PREDICTING $PM_{2.5}$ CONCENTRATION USING ANN AND ASSESSING ITS HEALTH EFFECTS IN DELHI, INDIA

A DISSERTATION

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CANDIDATE'S DECLARATION

I, Rahul Dev Gautam, Roll No. 2K21/ENE/07 student of M. Tech (Environmental Engineering), hereby declare that the project Dissertation titled "Predicting $PM_{2.5}$ concentration using ANN and assessing its health effects in Delhi, India" which is submitted by me to the Department of Environmental Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "Predicting $PM_{2.5}$ concentration using ANN and assessing its health effects in Delhi, India" which is submitted by **Rahul Dev Gautam, Roll No. 2K21/ENE/07**, Department of Environmental Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

31-5-2023

Place: Delhi

Date: 31.5.2023

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ABSTRACT

The primary goal of the current study was to use an artificial neural network (ANN) to predict the linked health endpoint of $PM_{2.5}$. The study area having 37 monitoring stations was taken and the air monitoring data for 2015 to 2019 was considered. The neural network utilised in this study has an output layer, an input layer with 8 parameters, and a hidden layer of neurons. At first the ANN was trained using 80% dataset and then it was further trained with 90% of data set. For these two networks' respective R values for data validation were 80% and 82% respectively. The World Health Organization's AirQ + programme was used to evaluate the effects of $PM_{2.5}$ levels on health. The mean $PM_{2.5}$ over the 5-year study period was 121.462(μg/m^3), about twenty-four times higher than the WHO guideline. However, if we compare the annual mean of $PM_{2.5}$ concentration during the 5-year study it was shows that from 2015 the concentration dropped nearly by 8%. Out of which maximum and minimum annual mean concentration of $PM_{2.5}$ was observed in 2016 and 2019 respectively. This fluctuating pollutant concentration led to maximum number of deaths 51228 in 2016 and minimum no of deaths 44920 in 2019 for all natural cases (adults age 30+ years). Additionally, a positive association between $PM_{2.5}$ concentration, temperature, and wind speed were discovered. Considering the significance of predicting $PM_{2.5}$ concentration for accurate and timely decisions plus the accuracy of ANN used in this study, the ANN can be utilized as an effective instrument to reduce health and economic repercussions.

Keywords: Artificial neural network, Health Impact, AirQ+, Air quality.

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CHAPTER 1

INTRODUCTION

Air pollution is a very serious issue for many parts of the world due to rapid urbanization along with industrialization. This situation poses a serious risk to the well-being of people, affecting their health adversely. Additionally, it also has substantial effects on the environment and ecosystems.[1] One of the predominant challenges faced by numerous Asian cities relates to the abundance of fine particulate matter in the atmosphere. These particles possess an aerodynamic diameter of 2.5 µm or smaller and are commonly known as $PM_{2.5}$. The inhaled PM is deposited in different zones of respiratory traces (tracheobronchial, alveolar areas, and head) depending on the size of the particle.[2] Even at minor concentration of deposited PM it is enough to cause a health impacts. These particles have both immediate and long-term consequences for human health. They can result various health issues such as decreased heart function, increased hospitalizations due to acute lower respiratory infections (ALRI), chronic obstructive pulmonary disease (COPD), pneumonia, cardiovascular diseases (CVD), DNA damage, and even contribute to low birth weight in new-borns. A study conducted in 2017 found that ambient $PM_{2.5}$ was identified as the fifth leading cause of mortality in 2015. It projected a staggering 4.2 million deaths attributed to $PM_{2.5}$. These findings underscore the significant impact of $PM_{2.5}$ on human lives and emphasize the urgent need for effective measures to address this issue. These forms of air pollution managed approximately 7 million deaths globally in 2016. (World Health Statistics 2022). In 2016, it was estimated that approximately 4.2 million deaths occurred as a result of breathing in polluted air. These deaths were attributed to various health conditions such as stroke, heart related disease, lung cancer, lower respiratory infections, and chronic obstructive pulmonary disease (COPD). These alarming figures highlight the severe impact of ambient air pollution that can case a serious issue for human health and emphasize the urgent need for effective actions to mitigate this issue.

For several decades, the levels of air pollution in the National Capital Territory of Delhi (NCT Delhi) have consistently exceeded those found in most other capitals of developing countries. This persistent issue has made Delhi stand out as a megacity grappling with higher levels of air pollution compared to its counterparts.[3] Estimating health effects could aid in launching national and international efforts to enhance the NCT Delhi's air quality by enacting new policies and regulations.[1] Concentration of $PM_{2.5}$ remains way more higher than the CPCB standards of 60 µg/m^3, throughout the year and also higher than the WHO prescribed limit of 5 µg/m^3.

During the winter of 2013, it was observed that the concentrations of certain specific tracer species were significantly higher compared to the concentrations observed during the summer season. Notably, several polycyclic aromatic hydrocarbons (PAHs) and trace metals exhibited concentrations several times greater during winter, highlighting the seasonal variation and the potential impact of these pollutants on air quality. These came after ambient $PM_{2.5}$ samples were collected at a heavy traffic area (summer and winter 2013) and analysed by [4]. $PM_{2.5}$ average concentration for 2015-2016 was 117.3665 µg/m^3 which is 23 folds higher than the WHO standards of 5 µg/m^3 and this scenario remains same throughout the year. Number of days exceeding the limit of 25 µg/m^3 i.e., the cut-off value of AIRQ+ software was 363 out of 36 days in a year. By this we can have an idea of how severely it will affect the health of the residents and the people living in Delhi. [5] conducted a study between 2011 and 2014, along an 8.3-kilometer route in Delhi, revealed a shocking finding. It showed that during the morning rush hour, the concentration of $PM_{2.5}$ (fine particulate matter) was 40% higher compared to the entire-day dose recorded in cities like Tokyo, London, and New York. This finding highlights the alarming extent of air pollution during peak traffic hours in Delhi, surpassing the levels observed in other major cities around the world. Starting from 2017, the CPCB implemented the National Air Quality Monitoring Programme (NAMP). As part of this initiative, they began sharing real-time hourly updates on the concentrations of criteria pollutants at various locations in each city. These observations, along with the corresponding air quality index (AQI) based on these pollutants, were made accessible to the public. This effort aimed to provide transparent and readily available data of the air quality conditions in different areas. But AQI does not helps us in justifying the effects due to these because it does not take health impacts caused due to exposure of these pollutants into its consideration. [6]

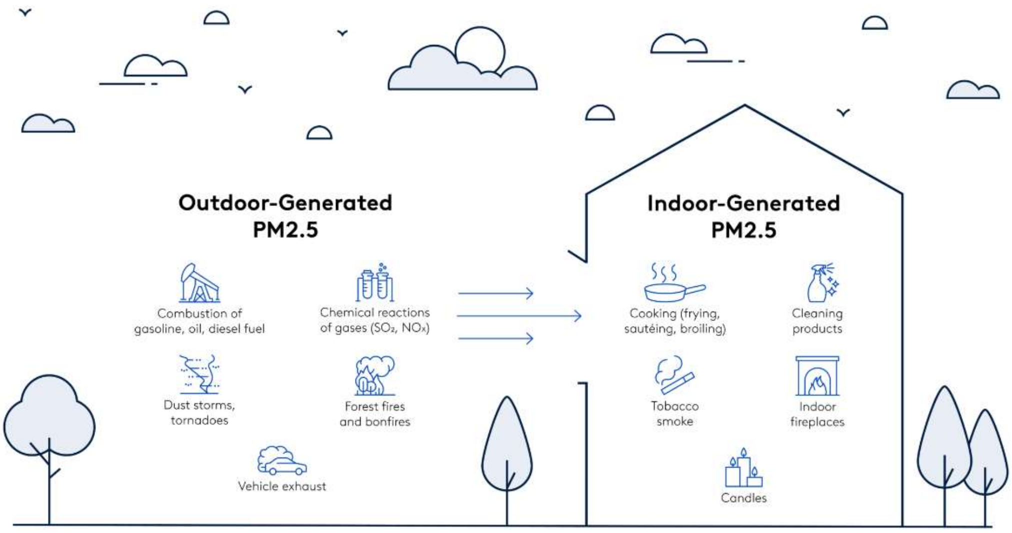

Figure 1.1 Sources of $PM_{2.5}$

The atmosphere's particulate matter is a complicated amalgam of various chemical species and various sources. Natural and artificial processes both directly emit particulate matter into the atmosphere. Secondary particulate matter (PM) is mostly produced by human activity and is made up of precursor gases such sulphide (SO_2), nitrogen oxides (NOx), ammonia (NH_3), and non-methane volatile organic compounds (NMVOCs, often known as VOCs). In addition to these components, carbonaceous particles have drawn a lot of interest recently due to potential negative effects on human health and the environment.[7]

A study by [8] found that residents of Delhi are 12 times more likely than residents of other regions of the country to experience the health issues listed above. In order to help sensitive population groups, receive important information that would enable them to reduce their exposure time, as well as to increase public awareness of extreme air pollution occurrences, it is necessary to construct an accurate air quality forecasting model.

