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Time Series Analysis and Forecasting of Air Pollution Particulate Matter ($PM_{2.5}$): An SARIMA and Factor Analysis Approach

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ABSTRACT Current development of Pakistan's economy, transportation and industry with the improvement of urbanization, environmental pollution problems have gradually become prominent, but this is contrary to people's vision of pursuing a high-quality life. Now the problem of haze, photochemical problems in the air, and global warming is already a key issue of global concern. This is focused on the ambient air quality of Lahore city of Pakistan. The study reveals that the particulate matter in the Lahore season ($PM_{2.5}$, PM_{10}) exceeds Pakistan's National Environmental Quality Standards (NEQS). Correlation study suggests the positive correlation between the particulate matter and other mass concentration particles like Ozone (O_3), Nitrogen Oxide (NO), Sulphur Dioxide (SO_2). Higher values of CO/NO suggest that mobile sources are one of the major factors of this increase in NO. Further estimation of backward trajectory is done by the Hybrid-Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model which provides the path of those particles in the last year period and the source of origin is from Afghanistan. This study provides in depth analysis of all factors of air pollutants by correlation between those factors. Prediction of future concentration of $PM_{2.5}$ is predicted using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model which gives the increasing value of $PM_{2.5}$ in next year and provides the lowest and highest predicts (more than 100 $\mu g/m^3$).

INDEX TERMS Particulate matter, $PM_{2.5}$, PM_{10}, air pollution.

I. INTRODUCTION

The quality of the atmospheric environment is an important condition for the long-term survival of humans on earth. A clean suitable atmospheric environment is required for the healthy development of human beings [1]. However, with the rapid development of Pakistan's economy and industry and the continuous increase in the level of urbanization, the air in Pakistani is seriously polluted [2]–[4]. Increased air pollution affects people's physical health, and increases the risk of respiratory infections, heart disease, and lung cancer [5]–[8]. Because of frequent environmental pollution accidents and severe smog pollution incidents across Pakistan, the government as well as the public are very concerned about air pollution [9], [10].

2016 WHO report concluded that 7 million people worldwide die each year as a result of exposure to ambient (outdoor + indoor) air pollution [11]. Most susceptible to air pollution are people who are elderly, very young, with pre-existing respiratory diseases or low socioeconomic status. Particulate matter (PM), ozone (O_3), nitrogen dioxide (NO_2), and sulfur dioxide (SO_2) are the pollutants with the strongest evidence of health effects.

Particulate matter is one of the atmospheric pollutants caused by burning coal as an energy source or from automobile exhaust. Due to the arrival of PM, the formation of different chemical composition, particle size distribution, and other physical and chemical properties are very different in the atmosphere, and their behavioral impact causing different

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biological effects on human health. Therefore, it is much important for every country and metropolitan cities to keep control and monitor the $PM_{2.5}$ in atmosphere to maintain good health and safe environment. This study proposes an approach for prediction of future forecasting of air quality of metropolitan city.

According to the Air Quality Life Index (AQLI) [12], Pakistan was ranked the 5th most polluted country in the world in 2016. The National Environmental Quality Standards for Ambient Air cover sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), suspended particulate matter, particulate matter (PM_{10} and $PM_{2.5}$), lead (P_b), and carbon monoxide (CO). In 2017 the Smog Commission was established to investigate the reasons for the poor air quality across Lahore and to formulate plans to improve it [36]–[38].

Lahore, Faisalabad, and Gujranwala are the cities most affected by smog in Pakistan with high levels of air pollution. In November 2019 the Punjab education department closed public and private schools due to poor air quality [19]. It also banned children from any outdoor activities until the end of December and required children to wear anti-haze masks during class hours. In November 2019, three teenagers sought legal action against the government of Punjab, for the ''violation of their fundamental right to a clean and healthy environment'' demanding urgent action be taken [39]. Another Lahore study shows that children living and attending school in a very high $PM_{2.5}$ region had a significantly higher blood pressure compared to children with less exposure [46]. Study shows that traffic-related urban pollution can contribute to their later risk of hypertension and cardiovascular complications, even in children, if that increased blood pressure persists. Reference [47] finds that the higher $PM_{2.5}$ with higher smog leads towards the adverse health impact. The study reviews the current situation of Lahore and concluded that the current situation is likely to deteriorate due to the lack of an appropriate action plan on the part of the government and the inability of the authorities concerned to take note of the severity of the situation.

To effectively prevent atmospheric pollution, it is necessary to monitor and forecast air quality [16]. It is important that stringent emission control policies are evaluated and, if suitable, implemented. Reference [13] used the Greenhouse gas and Air pollution INteractions and Synergies (GAINS) model to study the impact of emission scenarios on $PM_{2.5}$, SO_2 and NOx concentrations. They found that due to the projected economic development across Pakistan emissions of SO_2, NOx and $PM_{2.5}$ would increase between 2007 and 2030 by a factor of 2.4, 2.2, and 2.5, respectively. As a result, $PM_{2.5}$ concentrations were forecast to be more than 150 $\mu g/m^3$ across Punjab. In a more detailed study of the Khyber Pakhtunkhwa and Balochistan regions [40] concluded that SO_2 emission would be 3 times higher in 2030 compared to 2000. Reference [41] used an autoregressive integrated moving average (ARIMA) model to predict air quality time series data and then assessed its application in air quality management decision making. They identified the importance of temperature, humidity, and precipitation on the spatial variability of air pollutant concentrations. Several authors have used the ARIMA model and other machine learning models to forecast air quality and develop weather applications [42]–[51]. Hai *et al.* [52] proposed machine learning based extreme learning model for climate and compared extreme learning machine (ELM) model with multiple linear regressions (MLR) and ARIMA models. SVM-FFA [53] also provide the improved accuracy in prediction of rainfall after hybridization with firefly optimization algorithm (FFA) with support vector machine (SVM). Our study is focused on seasonal analysis of variation in time series for PM dataset.

In this paper we characterize the air pollutants in the ambient air of Lahore, Pakistan; examine annual variations; use backward air mass trajectories to identify pollution sources; perform a correlation and regression analysis of the measured pollutants ([CO], [NO], [SO_2], [O_3]) with particulate matter; and compare these results with the source of production of those particles. This study gives the complete analysis of relationship of pollutants as well as there source of generations by trajectory methods. Finally, we use a time series model for the prediction of particulate matter concentrations.

