HAILE BELETE SHAMA

ANALYSIS OF DIFFERENT COMBINATION OF METEOROLOGICALPARAMETR IN PREDICTING WIND SPEED WITH DIFFERENT PREDICTIVE TOOLS:
A CASE STUDY

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ANALYSIS OF DIFFERENT COMBINATION OF METEOROLOGICAL PARAMETERS IN PREDICTING WIND SPEED WITH DIFFERENT PREDICTIVE TOOL'S A CASE STUDY

ATHESIS SUBMITTED TO THE GRADUATE SCHOOL OF APPLIED SCIENCE OF NEAR EAST UNIVERSITY

By
HAILE BELETE SHAMA

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

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This thesis is my original work and has not been presented for a degree in any other university and I declare that all information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct and also all sources of material used for this thesis have dully acknowledged.

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To my parents…

ABSTRACT

In this study, three predictive tools namely; ANN, MLR and RSM models were used to predict the wind speed at four selected regions in North Cyprus. prediction of wind speed by usage of the weather data at four selected locations across northern region of Cyprus, namely; Gazimağusa, Güzelyurt, Lefkoşa,and Girne, was carried out, using the weather data collected from the meteorological department for a nine-year period 2009 to 2017 were used. Three worldwide statistics of the; Root mean square error (RMSE), Mean Square Error (MSE), and Coefficient of Determination(R^2) were applied to evaluate the performance of the proposed models. Results show that the proposed model using AI based models efficient but more accurate in predicting wind speed results are founded in mathematical approach-based models. Six ANN Combination Models have been developed that provide the best predicted performance in determination of coefficient (R^2) Training and Testing values Güzelyurt area (79.91% and 76.01%); Gazimağusa Area (98.69% and 97.61%); Lefkoşa Area (93.56% and 84.67 %); Girne Area (98.21% and 97.01%) and six MLR Models was developed, with (64.93% and 77.94%) results, which yielded the best predictive performance model values (R^2) for Gazimağusa and Lefkoşa, respectively. The adequacy of The RSM models show that (R^2) can predict 83.58% of the response in Lefkosa. The best model's performance of the wind speed prediction in Lefkoşa area by ANN, MLR and RSM model results of determination of coefficient (R^2) (93.56%, 77.94% and 83.58%) values are respectively.

Keyword: North Cyprus; Weather data, Artificial Neural Network (ANN); Multiple Linear Regression; Response Surface Methodology; Wind Speed

ÖZET

Bu çalışmada, üç tahmin aracı yani; ANN, MLR ve RSM modelleri Kuzey Kıbrıs'ta seçilen dört bölgede rüzgar hızını tahmin etmek için kullanıldı. Kıbrıs'ın kuzey bölgesinde seçilen dört noktada, yani hava durumu verilerinin kullanımı ile rüzgar hızının tahmini; Gazimağusa, Güzelyurt, Lefkoşa ve Girne, meteoroloji bölümünden 2009-2017 yılları arasında dokuz yıllık bir süre için toplanan hava verileri kullanılarak gerçekleştirilmiştir. Dünya çapında üç istatistik; Önerilen modellerin performansını değerlendirmek için kök ortalama kare hatası (RMSE), Ortalama Kare Hatası (MSE) ve Kararlılık Katsayısı(R^2) uygulanmıştır. Sonuçlar, AI baz modelleri verimli ancak rüzgar hızı sonuçlarının tahmin inde daha doğru olan yani önerilen modelin matematiksel yaklaşım tabanlı modellerde kurulduğunu göstermektedir. Katsayı (R^2) Eğitim ve Test değerlerinin belirlenmesinde öngörülen en iyi performansı sağlayan altı ANN Kombinasyon Modeli geliştirilmiştir (%79.91ve %76.01); Gazimağusa Bölgesi (%98,69 ve %97,61); Lefkoşa Alanı (%93,56 ve %84,67); Girne Bölgesi (%98,21 ve %97,01) ve altı MLR Modelleri geliştirilmiştir, (%64.93 ve %77.94) sırasıyla Gazimağusa ve Lefkoşa için en iyi tahmine dayalı performans modeli değerlerini (R^2) veren sonuçlardır. RSM modellerinin yeterliliği tahmin edebilirsiniz göstermektedir. Katsayısı (R^2) (93,56%, %77,94 ve %83,58) ile Lefkoşa bölgesinin rüzgar hızı tahmininin modeli ile en iyi modelinin performans değerleri sırasıyla ANN, MLR ve RSM dır.

Anahtar Kelimeler: Kuzey Kıbrıs; Hava durumu verileri, Yapay Sinir Ağı (ANN); Birden çok Lineer Regresyon; Yanıt Yüzey Metodolojisi; Rüzgar Hızı

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LIST OF ABBREVIATIONS

ANN: Artifical Neural Network

ANFIS: Adaptive neuro-fuzzy inference system

RSM : Response Surface Methodology

MLR: Multiple Linear Regressions

IPCC: Inter Governmental penal Climate change

Tmin: Minimum Temperature

Tmax: Maximum temperature

DT: Difference of temperature

Gsr: Global solar radiation

WS: Wind Speed

Ss: Sunshine

AvT: Average temperature

NM: Number of Month

LVM: Levernbreg-Marquardt

FIS: Fuzzy inference system

DoE: Design of the experiments

CCD: Central Composite design

MFs: Membership function

ANOVA: Analysis of the Variance

FFANN: Feed forward artificial neural network

MLPNN: Multilayer perceptions neural network

SVR: Support Vector regressions

MLFFNN: Multi-layer feed forward neural network.

CHAPTER 1

INTRODUCTION

1.1 Overview of The Wind Speed

Wind speed is one the most significant contribution it's required for continuous and suitable for Wind power plants and electric power generate. For the consistency and value of the electric power structure, it is requisite to grow highly perfect the wind speed estimation techniques(Filik et al., 2017).

Naturally the phenomenon existing among on the surface of the world is wind, which is not we deal a regular foundation for in our day-to-day survives. The movement of air direction in the atmosphere towards a specific attitude at assured speed is stated that as a wind. The distinction existing between the recognized weight of pressure focuses on results to the heading at which the wind development will be, which dependably drives towards the lower pressure direction, and being reliant on the speed of the extent of the pressure dominant between the points.

Wind speed forecasting is now a part of climate estimating for a long time where it is being utilized for ship route, Missile direction, Air traffic control and Satellite dispatch. The current period of computing technologies with more processing speed and computing power are helping the researchers to work on different forecasting models like artificial neural network model (Melan Bhaskar et al., 2014).

Today, the application of the artificial intelligence based models are in order to advance for the prediction models are becomes very motivating in research areas and in order to predict the wind speed is noted by (Marović et al., 2017).

1.2 Wind Power and Wind Energy

1.2.1 Wind power

Wind power counter to the turbine is sufficient to produce electric power for the whole urban areas all in all. The turbines in variation of the shapes and sizes as respects to the reason they are to work for are associated with the power generators and are put at very windy zones. Fans of turbines are moving by wind to produce electric power. A number of a wind homesteads existing over the place of the world which is produces a large number of megawatts, case of these farmsteads existing in China and the United States (International Energy Agency, 2017).

Any way of the fast improvement of the wind power in current times, it's upcoming still leftovers undistinguishable and so unclear. However, about fifty world countries are presently utilizing the wind power, using the highest effort of a small number of countries below the leading countries of Germany, Spain, and Denmark. It pillars for the other world countries to fundamentally increase their industries standard for the generating wind energy to take along about understanding of general objectives. In future, utilization of energy all over the world prediction shown that 12% from the wind power by 2020 (International Energy Agency2018)

1.2.2 Wind Energy

The way of the wind vitality improvement will be undertaking a massive work to satisfy the future energy demand and reduce the environmental pollution to a certain degree. Energy is existing in two alternatives energy sources, renewable energy (solar, wind, hydro, wave) and non-renewable energy (coal, fuel, natural gas) sources. (Sharma & Mishra et al., 2014).

Wind energy is currently observed as a significant energy asset all through the world. Use of sustainable power source assets seems, by all accounts, to be a standout amongst the most proficient and viable routes in accomplishing reasonable advancement, that is currently generally observed as critical to overall popular feeling. Amongst the renewable energy sources, wind energy, which is a free, clean, and renewable source of energy, which will never run out, plays a big role. With this rapid growth, it is important to achieve a better understanding of how wind energy is being observed by the public (Bohidar et al., 2014).

Under subject of energy, the knowledge of the wind speed and its directions are very significant for the production of the wind energy, management and integration. The quantity of the produce of the wind energy is important for safe and operative action of the stochastic renewable energy sources including wind turbines and the wind farms (P.Krömer et al.. 2017).

Wind energy fulfilled around 0.2% from the total worldwide energy request and expected 1.8% the all the global electricity is being produced by the wind energy (Tansu Filik et Al., 2017).The (IPCC) in its current report has expected about 20% of the demand of the world's electricity would be satisfied by the wind energy by year of the 2050 (Tabassum et al., 2014).

1.3 General Objectives of The Study

General objective of this study is to predicted wind speed at four specifically locations; Güzelyurt, Gazımağusa, Lefkoşa and Girne in KKTC.

1.3.1 Specific objective of the study

1. To develop the ANN models for predicting the wind speed by using the location, the month number (Mn), minimum temperature (Tmin), maximum temperature (Tmax), difference of maximum and minimum temperature (DT), average of Temperature, Sunshine (Ss), wind speed (Ws) and Solar radiation (Gsr) as input parameters for the selected location of North Cyprus.

2. To applying the AI-based (ANN) and (MLR, RSM) models to predict wind Speed in North Cyprus and use the statistical tools (R^2 and RMSE) comparison of their performance's validation.

3. To define the appropriateness and suitability of the models for the prediction of the wind speed in North Cyprus.

Research questions for this study are stated below:

- What type of parameters are impacted for predicted wind speed at selected locations?
- How do we find the best combination of the developed models for each site?
- Which locations offer highest performance of model found?
- Are we find the best predictors of the wind speed in each location?

➢ Which predictive tool is more predicted performance for predicting wind speed?

➢ Is it electricity produced by wind, which is good option for to get wind energy or Not?

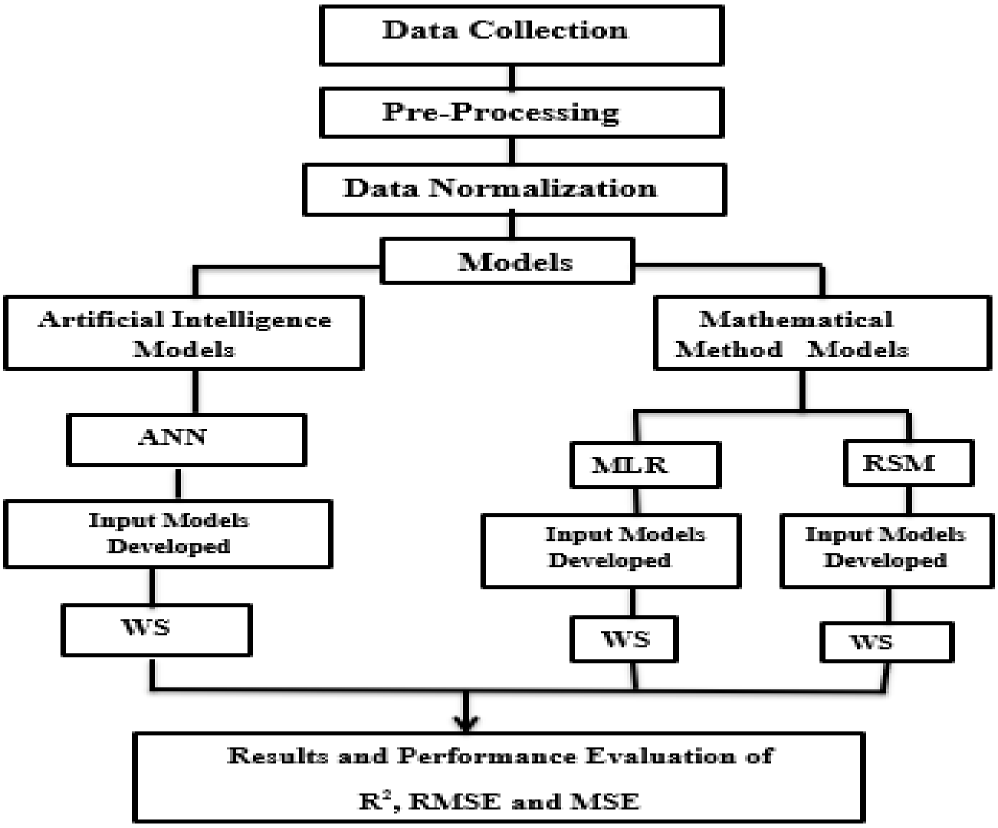

Figure 1.1: The proposed Plan of Drawing of the Methodology

1.4 Significance of The Study

The domain of wind speed prediction, modern investigation of the articles that published proposed that:

- This study will be the first that employed to use one Artificial Intelligence models and two mathematical method models used to predicted wind speed in North Cyprus.
- This will be the main investigation to use developed combination models for ANN models used for the prediction of the wind speed in North Cyprus.

- This study will be the first in North Cyprus perform the Response Surface Methodology and multiple linear Regression models using to predict the wind speed.

- Therefore, the effective conclusion of this investigation, a great deal of issues concerning the wind speed in North Cyprus particular and on the everywhere could be settled, including probability of utilizing combination models based used to predicted wind speed in North Cyprus, the best combination model to apply in North Cyprus to accomplish better estimation with many dominant parameter inputs sources.

1.5 Overview of The Study

Under this thesis study contain the following component explains.

- **Chapter 1:** under this chapter, it deals the introductory description information about wind speed and the objectives of the study and overview of thesis.

- **Chapter 2:** under this chapter describes the review of the previous studies by predictive tool's concept of the wind speed prediction relations of the different parameters.
- **Chapter 3:** under this chapter, the proposed methodology parts of the studies are presented, for the four predictive tool's models used to predict wind speed in selected area.

- **Chapter 4:** under this chapter provides results and discussion based on the predictive tool's models to evaluate their performance that predict with stated input parameters.
- **Chapter 5:** under final chapter of this study which provides the conclusion recommendations centered on the results gotten from this study.

CHAPTER 2
LITERATURE REVIEW

2.1 Wind Farm

Cyprus region is one of the suitable for the electricity power generation from the wind sources. Northern part of Cyprus has a wind speed of 5-7 m/s. Estimated the wind capacity is between the 30 up to 60 MW. The map of the Wind speed of South Island was created. But the North Cyprus part of the wind map research studies are still in progress (Ozerdem et al, 2011).

To applied the Weibull statistical distribution method by using Weibull probability density function can be used to estimate the wind speed, wind density and wind energy potential for North Cyprus (Y.Kassem et al, 2018)

In currently, the population growth and other issues in the Northern Cyprus have run to an intensification of the demand of energy source such as fossil fuels. The environmental constraints that associated with use of the fossil fuels have needed for the improvement of the alternative energy bases such as the wind energy for the electricity power production.

2.2 Wind Energy in North Cyprus

Cyprus on island which is surrounded by Mediterranean Sea. Its weather is categorized as two different seasons. The first season is rainy or wet season, starting November to March, and also started from west to east. The second a long season which is the dry season that beginning from the April and the end of the October even as the island is exposed to the shallow low pressure which extends through from the mainland depression center over the Asia. On other way, in the coastal parts of the local sea-wind circulation is commonly very resilient due to the large degree of difference heating system between the sea and land(Redfern et al, 2010).

2.3 Availability of Renewable in North Cyprus

Most kinds of asset must be accessible, specialized and ecological issues likewise assume a crucial job sustainable power source asset have genuinely settled innovations and their misuse depends primarily on the happening financial matters that apply for the specific site being referred to While satisfactory in the task's feasibility and manageability.

So as to have the option to analyze diverse sustainable assets, a shared factor or a typical base should be made. On this premise all out capital cost, land costs and accessible regular asset are utilized for correlation. Notwithstanding wind and sun powered vitality sources, there is a tidal potential. This has been evaluated by the investigations directed by Barker and it has reasoned that locales which have a mean range surpassing 3m can be misused. Moreover, Barker has built up that none of this potential exists in the Eastern Mediterranean.

Absence of waterways with noteworthy yearly streams additionally adheres to a meaningful boundary under the hydropower opportunity in Cyprus. Geologically there are no geothermal assets, where warmth put away in shake is passed on to the surface by methods for liquids and steam, is existing in Cyprus.

On second way, obviously two main renewable resources, solar and wind are energy based oriented, are expressly accessible and misused in Cyprus.

2.4 Wind Energy in Future 2050

Today wind vitality has accomplished a worldwide entrance level of around 4%. Improvements in worldwide and national arrangements, innovative advancements and worldwide natural and vitality security concerns demonstrate that these infiltration levels will get upgraded fundamentally. There are numerous urban areas and nations that have promised to 100% sustainable power source framework, in which clearly wind will be a significant segment with hydro and sun based. The power lattice itself and its administration practice will advance around engrossing greatest breeze control into the framework, while holding solidness in power framework and power supply (World Wind Energy Association, 2015).

2.5 Wind Power Growth

Exponential development in wind control advancement over the world, especially over the most recent couple of years, has led to wind vitality involving a conspicuous position in the power segment. Proceeded with techno-sensible improvement and development in structure and assembling has brought about wind turbines being sent on a huge scale in inland tasks and to a critical degree in seaward undertakings. Today with wind contributing almost 4% of by and large power age, 393 GW of introduced age limit and sending in more than100 nations (Source: WWEA, 2015).

Over the most recent couple of years, wind and sun-based vitality have developed as a standard vitality choice for the lattice and so as to assimilate characteristically fluctuating vitality from these sources, the customary power framework it-self needs to experience an demonstrative change.

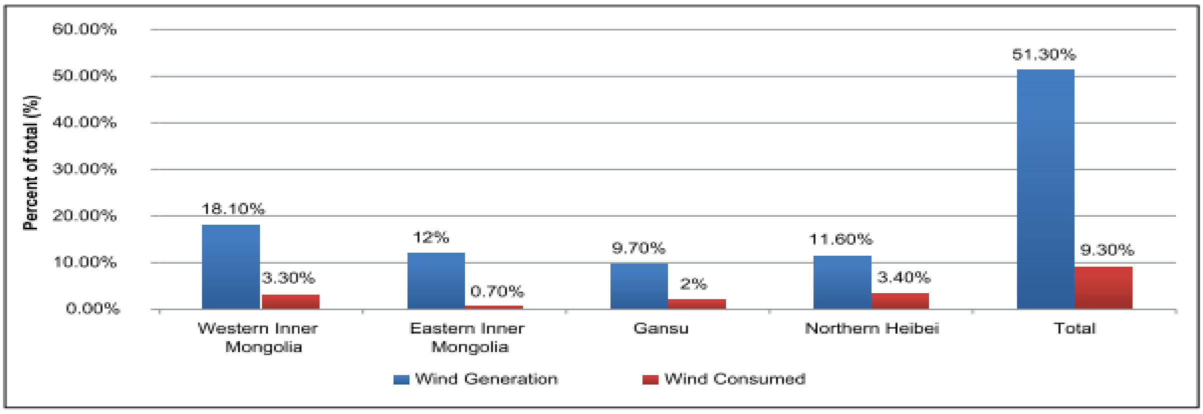

Figure 2.1: Wind power generation Vs Consumptions of the wind produced electricity in 2050 (WWEA, 2015)

2.6 Review on Different Predictive Tools for Wind Speed Prediction

Artificial neural networks are in effect way of the predict, modeling of the complex and purpose of the problem's approximation. Good effectiveness more exactly when a parameters elaborates are the non-linear in the nature of the main advantage of ANN application(Mohsin, 2019).Predicting of the wind speed and its direction in specific sites is an significant part of operating the weather forecasting and has numerous applications in the different areas including traffic, energy, logistics and planning, and e.g. for the emergency response(Jan Platoš et al., 2017).Three machine learning algorithm models are used to applied the predicted the wind direction , wind speed and the output of the wind turbine power (Khosravi et al., 2018).

In Ercan district in Northern Cyprus by applied four predictive tools such as Auto Regressive Integrated Moving Average, Radial Basis Function Neural Network and Multilayer Perception Neural Network are using to predict the wind power density (Kassem et al., 2019). Studied the performance of forecasting of Artificial Neural Networks and Auto-Regressive Integrated Moving Average models are used for predicting the wind speeds in four areas of in Northern Cyprus (Kassem et al., 2019). By Using the Artificial Neural Networks Model Created on Several Local Mensuration to predicted the wind speed in the Eskisehir cities (Filik et al., 2017).

Today, the application of the artificial neural networks (ANN) in order to advance the prediction models are becomes very motivating in research areas and in instruction to predicted wind speed is noted by (Marović et al., 2017). Two diverse NN models were created utilizing perceptions and numerical weather prediction (NWP) information as input. The interim based NN (iANN) approach out performed the NWP models and Modes output statistics (MOS) based predict and had the capacity to replicate the perceptions at 25 delegate Austrian observation Locations (Schicker et al., 2017).

ANFIS is a hybrid artificial intelligence method utilizes the parallel calculation ability of artificial neural networks and estimation of the fuzzy logic.Implementation of the Machine learning algorithms are including support vector regression (SVR),multilayer feed-forward neural network (MLFFNN), fuzzy inference system (FIS), adaptive Neuro-fuzzy inference system (ANFIS), collections of method of data supervision to predicting the wind speed data for Osorio wind farm that is founded near the Osorio city in south of Brazil (Khosravi et al., 2018). Suggest a double phase categorized adaptive Neuro-fuzzy inference system (double-phase hybrid ANFIS) for a micro grid wind farm short-term wind power prediction of in Beijing, China. Adaptive Neuro-fuzzy inference system phase engagements numerical weather prediction of meteorological elements to forecast the wind speed at the wind farm exact location and turbine hub height. A second phase models the real wind speed and the power interactions (Zheng et al, 2017).

A hybrid technique linking ensemble practical mode of decomposition, Adaptive Neural network centered fuzzy inference system (ANFIS) and seasonal auto-regression integrated moving average (SARIMA) are explained for short-term wind speed estimating (Zhang et al. 2017). At present studies by used the combination of the (FFANN) and (ANFIS) the methods are selected to be linked in an adaptive approach. This arrangement can be one of the most of accurate contestants for the hourly predicts and the system gives significantly low prediction inaccuracies in expressions of three dissimilar error trials (Okumus et al., 2016).

A short-term of wind power predictions model are suggested based on improved support vector machine method, data mining technology and on wavelet transform method. In this model, data mining is engaged to investigate the correlations between the wind speed and wind power output results and then adjust the unacceptable original data (Liu et al ., 2018). Intensive determination for extra accurate forecasts and shows the current improvements outstanding to the advanced machine learning methods focuses on numerical prediction methods (Dinler et.al, 2016).

A comparative predicting approach based on soft computing techniques are recommended to improve the prediction of the short-term wind speed at different heights 30m ,50m, and 60m by utilize algorithms of the (ANFIS) and (MLPNN) to prediction wind speed with lowest errors (Korkmaz et.al., 2018).

Statistical prediction two approaches based on time-series models such as autoregressive and moving average models and soft computing models (such as artificial neural networks, fuzzy logic) models are used to predicted the wind speed prediction for wind power plants in China (Korkmaz et al., 2018). The Wind Power Predictive Tool is a statistical model advanced by Technical University of Denmark and it contains of the semi-parametric power curve model for wind farms enchanting into justification for both direction and wind speed (Svensson, 2015). An optimal neural network predictive tool based on two approach of Adaptive Neuro-Fuzzy Inference System (ANFIS) models are evaluated and tested the prediction of time horizon (Dragomir et.al. 2015). The intelligent ensemble neural model based wind speed predicting is designed by be an average of the predicted results from multiple neural network models such as back propagation neural network, multilayer adaptive linear neuron, multilayer perceptron (MLP) and probabilistic neural network so as to get better accuracy in wind speed prediction with least error (Ranganayaki et al., 2016). By using three machine learning models such as (SVR) with the a radial center function, (MLFFNN) that is educated with the diverse data of the training procedures, and (ANFIS) that is adjusted with the a partial swarm of the optimization system (ANFIS-PSO) by considered Temperature, relative humidity, pressure, and local time are used as input variables for the models are applied to predict the wind directions, wind speed and the output of the wind turbine power (Nunes et al., 2018).

