FORECASTING AIR POLLUTION: CASE STUDY INVESTIGATING THE TRUE IMPACT OF COVID-19 LOCKDOWNS ON AIR QUALITY IN SOUTH ASIA

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ABSTRACT

Air pollution is a modern anthropological catastrophe faced by all humanity. Most of the world's pollution hotspots are located in the South Asian region where most countries are recognized as developing countries. Management of air quality in the region is directly linked to the insufficient infrastructure in the region to monitor and analyse air pollution. Regional air pollution studies are limited and excessively focused on analysing the current pollution landscape rather than developing forecasting tools suitable for the region. The study has focused on the analysis and development of an air pollution forecasting model to predict air quality variations based on the Auto Regressive Integrated Moving Average (ARIMA) method. The model was developed and validated using available historical PM2.5 pollution data from the region. Additionally, the model was used to analyse the true impact of COVID-19 lockdowns on regional air quality. The analysis includes investigations of PM2.5 pollutant levels in Colombo, Chennai, Dhaka, Delhi, Kathmandu, Islamabad, and Hyderabad. The developed model performed well with RMSE values of less than 12% in all instances relative to the pollutant concentration ranges for each city. Forecasted and historical data comparison identified that the impact of COVID-19 lockdowns is underestimated in cities such as Kolkata, Colombo, and Chennai by more than 10%. Vice versa was observed for Delhi, Islamabad, and Hyderabad where the pollution trend is decreasing. Traditional time series analysis will certainly underestimate or overestimate the impact of COVID-19 lockdowns as expected.

KEYWORDS: *Air pollution, COVID-19, Pollution forecasting*

1. INTRODUCTION

South Asian countries such as India, Pakistan, Nepal, Bhutan, Bangladesh, and Sri Lanka are considered to be low-income or middle-income, developing nations. According to air quality surveys, 18 out of the top 20 most polluted cities in the world, are in this region [1]. Poor environmental protection regulations, poor availability of legal and scientific infrastructure, and excessive biomass burning are observed to be common attributes in the region.

Increased pollution landscapes in the region are largely assisted by industrial emissions, vehicular emissions, and biomass burning [2], [3]. Particulate Matter (PM) has been identified as the prominent pollutant in the region [4], [5], [6]. Particulate Matter pollution and its effects were first studied in the early 19th century, especially during the London Smog events [7]. According to regional research, weaker emission controls and environmental regulations, use of low-quality fuel, and inaccessibility to reliable energy sources have led to the increase in particulate matter levels in South Asia [8], [9].

India is considered the largest economy in the region. India has heavily invested in air quality monitoring, after being exposed to serious pollution episodes in major cities. Though similar circumstances are observed in the other countries, most South Asian countries lack the required technical infrastructure for effective monitoring and regulation of air quality. Due to the alarming conditions, numerous attempts have taken place recently in the region to manage air quality and minimize severe pollution exposure. Positive signs of these attempts are already visible through the collected data from previous research [10], [11], [12].

Air Pollution Forecasting can be divided into two main branches. The first is modelling pollutant dispersion patterns and forecasting behaviour of air pollution over time in a specified region. This approach requires significant data on emission landscape, meteorological conditions, and chemical aspects of the pollutant mix. The second approach is analysing the past and present pollution trends to forecast pollution behaviour over time. This approach requires considerably less historical data for forecasting.

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and is comparatively less complex than the first method. Due to the complexity and lack of data, research into pollutant dispersion modelling is less frequent [05], [06], [13].

Air pollution trend analysis is conducted using either traditional statistic related regression methods or using machine learning algorithms. With the increased popularity of data science, machine learning and other computer-based algorithms are now widely used for most forecasting approaches. These methods can consider either the trend alone or other influencing factors such as meteorology [14].

Severe meteorological events result in considerable changes to air quality as observed in previous research [15], [16].

