Modeling and Forecasting Weather Parameters using ANN-MLP, ARIMA and ETS model: A case study for Lahore, Pakistan

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ABSTRACT

This paper demonstrate a comparison of Artificial Neural Networking Multilayer Perceptron (ANN-MLP) with automatic Exponential Smoothing Algorithm (ETS) and Auto Regressive Integrated Moving Average (ARIMA) models for forecasting the key weather parameters of Lahore, Pakistan. Models are developed by considering average of monthly maximum and minimum temperature, relative humidity, wind-speed and amount of precipitation For developing the models, thirty years data (1987-2016) comprising are used. ANN-MLP is a mathematical technique and ARIMA and ETS are statistical techniques. We divide the thirty years data (1987-2018) data into training (1987 till 2016) and test (2017 till 2018) set to ensure the efficiency and reliability of all these models along with the performance criteria of the estimates. This paper explains in brief how ANN-MLP can be formulated using different learning methods. The most appropriate model and network structure are decided according to their forecast performance. MAE (Moving Average Error), RMSE (Root-Mean-Square error), ME (mean error), MASE (Mean absolute scaled error) indicate that ANN-MLP yields better results.

Index item: *Weather parameter forecasting, ARIMA, ANN-MLP, automatic ETS, forecasting.*

1. Introduction

Weather expectation plays a vital rule in water resource management, nutrition plan, farming and all movement designs in the nature. The event of delayed dry time allocation or critical tempests at the key times of the procure headway and improvement may incite gigantic sinking in defer. Pakistan is a rural country, and economy of Pakistan is to a great extent needy on yield profitability.

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Along these lines precipitation expectation turns into a noteworthy factor in agrarian nations like Pakistan. Rainfall gauging has been a standout amongst the most logically and innovatively difficult issues far and wide in the only remaining century. Precipitation forecast demonstrations includes a blend of probabilistic models, perception and information of patterns and examples. Utilizing these strategies, sensibly exact gauges can be made up. A few late research contemplates have created precipitation expectation consuming different climate and atmosphere anticipating procedures. Various examinations have been directed about precipitation gauging in Pakistan and different nations.

Climate gauging is an essential issue in the field of climatology and meteorology everywhere throughout the world. A few components contribute significantly to expand the conjecture accuracy. Several efforts have been done to create and improve the current time arrangement climate, through models by utilizing distinctive procedures.

Atmosphere check systems are among the most awesome condition structures. An unparalleled measure of data, starting from satellites, ground stations and sensors arranged around our planet send data each day that must be used to foresee the atmosphere condition in every one hours all around the world. Climate forecasts give conjecture for next 24, 48 and 72 hours for wide territories (Tektas (2010)). Atmosphere guesses give essential information about future atmosphere. There are distinctive procedures drawn in with atmosphere gauging, from respectably clear impression of the sky to exceedingly complex modernized numerical models.

2. Literature Review

Predicting climate is a great challenge among the most troublesome issues over the world, in two ways; its real-world motivating power in meteorology and understood hover ideas for authentic research.

Afsar et al., (2013) examine temperature and precipitation instability in Gilgit Bultistan region. They used regression and stochastic models to demonstrate the anticipation of temperature and rainfall. They observed that the precipitation prolonged with rising temperature. During 2007 to 2011 a reduction in the amount of precipitation is observed with rise in the monthly average maximum temperature. They found AR(1) to be most suitable for forecasting temperature. In 2015 Ahmed et al., explored change in the pattern of rainfall across 15 locations in the Swat river, Pakistan over the time length of 51 years (1961– 2011). They used Mann Kendall and Spearman's rho non-parametric tests to recognize variety of patterns in rainfall across stations. Faisal and Ghaffar, (2012) worked on Thiessen Polygon technique to evaluate area weighted rainfall (AWR) of Pakistan of 56 stations for 50-year duration (1961-2010) . Month to month precipitation documents of fifty six stations, storm measures for the season of fifty years (1961-2010) had been used and a size relationship of normal precipitation used to be made by utilizing the Theissen Method.

Yamoah et al., (2016) proposed "SARIMA (0,0,0)×$[(1,1,1)]_{12}$" for forecasting mean monthly precipitation for "Brong Ahafo" Region of Ghana. Yusof and Kane, (2012) suggested "SARIMA (1, 1, 2)$(1, 1, 1)_{12}$, SARIMA(4, 0, 2)(1, 0, 1)$_{12}$" along with ETS to be adequate models for predicting rainfall in Malaysia. They also reported that the information for predicting exact readings of monthly average rainfall are not adequate. Kane (2013) modelled the highest rainfall event of Chui Chak in Malaysia for the period 01/01/1975-31/12/2008 via functional ARIMA amplified with the GARCH model. Autocorrelation was test by the Ljung-Box test. The test proves ARFIMA-GARCH combine model can capture hazardous situation related to rainfall.

Kambezidis et al., (2010) examine the spatial distribution of average yearly rainfall in Greece for the period (1962– 2002) through Kriging interpolation method. They also examine the mean monthly rain intensity while using 32 meteorological stations. They used short-cut Bartlett test of homogeneity to analyze the rain time series. They find significant negative trend in the west sub-regions of Greece and having positive trend in the wider area of Athens.

Sakellariou and Kambezidis (2003) examine pattern of annual rainfall in the Athens district, Greece. They consider rainfall in shorter time intervals (less than a month) as they think that considering annual average or total may ignore nature and can lead to miss any climate signals that occur during months or within a month. They found a connection in rainfall in a non-linear manner with the correlation of variability.

Menabde and Sivapalan (2000) suggested a model that can successfully replicate extreme events and scaling behavior through 'fattailed' Levy-stable distribution for rainfall time series. They examine the model by comparing it with model based on gamma distribution and another model based on self-similar random cascade. The gamma distribution based model underestimate whereas, the other self-similar model overestimate individual storms.