II. METHODOLOGY

A. SITE DESCRIPTION

Lahore is the second-largest city in Pakistan with a metropolitan population of around 9.4 million. It is located between 31°15′—31°45′ N and 74°01′—74°39′ E and covers an area of 1014 km^2 **(Fig. 1).**

B. METEOROLOGY

Lahore experiences a hot semi-arid climate with typical temperatures in the range 9°C to 39°C. The average hot season lasts around 3 months from mid-April to the end of July. The monsoon season starts in July and lasts up to September. The winter season covers the period from December to the middle of February. This season is dry with haze in the atmosphere. The average monthly rainfall is 13 mm with around 146 mm in July.

C. DATASET AND INSTRUMENTS

The Federal and Provincial Environmental Protection Agencies collected air quality monitoring data for 6 years (2014–2019) using automated fixed and mobile air monitoring stations (AMSs) for the atmospheric concentration of six major pollutants and meteorology. Records with the status of SNO (station not operative) and SNA (Station not available) were excluded from the study because of the non-significance of those values (2.5% $<$ of the data) due to technical fault in site instruments. Data has been taken from different sites (2 static stations and one mobile station) on hourly basis and average is computed. List of different measuring methods air particles is mentioned in Table 1.

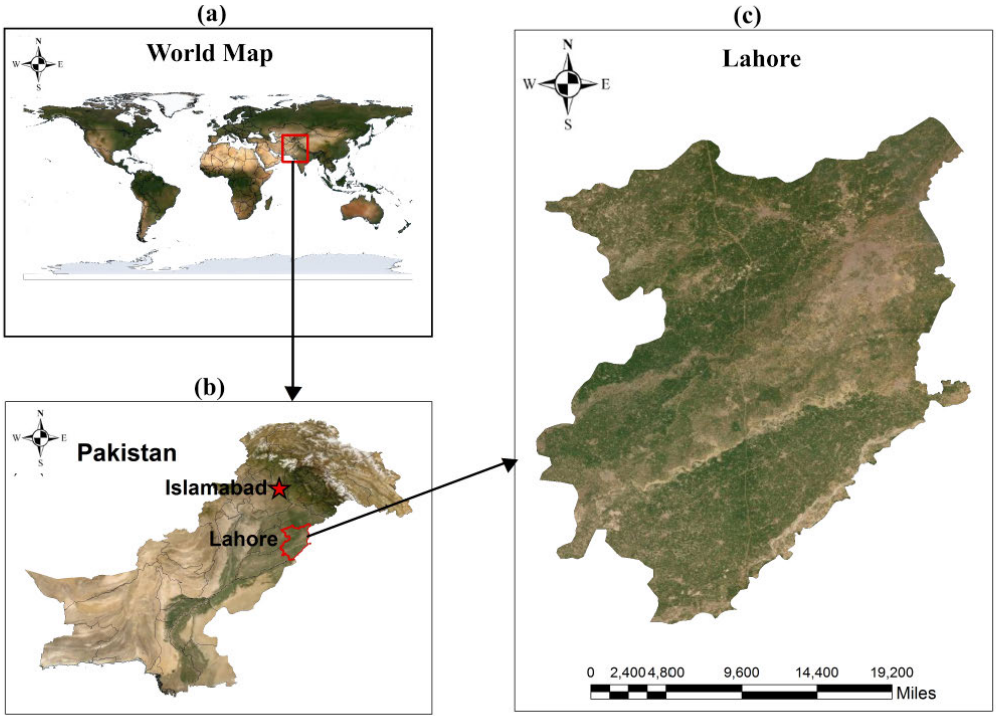

FIGURE 1. Location Map of Lahore (a) Location in World Map (b) Location in area of Pakistan (c) Lahore covered area.

TABLE 1. List of pollutants and there measuring methods in Lahore.

Pollutant	Method of Measurement
Sulfur Dioxide (SO_2)	Ultraviolet Fluorescence method
Oxides of Nitrogen as (NO)	Gas phase Chmiluminescence
Oxides of Nitrogen as (NO2)	Gas phase Chmiluminescence
Ozone (O_3)	Non dispersive UV absorption method
Suspended particulate Matter (SPM)	High volume sampling. (flow rate not less than 1.1 m^3/min)
Respirable particulate Matter PM_{10}	Preferable β-Ray absorption method
Respirable particulate Matter $PM_{2.5}$	Preferable β-Ray absorption method
CO	Using nondispersive infrared ray method

D. DATA ANALYSIS

Data analysis was carried out using R to analyze univariate time series forecasts including exponential smoothing via state-space models and automatic ARIMA modeling using the 'forecast' package. The 'tseries' package was used for time series analysis of the dataset.

E. BACKWARD TRAJECTORIES

The HYSPLIT [37] used for the study was released jointly by the National Oceanic and Atmospheric Administration's (NOAA) Air Resources Laboratory (ARL) and the Australian Meteorological Agency. The model can handle meteorological transmission and diffusion at different heights. Backward air mass trajectories at different altitudes, centered on Lahore, were generated by the HYSPLIT model based on Global Forecast System meteorological data. Data has been taken from last 365 days on the daily basis for backmass for every 25hrs from 2018 Dec to 2019 Dec.

F. SARIMA MODEL

1) MODEL THEORY

In the 1960s, the American scholar BOX and the British statistician JENKINS proposed a complete set of methods for time series analysis, prediction, and control, known as the BOX-JENKINS modeling method [24], [25]. The ARIMA model is divided into a simple seasonal model ($P = D = 0$) and a product seasonal model according to the difficulty of extracting seasonal effects. When there are both short-term correlations and seasonal effects in the sequence and there is a more complex between the two that can be used to fit the model of the sequence. In this study, the product seasonal model [denoted as ARIMA (p, d, q) (P, D, Q) s] is used to describe the autocorrelation between a group of time-dependent random variables. The general expression of the ARIMA product seasonal model is ARIMA (p, d, q) (P, D, Q) s, where p, d, q and P, D, Q represent continuity and seasonal auto-regression differences respectively. The order of the moving average represents the length of the seasonal cycle.

The stability of the time series can, generally, be judged by drawing a timing or sequence autocorrelation chart. When the autocorrelation coefficient (ACF) fluctuates around a fixed horizontal line with a gradual decay trend, it can be considered that the sample time series is stable. For time series with poor stability, logarithmic transformation and differential transformation may be used to make the time series stable. This study mainly uses a differential transformation to achieve the stability of the sequence [26].

