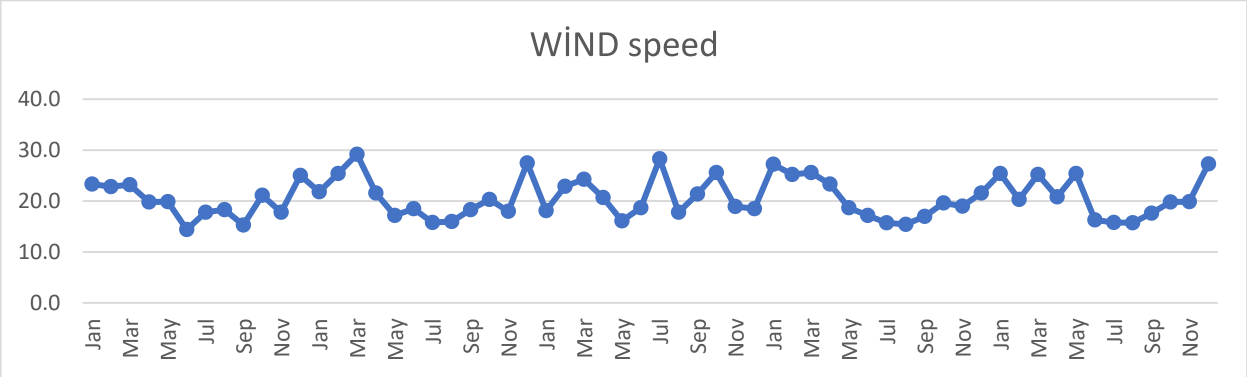


Figure 5.22: Trends in average wind speed for Famagusta

The above figure 5.22 shows the trends in average wind speed for Famagusta. The average pattern of the wind speed is constant with very few variations. The wind speed is highest for the winter and rainy season that also favors the precipitation in Famagusta and low in the summer season when there is zero or less rainfall.

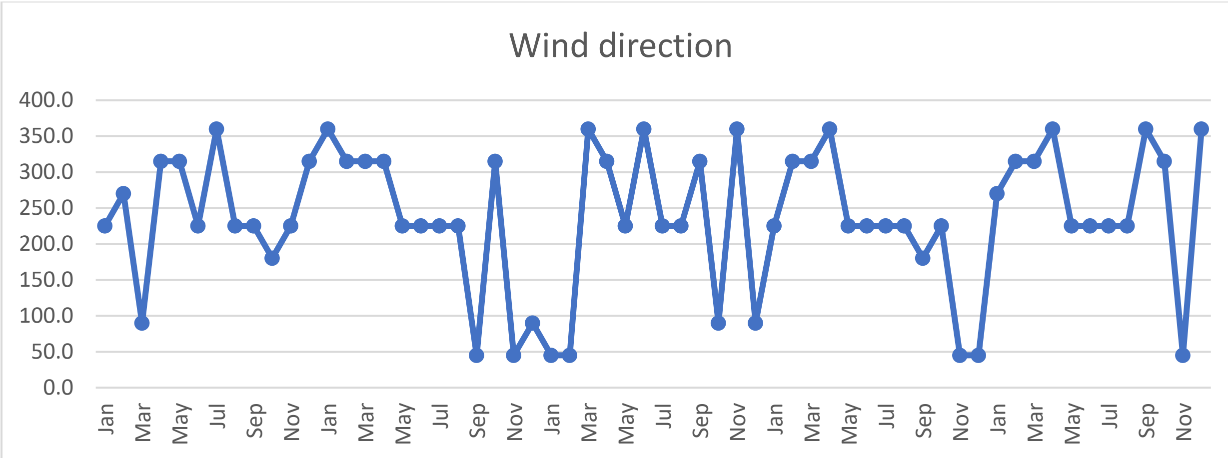


Figure 5.23: Average wind direction for Famagusta

The above figure 5.23 shows the trends in the average wind direction for Famagusta. The wind direction is in favor of the rainfall season that is from September to May. The wind direction is therefore, an important parameter for predicting rainfall for Famagusta in this study.

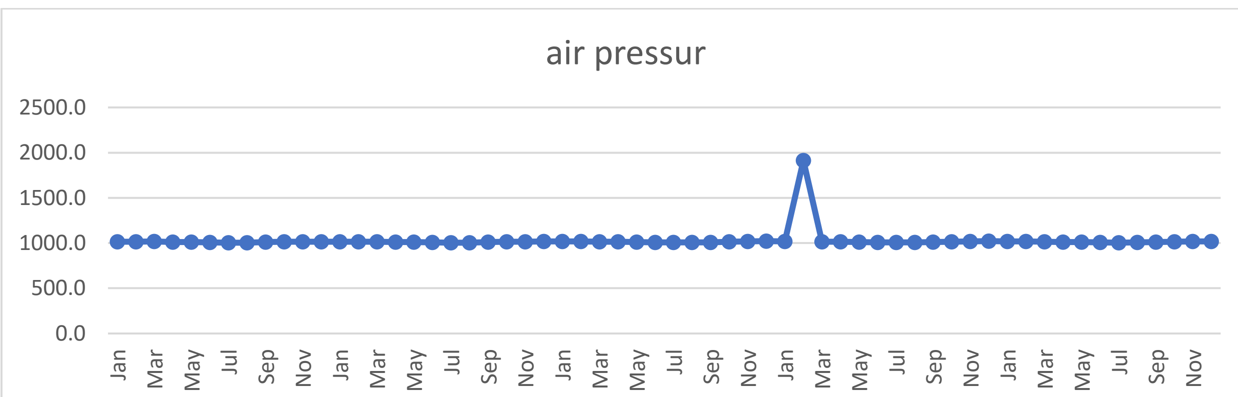


Figure 5.24: Trends in average air pressure for Famagusta

The above figure 5.24 represents the trends in the average air pressure for Famagusta. The air pressure is constant throughout the years with single variation observed in February with 2000 Pascal. The normal air pressure as observed from data is 1000 Pascal. This means that the air pressure is also a significant parameter for Famagusta's prediction of rainfall.

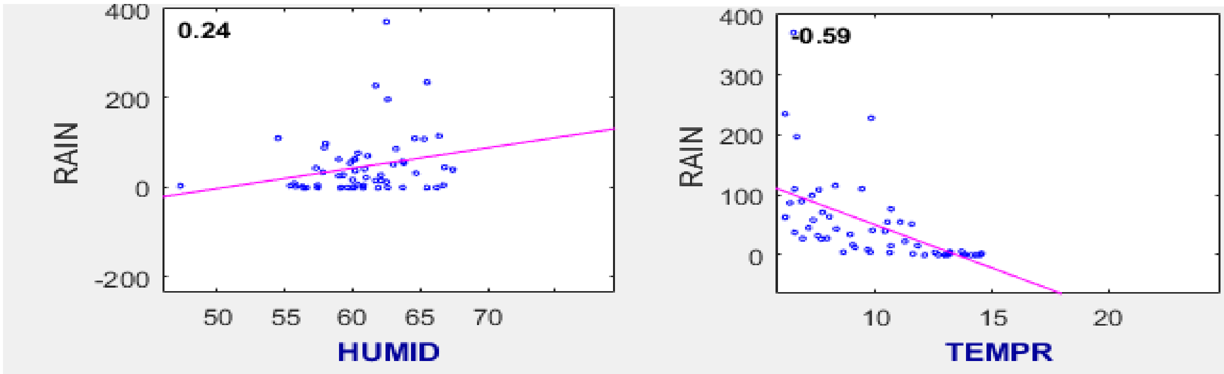


Figure 5.25: Correlation for rainfall with humidity and temperature

The above figure 5.25 presents the correlation for the humidity with rainfall and rainfall with temperature respectively. The correlation between humidity and rainfall is observed to be 24% in Famagusta and 59% between temperature and rainfall. The correlations observed are closely linked to the rainfall and therefore, this study will focus on humidity and temperature as inputs to predict rainfall in Famagusta.

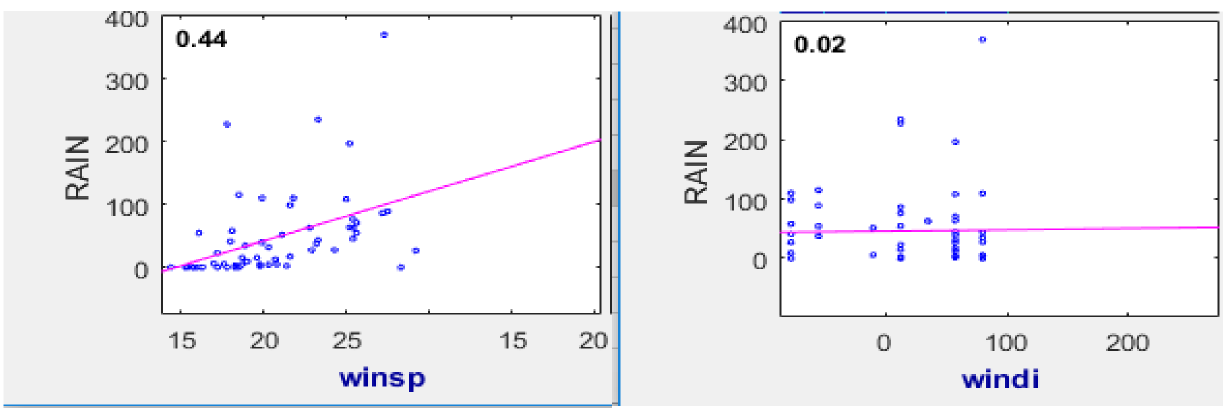


Figure 5.26: Correlation between rain and wind direction and rainfall with wind speed

The figure 5.26 above illustrates the correlation between rainfall and wind direction along with its correlation with wind speed. The correlation between rainfall and wind direction is 44% and that of wind direction is only 2%. The speed of the wind is closely linked to the rainfall prediction and therefore is efficient input in this study.

Table 5.3: Correlation between inputs and outputs using SPSS for Famagusta

Correlations

		TEMPRATURE	HUMIDITY	WİND speed	RAİN	wind derection	air pressur
TEMPRATURE	Pearson Correlation	1	-.231	-.678**	-.586**	-.011	-.202
	Sig. (2-tailed)		.075	.000	.000	.931	.121
	N	60	60	60	60	60	60
HUMIDITY	Pearson Correlation	-.231	1	.083	.238	.032	.072
	Sig. (2-tailed)	.075		.529	.067	.808	.586
	N	60	60	60	60	60	60
WİND speed	Pearson Correlation	-.678**	.083	1	.441**	.153	.177
	Sig. (2-tailed)	.000	.529		.000	.242	.175
	N	60	60	60	60	60	60
RAİN	Pearson Correlation	-.586**	.238	.441**	1	.017	.308*
	Sig. (2-tailed)	.000	.067	.000		.896	.017
	N	60	60	60	60	60	60
wind derection	Pearson Correlation	-.011	.032	.153	.017	1	.095
	Sig. (2-tailed)	.931	.808	.242	.896		.471
	N	60	60	60	60	60	60
air pressur	Pearson Correlation	-.202	.072	.177	.308*	.095	1
	Sig. (2-tailed)	.121	.586	.175	.017	.471	
	N	60	60	60	60	60	60

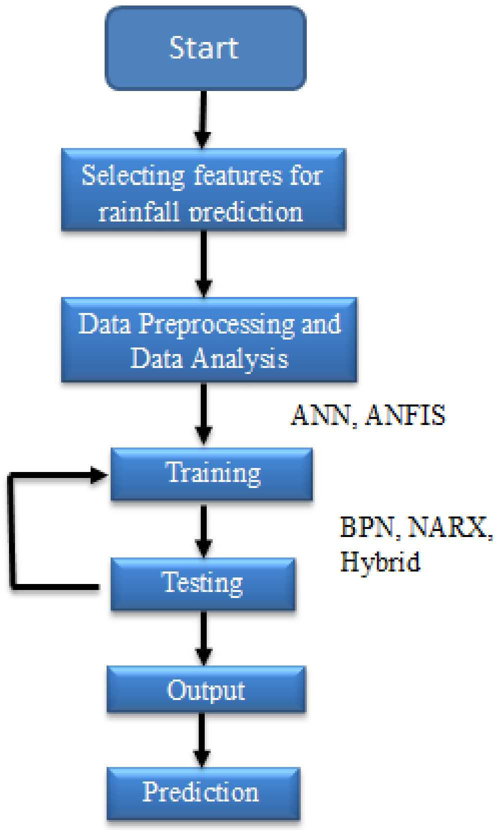
**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The above table 5.4 illustrates the correlation between the inputs and outputs using SPSS statistics. The correlation is closely observed for the temperature, humidity, air pressure with wind speed as significant for predicting the rainfall in Famagusta.

5.2 Flowchart for rainfall prediction

The below data flowchart outlines the selection of input and the procedure to get the output that in this study is the rainfall prediction. The flowchart illustrates the first step as a selection of inputs that are parameters, processing of these inputs and completing training, testing and validation for accurate and precise output that is rain forecast.