Wind speed or wind control predicting stage a significant job in substantial scale wind control infiltration because of their vulnerability. Support vector relapse, broadly utilized in wind speed or wind control estimating, goes for finding common structures of wind variety covered up in recorded information. Most present relapse calculations, including least squares bolster vector relapse (SVR), accept that the clamor of the information is Gaussian with zero mean and a similar difference. Nonetheless, it is found that the vulnerability of transient breeze speed fulfills Gaussian conveyance with zero mean and heteroscedasticity in his works. Furthermore, its present the stochastic slope descent (SSD) strategy to explain the proposed model, which drives the models to be prepared on the online. At last, it uncover the vulnerability properties of wind speed with two facts in world datasets and test the proposed of algorithms on these information(Member et al, 2016).Currently, two methods used for wind power prediction are physical and statistical models are Considering the meteorological system of physical mechanism, physical models applied to atmospheric motion formula to calculate future value of meteorological parameters, then prediction of the wind power based on some predicted meteorological element (e.g. wind speed). The physical model is based on statistical weather prediction, which is predict the wind speed then convert to wind speed into equivalently to wind power (Ouyang et al, 2019). Presented a novel hybrid methodology for short-term wind power predicting, successfully combinations of three individual predicting models using the back propagation neural network (BPNN), adaptive Neuro-fuzzy inference system, least squares support vector machine (LSSVM)and radial basis function neural network (RBFNN), are selected as the individual predicting model (Wang et al., 2017).

There are three different paradigms in wind speed prediction such as physical, spatial correlation; and statistical (also called data-driven). The physical model attempts to estimate wind flow around and inside the wind farm using physical laws governing the atmospheric behavior. However, the temporal and spatial resolutions are usually enough for wind power forecasting. Spatial correlation models consider the spatial information of the wind speed from remote measurement stations (Hu et al., 2016).

Focuses around the issue of improving of the extreme the wind speed prediction for areas with just for short time series arrangement of estimated values accessible, allowed the chance to utilize a profoundly associated long time arrangement of wind speed information. For this reason, a productive exchange of data is fundamental between two exceptionally corresponded stochastic procedures. To delineate the productivity of the proposed procedure, two arrangements of two very associated time arrangement of wind speed information are utilized in Norwegian wind speed estimation presented by (Gaidai et al., 2019). The most significant three decomposing algorithms are Wavelet Packet Decomposition, Wavelet Decomposition, Empirical Mode Decomposition and a most recent decomposing algorithm Fast Ensemble Empirical Mode Decomposition are all adopted to recognize the wind speed highest accurate predictions with two demonstrative networks (Multilayer Perceptron Neural Network/Adaptive Neuro-fuzzy inference system Neural Network (Tian et al.,2015).

A new hybrid model is proposed for the model combination of extreme learning machine with improved corresponding the ensemble empirical mode disintegration with adaptive noise (ICEEMDAN) and autoregressive integrated moving average (ARIMA) short-term wind speed predicting errors for wind farms in China (Wang et al., 2018). To implement the researchers have been developed the multiple significant estimating methods, which can be separated into four classifications: (1) physical methods (2) machine- learning methods, (3) statistical methods, and (4) hybrid methods are used time horizons of short term and long term predictions of wind speed forecasting (Lili et al., 2018). Applied hybrid model of the artificial bee colony algorithm-based relevance vector machine and wavelet decomposition is offered for the wind speed prediction (Fei et al.,2015). To investigate the forecasting architecture based on a new hybrid decomposition technique and an improved flower-pollination algorithm-back propagation neural network prediction algorithm Proposed model, the wind speed data collected from two different wind farms in Shandong, China were used for the future wind forecasting (K. Zhang et al., 2019).

To demonstrate the efficiency of the two proposed methods, they are linked with the classical echo state networks (ESN) and with adaptive Neuro-fuzzy inference system (ANFIS). This methods are based on the nonlinear relations between the tested with direction data and wind speed forecasting provided by the Nevada department of transportation (NDOT) roadway meteorological stations in the Reno, NV Locations (Chitsazan et al., 2019).Based on the planned filtering approach, a combination of the predictor such as SVR + SDA + UKF (Support Vector Regression + Stacked De-noising Auto- encoder + Unscented Kalman Filter) are proposed and validated to ensures the short-term prediction accuracy of wind Speed prediction plays most important part in the wind farm maintenance and operation(Chen et al., 2018). Presents a new hybrid multi-objective model which is the combination of variation mode decomposition (VMD), Multi- kernel robust ridge regression (MKRR) and a multi-objective Chaotic water cycle algorithm (MOCWCA) are applied to estimate the wind speed and wind power prediction interval nominal confidence levels (PINC) of 80%, 85%,90% and 95%, respectively (Naik et al., 2018).

Applied to hybrid numerical climate expectation model and a Gaussian procedure regression (GPR) show for close surface wind speed forecast up to 72h ahead utilizing information partions on environmental solidity class to improve demonstrate execution. output demonstrate the GPR show improves gauge precision over the actual Numerical Weather Prediction data, and thought of climatic stability of further diminishes forecast error (Hoolohan et al., 2018.To present the Hybrid models contain a combination of the time series models (with the exogenous parameters of pressure, precipitation and temperature as inputs) with artificial intelligence to providing accurate wind speed monthly average forecasts in the Brazilian Northeast region (do Nascimento Camelo et al., 2018).

Two preprocessing techniques are proposed for the simulations shown that the hybridization of preprocessing and Pattern Sequence based Forecasting (PSF) techniques has essentially outperformed other best approaches for short time term wind speed forecasting (Bokde et.al., 2018). Proposed the two models have been the widespread techniques in modern periods are Statistical methods (includes, Auto- Regressive Integrated Moving Average (ARIMA) and hybrid methods (includes, Wavelet Transform (WT) based ARIMA (WT-ARIMA) model presented for short-time and very short-time predicting of the wind speed (Aasim et al., 2019). Using Multi-layer perceptron (MLP) and Generalized Regression Neural Network (GRNN) in 67 cities of India was predicted the wind Speed (Kumar & Malik et al., 2016).

Employed the proposed of the novel approach or method by using the nonlinear-Learning of the deep learning of the ensemble of the prediction of the time series constructed on the LSTMs (Long and Short Period prediction of the wind speed by using the Memory of neural networks), (Support vector regression machine)SVRM and EOA(Extremal optimization algorithm) on two case studies data collected from a wind farm in Inner Mongolia, China(Chen & Zhou et al., 2018). For forecasts beyond the hour-ahead, methods such as artificial neural network (ANN), genetic algorithms (GA), random forest approaches, and hybrid methods combining ANN with GA are now widely used. A time-based interval estimating of method for wind speed was established using (FFNN) using combination of the observation and the NWP data as used input (Schicker et al., 2017).

Currently, numerous analysts and utilities have enthusiasm for wind speed expectation of examinations. These wind speed estimating methods are characterized into three kinds as pursues: physical methodology, statistical methodology, and hybrid method. Physical methodology uses the past data got from climate stations, for example, power and Numerical Weather Predictions (NWP). It is appropriate for long time forecasting as demonstrating of these are unpredictable. Statistical methodology, for example, autoregressive moving normal (ARMA) demonstrate, variations of ARMA and artificial neural system (ANN) models will utilize recorded time-arrangement information for displaying and estimating the future results (Santhosh et al., 2018).

CHAPTER 3
METHODOLOGY

3.1. Description of the study locations

Four locations taking illustrious the geographical backgrounds were measured in this study. Moreover, Turkish Republic of North Cyprus map is existing in the Figure 3.1 four selected locations showing in obvious way. The department of Meteorological in Lefkoşa, provided each location of the data. The data were collected from through the different locations are demonstrated below in Table 3.1.

Table 3.1: Summary of data uses for studied locations

Data of four Locations of North Cyprus are used for the Studied					
S.N	cities	Longitude	Latitude	Long(Deg)	Lat(Deg)
1	Gazimağusa	33°56'20.18"E	35°7'13.94"N	33.989	35.1554
2	Girne	33°19'2.24"E	34°7'49.30"N	33.323	34.2536
3	Güzelyurt	32°59'36.17"E	35°11'55.28"N	33.0838	35.3369
4	Lefkoşa	33°21'51.12"E	35°10'31.12"N	34.492	35.2531

Figure 3.1: The map of the studied location of North Cyprus

3.2. Weather Data Source

The meteorological data that used for this thesis have been collected from Department of meteorological office, North Cyprus over the region four selected cities. The dataset had Seven (7) attributes containing monthly averages data. In this study only the most influencing variables (maximum Temperature, Minimum Temperature, difference of Temperature, average Temperature, wind speed and sunshine and solar radiation) that effect on the long-term wind speed prediction out by above variables was used.

3.3 Predictive Tools

3.3.1 Artificial Neural Network Model

ANN is one of the Artificial Intelligence based that follows works as the function of the human nerve system. ANN model's application become different predictable techniques are used in wind speed predictions. ANN model has the competence for any linear and non-linear systems. ANN design generally contains input, hidden and output layer, which is connected of the weights and the biases, summation of node and activation function.

ANN functions are separated into two phases: generalization and learning stage. The learning methods are separated into managed, unsupervised, strengthening and developmental learning. The Neural networks preparing or training which is the end goal that specific information leads a particular target results or output. The system output coordination of the objective and the Mean Square Error is resolved or adjusted. MSE is determined or decides the carrying out of the system. According, to the mean square of the errors. The learning procedure is ended when the MSE values is become small.

3.3.1.1 Data Normalization

One of the steps of data pre-processing is data normalization could useful. For example, it might improve the accuracy and efficiency of taking out algorithms involving distance measurements. The need to make coordination and balance between data, data must be normalized between 0 and 1. (Eq. 3.1) were used to normalize our dataset.

$$\mathrm{Xn} = \frac{Xactual - Xmin}{Xmax - Xmin} \tag{3.1}$$

$$\mathrm{Xactual} = Xn\,(Xmax - Xmin) + Xmin \tag{3.2}$$

Where

X is actual data and X_{min} is minimum value of original attribute’s values and

X_{max} is maximum value of original attribute’s values

According, to (LVM) optimization. The back-propagation algorithm which is used as the learning and its algorithm gradient descent. The gradient descent which is calculated by the feed forward propagation networks for the nonlinear of multilayer. The activation function for neurons can be linear or non-linear. A sigmoid function is used as activation function whose output lies between 0 and 1 and is defined as.

$$\text{Log sigmoid function } (fx) = \frac{1}{1 + e - x} \tag{3.3}$$

3.3.1.2 Procedure for the development of model

Designs were repetitive for a period of Nine years (2009 to 2017). Data of seven years (2005 and 2015) were used to train the Artificial Neural Network and two-year (2016-2017) data was used for validation determination.

Seven parameters were used as inputs for the model development considered and the inputs are average temperature,(avT) minimum temperature (Tmin) difference of temperature (DT),maximum temperature (Tmax),wind speed(Ws) Sunshine (Ss),and Solar radiation (Gsr) are measured input parameters values obtained from different four stations in North Cyprus at Gazimağusa, Girne, Güzelyurt and Lefkoşa. the seven parameters data are readily available for their Locations.

Table 3.2: Test condition for followed for this study

Network Name	Feed forward Propagation
Training function	TRAINLM
Function of the Adaptive learning	LERARNGDM
Function of the Performance	MSE
Number of Inputs	Varied from 1 to 7
Number of the Output	1
Number of hidden	2
Number of the hidden neurons	Vary from 2 to 20
Transfer function	Log sigmoid

3.3.1.3 **Wind speed prediction by ANN model**

seven conditions of the combinations are considered in the model developed using Artificial Neural Network. based on combination of the inputs, the ANN models were namely as the ANN-1 model up to ANN-6 model as presented in Table 3.3. ANN-1 and ANN-6 represent that one input and six inputs were used for training of the ANN models respectively. The input data such as the daily minimum temperature (Tmin), daily maximum temperature (Tmax), difference of maximum and minimum temperature (Tmax -Tmin =DT), Wind speed (Ws) Sunshine (Ss), and solar radiation

(Sr) were used for making different possible combinations (total **30** combinations) to train the ANN. The target for ANN model were used monthly wind speed data. Best ANN model is identified with the help of the statistical tools adjusted and are compared with the proposed ANN models. The models considered are given by Table (3.3). The leaning algorithm tested is feed forward propagation, the most used.

Table 3.3: Combination Different Inputs for ANN Model

Model Inputs	Combination of The Input parameters	Name of Model
Model One	Tmin Tmax Gsr avT Ss Nm DT	ANN-1
Model Two	Tmin, Tmax Gsr, avT DT, Gsr DT, avT DT, Ss DT, Nm Ss, Gsr	ANN -2
Model Three	DT, Tmin, Tmax, Tmin, Tmax, Gsr Tmin, Tmax, avT Tmin, Tmax, Ss Tmin, Tmax, Nm DT, Ss, Gsr	ANN-3
Model Four	Tmin, Tmax, Gsr, avT Tmin, Tmax, DT, Gsr Tmin, Tmax, avT, DT Tmin, Tmax, DT, Ss Tmin, Tmax, DT, Nm	ANN-4
Model Five	Tmin, Tmax, DT, avT, Gsr Tmin, Tmax, DT, Nm, avT Tmin, Tmax, DT, Ss, avT Tmin, Tmax, DT, Nm, avT	ANN- 5
Model sex	DT, Tmin, Tmax, Nm, avT, Ss, Gsr	ANN- 6

Table 3.4: Ranges of Root Mean Square Error to analyze the ANN models Performance (Rao K, Premalatha, & Naveen., 2018)

Range of RMSE	Performance
< 10%	Excellent
10% < RMSE < 20%	Good
20% < RMSE < 30%	Fair
> 30%	poor

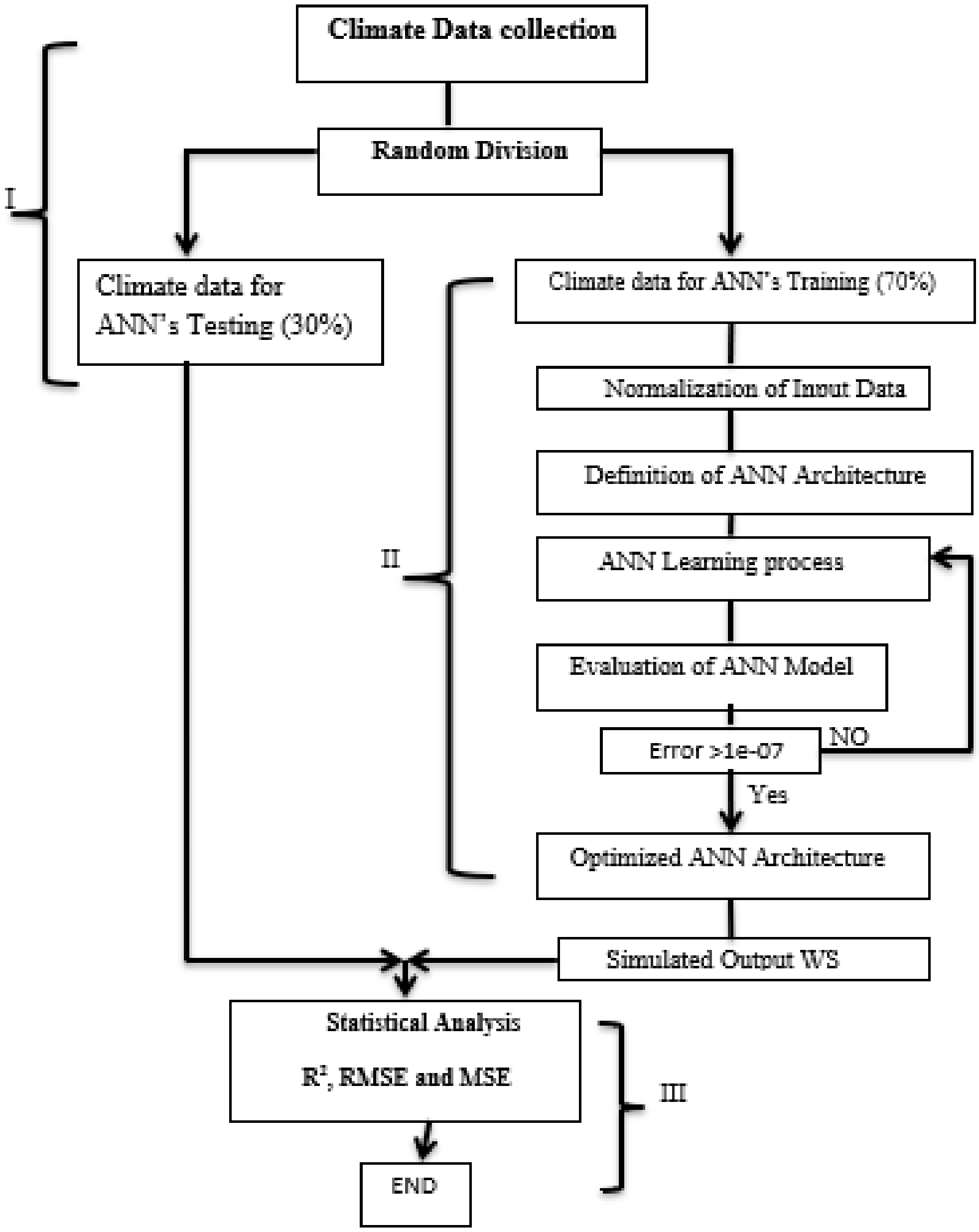

Figure 3.2: Flow chart for ANN Model steps predicting wind speed

3.3.2 Multiple Linear Regression Model

MLR is a well-known mathematical method modeling to produce a linear correlation between the one or more dependent and independent parameters or variables. The variables of independent parameters that are used to calculate the dependent variables or outcomes.

Generally, y is the variable of dependent and n is the regression of variables. This model is defined as the n regression expressed as follows as

$$y = \mathbf{b_0} + \mathbf{b_1 x_1} + \mathbf{b_2 x_2} + \mathbf{b_3 x_3} + \cdots + \mathbf{b_i x_i} \qquad (3.4)$$

Where,

X_i = values of the i^{th} Predictors

b_o = constants of regression

b_i = is the coefficient of the i^{th} predictors

3.3.3 The Response Surface Methodology Model

(RSM) is a composing of the mathematical approaches, statistical interpretation and investigational strategies, which was working for the mathematical demonstrating and investigative engineering complications, where a lot of the parameters or variables, influence the response of the apprehension or concern. RSM is as well defined as a statistical performance, which works the quantitative of data commencing the proper investigates, to create and the concurrently resolution of the equations of multi-variable. The investigational design to associated by RSM is worked for the depicting of the variation of the inputs independent variables, and the model of empirical the mathematical method helps to examine an proper Predicting connection among with output or predicted responses and the variables of the input data, and estimate the influence of the independent parameters on the selected variable response and optimization procedures for the accomplishing of the best value of possible result for the development of the specifications, which makes the suitable value of the output responses results.

A proposed the second order of the model supports in Predicting accurate response a section surface with the parabolic curving. During seconder order model contains all expressions that originate in first order linear model beside over the quadratic expressions like $\boldsymbol{\beta_{11} x^2_1 i}$ and cross the product expressions like $\boldsymbol{\beta_{18} x_1 i x_8 j}$.It is generally expression as

$$y = \beta o + \sum_{i=1}^{n} \beta i x i + \sum_{i=1}^{n} \beta i i x i^2 + \sum_{i}^{n-1} \sum_{i=i+1}^{n} \beta i j x i x j + \varepsilon \qquad (3.5)$$

Where,

y is Represents the predicted response;

βo is the offset term; β_i is the linear coefficient;

the second-order coefficient and β_{ij} is the interaction coefficient;

x_i and x_j are the independent variables

The 2nd order proposed model is able to being transformed into the different well-designed forms and the locally prediction of response; therefore, it competently predicts the accurate response.

3.3.3.1 Design of the experiments (DOE)

DOE is one of the universally engaged in many Science of fields it supports, such as, reducing the experiments number that necessary to stand the accomplished. The (CCD), for instance one of the Response Surface Methodology proposal, was the introduced for two levels objective by employing of all factor and accordingly with the conventional experimental number of a points. The work of the Central Composite Design must be controlled to the condition, which is not too extreme in predicting strong responses. Additionally, this design of proposal is rotatable, its meaning that the model creates a constant circulation of rationally scaled for the prediction variation of the accurate experimental value of the design area. The significant development of Parameters for response surface methodology that to impacts on predicting the wind speed Variables are: Minimum Temperature, Maximum Temperature, Global solar radiation. Average Temperature, difference of Temperature, Sunshine, wind speed and Number of Month were used. RSM is used to advanced mathematical modeling and the analysis of statistical of the interaction of the Parameters to conduct the response by Minitab Software.

CHAPTER 4
RESULTS AND DISCUSSIONS

As the planned methodology comprehend in three sections, the results of the proposed models are similarly Presented in three parts as (i) Focusing the Analysis of Sensitivity on the influence of each parameters on Wind Speed. (ii) Application of three proposed models, one Artificial Intelligence based on nonlinear and two mathematical method of models are utilizing different parameter input of the combination models to predicted the Wind Speed (iii) Finally, each proposed model method results are provided to evaluate the development in performance that might be accomplish over developed models. The measured and predicted values of the Wind Speed Prediction for the City of Güzelyurt, Gazimağusa, Lefkoşa, and Girne in North Cyprus the results of the developed ANN model are shown in Tables and graph plots are below in each Part of results provided.

4.1 Analysis of Sensitivity Results

The most Significant tasks of any Artificial Intelligence dependent on selection of the modeling is the most influential input variables. To get optimum outcomes, the most influential variables ought to be incorporated in the layer of input while superfluous and the less successful variables ought to be disposed. In perspective on this, a neural system based- the analysis of sensitivity was employed to investigate the major input of parameters for the wind speed predicting models developed over selected area of North Cyprus. According the outcomes of in training, testing and validation of each models are shown in tables. seven parameters were engaged with the investigation containing Tmin,Tmax,avT,DT,Gsr,Ss,and Number of months were used.

4.2 Results of The Models (ANN, AND MLR, RSM)

Under this part, the outcomes of the one Artificial intelligence-based methods (ANN) and two mathematical approach (MLR and RSM) models are provided for the wind speed prediction for four selected cities of North Cyprus regions using the different combinations of input dependent on the analysis of sensitivity presented.

ANN where using the Levenberg-Marquardt Algorithm to train with the hidden layer and different number of the neuron used for the wind speed simulation. Determination of the hidden layer of the minimum nodes number by using the trial and error techniques for each model.

The MLR and RSM models which are expresses in linearly the correlation between the independent parameters and the dependent variables was used for this thesis work as well manner.

4.2.1 Wind speed prediction based on developed ANN models for Güzelyurt

4.2.1.1 ANN-1 model

For this model there are seven input variables selected, individually inputs are each applied to the artificial neural network named as ANN-1 Model. Identification of effects of each input on the Monthly average wind speed prediction has obtained. By training developed to get best performance of the network of ANN-1 model to shown until reach the mean square error show small value. Form the predicted value result, all inputs the [Tmin] has given good prediction Wind speed values and the best predicted value has obtained in [DT] input parameter. The statistical tools of training and testing performance of ANN-1 model shown in Table (4.1) below.