The prerequisite for fitting a time series model is the stability of the series. When the time series is a non-stationary series, it needs to be stabilized by data processing before further analysis. The differential order values d and D of the model are determined according to the number of different data processing. According to the characteristics of the sample ACF and the sample partial autocorrelation coefficient (PACF) in the timing diagram after the difference, the order values of the model are initially determined, that is, the autoregressive order values P, p and the moving average order values Q, q [27]. The ARIMA product seasonal model parameter estimation methods include least squares, maximum likelihood, and moment estimation. In this study, least squares has been used to estimate model parameters and test their significance. The white noise test is very important in the research and analysis of time series. Only if the residual sequence passes the white noise test can further analysis be undertaken. If it does not pass the white noise test, then the analysis process must be repeated from the model recognition stage. The Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC) are used to evaluate the goodness of fit of the model [28], [29]. It is generally considered that the model with the relatively smallest statistic value has the best fitting effect, which is then used as the optimal model.

2) MODEL IMPLEMENTATION

For stationary time series data, an autoregressive moving average ARMA (p, q) model can be established in the form of:

$$X_t = \varphi_0 + \varphi_1 X_{t-1} + \ldots + \varphi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \tag{1}$$

Among them, X_t is the sequence value of the first period, ε_t refers to the residual of the t period, and φ_1, θ are the parameters to be estimated by the model which can also be written as:

$$X_t = \frac{\theta(B)}{\varphi(B)} \varepsilon_t \tag{2}$$

where B is a backward shift operator, which satisfies;

$$X_{t-1} = BX_t$$

For non-stationary time series with short-term trends, if a difference of order d is used to achieve stationary, then a differential autoregressive moving average model is established, which is denoted as ARIMA (p, d, q) model.

$$\Delta^d X_t = \varphi_0 + \varphi_1 \Delta^d X_{t-1} + \ldots + \varphi_p \Delta^d X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \ldots - \theta_q \varepsilon_{t-q} \tag{3}$$

where $\Delta^d X_t$ represents the t-t sequence value after the d-th order difference.

The form expressed by the back shift operator is:

$$\Delta^d X_t = \frac{\theta(B)}{\varphi(B)} \varepsilon_t \tag{4}$$

For the ARIMA model with seasonal effects, the seasonal difference can be converted into a stationary sequence model. The seasonal effect and other effects in the sequence are additive relationships. A simple seasonal model can be established as;

$$\Delta_D \Delta^d X_t = \frac{\theta(B)}{\varphi(B)} \varepsilon_t \tag{5}$$

where $\Delta_D \Delta^d X_t$ represents the t-th sequence value after d-step D-step difference.

If the seasonal effects, long-term trend effects, and random fluctuations of the sequence have complex correlations, and the simple seasonal model cannot fully extract the correlations among them, the seasonal product model should be used, and the ARMA (p, q) model Short-term correlation, using ARMA (p, q) model with period step S as the unit to extract seasonal correlation, the model form is:

$$\Delta_D \Delta^d X_t = \frac{\theta(B)\theta_S(B)}{\varphi(B)\varphi_S(B)} \varepsilon_t \tag{6}$$

The above theory shows that, according to the characteristics of data stability, seasonality, trend, etc., an appropriate method should be selected for modeling.

III. RESULTS

A. POLLUTANTS CONCENTRATION

The yearly concentration of different pollutant factors of Lahore is shown in Fig. 2 (a-g) on average basis. As the CO standard is an 8h standard, and the O_3 is 1h average. Fig. 2f and 2g provide the numbers of exceedances of ambient concentration for CO and O_3 during the last 6 years. The average annual concentration of $PM_{2.5}$ in Lahore exceeds the standard of the NEQS of Pakistan which is $15\mu gm^{-3}$. In Lahore, the annual average $PM_{2.5}$ mass concentration is 66.95 ± 47.4, 74.95 ± 51.4, 81.35 ± 39.57, 87.75 ± 46.13, 81.13 ± 47.4, 60.44 ± 51.34 μgm^{-3} during 2014 to 2019 respectively and the highest value is 217 μgm^{-3} in January 2018, 215 μgm^{-3} in February 2018, 192.93 μgm^{-3} in November 2018 and 152 μgm^{-3} in November 2017. The reason of high mass concentration of those particulate matters are black carbons which are further discussed in discussion part. High $PM_{2.5}$ is associated with adverse human health effects [30], [31]. THE average PM_{10} mass concentration is