Yusof et al., (2013) used a rainfall amount to be categorized into seven categories (extremely wet to extremely dry) to analyzed dry and wet events using data of Peninsular Malaysia. The used standardize precipitation index (SPI) to model the best fitted distribution in representing the rainfall. Lognormal distribution is found to be best-fitted distribution to the daily rainfall in the region, in comparison with Gamma and Weibull distributions.

Zahid and Rasul, (2011) investigated extreme temperature events and rainfall of Pakistan for the period 1965-2009 to calculate the frequency in Pakistan. They used F-test to evaluate minimum and maximum extreme temperature events in the country. They pointed out that these extreme events are increasing all over the country. For rainfall extreme events they used K-S test at 95% confidence interval and concluded that due to global warming and climate change southern half of Pakistan is facing more wet spells.

Abbot and Marohasy (2012) inspected rainfall data including climate indices, monthly rainfall and temperature in Queensland, Australia. They introduced ANN to forecast monthly rainfall in the region. They proposed that this prototype design have room for improvement. Nayak et al., (2013) provides a detailed literature survey of ANN for rainfall forecasting carried out by different researchers as they found that forecasting through ANN is more appropriate than done by traditional statistical and numerical methods. Bilgili and Sahin (2010) also analyzed ANN to predict lasting monthly temperature and rainfall for the period 1975-2006 from 76 stations of Turkey at any point on the basis of neighboring stations information. They divide 76 measuring stations into training and testing sets. The model fitted was adequate as the errors are within the acceptable limits.

In this paper we will be going to compare automatic ANN-MLP with ARIMA and ETS techniques to show superiority of ANN-MLP in terms of forecasting and minimum error, using weather parameter of Lahore, Pakistan. The paper is organized as follows. In the above section we describe introduction and literature review. In the next section we describe material and method used for analysis, in Section 3 we discuss result and provide discussion on the outcome. Finally, in section 4 some concluding remarks are given.

3. Data Analysis and Case Study Characteristics

In this article, we are using secondary data set of monthly averages of minimum temperature, maximum temperature, wind speed, relative humidity and amount of precipitation that are considered as main weather parameters of Lahore, Pakistan. The data is considered for thirty-year period (from 1987 to 2016), obtained from the site (www.http://sdwebx.worldbank.org). We divide the data into training and testing sets. The first twenty eight years of the selected period are used for training (1987-2014), while the last two years (2015-2016) will be used to verify the forecasting performance of the automatic seasonal ARIMA, automatic ETS and automatic ANN-MLP. This study will helps to determine the forecast of main whether parameters. These forecasting are useful in atmospheric sciences, agriculture science and climatology and also can also be use by service providing companies to assess expected demand in near future.

In Lahore there are mainly two spans of rainfall. The first span starts from June and end in September. The second span start from December and continue till February. The highest recorded rainfall with 1,576.8 millimeters was in 2011(Wikipedia; https://en.wikipedia.org/wiki/Climate_of_Lahore#cite_note-5)

Each year maximum temperature reported in the month of June in Lahore, with an average high temperature exceeding 40 °C (104.0 °F). The recorded maximum temperature was 48 °C on 9th June 2007. The minimum temperature is usually observed during January and the July is known to be the wettest month of Lahore. The minimum ever temperature documented is –1°C reported on 13 January 1967.

4. METHODOLOGY

4.1 Automatic Seasonal ARIMA

In applications purposes, a lot of processes in time series can be represent as follows: $y_{t-p}, \cdots, y_{t-2}, y_{t-1}, y_t$

For building a forecast the use of techniques related to time series, a excellent selection of tactics are existing. forecast of time collection {y(n)} refers to the challenge of finding approximation of succeeding future

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sample {y ̂(n+1)} based on present and past information, i.e. samples y(n), y(n-1).

A non-seasonal processes in time series such as ARIMA (r,d,u) process which is given by$(1-B^d)y_t = l + \emptyset(B)y_t + \theta(B)z_t$
Where;
B is the backshift operator
$\{z_t\}$ is a white noise process its mean and variance is “0” and "σ^2"
$\emptyset(B)$ and $\theta(B)$ are polynomials of order r and u, respectively.
l represents the hidden polynomial of order d in the forecast function.
According to Brockwell and Davis (1991) it is assumed that $\emptyset(B)$ and $\theta(B)$ have no roots for $|B| < 1$ in order to make sure regarding causality and invertibility of the process.
The seasonal ARIMA (r,d,u)$(R, D, U)^s$ process is given by:$(1-B^s)^D(1-B^d)y_t = l + \varphi(B^s)\emptyset(B)y_t + \vartheta(B^s)\theta(B)z_t$
Where
$\varphi(B^s)$ and $\vartheta(B^s)$ are polynomial of order R and U respectively,
$l = 0$ represents an implicit polynomial of order $d + D$ in the forecast function
Box and Jenkins (1976) mentioned that $\varphi(B^s)$ and $\vartheta(B^s)$ contain no root inside the unit circle.

Selecting an appropriate model order is the main task in automatic Seasonal ARIMA, that is, the values of r, u, R, U, D, d. If d and D are known, information criteria(s) can be used to select the order $r, u, R\ and\ U$, for example AIC.
AIC= $-2\log(L) + 2(r + u + R + U + m)$
Where; L represents the maximum likelihood of the fitted model.
Hyndman (2008) developed a package named “forecast” in R.Gui environment. The package provide algorithms for automatic univariate time series forecasting models.

4.2 Exponential Smoothing State Space (ETS) (Error, Trend, Seasonal)

Initially, Pegels (1969) is known for defining ETS classification which further comprehended and modified by Gardner (1985) and Rob Hyndman et al. (2002). Table 1 shows methods with all possible number of ETS components. The ETS model flexibility is defined by its capability to grasp trend and seasonal components of different traits. Table 2 represents list of all possible traits.