5.3 Selection of the input and output data

In this study, the database is collected directly from the metrological departments to analyze the inputs and outputs. The significant inputs are highlighted as average temperature, air pressure, wind speed, wind direction and humidity and the output are rainfall for the years 2012-2017. The rainfall season for Erbil is observed from November up to May; 7 months of rainfall in a year. The rainfall season for Nicosia as highlighted by the data starts from September and ends in May; that is around 9 months according to the data. For Famagusta, the rainfall season is similar to that of Nicosia. Therefore, to predict rainfall for these three cities above mentioned parameters will be considered as significant inputs to forecast precipitation.

5.4 Feature Extraction

This study is focusing on average temperature, air pressure, wind speed, wind direction and humidity. The parameters are defined as:

1. TEMPERATURE

It is the degree to which something is hot or cold. It is affected by several factors like latitude, altitude, and distance from the sea, wind with ocean current. It affects the rainfall in a way that the amount of water vapour in the atmosphere determines the amount of rainfall as light or with a heavy shower. Thus, at high temperatures there is heavy rainfall.

2. WIND DIRECTION

It is the origin of the wind from where it generates. The direction of the wind determines the precipitation. Therefore, it is also important to analyze the direction of the wind as a parameter for the rainfall prediction.

3. WIND SPEED

It is the velocity of the air moving from high pressure to low pressure. The wind speed is in close correlation to the rainfall and it is necessary to consider it as an input for prediction. The increase in the wind speed decreases the intensity of the rainfall. Therefore, to experience more precipitation during the rainy season; the favourable wind speed is low rather than high.

4. HUMIDITY

It is the amount of water vapour present in the air for a given temperature that is significant for saturation of vapours to form clouds. The increased moisture in the air will accommodate high saturation. The humid weathers experience more precipitation than the dry weather.

5. AIR PRESSURE

The air pressure is the pressure within the atmosphere of the earth. The air pressure decreases with the increase in the elevation from the earth surface. For example: the air pressure on mountains is less as compared to plains.

5.5 Training, Testing and Validation

The creation of a database from inputs and outputs; the succeeding phase is the training the input through back propagation algorithm, NARX and hybrid models. The training of the input data is done by the MATLAB software by using the NNTOOL and ANFISTOOL. Training is preceding step to testing of the input data with acceptable error is achieved. The NNTOOL automatically retains 30% of the input data for testing and validation and 70% of input data for the training. The ANFISTOOL requires manual retention of the input data for training, testing and validation. The ANFISTOOL manually fed with 60% of the input for training and 40% for testing.

5.6 ANN

The artificial neural networks are multipurpose and feasible set of the system. These are basically the computational methodologies that are used in diverse fields. The artificial neural networks are based on elements called neurons and these neurons receive inputs for processing the required results. The neural networks are multilayered nodes that are nonlinear and connected by the weighted lines (Abraham, 2005). When the input is presented to the neural networks during the training of the data; the successful training then offers the neural networks that are capable of predicting the output. The neural networks are capable of classifying an object, recognizing a particular pattern of multifactorial data, approaching a function and even configuration (Mitchell, 1997). This study will focus on the learning algorithms like the feed-forward backpropagation and NARX model to predict the rainfall using the inputs described above.

5.6.2 Applying backpropagation and NARX model for Erbil

This study is focusing on the backpropagation for Erbil to obtain accuracy for training, testing and validation of input and output data.

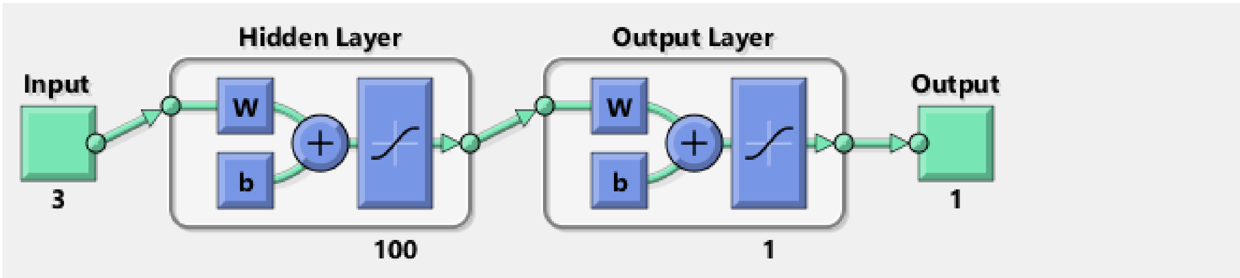


Figure 5.27: Proposed back propagation network architecture for Erbil

The above figure 5.27 represents the back-propagation network architecture for Erbil. The architecture proposed 3 inputs for processing; temperature, humidity and wind direction. The other parameters for predicting rainfall including wind speed and air pressure is not considered as they are least correlated. The total number of neurons for this propagation is 100 with two hidden layers. The output of this proposed back propagation network is rainfall. For the training of this input data; Levenberg Marquardt (trainlm) which is one of the most effective and fast algorithm functions in the toolbox, also it modernizes the weight and bias values with respect to the Levenberg Marquardt and is used by the proposed back propagation network architecture because of its high efficiency.

After training the data with 300 epochs, the result of the training, testing and validation is obtained to check the accuracy as demonstrated in figure 5.28 below.

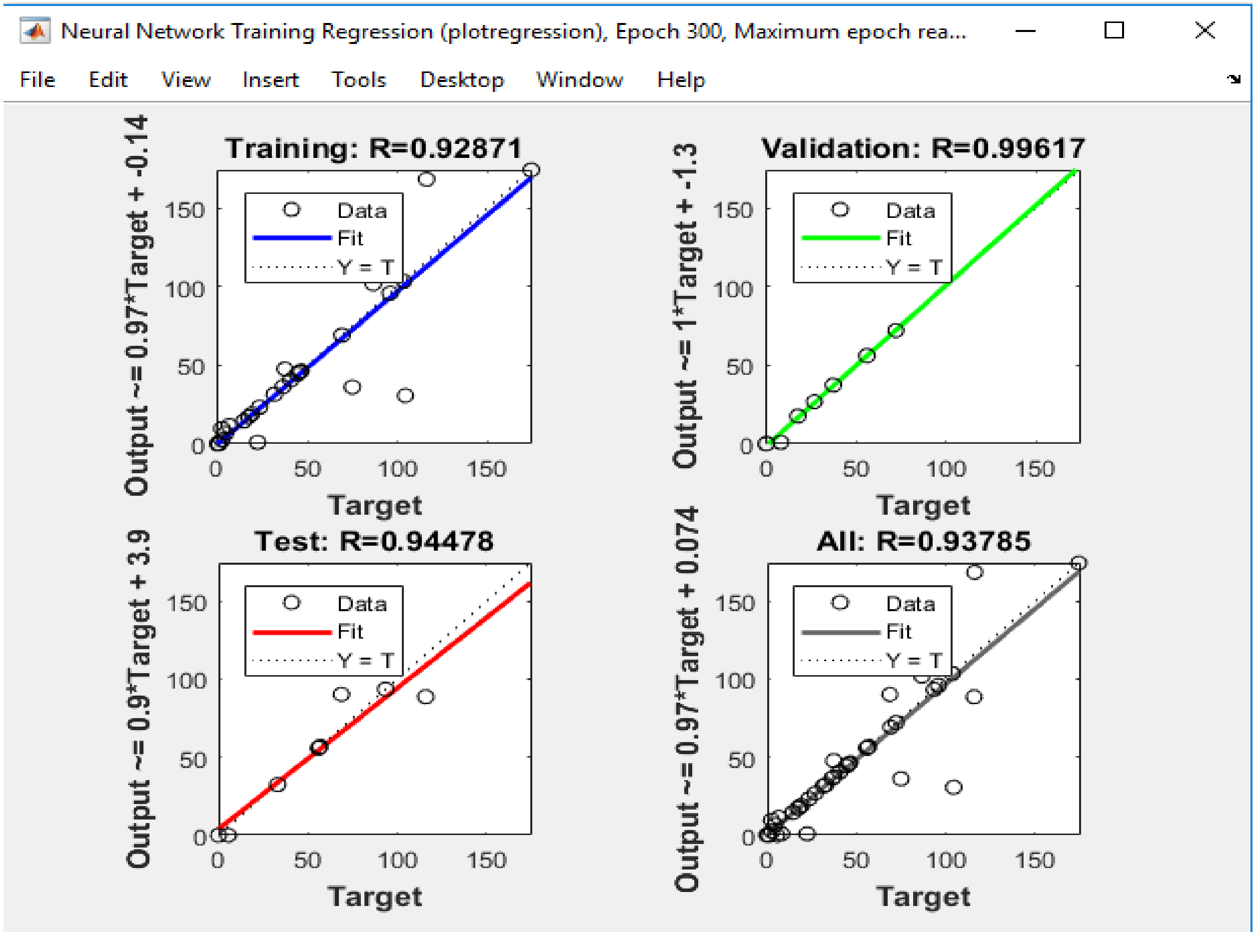


Figure 5.28: Snapshot of regression using NNTOOL

The accuracy of the training is 0.92 out of 1 which is absolutely precise and accurate result of the training. Similarly, the accuracy of testing is 0.94 that outlines the accuracy and precision of the tested data. Lastly, the accuracy of validation is 0.99 out of 1; that indicates the perfect result for validation as well.

The proposed NARX network architecture has an input layer with two hidden layers and an output layer. The network has a feedback connection for the neuron processing. There are three inputs for this network; temperature, wind direction and humidity. The most suitable number of neurons observed for this network is taken as 100. The output obtained is the predicted precipitation for Erbil. The tapped delay lines TDL that are; 0:1 and 1:2 at the input side as shown in the below figure 5.29, are supposed of length two. These are useful to sort the predicted values during the training phase; concurrently reducing the complexity of the network.

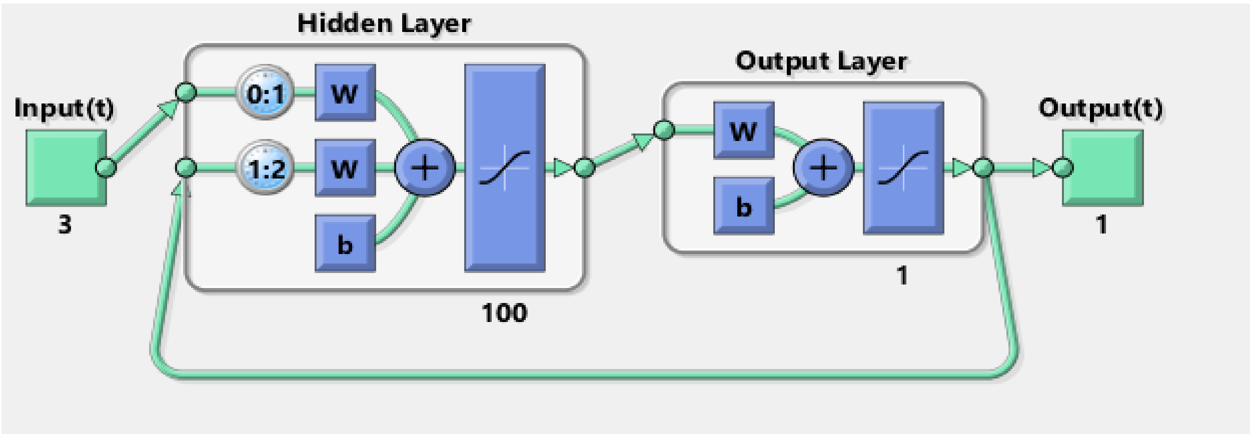


Figure 5.29: Proposed NARX network architecture for Erbil

After training the data with the function of Levenberg Marquardt (trainlm), following results are achieved. The gradient is equal to 0.45 at epoch 150. The Mu is equal to 0.01 out of 1.00e+10 and the validation checks (that are safeguard for overtraining and overfit of the net. Validation) is equal to 150 at epoch 150 out of 1000 of max _fail, as shown in figure 5.30 below.