Table 4.1: Statistical tools of Training Performance for ANN-1Model

Performance of ANN Model Results of Güzelyurt Area						
ANN-1inputs		**MSE**	**R^2**	**No,of neuron**	**No, of hidden Layer**	**Function**
Tmin	Training	0.00111	0.72559			
	Testing	0.00945	0.74030	5	2	

Table (4.1): Continued

Tmax	Training	0.00107	0.73033	4	2	
	Testing	0.00957	0.72139			Training (TRAINLM)
Gsr	Training	0.00106	0.74732		2	Adaptive Learning
	Testing	0.00806	0.77173	8		(LEARNGDM)
avT	Training	0.00103	0.72755			Transfer
	Testing	0.00940	0.74939	6	2	(Log sigmoid)
Ss	Training	0.00858	0.77995			
	Testing	0.00135	0.71089	8	2	
Nm	Training	0.00123	0.60605			
	Testing	0.00145	0.60259	10	2	
	Training	0.00115	0.65335	12	2	
DT	Testing	0.00146	0.61244			

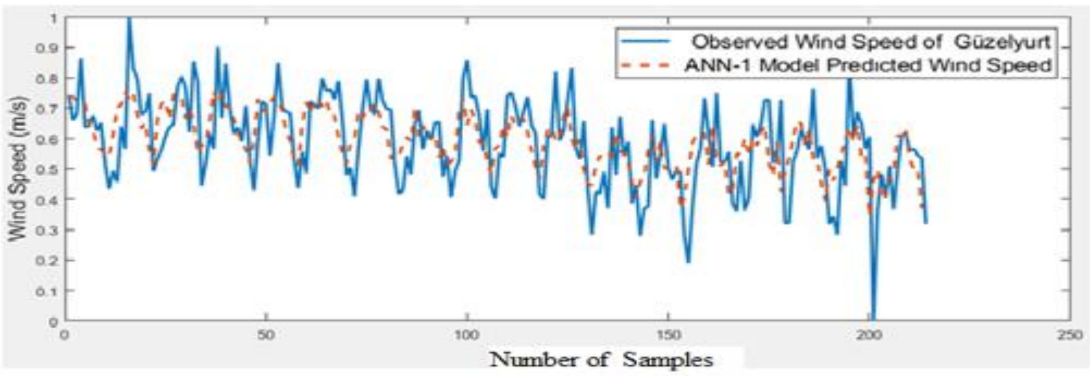

Figure 4.1: Diagram for Güzelyurt Observed with best Predicted wind speed by ANN-1 Model

4.2.1.2 ANN-2 model

Seven combinations at ANN-2 model are formed with two inputs variables and each of combination of the inputs variable on monthly wind speed was known. All combination of formed the artificial neural network trained combination of [Tmin,Tmax] has given results better prediction of the wind speed and the combination of [DT,Ss] have obtained the higher accuracy predicted error value is 2.253. The combination of [DT, avT] has best prediction combination with accurate error value. The statistical tools of training and testing performance of ANN-2 has shown in Table (4.2) below

Table 4.2: Statistical tool's Training performance for ANN-2 Model

Performance of ANN-2 Model Resuts for Güzelyurt						
ANN-2 Inputs		MSE	R^2	No,of neuron	No, of hidden Layer	Function
Tmin ,Tmax	Training	0.0098	0.7452	4	2	
	Testing	0.0083	0.7217			
Gsr,avT	Training	0.0089	0.7920	6	2	Training
	Testing	0.0073	0.7574			(TRAINLM)
DT,Gsr	Training	0.0091	0.7707	4	2	Adaptive
	Testing	0.0090	0.7399			Learning
DT,avT	Training	0.0092	0.7773	6	2	(LEARNGDM)
	Testing	0.0076	0.7491			Transfer (Log sigmoid)
DT, Ss	Training	0.0096	0.7495	7	2	
	Testing	0.0011	0.7336			
DT,Nm	Training	0.0099	0.7060	6	2	
	Testing	0.0011	0.7327			

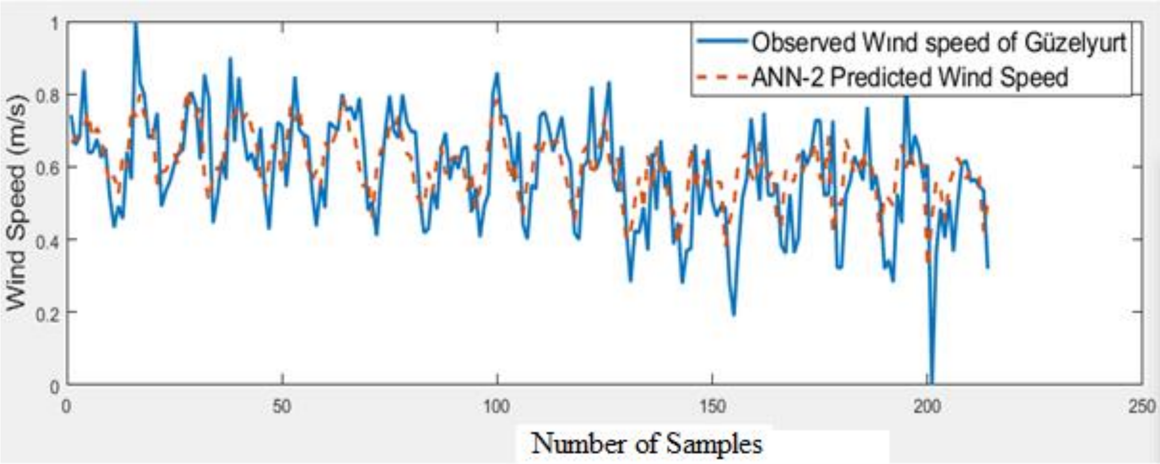

Figure 4.2: Diagram for Güzelyurt Observed with best predicted wind speed by ANN Model

4.2.1.3 ANN-3 model

For this model of artificial neural network three trained with the combinations of [Tmin,Tmax,Ss]and[DT,Ss,Gsr] have given same results of prediction values obtained and good accuracy of predicting . The combination of [Tmin,Tmax,avT] has best combination of prediction of wind speed with predicted error accuracy value and also the combination of [Tmin,Tmax,Nm] has produced the highest accuracy error value 1.2994 obtained. The statistical tools of training and testing performance of ANN-3 has shown in Table (4.3) below.

Table 4.3: Statistical tool's performance of Training of ANN-3 Model for Güzelyurt

Performance of ANN-3 Model Results of Güzelyurt						
ANN-3 Inputs		MSE	R^2	No,of neuron	No, of hidden Layer	Function
Tmin,Tmax,DT	Training	0.0099	0.757	2	2	

Table (4.3): continued

	Testing	0.0080	0.748			
Tmin,Tmax,Ss	Training	0.0081	0.789	4	2	
	Testing	0.0080	0.7492			
TminTmax, avT	Training	0.0097	0.7600	6	2	Training (TRAINLM) Adaptive Learning (LEARNGDM) Transfer (Log sigmoid)
	Testing	0.0089	0.796			
Tmin,Tmax,Nm	Training	0.0096	0.767	8	2	
	Testing	0.0092	0.757			
Tmin,Tmax,Gsr	Training	0.0090	0.778	10	2	
	Testing	0.0083	0.720			
DT,Ss,Gsr	Training	0.0092	0.780	14	2	
	Testing	0.0076	0.811			

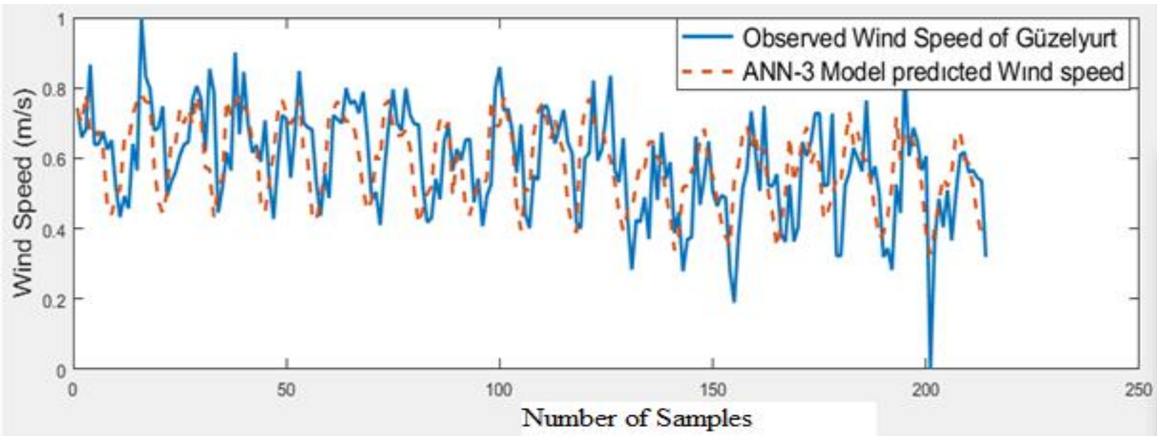

Figure 4.3: Diagram for Güzelyurt and best predicted wind speed by ANN-3 Model

4.2.1.4 ANN-4 model

For this model the totally six combination were formed four input parameters to train and validation of the artificial neural network named as ANN-4 model .The artificial neural network four trained with possible combination of [Tmin,Tmax, DT,avT] have the best prediction results shown and the combination of [Tmin,Tmax,DT,Nm] has produced highest prediction accuracy error value is 1.146 obtained.

The combination of [Tmin,Tmax,Gsr,avT]and[Tmin,Tmax,DT,Gsr] have obtained the similar prediction wind speed results shown. The statistical tool's performance results shown in Table (4.4) below.

Table 4.4: Statistical tool's performance of Training of ANN- 4Model for Güzelyurt

Performance of ANN-4 Model Results of Güzelyurt						
ANN-4 Inputs		MSE	R^2	No,of neuron	No,of hidden Layer	Function
Tmin,Tmax,Gsr, avT	Training	0.009	0.753	2	2	Training (TRAINLM) Adaptive Learning (LEARNGDM) Transfer (Log sigmoid)
	Testing	0.007	0.741			
Tmin,Tmax,DT,Gsr	Training	0.009	0.767	4	2	
	Testing	0.007	0.752			
Tmin,Tmax,DT, avT	Training	0.009	0.792	6	2	
	Testing	0.007	0.762			
Tmin,Tmax,DT, avT	Training	0.008	0.775	8	2	
	Testing	0.007	0.774			
Tmin,Tmax,DT, Nm	Training	0.009	0.751	10	2	
	Testing	0.009	0.791			

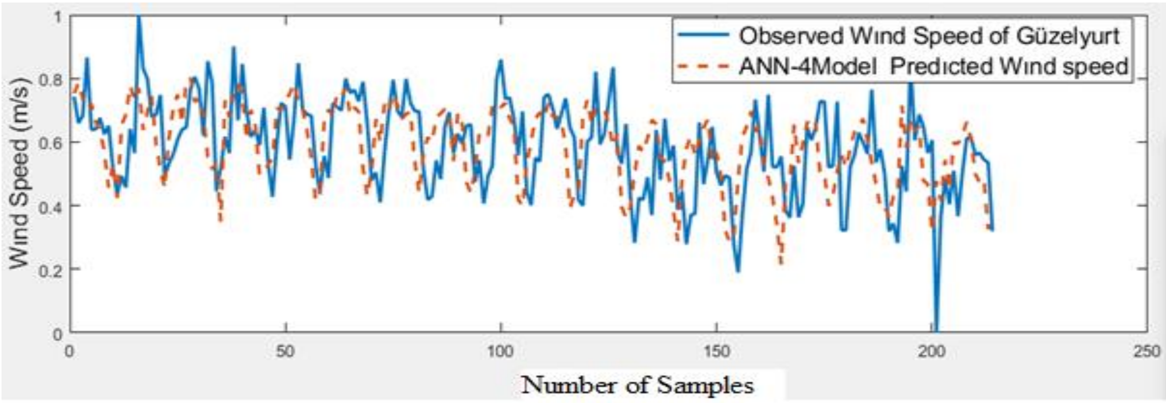

Figure 4.4: Diagram for Güzelyurt Observed with best predicted wind speed by ANN-4 Model

4.2.1.5 ANN-5 model

Total five possible arrangements were formed with different five input parameters to train and validation of the artificial neural network names as ANN-5 Model. The artificial neural network five model trained with the variables combine of [Tmin, Tmax,DT, Gsr,avT] this combination has given best predicted wind speed results shown and another combination inputs of [Tmin,Tmax,DT,Nm,avT] has produced results shown the highest values of Accuracy Error is 1.4594 obtained. The Statistical tool's performance and graphic results shown in Table (4.5) below.

Table 4.5: Statistical tool's performance of Training of ANN-5 Model Güzelyurt

Performance of ANN-5 Model Results of Güzelyurt						
ANN-5 Inputs		MSE	R^2	No,of neuron	No,of hidden layer	Function
Tmin,Tmax DT,avT,Gsr	Training Testing	0.008 0.008	0.78 0.73	2	2	Training (TRAINLM Adaptive Learning (LEARNGD M) Transfer (Log
Tmin,Tmax DT,Nm,aT	Training	0.008	0.78	4	2	

Table (4.5): continued

	Testing	0.009	0.76		
Tmin,Tmax	Training	0.009	0.78	6	2
DT,Ss,avT	Testing	0.008	0.77		
Tmin, Tmax,DT,	Training	0.009	0.77		
Gsr, avT	Testing	0.007	0.727	8	2

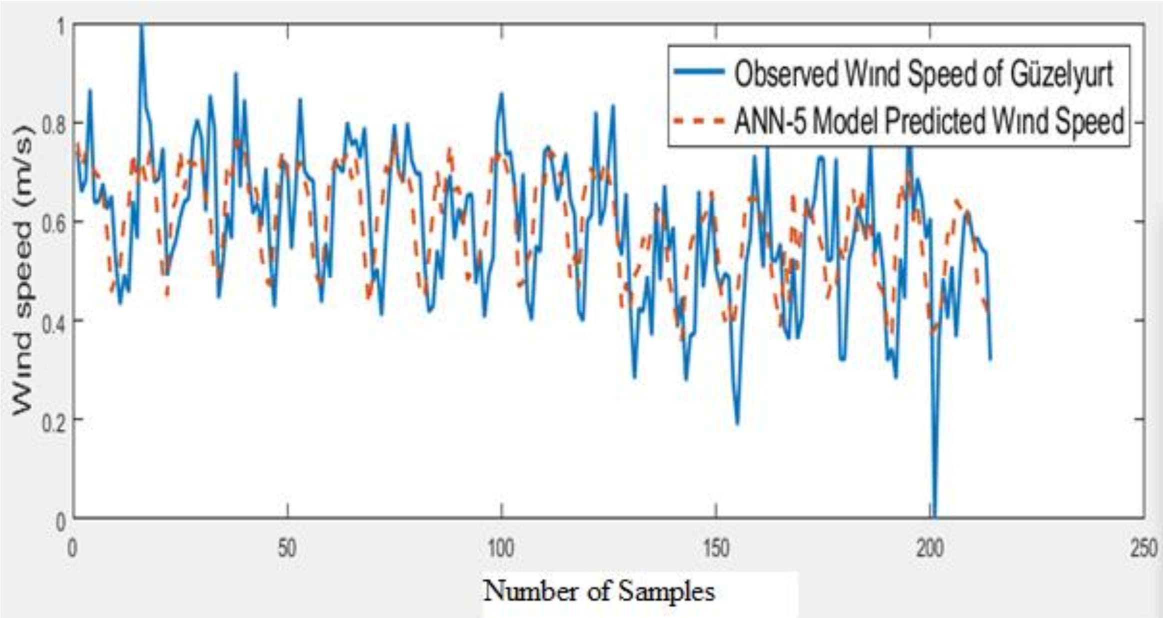

Figure 4.5: Diagram for Güzelyurt observed Wind Speed and best predicted Wind Speed by ANN-5 Model

4.2.1.6 ANN-6 model

This artificial neural network (ANN-6) model of all eight input parameters are applied to trained, test and validation of the ANN it named as ANN-6. The ANN-6 model shown results prediction accuracy error value is 0.71435. During the train and testing the statistical tool's performance results are shown Table 4.6 below.

Table 4.6: Statistical tools Performance Training of ANN-6 model for Güzelyurt

Performance of ANN-6 Model Results of Güzelyurt						
ANN-6 Inputs		MSE	R^2	No,of neuron	No, of hidden Layer	Function
DT, Tmin,Tmax,,avT, Ss,Nm,Gsr	Training	0.008	0.77	10	2	Training (TRAINLM adaptive Learning (LEARNGDM)
	Testing	0.0063	0.80			

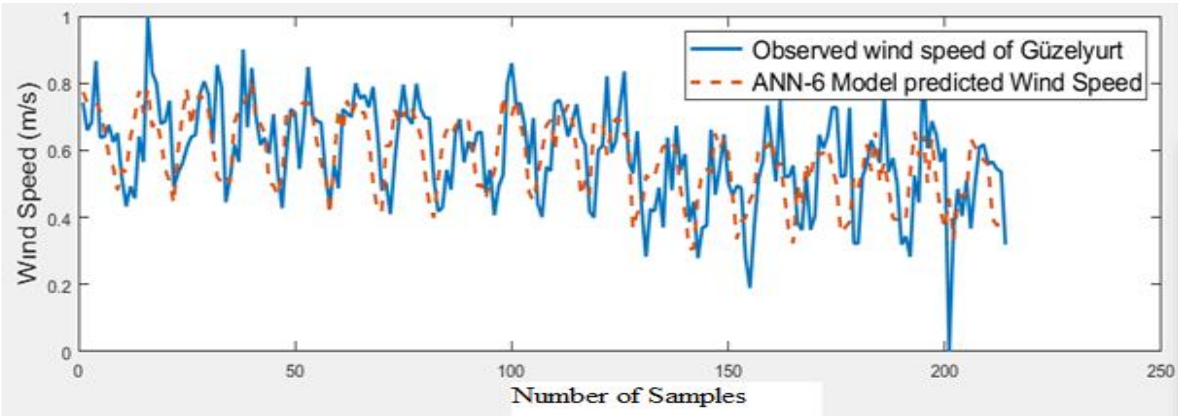

Figure 4.6: Diagram for Güzelyurt Observed With best predicted Wind Speed ANN Model

4.2.1.7 Observation from the ANN developed model

The results obtained from model prediction of the monthly wind speed values getting by the best input arrangement of the all the artificial neural network developed models are compared with actual values and selected best combination for their model. From the six best artificial neural network models, ANN-1, ANN-2 and ANN-5 have obtained the best prediction of the arrangement inputs of [DT],[DT,Nm] and [Tmin,Tmax,DT,Gsr,avT] respectively. The best combination of each ANN developed Models are list in Table (4.7) Below.

Table 4.7: Best combination of each ANN model for Güzelyurt

	S.no	ANN model	Inputs to the ANN
Güzelyurt	1	ANN-1	Tmax
	2	ANN-2	DT, Nm
	3	ANN-3	Tmin,Tmax,avT
	4	ANN-4	Tmin,Tmax,DT,Ss
	5	ANN-5	Tmin,Tmax,DT,avT,Gsr

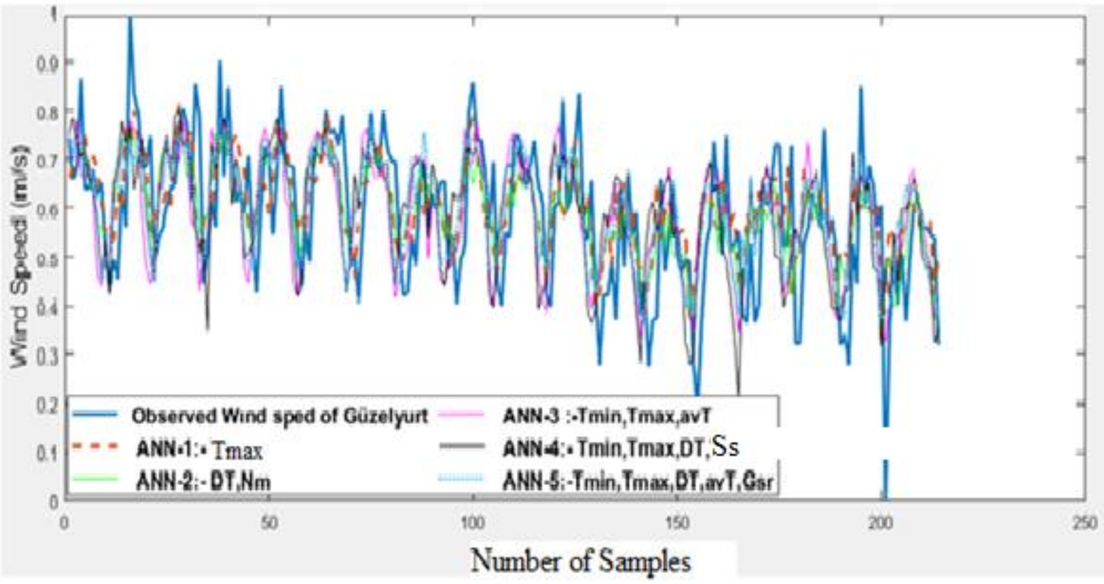

Figure 4.7: Comparison between Observed in Güzelyurt and predicted values by all best combination of inputs (ANN-1 to ANN- 5)

Table 4.8: Comparison of the Models between the Statistical tools Performance of ANN-1to ANN-6 for Güzelyurt

S. No	Model	Inputs	Error	Performance analysis based on output Error	RMSE (%)	Performance analysis based on RMSE
1		Tmin	-1.311	Least prediction accuracy Error	0.62	Excellent
2		Tmax	0.168	High prediction accuracy error	10.69	Good
3		Gsr	-1.003	Least prediction accuracy Error	2.72	Excellent
4	ANN-1	avT	0.473	High prediction accuracy Error	12.76	Good
5		Ss	1.212	high prediction accuracy error	17.79	Good
6		Nm	-0.539	Least prediction accuracy Error	5.88	Excellent
7		DT	-4.348	Low prediction accuracy Error	2.04	Excellent
1		Tmin, Tmax	0.387	High prediction accuracy Error	12.18	Good
2		Gsr, avT	-0.198	Least prediction accuracy Error	8.20	Excellent
3	ANN-2	DT, Gsr	2.458	High prediction accuracy Error	26.27	Fair
4		DT, avT	-1.639	Least prediction accuracy error	1.61	Excellent
5		DT, Ss	2.254	high prediction accuracy Error	24.49	fair
6		DT,Nm	-1.982	Low prediction accuracy Error	3.94	Excellent
7		Ss, Gsr	2.184	low prediction accuracy error	5.23	Excellent
1		Tmin,Tmax, DT	0.508	High prediction accuracy Error	13.00	Good
2		Tmin,Tmax, Ss	-0.276	least prediction accuracy Error	7.67	Excellent
3	ANN-3	Tmin,Tmax, avT	-1.454	low prediction accuracy Error	1.71	Excellent
4		Tmin, Tmax, Nm	1.299	High prediction accuracy error	18.39	Good
5		Tmin,Tmax, Gsr	-1.291	Least prediction accuracy error	0.76	Excellent

Table (4.8): continued

6		DT,Ss, Gsr	-0.925	Least prediction accuracy error	3.25	Excellent
1		Tmin,Tmax, Gsr,avT	0.079	High prediction accuracy Error	13.20	Good
2		Tmin,Tmax, DT,Gsr	0.057	High prediction accuracy error	12.67	Good
3	ANN-4	Tmin,Tmax, DT,avT	0.523	High prediction accuracy Error	13.10	Good
4		Tmin,Tmax , DT,Ss	0.771	high prediction accuracy Error	14.79	Good
5		Tmin,Tmax, DT,Nm	-1.402	Low prediction accuracy Error	1.90	Excellent
1		Tmin, Tmax,DT, avT,Gsr	0.238	High prediction accuracy Error	11.16	Good
2		Tmin, Tmax,DT, Nm,avT	1.459	high prediction accuracy Error	19.47	Good
3	ANN-5	Tmin, Tmax,DT, Ss,avT	-1.717	Least Prediction accuracy Error	2.14	Excellent
4		Tmin, Tmax,DT, Gsr,avT	-2.632	Low Prediction accuracy Error	8.37	Excellent
1	ANN-6	DT,Tmin,Tmax,, avT,Ss,Gsr	0.714	High Prediction accuracy error	14.41	Good

4.2.2 Wind Speed Prediction based on developed ANN Models for Gazimağusa

4.2.2.1 ANN-1 model

For this model there are eight input variables selected, individually inputs are each applied to the artificial neural network named as ANN-1 Model. Identification of effects of each input on the Monthly average wind speed prediction is obtained. By training developed to get best performance of the network of ANN-1 model to shown until reach the mean square error show small value. Form the predicted value result, all inputs the [Tmin],[Tmax] has shown similar prediction value and best predicted value is obtained in [Nm] input parameter. The statistical tools of training and testing performance of ANN-1 model shown in Table(4.9) below.