Table 1. Possible Number of ETS Components

Trend Components	**Seasonal Components**		
	No (None)	**Ad (Additive)**	**Mu (Multiplicative)**
No(None)	**NoNo**	**NoAd**	**NoMu**
Ad(Additive)	**AdNo**	**AdAd**	**AdMu**
Ada(Additive Damped)	**AdaNo**	**AdaAd**	**AdaMu**
Mu(Multiplicative)	**MuNo**	**MuAd**	**MuMu**
Mda(Multiplicative Damped)	**MdaNo**	**MdaAd**	**MdaMu**

Table 2. **Number Of Possible Combination Of ETS model**

Model	**Model**	**Model**
ETS(Mu,Mu,No)	ETS(Ad,Mu,Ad)	ETS(Mu,No,Mu)
ETS(Mu,Ad,No)	ETS(Ad,Mda,No)	ETS(Mu,No,Ad)
ETS(Mu,Ad,Mu)	ETS(Ad,Mda,Mu)	ETS(Mu,No,No)

ETS(Ad,Mu,No)	ETS(Ad,No,Ad)	ETS(Mu,Ad,Ad)
ETS(Ad,No,No)	ETS(Mu,Ada,Mu)	ETS(Ad,Ada,Mu)
ETS(Ad,Ad,Mu)	ETS(Mu,Ada,No)	ETS(Mu,Mu,Ad)
ETS(Mu,Mu,Mu)	ETS(Mu,Mda,Mu)	ETS(Ad,Ad,Ad)
ETS(Ad,No,Mu)	ETS(Ad,Ada,No)	ETS(Ad,Ada,Ad)
ETS(Ad,Ad,No)	ETS(Mu,Mda,Ad)	ETS(Mu,Ada,Ad)
ETS(Ad,Mu,Mu)	ETS(Mu,Mda,No)	ETS(Ad,Mda,Ad)

The package "forecast" by Hyndman (2008) in R.Gui, use the following steps to obtain relevant automatic ETS forecasting model.

1. Appropriate models (as shows in Table 2) are applied to each array, as well as optimize the parameters (both smoothing parameters and the essential state variable) of the model for each case.
2. AIC will decide which model is best fitted.
3. Using the best model, forecast the points for as many steps as required and obtain the prediction intervals.

4.3 Automatic Artificial Neural Networks Multilayers Layers Perceptron (ANN-MLP)

An ANN algorithm is an interrelated crowd of artificial neurons that has a characteristic property for putting away experimental learning and building it accessible for use. The main least complex type of feedforward neural system, called perceptron has been presented by Rosenblatt in 1957. This unique perceptron show restricted just a single layer, inputs are encouraged straightforwardly to the yield unit by means of the weighted associations. In spite of the fact that the perceptron at first appeared to be encouraging, it was in the long run demonstrated that perceptron's couldn't be prepared to perceive numerous classes of examples. From that point onward, multilayer perceptron (MLP) demonstrate was determined in 1960 and bit by bit wound up a standout amongst the most generally actualized neural system. Multilayer perceptron's implies a feed forward connect with at least one layers of hubs between the information and yield hubs. The MLP conquers numerous confinements of the single layer perceptron's, their abilities come from the non-straight connections among the hubs (Lippmann, 1987).

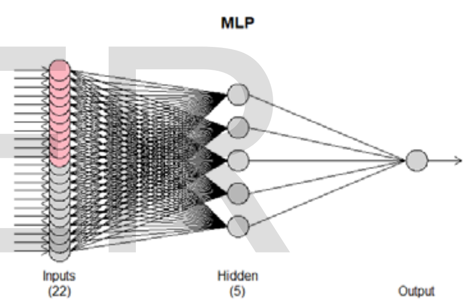


Figure 1: Structure Of best fitted ANN-MLP model, the magenta ones are deterministic inputs (shows seasonality in this case) While the grey input nodes are auto regressions. The figure indicate that the resulting network has 5 hidden nodes, it was trained 20 times and the different forecasts were combine using median operator

A best possible ANN design might be considered as the one acquiescent the best execution as far as error minimization, while holding a basic and smaller structure. There are two vital issue regarding the execution of ANN. The first is to determining the

Networks design and secondly finding the optimal qualities for the association loads (determination of training algorithm). In the process of identify the network size, an inadequate number of hidden nodes cause difficulty in learning data. whereas an unnecessary number of unseen nodes might lead to preventable training time with marginal enhancement in training result (Zealand et al., 1999). A high number of nodes in unseen layer tend the memorization of network, instead of learning and simplification, and it leads to the difficulty of local minima. On the other hand, increase the unseen nodes will help to adjust to larger rise and fall of objective function and allow the model to think the presence of volatilities in the given data. Such as trends and seasonal discrepancy frequently become visible a lot with rainfall and others weather parameters predictions. There is in fact no precise rule to decide the appropriate number of unseen nodes. The modeling framework for automatic artificial Neural Network time series forecasting models, which is improved learning method for multilayers perceptron (Nikolaos Kourentzes, 2014). The Multi-Layer Perceptron with one hidden layer is extensively used for the forecast in most studies on time series modeling (Howard and Mark,2000). It has been proven that neural network with one hidden layer are clever to provide a good approximation for any model (Battiti,1992).