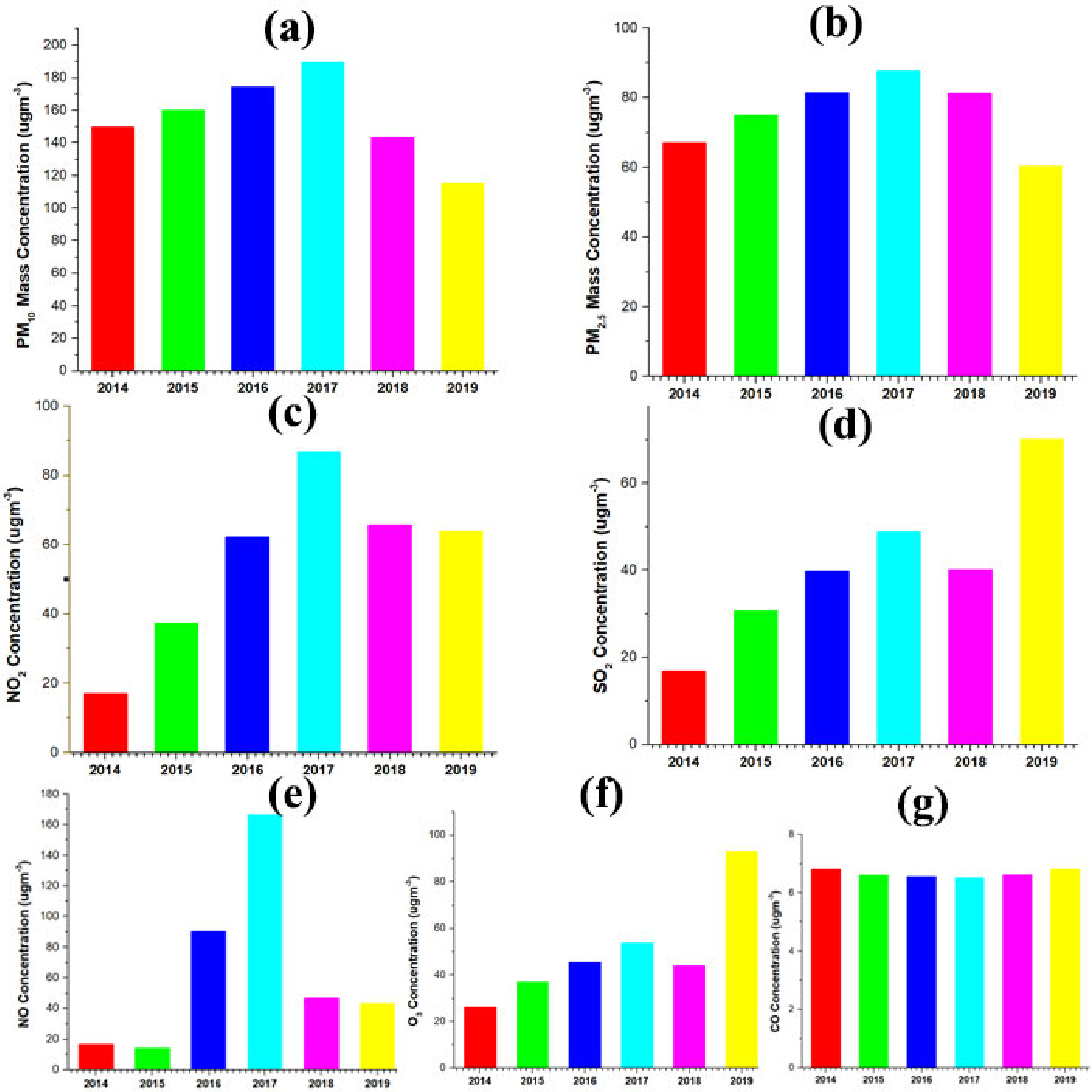

FIGURE 2. **Average yearly Concentration of (a) PM_{10} (b) $PM_{2.5}$ (c) NO_2 (d) SO_2 (e) NO (f) O_3 [exceedances] (g) CO[exceedances].**

high from 2014 to 2018 as per the standard of NEQS which is 120μgm^{-3} annually which goes low in 2019. The yearly value of PM_{10} is 150.15 $\pm$ 25.16, 174.69 $\pm$ 31.24 μgm^{-3}, 189.38 $\pm$ 11.41 μgm^{-3}, 143.29 $\pm$ 13.11 μgm^{-3}, 114.83 $\pm$ 16.42 μgm^{-3} respectively from 2014 to 2019. With the highest value of PM_{10} is 411 μgm^{-3} in January 2018, 218 μgm^{-3} in December 2017.

The annual average concentration of NO is higher than the standard of NEQS value 40 μgm^{-3} in years from 2015 to 2019. The average concentration of NO is 16.88 $\pm$ 13.02 μgm^{-3}, 13.96 $\pm$ 9.13 μgm^{-3}, 90.26 $\pm$ 14.18 μgm^{-3}, 166.57 $\pm$ 29.14 μgm^{-3}, 47.18 $\pm$ 17.21 μgm^{-3}, 43.00 $\pm$ 19.82 μgm^{-3}. The highest record values are in November 2017 i.e., 358 μgm^{-3} and in November 2018 it is 207 μgm^{-3}. The concentration of SO_2 is as per standard of NEQS which is 80 μgm^{-3}. But the alarming situation is that in Lahore the concentration of SO_2 every year is increasing which is possible to exceed in the current year 2020 if necessary steps are not taken. The yearly average concentration of SO_2 is 16.88$\pm$11.42, 30.65$\pm$22.12, 39.73$\pm$13.45, 48.80$\pm$16.71, 40.18$\pm$21.12, 70.18$\pm$31.11 from the period year 2014 to 2019 respectively. The highest percentage increase of SO_2 is 43% from the year 2017 to 2018, which makes important alarm to take necessary steps to make it under standards in 2020. Higher value SO_2 in ambient air is the reason of higher chemical production or mineral processing. Lahore urbanization is increasing a lot with continuous development of factories related to chemical and garments. The graphical representation of particulate matter is shown in **Fig 2.**

B. BACKWARD TRAJECTORY

The back-trajectory analysis using the NOAA HYSPLIT was conducted to further analysis the direction of air particles

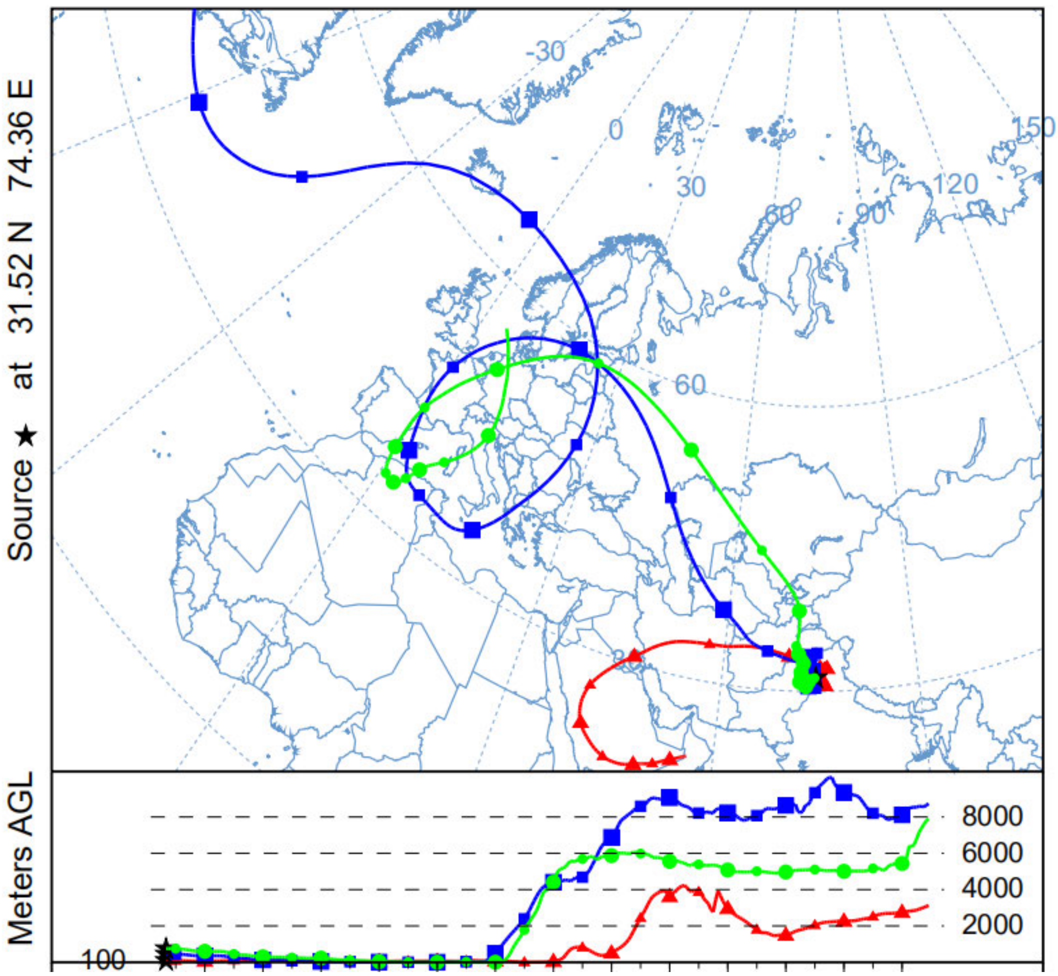

FIGURE 3. Backward trajectory analysis.