Table 4.9: Statistical tool's performance of Training of ANN-1Model for Gazimağusa

Performance of ANN-1 Model Results of Gazimağusa						
ANN-1 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden layer**	**Function**
Tmin	Training	0.0045	0.97498	4	2	
	Testing	0.0050	0.95919			
Tmax	Training	0.0032	0.98102	6	2	
	Testing	0.0014	0.91193			Training(TRAINLM Adaptive Learning (LEARNGD) Transfer(Logsigmoid)
Gsr	Training	0.0025	0.98575	4	2	
	Testing	0.0031	0.97898			
avT	Training	0.0037	0.97811	5	2	
	Testing	0.0049	0.96519			
Ss	Training	0.0039	0.97453	8	2	
	Testing	0.0071	0.95434			
Nm	Training	0.0021	0.98757	6	2	
	Testing	0.0073	0.95258			
DT	Training	0.0035	0.97771	5	2	
	Testing	0.0098	0.93970			

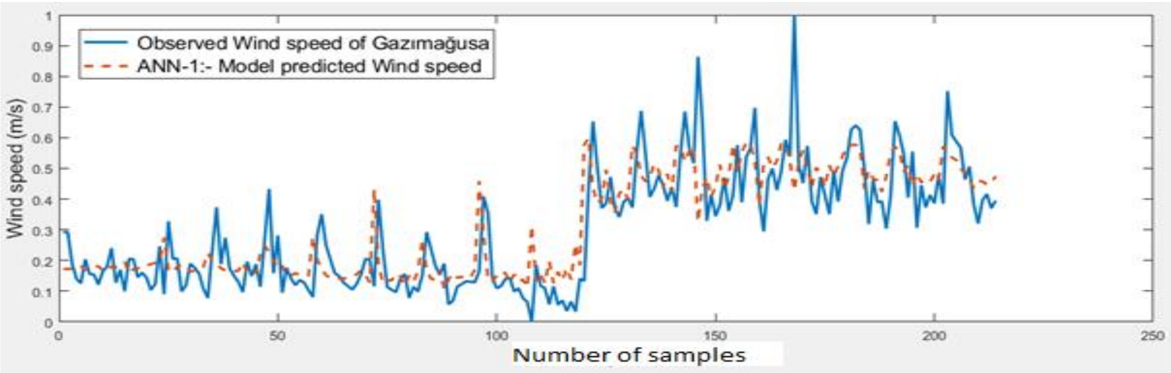

Figure 4.8: Diagram for Gazimağusa observed with best predicted Wind Speed by ANN-1 Model

4.2.2.2 ANN-2 model

Seven combinations at ANN-2 model are formed with two inputs variables and each of combination of the inputs variable on monthly wind speed was known. All combination of formed the artificial neural network trained combination of [Tmin,Tmax],[DT,Ss]and [Nm,DT] are results have produced the same approach the prediction of the wind speed and the combination of [DT,Ws] has obtained the higher accuracy predicted error value is 0.574405. The combination of [Gsr,avT] has best prediction of accurate error value. The statistical tools of training and testing performance of ANN-2 result has shown in Table (4.10) below.

Table 4.10: Statistical tool's performance of Training of ANN-2 Model for Gazimağusa

Performance of ANN-2 Model Resuts of Gazimağusa

ANN-2 Inputs		MSE	R^2	No,of neuron	No, of hidden Layer	Function
Tmin ,Tmax	Training	0.0032	0.980	5	2	Training(TRAINLM) Adaptive Learning(LEARNGD) Transfer (Log sigmoid)
	Testing	0.0056	0.964			
Gsr,avT	Training	0.0022	0.986	8	2	
	Testing	0.0038	0.976			
DT,Gsr	Training	0.0022	0.980	6	2	
	Testing	0.0041	0.972			
DT,avT	Training	0.0038	0.977	4	2	
	Testing	0.0058	0.947			
DT,Ss	Training	0.0044	0.973	5	2	
	Testing	0.0055	0.959			
DT,Nm	Training	0.0027	0.984	5	2	
	Testing	0.0042	0.974			
DT,Ws	Training	0.0041	0.974			
	Testing	0.0019	0.946	8	2	

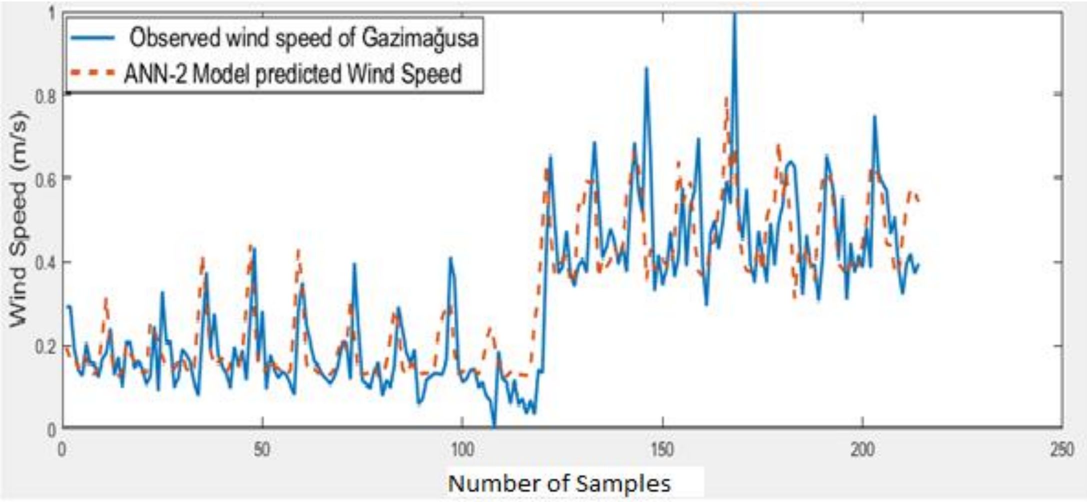

Figure 4.9: Diagram for Gazimağusa Observed Wind Speed and best predicted Wind Speed of wind Speed by ANN-2 Model

4.2.2.3 ANN-3 model

For this model of artificial neural network three trained with the combinations of [Tmin,Tmax,Ss],and[Tmin,Tmax,Gsr]have the same produced to Prediction value and good accuracy in predicting of the wind speed. The combination of [Tmin,Tmax, Nm] has best prediction of wind speed with least predicted accuracy errors value and also the combination of [DT,Ss,Gsr] has produced the highest prediction accuracy error value 1.223 and 1.345 are respectively obtained.The statistical tools of training and testing performance of ANN-3 result has shown in Table (4.11) below.

Table 4.11: Statistical tool's performance of Training and Testing for ANN-3 Model for Gazimağusa

Performance of ANN-3 Model Results of Gazimağusa						
ANN-3 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden layer**	**Function**
Tmin,Tmax,DT	Training	0.0038	0.975	2	2	Training(TRAINLM) Adaptive Learning(LEARNGD) Transfer (Log sigmoid)
	Testing	0.0077	0.961			
Tmin,Tmax,Ss	Training	0.0045	0.973	4	2	
	Testing	0.0053	0.965			
Tmin,Tmax, avT	Training	0.0028	0.982	6	2	
	Testing	0.0064	0.957			
Tmin,Tmax, Nm	Training	0.0021	0.986	8	2	
	Testing	0.0051	0.961			
Tmin,Tmax,Gsr	Training	0.0027	0.984	10	2	
	Testing	0.0074	0.959			
Tmin,Tmax, Ss	Training	0.0031	0.981	12	2	
	Testing	0.0096	0.950			
DT,Ss,Gsr	Training	0.0022	0.986	14	2	
	Testing	0.0051	0.967			

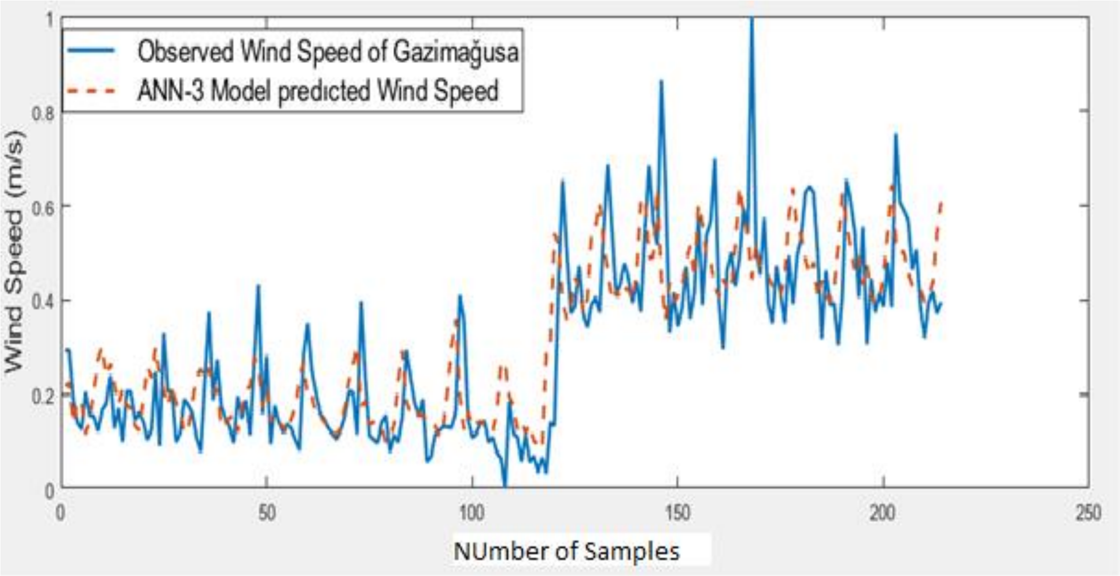

Figure 4.10: Diagram for Gazimağusa Observed with best predicted Wind Speed of wind Speed by ANN-3Model

4.2.2.4 ANN-4 model

For this model the totally six combination were formed four input parameters to train and validation of the artificial neural network named as ANN-4 model .The artificial neural network four trained with possible combination of [Tmin,Tmax,DT,Ws] has the best prediction results shown and the combination of the [Tmin,Tmax,Gsr,avT] and [Tmin,Tmax,DT,avT] have produced highest prediction accuracy error values was obtained.The combination of [Tmin,Tmax,Gsr,avT]and[Tmin,Tmax,DT,avT] have obtained the similar prediction wind speed results shown. The statistical tool's performance results shown in Table and graphic plotted below.

Table 4.12: Statistical tool's Performance of Training for ANN-4 model for Gazimağusa

	Performance of ANN-4 Model Results for Gazimağusa					
ANN-4 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden Layer**	**Function**
Tmin,Tmax,Gsr, avT	Training Testing	0.0013 0.0036	0.992 0.974	8	2	Training(TRAINLM) Adaptive Learning(LEARNGM Transfer (Log sigmoid
Tmin,Tmax,DT, Gsr	Training Testing	0.0034 0.0068	0.978 0.962	7	2	
Tmin,Tmax,DT, avT	Training Testing	0.0026 0.0046	0.983 0.973	6	2	
Tmin,Tmax,DT, avT	Training Testing	0.0034 0.0066	0.980 0.958	6	2	
Tmin,Tmax,DT, Nm	Training Testing	0.0039 0.0053	0.974 0.968	5	2	

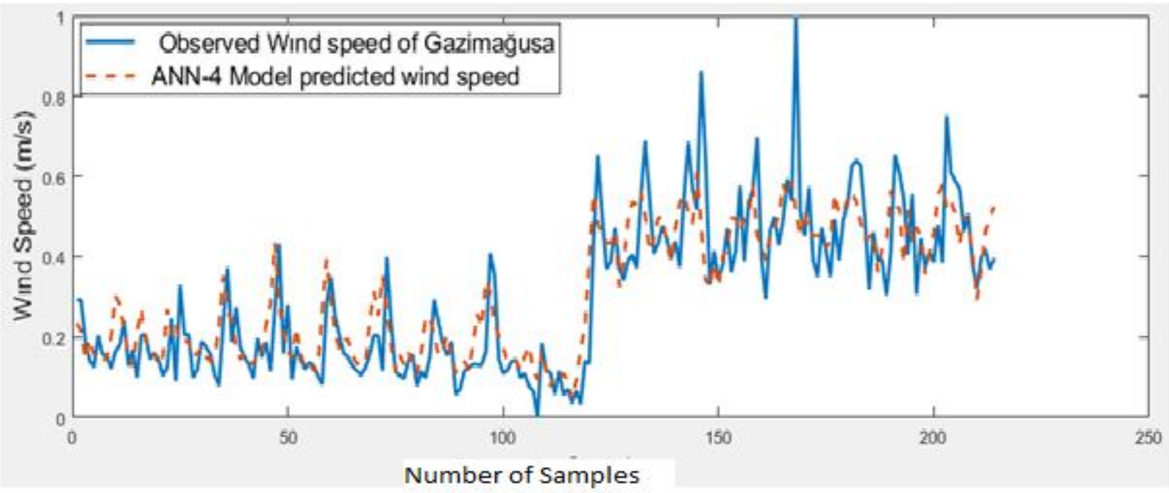

Figure 4.11: Diagram for Gazimağusa Observed With best predicted Wind Speed of wind Speed by ANN-4 Model

4.2.2.5 ANN-5 model

Total five possible arrangements were formed with different five input parameters to train and validation of the artificial neural network names as ANN-5 Model. The artificial neural network five model trained with the variables combine of [Tmin,Tmax,DT,Gsr,avT]and [Tmin,Tmax,DT,Nm,avT] this combination have to best prediction results shown and another combination inputs of [Tmin,Tmax,DT,Ss,avT] has results shown the highest Accuracy Error value 2.1271 is obtained. The statistical tool's performance and graphic results shown in Table (4.13) below.

Table 4.13: Statistical tool's performance of Training of ANN-5 Model for Gazimağusa

Performance of ANN-5 Model Results of Gazimağusa						
ANN-5 Inputs		**MSE**	R^2	**No,of neuron**	**No,of hidden Layer**	**Function**
Tmin,Tmax, DT,avT,Gsr	Training Testing	0.0013 0.0017	0.991 0.989	8	2	Training(TRAINLM AdaptivLearning (LEARNGD) Transfer (Logsigmoid
min,Tmax, DT,Nm,avT	Training Testing	0.0025 0.0073	0.984 0.961	4	2	
Tmin,Tmax, DT,Ss,avT	Training Testing	0.0055 0.0074	0.912 0.888	6	2	
Tmin,Tmax, DT,Gsr,avT	Training Testing	0.0077 0.0091	0.891 0.833	8	2	
Tmin,Tmax, DT,Ws,avT	Training Testing	0.0068 0.0088	0.902 0.879	10	2	

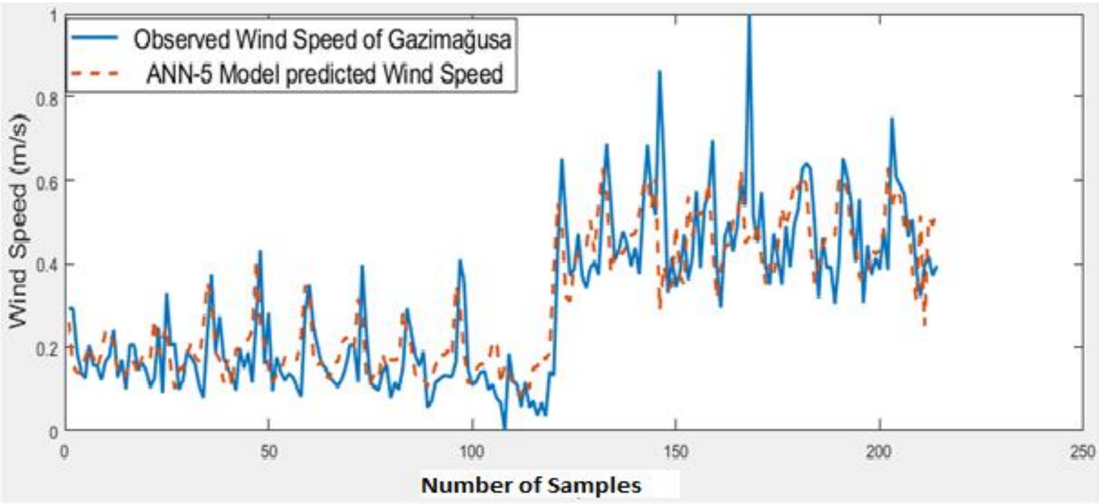

Figure 4.12: Diagram for Gazimağusa Observed with best predicted Wind Speed of wind Speed by ANN-5Model

4.2.2.6 ANN-6 model

This artificial neural network (ANN-6) model of all eight input parameters are applied to trained, test and validation of the ANN it named as ANN-6. The ANN-6 model shown results prediction accuracy error value is 0.03905. During the train and testing the statistical tool's performance results are shown Table (4.14) below.

Table 4.14: Statistical tools Performance of Training of ANN-6 Model for Gazimağusa

Performance of ANN-6 Model Results of Gazimağusa					
ANN-6 **Inputs**	**MSE**	R^2	No,of neuron	No, of hidden Layer	**Function**

Table 4.14: Continued

DT,Tmin,Tm, avT,Ss,Nm,Gsr	Training	0.00408	0.9383	10	2	Training(TRAINLM)
	Testing	0.00568	0.9139			AdaptiveLearning (LEARNGDM) Transfer(Logsigmoid)

4.2.2.7 Observation from the ANN developed model

The results obtained from model prediction of the monthly wind speed values getting by the best input arrangement of the all the artificial neural network developed models are compared with actual values and selected best combination for this model. From the six best artificial neural network models, ANN-1, ANN-2 and ANN-3 have obtained the best prediction of the arrangement inputs of [Nm], [Gsr, avT] and [Tmin,Tmax,Nm]are respectively. The best combination of each ANN developed Models are list in Table (4.15) below.

Table 4.15: Best combination of each ANN model developed for the Gazimağusa

	S.no	ANN model	Inputs to the ANN
Gazımağusa	1	ANN-1	Nm
	2	ANN-2	Gsr,avT
	3	ANN-3	Tmin,Tmax,Nm
	4	ANN-4	Tmin,Tmax,DT,avT
	5	ANN-5	Tmin,Tmax,DT,avT,Gsr

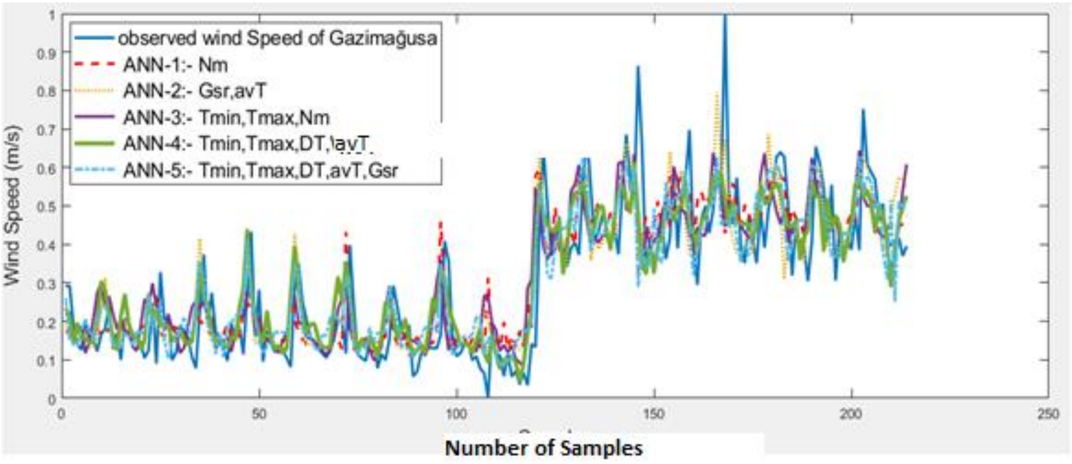

Figure 4. 13: Comparison between Observed Wind Speed in Gazimağusa and predicted values by all best combination of Inputs (ANN-1 to ANN- 5)

Table 4.16: Comparison of the Models between Statistical tools Performance of ANN-1 to ANN-6 for Gazimağusa

S. No	Model	Inputs	Error	Performance analysis based on Error	RMSE (%)	Performance analysis based on RMSE
1		Tmin	0.485	High prediction accuracy Error	7.274	Excellent
2		Tmax	0.292	High prediction accuracy error	5.976	Excellent
3	ANN-1	Gsr	3.564	Higher prediction accuracy Error	28.295	Fair
4		avT	0.067	High prediction accuracy Error	4.444	Excellent
5		Ss	-0.079	high prediction accuracy Error	3.451	Excellent

Table 4.16: Continued

6		Nm	-2.859	Low prediction accuracy Error	15.511	Good
7		DT	-0.281	Least prediction accuracy Error	2.073	Excellent
1		Tmin ,Tmax	-0.411	Least prediction accuracy Error	1.187	Excellent
2		Gsr,avT	-2.146	Low prediction accuracy Error	10.646	Good
3		DT,Gsr	-0.123	Least prediction accuracy Error	3.149	Excellent
4	ANN-2	DT,avT	-1.055	Least prediction accuracy error	3.206	Excellent
5		DT,Ss	-0.040	Least prediction accuracy Error	3.715	Excellent
6		DT,Nm	0.327	High prediction accuracy Error	6.221	Excellent
7		Ss ,Gsr	0.574	High prediction accuracy Error	7.906	Excellent
1		Tmin,Tmax,DT	0.200	High prediction accuracy Error	5.352	Excellent
2		Tmin,Tmax,Ss	-0.778	Least prediction accuracy Error	1.593	Excellent
3		Tmin,Tmax, avT	0.071	High prediction accuracy Error	4.475	Excellent
4	ANN-3	Tmin, Tmax, Nm	-2.165	Low prediction accuracy error	10.775	Good

Table (4.16): Continued

5		Tmin,Tmax,Gsr	-0.446	Least prediction accuracy error	0.94	Excellent
6		DT,Ss,Gsr	1.345	High prediction accuracy error	13.1	Good
1		Tmin,Tmax,Gsr,avT	0.995	High prediction accuracy Error	10.7	Good
2		Tmin,Tmax,DT,Gsr	0.374	High prediction accuracy error	6.53	Excellent
3	ANN-4	Tmin,Tmax, DT,avT	0.945	High prediction accuracy Error	10.4	Good
4		Tmin,Tmax ,DT,Ss	-1.966	Least prediction accuracy Error	9.41	Excellent
5		Tmin,Tmax,DT,Nm	-0.534	Least prediction accuracy Error	0.34	Excellent
1		Tmin,Tmax,DT,avT,Gsr	-1.472	Low prediction accuracy Error	6.05	Excellent
2		Tmin,Tmax,DT,Nm,avT	1.129	high prediction accuracy Error	11.6	Good
3	ANN-5	Tmin,Tmax,DT,Ss,avT	0.285	high prediction accuracy Error	6.32	Excellent
4		Tmin,Tmax,DT,Gsr,avT	0.469	Low prediction accuracy Error	7.18	Excellent
5		Tmin,Tmax,DT,Ws,avT	-0.858	Least prediction accuracy Error	1.86	Excellent
1	ANN-6	DT,Tmin,Tmax,avT, Nm,Ss,Gsr	0.390	High prediction accuracy error	4.64	Excellent

4.2.3 Developed ANN models Prediction wind speed for Lefkoşa

4.2.3.1 ANN-1 model

For this model there are eight input variables selected, individually inputs are each applied to the artificial neural network namely as ANN-1 Model. Identification of effects of each input on the Monthly average wind speed prediction was obtained. By training developed to get best performance of the network of ANN-1 model to shown until reach the mean square error show small value. Form the predicted value result, all inputs the [Tmax] and [Ss] have shown similar prediction value. The input parameter of [Nm] and [DT] have produced the best prediction inputs in model of ANN-1 and it’s have low prediction accuracy error values -1.500 and -1.264 are respectively. The Statistical tools of training and testing performance of ANN-1 model results shown in table (4.17) below.