The **nnfor** package for R facilitates time series forecasting with **Multilayer Perceptrons** (MLP). It does not support deep learning, though the plan is to extend this to this direction in the near future. Currently, it relies on the available package in R**,** namely **neuralnet**, which gives all the machinery to train MLPs. Training of MLPs is written within the **nnfor** package. Note that since **neuralnet** cannot tap on GPU processing, large networks tend to be very slow to train. **nnfor** differs from existing neural network implementations for R in that it provides code to automatically design networks with reasonable forecasting performance, but also provide in-depth control to the experienced user. The automatic specification is designed with parsimony in mind. This increases the robustness of the resulting networks, but also helps reduce the training time.(Nikolaos Kourentzes, 2014)

4.4 Forecast Performance

For the evaluation of the forecast performance for different model, four dissimilar forecast performance measures are apply. The primary is mean error (ME), which is describe as

mean = $|e_i|$, where e_i is the forecast error; $e_i = y_i - \hat{y}_i$

The second measure for performance comparison is the mean absolute error (MAE), which is described as

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

The third is the root mean absolute scaled error (MASE), which can be presented as for a seasonal time series,

$$\text{MASE} = \frac{1}{N}\sum_{t=1}^{T}\left(\frac{|e_t|}{\frac{1}{T-m}\sum_{i=m+1}^{N}|y_t - y_{t-m}|}\right)$$

The fourth is the root mean squared error (RMSE), which can be presented as

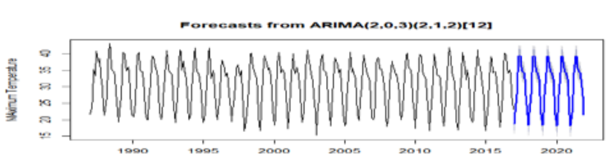
$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

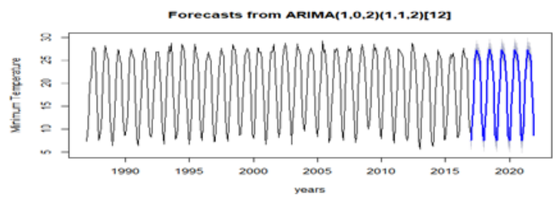
where N is the number of data points available in given data sets which is 900 in our case, y_i and $\hat{y}_i$ stand for the real and forecasting values correspondingly. MAE, MAPE and RMSE are estimates of the forecasting error of the model.

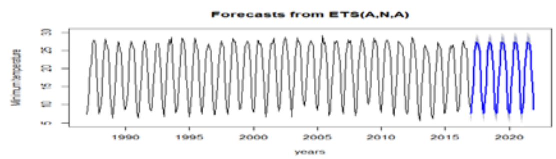
5. Results:

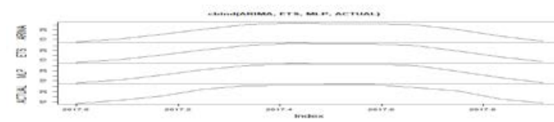
This section presents the results of ARIMA, ETS, and ANN-MLP for forecasting important weather parameters. For selecting best forecasting model for individual weather parameters, we consider the data from 1987 to 2016. Figures 2,3,4,5 and 6 represent the average on monthly basis significant weather parameters plots of different series which illustrate an obvious regular seasonality from 1987 to 2016. These figures also depicts five year (2017-2021) forecasted values (bold lines with shaded intervals), obtained through all three methods, of monthly average minimum and maximum temperature, relative humidity, wind speed and amount of precipitation.

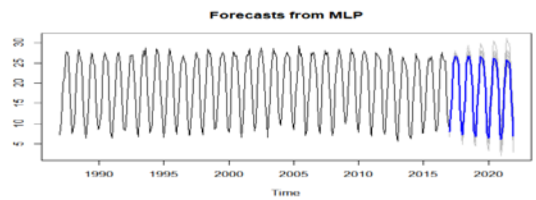
Figure 2: Plot of monthly average minimum temperature in Lahore, Pakistan during 1987-2016 along with 5 year forecast values obtained through (a) ARIMA (b) ETS (A,N,A) (c) ANN-MLP whereas, (d) represent the comparison plot of testing actual and forecasted values of minimum temperature for year 2017 from ARIMA, ETS and ANN-MLP.

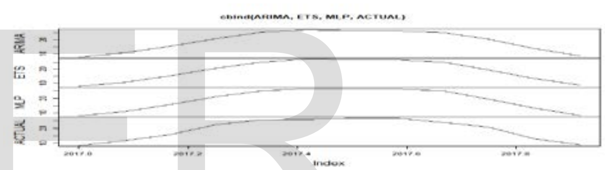


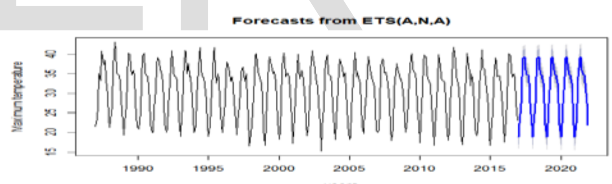












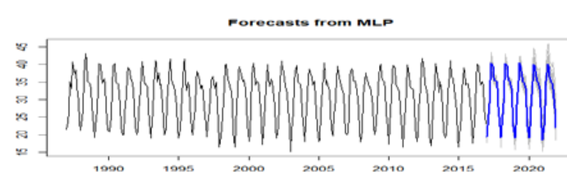


Figure 3: : Plot of monthly average maximum temperature in Lahore, Pakistan during 1987-2016 along with 5 year forecast values obtained through (a) ARIMA (b) ETS (A,N,A) (c) ANN-MLP whereas, (d) represent the comparison plot of testing

actual and forecasted values of maximum temperature for year 2017 from ARIMA, ETS and ANN-MLP.