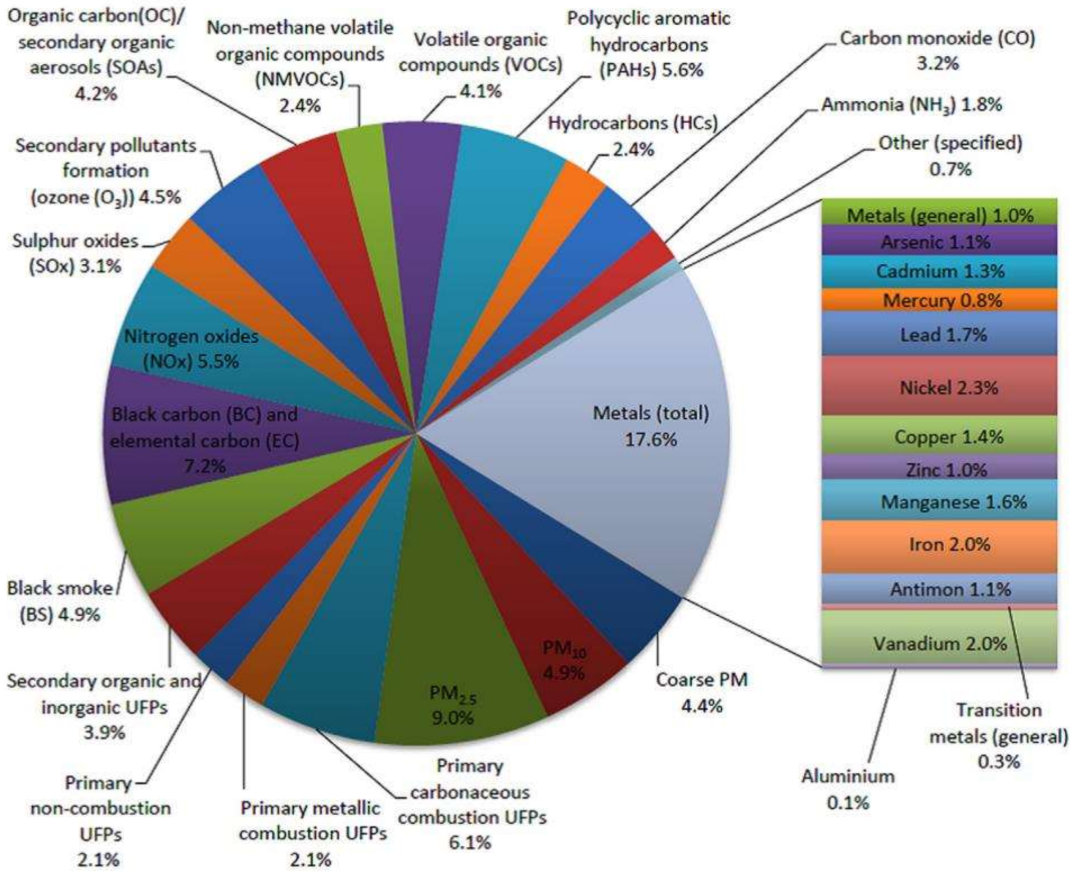

Figure 1.2 The proportionate impact of various air pollutants on human health risk Source WHO, 2013

Although these models are crucial for predicting air pollution, it can be challenging to effectively describe non-linear natural occurrences. On the other hand, machine learning techniques like ANN offer quicker prediction, more accuracy, and simplicity when working with multidimensional data. Several studies have successfully used machine learning techniques for anticipating air pollution.

The goal of the current research was to assess how well machine learning techniques, such as ANN, could be used to anticipate $PM_{2.5}$ levels for New Delhi. This study has three objectives. First, using ANN approaches, a $PM_{2.5}$-based prediction model was created with pollutant concentrations as inputs. Thereafter, the prediction performance of both models was compared using two distinct training data sets and comparing their R^2 values. Second, is to correlate the dial variation of $PM_{2.5}$ with metrological parameters wind speed (WS), temperature (Temp), and relative humidity (RH) and finally assessing the chronic health effects resulting from $PM_{2.5}$ exposure in Delhi using the AIRQ+ model.

1.1 Effects of air pollution on human health

Exposure to air pollution, particularly fine particulate matter, poses diverse health risks with a range of implications for respiratory well-being. These risks encompass minor upper respiratory discomfort, chronic respiratory and heart conditions, lung cancer, and acute respiratory infections. The impact of air pollution on respiratory health is extensive and it is associated with a broad spectrum of consequences.

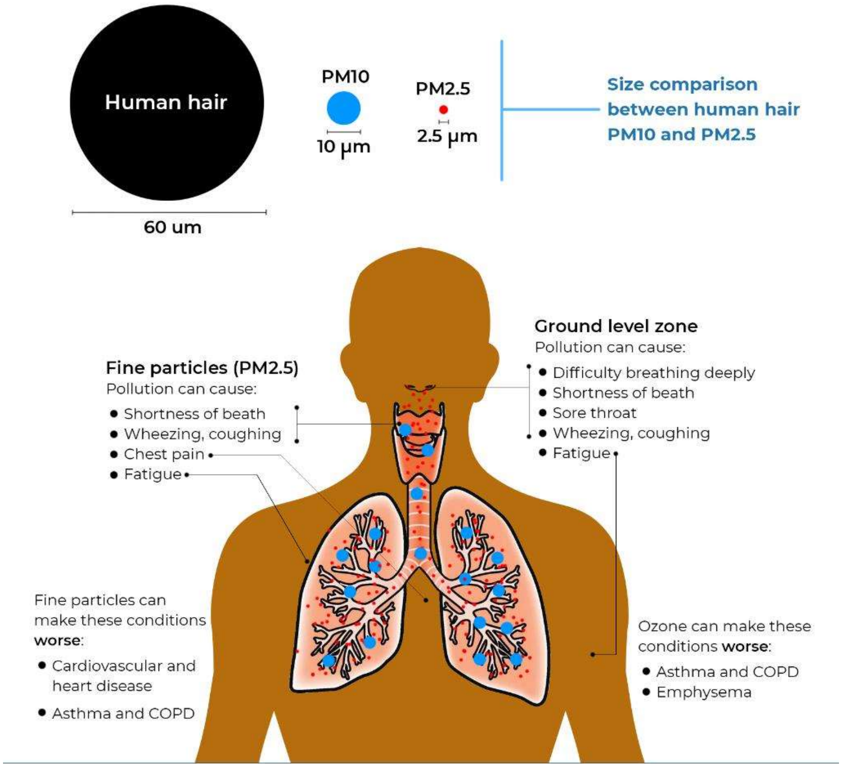

Figure 1.3: PM_{10} and $PM_{2.5}$ size and its health effects

It can worsen existing heart and lung conditions and can lead to more severe results. Early death and a shorter life expectancy have been linked to both prolonged and brief exposures over time. The contaminants with the highest evidence of affecting respiratory health include PM, O3, NO2,

SO_2, and CO. PM is categorized according to its size and serves as one of the main factors for assessing air quality. Figure 1.4 shows A “Pyramid of Effects” from air pollution