Table 4.17: Statistical tools performance Training for ANN-1Model for Lefkoşa

		Performance of ANN-1 Model Results of Lefkoşa				
ANN-1 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden Layer**	**Function**
	Training	0.0015	0.9552	14	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
Tmin	Testing	0.0039	0.9144			
Tmax	Training	0.0038	0.8837	10	2	
	Testing	0.0055	0.8385			
Gsr	Training	0.0051	0.8549	6	2	
	Testing	0.0067	0.8033			
avT	Training	0.0036	0.8988	9	2	
	Testing	0.0047	0.8316			
Ss	Training	0.0014	0.7730	8	2	
	Testing	0.0088	0.7083			
Nm	Training	0.0069	0.7954	14	2	
	Testing	0.0092	0.7714			
	Testing	0.0036	0.889			
DT	Training	0.0086	0.7489	11	2	
	Testing	0.0073	0.7142			

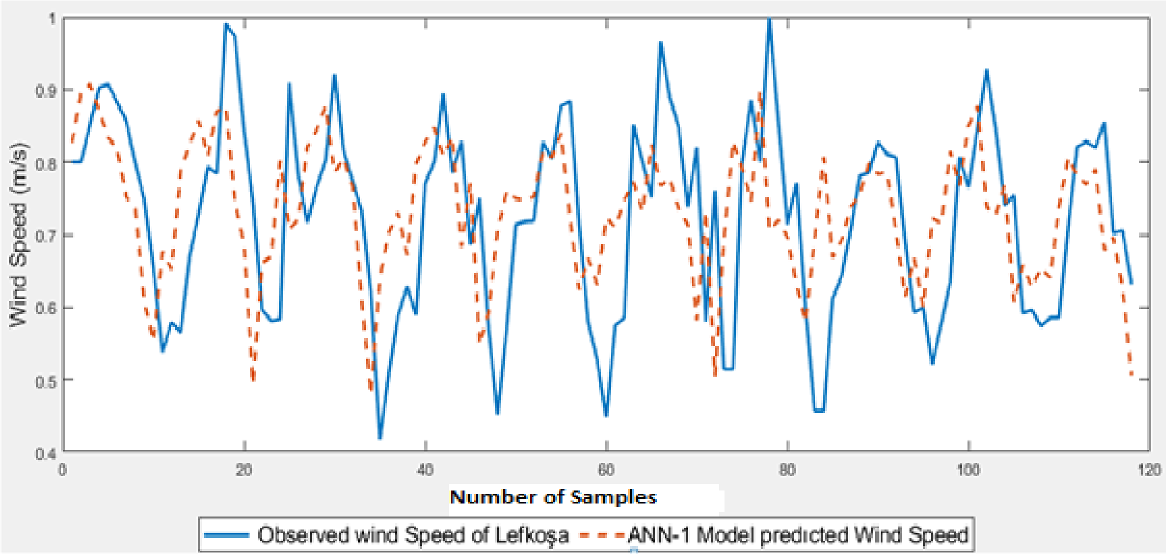

Figure 4.14: Diagram of Lefkoşa actual wind speed with best predicted wind speed of ANN-1 Model

4.2.3.2 ANN-2 model

Seven combinations at ANN-2 model are formed with two inputs variables and each of combination of the inputs variable for wind speed was known. All combination of formed the artificial neural network trained combination of [Gsr,avT], [DT,Gsr]and [DT,Ws] results have produced the similar prediction of the wind speed and the combination of [Gsr,avT] has obtained the higher accuracy predicted error value is 0.5128. The combination of [DT,avT] has best prediction with accurate error value is -0.5213. The Statistical tools of training Performance of ANN-2 model result shown in Table (4.18) below.

Table 4.18: Statistical tool's performance of Training of ANN-2 Model for Lefkoşa

Performance of ANN-2 Model Results for Lefkoşa						
ANN-2 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden Layer**	**Function**
Tmin,Tmax	Training	0.0036	0.894	7	2	Training (TRAI LM) AdaptiveLearning (LEARNGDM) Transfer (Log sigmoid)
	Testing	0.0045	0.869			
Gsr,avT	Training	0.0044	0.870	10	2	
	Testing	0.0062	0.841			
DT,Gsr	Training	0.0045	0.863	8	2	
	Testing	0.0068	0.820			
DT,avT	Training	0.0034	0.8922	4	2	
	Testing	0.0076	0.8724			
DT,Ss	Training	0.0086	0.7318	20	2	
	Testing	0.0076	0.7284			
DT,Nm	Training	0.0092	0.7337	13	2	
	Testing	0.0073	0.7240			

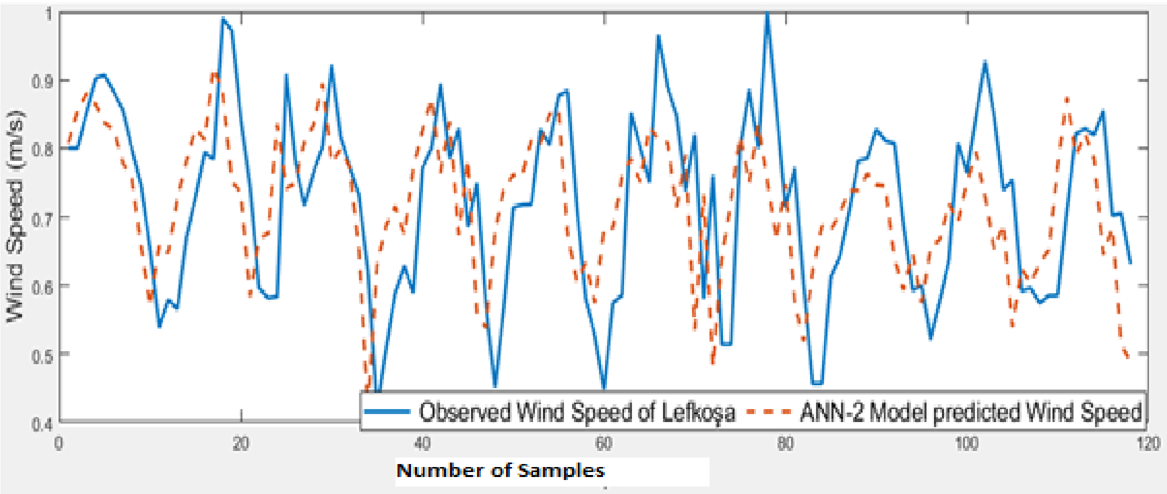

Figure 4.15: Diagram of Lefkoşa Observed wind speed and best predicted wind speed of ANN-2 Model

4.2.3.3 ANN-3 model

For this model of artificial neural network three trained with the combinations of [Tmin,Tmax,Nm] and[Tmin,Tmax,avT] have produced the same prediction value and good accuracy in predicting of the wind speed. The combination of [Tmin,Tmax,Ss] has best prediction of wind speed with low prediction accuracy errors value is -1.036 and also the combination of [Tmin,Tmax,DT] has produced the high prediction accuracy error value is 0.327 obtained. The statistical tools of training and testing performance of ANN-3 model result shown in Table (4.19) below.

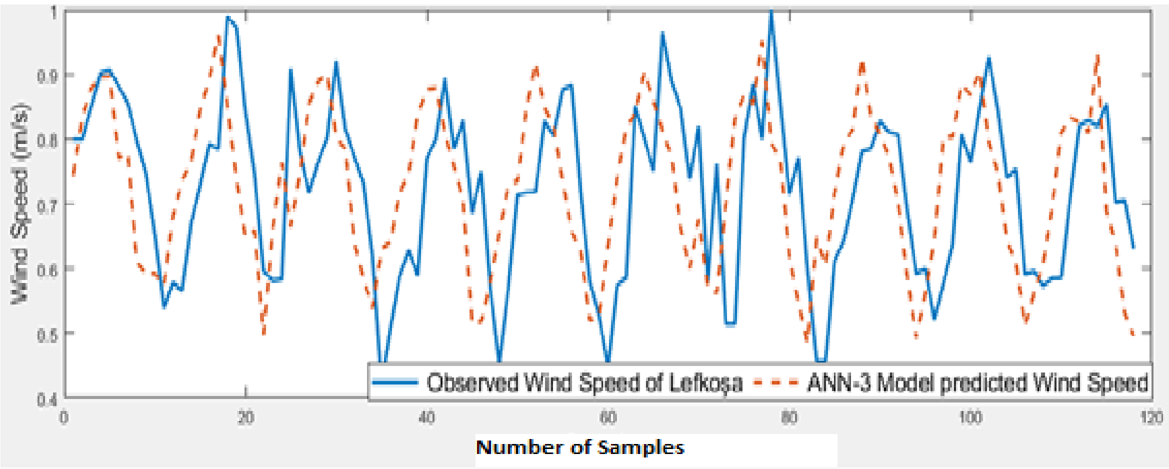

Figure 4.16: Diagram of Lefkoşa observed wind speed and best predicted wind speed of ANN-3

Table 4.19: Statistical tool's performance of Training of ANN-3 Model for Lefkoşa

Performance of ANN-3 Model Results of Lefkoşa						
ANN-3 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden Layer**	**Function**
Tmin,Tmax,DT	Training	0.0032	0.9034	10	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
	Testing	0.0053	0.8683			
Tmin,Tmax,Ss	Training	0.0024	0.9276	4	2	
	Testing	0.0076	0.8728			
Tmin,Tmax,avT	Training	0.0038	0.8837	5	2	
	Testing	0.0065	0.8232			
Tmin,Tmax,Nm	Training	0.0031	0.9134	6	2	
	Testing	0.0050	0.8624			
Tmin,Tmax,Gsr	Training	0.0037	0.8941	2	2	
	Testing	0.0048	0.8424			
Tmin,Tmax,Ws	Training	0.0039	0.8935	5	2	
	Testing	0.0069	0.8131			
DT,Ss,Gsr	Training	0.0042	0.8764	6	2	
	Testing	0.0073	0.8178			

4.2.3.4 ANN-4 model

For this model the totally seven combination were formed four input parameters to train and validation of the artificial neural network named as ANN-4 model .The artificial neural network four trained with possible combination of [Tmin,Tmax,DT,Ss] has best prediction results shown and its prediction accuracy error value is -1.6144.The combination of [Tmin,Tmax,DT,avT] has produced highest accuracy error value is 1.5314 obtained. The two combination of [Tmin,Tmax,DT,Gsr]and[Tmin,Tmax,DT,Nm] have similar prediction results shown. The statistical tool's performance results shown in Table (4.20) below.

Table 4.20: Statistical tool's performance of Training of ANN-4 Model for Lefkoşa

Performance of ANN-4 Model Results of Lefkoşa						
ANN-4 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hiddn Layer**	**Function**
Tmin,Tmax,Gsr,avT	Training	0.00490	0.87000	6	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid
	Testing	0.00366	0.90951			
Tmin,Tmax,DT,Gsr	Training	0.00342	0.90367	7	2	
	Testing	0.00264	0.92635			
Tmin,Tmax, DT,avT	Training	0.00227	0.93562	8	2	
	Testing	0.00534	0.84672			
Tmin,Tmax ,DT,avT	Training	0.00325	0.90263	10	2	
	Testing	0.00506	0.86768			
Tmin,Tmax,DT,Nm	Training	0.00213	0.94855	9	2	
	Testing	0.00368	0.88594			
Tmin,Tmax, DT,Ss	Training	0.00444	0.87501	12	2	
	Testing	0.00343	0.93510			

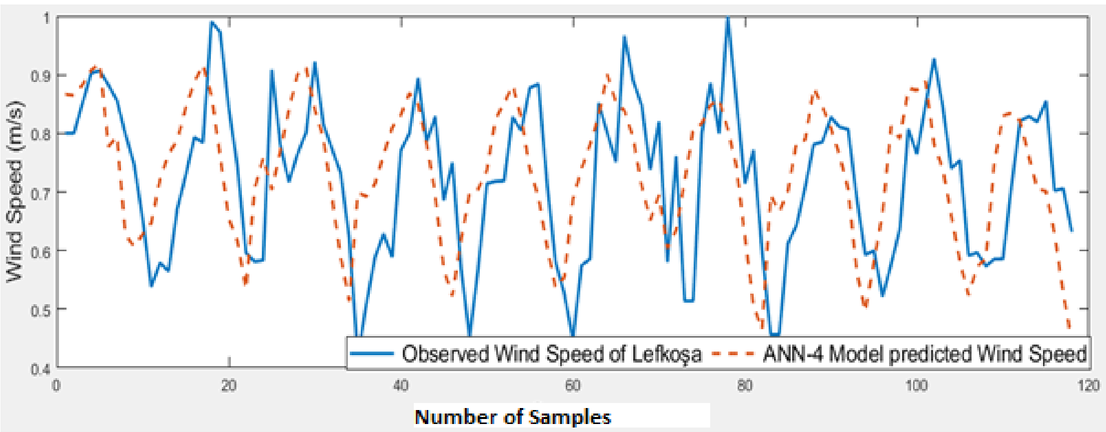

Figure 4.17: Diagram of Lefkoşa Observed wind speed and best predicted wind Speed of ANN-4 Mode

4.2.3.5 ANN-5 model

Total five possible arrangements were formed with different five input parameters to train and validation of the artificial neural network names as ANN-5 Model. The artificial neural network five model trained with the variables combine of [Tmin,Tmax,DT,Gsr,avT] has produced the best prediction of wind speed results shown and this combination its prediction accuracy error value is -1.256. From five combination inputs of [Tmin,Tmax,DT,Nm,avT] has results shown the high prediction accuracy error value is 0.15054 obtained. The Statistical tool's Performance results shown in Table (4.21) below.

Table 4.21: Statistical tool's performance of ANN-5 Model for Lefkoşa

Performance of ANN-5 Model results of Lefkoşa						
ANN-5 Inputs		**MSE**	R^2	**No,of neuron**	**No,of hidden layer**	**Function**
Tmin,Tmax,DT, avT,Gsr	Training	0.00430	0.87902	2	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid
	Testing	0.00312	0.90889			
Tmin,Tmax,DT, Nm,avT	Training	0.00408	0.88496	4	2	
	Testing	0.00396	0.85706			
Tmin,Tmax,DT, Ss,avT	Training	0.00301	0.90957	6	2	
	Testing	0.00422	0.86810			
Tmin,Tmax,DT, Gsr,avT	Training	0.0024	0.91920	8	2	
	Testing	0.0051	0.87236			
Tmin,Tmax,DT, Ws,avT	Training	0.0047	0.87693	10	2	
	Testing	0.0030	0.90897			

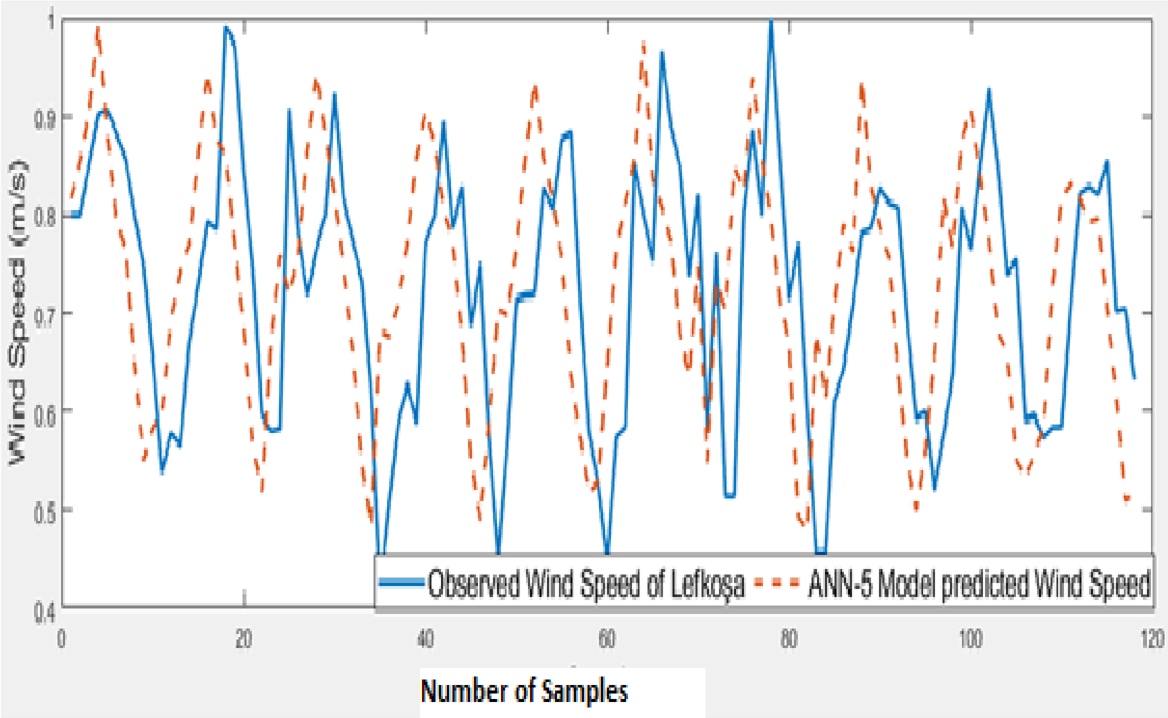

Figure 4.18: Diagram of Lefkoşa Observed wind speed and best predicted wind speed of ANN-5 Model

4.2.3.6 ANN-6 model

This artificial neural network (ANN-6) model of all eight input parameters are applied to trained, test and validation of the ANN it named as ANN-6. The ANN-6 model results shown the prediction accuracy error value is -0.00111. During the training of the statistical tool's performance results are shown Table (4.22) below.

Table 4.22: Statistical tool's performance of Train and Testing of ANN-6 Model for Lefkoşa

Performance of ANN-6 Model Results of Lefkoşa						
ANN-6 Inputs		MSE	R^2	No,of neuron	No, of hidden Layer	Function
DT,Tmin,Tmax, avT,Ss, Nm,Gsr	Training	0.00323	0.905	18	2	Training (TRAINM)
	Testing	0.00453	0.878			AdaptiveLearning (LEARNGDM) Transfer (Log sigmoid)

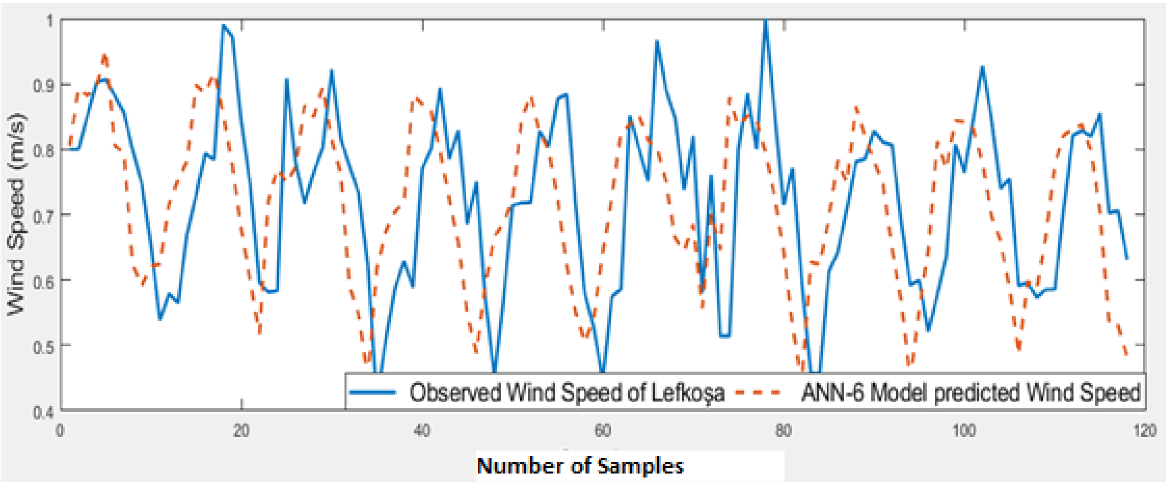

Figure 4.19: Diagram of Lefkoşa Observed with best predicted wind speed of ANN-6 Model

4.2.3.7 Observation from the ANN developed model for Lefkoşa

The results obtained from model prediction of the monthly wind speed values getting by the best input arrangement of the all the artificial neural network developed models are compared with actual values and selected best combination for their model. From the six best artificial neural network models are ANN-4 and ANN-5 have obtained the best prediction of the arrangement inputs of [Tmin,Tmax,DT,Ss] and [Tmin,Tmax,DT,Gsr,avT] are respectively.The best combination of ANN developed Models are in Table (4.23) below.

Table 4.23: Best combination of each ANN model for Lefkoşa

	S.No	ANN model	Inputs to the ANN
Lefkoşa	1	ANN-1	Nm
	2	ANN-2	DT,avT
	3	ANN-3	Tmin,Tmax,Ss
	4	ANN-4	Tmin,Tmax,DT,Ss
	5	ANN-5	Tmin,Tmax,DT,avT,Gsr

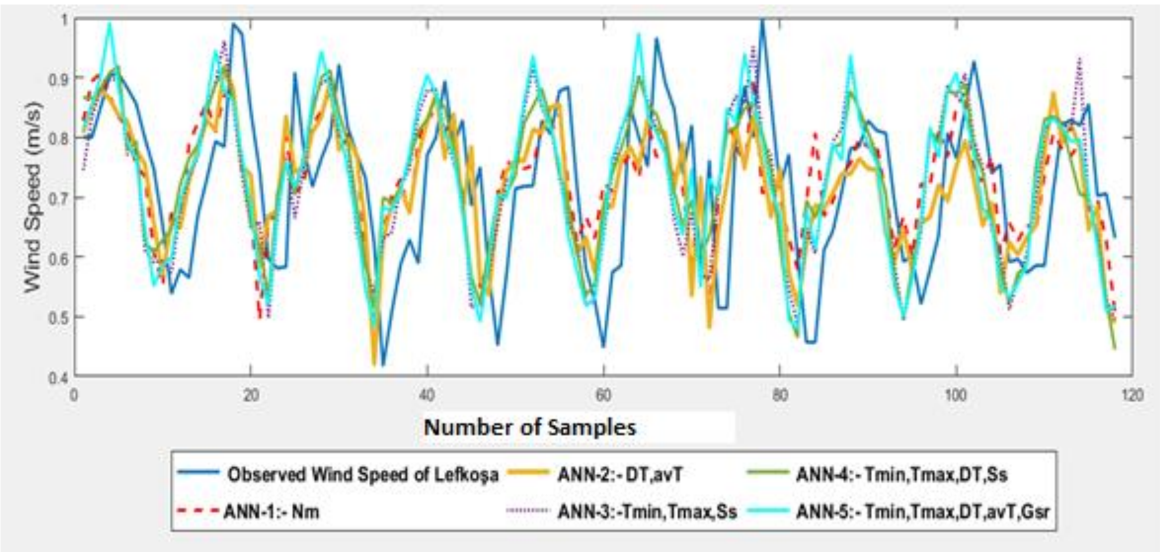

Figure 4.20: Comparison between Lefkoşa observed with predicted Values by all the best combination of inputs (ANN-1 to ANN-5).

Table 4.24: Comparison of the Models between statistical tools Performance of ANN-1 to ANN-6 for Lefkoşa

S. No	Model	Inputs	Error	Performance Analysis based on Error	RMSE (%)	Performance analysis based on RMSE
1		Tmin	-1.311	Least prediction accuracy Error	0.62	Excellent
2		Tmax	0.168	High prediction accuracy error	10.69	Good
3		Gsr	-1.003	Least prediction accuracy Error	2.72	Excellent
4	ANN-1	avT	0.473	High prediction accuracy Error	12.76	Good
5		Ss	1.212	high prediction accuracy error	17.79	Good
6		Nm	-0.539	Least prediction accuracy Error	5.88	Excellent
7		DT	-4.348	low prediction accuracy Error	2.04	Excellent
1		Tmin ,Tmax	0.387	High prediction accuracy Error	12.18	Good
2		Gsr,avT	-0.198	Least prediction accuracy Error	8.20	Excellent
3	ANN-2	DT,Gsr	2.458	High prediction accuracy Error	26.27	fair
4		DT,avT	-1.639	Least prediction accuracy error	1.61	Good
5		DT,Ss	2.254	high prediction accuracy Error	24.49	fair
6		DT,Nm	-1.982	Low prediction	3.94	Excellent
7		Ss,Gsr	-1.57	accuracy Error	4.58	Excellent
1		Tmin,Tmax,DT	0.508	High prediction accuracy Error	13.00	Good
2		Tmin,Tmax,Ss	-0.276	Least prediction accuracy Error	7.67	Excellent
3	ANN-3	Tmin,Tmax, avT	-1.454	Low prediction accuracy Error	1.71	Excellent

Table 4:24 continued

4		Tmin, Tmax, Nm	1.299	High prediction accuracy error	18.39	Good
5		Tmin,Tmax,Gsr	-1.291	Least prediction accuracy error	0.76	Excellent
6		DT,Ss,Gsr	-0.925	Least prediction accuracy error	3.25	Excellent
1		Tmin,Tmax,Gsr,avT	0.079	High prediction accuracy Error	13.20	Good
2		Tmin,Tmax,DT,Gsr	0.057	High prediction accuracy error	12.67	Good
3	ANN-4	Tmin,Tmax, DT,avT	0.523	High prediction accuracy Error	13.10	Good
4		Tmin,Tmax ,DT,Ss	0.771	high prediction accuracy Error	14.79	Good
5		Tmin,Tmax,DT,Nm	1.146	High prediction accuracy Error	17.34	Good
1		Tmin,Tmax,DT,avT,Gsr	0.238	High prediction accuracy Error	11.16	Good
2		Tmin,Tmax,DT,Nm,avT	1.459	high prediction accuracy Error	19.47	Good
3	ANN-5	Tmin,Tmax,DT,Ss,avT	-1.717	Least prediction accuracy Error	2.14	Excellent
4		Tmin,Tmax,DT,Gsr,avT	-2.632	low prediction accuracy Error	8.37	Excellent
1	ANN-6	DT,Tmin,Tmax,avT,Ss, Nm,Gsr	0.714	High prediction accuracy error	14.41	Good

4.2.4 Developed ANN models Predicting wind speed for Girne

4.2.4.1 ANN-1 model

For this model there are eight input variables selected, individually inputs are each applied to the artificial neural network named as ANN-1 Model. Identification of effects of each input on the Monthly average wind speed prediction is obtained. By training developed to get best performance of the network of ANN-1 model to shown until reach the mean square error show small value. The best predicted value is obtained in [Ss]. The statistical tools of training Performance of ANN-1 model shown in table (4.25) below.