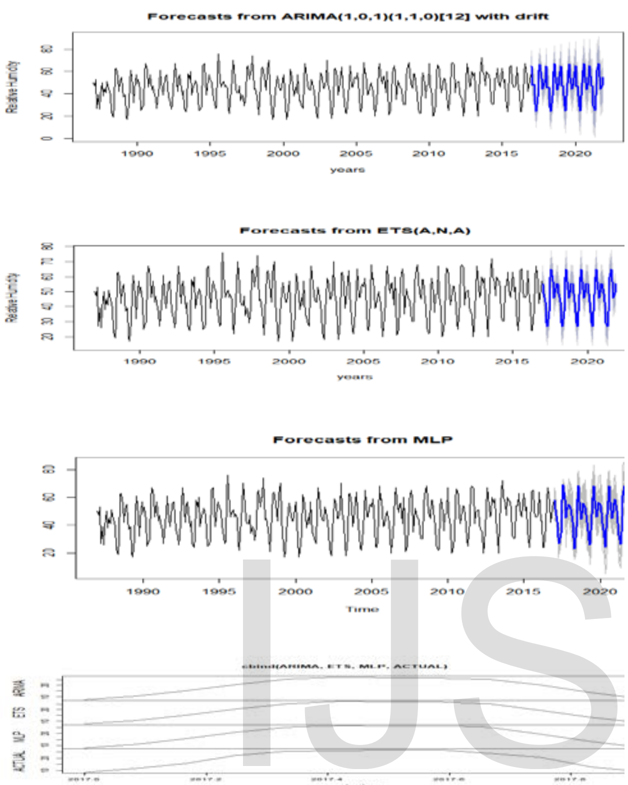
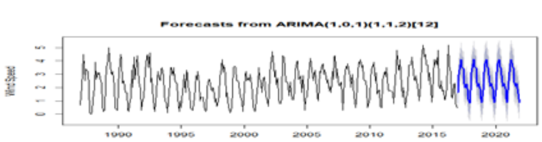
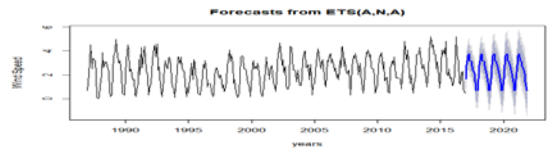
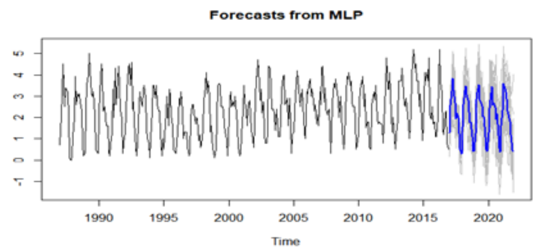


Figure 4: : Plot of monthly average relative humidity in Lahore, Pakistan during 1987-2016 along with 5 year forecast values obtained through (a) ARIMA (b) ETS (A,N,A) (c) ANN-MLP whereas, (d) represent the comparison plot of testing actual and forecasted values of relative humidity for year 2017 from ARIMA, ETS and ANN-MLP.







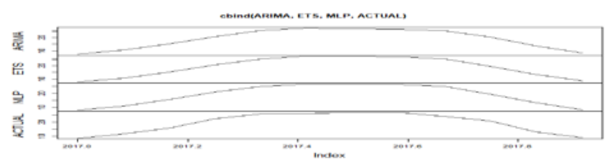
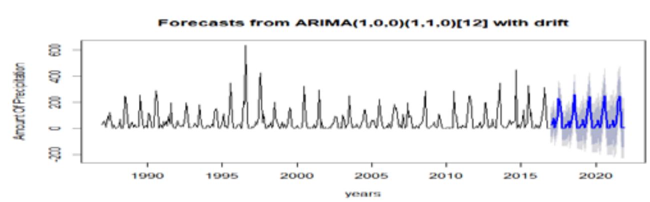


Figure 5: : Plot of monthly average wind speed in Lahore, Pakistan during 1987-2016 along with 5 year forecast values obtained through (a) ARIMA (b) ETS (A,N,A) (c) ANN-MLP whereas, (d) represent the comparison plot of testing actual and forecasted values of wind speed for year 2017 from ARIMA, ETS and ANN-MLP.



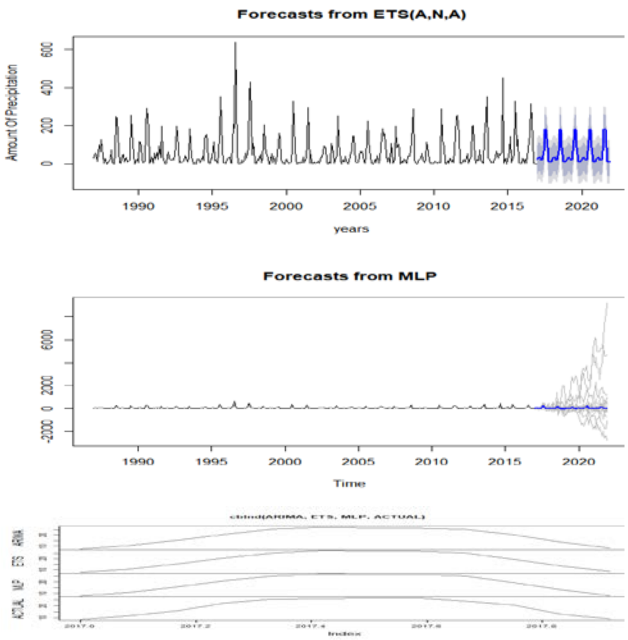


Figure 6: Plot of monthly average amount of precipitation in Lahore, Pakistan during 1987-2016 along with 5 year forecast values obtained through (a) ARIMA (b) ETS (A,N,A) (c) ANN-MLP whereas, (d) represent the comparison plot of testing actual and forecasted values of amount of precipitation for year 2017 from ARIMA, ETS and ANN-MLP.