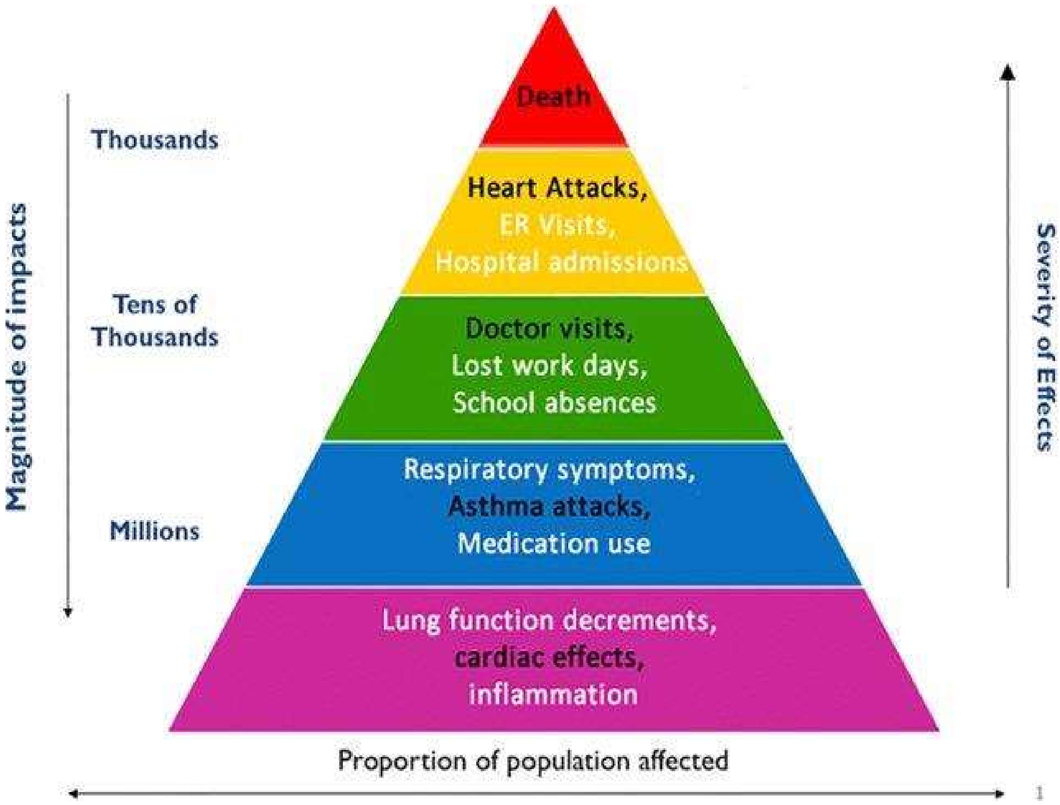

Figure 1.4: A “Pyramid of Effects” from air pollution

CHAPTER 2

LITERATURE REVIEW

Fallahizadeh et al. 2021 [9] Researchers aimed to investigate the impact of climatic conditions on PM_{10} (PM with a diameter of 10 µm or less), analyse its effects on health, and predict its concentrations in Yasuj, an Iranian city. Data on demographics, climate, and PM_{10}focused air quality data were collected for the duration of March 2013 to March 2018. The AirQ+ software was utilized to assess the health effects of PM_{10}, while a combination of daily average PM_{10}concentrations trend with meteorological data was used to forecast PM_{10}levels. The study revealed a higher risk of respiratory symptoms, such as asthma and bronchitis, in children and chronic bronchitis in adults, as well as increased post-neonatal infant mortality associated with PM_{10}exposure. The relative risks were determined to be 1.028, 1.08, 1.117, and 1.04, respectively. Additionally, an MLP-ANN model proved to have a strong predictive capability with a correlation coefficient (R^2) of 0.87. Lower levels of PM_{10}were linked with reduced symptoms of bronchitis and asthma in children and bronchitis in adults. The ANN modelling approach offers practical insights for air pollution management strategies. The study identified dust storms in the western and southwestern regions of Iran as the primary cause of elevated PM_{10}concentrations, which can be attributed to drought, reduced rainfall, decreased soil moisture content, and vegetation cover degradation.

Goudarzi et al. 2021 [10]The study focused on using an ANN (Artificial Neural Network) to predict the health effects associated with $PM_{2.5}$. The neural network employed had 27 neurons in its hidden layer, 8 parameters in the input layer, and finally an output layer. The ANN was trained using eighty percent of the available data, followed by further training using ninety percent of the data. The R values for these two networks' data validation were 0.80 and 0.83, respectively. For analysing the health impacts of $PM_{2.5}$ levels, the World Health Organisation AirQ + software was used. The average $PM_{2.5}$ concentration for the 9-year study period was 63.27(µg/m^3), which was nearly six times higher than the WHO recommendation. However, $PM_{2.5}$ concentration has reduced by around 25%. Finally, by examining the time trends of essential air marker. From 2008 to 2017, we estimated the long-term health impacts of the pollutant $PM_{2.5}$ in Ahvaz using the WHO AirQ+ software. According to the findings, annual $PM_{2.5}$ concentrations have decreased by around 25% in recent years. The residents of Ahvaz continue to experience high levels of $PM_{2.5}$ pollution that surpass the recommended limits set by the U.S., WHO, EPA, and Iranian standards.

Gurjar et al. 2010 [11] The goal of this study was to examine the prolonged and immediate health consequences of air pollutants in New Delhi across 36 transport corridors. They utilised Ri-MAP model to examine the health impacts of PM_{10}, $PM_{2.5}$, SO_2, and NO_2 in 2016. The study area was divided into 2Km x 2Km grids near each corridor, and based on guidelines provided by WHO, the mortality and morbidity rates of the population exposed to these pollutants were evaluated accordingly. The findings reveal a substantial volume of vehicles on the roadways in the area under investigation. The ISBT Flyover recorded the maximum number of additional cases of breathing, cardiovascular, and overall mortality (365, 1399, and 2136 cases, respectively), in second place Wazirabad Road experienced a total of 362, 1378, and 2096 cases, respectively. Two areas with the maximum morbidity rates observed were related to a significant number of hospital admissions for COPD and cardiovascular disease, with 18,979 and 4,762 cases, respectively. The analysis indicates a concentration of cases near Delhi's megacity, beyond the considered grid area. This study offers valuable information regarding the health hazards linked to pollution caused by traffic, both in non-residential and residential areas. Such studies contribute to the improvement of transport corridor design at the same time they also aid health institutions in effectively managing and addressing the impact on affected individuals in the city and nationwide.

Guo et al. 2019 [12] have discussed that study is helpful to investigate the temporal and spatial fluctuations of $PM_{2.5}$ concentrations using observation data recorded form ten locations of Delhi (2017). The relationships between various contaminants at available places were studied. Two extreme $PM_{2.5}$ instances have been selected to investigate the effects of climatic conditions and pollution sources. Based on HAQI, the health hazards associated with six criterion pollutants were assessed. This research is useful for developing ways to reduce air pollution in Delhi. The results indicate that yearly fine particulate matter ($PM_{2.5}$) concentrations exceeded the NAAQS of 60 μg/m^3 at all sites, ranging from 105.51 μg/m^3 (site 10) to 143.23 mg/m3 (site 7). $PM_{2.5}$ concentrations were lower in sub-urban areas (sites 8, 9, and 10) than in urban areas. With yearly averages of 399.56 μg/m^3 and 75.69 ppb, PM_{10} and ozone (O_3) were also significant. Among all these pollutants, PM_{10} demonstrated a statistically significant weekly difference, with a ratio of 1.5 (weekdays/weekend's). The $PM_{2.5}$ and PM_{10} ratio was higher on episode days with $PM_{2.5}$ levels more than 60 μg/m^3.According to Pearson correlation coefficients, O_3 has a negative relationship with CO, SO_2, and NO_2, whereas $PM_{2.5}$ has a positive relationship with these pollutants. Future research in north India will focus on the mechanism of local pollution on a broader level as well as a longer time frame.

Goel et al. 2015 [13] The study revealed that the monthly average ambient concentrations of $PM_{2.5}$ lies between 130 μg/m^3 to 250 μg/m^3. On-site measurements showed higher levels, exceeding ambient readings by approximately 40% when walking, 10% when cycling, 30% when driving a motorised two-wheeler, 30% when driving a car with open windows, 30% when driving an auto rickshaw, 20% when driving an open-windowed bus, 20% at a bus stop, and 30% at an underground metro station. On the other hand, the levels of pollutants were diminished by 50% when inside car with an air-conditioned and by 20% while traveling in a metro rail carriage. Furthermore, the study found that an hour of cycling during the morning rush hour in Delhi resulted in a $PM_{2.5}$ exposure that was 40% higher compared to an entire-day exposure in cities like Tokyo, London, and New York, where outdoor concentrations range from 10 to 20 μg/m^3. It was observed that unenclosed modes of transportation in Delhi had 10-40% higher $PM_{2.5}$ concentrations than the surrounding ambient areas. The analysis also highlighted that the ratios of on-road to ambient concentrations were significantly lower in Delhi in comparison to countries with cleaner air and higher income levels, the air quality in the mentioned location is comparatively poorer.

Overall, these findings emphasize the higher levels of on-road $PM_{2.5}$ concentrations in Delhi compared to ambient areas, while also highlighting the relatively lower on-road to ambient concentration ratios in Delhi compared to countries with cleaner air.

Sreekanth et al. 2018 [14] have discussed the concentrations of ambient fine particulates across the fast developing and agglomerating Indian cities. Despite various pollution-reduction initiatives and policies in place, Delhi had the highest $PM_{2.5}$ levels of any of the research cities, across all seasons and times of day. The temporal fluctuations in levels of $PM_{2.5}$ in Indian megacities are presented, along with an analysis of the factors that contribute to their concentrations. On an annual and seasonal basis, daily mean $PM_{2.5}$ readings increased northward. With changes in shape, the form of the $PM_{2.5}$ diurnal variations change gradually. The graphic factors determining concentrations and their modulation by weather and other natural occurrences were thoroughly examined. The statistics and analyses offered in the book are extremely beneficial for policymakers in strategizing their region-specific mitigation measures.

Ansari et al. 2019 [15] The AirQ+ software was utilized in this study to evaluate mortality cases resulting from exposure to particulate matter with a diameter smaller than $_{2.5}\mu m$. This study identified a connection between particulate matter and meteorological parameters. In Tehran, the all-cause of mortality, ALRI, LC, IHD and COPD caused by exposure to $PM_{2.5}$ was estimated. The data used in this study was collected from official government departments such as population, particulate matter and baseline incident rates in Tehran. The study used correlation analysis to determine the relationship between meteorology and PM. The findings indicate a correlation between particulate matter and monthly temperature and humidity in Tehran. Total number of cases for all-cause mortality, ALRI, LC, IHD and COPD are 6710, 27, 135, 3797 and 172 respectively. As per results of the study between $PM_{2.5}$ and the number of cases, an increase of 1 μgm^{-3} of $PM_{2.5}$ will result in addition of roughly 27 instances to air pollution mortality in Tehran as per the prediction.