When analysing and forecasting time series data, there are key factors that contribute to choosing a suitable machine learning algorithm. The selection of machine learning algorithm is based on whether the time series is univariate or multivariate. Then, depending on the number of historical data points and the availability of the seasonality effect, the complexity of the model can be decided. The most common models used for time series forecasting are the Auto-Regressive (AR) models [17].

The basic AR model uses the correlation between the time lags of the data points to predict future values. Another similar model is the Moving Average (MA) model, which uses the mean of residual errors as a linear function. The Auto-Regressive Moving Average (ARMA) model is developed by combining these two models for better accuracy. However, all three of these models are suitable for a univariate time series without seasonality or visible trend. Therefore, making them unsuitable for air quality forecasting when used separately. However, this issue was resolved by the Auto-Regressive Integrated Moving Average (ARIMA) model. It combines the AR and MA models and adds an integration step in between to make the series stationary. This allows using the ARIMA model for univariate time series data with a trend but without a seasonality effect. The SARIMA model which is also called the Seasonal ARIMA, is the next step in the AR model path, where it includes a parameter that considers the seasonality [18].

However, the ARIMA model can be used for seasonal data by removing the seasonality effect and using the remainder for forecasting. This is done when the seasonality is a regular cyclical pattern and not an irregular pattern. After the forecasting is done using ARIMA, to get the final result, the seasonality values should be added back [19]. When the series is multivariate, the Vector Auto-Regressive and Moving Average (VARMA) models can be used [18]. As for time series with large amounts of data showing irregular seasonal patterns and more advanced climatic changes, machine learning techniques like neural networks can be used.

Donnelly, Misstear, and Broderick [20] used a similar approach for predicting the behaviour of NO_2 concentration levels and forecasted pollution trends for 48 hours with considerable accuracy.

Gourav et al., [21] also used a similar approach in the short-term prediction of NO_2 and SO_2 levels with considerably satisfactory results. However, both of these studies focus on a single parametric analysis. A hybrid method was experimented by Díaz-Robles et al., [22] using both Artificial Neural Networks (ANN) and Multi Linear Regression (MLR) on forecasting particulate matter pollution in Chile. Meteorological elements and seasonality were considered for the study. It was observed that the method used in the study generated reliable and accurate forecasts while including extreme pollution events. The authors of this study aimed to evaluate the applicability of an ARIMA based method considering seasonality, for the purpose of trend forecasting in different regions in South Asia. Novelty of the study is based on the evaluation of the applicability of an ARIMA forecasting model considering regional seasonality over several cities in South Asia.

Available studies on regional air pollution primarily utilize various monitoring methods and instruments to arrive at the data required for the study. Variations in instrumental sensitivity result in non-homogeneous data. A variety of accuracy-related complications arise when data from different sources are used in congestion. Kandari and Kumar [23] investigated the variation of air quality over eight Asian countries using data from variety of sources including websites (aqicn.org; worldometers.info; iqair.com, etc.), World Health Organization, United Nations Environment Programme, National Aeronautics and Space Administration. Using a range of sources creates non-uniformity in the collected data. Manikanda et al., [24] only used data from Central Pollution Control Board, India (CPCB) to overcome this and study air quality over 10 Indian cities comparing reference years 2017 to 2019 against 2020 on an annual average. Authors of this study, as a novel approach utilized data from the network of Automated Air Quality Monitoring Stations (AAQMS) located in the United States Embassy and Consulates in the region (airnow.gov) as a novel approach. These raw data from AAQMS provided access to homogeneous data to train and evaluate the developed ARIMA forecast model over different backgrounds.

Worldwide, the air pollution trend was significantly affected by the COVID-19 lockdowns. The decrease in industrial activities and the travel restrictions resulted in a phenomenal decrease in pollution levels during lockdowns [25], [26]. It was also observed that air pollution steeply reduced during the period [26]. The upper atmosphere and the Ozone layer also illustrated improvements due to reduced pollution [27], [28]. A reduced number of cases of respiratory illnesses on the ground was also evident [29].