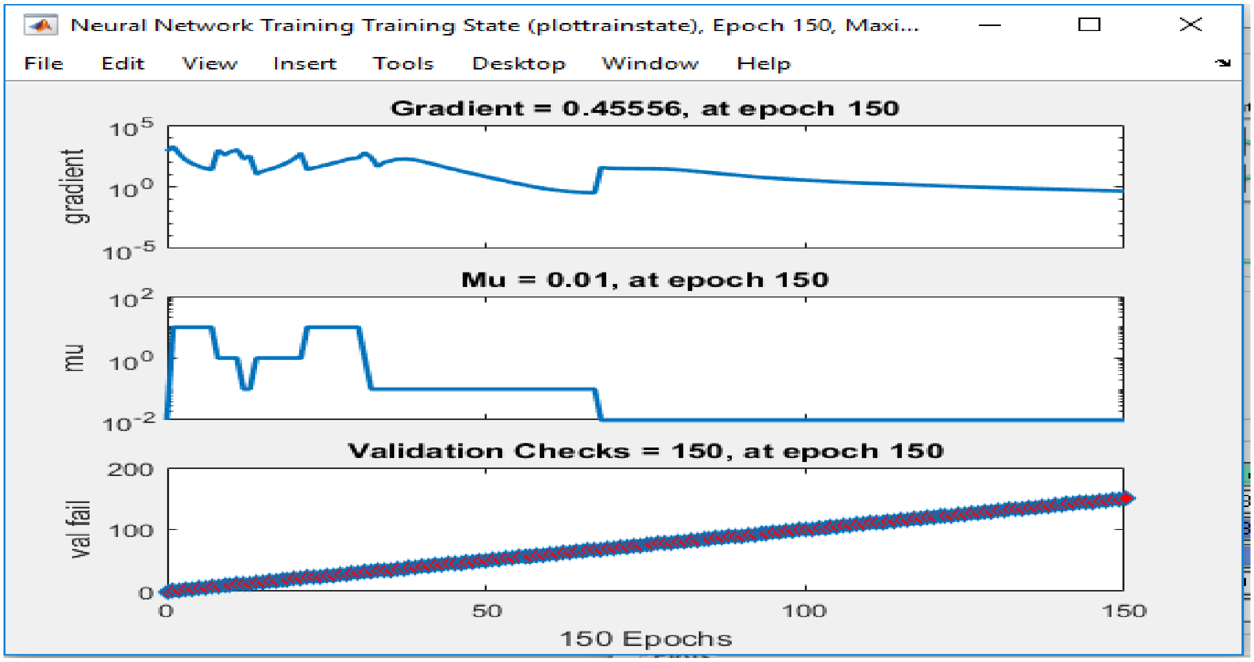


Figure 5.30: Training state for NARX

5.6.3 Applying backpropagation and NARX model for Nicosia

Similarly, this study focused on back propagation model for training, testing and validation for Nicosia.

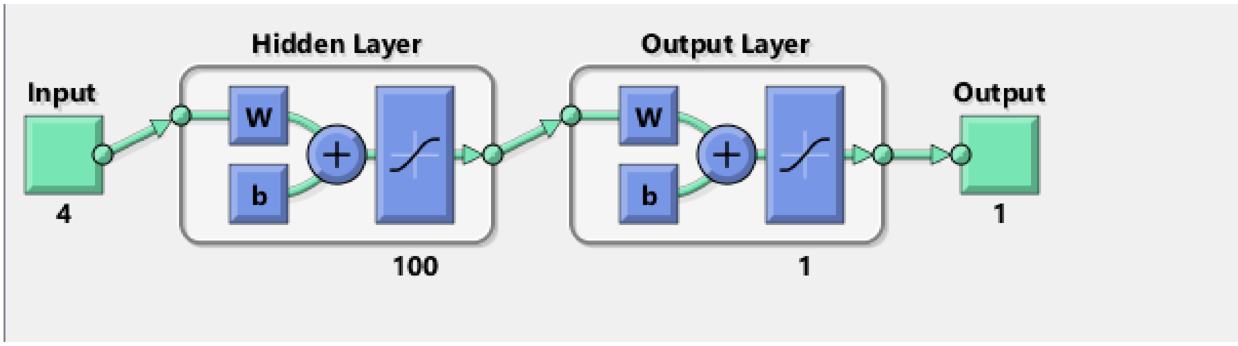


Figure 5.31: Proposed back propagation network architecture for Nicosia

The above figure 5.31 illustrates the proposed back propagation architecture for Nicosia. This architecture is training with four parameters of rainfall in Nicosia that were significant in predicting the precipitation. These input parameters include; temperature, wind speed, humidity and air pressure and the output is rainfall. The proposed back propagation network architecture is using 100 neurons for the input processing with one in out and one output layer. It has two hidden layers and the training of the input is done using Gradient Descent with Momentum & Adaptive LR (traingdx) algorithm. The traingdx is the function that trains the network that upgrades weight and bias according to the gradient descent momentum and adaptive learning. The algorithm is using 400 epochs for training the inputs and the output is rainfall that appears in the output layer.

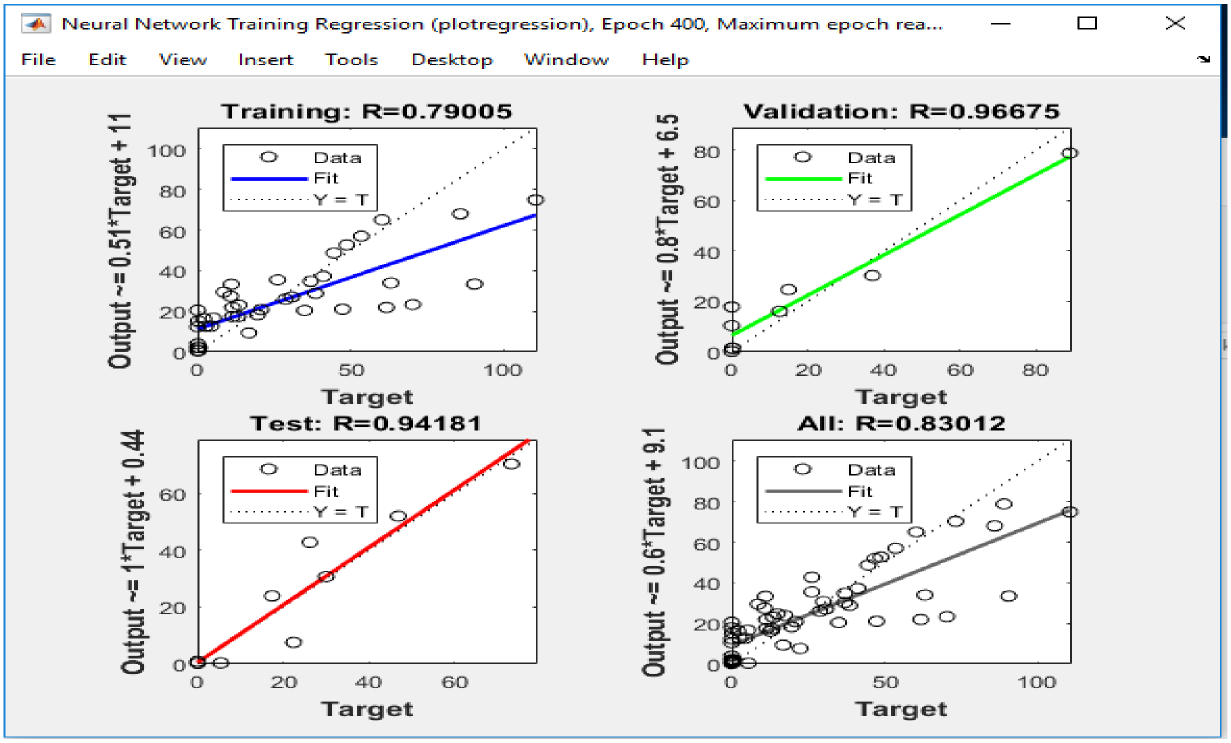


Figure 5.32: Snapshot of regression using NNTOOL

After training the network with 400 epochs, the results are obtained for training, testing and validation. These results are checked for the accuracy and efficiency of the training network as shown in the figure 5.32 above. The accuracy of training is 0.79 out of 1, the accuracy check for testing is 0.94 and the validation accuracy is obtained as 0.96 out of 1. The results outline that the accuracy of the training is precise and efficient by these four input parameters for Nicosia.

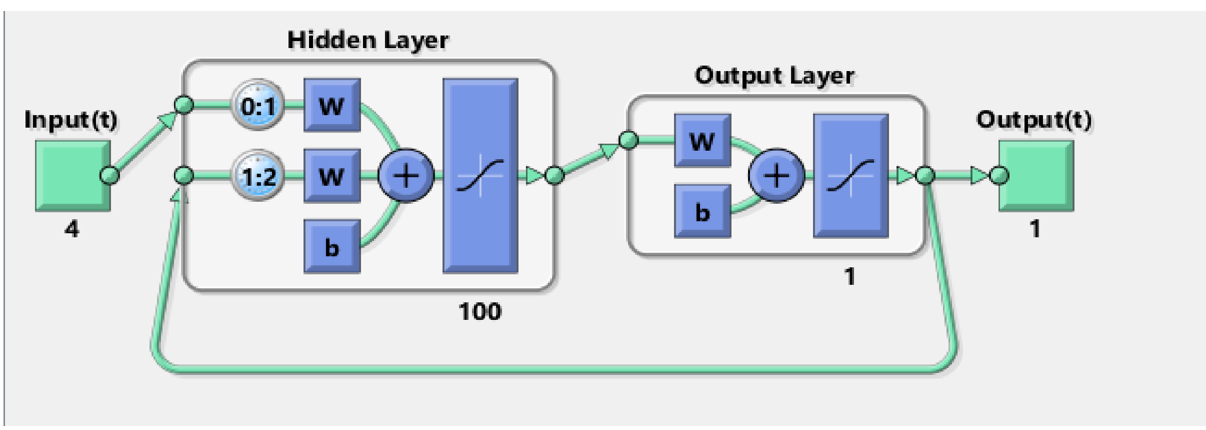


Figure 5.33: Proposed NARX network architecture for Nicosia

The above figure 5.33 demonstrates the proposed NARX network architecture for Nicosia. The network uses 100 neurons and a feedback connection for processing the inputs. The network function uses four input parameters for the training that are: temperature, wind speed, humidity and air pressure. The function has one input layer and one output layer with two hidden layers and the output obtained is the rainfall. The network architecture has tapped delay lines TDL; 0:1 and 1:2 that will help in predicting the values of the output during the training and helps in simplification.

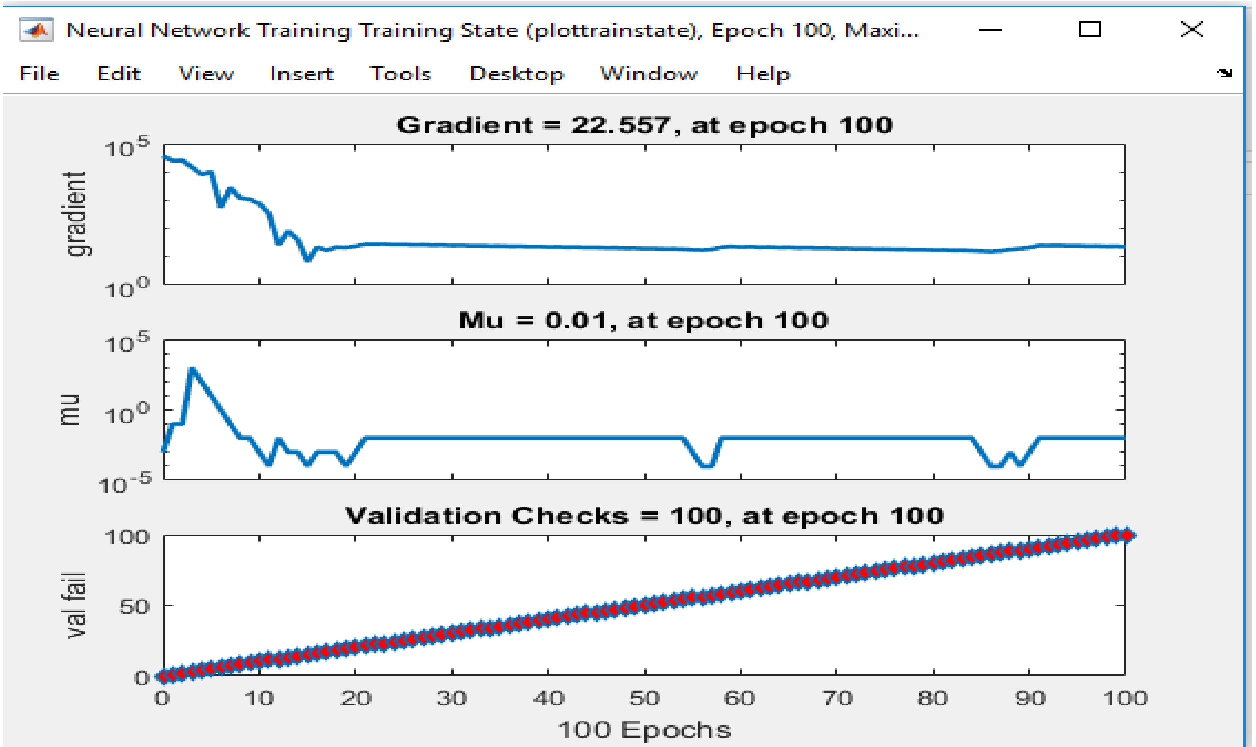


Figure 5.34: Training state for NARX

After training the data with Gradient Descent with Momentum & Adaptive LR (traingdx) function. The network obtained the following results; the gradient is equal to 22.57 epochs 100 as shown in the figure 5.34 above. The Mu is equal to 0.01 out of 1.00e+10 and the validation checks are equal to 100 at epoch 100 out of 1000 of max _fail.