Pant et al. 2015 [16] have discussed that Particulate matter concentrations are very frequently found to exceed as per Indian Standards and this research has recognised PM as a critical public health concern and risks, especially in cities. Emissions from vehicle, industries and coal fire power plants, road dust and waste burning, construction activities, etc. have been identified as the primary sources of air pollution in India. Delhi is listed as one of the most polluted cities in the world, with air pollutant concentrations frequently exceeding the NAAQS. According to the Delhi

Statistical Handbook (2013), the city has 29 planned industrial districts and 585 factory complexes The sulphur level of the coal used in Delhi's 88 power plants normally fluctuates between 0.35% and 0.50%. Diesel is used for both road transport (cars, utility vehicles, and heavy-duty trucks) and power generation. A significant proportion of the PM has been attributed to car emissions, road dust, and other sources. coal combustion and domestic emissions were studied in many studies. According to Goyal et al. (2010), diesel vehicles generate approximately 28 percent of total PM in Delhi. Winter concentrations were found to be substantially greater than summer concentrations. Pollutant concentrations are influenced by both meteorological and source strength. There is a significant difference in average temperature between the summer and winter seasons in Delhi, which could explain some of the discrepancies in species concentrations between the two seasons. Several species are easily volatilized at higher temperatures, and reactive species frequently undergo chemical reactions in the presence of sunlight.

CHAPTER 3

METHODOLOGY

3.1 Study area

The National Capital Region (NCR) of India is experiencing rapid urban growth, with Delhi positioned at its core. The region encompasses significant socio-economic districts of neighbouring states, including Gurgaon, Ghaziabad, Faridabad, Noida, Greater Noida, Sonipat, and Bahadurgarh. The overall geographical area of these districts is 46,208 km2.In this study considered Our study focuses on Delhi, which is situated between latitudes 28.3°24′15″ and 28°53′00″ N, and longitudes ranges from 76°50′24″ E and 77°20′30″ E. Delhi covers a total geographical area of 1483 km2 and exhibits diverse pattern of land use throughout its region. It falls under Indo-Gangetic Plains, at an elevation ranging from 198 to 220 m above mean sea level. [17] The monitoring sites for the current study are presented in the following Figure 3.1.

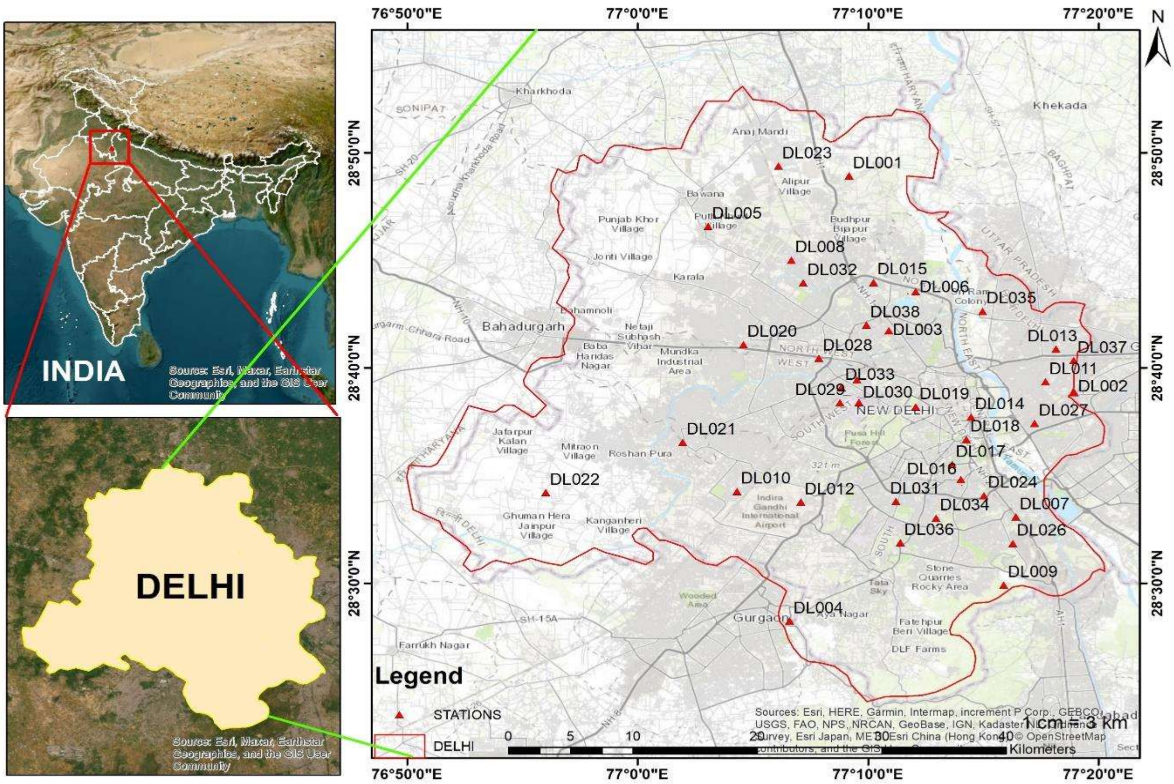

Figure 3.1: Study site location in Delhi

Between 1991 and 2016, the population of Delhi grew from 9.4 million to 25 million, an increase of about 62%. According to the World Urbanization Project by the United Nations, Delhi is projected to have a population count of 37 million residents by 2030. This rapid surge in population has resulted in a significant rise in the number of automobiles. The growing population density in the city can now be compared to the density of vehicles, which is because the favourable economic conditions status of individuals in the region. (CPCB 2010).

Vehicular emissions are a major source of pollution in the environment. Cars, trucks, buses, and other vehicles emit harmful gases such as CO, CO_2 and NO and hydrocarbons containing lead which are left unburnt. These gases pose a serious threat to both human health and the environment. Carbon monoxide (CO) constitutes the largest proportion of pollutants released by the transportation sector, making up approximately 90% of the overall emissions.

A comprehensive analysis conducted by the World Health Organization (WHO) on 1,650 cities globally, Delhi, the capital region of India, was identified as the city with the most critical air quality among all major metropolitan cities worldwide. The problems associated with air pollution is just not related to Delhi, but it also tends to affect the surrounding neighbourhoods as well. Studies suggest that air pollution is accountable for approximately two million deaths in India annually, therefore it the sixth fastest growing cause of death in the country. According to a report published in The Lancet Planetary Health, India has the highest mortality rate from chronic respiratory diseases, including asthma. The severe air pollution in Delhi has a long-lasting impact on the lungs of approximately 2.2 million young individuals.

Throughout the year, the AQI of Delhi typically varies within the moderate range (101-200) from January to September. However, due to certain reasons such as burning of stubble, roadside dust, vehicular emissions, and low temperatures, the AQI quickly drops to very poor (301-400), severe (401-500), or even hazardous levels (500+). In November 2017, Delhi experienced the Great Smog, a severe episode of air pollution. During this period pollution levels exceeded way beyond the acceptable limits. The permissible limits of 60 $\mu g/m^3$ for $PM_{2.5}$ and 100 $\mu g/m^3$ for PM_{10} particulate matter were surpassed, reaching an alarming level of 999 $\mu g/m^3$.

3.2 Artificial neural network (ANN)

Artificial Neural Networks (ANNs) are designed based on a mathematical representation that emulates the structure of the human brain. [18] In this context, an ANN can be envisioned as having a primary layer that collects input data, an output layer that provides the desired results or collected values, and one or more intermediate layers in between. This arrangement allows the ANN to process information in a manner similar to how our brain functions.[19]

The process through which the neural network functions is as follows: each neuron in the primary layer gathers input variable data, which is then presented based on an input vector.

$$\mathrm{X}^{\mathrm{p}} = \left(\mathrm{X}_1^{\mathrm{p}}, \mathrm{X}_2^{\mathrm{p}}, \dots, \mathrm{X}_{\mathrm{N}}^{\mathrm{p}}\right)^{\mathrm{T}} \qquad (1)$$

According to the propagation rule, this input vector is further extended to the middle layer as follows:

$$\{S\}_i^p = \sum_{\{j=1\}}^{N} w_{\{j\ i\}x_j^p} + \{b\}_i \qquad (2)$$

In the given equation, N represents the number of networks in the input neurons. The variable w_{ji} denotes the weight assigned to the connection between neuron i from the hidden layer and neuron j associated with the input layer. The variable b_i represents the bias value associated with neuron i. In simpler terms, the equation describes the interrelationships between neurons in the network, where weights and biases play a role in determining the output of each neuron based on inputs from other neurons.

If a network input vector's function is the activation phase of neuron i, then the network output is:

$$y_i^p = F\left(S_i^p\right) \qquad (3)$$

As a result, the following equations can be used to determine the activation phase of each neuron k from the output layer:

$$S_k^p = \sum_{\{j=1\}}^{L} w_{\{i\ k\}}\mathrm{Y}_i^p + b_k \qquad (4)$$

$$y_k^p = F_k(S_k^p) \quad (5)$$

In the above equation, the variable L represents the number of total neurons present in intermediate layers. The variable w_{ik} denotes weight associated with the connection between neuron i of intermediate layer and neuron k of output layer. The variable b_k refers to bias value specific to neuron k. Simply put, this equation describes the connections between neurons in the intermediate and output layers, where weights and biases influence the output of each neuron based on inputs from the intermediate layer.