in last year for 365 days. From Fig. 3 it can be observed that the major pollutants are from the Afghanistan direction, particularly Kabul and Jalalabad. The air pollution in Afghanistan in 2019 is worst and had much impact on health of local residents [33]. This impact is also transferred to nearby countries which are neighbours specially Pakistan. Trajectory analysis shows the impact of air pollutants on Lahore city of Pakistan**(Fig. 3).**

C. CORRELATION

Fig. 4 shows the relationship between air pollutants. Linear regression of monthly averages of nitrogen oxides (NO_x) and particulate matter ($PM_{2.5/10}$) in the four years from 2016 to 2019. Since diesel combustion (from heavy vehicles and generators) is the main source of nitrogen oxides (NO_x) and particulate matter ($PM_{2.5/10}$), the correlation between particulate matter ($PM_{2.5/10}$) is used to determine these three types of pollution. Fig. 4 also shows that particulate matter ($PM_{2.5/10}$) is significantly correlated with nitrogen oxides (NO) ($R_2 = 0.236$ and 0.266; p-value = 0.00066 and 0.00028). Particulate matter ($PM_{2.5/10}$) was significantly correlated with nitrogen oxides (NO_2) ($R_2 = 0.232$ and 0.276; p-value = 0.00073 and 0.00021). It can be inferred from this graph that sources other than automobiles (generators) also contribute to the primary and secondary particulate matter ($PM_{2.5/10}$) in the atmosphere (because of the correlation of nitrogen oxides (NOx) mainly comes from automobiles). The correlation between nitrogen oxides (NOx) and nitrogen oxides has many common anthropogenic sources, including mobile sources (i.e. cars) and point sources (i.e. energy production). Therefore, it is interesting to check the relationship of these substances in the surrounding air, especially in the urban environment, where photochemical conversion (including removal mechanisms) can be ignored, and then check these relationships against the emission inventory. The relationship between particulate matter ($PM_{2.5/10}$) and sulfur dioxide (SO_2) is positively significant ($R_2 = 0.262$ and 0.283; p-value = 0.00031 and 0.00021). Fossil fuels contain traces of sulfur compounds, and sulfur dioxide is produced when burned. Most of the SO2 emitted into the air comes from power generation, and there is very little contribution from transportation sources (except transportation). The sulfuric acid produced by the reaction of SO_2 in the atmosphere is the main component of acid rain, and the ammonium sulfate

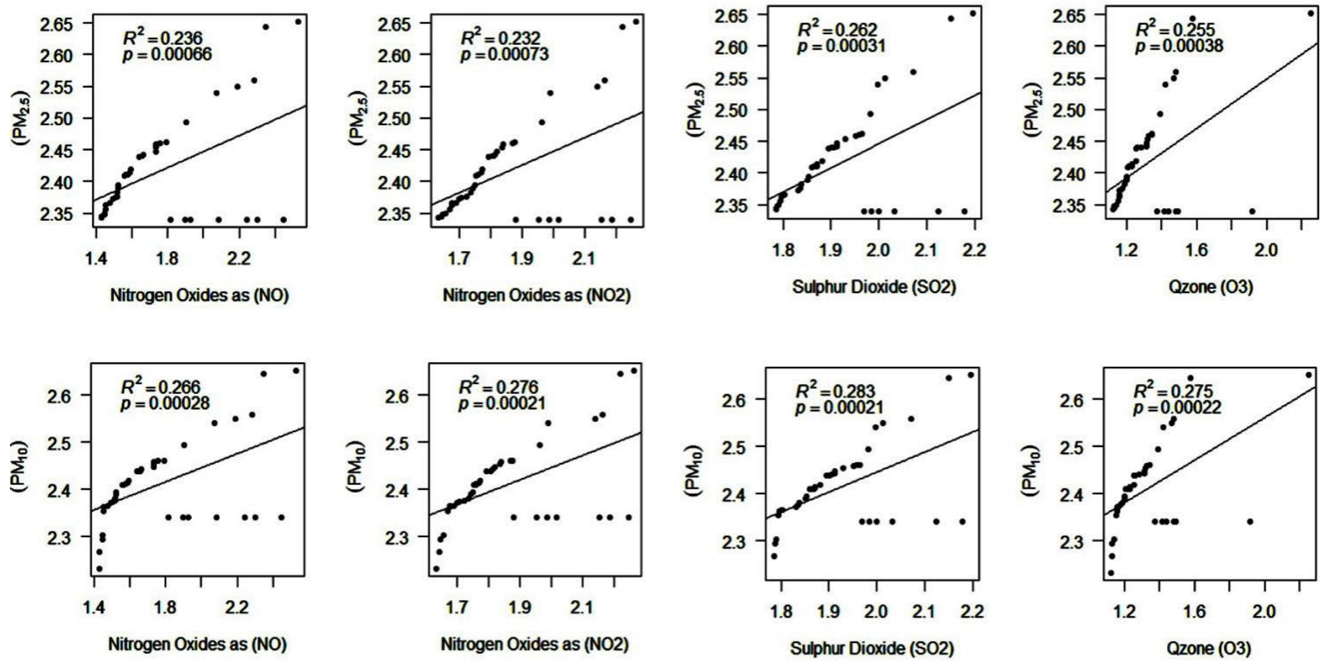

FIGURE 4. Correlation of Air pollutants.

particles are the secondary particles with the highest content in the air. The relationship between further particulate matter ($PM_{2.5/10}$) and ground ozone (O_3) was positively significant ($R_2 = 0.255$ and 0.275; p-value = 0.00038 and 0.00022). Unlike the other pollutants mentioned above, the surface ozone (O3) is not released directly into the atmosphere but is a secondary pollutant created by the reaction of nitrogen dioxide (NO2), hydrocarbons and sunlight.