5.6.4 Applying backpropagation and NARX model for Famagusta

The input and output parameters for Famagusta are also trained with back propagation model in this study. The inputs are trained to check the accuracy of the output that is rainfall to validate the predictions made through this network.

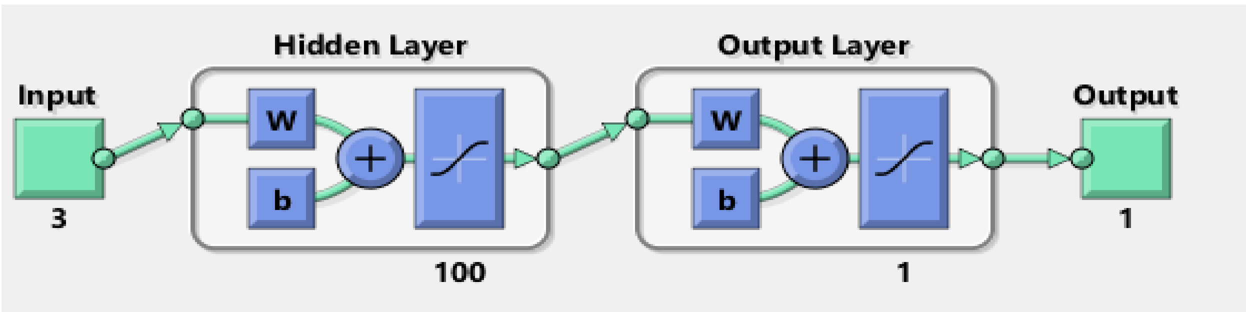


Figure 5.35: Proposed back propagation network architecture for Famagusta

The above figure 5.35 illustrates the proposed back propagation network architecture for Famagusta. This propagation network is trained with four input parameters including; temperature, humidity, and air pressure. The number of effective neurons is observed to be 100 for this training. The network has one input layer, one output layer for obtaining the output that in this case is rainfall for Famagusta and two hidden layers. The Levenberg Marquardt (trainlm) function is used for the processing of the input and output in this network.

After training the inputs and outputs with trainlm function; the following results are obtained as shown in the figure 5.36 below. The result for training outlines accuracy equal to 0.64. Similarly, the accuracy of the testing is 0.96 and lastly, the result of validation is equal to 0.81. These results are obtained out of 1 that represents the enhanced accuracy and efficiency of the input parameters to predict the rainfall in Famagusta. Therefore, temperature, humidity and air pressure could be taken as reliable and effective input parameters to predict the rainfall in Famagusta.

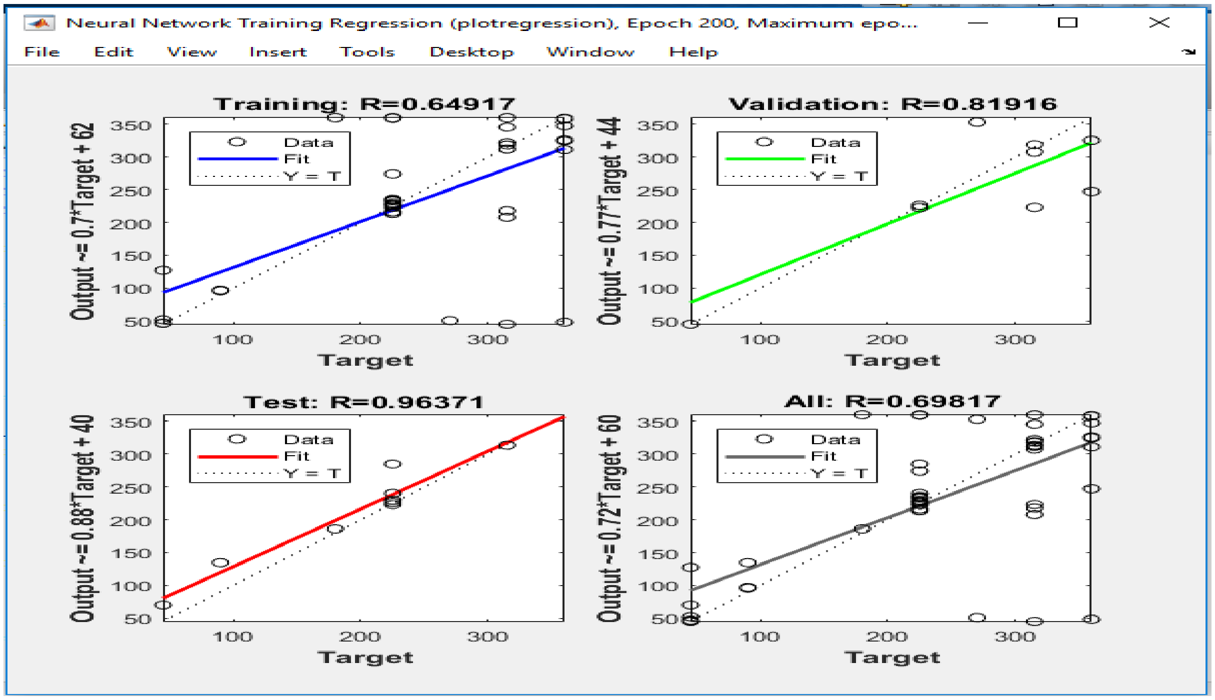


Figure 5.36: Snapshot of regression using NNTOOL

The figure 5.37 below represents the proposed NARX network architecture for Famagusta. The NARX network uses four input parameters and the output is the rainfall. The NARX network utilizes 100 neurons as effective for the prediction using (trainlm) function. There are two hidden layers and the TDL 0:1 and 1:2 are expected to be of length 2 for an enhanced accuracy and to minimize the complexity of the network.

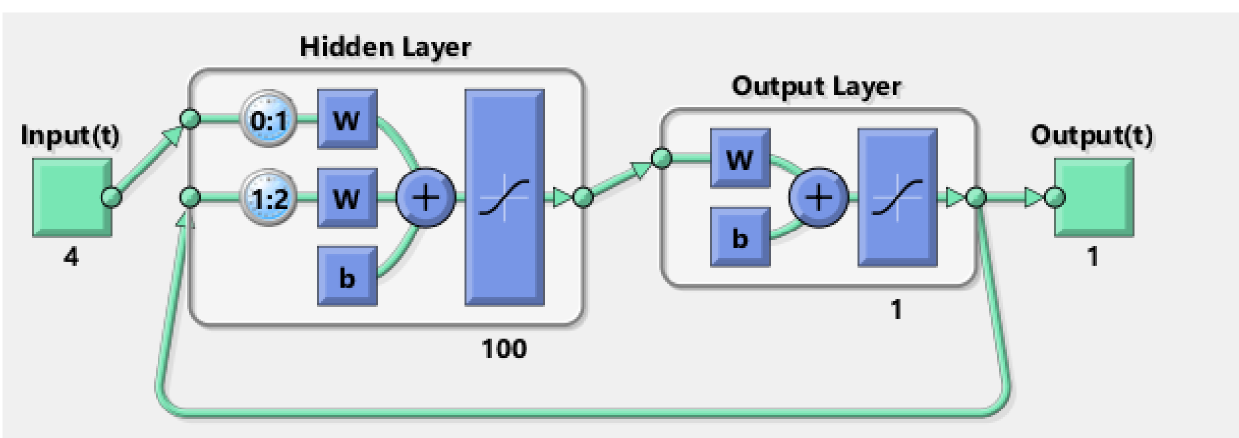


Figure 5.37: Proposed NARX network architecture

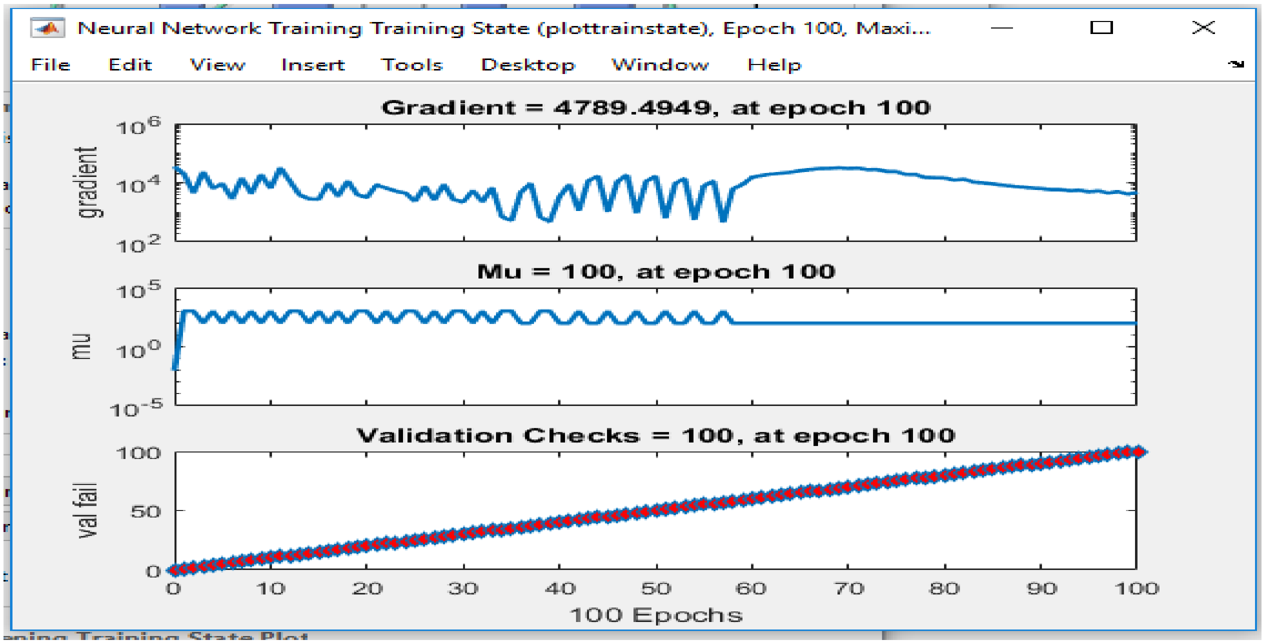


Figure 5.38: Training state for NARX

The above figure 5.38 demonstrate the training state for NARX after training the inputs and output, following results are achieved. The gradient is equal to 4789.49, the Mu is equal to 100 at 100 epochs and the validation checks are recorded as 100 at the total epoch of 100 out of 1000 of max _fail, as shown above.

5.7 ANFIS

The ANFIS network is aimed at predicting the rainfall by using the data with inputs and outputs from the past years. The prediction of the rainfall is a nonlinear system as discussed in this study therefore, ANFIS is appropriate for making this prediction through training the algorithm, testing with different functions and then checking. Subsequently, the model is tracked with several FIS algorithms and with certain error tolerance and epochs to make the perfect predictions. The parameters are analyzed through changing epochs and error tolerance to check the effect on RMSE and to forecast rain. The model is aimed at minimizing the errors between the predicted and the actual output that is rainfall.

5.7.1 Applying ANFIS for Erbil

For this study, the input and output parameters are trained using ANFIS for each city separately. The input parameters are fed into the ANFIS algorithm manually, allocating 60% for training, 40% for testing the results obtained.

The below figure 5.39 illustrates the proposed ANFIS architecture for the city of Erbil. The ANFIS model depends on the number of parameters and criterion. The ANFIS model has three input criteria for Erbil that are: temperature, humidity and wind direction. The ANFIS model is operated by using the hybrid algorithm with 100 epochs. 0.001 error tolerance is observed to be suitable for the training. The architecture uses gauss2mf as the input from the MF type and linear MF for the output. After training, testing and checking the ANFIS model with 3 inputs and 1 output; the error is obtained as 0.025 which is absolutely accurate and authentic for making the prediction.