The error term for output neuron is given by:

$$E^p = \frac{1}{2}\sum_{\{k=1\}}^{M}\left(d_k^p - y_k^p\right)^2 \quad (6)$$

At this point, the neural network training process is concluded after making necessary adjustments to the previously calculated values. However, the procedure is repeated by adjusting with respect to previously created error margins, until we obtain our desired error value. [19]

A mathematical procedure called a multilayer perceptron (MLP) was employed in order to carry out a stochastic estimation of multivariate functions. For determining the MLP, Equations number (7) and (8) reflect the transfer function that are more realistic.

$$Sigmoidal\colon\ f(x) = \frac{1}{1+exp^{\,(-x)}} \quad (7)$$

$$Tansig\ :\ f(x) = \frac{2}{1+exp^{(-2)}} \quad (8)$$

Levenberg-Marquardt backpropagation algorithm was employed for training the neural network in this particular study. This algorithm was chosen for its ability to enhance the accuracy of the results and expedite the convergence process. The transfer functions used in the hidden layer and output layer are implemented through utilising linear transfer and tan-sigmoid functions. These functions facilitate the conversion of input signals within the neural network, allowing for appropriate transformations and computations in both the output and hidden layers. (Eq. (8)). In order to achieve the lowest RMSE values, quick convergence, and scale-commensurability of the inputs, all the specimens had to go through normalization and assigned a value between 0 and 1. The normalised data values are as follows:

$$X_i = \frac{X_1 - X_{\{min\}}}{X_{\{max\}} - X_{\{min\}}} \tag{8}$$

where X1, Xmax, Xmin, and stand for the actual, max, and min data, respectively.[20]

- Training —used to prepare a neural network for use.
- Verifying —used to confirm the network's effectiveness after training.
- Testing —used to evaluate the neural model's accuracy and predictability on

Determination (R) was used in the current work to analyse the working performance of the ANN models. Model having higher R^2 revealed the best linear model.

3.3 AirQ+ Software

AirQ+ is a software that aids in quantifying the health effects of air pollution in terms of long-term and short-term effects. It analyses how much air pollution can shorten people's lives and uses scientific studies to understand how it affects health. It can also provide inform of the most dangerous pollutants. For instance, it can inform us of the pollutants that cause the greatest number of illnesses and fatalities. Governments and other organisations can use this information to make decisions about how to safeguard the public's health and minimise air pollution.

AirQ+ serves as a valuable tool in evaluating the impact of air pollution on human health. By utilizing World Health Organization's default measurements, such as the relative risk (RR) per 10 $\mu g/m^3$ increase in 24-hour average $PM_{2.5}$ and the burden of disease (BI) values per 100,000 people, it allows for the assessment of the severity of health effects associated with air pollution. These measurements are indicative of the potential link between specific diseases and the causes that contribute to mortality and morbidity. Literature was used to determine the values for RR and BI. Now in order to calculate the prolonged and immediate health consequences of air pollution we need to have certain data such as daily Air monitoring data to calculate annual mean $PM_{2.5}$ concentration, Census database for calculating population at risk because of the exposure, and database of baseline rate of health cases. For long-term health impacts cut-off value to be considered is 10 μgm^{-3} and for the assessment of short-term health effects cut-off value to be considered is 25 μgm^{-3}. (WHO 2017 n.d.)

The RR is evaluated by Eq- 9 [15]

$$RR = exp[\beta ln(x - x^{\circ})] \quad (9)$$

Where concentration of pollutants is denoted by x, counterfactual value is denoted by x^{o}, and $\beta$is a Confidence interval (95 percent) that relies on the type of health endpoint. The attributable percentage (AP), which may be computed using Eq. 10, is the portion of a health result that is attributed to population being exposed to these pollutants over a specific time period.

It is calculated using Eq-10 [15]

$$AP = [(RR(c) - 1) * p(c)]/[RR(c) * p(c)] \quad (10)$$

Where RR stands for relative risk and p(c) (c) represents the percentage of the population that falls into the exposure group. Eq. (11) can be used to determine the number of instances per unit population (BE) in the population for a certain value of BI of corresponding health outcome.

$$BE = B * AP \quad (11)$$

By considering the population size denoted as N, we can estimate the number of attributable cases (NE) using the following approach. Eq.(12). [15]

$$NE = BE * N \quad (12)$$

For specific health outcomes analysed in the study, AirQ+ utilized predefined relative risk values. To assess the relative risks associated with specific pollutant concentrations, a linear log approach was employed. The excess number of cases (ENAC) represents the estimated number of cases that can be attributed to the evaluated pollutant levels as determined by the AirQ+ software.

Pollutant	Mortality/Morbidity	Relative Risk(RR) (95%CI) per 10μg/m³	Baseline Incidence Per 100000 (I)
		Long-term effects	
$PM_{2.5}$	Mortality, all natural cases (adults age 30+ years)	1.062(1.04-1.083) GBD 2015/2016	1013
	Mortality due to ALRI for children (0-5 years)	(INTERGRATED FUNCTION 2016) GBD 2015/2016	49
	Mortality due to COPD for adults(25+ year)	(INTERGRATED FUNCTION 2016) GBD 2015/2016	101
	Mortality due to LC for adults (25+ years)	(INTERGRATED FUNCTION 2016) GBD 2015/2016	132
	Mortality due to IHD for adults (25+ years)	(INTERGRATED FUNCTION 2016) GBD 2015/2016	436
	Mortality due to Stroke for adults (25+ years)	(INTERGRATED FUNCTION 2016) GBD 2015/2016	436
		Short-term effects	
	Hospital admission respiratory disease	1.019(0.9982-1.0402)	1260
	Hospital admission cardiovascular disease including stroke	1.0091(1.007-1.0166)	101
	Mortality all natural cases 30+ years	1.0123(1.0045-1.0201)	1013

Table 3.2.1 Table for Relative Risk and Baseline Incidences for mortality and morbidity

The above values of BI and RR for their associated health impact was taken from literature [22]

3.3.1 Steps to evaluate the health impacts due to exposure of $PM_{2.5}$.

Steps 1: Figure 3.3.1.1 shows the welcome screen of the software, click on '+' button and select create new assessment.

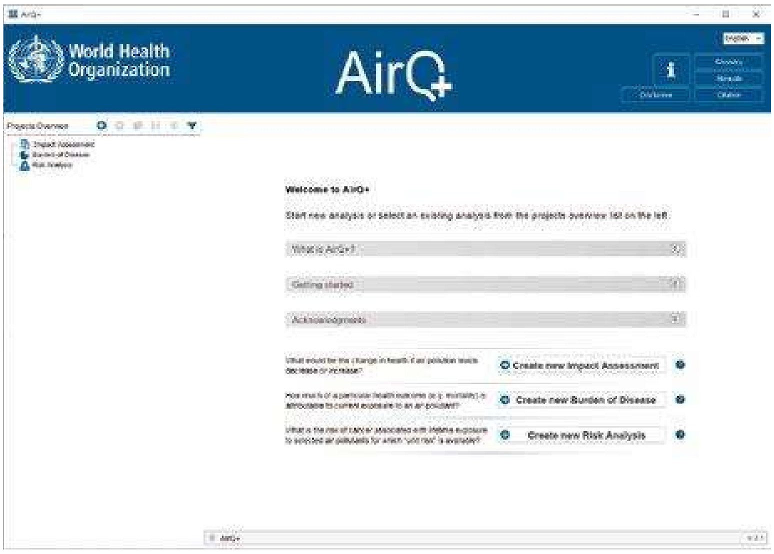

Figure 3.3.1.1. AirQ+ welcome screen

Figure 3.3.1.2. AirQ+ toolbar for management of assessments

Step 2 – On the generation of new impact assessment, a pop-up window will appear, as shown in Figure 3. From this window, we have the option to pick the specific parameters you wish to calculate and analyse.

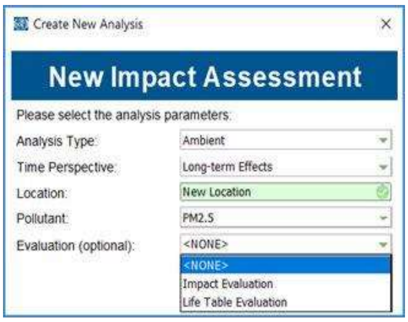

Figure 3.3.1.3. AirQ+ Create New Analysis: New Impact Assessment window.

Within the New Impact Assessment window, choose the options for analysing ambient pollution, assessing long-term effects, focusing on $PM_{2.5}$. To perform this assessment, you will need to input the mean value. Select the option for Input Mean Value in the Analysis Properties window, and enter the value of 27.955 g/m^3 in the input field. For Total Population, enter the number "1690109" (as shown in Figure 3.3.1.4). It's important to note that AirQ+ does not analyse the entire population, so this additional descriptive data will be included as well.