D. TIME SERIES PREDICTION

Prediction and verification of the model are done by using monthly Particulate matter data from Jan 2014 to Feb 2020 in Lahore city to fit the ARIMA product seasonal model, and use the optimal model to predict the 12-month monthly $PM_{2.5}$ data through comparison forecast data and actual data to evaluate the model.

The monthly average PM of Lahore city is 70.45 ± 46.15 in year 2019 with the highest monthly average is observed in January of each year and highest observed value in 2019 is 448.15 in a day. Fig. 4 shows the seasonal pattern of particulate matter in Lahore. Table 2 presents the Augmented Dickey-Fuller (ADF) test of unit root presence and suggests trend stationarity of the Lahore data.

The original PM2.5 value plots of the ACF and PACF at Lahore, as shown in Fig. 5(a), implies the seasonality of the data needed to be de-seasonalized. At lag 10 the first seasonal difference is found to be sufficient for Lahore, Fig. 5(b, c, d) presents ACF and PACF with deseasonalized and stationary AQI data from both divisions showing disappearing ACF and PACF spikes over lag implying data non-seasonality. For this reason, the process of SARIMA(p,0,q)(P,1,Q) and SARIMA(p,1,q)(P,1,Q) is

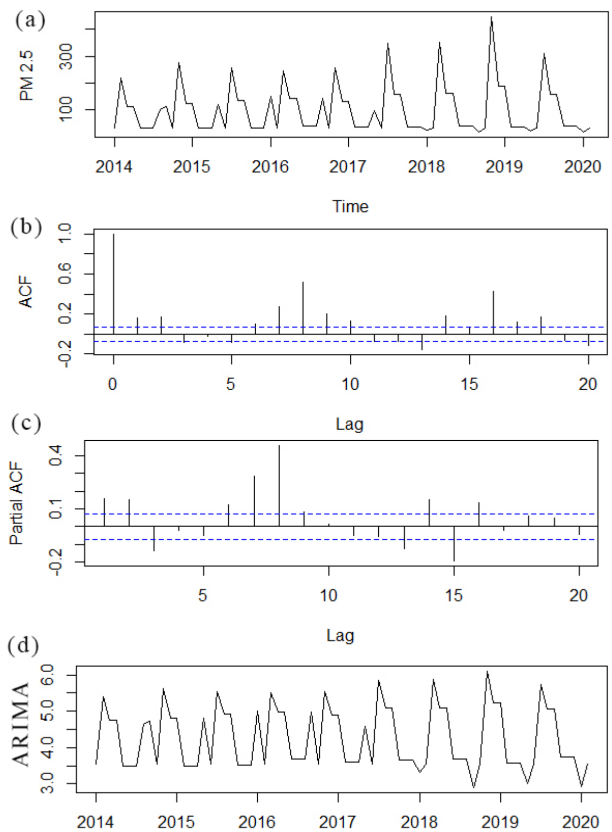

FIGURE 5. Time series estimation yearly (a) Yearly $PM_{2.5}$ (b) ACF (log converted) (c) PACF (log converted) (d) ARIMA (log converted.

sufficient to model Lahore PM2.5 data. Now, the time series is defined and the components are analyzed as shown in Fig. 6:

From the above we see that the time series contains a clear seasonal component. As a result it is highly likely

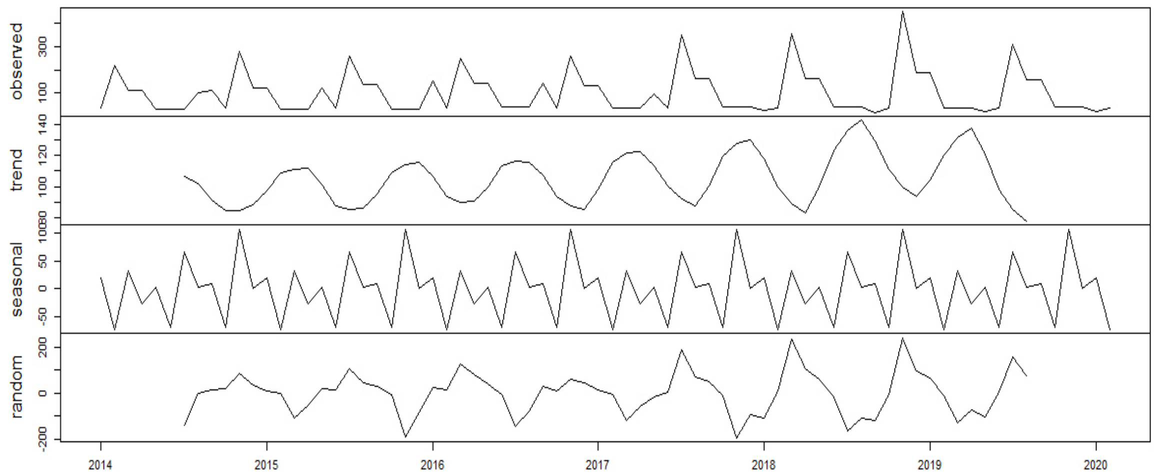

FIGURE 6. Time series components in different series of estimation.

TABLE 2. Augmented Dickey-Fuller test of stationarity (alternative hypothesis: stationary).

Test Component	Value
Test statistics value	-3.9953
p-value	0.01

TABLE 3. Parameters of coefficient of ARIMA model.

Model Lahore:	Parameter	Estimate	Standard Error
Model :ARIMA(1,0,2)(1,0,0) (Greenstone et al 2008)	AR1	-0.9885	0.0155
AIC=856.76	MA1	1.2467	0.1704
BIC=870.58	MA2	0.3514	0.1811
AICc=858.01	SAR1	-0.5728	0.0994
P<0.01	Mean	102.7621	7.1939

that an attached seasonal component will be needed for the ARIMA model. On the basis of AIC and BIC fitting model selection criteria ARIMA(1,0,2)(1,0,0) was found best model. Table 3 presents coefficients of fitted SARIMA models for Lahore with AIC = 856.76 and BIC = 870.58. In the Lahore model, all autoregressive (AR), moving average (MA), and seasonally moving average parameters are found to be significant.

Fig. 7 predicts future $PM_{2.5}$ with 95% confidence intervals for Lahore up to Dec 2023 on monthly basis (which can be converted to weekly or seasonal basis as well). It can be observed that in future the $PM_{2.5}$ value keep remaining more than 100 μgm^{-3} which require by government to keep it remain below the threshold value in order to improve health conditions.

Table 4 predicts future $PM_{2.5}$ with 95% confidence intervals for Lahore up to Dec 2023 on monthly basis (which can be converted to weekly or seasonal basis as well).