Vikas Singh et al. [30] used data from 134 different calibres of measurement devices belonging to CPCB to analyse the decrease in air pollution over several cities of India and isolated the effects of lockdowns on pollution reduction. In a novel attempt, the authors of this study compared the forecasted pollution trend and actual pollution during the lockdowns and isolated the actual impact of COVID-19 lockdowns on decreasing air pollution.

2. METHODOLOGY

Data Collection and Pre-processing

As the first step, the impact of meteorological events during 2017 to 2020 was analysed in a lower resolution using data from the MERRA-2 programme as suggested by Vikas Singh et al. [9], Sharma, S. et al. [28], who believe that Air Quality Index (AQI) better reflects the change in air quality than any other individual parameter when actual exposure conditions are concerned. However, the study considered Particulate Matter as the focus parameter.

The granularity of the raw dataset is in hourly averaged intervals. The raw data was cleaned and pre-processed to ensure quality and consistency. Data from the AQQMS archives were observed to contain outliers and Instrument codes (for when the measuring device was in calibration or non-functioning). Data cleaning and transformation methods were applied to remove the outliers and smoothened by the quantile clipping method. “Quantile clipping” is an anomaly smoothing method that replaces the data points with values higher or lower than the 95th or 5th percentile respectively to the percentile point value. Data cleansing was done by first replacing the instrumental codes with missing values strings (NaN) and then using linear interpolation to fill in the said missing value strings. Python data analysis and modelling libraries including pandas, matplotlib, and stats models were used for the process. The processed data were then resampled into daily averages before being used for the study.

Time Series Analysis of the Air Quality

Pre-processed data, averaged per day were used to study air quality in selected cities. This initial analysis was done through a time series analysis in the form of a graph. Air quality in eight locations in five South Asian countries was graphed separately for 2018, 2019, and 2020. Macro investigations of the trend were concluded by using combined 2018 to 2019 monthly data as reference and the data from 2020 as a comparison.

Quantitative values of the variation were obtained through the Equation 1 in terms of percentage. M_c refers to the 2020 data set, while M_r refers to the reference data set. It was expected that a significant decrease in air pollution would occur, overlaying the lockdown period.

$$Change\ in\ Air\ Pollution = \frac{M_c - M_r}{M_r} \times 100 \qquad \text{Equation 01}$$

Time Series Forecast and Comparison

The time series forecast was obtained by training an Auto-Regressive Integrated Moving Average (ARIMA) model. ARIMA is a statistical model used for non-seasonal, time-series data analysis and forecasting based on the behaviour of past values. The observed values from January 2018 to December 2019 (Reference Dataset) were considered the training dataset of the model. The forecast was done for the next six months in daily granularity, that is, from January 2020 to June 2020.

Seasonal decomposition was performed on a complete dataset to identify the availability of a seasonal effect. Time series data can be divided into the components of Equation 2 according to additive decomposition.

$$Observed\ value = Trend + Seasonality + Residual$$

Equation 02

Decomposition results indicated seasonality to be present in the data set. Therefore, seasonality should be removed before the training data is fitted into the ARIMA model. This was done by differencing each data point by the previous value.

The next step involved selecting the model parameters. In order to decide the AR factor for the model, the autocorrelation plots were obtained for each city. A general AR factor of 5 was decided after observing the plots through the trial and error method.

The developed model needed to be trained and validated before applying the reference dataset to measure reliability and accuracy. Therefore, the reference dataset was again divided into train and validation sets on the ratio of 60:40, respectively. Table 1 shows the root mean square error (RMSE) between the predicted and expected values of the validation data of each city. The dataset range is given in Table 1 to understand the effect of the RMSE on the data.

Finally, the complete reference dataset was fitted to the developed ARIMA model, and forecasts were obtained for the next six months. The complete dataset was plotted, including the forecasted and actual trends. Through the comparison of forecast data and observed data, the study aimed to better understand the impact of lockdown on regional pollution scenarios.