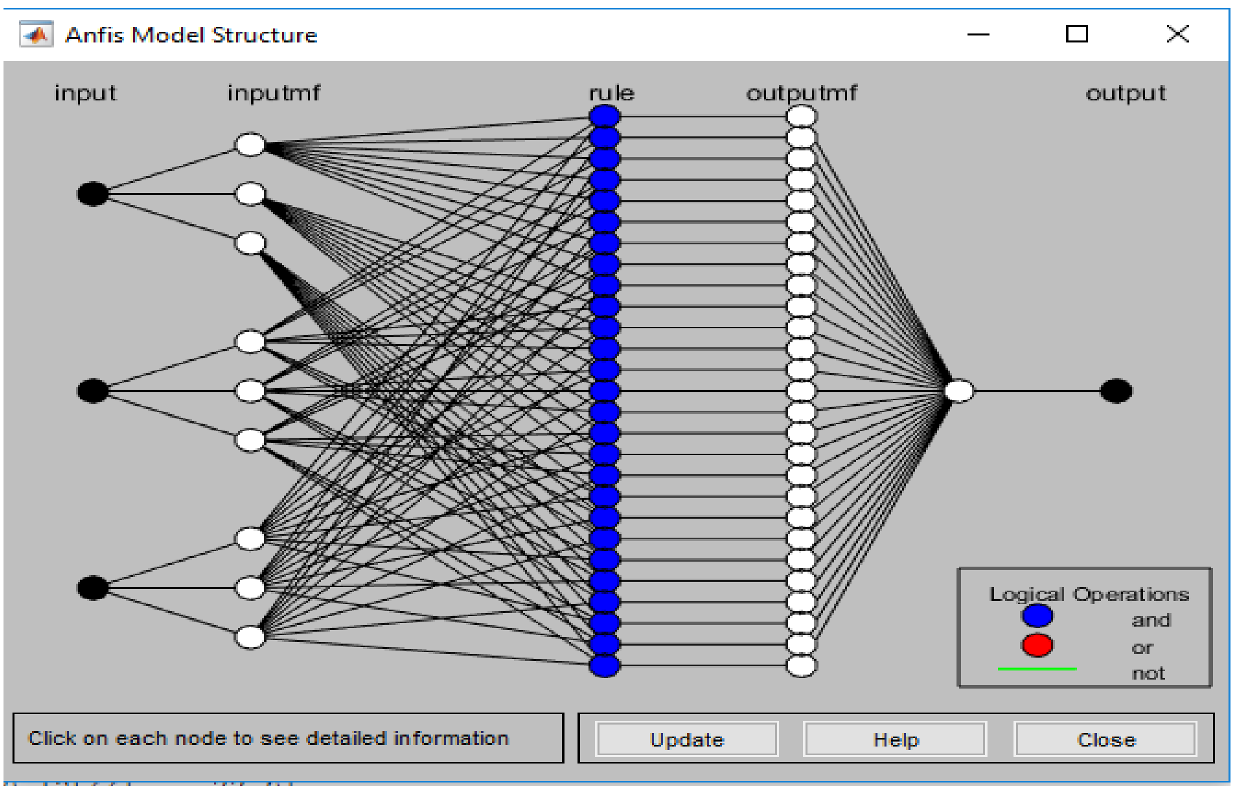


Figure 5.39: Proposed ANFIS architecture for Erbil

ANFIS after training the data with inputs and outputs, automatically generate the rules as shown in the figure 5.40 below. After developing the rules by inputs, it gives output as rainfall prediction. For each input it has different set of rules established.

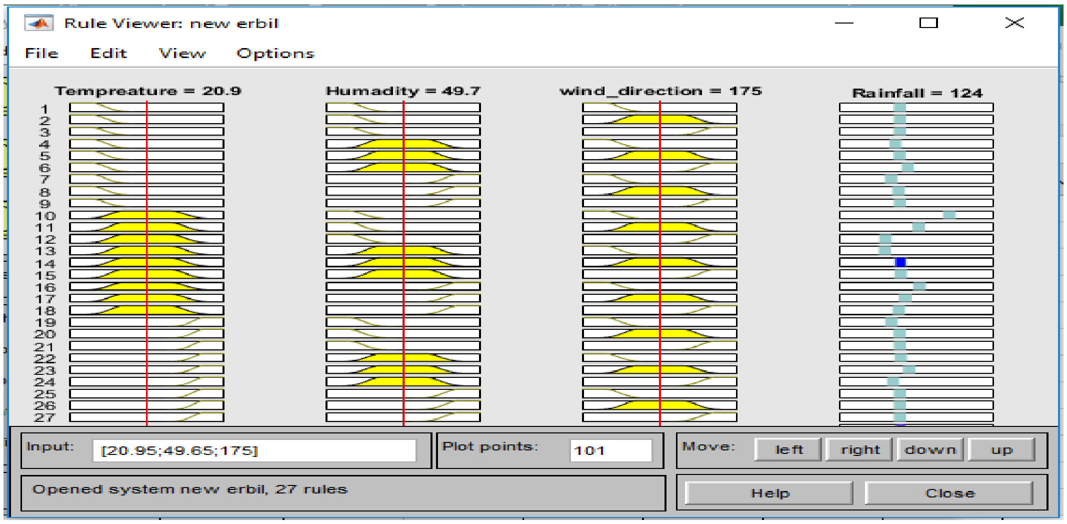


Figure 5.40: ANFIS rule viewer for Erbil

5.7.2 Applying ANFIS for Nicosia

The ANFIS model for Nicosia is trained with four input criteria. The parameters are temperature, humidity, air pressure and wind speed. The number of epochs is limited to 100 with the error tolerance of 0.01 as shown in figure 5.38 below. The function of gauss2mf as the input and linear MF for the output is selected for this model. After the training, testing and checking of the parameters; the error is obtained as 0.011, indicating the precision and accuracy for the ANFIS training of inputs and output.

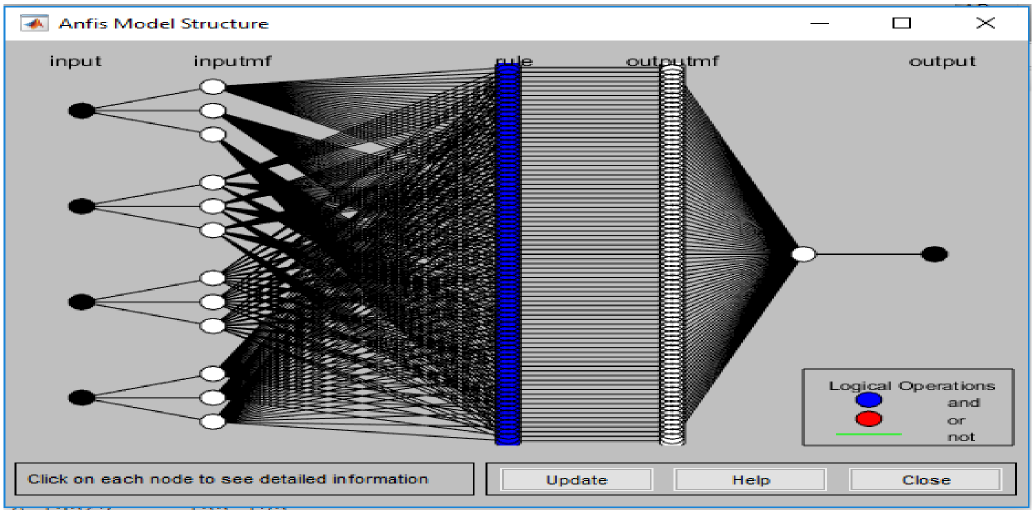


Figure 5.41: Proposed ANFIS architecture for Nicosia

The figure 5.42 illustrates the AFIS rule viewer for Nicosia. The ANFIS used four inputs and the output is rainfall prediction. The ANFIS generated different rules for the inputs for Nicosia.

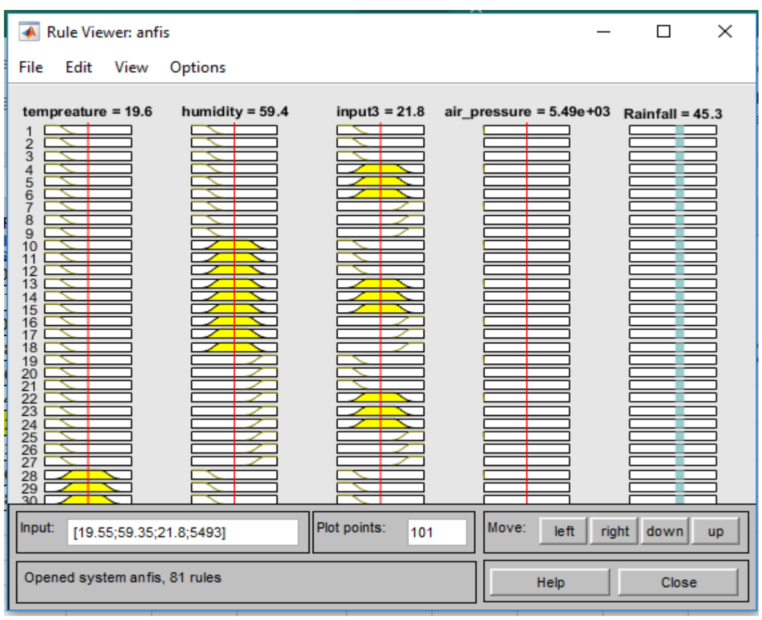


Figure 5.42: ANFIS Rule viewer for Nicosia

5.7.3 Applying ANFIS for Famagusta

The below figure 5.41 demonstrate the proposed ANFIS model for Famagusta. The ANFIS model is trained with four input criteria. The parameters are temperature, air pressure, humidity and wind speed. The epochs are 100 for this training with an error tolerance of 0.01. The function of gauss2mf as input is used and the linear MF for output is fixed as well. The error of 0.015 is obtained as a result of training, testing and checking. Therefore, ANFIS is also perfect and most suitable model for forecasting precipitation to get accurate and precise data.

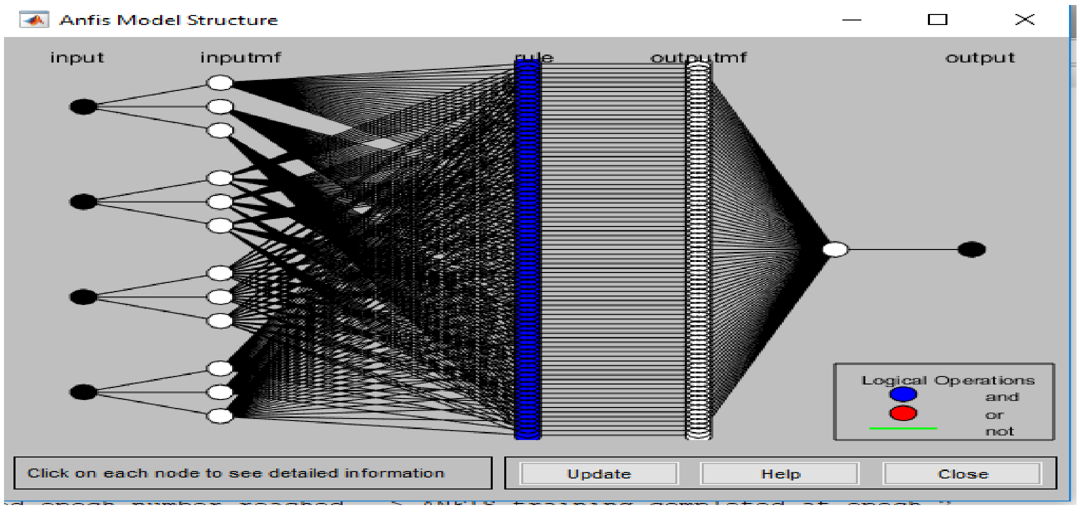


Figure 5.43: Proposed ANFIS architecture for Famagusta

The above figure 5.44 illustrate the ANFIS rule viewer for Famagusta. It is using four inputs for Famagusta and predicted rainfall. The rules for Famagusta inputs are different from those of Erbil and Nicosia.

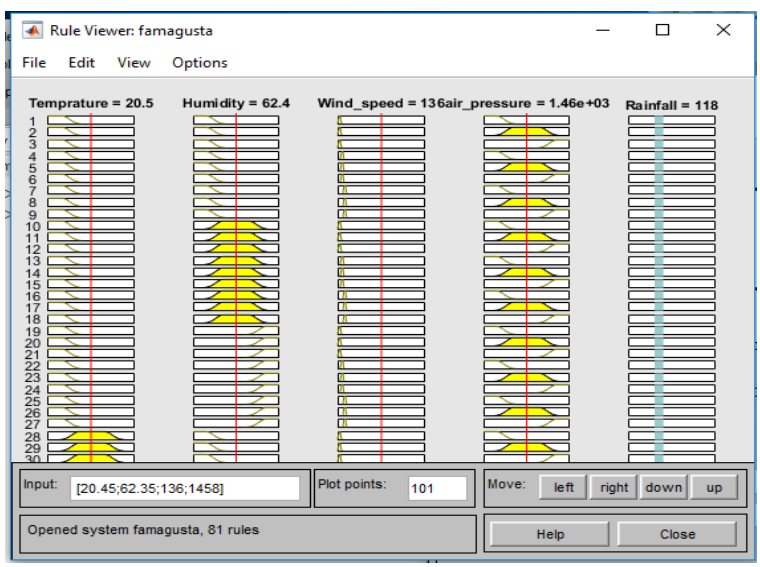


Figure 5.44: ANFIS Rule Viewer for Famagusta

Table 5.4 below summarized the training, testing and validation for the data of Erbil, Nicosia and Famagusta using backpropagation.