Step 3 – Fill in the necessary information in the provided fields, including details such as population size, city name, study year, $PM_{2.5}$ values, and so on.

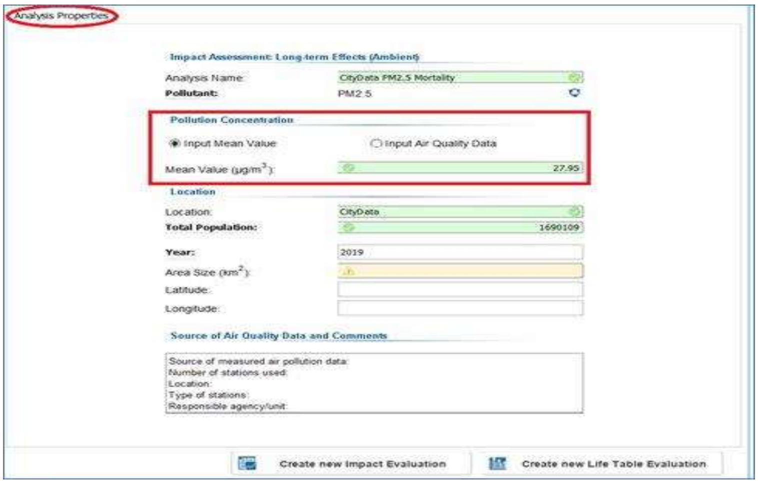

Figure 3.3.1.4: AirQ+ Analysis Properties window for ambient air pollution

Tap on the "Create new Impact Evaluation" option (refer to Fig. 3.3.1.4), which will open the Impact Evaluation window (refer to Fig. 3.3.1.5). In this window, enter the required data as follows:

Step 4 – In the name of the evaluation section, select the disease and enter the corresponding data from table 3:

- Example evaluation name: "AAP7 $PM_{2.5}$ long-term adult mortality"
- Mortality incidence for adults (aged 30+ and above), for all-natural causes, per 100,000 population: 939.73.
- Enter total no of adults who are 30+ and add population exposed to the pollutant: 1,156,588. We can also give the value of exposed population in percentage.

- Default RR values for all-natural case mortality: 1.062 (with a 95% confidence interval of 1.040-1.083).
- Default cut-off value recommended by the 2005 WHO Air Quality Guidelines: 10 μg/m^3.

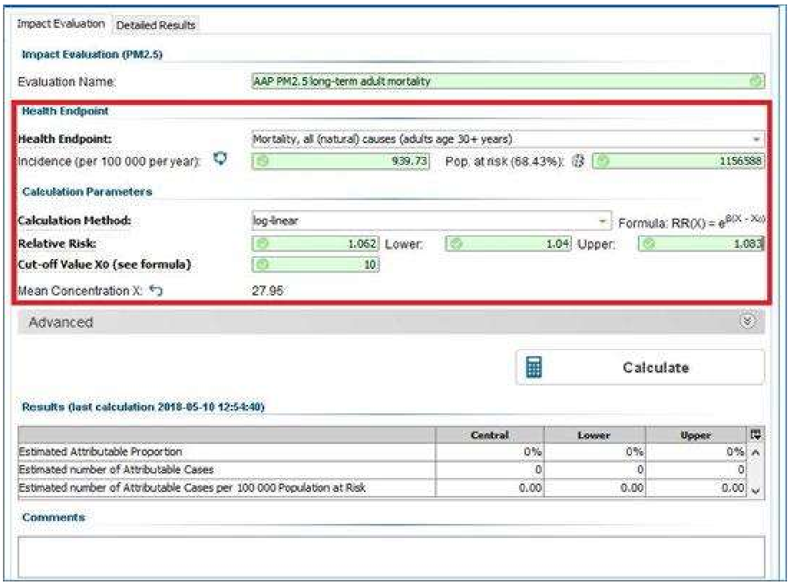

Figure 3.3.1.5: AirQ+ Impact Evaluation screen

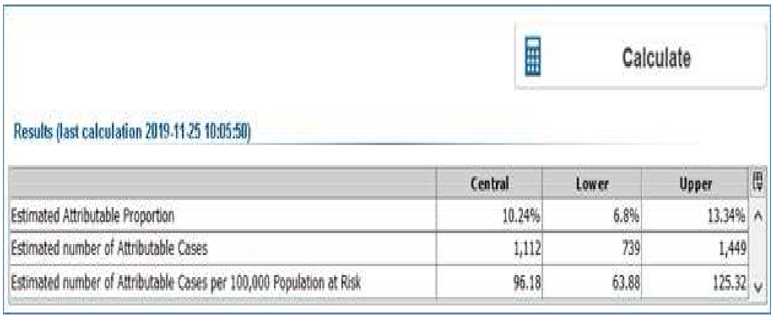

Figure 3.3.1.6: Figure showing results for ambient air pollution

According to the output window (Figure 3.3.1.6), it is estimated that there would have been 1112 fewer premature deaths caused by long-term exposure to $PM_{2.5}$ if the $PM_{2.5}$ conc. had not exceeded 10 μg/m3. This value aligns with the threshold limit recommended by the 2005 WHO Air Quality Guidelines. The outcomes in the Lower and Upper columns of the table represent the lower and upper limits of the confidence interval for the relative risk. These values indicate the range of uncertainty associated with the estimates of the RR for all-cause mortality that were entered by the user during the creation of the Impact Evaluation. The 95% confidence interval reflects the level of uncertainty in the relative risk values and provides an understanding of the range of possible outcomes.

3.4 Data collection

3.4.1 Air quality data

For this study, hourly air quality data was collected from 01 January 2015 to 01 January 2020. It was obtained from the official website of the Central Pollution Control Board (CPCB). The daily 24-hour data was collected for all the stations mentioned in Figure 3.1.

To determine the overall $PM_{2.5}$ concentration for Delhi on a particular day, the average of $PM_{2.5}$ concentrations at all the stations was calculated. This provided the final $PM_{2.5}$ concentration for that day.

Table 3.4.1: Sample data set for air quality monitoring data

Date	Time	$PM_{2.5}$	PM_{10}	NO	NO2	NOx	NH3	CO	SO2	O3
01/01/2015	01:00:00	454.58	935.18	81.52	41.78	187.66	27.54	9.29	3.41	54.94
01/01/2015	02:00:00	440.44	821.13	70.8	43.46	176.83	27.72	13.28	3.88	50.53
01/01/2015	22:00:00	327.68	73$_{2.5}$9	129.53	43.87	226.67	53.74	13.66	12	48.34
01/01/2015	23:00:00	335.18	776.36	147.06	45.35	243.13	58.59	12.2	10.17	44.82
01/01/2020	00:00:00	600.85	693.07	203.35	73.74	218.45	76.68	5.1	22.49	38.95

3.4.2 Meteorological data

The daily temperature, relative humidity, and wind speed data were obtained from NASA's meteorological department.

3.4.3 Population Data

Population data for Delhi was collected from Census of India 2011, and growth rate was also taken from the same i.e., 21.21%. Using this growth rate population for 2015, 2016, 2017, 2018, and 2019 was forecasted using geometric mean method.

$$\{P^{\circ} = P(1 + r/100)^{n}$$

Where,

The population data for the cities was collected for the year 2011, including the population at the nth decade, represented as P^{o}, population represented as P, growth rate represented as r, and the number of decades represented as n. The table provides the population for 2011 and the projected population for future years.

Table 3.4.2 Forecasted population for the study period

Years	Population
2015	18130626
2016	18482753
2017	18841718
2018	19207655
2019	19580699

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Artificial neural network

As was previously mentioned, the collected data in this investigation were divided into three categories. We separately discussed the results of the ANN using 90% of the training data plus 5% training data and 5% for validation and when 80% for training data is used 10% is used for testing and 10% is used for validation data.

The figures 4.1.1 and 4.1.2 depict the relationship between the predicted and measured values of $PM_{2.5}$ concentration for 80% and 90% of the training data, respectively.