3. RESULTS & DISCUSSION

Time Series Analysis

An apparent decrease in air pollution levels was observed in early 2020. It was clear that this occurred due to the impact of the COVID-19 lockdown. In most countries, the earlier half of the year was recognized as the most concerning period when it comes to air quality due to seasonality. This enabled the comparison to be more fruitful.

When 2018/19 combined reference data was compared against the 2020 data, the highest reduction of pollution levels were recorded from cities with a history of severe air pollution complications such as Delhi, Kolkata, Dhaka, and Colombo. Figure 01 to 07 illustrates the behaviour of the daily median pollution during the combined reference years and 2020.

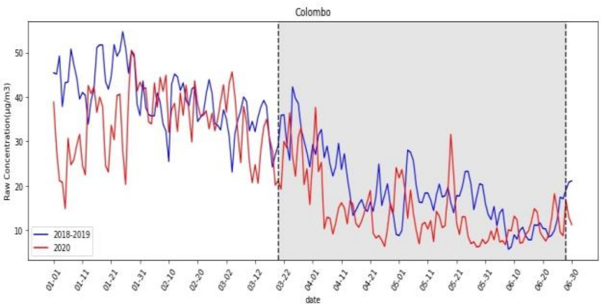

Figure 1: Air pollution variation in Colombo

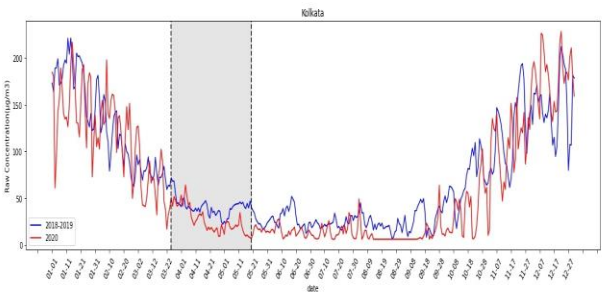

Figure 2: Air pollution variation in Kolkata

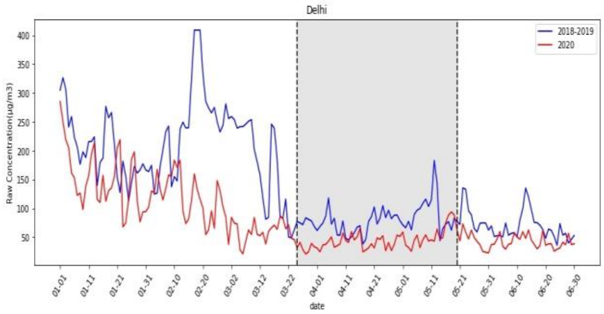

Figure 3: Air pollution variation in Delhi

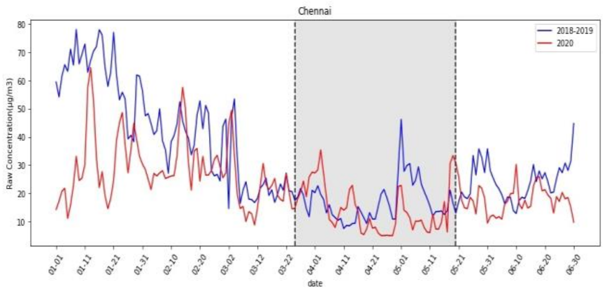

Figure 4: Air pollution variation in Chennai

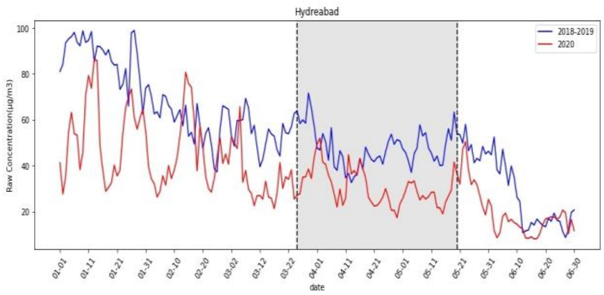

Figure 5: Air pollution variation in Hyderabad

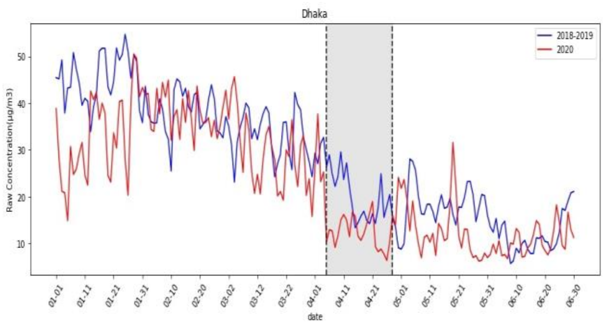

Figure 6: Air pollution variation in Dhaka

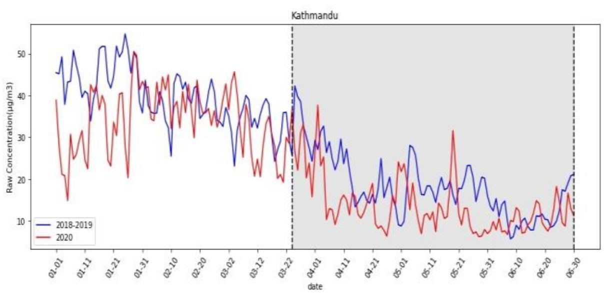

Figure 7: Air pollution variation in Kathmandu

Accuracy of the Developed ARIMA Model

Root Mean Square Error (RMSE) between the predicted and expected values of the validation data of each city is included in Table 1 with the range of the dataset to understand the effect of the RMSE on the data.

Table 1: Test RMSE details for the ARIMA model

City	Data Range	RMSE
Colombo	0-50	5.440
Kolkata	0-250	21.093
Delhi	0-400	34.958
Chennai	0-80	8.107
Hyderabad	0-150	8.513
Dhaka	0-55	5.443
Kathmandu	0-50	5.455
Islamabad	0-120	12.369

As per the above results, the forecasts of the model seemed to be within the acceptable range. In most cases, the value did not exceed 12% of the original data range from the sample. During the additive decomposition of the data set, significant seasonality was observed in most major cities in Bangladesh, India, and Sri Lanka. Apart from the seasonality, the trend was also isolated from the data set. Kathmandu, Chennai, Kolkata, and Colombo were observed to illustrate an increasing pollution trend while Delhi, Islamabad, and Hyderabad demonstrate a decreasing pollution trend.