Table 5.4: Training, testing and validation by BPNN for Erbil, Nicosia and Famagusta

Place	neurons	epoch	Inputs	output	Function	Training	testing	validation
Erbil	100	300	temperature, humidity and wind direction.	Rainfall	Trainlm	0.92	0.94	0.96
Nicosia	100	400	temperature, wind speed, humidity and air pressure.	Rainfall	traingdx	0.79	0.94	0.96
Famagusta	100	200	temperature, humidity and air pressure	Rainfall	Trainlm	0.64	0.96	0.89

Table 5.5 below highlights the summary of data trained, tested, and validated using NARX model.

Table 5.5: Training, testing and validation by NARX for Erbil, Nicosia and Famagusta

Place	Neurons	Epoch	Inputs	output	Function	gradient	Mu	Validation Checks
Erbil	100	150	temperature, humidity and wind direction.	Rainfall	Trainlm	0.45	0.01	150
Nicosia	100	100	temperature, wind speed, humidity and air pressure.	Rainfall	traingdx	22.5	0.01	100
Famagusta	100	200	temperature, humidity and air pressure	Rainfall	Trainlm	0.29	0.001	200

Table 5.6 below outlines the training, testing, and validation of data using Hybrid model for Erbil, Nicosia and Famagusta.

Table 5.6: Training, testing and validation by Hybrid for Erbil, Nicosia and Famagusta

Place	**MF type**	**Epoch**	**Inputs**	**output**	**Function**	**Error tolerance**	**Obtained error**
Erbil	Linear MF	100	temperature, humidity and wind direction.	Rainfall	gauss2mf	0.01	0.025
Nicosia	Linear MF	100	temperature, wind speed, humidity and air pressure.	Rainfall	gauss2mf	0.01	0.011
Famagusta	Linear MF	100	temperature, humidity and air pressure	Rainfall	gauss2mf	0.01	0.015

CHAPTER 6

DISCUSSION AND RESULT

The study focused on using the artificial neural networks for predicting the rainfall on monthly basis. The study proved that using back propagation and NARX with hybrid models can be used to obtain accurate and precise forecast readings for rainfall, as demonstrated in this study. Although, the networks were trained before testing and validation; the foremost challenge of the study was to achieve maximum accuracy and efficiency in making the prediction.

Thus, the study trained and tested the monthly data for last 6 years of three different locations from two different regions. For this purpose, the study focused on neural networks collaborated with neuro-fuzzy. The study tested the rainfall data from 2012-2017. The areas for the data collection and data testing were: Erbil, Nicosia and Famagusta using MATLAB software with its NNTOOL and ANFISTOOL

6.1 Comparing results

Table 6.1: Obtained RMSE after training and testing

Location	No. of neurons	RMSE		RMSE HYBRID
		BPNN	NARX	
Erbil	100	3.7554	15.6513	0.025
Nicosia	100	8.8172	13.4775	0.011
Famagusta	100	57.3014	85.8441	0.015

The above table 6.1 illustrates the root mean square error obtained for Erbil, Nicosia and Famagusta. The table demonstrates that the most effective result is obtained for Nicosia using hybrid algorithm of ANFIS model with RMSE equal to 0.011.

6.2 Actual and predicted data for Erbil

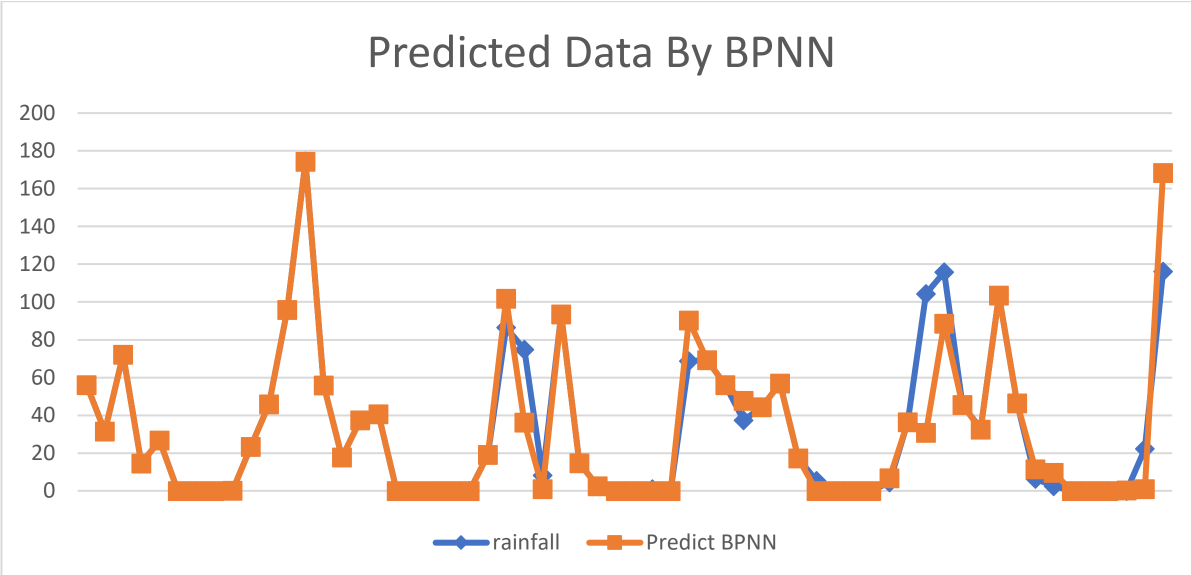


Figure 6.1: Comparing actual and predicted data for Erbil using BPNN

The above figure 6.1 illustrates the graph comparing actual and predicted data for Erbil using BPNN. The graph demonstrates that there is some difference between the actual and the predicted data using BPNN. Similarly, the graph below highlights the comparison between the actual and predicted data using NARX that highlights there is a more difference as show in figure 6.3 below.

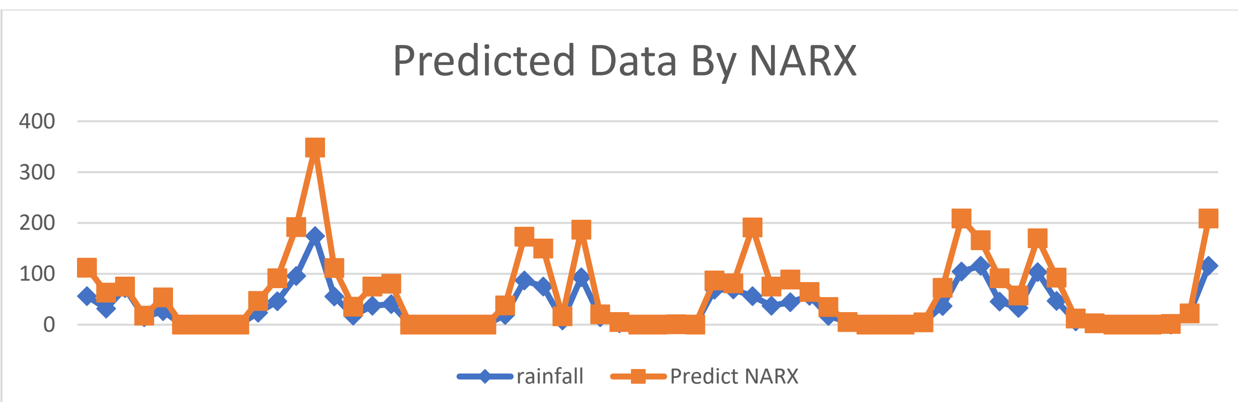


Figure 6.2: Comparing actual and predicted data for Erbil using NARX

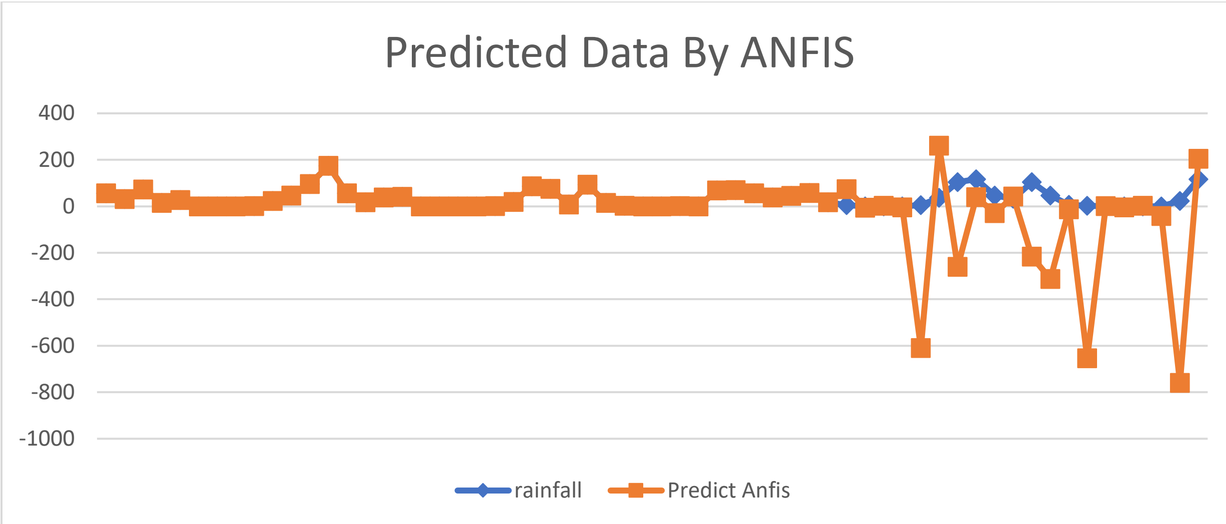


Figure 6.3: Comparing actual and predicted data for Erbil using Hybrid

The above figure 6.3 illustrates the comparison between actual and predicted data as observed by using hybrid algorithm. The graph demonstrates a perfect result for actual and predicted data as that of Erbil. The data shows accuracy and precision in the output data obtained that is the rainfall prediction. The RMSE for hybrid was only 0.025 as discussed above in table 6.1.

6.3 Actual and predicted data for Nicosia

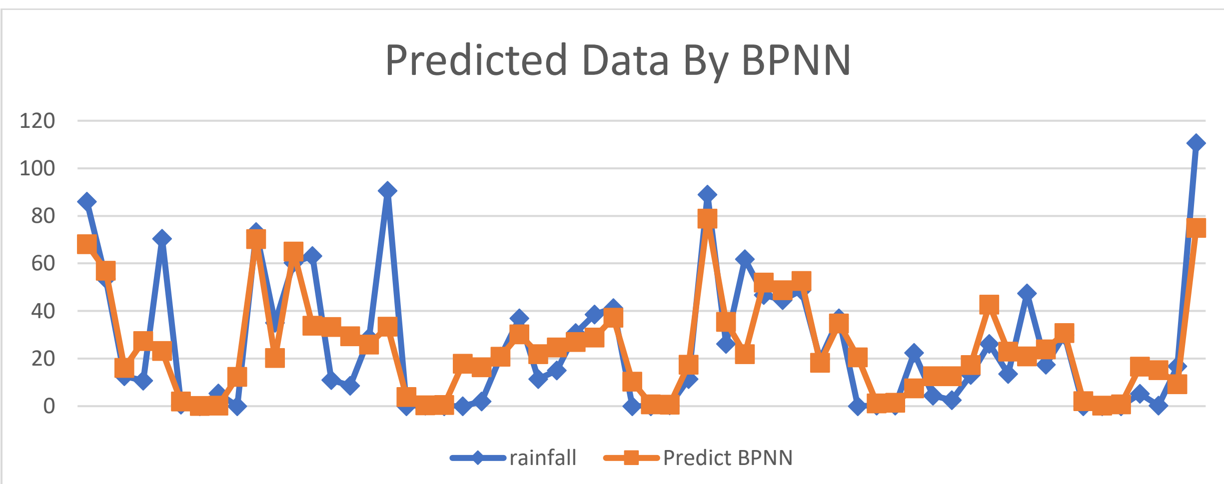


Figure 6.4: Comparing actual and predicted data for Nicosia using BPNN

The above figure 6.4 illustrates the graph comparing actual and predicted data for Nicosia using BPNN. The graph highlights that there is a not much similarity and accuracy between the actual and predicted data. Thus, the BPNN is not much efficient for Nicosia as well.