Table 4.25: Statistical tool's performance of Training of ANN-1Model for Girne

Performance of ANN-1 Model Results of Grine						
ANN-1 Inputs		**MSE**	R^2	**No,of neuron**	**No, ofhidden Layer**	**Function**
Tmin	Training	0.011	0.611	2	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
	Testing	0.012	0.509			
	Training	0.010	0.643	4	2	
Tmax	Testing	0.011	0.667			
Gsr	Training	0.015	0.507	6	2	
	Testing	0.012	0.618			
avT	Training	0.001	0.991	8	2	
	Testing	0.005	0.974			
Ss	Training	0.001	0.998	10	2	
	Testing	0.001	0.998			
Nm	Training	0.013	0.621	12	2	
	Testing	0.014	0.593			
Ws	Training	0.009	0.984	14	2	
	Testing	0.008	0.939			
DT	Training	0.004	0.972	16	2	
	Testing	0.010	0.945			

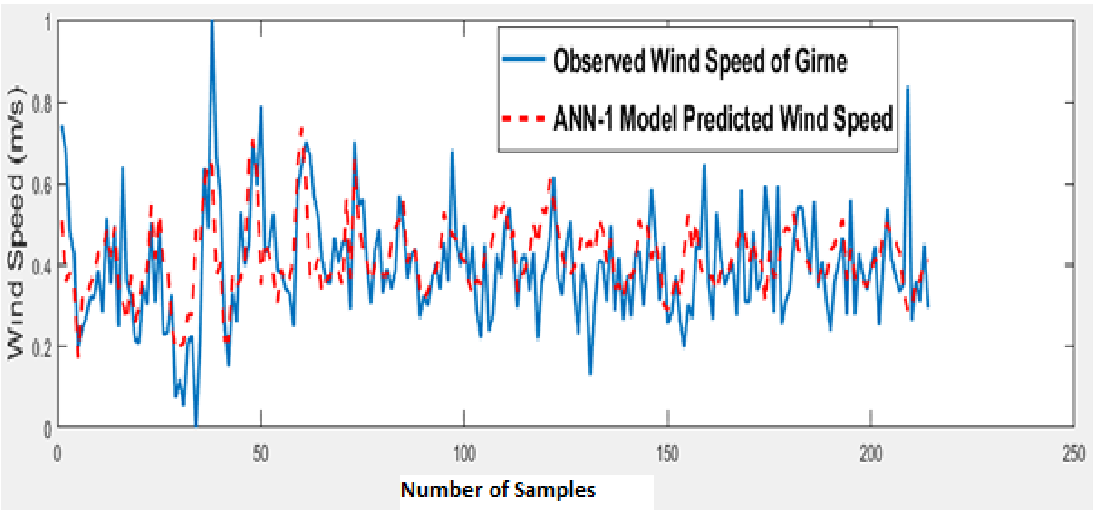

Figure 4.21: Diagram for Girne observed wind speed and best predicted wind speed by ANN-1model

4.2.4.2 ANN-2 Model

Seven combinations at ANN-2 model are formed with two inputs variables and each of combination of the inputs variable on monthly wind speed was known. All combination of formed the artificial neural network trained combination of [DT, Ss] results has produced the Good prediction of the monthly wind speed and with the accurately high predicted error value of 0.333. The combination of [DT,avT] has best prediction with accurate error value. The statistical tools of training and testing performance of ANN-2 has shown in Table (4.26) below.

Table 4.26: Statistical tool's Training and Testing performance of ANN-2Model for Girne

Performance of ANN-2 Model Results for Girne						
ANN-2 Inputs		**MSE**	R^2	**No,of neuron**	**No, of hidden Layer**	**Function**
Tmin ,Tmax	Training	0.0110	0.6636	4	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
	Testing	0.0127	0.5729			
Gsr,avT	Training	0.0026	0.8037	6	2	
	Testing	0.0044	0.8307			
DT,Gsr	Training	0.0011	0.8518	8	2	
	Testing	0.0015	0.8842			
DT,avT	Training	0.0012	0.9821	12	2	
	Testing	0.0018	0.9702			
DT,Ss	Training	0.0111	0.6558	10	2	
	Testing	0.0250	0.5804			
DT,Nm	Training	0.0128	0.8939	12	2	
	Testing	0.0195	0.8248			
Ss,Gsr	Training	0.0049	0.9828	14	2	
	Testing	0.0084	0.9457			

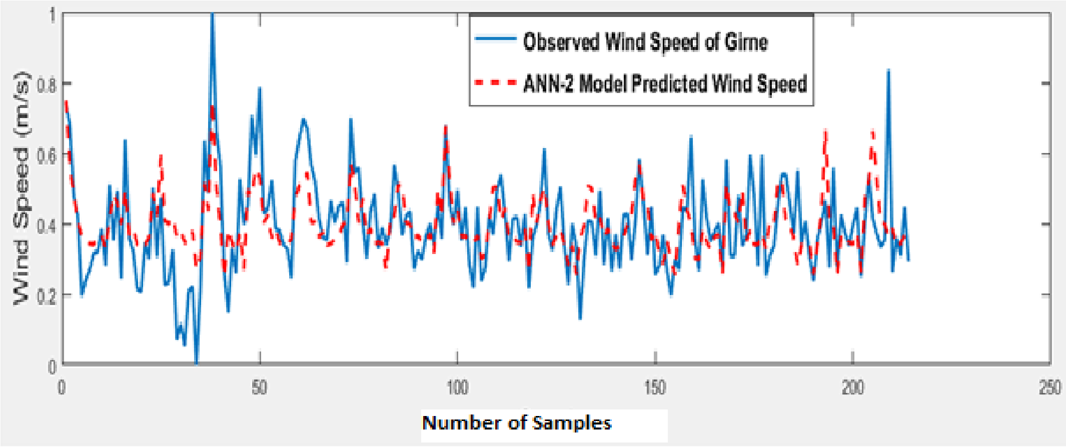

Figure 4.22: Diagram for Girne Observed With best predicted Wind Speed by ANN-2 Model

4.2.4.3 ANN-3 model

For this model of artificial neural network three trained with the combinations of [Tmin,Tmax, Nm] has produced good predicted the wind speed. In ANN-3 Model combination of [Tmin,Tmax,Ss] has produced the least predicted wind speed result shown and it has highest prediction accuracy error value is 4.378 shown. The combination of [Tmin,Tmax,Gsr] has best prediction of wind speed with least errors value. The statistical tool of training performance of ANN-3 has shown in Table (4.27) below

Table 4.27: Statistical tool's Performance of Training and Testing of ANN-3Model for Girne

		Performance of ANN-3 Model	**Results for Grine**			
ANN-3 Inputs		**MSE**	R^2	**No, of neuron**	**No, of hidden Layer**	**Function**
Tmin,Tmax,DT	Training	0.002	0.985	2	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
	Testing	0.002	0.980			
Tmin,Tmax,Ss	Training	0.001	0.990	4	2	
	Testing	0.001	0.924			
Tmin,Tmax,avT	Training	0.004	0.962	6	2	
	Testing	0.001	0.868			
Tmin,Tmax,Nm	Training	0.005	0.962	8	2	
	Testing	0.003	0.834			
Tmin,Tmax,Gsr	Training	0.002	0.846	10	2	
	Testing	0.003	0.831			
DT,Ss,Gsr	Training	0.008	0.893	14	2	
	Testing	0.001	0.827			

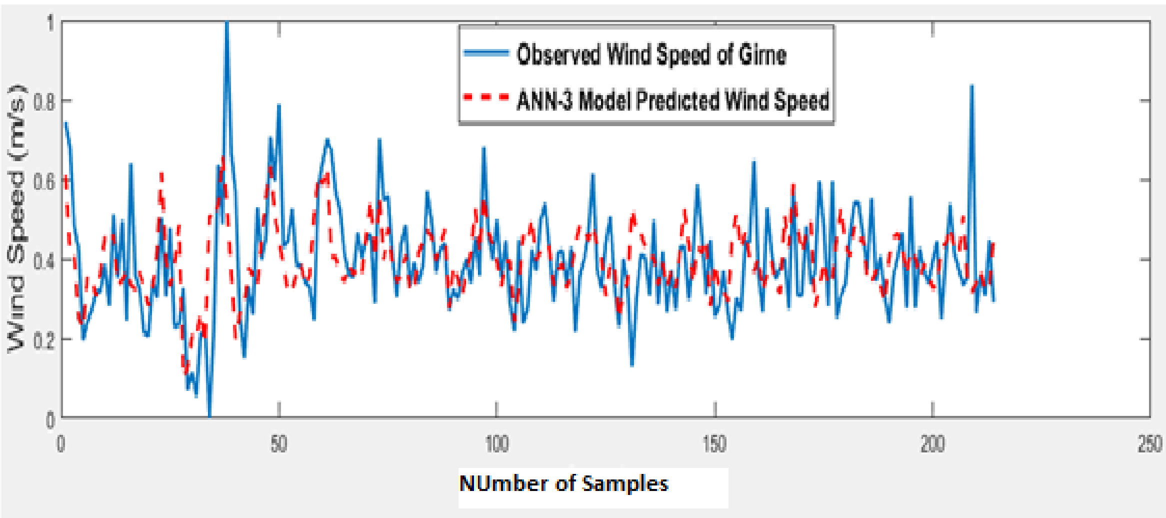

Figure 4.23: Diagram for Girne Observed With best predicted Wind Speed by ANN-3 Model

4.2.4.4 ANN-4 model

For this model the totally six combination were formed four input parameters to train and validation and test of the artificial neural network named as ANN-4 model .The artificial neural network four trained with possible combination of [Tmin,Tmax,DT,Nm] has best predicted wind speed result shown and the combination of [Tmin,Tmax,DT,Gsr] and [Tmin,Tmax,DT,Ss] have given the highest prediction accuracy error values 1.9572 and 1.2236 are respectively obtained. The statistical tool's performance results shown in Table (4.28) below.

Table 4.28: Statistical tool's performance of Training and Testing of ANN-4 Model for Girne

Performance of ANN-4 Model Results of Girne						
ANN-4 Inputs		**MSE**	R^2	**No, of neuron**	**No, of hidden Layer**	**Function**
Tmin,Tmax, Gsr,avT	Training	0.0120	0.8463	2	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
	Testing	0.0176	0.8260			
Tmin,Tmax, DT,Gsr	Training	0.0052	0.9585	4	2	
	Testing	0.0075	0.9356			
Tmin,Tmax, DT,avT	Training	0.0061	0.9268	6	2	
	Testing	0.0100	0.8796			
Tmin,Tmax ,DT,avT	Training	0.0093	0.9827	8	2	
	Testing	0.0016	0.9303			
Tmin,Tmax, DT,Nm	Training	0.0031	0.9805	10	2	
	Testing	0.0091	0.9299			

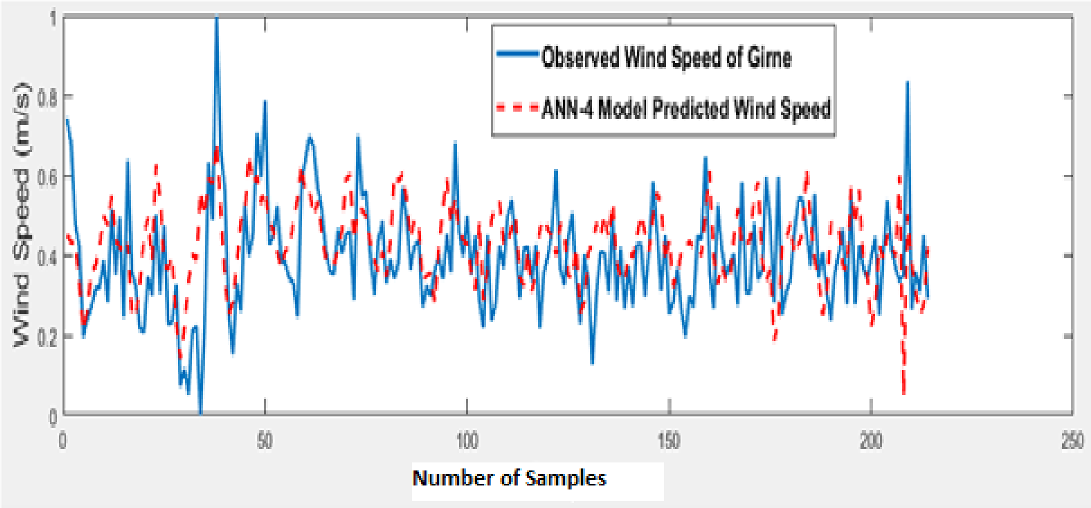

Figure 4.24: Diagram for Girne Observed With best predicted Wind Speed by ANN-4 Model

4.2.4.5 ANN-5 model

Total four possible arrangements were formed with different five input parameters to train and validation of the artificial neural network names as ANN-5.The artificial neural network five model trained with the variables combination of [Tmin,Tmax,DT,Gsr,avT] this combinations has to best predicted results Shown and another combination inputs of [Tmin,Tmax,DT,avT,Gsr] has results shown the highest prediction accuracy Error value 1.71021 has given. The statistical tool's performance and graphic results shown in Table (4.29) below.

Table 4.29: Statistical tool's performance of ANN Model Results of Girne

Performance of ANN-5 Model Results of Girne						
ANN-5 Inputs		**MSE**	R^2	**No,of neuron**	**No,of hidden layer**	**Function**
Tmin,Tmax, DT,avT,Gsr	Training	0.002	0.996	2	2	Training(TRAINLM) Adaptive Learning(LEARNGDM) Transfer (Log sigmoid)
	Testing	0.004	0.972			
Tmin,TmaxDT ,Nm,avT	Training	0.001	0.993	4	2	
	Testing	0.008	0.958			
Tmin,Tmax, DT,Ss,avT	Training	0.002	0.986	6	2	
	Testing	0.008	0.962			
Tmin,Tmax, DT,Gsr,avT	Training	0.004	0.943	14	2	
	Testing	0.006	0.914			
Tmin,Tmax, DT,Ws,avT	Training	0.007	0.941	10	2	
	Testing	0.008	0.933			

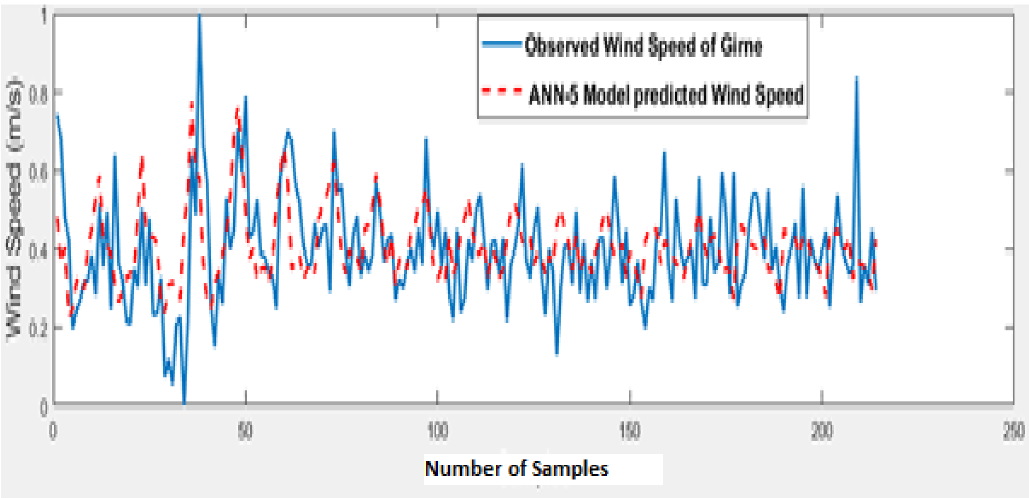

Figure 4.25: Diagram for Girne Observed With best predicted Wind Speed by ANN-5 Model

4.2.4.6 ANN-6 model

This artificial neural network (ANN-6) models of all seven input parameters are applied to training, testing and validation of the ANN it named as ANN-6. The ANN-6 model shown results prediction accuracy error value is -0.899. During the training and testing the statistical tool's performance results are shown in Table (4.30) below.

Table 4.30: Statistical tool's performance of Training and Testing for ANN-6 Model for Girne

Performance of ANN-6 Model Results of Girne						
ANN-6 Inputs		MSE	R^2	No,of neuron	No, of hidden Layer	Function
DT,Tmin,Tmax, Nm,,avT,Ss,Gsr	Training	0.0023	0.9862	16	2	Training(TRAINLM)
	Testing	0.0073	0.9032			AdaptiveLearning (LEARNGDM) Transfer (Log sigmoid)

4.2.4.7 Observation from the ANN developed model for Girne

The results obtained from model prediction of the monthly wind Speed values getting by the best input arrangement of the all the Artificial Neural Network developed models are compared with actual values and selected best combination for their model. From the six best artificial neural network models, ANN-4 and ANN-5 have obtained the best prediction of the arrangement inputs of [Tmin,Tmax,DT,Nm] and [Tmin,Tmax,DT,Gsr,avT] are respectively. The best combination of each ANN developed Models are list in Table (4.31) below.

Table 4.31: Best combination of each ANN model for Girne

Girne

S.no	ANN model	Inputs to the ANN
1	ANN-1	Ss
2	ANN-2	DT,avT
3	ANN-3	Tmin,Tmax,Gsr
4	ANN-4	Tmin,Tmax,DT,Nm
5	ANN-5	Tmin,Tmax,DT,Gsr,avT
6	ANN-5	Tmin,Tmax,DT,Ss,avT,

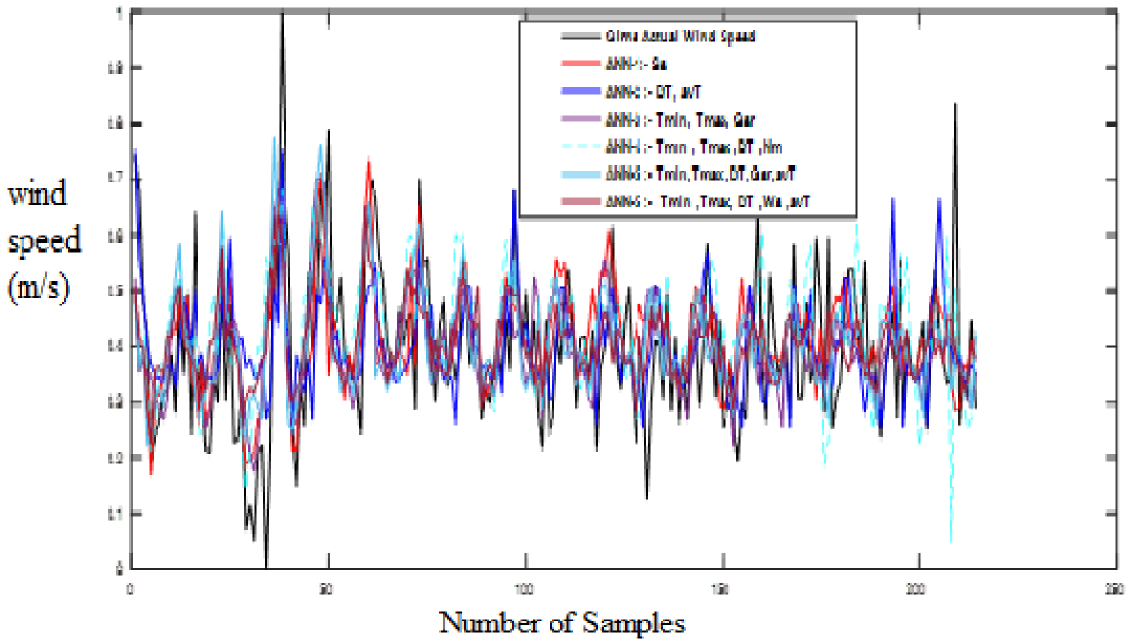

Figure 4.26: Comparison between Actual Wind Speed in Girne and Predicted values by all best combination of inputs (ANN-1 to ANN-5)

Table 4.32: Comparison of the Models between the Statistical tools Performance of ANN-1 to ANN-6 for Girne

S.No	Model	Inputs	Error	Performance Analysis Based on	RMSE	Performance Analysis Based on

				Error	(%)	RMSE
1		Tmin	-0.164	Least prediction accuracy Error	8.53	Excellent
2		Tmax	0.845	High prediction accuracy error	15.40	Good
3		Gsr	-1.461	Least prediction accuracy Error	0.29	Excellent
4	ANN-1	avT	0.924	High prediction accuracy Error	15.94	Good
5		Ss	-4.708	Low prediction accuracy Error	22.38	Fair
6		Nm	1.409	high prediction accuracy Error	19.24	Good
7		DT	-1.819	Least prediction accuracy Error	2.73	Excellent
1		Tmin ,Tmax	-0.429	Least prediction accuracy Error	5.71	Excellent
2		Gsr,avT	-0.239	Least prediction accuracy Error	8.02	Excellent
3	ANN-2	DT,Gsr	-1.068	Least prediction accuracy Error	2.38	Excellent
4		DT,avT	2.315	High prediction accuracy Error	0.87	Excellent
5		DT,Ss	0.333	high prediction accuracy Error	12.93	Good
6		DT,Nm	0.310	high prediction accuracy Error	12.68	Good
7		Ss,Gsr	0.57	high prediction accuracy Error	10.9	Good
1		Tmin,Tmax,DT	-0.354	Least prediction accuracy Error	7.24	Excellent
2		Tmin,Tmax,Ss	4.379	high prediction accuracy Error	39.44	Poor

Table 4:32 continued

3	ANN-3	Tmin,Tmax, avT	1.195	high prediction accuracy Error	17.78	Good

4		Tmin, Tmax, Nm	-0.59	Least prediction accuracy error	4.21	Excellent
5		Tmin,Tmax,Gsr	-1.43	Low prediction accuracy error	0.08	Excellent
6		DT,Ss,Gsr	-0.61	Least prediction accuracy error	5.46	Excellent
1		Tmin,Tmax, Gsr,avT	-2.31	Least prediction accuracy Error	6.07	Excellent
2		Tmin,Tmax, DT,Gsr	1.957	High prediction accuracy error	22.96	Fair
3	ANN-3	Tmin,Tmax, DT,avT	-0.29	Least prediction accuracy Error	7.61	Excellent
4		Tmin,Tmax ,DT,Ss	1.224	high prediction accuracy Error	17.98	Good
5		Tmin,Tmax,D, Nm	-7.50	Low prediction accuracy Error	41.40	Good
1		Tmin,Tmax,DT, avT,Gsr	1.710	Highprediction accuracy Error	21.28	Fair
2		Tmin,Tmax,DT, Nm,avT	0.486	High prediction accuracy Error	12.96	Good
3	ANN-4	Tmin,Tmax,DT, Ss,avT	0.743	Highprediction accuracy Error	14.70	Good
4		Tmin,Tmax,DT, Gsr,avT	-3.23	Low prediction accuracy Error	12.34	Good
1	ANN-6	DT,Tmin,Tmax, avT,Ss ,Nm,Gsr	-0.89	Leastprediction accuracy error	3.53	Excellent

4.4 Developed the Multiple Linear Regressions Model for Predicting Wind Speed

Multiple linear Regressions generalize the prediction methodology to allow for multiple predictor variables, such as Maximum Temperature, Minimum Temperature, average Temperature, Global solar radiation, Wind Speed, Sunshine, Difference of Temperature and Number of months correspondingly. Multiple Linear regressions model used as follows.

$$Ws = \beta_0 + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \beta_3\mathbf{x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5} x_{\mathbf{5}} + \boldsymbol{\beta_6 x_6} + \boldsymbol{\beta_7} x_7 \tag{4.1}$$

Where:

Ws = Dependent Variable

β_0 = Constant

$\beta(1\text{-}7)$ = Unstandardized Coefficient for each predictor Variable

X_1- Minimum Temperature

X_2 - Maximum Temperature

X_3 - Global Solar Radiation

X_4 - Average Temperature

X_5 -Sunshine

X_6 -Number of Months

X_7 - Difference of Temperature

The best model Summarized and the Regression Equations result shown in Table (4.33) shown below. The model was settled for the following predictor variables employed ranges and fixed based on the climate situation that the carry the months over the past year of meteorological climate data.