When a trend is present, the assumption made by most previous research on pollution behaviour, especially related to COVID-19 lockdowns can be understated or overstated. The impact of the lockdown can be only accurately measured by comparing forecasted data against observed data.

Time Series Forecast and Comparison

The observed data and reference data were first compared with each other to identify the observable impact of the lockdown. This simple analysis ignored the presence of trend and seasonality in the data set. Secondly, observed data was compared with the forecasted data in order to obtain more accurate measurements of impact of the lockdown on regional air pollution.

An apparent variation in the decreased levels was identified when the forecasted values were used in the comparison. The decrease in pollution levels even surpassed the previously investigated levels on some occasions. Table 2 illustrates how the levels of pollution have decreased between the results obtained through the two methods.

Table 2: Decrease in pollution levels – Comparison between the results of the two methods

City	Month	Comparison with historical data (Percentage Decrease)	Comparison with forecasted data (Percentage Decrease)
Kathmandu	June	61.98	71.25
	May	53.33	52.06
	April	15.30	29.95
Delhi	June	35.75	29.56
	May	42.86	32.52
	April	44.39	34.59
Chennai	June	26.53	36.62
	May	33.57	24.79
	April	5.08	12.87
Colombo	June	10.65	33.51
	May	30.32	50.62
	April	28.03	37.86
Kolkata	June	50.39	66.52
	May	49.98	57.29
	April	25.69	38.39
Dhaka	June	0.04	24.50
	May	47.32	8.30
	April	26.76	15.61
Islamabad	June	8.17	13.59
	May	33.77	8.09
Hyderabad	June	38.34	-7.97
	May	37.96	26.58
	April	29.67	28.37

Results from the above table verify the observed trend over the years. Based on the results, most previous research on the impact of COVID-19 lockdowns undermined the actual impact.