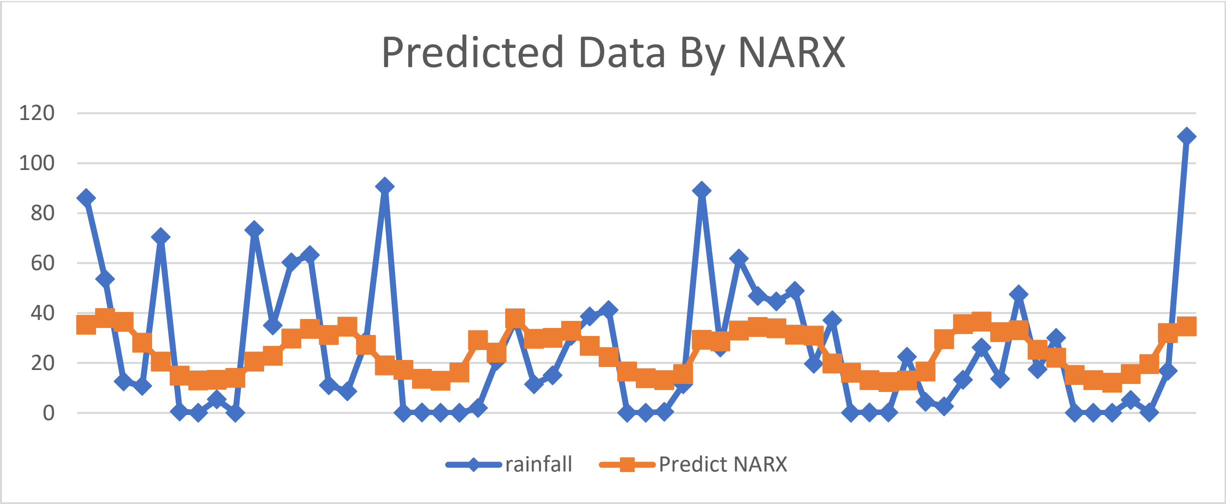


Figure 6.5: Comparing actual and predicted data for Nicosia using NARX

The above figure 6.5 demonstrates the graph of predicting data in comparison to the actual data using NARX. There is a huge difference between actual and predicted data and accuracy is far to achieve.

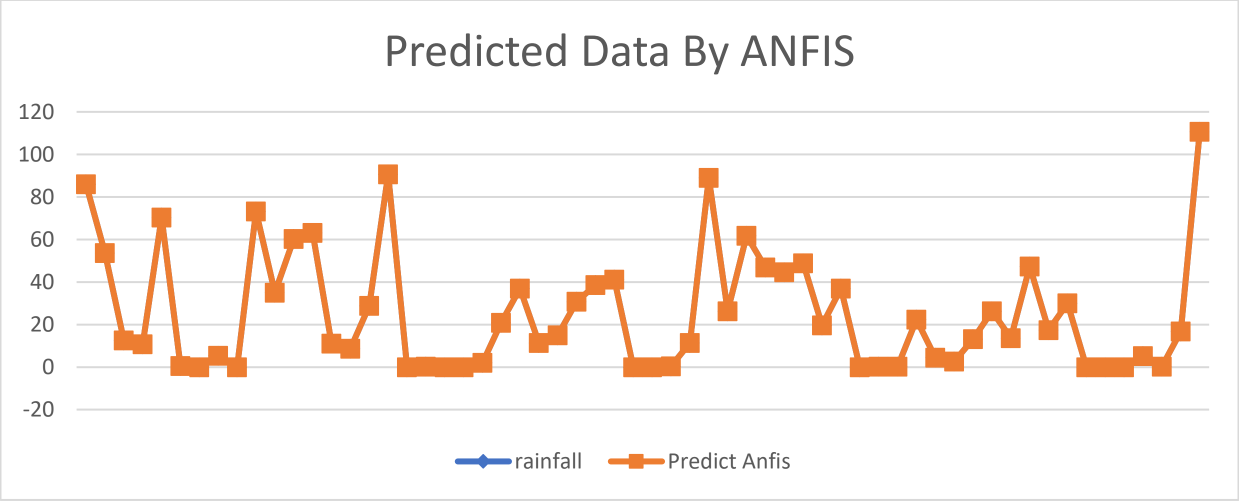


Figure 6.6: Comparing actual and predicted data for Nicosia using Hybrid

The above figure 6.6 illustrates the comparison between actual and predicted data using Hybrid model. The graph outlines that there is a close relation between the actual and predicted data with maximum accuracy.

6.4 Actual and predicted data for Famagusta

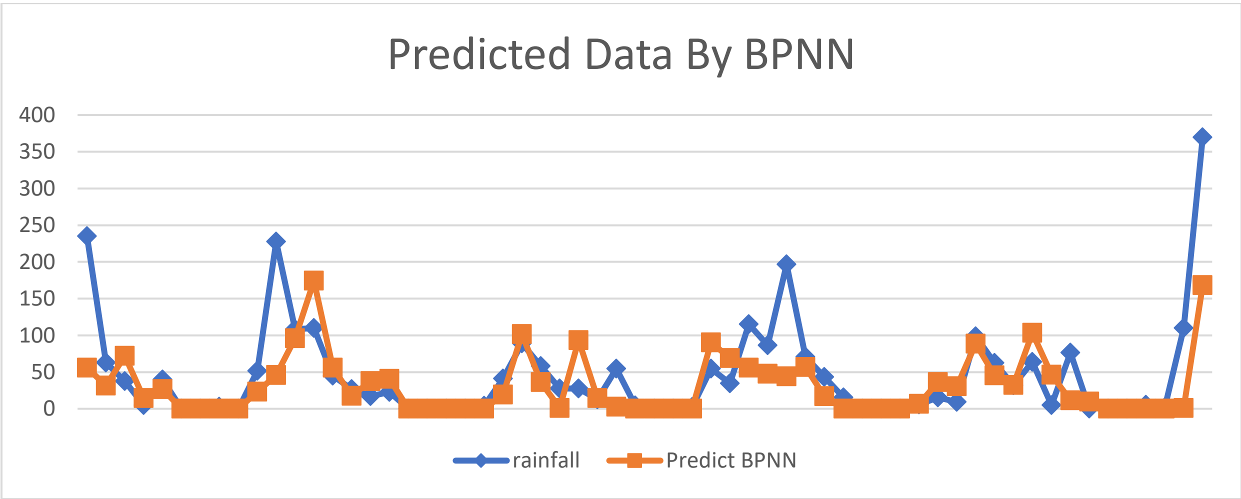


Figure 6.7: Comparing actual and predicted data for Famagusta using BPNN

The above figure 6.7 illustrates the graph making comparison between the actual and predicted data using BPNN for Famagusta. The graph outlines that there is a much difference between the actual and predicted data throughout the graph.

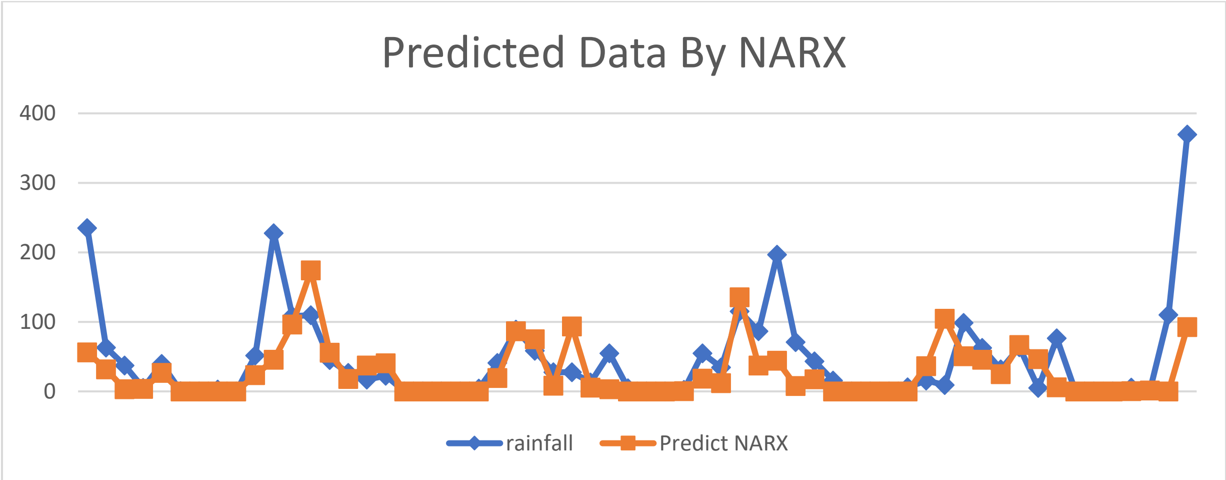


Figure 6.8: Comparing actual and predicted data for Famagusta using NARX

The figure 6.8 above represents the comparison between the actual and predicted data for Famagusta using NARX. The graph illustrates that there is just some similarity between the actual and predicted data.

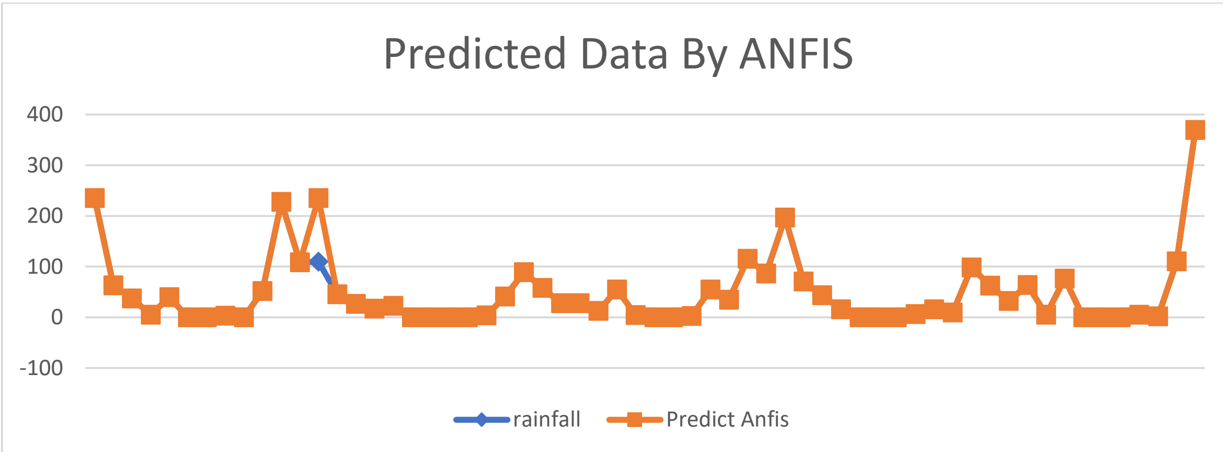


Figure 6.9: Comparing actual and predicted data for Famagusta using Hybrid

The above figure 6.9 illustrates the comparison between the actual and predicted data for Famagusta using the Hybrid model. The graph shows that the actual and predicted data is much similar and accurate.

CONCLUSION

Rainfall is one the most significant natural phenomenon that is not only important for the human beings only but the living beings. Due to the changing climatic conditions, rainfall cycles are also changing and the temperature of the earth is rising. The changing temperature is also affecting the agriculture, industry and sometimes may cause flooding and land slide. Therefore, it is essential for the human beings to keep a check upon this natural phenomenon in order to survive. The water is a scarce natural resource without which human life is impossible and also there is no substitute to this natural resource. Thus, predicting the rainfall for agriculture and water reserves, also it also good for keeping human beings alert of natural disasters like flood and landslide. However, to overcome these issues and meet the demands, a system to forecast rainfall is essential using artificial intelligence of neural that is popular within the modern technology.

The study aimed at building a predicting system using neural networks that could predict monthly rainfall accurately and efficiently with minimum error. The study incorporated different areas and used their rainfall data with different neural networks like ANFIS and ANN, through training the networks with these inputs and outputs. The trained data is tested and then validated by making a comparison between actual and predicted data. The system used feature extraction to deduce the output prediction that could be more precise and accurate. The neural networks with different algorithms and functions were trained with rainfall parameters and the previous rainfall data to predict the results in this study. After training and testing; the results were compared to check the efficiency of the system; the RMSE's were recorded to make sure that the system will operate not only to make the prediction but also the accurate data will be obtained. The study utilized back propagation, NARX and Hybrid algorithms to forecast the rainfall.

Lastly, the rainfall predictions after training, testing are obtained that are quite accurate and through comparison outlined that the actual and predicted data for these areas illustrated finest results using the certainly different parameters of the rainfall that are different for different areas with minimum error observed using ANFIS only. The AFIS model outlined efficiency for Erbil, Nicosia and Famagusta. The NARX network performed not so well in the comparison for actual and predicted data.