Table 3: Best Fitted ARIMA model for weather Parameters of Lahore, Pakistan

Model	**Parameters**	**Values**	**P-Value**	**95% Confidence Interval**	
Maximum Temperature ARIMA(2,0,3)(2,1,2) [12]	ar1	0.3133	0.00	-0.5438	1.1703
	ar2	0.6685	0.00	-0.3067	1.643376
	ma1	-0.0853	0.00	-0.9387	0.76813
	ma2	-0.6087	0.00	-1.4678	0.2504
	ma3	-0.0988	0.00	-0.5228	0.32519
	sar1	-0.0988	0.00	-0.5228	0.32519
	sar2	-0.0980	0.00	-0.4268	0.25418
	sma1	-0.0778	0.00	-0.21615	0.605
	sma2	-0.8634	0.00	-0.96043	-0.7663
Minimum temperature ARIMA(1,0,2)(1,1,2)[12]	ar1	0.9874	0.00	0.9616	1.0131
	ma1	-0.6853	0.00	-0.7969	-0.5737
	ma2	-0.2034	0.00	-0.3122	-0.095
	sar1	-0.42844	0.00	-1.0234	0.0546
	sma1	-0.4376	0.00	-0.9956	0.16782
	sma2	-0.3145	0.00	-0.7969	0.16782
Relative humidity ARIMA(1,0,1)(1,1,0)[12]	ar1	0.2433	0.00	0.1377	0.3488
	ma1	-0.0853	0.00	-0.9387	0.76813
	sar1	-0.5143	0.00	-0.6097	-0.418
Wind speed ARIMA(1,0,1)(1,1,2)[12]	ar1	0.8246	0.00	0.693723	0.9555
	ma1	-0.5389	0.00	-0.7334	0.3444
	sar1	0.1799	0.00	-1.9355	2.2952

	sma1	-0.9672	0.00	-3.0944	1.1599
	sma2	0.1023	0.00	-1.6545	1.85909
Amount of precipitation ARIMA(1,0,0)(1,1,0)[12]	ar1	0.4429	0.00	0.33202	0.5537
	sar1	0.2577	0.00	0.142039	0.3734

In the study of Seasonal ARIMA and ETS model parameter estimates obtained by Maximum Likelihood (ML) method. The ML method as best approach for estimating the model parameters. The best fitted automatic ARIMA models for seasonal forecasting along with the estimates of significant model parameters (p-value < 0.05), and also along with 95% interval estimates of the parameters are shown in Table 3.

The best fitted ARIMA models for of monthly average minimum and maximum temperature, relative humidity, wind speed and amount of precipitation is presented in Table 3. The Seasonal ARIMA(2,0,3)(2,1,2)[12] found the best model for maximum temperature time series, there are two significant (p-value<0.05) AR term and also three significant moving average term including first order seasonal differencing. In case of minimum temperature the seasonal ARIMA (1,0,2)(1,1,2)[12] found the best model

Table 4: Forecasting performance of different models using ME, RMSE, MAE and MASE of monthly average minimum and maximum temperature, relative humidity, wind speed and amount of precipitation.

	ME			RMSE			MAE			MASE		
	Automatic	ETS	ANN-MLP	Automatic	ETS	ANN-MLP	Automatic	ETS	ANN-MLP	Automatic	ETS	ANN-MLP
Maximum Temperature	-0.1533	-0.0711	0.0033	1.1541	1.5171	0.7341	1.1442	1.1831	0.5581565	0.71486	0.7397	0.35135
Minimum Temperature	-0.013429	-0.010673	0.004775	1.049144	1.0678	0.6676961	0.824141	0.8521706	0.5191262	0.69051	0.713998	0.4369092
Relative Humidity	0.0208187	0.357369	-0.00867	7.213378	6.240662	2.64244	5.595414	4.966311	1.980541	0.81296	0.7215626	0.2860884
Wind Speed	0.3971777	0.0163119	0.0077084	0.5867138	0.5928702	0.232421	0.4581693	0.4826857	0.1747896	0.726968	1.4362936	1.45135
Amount Of Precipitation	0.4433138	0.7961404	0.2727724	64.51905	58.17959	25.19354	39.98838	33.05384	17.26252	0.8924748	0.7377072	0.4045448

For monthly average wind speed, there are one significant AR and two significant MA term also including first order seasonal difference. Whereas, the first order seasonal difference and one AR is enough to model average monthly rainfall.

Table 4 gives the forecast for important weather parameters from 2017-2021. According to Table 4 the ANN-MLP models in studying all variables have effectively learned and predict the forecast with minimum error as compared to ETS and ARIMA. ANN-MLP have emerged as an important tool for forecasting weather parameters and has gained a great popularity in time-series prediction because of its simplicity and reliability.

6. Conclusion

In this research, a study of the climates parameters of Lahore city has been discussed using three different methods of time series, using automatic ARIMA, ETS and MLP. These methods are useful tools and make it better to understand the analysis and plays an important role in the field. We are focusing on the comparison of these three models fitting for the prediction of different climate parameters such as Maximum Temperature, Minimum temperature, humidity, precipitation and wind speed. The used methods are check on the long range of climate parameters which predictions can be recognize for the Punjab region and illustrate a reasonable performance and forecasting accuracy. The comparison is done through the values of ME, RMSE, MAE and MAPE. Our research has shown that the best results has been obtained by the fitting of ANN-MLP model, which has the lowest ME, RMSE,MAE and MAPE values for the climate parameters. The parameters obtained by the ANN-MLP model has significance, which shows that the data forecasted through the model shows more reliable and near to the current values. Compared to the ARIMA, and ETS the ANN-MLP can more efficiently capture dynamic behavior of the important weather parameters, resulting in a more compact and natural internal representation of the sequential information contained in the weather summary.

Table 4: Average Monthly 5 years forecasts for important wheather parameters obtained from Automatic Seasonal (ARIMA), Exponential Smoothing State Space algorithm (ETS) and Artificial Neural Network Multilayer Perceptron. (ANN-MLP)