Now, the data after conversion original format by calculating the exponent of the log predictions. These predictions are then compared against the test data (which are values from 2019) to identify the actual error. The mean percentage error (or average of all percentage errors) is −0.3%. The number of predictions with a percentage error below 7% relative to the actual is over 75%. Thus prediction error is less and forecasting is providing the better results for the test dataset i.e., from 2019-year particulate value.

IV. DISCUSSION

$PM_{2.5}$, also known as fine particles, and PM_{10}, O_3, SO_2, NO_2, CO, etc. are the main pollutants that affect the quality of the atmospheric environment. In addition, $PM_{2.5}$ in the air can cause great health risks to the human body and even affect the climate. In view of the current problems in the study of atmospheric $PM_{2.5}$ in Lahore City (combined with the research on the analysis of related meteorological trajectories), this study uses theoretical knowledge such as environmental science, atmospheric chemistry, meteorology and geochemistry, from September 2014 to 2019. During this period, samples of $PM_{2.5}$ in Lahore city were collected, and the pollution characteristics of different pollutants with $PM_{2.5}$ and PM_{10} were preliminarily analyzed. At the same time, online trajectory sources were used to analyze and quantify the contribution of different pollution sources to ions in atmospheric particles, combined with HYSPLIT backward airflow.

Because the atmospheric environment system is a system with both complexity and variability, a huge amount of monitoring data has been accumulated in the past few decades, and

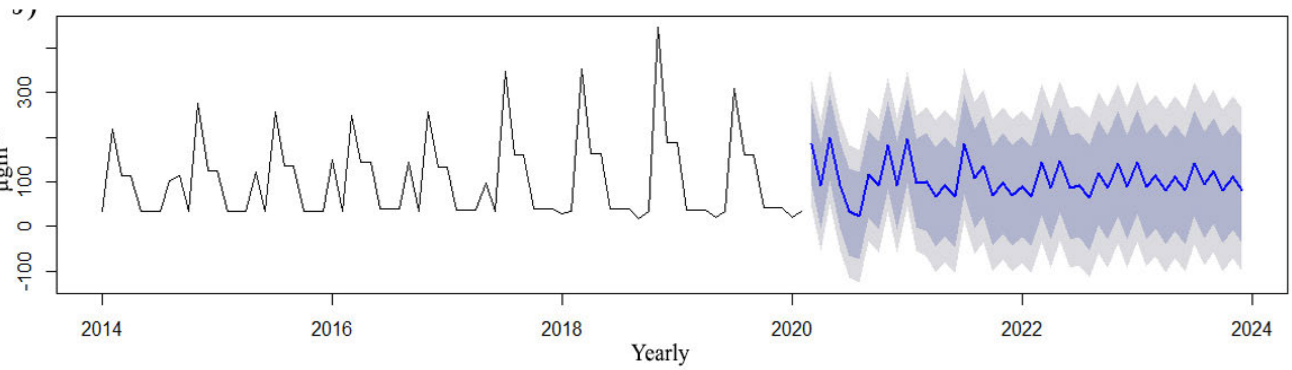

FIGURE 7. Time series prediction of future estimated values with upper and lower limit thresholds.

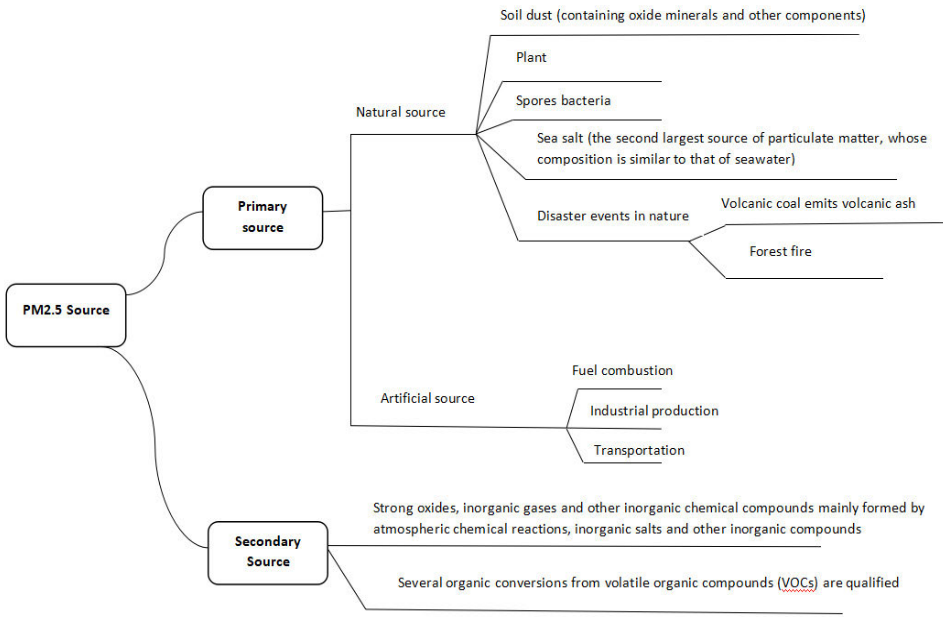

FIGURE 8. $PM_{2.5}$ sources of emission and factors need to be controlled.

traditional prediction models are difficult to capture effective information from a large amount of historical monitoring data, which leads to unsatisfactory prediction results. Therefore, in the study of air quality forecasting, the establishment of an effective air pollution forecasting model has become a reliable tool to reduce the negative impact of environmental pollution on health and to formulate more complete prevention policies. In recent years, deep learning methods have been widely used in various time series forecasting problems. Among them, the time series models demonstrated its powerful time series processing capabilities. However, the use of attention mechanism to predict the air quality research has also Nothing. This paper proposes to build a time series forecasting model using long and short-term memory network combined with attention mechanism, and apply it to the air quality forecasting field. With its strong nonlinear processing ability and noise tolerance ability, it can realize the efficient forecast of air quality. Study reveal important results for forecasting of particulate matter in the weather. Fluctuations in forecasting gives prediction of lower and upper value with better understanding of critical situation in seasons.

The importance of particulate matter still exists in order to improve the health conditions in city. Reference [5] finds that the cardiovascular diseases (CVD) in India and Pakistan are directly relevant with the air pollution. Since healthcare systems are already overburden because of different diseases in this south Asia region therefore a continuous research is required to quantify the air pollution future aspects on healthcare system. Research focused on these areas are helpful for government to find out the main cause of the diseases related to the respiratory system of human. Reference [6] carried out research on 14 WHO regions for estimating the impact of outdoor air pollution on diseases burden. Research findings include economic, meteorological and demographic data and available PM measurements in 304 cities used to estimate

TABLE 4. Forecast value from ARIMA Model.