Summary of MLR Model Equation developed for Güzelyurt

$$\mathrm{Ws} = 0.6921 - 0.2160\ \mathrm{Nm} \tag{4.2}$$

$$\mathrm{Ws} = 0.6899 + 0.0055\ \mathrm{DT} - 0.2151\ \mathrm{Nm} \tag{4.3}$$

$$\mathrm{Ws} = 0.4184 + 0.757\ \mathrm{Tmin} - 1.319\ \mathrm{Tmax} + 0.8650\ \mathrm{Ss} \tag{4.4}$$

$$\mathrm{Ws} = 0.4149 + 0.759\ \mathrm{Tmin} - 1.319\ \mathrm{Tmax} + 0.0142\ \mathrm{DT} + 0.8617\ \mathrm{Ss} \tag{4.5}$$

$$\mathrm{Ws} = 0.8558 - 2.599\ \mathrm{Tmin} - 3.102\ \mathrm{Tmax} - 0.1235\ \mathrm{DT} - 0.2387\ \mathrm{Nm} + 5.452\ \mathrm{avT} \tag{4.6}$$

$$\mathrm{Ws} = 0.7262 - 1.348\ \mathrm{Tmin} - 2.564\ \mathrm{Tmax} - 0.0833\ \mathrm{DT} + 0.255\ \mathrm{Ss} + 0.1455\ \mathrm{Gsr} - 0.193\ \mathrm{Nm} + 3{,}490\mathrm{avT} \tag{4.7}$$

Table 4.33: Summary of best model results of MLR for Güzelyurt

Best MLR Models developed Result for Güzelyurt		
Models	Models input	R^2
Model -1	Nm	17.16%
Model -2	DT, Nm	17.56%
Model -3	Tmin,Tmax,Ss	35.54%
Model-4	Tmin,Tmax,DT,Ss	35.59%
Model-5	Tmin,Tmax,DT,Nm,avT	49.70%
Model-6	Tmin,Tmax,DT,Ss ,Gsr,Nm,avT	**54.27%**

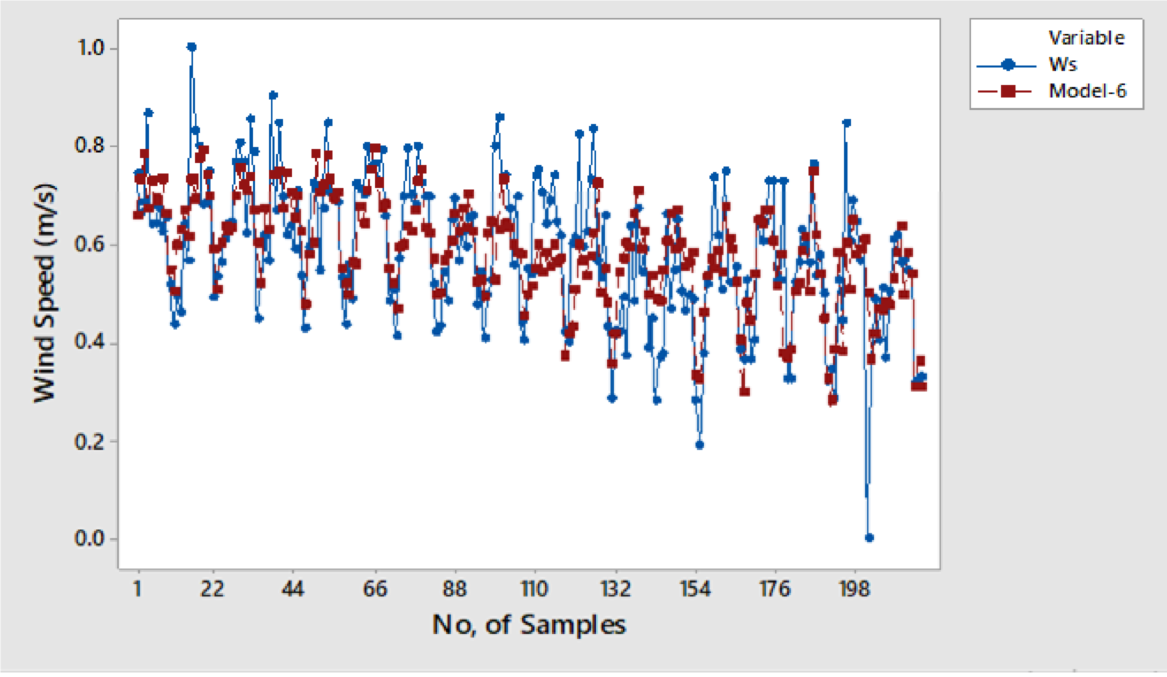

Figure 4.27: Diagram of the MLR Model-6 Predicted with Actual Wind Speed of Güzelyurt

Table 4.34: MLR Model Summary and Regression equation for Gazimağusa

Best MLR Model developed for predicting wind speed for Gazimağusa		
Models	Model inputs	R^2
Model-1	DT	16.33%
Model-2	DT, Nm	48.84%
Model-3	Tmin ,Tmax, Nm	58.97%
Model-4	Tmin, Tmax, DT, Nm	60.86%
Model-5	Tmin,Tmax , Nm, avT	64.09%
Model-6	Tmin,Tmax, DT,Ss,Gsr, Nm,avT	**64.93%**

Summary of MLR Model Equation developed for Gazimağusa

$$Ws = 0.2016 + 1.179\ DT \quad (4.8)$$

$$Ws = 0.0632 + 0.437\ DT + 0.4028\ Nm \quad (4.9)$$

$$Ws = 0.2019 + 0.2910\ Tmin - 0.4762\ Tmax + 0.3672\ Nm \tag{4.10}$$

$$Ws = 0.1840 + 0.2335\ Tmin - 0.4288\ Tmax + 0.447\ DT + 0.3383\ Nm \tag{4.11}$$

$$Ws = 0.2079 + 1.205\ Tmin - 0.163\ Tmax + 0.451\ DT + 0.3247\ Nm - 1.190\ avT \tag{4.12}$$

$$Ws = 0.2086 + 1.295\ Tmin - 0.112\ Tmax + 0.452\ DT + 0.1254\ Ss - 0.1490\ Gsr + 0.3209Gsr - 1.300avT \tag{4.13}$$

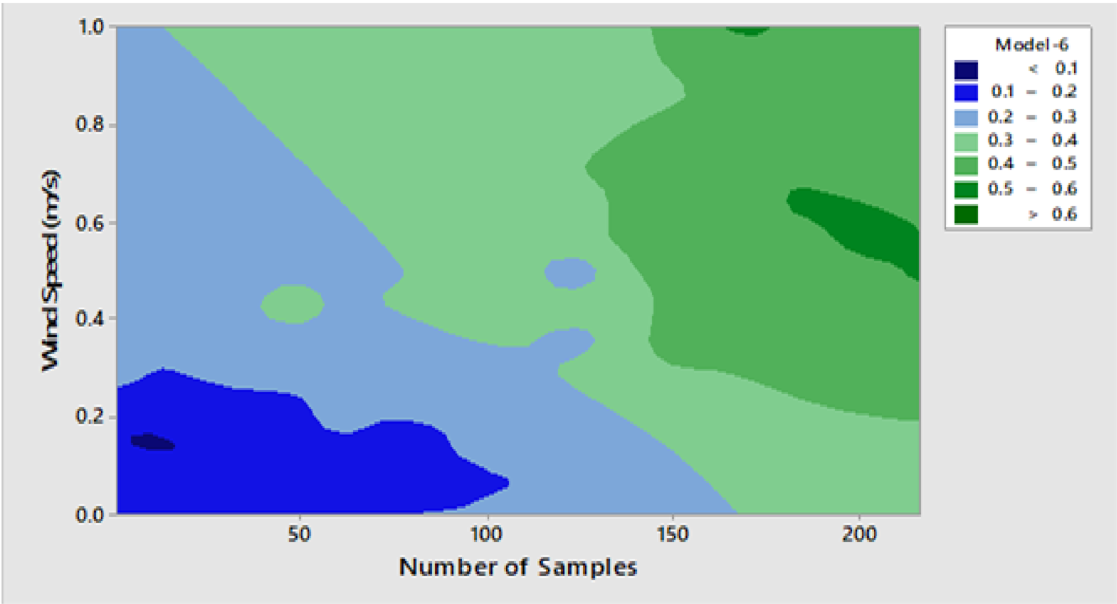

Figure 4.28: Contour plot of best MLR Model -6 Predicted with Actual wind speed of Gazimağusa

Table 4.35: The MLR Model Summary and Regression equation for Girne

Best MLR Model developed for predicting wind speed for Girne		
Models	**Preformance**	R^2
Model-1	Tmax	21.78%
Model-2	DT,avT	27.92%
Model-3	DT,Tmin ,Tmax	29.13%
Model-4	Tmin,Tmax, DT,avT	32.29%
Model-5	Tmin,Tmax, DT,avT, Gsr	33.30%
Model-6	Tmin, Tmax ,Nm ,avT,Ss,Gsr	34.71%

Summary of MLR Model Equation developed for Girne

$$Ws = 0.4979 - 0.2145\ Tmax \tag{4.14}$$

$$Ws = 0.5487 - 0.1759\ DT - 0.2008\ avT \tag{4.15}$$

$$Ws = 0.5476 - 0.1697\ DT + 0.185\ Tmin - 0.390\ Tmax \tag{4.16}$$

$$Ws = 0.5865 - 0.250\ Tmin - 1.792\ Tmax - 0.2044\ DT + 1.760\ avT \tag{4.17}$$

$$Ws = 0.5680 - 0.169\ Tmin - 1.908\ Tmax - 0.1905\ DT + 1.748\ avT + 0.0745\ Gsr \tag{4.18}$$

$$Ws = 0.5710 + 0.553\ Tmin - 1.835\ Tmax - 0.1780\ DT - 0.0943\ Nm + 0.945\ avT + 0.0644\ Ss + 0.1031Gsr \tag{4.19}$$

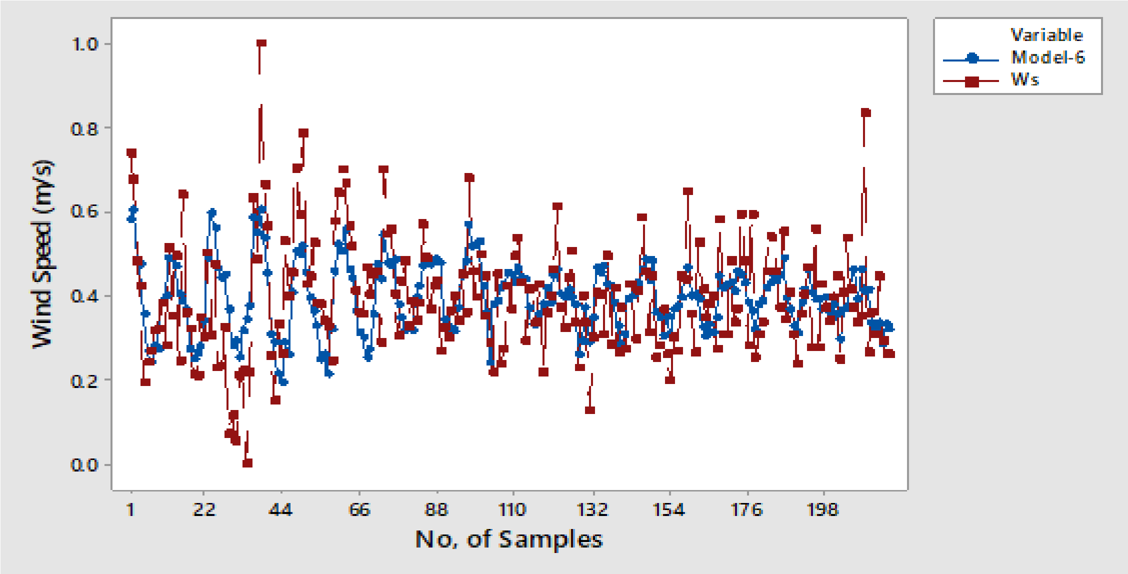

Figure 4.29: Diagram of Time series best MLR Model-6 predicted Vs Actual Wind Speed for Girne

Table 4.36: The MLR Model Summary and Regression equation for Lefkoşa

Best MLR Model developed for predicting wind speed for Lefkoşa		
Models	**Model inputs**	R^2
Model-1	Gsr	40.21%
Model-2	Ss, Gsr	66.50%
Model-3	DT,Ss,Gsr	68.35%
Model-4	Tmin,Tmax, DT,avT	58.94%
Model-5	Tmin .Tmax, DT Ss , Gsr	75.83%
Model-6	Tmin, Tmax, DT,Ss ,Gsr, Nm, avT	**77.94%**

Summary of MLR Model Equation developed for Lefkoşa

$$Ws = 0.5486 + 0.2953\, Gsr \quad (4.20)$$

$$Ws = 0.4109 + 0.4159\, Ss + 0.4764\, Gsr \quad (4.21)$$

$$WS = 0.5054 - 0.1311\, DT + 0.3315\, Ss + 0.4710\, Gsr \quad (4.22)$$

$$Ws = 0.7006 - 3.912\ Tmin - 4.207\ Tmax - 0.0360\ DT + 8.137\ avT \tag{4.23}$$

$$Ws = 0.4110 + 0.552\ Tmin - 0.738\ Tmax - 0.1115\ DT + 0.6305\ Ss + 0.7543\ Gsr \tag{4.24}$$

$$Ws = 0.4837 - 0.950\ Tmin - 2.234\ Tmax - 0.17\ DT + 0.44\ Ss + 0.6227\ Gsr + 0.06\ Nm + 2.992\ avT \tag{4.25}$$

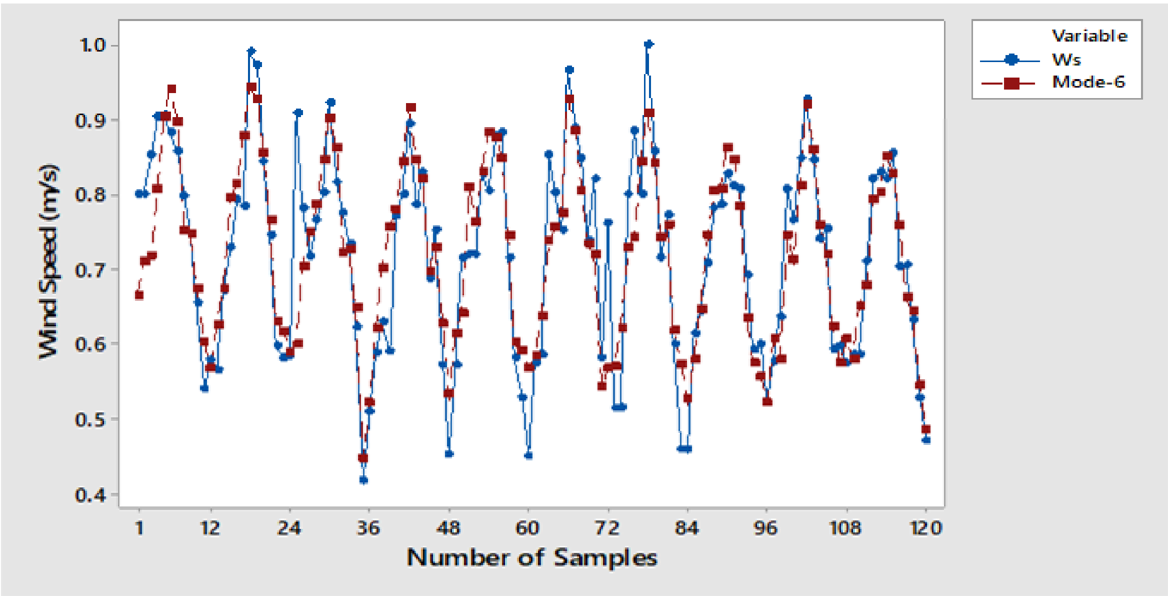

Figure 4.30: Diagram of Time series best MLR Model-6 predicted Vs Actual Wind Speed for Lefkoşa

The Comparison of Multiple Linear Regression Model Results performance for Güzelyurt, Gazimağusa, Girne and Lefkoşa

From above results shows, the performance of the parameters results that shows table (4.34) up to table (4.37) for Güzelyurt, Gazimağusa, Girne and Lefkoşa their statistical performance by multiple Linear regression model used to predicted the wind speed. From those parameters about 77.94% performance better results obtained in Lefkoşa and for

Güzelyurt (54.27%), Gazimağusa(64.93%), Girne(34.71%) models performance for the predicted wind Speed for the Area.

4.5 Results of (RSM) Mathematical Model Using to Predict Wind Speed

The Response Surface methodology based the Mathematical Model developed. The (DOE) is necessary to confirm the significance and the model competency; its determination of the quadratic developed model whether is important. The Adequacy of the models demonstrated by the calculation of the determination of coefficient R^2 was the calculated values and based on the greater R^2 values show that the models was adequate. It's satisfactory for model of response surface regression done by different combination the weather parameters and their collaboration or interaction for great correspondence of the response of Predicted Wind Speed values for the locations, Finally, the analysis was done using Coded variable and estimation of the best response surface regression models are list each location stated as follows.

Table 4.37: Summary of best developed Response Surface Regression Model Results for Güzelyurt

Best Response Surface Regression Model for Güzelyurt:		
Models	**Models input**	R^2
Model-1	Nm	17.93%
Model-2	DT, Nm	23.70%
Model-3	Tmin, Tmax, Ss	41.23%
Model-4	Tmin,Tmax ,avT ,DT	45.36%
Model-5	Tmin,Tmax, DT, Nm,avT	55.35%
Model-6	DT,Tmin,Tmax,Nm,avT, Gsr	65.26%

$$\mathrm{Ws} = 0.767 - 0.041\,\mathrm{Nm}\,0.261\,\mathrm{Nm}^2 \tag{4.26}$$

$$\mathrm{Ws} = -0.720 + 2.57\,\mathrm{DT} + 1.661\,\mathrm{Nm} - 0.735\,\mathrm{DT}^2 -$$

$$0.449\ \mathrm{Nm}^2 - 2.131\ \mathrm{DT} * \mathrm{Nm} \tag{4.27}$$

$$\mathrm{Ws} = -1.167 + 7.62\ \mathrm{Tmin} - 7.75\ \mathrm{Tmax} + 4.17\ \mathrm{Ss} + 2.51\ Tmin^2 - 1.2\ Tmax^2 - 4.64\ Ss^2 - 5.2 Tmin * Tmax - 7.31\ Tmin * Ss + 13.58\ Tmax * Ss \tag{4.28}$$

$$\mathrm{Ws} = -0.820 + 23.41\ \mathrm{Tmin} + 15.72\ \mathrm{Tmax} - 36.1\ \mathrm{avT} + 2.01\ \mathrm{DT} - 80.5\ \mathrm{Tmin}^2 - 94.3\ \mathrm{Tmax}^2 - 312\ \mathrm{avT}^2 - 1.826\ \mathrm{DT}^2 - 170.0\ \mathrm{Tmin} * \mathrm{Tmax} + 312\ \mathrm{Tmin} * \mathrm{avT} - 22.93\ \mathrm{Tmin} * \mathrm{DT} + 342\ \mathrm{Tmax} * \mathrm{avT} - 16.86\ \mathrm{Tmax} * \mathrm{DT} + 39.8\ \mathrm{avT} * \mathrm{DT} \tag{4.29}$$

$$\mathrm{Ws} = -0.816 + 17.41 \mathrm{Tmin} + 7.40\ \mathrm{Tmax} + 1.6 \mathrm{DT} + 2.01\ \mathrm{Nm} - 23.5\ \mathrm{avT} - 57.9\ \mathrm{Tmin}^2 - 58.5\ \mathrm{Tmax}^2 + 0.333\ \mathrm{DT}^2 - 2.065\ \mathrm{Nm}^2 - 221\ \mathrm{avT}^2 - 116.6\ \mathrm{Tmin} * \mathrm{Tmax} - 14.50\ \mathrm{Tmin} * \mathrm{DT} - 12.55\ \mathrm{Tmin} * \mathrm{Nm} + 227\ \mathrm{Tmin} * \mathrm{avT} - 9.78\ \mathrm{Tmax} * \mathrm{DT} - 3.15\ \mathrm{Tmax} * \mathrm{Nm} + 226\ \mathrm{Tmax} * \mathrm{avT} - 1.062\ \mathrm{DT} * \mathrm{Nm} + 23.0\ \mathrm{DT} * \mathrm{avT} + 17.48\ \mathrm{Nm} * \mathrm{avT} \tag{4.30}$$

$$\mathrm{Ws} = -5.98 + 7.08\ \mathrm{DT} + 52.2\ \mathrm{Tmin} + 16.0\ \mathrm{Tmax} + 3.68\ \mathrm{Nm} - 72.4\ avT + 9.32\ Ss + 3.66\ Gsr - 0.21 DT^2 - 104.4 Tmin^2 - 26.3 Tmax^2 - 2.05 Nm^2 - 277 avT avT^2 + 3.13 Ss^2 + 3.13 Gsr^2 - 38.4\ DT * Tmin - 13.29\ DT * Tmax - 2.152 DT * Nm + 55 DT * avT - 12.61 DT * Ss + 2.68 DT * Gsr - 117.2\ Tmin * Tmax - 16.88\ Tmin * Nm + 343\ Tmin * avT - 41.9\ Tmin * Ss - 0.2\ Tmin * Gsr - 4.17\ Tmax * Nm + 178\ Tmax * avT - 31.3\ Tmax * Ss + 9.4\ Tmax * Gsr + 22.9\ Nm * avT - 1.66\ Nm * Gsr + 78.0\ avT * Ss - 6.2\ avT * Gsr - 13.43\ Ss * Gsr \tag{4.31}$$

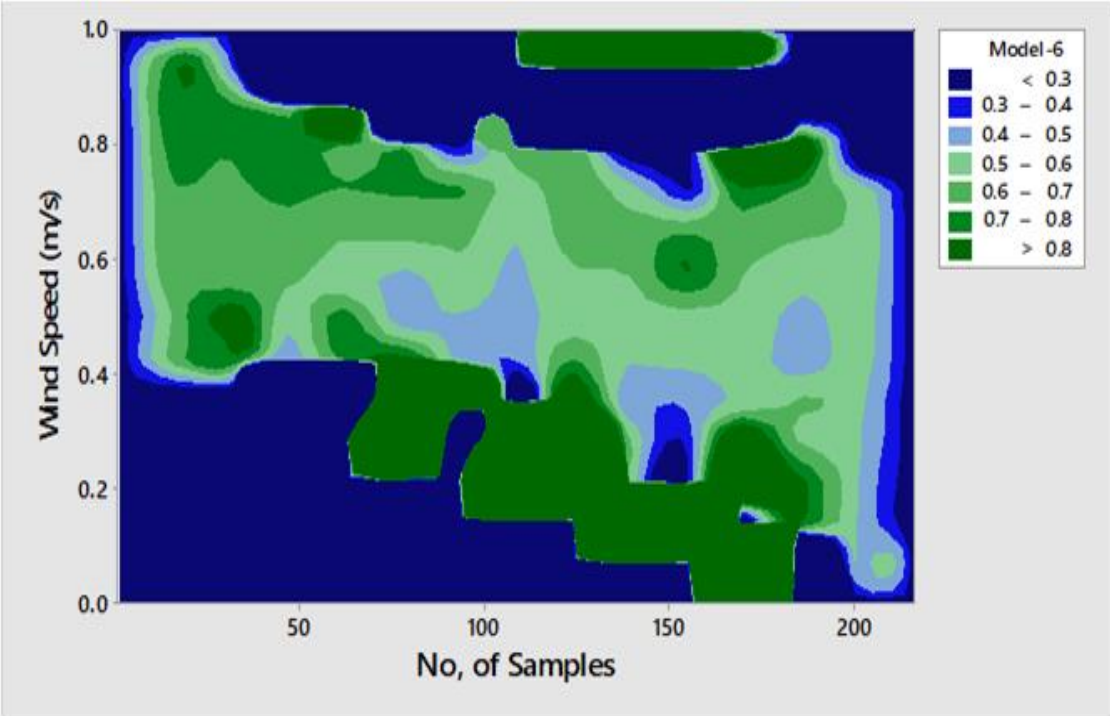

Figure 4.31: Contour Area plot of best RSM Model-6 by Akima's Polynomial method for Güzelyurt.