		Maximum Temperature			Mininmum Temperature			Relative Humidity			Wind Speed			Amount Of Precipitation		
years	Months	ARIMA	ETS	MLP	ARIMA	ETS	MLP	ARIMA	ETS	MLP	ARIMA	ETS	MLP	ARIMA	ETS	MLP
2017	jan	18.66892	18.80628	19.13547	7.549598	7.589218	7.979579	64.80846	55.16391	57.96577	1.6068899	1.6550072	1.2797083	25.900834	19.46703	12.67776
	feb	22.27979	22.36934	22.9289	10.521822	10.389045	10.985784	47.33542	48.56679	51.43593	2.9674057	2.8397354	2.5543336	29.519308	32.90048	41.85856
	mar	27.64943	27.46933	28.52838	15.412301	15.160747	15.819	48.57982	43.06357	42.36351	3.6919184	3.5827733	3.2150208	78.653944	33.30607	35.56436
	apr	34.43833	34.27645	34.83948	20.792855	20.639355	21.087854	30.44552	29.07538	31.58217	4.0905243	3.7735406	3.8307753	4.95366	16.71343	24.4029
	may	39.30513	39.04181	40.15014	25.455321	25.162517	25.042085	24.328	26.59402	26.79077	3.5224902	3.1594769	3.2694299	32.463647	17.25508	8.606813
	jun	39.31662	39.36697	39.7489	27.232235	27.322624	26.644645	37.27399	36.80389	34.32632	3.416638	3.1413161	2.6648242	87.380326	64.08059	64.27131
	jul	35.84186	35.91474	36.07884	26.480265	27.157693	26.450577	61.2882	59.69341	58.29071	2.2543342	2.7284179	1.9392297	230.121621	181.3174	95.79094
	aug	34.66804	34.81019	35.04742	26.34321	26.743913	26.464004	66.24865	64.97225	69.08185	1.9882244	2.4099394	2.1914261	218.533657	180.5681	252.444
	sep	34.3075	34.67127	34.71105	25.060734	25.110372	24.978817	53.73207	56.66382	58.29363	2.2688267	2.1568258	2.0038448	128.349192	84.42021	95.86056
	oct	32.32634	32.60959	32.769	20.425566	19.64217	19.47204	44.26074	45.82534	45.24252	1.9046864	1.3748928	1.2606742	3.048667	11.83821	3.188179
	nov	27.23477	27.55864	27.96861	13.526308	13.345434	13.252635	46.74137	49.08323	50.79274	1.106738	0.7040106	0.489404	1.331978	8.488768	1.773821
	dec	21.46565	21.81823	22.27129	8.451326	8.628303	8.13667	52.71217	55.53429	55.05006	0.8276098	0.6822675	0.275488	1.088089	8.855184	2.657261
2018	jan	18.22217	18.80628	19.05729	7.403302	7.589218	7.24039	64.64491	55.16391	53.60971	1.7837407	1.6550072	1.5262559	28.173577	19.46703	-6.57999
	feb	22.10561	22.36934	22.25117	10.318888	10.389045	10.166804	45.39566	48.56679	51.66586	3.1248576	2.8397354	2.5790751	18.836501	32.90048	29.99838
	mar	27.58095	27.46933	27.94426	15.477528	15.160747	15.226229	46.01332	43.06357	42.16932	3.7843734	3.5827733	3.241539	57.202975	33.30607	13.58765
	apr	34.34758	34.27645	34.50357	20.789023	20.639355	20.447894	27.44304	29.07538	30.83201	4.1131373	3.7735406	3.4747141	5.096515	16.71343	5.920372
	may	39.26468	39.04181	40.07058	25.436354	25.162517	25.044822	24.40589	26.59402	22.84365	3.5748547	3.1594769	3.0891119	32.953236	17.25508	17.53442
	jun	39.20111	39.36697	40.27083	27.356452	27.322624	26.579221	38.38612	36.80389	38.49644	3.4679735	3.1413161	2.7993294	101.951167	64.08059	66.75891
	jul	35.72363	35.91474	36.3178	26.491938	27.157693	26.677372	59.87548	59.69341	58.70592	2.3382635	2.7284179	2.2432188	196.746859	181.3174	140.5104
	aug	34.52962	34.81019	35.18787	26.24251	26.743913	25.846713	66.86999	64.97225	68.29783	2.0593116	2.4099394	1.7775645	261.960469	180.5681	187.7977
	sep	34.2812	34.67127	34.76917	25.126189	25.110372	24.713175	55.11707	56.66382	56.59235	2.2969412	2.1568258	1.8035623	129.108463	84.42021	49.62694
	oct	32.33956	32.60959	33.04667	20.469848	19.64217	19.466564	43.36538	45.82534	44.05663	1.9068268	1.3748928	1.1125251	3.018155	11.83821	0.048931
	nov	27.18715	27.55864	27.64897	13.468357	13.345434	12.890056	47.1146	49.08323	48.31424	1.1309816	0.7040106	0.3927559	1.879356	8.488768	-16.0933
	dec	21.50651	21.81823	22.20098	8.553842	8.628303	8.141358	55.11426	55.53429	55.59185	0.8556562	0.6822675	0.388546	1.654729	8.855184	-11.1178
2019	jan	18.19349	18.80628	18.78836	7.398881	7.589218	6.834603	64.97026	55.16391	52.5573	1.8120585	1.6550072	1.2642882	28.220278	19.46703	-20.9524
	feb	22.06027	22.36934	22.62826	10.434379	10.389045	9.756987	46.61541	48.56679	47.47688	3.1517487	2.8397354	2.8522514	24.569345	32.90048	21.68258
	mar	27.53977	27.46933	28.07674	15.449772	15.160747	14.515776	47.54865	43.06357	42.06876	3.796491	3.5827733	3.1711266	67.661925	33.30607	18.79669
	apr	34.31252	34.27645	34.5042	20.797969	20.639355	19.879257	29.19791	29.07538	29.01142	4.1085346	3.7735406	3.5372504	6.078016	16.71343	13.79272
	may	39.21671	39.04181	40.13755	25.45323	25.162517	24.807095	24.60967	26.59402	25.71312	3.5805468	3.1594769	2.8067487	33.782556	17.25508	7.727671
	jun	39.17955	39.36697	39.21458	27.29678	27.322624	26.550205	38.06912	36.80389	36.42952	3.475061	3.1413161	2.7226684	96.600277	64.08059	33.6748