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APPENDICES

APPENDIX A

DATABASE FOR ERBIL

Month	Year	Temperature	Humidity	Wind direction	Windspeed	Rainfall	Air pressure
Jan	2012	8.2	74.4	120	1.5	56.1	0.0
Feb	2012	9.55	63.6	160	2.3	31.5	0.0
Mar	2012	11.2	61.7	150	1.9	72.1	0.0
Apr	2012	21.95	49	190	2.9	14.5	0.0
May	2012	27.1	41.5	270	2.4	26.8	0.0
Jun	2012	33.15	25.8	270	2.8	0	0.0
Jul	2012	35.9	22.1	270	2.5	0	0.0
Aug	2012	35.15	28.5	220	1.8	0	0.0
Sep	2012	30.8	29	90	1.9	0.2	0.0
Oct	2012	24.45	48.6	120	2	23.4	0.0
Nov	2012	17.15	64.6	60	1.7	45.9	0.0
Dec	2012	6	77.2	150	1.7	95.9	0.0
Jan	2013	7.45	73.9	140	2.2	174.4	0.0
Feb	2013	12.05	75.6	160	1.6	55.8	0.0
Mar	2013	14.95	61.6	140	1.9	17.7	0.0
Apr	2013	20.35	53.9	180	1.8	37.4	0.0
May	2013	25.3	47.7	290	1.9	40.6	0.0
Jun	2013	31.4	31.2	270	1.4	0	0.0
Jul	2013	34.3	29.1	270	1.2	0	0.0
Aug	2013	34.05	28.7	270	1.1	0	0.0
Sep	2013	28.8	37.8	270	0.8	0	0.0
Oct	2013	23.2	39.4	90	1.5	0.2	0.0
Nov	2013	17.4	67.9	90	1.1	19.1	0.0
Dec	2013	9.6	66	90	1.1	86.6	0.0
Jan	2014	10.6	72.1	90	1	74.9	0.0
Feb	2014	11.5	56	90	1.4	8.2	0.0
Mar	2014	15.8	66.2	120	2	93.4	0.0
Apr	2014	20.6	48.6	270	0.8	14.7	0.0
May	2014	27.3	39.8	270	0.2	2.5	0.0
Jun	2014	31.8	30.3	270	0.1	0	0.0
Jul	2014	35	29.1	270	0.1	0	0.0
Aug	2014	35.3	28.3	270	0.1	1	0.0
Sep	2014	29.6	39.8	270	0.1	0.0	0.0
Oct	2014	22.8	58.6	90	0.1	68.7	0.0
Nov	2014	14.6	65.6	100	0.2	69.2	0.0

Dec	2014	11.7	74.7	90	0.2	56.0	0.0
Jan	2015	9.05	72.5	90	0.2	37.4	0.0
Feb	2015	11	68.4	90	0.1	44.3	0.0
Mar	2015	14.2	64.3	90	0.2	56.8	0.0
Apr	2015	19.2	52.2	270	0.2	17.3	0.0
May	2015	27.4	34.5	270	0.2	5.4	0.0
Jun	2015	31.5	33.2	270	1.7	0	0.0
Jul	2015	36.15	25.4	270	1.3	0	0.0
Aug	2015	35.45	30.8	270	1.3	0	0.0
Sep	2015	32.25	29.9	90	1.9	4.5	0.0
Oct	2015	24.6	54.6	270	2.3	36.4	0.0
Nov	2015	15.05	69.8	90	1.3	104.4	0.0
Dec	2015	9.9	67.7	90	1.5	115.8	0.0
Jan	2016	7.9	76.4	270	1.4	45.6	0.0
Feb	2016	12.15	65.3	90	1.5	33.0	0.0
Mar	2016	17.6	55.2	90	1.9	103.5	0.0
Apr	2016	19.65	53.9	90	1.7	46.4	0.0
May	2016	26.1	40.5	270	1.7	6.4	0.0
Jun	2016	32.55	32	90	2.2	2.5	0.0
Jul	2016	35.45	27.3	270	1.2	0	0.0
Aug	2016	36.15	30.5	270	1.1	0	0.0
Sep	2016	29.5	39.4	270	1.2	0	0.0
Oct	2016	24.5	41	270	1.4	T.R	0.0
Nov	2016	15.55	47.5	90	1.1	22.3	0.0
Dec	2016	8.65	76.4	150	1.5	116.1	0.0

APPENDIX B

DATABASE FOR NICOSIA

Month	Year	Temp	Humidity	Wind speed	Wind direction	Air pressure	Rainfall
Jan	2012	9.0	74.8	18.5	360.0	999.5	86.0
Feb	2012	8.4	68.0	19.9	270.0	1000.2	53.6
Mar	2012	11.3	61.1	20.7	90.0	1001.7	12.6
Apr	2012	16.9	59.6	19.9	315.0	997.1	10.8
May	2012	20.8	60.0	18.2	315.0	996.1	70.4
Jun	2012	26.9	52.0	19.8	90.0	992.9	0.60
Jul	2012	30.4	46.2	19.6	360.0	989.4	0.0
Aug	2012	30.0	44.7	17.5	360.0	991.2	5.4

Sep	2012	26.2	54.9	12.8	270.0	995.1	0.0
Oct	2012	21.6	63.8	30.8	45.0	998.4	73.2
Nov	2012	17.0	68.2	14.2	360.0	1000.4	35.0
Dec	2012	12.0	77.7	20.0	370.0	999.9	60.3
Jan	2013	9.6	76.0	16.6	360.0	1000.5	63.2
Feb	2013	11.3	75.5	17.5	315.0	1000.6	11.0
Mar	2013	13.4	61.2	24.6	360.0	997.9	8.6
Apr	2013	17.7	57.0	18.2	360.0	997.2	28.8
May	2013	23.1	52.9	16.6	90.0	995.4	90.6
Jun	2013	26.2	47.6	21.0	360.0	993.2	0.0
Jul	2013	28.6	47.8	15.3	360.0	990.5	0.2
Aug	2013	29.5	47.0	13.9	360.0	991.1	0.0
Sep	2013	25.4	52.1	17.2	360.0	995.1	0.0
Oct	2013	20.0	41.0	17.8	45.0	1000.4	2.0
Nov	2013	17.3	63.9	14.8	90.0	1000.3	20.8
Dec	2013	10.2	63.1	24.4	360.0	1000.4	37.0
Jan	2014	11.6	76.0	14.6	180.0	1003.1	11.4
Feb	2014	11.6	75.5	15.7	360.0	1002.5	15.0
Mar	2014	14.5	61.2	24.6	360.0	998.1	30.8
Apr	2014	17.7	57.0	16.5	315.0	998.1	38.6
May	2014	20.9	52.9	15.5	315.0	996.7	41.2
Jun	2014	26.1	47.6	17.6	270.0	994.3	0.0
Jul	2014	28.5	47.8	16.2	270.0	991.7	0.0
Aug	2014	29.2	47.0	13.3	247.5	991.3	0.4
Sep	2014	25.6	52.1	15.2	270.0	995.1	11.4
Oct	2014	20.5	41.0	22.0	135.0	999.4	89.0
Nov	2014	14.7	63.9	13.6	90.0	1001.7	26.2
Dec	2014	12.9	63.1	18.1	360.0	1003.4	61.8
Jan	2015	9.2	75.6	17.3	270.0	1002.7	46.8
Feb	2015	9.7	75.8	17.3	45.0	997.8	44.6
Mar	2015	13.1	68.9	20.7	360.0	1001.0	48.8
Apr	2015	15.6	58.5	20.4	315.0	998.8	19.6
May	2015	21.8	56.3	16.2	270.0	996.2	37.0
Jun	2015	24.7	54.5	15.4	315.0	994.3	0.0
Jul	2015	28.7	49.0	13.9	360.0	992.1	0.2
Aug	2015	29.7	50.0	14.7	315.0	993.3	0.2
Sep	2015	27.0	57.1	14.3	45.0	996.1	22.4
Oct	2015	22.3	62.6	14.9	360.0	998.6	4.4
Nov	2015	16.4	55.6	17.0	360.0	1002.0	2.6
Dec	2015	11.3	62.4	19.2	360.0	1006.9	13.2
Jan	2016	9.3	69.0	19.8	360.0	1003.1	26.2

Feb	2016	13.2	64.6	19.8	315.0	1003.6	13.6
Mar	2016	14.4	59.4	22.6	270.0	998.2	47.4
Apr	2016	20.1	50.8	18.1	360.0	997.2	17.4
May	2016	21.7	51.8	18.2	315.0	996.1	30.0
Jun	2016	28.0	44.1	16.9	270.0	993.4	0.0
Jul	2016	30.2	46.4	20.3	135.0	990.6	0.0
Aug	2016	29.4	53.2	14.8	90.0	992.7	0.0
Sep	2016	25.8	52.1	16.4	270.0	996.4	5.2
Oct	2016	22.3	54.3	16.6	292.5	999.3	0.2
Nov	2016	15.4	55.2	19.3	360.0	1003.6	16.8
Dec	2016	9.9	72.8	20.0	315.0	1003.2	110.6

APPENDIX C

DATABASE FOR FAMAGUSTA

Month	Year	Temperature	Humidity	Wind speed	Wind direction	Air pressure	Rainfall
Jan	2012	12.2	70.5	23.3	225.0	1015.1	235.0
Feb	2012	12.2	64.0	22.8	270.0	1014.9	63.0
Mar	2012	13.0	65.2	23.2	90.0	1016.9	37.4
Apr	2012	17.2	71.7	19.8	315.0	1012.2	4.8
May	2012	20.8	72.4	19.9	315.0	1011.0	39.6
Jun	2012	25.4	70.5	14.4	225.0	1007.6	0.2
Jul	2012	29.0	64.1	17.8	360.0	1003.9	0.0
Aug	2012	29.1	60.8	18.3	225.0	1005.6	2.8
Sep	2012	26.2	65.8	15.3	225.0	1009.7	0.0
Oct	2012	23.1	68.0	21.1	180.0	1013.0	51.6
Nov	2012	19.6	66.7	17.8	225.0	1015.2	227.6
Dec	2012	15.1	70.3	25.0	315.0	1015.1	108.4
Jan	2013	13.0	69.6	21.8	360.0	1015.4	109.8
Feb	2013	14.2	71.8	25.4	315.0	1015.8	45.2
Mar	2013	15.3	64.0	29.2	315.0	1013.1	26.6
Apr	2013	18.0	65.0	21.6	315.0	1012.2	17.0
May	2013	22.5	66.0	17.2	225.0	1010.2	22.6
Jun	2013	25.4	62.4	18.5	225.0	1007.8	0.0
Jul	2013	27.7	61.4	15.8	225.0	1005.0	0.0
Aug	2013	28.6	61.6	16.0	225.0	1005.6	0.0
Sep	2013	25.9	65.0	18.3	45.0	1009.8	0.0
Oct	2013	21.2	52.3	20.3	315.0	1015.2	4.0

Nov	2013	19.7	65.9	18.0	45.0	1015.2	41.0
Dec	2013	13.6	62.9	27.5	90.0	1019.5	89.0
Jan	2014	14.6	68.7	18.1	45.0	1018.5	58.2
Feb	2014	13.7	67.1	22.9	45.0	1017.8	27.4
Mar	2014	15.8	64.3	24.3	360.0	1013.2	27.6
Apr	2014	18.2	67.5	20.7	315.0	1013.2	12.6
May	2014	21.0	68.8	16.1	225.0	1011.8	54.8
Jun	2014	25.1	60.4	18.7	360.0	1009.0	4.4
Jul	2014	27.5	68.7	28.3	225.0	1006.4	0.0
Aug	2014	28.2	71.2	17.8	225.0	1006.8	0.0
Sep	2014	26.4	61.3	21.4	315.0	1007.8	2.2
Oct	2014	22.1	64.8	25.6	90.0	1013.3	54.6
Nov	2014	17.8	62.8	18.9	360.0	1016.9	34.4
Dec	2014	16.5	71.4	18.5	90.0	1022.0	115.2
Jan	2015	12.6	68.2	27.2	225.0	1018.0	86.4
Feb	2015	13.2	67.6	25.2	315.0	1913.0	196.8
Mar	2015	15.4	66.1	25.6	315.0	1016.1	70.8
Apr	2015	16.6	62.3	23.3	360.0	1013.9	43.4
May	2015	21.3	66.7	18.7	225.0	1011.1	15.4
Jun	2015	24.2	66.9	17.2	225.0	1009.1	0.0
Jul	2015	27.6	65.1	15.7	225.0	1006.8	0.0
Aug	2015	29.0	64.2	15.4	225.0	1007.8	0.0
Sep	2015	27.4	65.4	17.0	180.0	1010.7	6.0
Oct	2015	23.6	67.1	19.6	225.0	1013.3	15.4
Nov	2015	19.3	60.7	19.0	45.0	1016.9	9.2
Dec	2015	14.5	63.0	21.6	45.0	1022.0	98.6
Jan	2016	12.2	65.1	25.4	270.0	1018.4	62.4
Feb	2016	15.0	69.7	20.3	315.0	1018.9	31.8
Mar	2016	16.0	65.2	25.2	315.0	1013.3	63.6
Apr	2016	19.5	65.8	20.8	360.0	1012.2	4.8
May	2016	21.3	65.4	25.4	225.0	1011.1	76.4
Jun	2016	26.0	64.6	16.3	225.0	1008.3	0.0
Jul	2016	28.6	66.9	15.8	225.0	1005.2	0.0
Aug	2016	28.7	67.6	15.7	225.0	1007.3	0.0
Sep	2016	26.4	62.4	17.6	360.0	1011.0	5.2
Oct	2016	23.2	65.1	19.8	315.0	1014.0	1.8
Nov	2016	18.8	59.5	19.9	45.0	1018.0	110.0
Dec	2016	12.9	67.5	27.3	360.0	1018.5	369.6