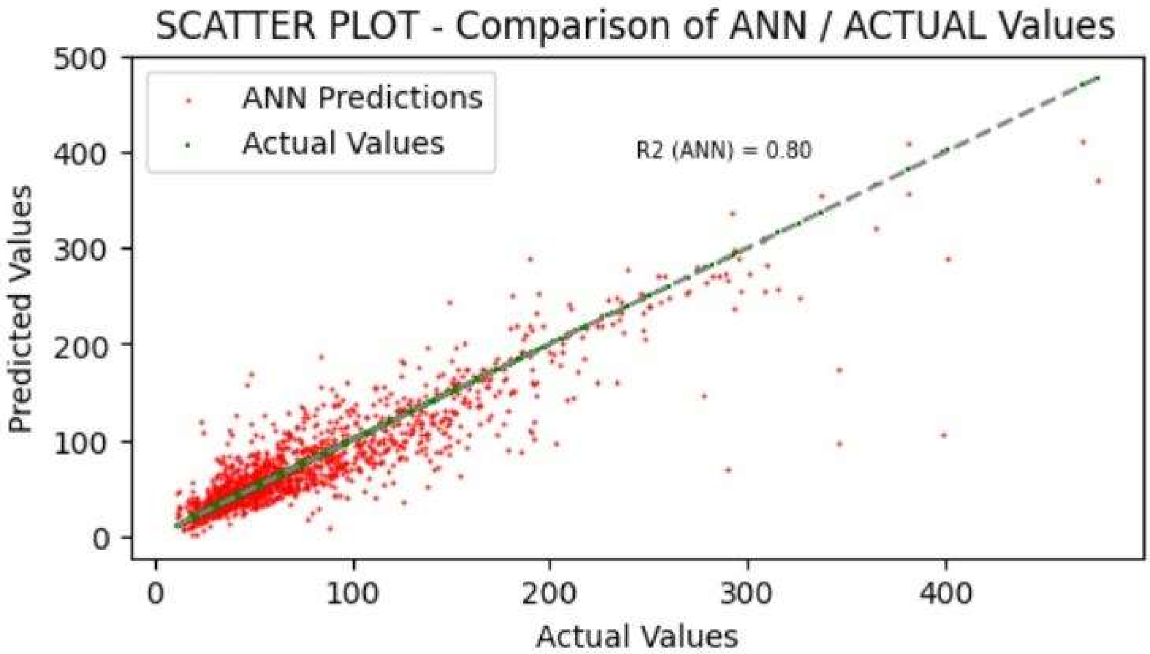

Figure 4.1.1: For 80% training data R- square = 80%

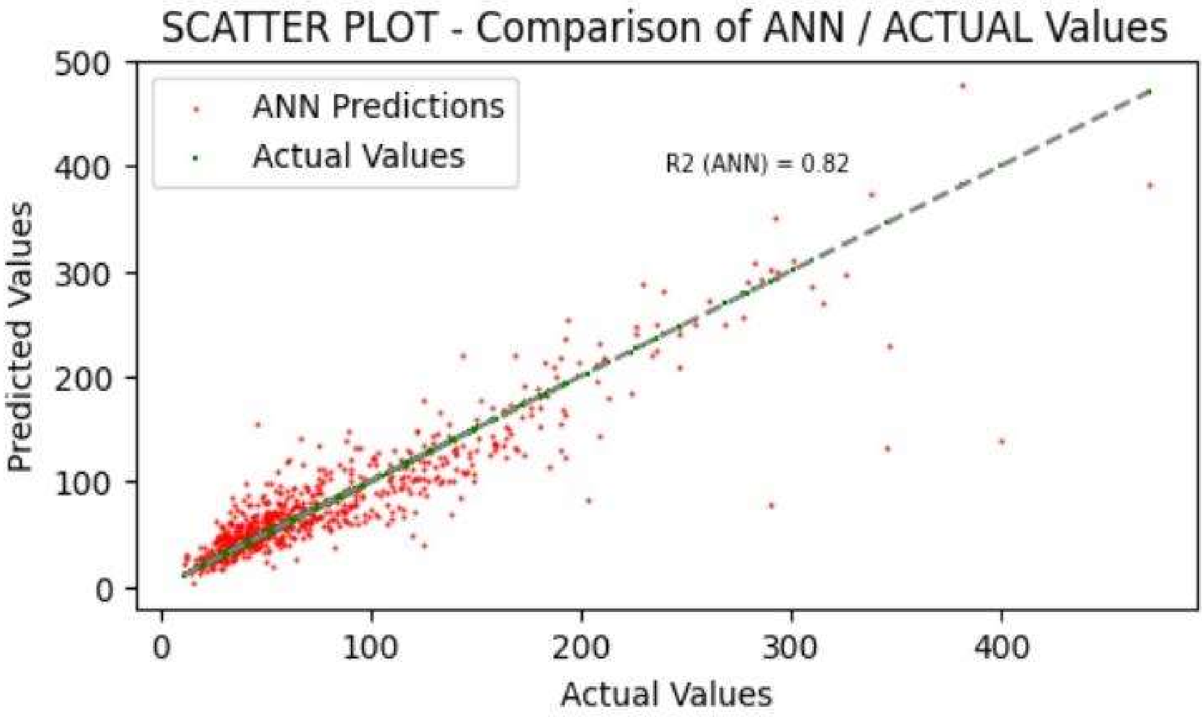

Figure 4.1.2: For 90% training data R- square = 82%

The figures illustrate the impact of training the network with different amounts of data (90% and 80%). The R2 values, which indicate the goodness of fit, were found to be 82% and 80% respectively. Furthermore, figures 4.1 and 4.2 present a linear graph comparing the projected and actual values of $PM_{2.5}$ concentration. The predicted and measured values have a higher degree of overlap and similarity as shown in Fig. 4.3, and Fig 4.4., allowing for the utilisation of additional training data.

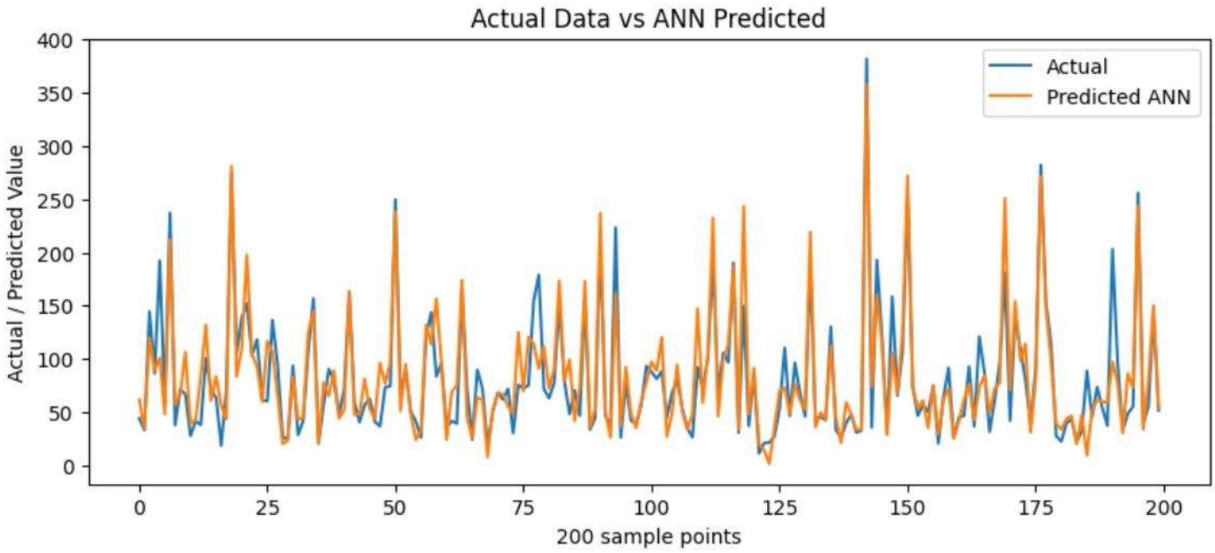

Figure 4.1.3: The image above depicts a plot that showcases the comparison between actual values and predicted values when 80% of the data

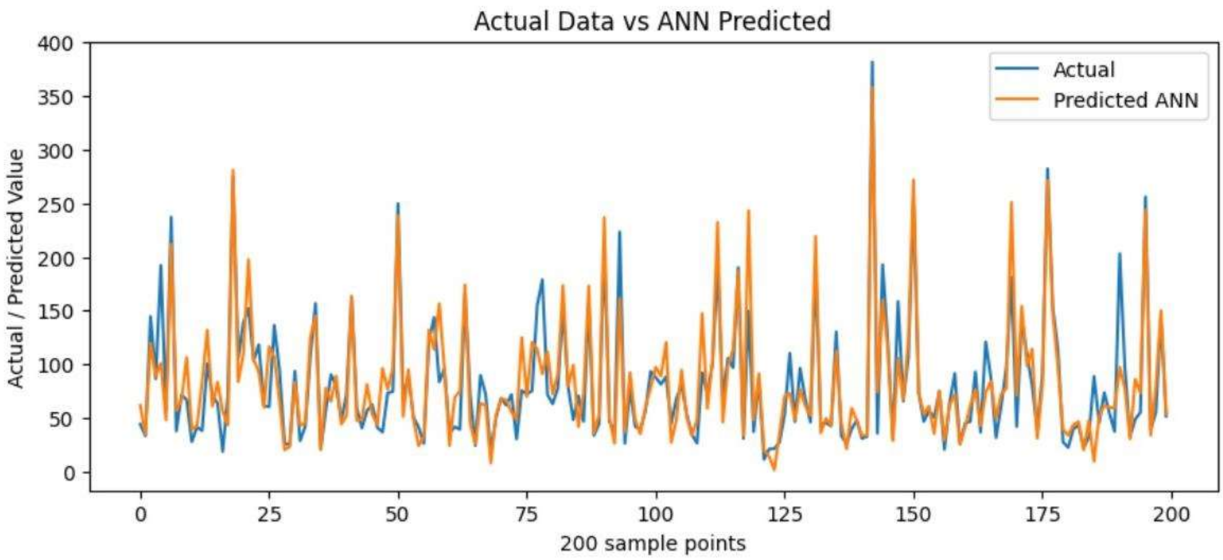

Figure 4.1.4: The image above depicts a plot that showcases the comparison between actual values and predicted values when 90% of the data was used for the purpose training..