	jul	35.70535	35.91474	36.40056	26.492182	27.157693	26.112366	60.82984	59.69341	59.67271	2.3557113	2.7284179	2.5228336	212.439118	181.3174	131.037
	aug	34.506	34.81019	35.28011	26.302581	26.743913	25.724758	66.80013	64.97225	68.0755	2.0743104	2.4099394	2.0271321	243.9448	180.5681	166.9352
	sep	34.24135	34.67127	34.47652	25.097463	25.110372	24.387726	54.66267	56.66382	57.67985	2.3009588	2.1568258	2.0087887	129.819421	84.42021	74.96747
	oct	32.30723	32.60959	32.58073	20.452289	19.64217	19.020052	44.05923	45.82534	45.8985	1.9043882	1.3748928	1.0929948	4.075746	11.83821	1.156611
	nov	27.16264	27.55864	27.96438	13.505222	13.345434	12.551891	47.16967	49.08323	50.54357	1.135228	0.7040106	0.4731311	2.683313	8.488768	-18.9296
	dec	21.47227	21.81823	22.40353	8.504954	8.628303	7.610886	54.14772	55.53429	56.30733	0.861422	0.6822675	0.3911173	2.450232	8.855184	52.06816
2020	jan	18.16396	18.80628	18.92395	7.406933	7.589218	6.442924	65.04944	55.16391	54.69698	1.8182786	1.6550072	1.2789209	29.24398	19.46703	36.43848
	feb	22.0365	22.36934	21.84477	10.378324	10.389045	9.363558	46.24422	48.56679	49.10608	3.1578814	2.8397354	2.4315463	23.09742	32.90048	18.00722
	mar	27.51213	27.46933	27.92496	15.470038	15.160747	14.182844	47.01856	43.06357	41.30925	3.7987912	3.5827733	2.8316779	64.11573	33.30607	-2.81501
	apr	34.28551	34.27645	34.11743	20.798535	20.639355	19.381433	28.55727	29.07538	31.20528	4.1064172	3.7735406	3.4457297	6.691438	16.71343	-1.81463
	may	39.20268	39.04181	39.29675	25.449451	25.162517	24.320247	24.75006	26.59402	24.37773	3.5814348	3.1594769	2.5641126	34.46277	17.25508	-4.45467
	jun	39.15074	39.36697	39.55732	27.333738	27.322624	26.170002	38.47175	36.80389	37.5983	3.4764655	3.1413161	2.6878354	99.992962	64.08059	92.74677
	jul	35.67767	35.91474	36.47461	26.497059	27.157693	25.836361	60.59229	59.69341	57.17607	2.3600831	2.7284179	2.4706558	206.596042	181.3174	111.0226
	aug	34.48752	34.81019	34.44407	26.275428	26.743913	25.311162	67.07831	64.97225	68.07313	2.0780914	2.4099394	1.9199902	252.89601	180.5681	259.8968
	sep	34.23438	34.67127	34.44791	25.11759	25.110372	23.984554	55.13448	56.66382	56.77758	2.3017762	2.1568258	2.1756662	130.551583	84.42021	72.07446
	oct	32.29479	32.60959	32.54297	20.466355	19.64217	18.773563	43.95285	45.82534	44.80246	1.9034784	1.3748928	1.1791506	4.655772	11.83821	-5.98436
	nov	27.14943	27.55864	27.20613	13.490148	13.345434	12.195173	47.38494	49.08323	48.68517	1.1362097	0.7040106	0.5703183	3.374658	8.488768	12.17502
	dec	21.46552	21.81823	21.45846	8.535542	8.628303	7.301884	54.87741	55.53429	55.99205	0.8628601	0.6822675	0.354142	3.145288	8.855184	24.69179
2021	jan	18.15919	18.80628	18.93612	7.407041	7.589218	6.126464	65.25257	55.16391	58.54355	1.8198716	1.6550072	1.6029844	29.83888	19.46703	40.11535
	feb	22.0299	22.36934	21.91731	10.412548	10.389045	8.957845	46.67413	48.56679	50.46331	3.1594742	2.8397354	2.3352835	24.787641	32.90048	22.96425
	mar	27.51076	27.46933	27.54558	15.463444	15.160747	13.566351	47.52848	43.06357	41.68775	3.7993449	3.5827733	3.5772229	66.716341	33.30607	21.49129
	apr	34.28524	34.27645	34.35245	20.802364	20.639355	18.936236	29.12286	29.07538	32.79734	4.1057663	3.7735406	3.479936	7.466408	16.71343	36.02718
	may	39.1937	39.04181	39.45558	25.455511	25.162517	24.053903	24.92237	26.59402	26.09863	3.5816267	3.1594769	3.1803674	35.208425	17.25508	30.23376
	jun	39.15483	39.36697	38.98217	27.317975	27.322624	25.727298	38.51201	36.80389	35.07814	3.4768102	3.1413161	2.8674141	99.548124	64.08059	8.407915
	jul	35.68219	35.91474	35.95516	26.498331	27.157693	25.383248	60.95491	59.69341	61.38833	2.3612557	2.7284179	2.3173907	210.204746	181.3174	135.944
	aug	34.48583	34.81019	34.24039	26.29371	26.743913	25.015697	67.18124	64.97225	67.97954	2.0791075	2.4099394	1.9633125	250.011555	180.5681	119.3785
	sep	34.22494	34.67127	34.49114	25.110562	25.110372	23.678949	55.13991	56.66382	56.28354	2.3019791	2.1568258	1.8266627	131.274439	84.42021	52.26594
	oct	32.29094	32.60959	32.062	20.462483	19.64217	18.424677	44.24942	45.82534	45.19501	1.9032086	1.3748928	1.1954238	5.4454	11.83821	12.70909
	nov	27.14701	27.55864	27.46578	13.501749	13.345434	11.732544	47.51955	49.08323	48.39153	1.136466	0.7040106	0.4604216	4.115428	8.488768	32.50433
	dec	21.45911	21.81823	21.70964	8.522701	8.628303	6.947817	54.75299	55.53429	55.3202	0.8632452	0.6822675	0.3988982	3.884429	8.855184	37.13333

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