While most cities indicated a variation in pollution levels over the three months considered, a decrease in pollution levels in Kathmandu significantly occurred only in June. The unique topographical characteristics of

Kathmandu have largely contributed to this. The city of Kathmandu is located in the Kathmandu valley, surrounded by the Himalayan Mountains range. This bowl-like topography surrounding the city traps pollution and negatively affects the air quality [31]. This clearly explains the observed variation in pollution behaviour.

Delhi and Kolkata have been considered pollution hotspots in India [32]. Research links paddy field burning across northern India to the significant seasonality air pollution behaviour found in these two cities [9], [33]. Forecast data illustrated that the pollution behaviour in Delhi is improving. Yet, the decrease in pollution levels was staggering as soon as the lockdown was enforced. However, the pollution trend in Kolkata has increased significantly and this led to the observed increase in the perceived impact of lockdowns on air pollution.

Pollution behaviour of Colombo between historical and forecasted has a significant difference. Premasiri *et al*., [35] suggest that the visible pollution in the city is lower than the reality because most of the pollution is carried inwards through the strong coastal winds, away from the city. It was identified that the dominant pollutant in the region is particulate matter, and traces of transboundary pollution is visible in Colombo's atmosphere [3]. Observations made by Gunasekara and Waraketiya, [26] also provide evidence of transboundary pollution. European studies into Long-range Transboundary Pollution have proven that the upper atmosphere could transfer pollutants over long distances [37]. The results of time series analysis from the study show similarities between the pollution behaviour in Delhi, Kolkata, and Colombo.

According to previously conducted research, Pollution in Dhaka is caused by two significant pollutants, PM2.5 and Lead [5]. Literature information also confirmed that the primary source of pollution in Bangladesh is Brick Kilns and Vehicular Emissions [5]. Lockdown was only enforced in April, hence significant pollution decrease was only recorded in April and May. The historical trend indicates that the pollution level in the city is decreasing. However, as Table 2 illustrates the effects of the lockdown are largely visible only in June. The air quality improvement was contradictory to the observed trend. 10% variation between historical and forecast comparisons is clearly influenced by the topography of the city.

Pollution levels in Hyderabad decreased similarly over the lockdown period from both perspectives. Compared to Delhi and Kolkata, Hyderabad reported lower pollution values throughout the years [24]. Since these are not industrial cities, pollution levels are quite low and illustrate high seasonality levels, suggesting that transboundary pollution is a crucial aspect.

4. CONCLUSION

In conclusion, the ARIMA based forecasting model developed for the purpose of predicting air pollution seemed applicable in lower-resolution air quality forecasts. Recorded RMSE values during the verification process were less than 12% for all cities, indicating that the model can be considered accurate. This simple method is beneficial in low-resolution air pollution forecasts for measuring the actual impact of air pollution mitigation strategies and estimating pollution events influenced by seasonality.

Observations from the time series analysis indicate that industrial cities such as Kolkata, Delhi, and Dhaka significantly improved air pollution compared to non-industrial cities such as Colombo, Hyderabad, Islamabad, and Chennai in 2020. Availability of seasonality in pollution trends, especially in non-industrialized cities, is evidence of transboundary pollution being present in the region.

Observations indicate that the pollutant concentration has been underestimated by 5% to 20% in Chennai, Colombo, and Kolkata when only historical data is used for comparison ignoring the pollution trend. The situation is reversed when cities with decreasing pollution trends are concerned. The trend is identified as a determining factor when low-resolution pollution forecasts are made. Studying the impact of COVID-19 lockdowns without considering the pollution trend will result in inaccurate results.

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