Month	Year	Forecast value	Lowest	Highest
Mar	2020	180.68	30.94	330.43
Apr	2020	87.17	14.88	159.46
May	2020	91.16	15.52	166.80
Jun	2020	27.53	4.67	50.38
Jul	2020	204.11	34.53	373.68
Aug	2020	96.11	16.21	176.01
Sep	2020	105.21	17.69	192.72
Oct	2020	27.46	4.60	50.31
Nov	2020	228.95	38.27	419.64
Dec	2020	93.16	15.52	170.79
Jan	2021	98.13	16.30	179.96
Feb	2021	81.57	13.51	149.63
Mar	2021	180.68	29.83	331.54
Apr	2021	87.17	14.35	160.00
May	2021	91.16	14.95	167.37
Jun	2021	27.53	4.50	50.55
Jul	2021	204.11	33.27	374.94
Aug	2021	96.11	15.62	176.61
Sep	2021	105.21	17.04	193.37
Oct	2021	27.46	4.43	50.48
Nov	2021	228.96	36.86	421.05
Dec	2021	93.16	14.95	171.36
Jan	2022	98.13	15.70	180.57
Feb	2022	81.57	13.01	150.13
Mar	2022	180.69	28.72	332.65
Apr	2022	87.17	13.81	160.54
May	2022	91.16	14.39	167.93
Jun	2022	27.53	4.33	50.72
Jul	2022	204.11	32.02	376.19
Aug	2022	96.11	15.03	177.20
Sep	2022	105.21	16.40	194.02
Oct	2022	27.46	4.27	50.65
Nov	2022	228.96	35.45	422.46
Dec	2022	93.16	14.38	171.94
Jan	2023	98.13	15.09	181.17
Feb	2023	81.57	12.50	150.63
Mar	2023	180.69	27.61	333.76
Apr	2023	87.17	13.27	161.07
May	2023	91.16	13.84	168.48
Jun	2023	27.53	4.16	50.89
Jul	2023	204.11	30.77	377.44
Aug	2023	96.11	14.44	177.79
Sep	2023	105.21	15.75	194.66
Oct	2023	27.46	4.10	50.82
Nov	2023	228.96	34.05	423.86
Dec	2023	93.16	13.81	172.51

PM10 levels in all 3211 cities worldwide with populations greater than 100,000 and capital cities. The results indicate that the impact of outdoor air pollution on the burden of disease in cities around the world is significant, but an assessment of sources of uncertainty, including the fact that only the mortality impacts of PM exposure have been estimated, suggests that the impact is actually underestimated.

Therefore, to improve the air pollution situation, it is necessary to enhance the residents' awareness of environmental protection, expand the area of urban green spaces, and reduce pollution emissions mainly from the industry and transportation industries. Industry needs to strengthen the structural adjustment of heavily polluting industries, strengthen source control, and promote the rationalization of industrial structure; In the transportation industry, priority is given to the development of public transportation to control the disorderly growth of the number of cars. In addition, environmental management should be integrated into the management of catering enterprises to control the discharge of sewage, chimneys and exhaust gas. The main source of particulate matter is shown in Fig. 8.

In Lahore, the emission of pollution sources has the following three aspects: 1) Coal-fired heating during the hot period. In winter, especially in the residential regions, where the temperature is low, heating, coal consumption increases significantly, and the local pollutant emission concentration increases, pollutants tend to accumulate under adverse meteorological conditions and cause the concentration of pollutants to increase. 2) There is also the burning of biomass in winter, which is also one of the "culprits" that can cause regional heavy pollution in winter. For example, the heavy pollution process in early December 2019 was due to excessive pollutant emissions. Unfavorable meteorological conditions were an important cause. The heavy pollution was mainly caused by coal-fired heating and biomass combustion emissions in winter 3) Increased exhaust emissions from motor vehicles. Car ownership continues to climb, and motor vehicle exhaust emissions should increase in winter compared to summer.

In terms of meteorological conditions, there are two reasons: 1) Meteorological conditions affect the concentration change of $PM_{2.5}$ and other pollutants. Among them, inversion is an important factor. Once this inversion stratification under cooling and heating is formed, the air cannot convict up and down, and it is difficult for the pollutants to diffuse. This kind of temperature inversion is most likely to occur in autumn and winter. In summer, on the contrary, active vertical movement of the atmosphere, coupled with frequent cyclone activity, makes it difficult for temperature inversion to occur. 2) The calm wind (breeze) has less precipitation. The air mass is dry in winter, the rainfall is low and the duration is short, the scouring effect on the pollutants in the air is not obvious, the wind speed and wind force are small, the pollutants are not conducive to diffusion and are easy to accumulate, resulting in a high concentration of pollutants such as $PM_{2.5}$.

Through data and analysis, we can see that the more developed areas are more polluted than the less developed areas, we cannot take the path of pollution first and then treat it, and we must look at economic and environmental issues from a development perspective. Sustainable development is growth that meets contemporary people's needs without undermining future generations' capacity to meet their needs. Current study is limited to single metropolitan city however in future we will compare it will other cities and highlights the ways how to reduce particulate matter in mega cities.

V. CONCLUSION

The main research work of this paper is to first analyze the current status of Lahore air quality, and conclude that the main pollutants in the atmosphere of Lahore, PM_{10}, $PM_{2.5}$, SO_2, CO, and NO_2 from 2014 to 2019 in the air are changing and there is a strong correlation between them. On this basis, the impact of several relevant factors, such as geographic location, meteorological conditions, and human activities (coal burning, transportation, dust, population, and policies) on the air quality of Lahore City are described. Through the exploratory analysis of the air quality of Lahore City over the years, it can be concluded that the overall air pollution situation in Lahore City has been severe for four years. The targeted analysis shows that the main pollutants in the atmosphere, $PM_{2.5}$ / PM_{10} / O_3, have the same seasonal changes as air quality. O_3 shows the opposite characteristics to several other atmospheric pollutants. Winter pollution is the most serious, followed by spring and autumn (spring is slightly higher than autumn), and summer is lightest. The quarterly analysis further confirmed this seasonal variation.

Future study will be more focused on expanding the research area across different metropolitan cities of countries with an in deep comparison with health factors with particulate matter. Further implementation of SARIMA model can be done on diseases burden to find other diseases trend in seasonal variation which can help in tackle out diseases burden timely.

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