Above figure(4.31) contour area color shows that the dark blue color indicated that the value of wind speed is less than 0.3m/s, blue color shows its value of wind speed ranges between (0.3- 0.4 m/s) , light blue color shows the wind speed value range between (0.4-0.5m/s), light green color shows that the wind speed of the area found range between (0.5-0.6m/s), the green color shows that value of wind speed of the area found between ranges of (0.6-0.7m/s) and the dark green color shows that the value of wind Speed is greater than 0.8m/s of distribution of the wind speed for the area of Güzelyurt.

Table 4.38: Summary of best developed Response Surface Regression Model for Gazimağusa

Response Surface Regression Model for Gazimağusa		
Models	**Models input**	R^2
Model -1	Nm	48.94%
Model -2	DT,Nm	53.17%
Model-3	DT,Tmin ,Tmax ,DT	72.95%
Model-4	Tmin, Tmax avT,DT	74.94%
Model-5	Tmin, Tmax,DT,Ss,avT	77.02%
Model-6	DT,Tmin,Tmax,Nm ,avT,Ss ,Gsr	79.80%

$$\mathrm{Ws} = 0.396 - 1.215\,\mathrm{Nm} + 1.400\,\mathrm{Nm}^2 \tag{4.32}$$

$$\mathrm{W\,s} = -0.45 + 18.98\mathrm{DT} - 6.85\mathrm{Nm} - 64.5\mathrm{DT}^2 + 0.561\mathrm{Nm}^2 + 25.42\,DT * Nm \tag{4.33}$$

$$\mathrm{Ws} = -5.34 + 26.71\mathrm{DT} + 16.84\mathrm{Tmin} - 12.99\mathrm{Tmax} - 12.4\mathrm{DT}^2 + 0.485\,Tmin^2 + 0.112\,Tmax^2 - 55.45\,\mathrm{DT} * \mathrm{Tmin} + 36.26\,\mathrm{DT} * \mathrm{Tmax} \tag{4.34}$$

$$\mathrm{Ws} = -12.9 + 16.4\mathrm{Tmin} - 15.65\mathrm{Tmax} + 1.6\mathrm{avT} + 89.3\mathrm{DT} - 32\,Tmin^2 + 23.7Tmax^2 - 13.7avT^2 - 136.4DT^2 + 69.6Tmin * avT - 72.8Tmin * DT - 45.4Tmax * avT + 41.05\,Tmax * DT + 14.5avT * DT \tag{4.35}$$

$$\begin{aligned}\text{Ws} = & -15.64 + 17.5\ \text{Tmin} - 16.10\ \text{Tmax} + 102.6\ \text{DT} + 8.50\ \text{Ss} \\ & - 4.6\ avT - 31.4\ Tmin^2 + 30.3\ Tmax^2 - 147.2\ DT^2 - 1.14\ Ss^2 \\ & - 12.6\text{avT}^2 - 70.8\text{Tmin} * \text{DT} - 4.78\text{Tmin} * \text{Ss} + 69\text{Tmin} * \\ & \text{avT} + 54.65Tmax * DT - 7.44\ Tmax * Ss - 55.5\ Tmax * avT \\ & - 32.75\ DT * Ss + 20.8\ DT * avT + 14.55\ Ss * avT \end{aligned} \tag{4.36}$$

$$\begin{aligned}\text{Ws} = & -13.94 + 79.6\text{DT} + 12.2\text{Tmin} - 11.7\text{Tmax} + 2.32\text{Nm} \\ & - 0.8\ avT + 12.32Ss - 5.86Gsr - 100.9DT^2 - 17.1\ Tmin^2 + \\ & 16.7\ Tmax^2 + 0.58Nm^2 - 9.1\ avT^2 + 2.9\ Ss^2 - 0.24\ Gsr^2 \\ & - 43.5\text{DT} * \text{Tmin} + 33.7\text{DT} * \text{Tmax} - 7.5\text{DT} * \text{Nm} + 3.4 \\ & \text{DT} * \text{avT} - 39.4\ DT * Ss + 23.8\ DT * Gsr - 4.08\ Tmin * Nm \\ & + 39.6\ Tmin * avT + 1.7Tmin * Ss - 2.60Tmin * Gsr + 2.31 \\ & Tmax * Nm - 32.5Tmax * avT - 14.06Tmax * Ss + 10.50 \\ & Tmax * Gsr + 2.3Nm * avT - 3.33\ Nm * Ss + 1.40\ Nm * Gsr \\ & +13.8avT * Ss - 2.9avT * Gsr - 6.47Ss * Gsr \end{aligned} \tag{4.37}$$

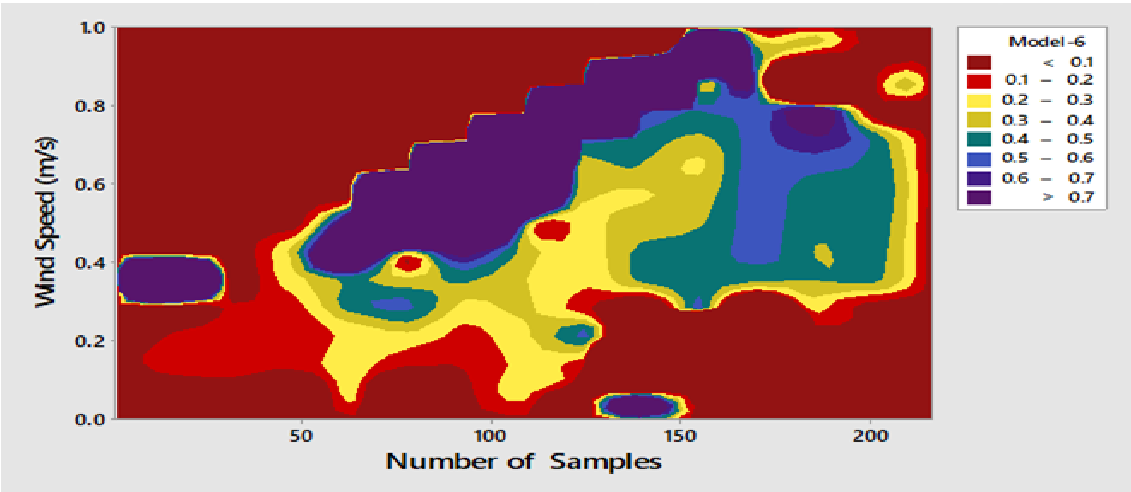

Figure 4.32: Contour area plotted by AKima’s polynomial Method for Gazimağusa

Above figure (4.32) contour area color shows that the brick red color indicated that the value of wind speed is less than 0.1m/s, red color shows its value of wind speed ranges between (0.1 - 0.2 m/s) , yellow color shows the wind speed value range between (0.2 - 0.3m/s), dark yellow color shows that the wind speed of the area found range between (0.3 -0.4m/s), the green color shows that value of wind speed of the area found between ranges of (0.4-0.5m/s) , blue color shows its value of wind speed ranges (0.5-0.6m/s) and the purple color shows that the value of wind Speed is found (0.6-0.7m/s) and dark purple color shows higher values of wind speed is 0.7m/s of distribution of the wind speed for the area of Gazimağusa.

Table 4.39: Summary of best developed Response Surface Regression Model for Lefkoşa

Response Surface Regression Models developed for Lefkoşa		
	Models input	R^2
Model-1	Gsr	57.36%
Model-2	Ss, Gsr	69.85%
Model-3	DT, Ss, Gsr	72.96%
Model-4	Tmin,Tmax ,Gsr, avT	76.89%
Model-5	Tmin, Tmax,DT ,avT ,Gsr	79.72%
Model-6	DT,Tmin ,Tmax,Nm ,avT Ss,Gsr	83.58%

$$\mathrm{Ws} = 1.733 - 3.448\,\mathrm{Gsr} + 2.651\,\mathrm{Gsr}^2 \tag{4.38}$$

$$\mathrm{Ws} = -50.6 + 100.8\,\mathrm{Ss} + 101.1\mathrm{Gsr} + 3.96\,\mathrm{Ss}^2 + 3.73\,\mathrm{Gsr}^2 - 207.0\,\mathrm{Ss} * \mathrm{Gsr} \tag{4.39}$$

$$\mathrm{Ws} = -46.7 - 7.24\,\mathrm{DT} + 100.2\,\mathrm{Ss} + 98.6\,\mathrm{Gsr} + 3.40\,\mathrm{DT}^2 + 2.26\mathrm{Ss}^2 + 3.83\mathrm{Gsr}^2 + 1.25\mathrm{DT} * \mathrm{Ss} + 1.117\mathrm{DT} * \mathrm{Gsr}$$

$$-204.1Ss * Gsr \quad (4.40)$$

$$Ws = 2.245 - 31.63Tmin - 22.9Tmax - 3.868Gsr + 53.2avT + 73.3\, Tmin^2 + 29\, Tmax^2 + 3.146\, Gsr^2 + 178\, avT^2 + 70Tmin * Tmax + 38.91Tmin * Gsr - 217Tmin * avT + 27.7Tmax * Gsr - 133Tmax * avT - 66Gsr * avT \quad (4.41)$$

$$Ws = 3.328 - 12.7\, Tmin - 12.7\, Tmax - 3.30\, DT + 24.1\, avT - 2.74\, Gsr + 100.7\, Tmin^2 + 62\, Tmax^2 + 2.13\, DT^2 + 304avT^2 + 2.74\, Gsr^2 + 141Tmin * Tmax - 21.6Tmin * DT - 338\, Tmin * avT + 32.7\, Tmin * Gsr - 14.3\, Tmax * DT - 269\, Tmax * avT + 28.1\, Tmax * Gsr + 35.9\, DT * avT - 0.73\, DT * Gsr - 60.4\, avT * Gsr \quad (4.42)$$

$$Ws = -217660 - 821591DT - 5086Tmin - 122.2Tmax + 1527Nm + 210\, avT - 724703\, Ss + 61061\, Gsr + 1253DT^2 - 399\, Tmin^2 + 313\, Tmax^2 - 7345Nm^2 + 1383\, avT^2 + 2279\, Ss^2 + 7.63\, Gsr^2 - 19662DT * Tmin - 102.7DT * Tmax + 2357DT * Nm + 172DT * avT + 362512\, DT * Ss + 239055\, DT * Gsr + 656\, Tmin * Tmax + 32539\, Tmin * Nm - 1455\, Tmin * avT - 18083\, Tmin * Ss + 100.5\, Tmin * Gsr + 152.7\, Tmax * Nm - 1296\, Tmax * avT + 90.0\, Tmax * Gsr - 228\, Nm * avT - 396100\, Nm * Gsr - 187.7\, avT * Gsr + 220401\, Ss * Gsr \quad (4.43)$$

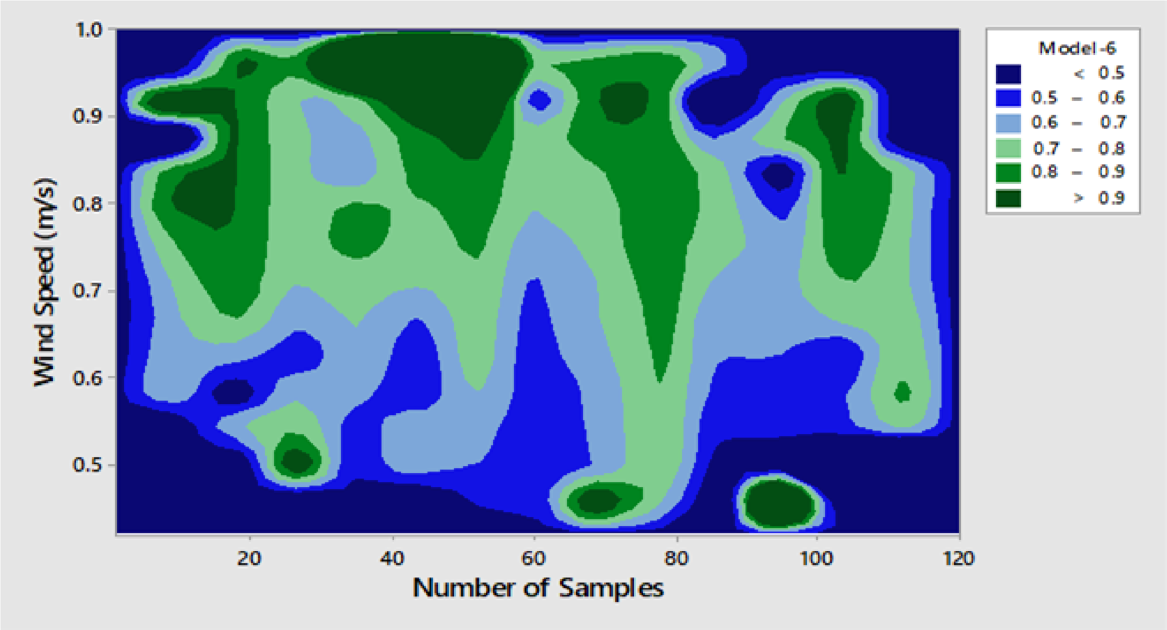

Figure 4.33: Contour area plotted by AKima's polynomial Method for Lefkoşa

Above figure(4.33) contour area color shows that the dark blue color indicated that the value of wind speed is less than 0.5m/s, blue color shows its value of wind speed ranges between (0.5-0.6 m/s) , light blue color shows the wind speed value range between (0.6-0.7m/s), light green color shows that the wind speed of the area found range between (0.7-0.8m/s), the green color shows that value of wind speed of the area found between ranges of (0.8-0.9m/s) and the dark green color shows that the value of wind Speed is greater than 0.9m/s of distribution of the wind speed for the area of Lefkoşa.

Table 4.40: Summary of best developed Response Surface Regression Model for Girne

Response Surface Regression Models developed for Girne		
Models	**Models input**	R^2
Model-1	Tmin	28.93%
Model-2	DT, avT	36.13%
Model-3	Tmin,Tmax,avT	40.24%
Model-4	Tmin,Tmax ,avT ,DT	44.64%
Model-5	Tmin.Tmax.DT, Ss,avT	47.93%
Model-6	DT, Tmin, Tmax,Nm ,avT ,Ss, Gsr	53.43%

$$\mathrm{Ws} = 2.039 - 4.109\,\mathrm{Tmin} + 2.454\,\mathrm{Tmin}^2 \qquad (4.44)$$

$$\mathrm{Ws} = 2.195 - 0.161\,\mathrm{DT} - 4.055\,\mathrm{avT} - 0.739\,\mathrm{DT}^2 + 2.021\,\mathrm{avT}^2 + 0.970\,\mathrm{DT} * \mathrm{avT} \qquad (4.45)$$

$$\mathrm{Ws} = 2.103 - 2.97\,\mathrm{Tmin} - 15.43\,\mathrm{Tmax} + 14.27\,\mathrm{avT} - 61.1\,\mathrm{Tmin}^2 + 35.9\,\mathrm{Tmax}^2 - 118.0\,\mathrm{avT}^2 - 77.3\,\mathrm{Tmin} * \mathrm{Tmax} + 201.2\mathrm{Tmin} * \mathrm{avT} + 22\mathrm{Tmax} * \mathrm{avT} \qquad (4.46)$$

$$\mathrm{Ws} = 2.430 + 3.76\,\mathrm{Tmin} - 16.63\,\mathrm{Tmax} + 8.2\,\mathrm{avT} - 0.15\,\mathrm{DT} - 54.0\,\mathrm{Tmin}^2 - 14.8\mathrm{Tmax}^2 - 164\,\mathrm{avT}^2 - 0.542\mathrm{DT}^2 - 82.0\mathrm{Tmin} * \mathrm{Tmax} + 190.5\mathrm{Tmin} * \mathrm{avT} - 7.86\mathrm{Tmin} * \mathrm{DT} + 127\mathrm{Tmax} * \mathrm{avT} + 2.8\,Tmax * DT + 5.9\,avT * DT \qquad (4.47)$$

$$Ws = 3.291 - 8.91\,Tmin - 18Tmax + 0.03\,DT - 2.65\,Ss$$
$$+ 22.2\,avT - 6.4\,Tmin^2 - 5.4\,Tmax^2 - 0.603\,DT^2$$
$$+ 1.53Ss^2 - 91avT^2 - 68.5Tmin * Tmax - 8.09Tmin * DT$$
$$+ 22.4\,Tmin * Ss + 77Tmin * avT - 0.8Tmax * DT$$
$$+4.8Tmax * Ss + 96Tmax * avT - 0.40\,DT * Ss$$
$$+ 10DT * avT - 26Ss * avT \tag{4.48}$$

$$Ws = 4.30 - 2.72\,DT - 12.2\,Tmin - 30.6\,Tmax - 0.06\,Nm$$
$$+37.2avT - 2.03Ss - 0.50Gsr + 0.60DT^2 - 43.3Tmin^2$$
$$+ 73.6Tmax^{2} - 2.52Nm^2 + 140\,avT^2 + 3.10\,Ss^2 -$$
$$1.27Gsr^2 - 15DT * Tmin + 8.9DT * Tmax + 1.98DT * Nm$$
$$+ 8.2DT * avT - 4DT * Ss + 2.85DT * Gsr + 135Tmin * Tmax$$
$$+19.6Tmin * Nm - 43Tmin * avT + 37Tmin * Ss - 31.4$$
$$Tmin * Gsr - 23.8Tmax * Nm - 260Tmax * avT + 39.1$$
$$Tmax * Ss - 6.3\,Tmax * Gsr + 3.2\,Nm * avT + 4.39\,Nm * Gsr$$
$$- 72.7\,avT * Ss + 37.8\,avT * Gsr - 3.32\,Ss * Gsr \tag{4.49}$$

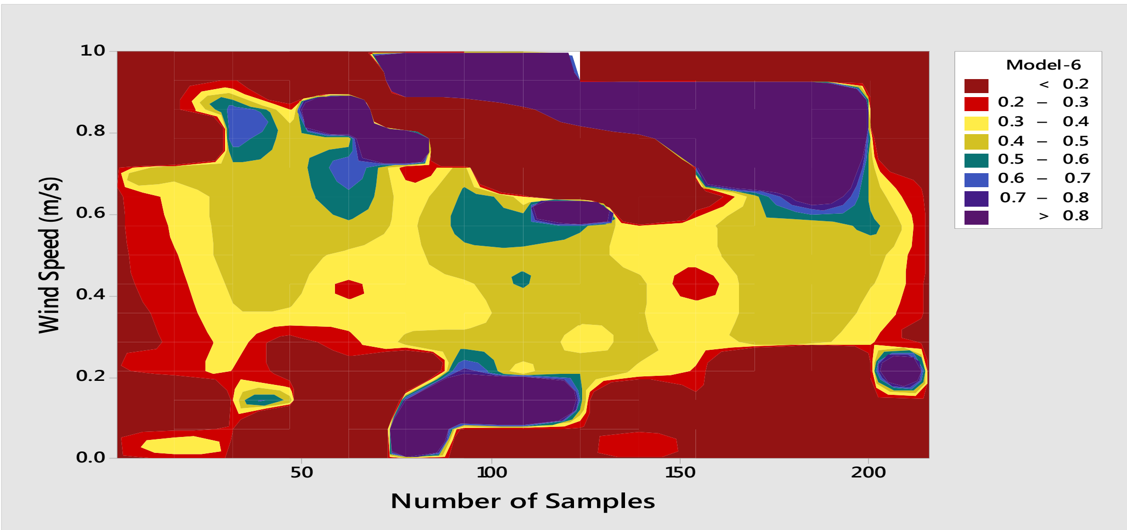

Figure 4.34: Contour area plotted best RSM Model-6 by AKima's polynomial Method for Girne

Above fıgure (4.34) the contour area color shows that the brick red color indicated that the value of wind speed is less than 0.2m/s, red color shows its value of wind speed ranges between (0.2 - 0.3 m/s) , yellow color shows the wind speed value range between (0.3 - 0.4m/s), dark yellow color shows that the wind speed of the area found range between (0.4 -0.5m/s), the green color shows that value of wind speed of the area found between ranges of (0.5-0.6m/s) , blue color shows its value of wind speed ranges (0.6 -0.7m/s) and the purple color shows that the value of wind Speed is found (0.7-0.8m/s) and dark purple color shows higher values of wind speed is 0.8m/s of distribution of the wind speed for the area of Girne

In this study, (RSM) had been applied to developed the Mathematical model between the key parameters of process and the response of the desired values. This model has been calculated based on a two-level-two-factor central Composite design method. The analysis of the Variance of the four selected area of North Cyprus results had been showed that the minimum Temperature, Maximum Temperature, Global solar radiation, average of Temperature, Sunshine, difference of Temperature, wind Speed and the number of months is the fundamental model relations with the wind speed. In this paper the results are presented to expect to be a certain extent advantageous to the wind energy designers as used to academic finding.

From above results shows, the performance of the parameters results that shows table (4.37) up to table (4.40) for Güzelyurt, Gazimağusa, Girne and Lefkoşa their statistical performance by response surface methodology model used to predicted the wind speed. From those parameters about 83.58% performance better results obtained in Lefkoşa and for Güzelyurt (65.25%), Gazimağusa(64.93%), Girne(53.43%) models performance for the predicted wind Speed for the Area.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSIONS

In this study, three predictive tools namely; ANN, MLR and RSM models were used to predict the wind speed at four selected regions in North Cyprus prediction of wind speed by usage of the weather data at four selected locations across northern region of Cyprus, namely;Gazimağusa, Güzelyurt, Lefkoşa,and Girne, was carried out, using the weather data collected from the meteorological department for a nine-year between 2009 to 2017 were used. In this approach, developed the different models with the different combination of inputs were applied and developed for the modeling to improve the performance each single model.

According to it outcomes, DT, Tmin, Tmax, Ss,avT and Gsr are the most impact of parameters in the simulation or prediction of the Wind Speed in north Cyprus. Based on the three worldwide statistics of the Mean Square Error (MSE), Root Mean Square Error (RMSE) and Determination of Coefficient (R^2) Were applied to evaluate the performance of developed models.

This thesis work presented that the influential parameters input combination models that can be responsible for the satisfactory outcomes for the prediction of the Wind Speed. The results presented that Artificial Intelligence models are more predictive performance and also superior to Mathematical method models outstanding of the facts that the RSM and MLR are linear model and such, models couldn't manage with the nonlinear characteristics.

From ANN Models results gained for this Study, it was perceived that of the maximum impact on the development of models that the performance occurred after the change of the inputs data types were used. This demonstrates that the one of a strong connection between the wind speed and other parameters of the variables (for instance Maximum Temperature, difference of Temperature and Sunshine) can be recognized, those parameters can used laterally with the wind speed as one input in order to developed ANN models that helps for the wind Speed Predicting more better.

Six ANN Combination Models were developed that gave the best prediction performance (R^2) maximum value of Testing is 97.01% were attained. When the models were the output results of the wind speed compared to the actual wind speed that developed models predicted better results provided.

six Combination Models for MLR developed were improved that gave the best prediction performance ranges of (R^2) between 34.71% and 77.94 % were attained. When the models were the output results of the wind speed compared to the actual wind speed that developed models predicted better results provided.

The Adequacy of the RSM models demonstrated by the calculation of the determination of coefficient R^2 was the calculated values to be found between 0.8358 were found in lefkoşa. As Results, show that the models adequate. The value of the model that might predict 83.58 % of the predictability is response. It's satisfactory for model of regression contained by the interval of the Climatic parameters and their collaboration or interaction.

Generally, the multiples Linear regression (MLR)and Response surface Methodology models are predicted the wind speed results shown for the area of Güzelyurt, Gazimağusa, Girne and Lefkoşa their results more accurate than the wind Speed predicted by the developed the combination Model of ANN predicted Wind Speed for the Area.

5.2 RECOMMENDATIONS

In this study the wind speed investigation needs increasingly more research and concentrate just as numerous other significant points for North Cyprus. Likewise, the accompanying focuses can be considered later on:

- Wind speed information every hour can be utilized to ascertain the yearly operational hours used for wind turbines plant installations.
- Different choices of sustainable power source can be contrasted with the examination completed in this model to give a chance to pick the best substitute for power age utilizing petroleum derivative plants.
- In this paper the results are presented to expect to be a certain extent advantageous to the Wind energy designers and researchers as used as reference for academic finding.
- **Generally**,the applications of the ANN,MLR and RSM models are more recomminded to used for predicted wind speed for selected areas of North Cyprus.

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