4.2 Changes in $PM_{2.5}$ concentration over time

The annual mean values of $PM_{2.5}$ concentration, maximum and minimum concentration (µg/m^3), and total number of days when the $PM_{2.5}$ concentration surpasses the WHO guideline have been provided with their standard deviation.

Table 4.2.1 Statistical analysis of $PM_{2.5}$ for 5-year

	MAX	MIN	Average	STD	DAYS >25
2015-2016	353.86	22.82	117.3665	63.04409	363
2016-2017	685.36	28.01	139.1395	99.82249	366
2017-2018	639.19	10.88	127.2862	89.43516	341
2018-2019	420.3	21.45	115.0196	75.66384	357
2019-2020	582.28	10.24	108.5015	85.42837	349

The variation shows that Max value for $PM_{2.5}$ was 685.36 in 2016 and Min value of 10.24 in 2019. In 2016 no of days exceeding the Annual $PM_{2.5}$ concentrations as per WHO (25 µg/m^3 i.e 366 days. In the year 2016, the pollution levels in Delhi experienced a significant increase following the Diwali festival, earning the city the distressing nickname of a "gas chamber." This rise in pollution was attributed to a combination of unfavourable meteorological conditions, including low WS, lower temperatures, and high RH. These factors contributed to the pollutants remaining closer to the ground for an extended period of time.[23] Hence we can see there is a rise in the average value and the maximum value for $PM_{2.5}$ was 685.36 µg/m^3. [24] conducted an analysis of air pollution in 2017, Delhi and concluded that Particulate Matter is going way more beyond severe condition mark i.e., 400-500. And this is also being reflected in our analysis maximum concentration for $PM_{2.5}$ reached 639.19 μg/m³. And average value of 139.13 μg/m³ which is 27 times higher them the WHO limit 5 μg/m³. (2021 AQG level). The concentration lowered down in the next year with the average concentration of 127.28 μg/m³, 25 times higher than WHO limit. And the trend continues to rise with increasing values of maximum concentration of 420.3 μg/m³ in 2018 and 582.28 μg/m³ in 2019. And an average of 115.0 μg/m³ and 108.50 μg/m³ which is 23 times and 21 time higher respectively.

4.3 Relationship between $PM_{2.5}$ Concentrations and Meteorological Factors

The data collected for studying the variation was daily data from that data hourly variation of WS, Rh and temp. and $PM_{2.5}$ was calculated using MS Excel. And their relative graphs were plotted for seeing their variation with respect to each other.

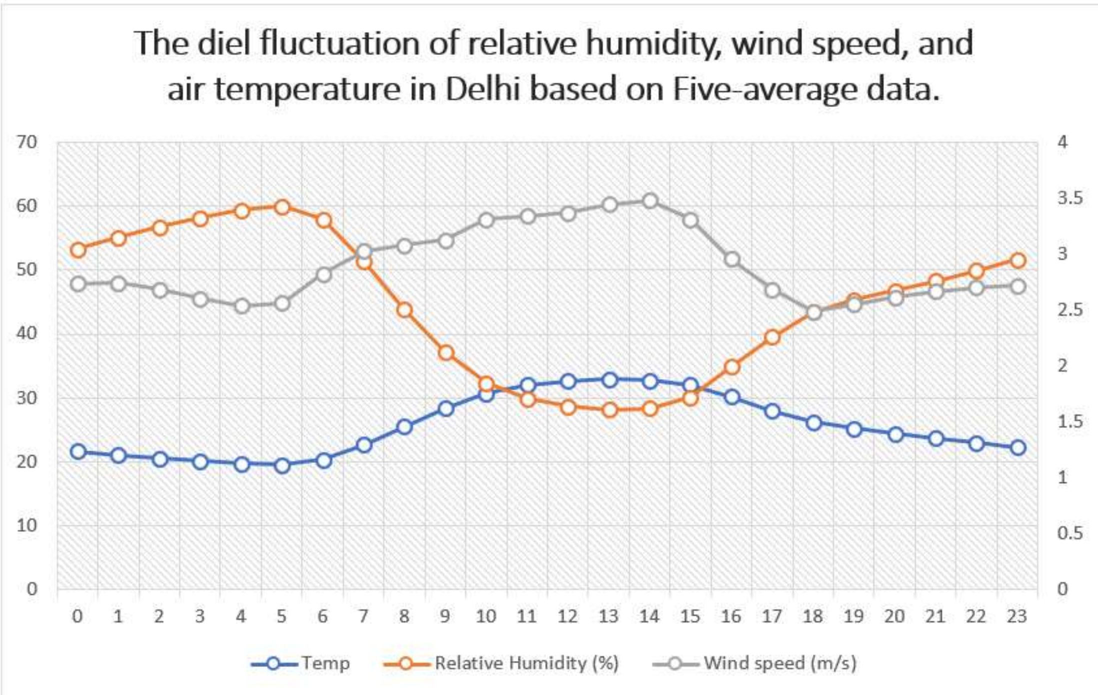

Figure 4.3.1 The diel fluctuation of relative humidity, wind speed, and air temperature in Delhi based on five-average data.

As represented in the figure 4.3.1 we can see that wind speed tend to rise from 05:00 AM in the morning to 02:00 PM in the afternoon and it starts to decline till 06:00 PM in the evening and then follows an increasing trend till midnight. Similar to wind speed temperature increases from 05:00 AM to 01:00 PM and follows a declining trend till 05:00 AM.

Whereas relative humidity shows the opposite trend to temperature and windspeed, as compared to the from 05:00 AM in the morning relative humidity shows declining trend till 02:00 PM in afternoon and then follows an increasing trend till 05:00 AM in the morning.

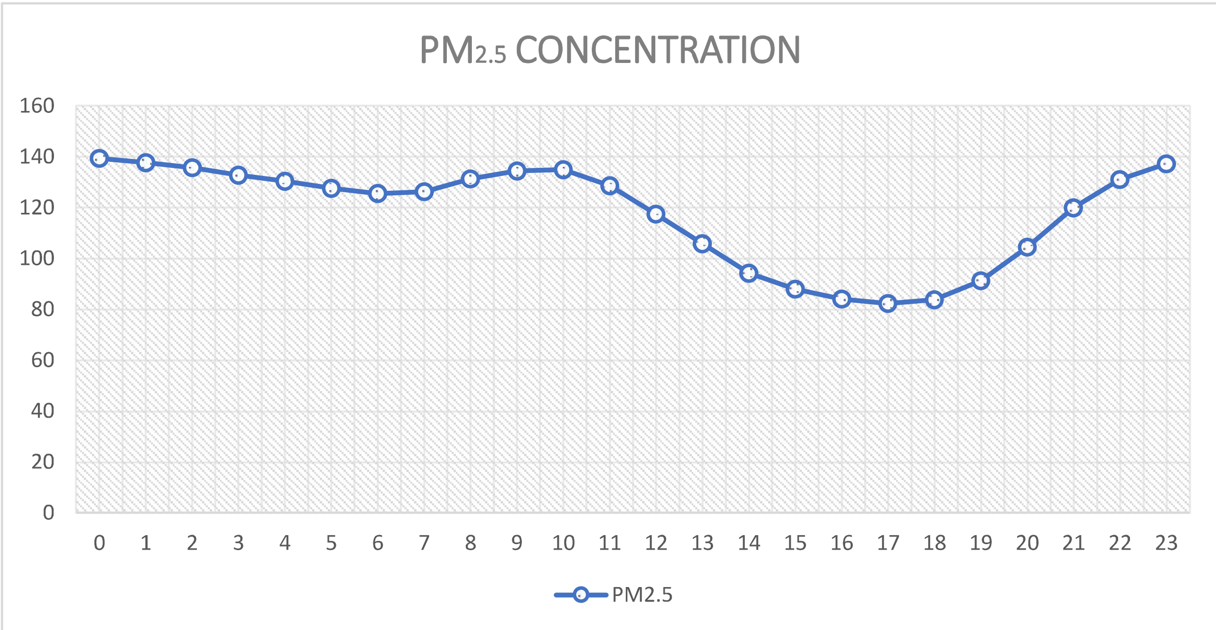

Figure 4.3.2: The diel fluctuations of $PM_{2.5}$ of 5 year average data

It is visible from the graph that there was a Peak rise due to emissions of morning rush hour 7 AM to 10 AM and reaches 134.98 μg/m^3 Then the concentration decreased from 11 AM to 5 PM and reached 82.30 μg/m^3 and it further increase from 6PM until midnight reaches 139.33 μg/m^3. The peak value is It is visible from the graph that there was a Peak rise due to emissions of morning rush hour 7 AM to 10 AM and reaches 134.98 μg/m^3 Then the concentration decreased from 11 AM to 5 PM and reached 82.30 μg/m^3 and it further increase from 6PM until midnight reaches

139.33 µg/m^3 which is 26 time higher them the WHO standards and 2 times higher them the NAAQS hourly standard of 60 µg/m^3.

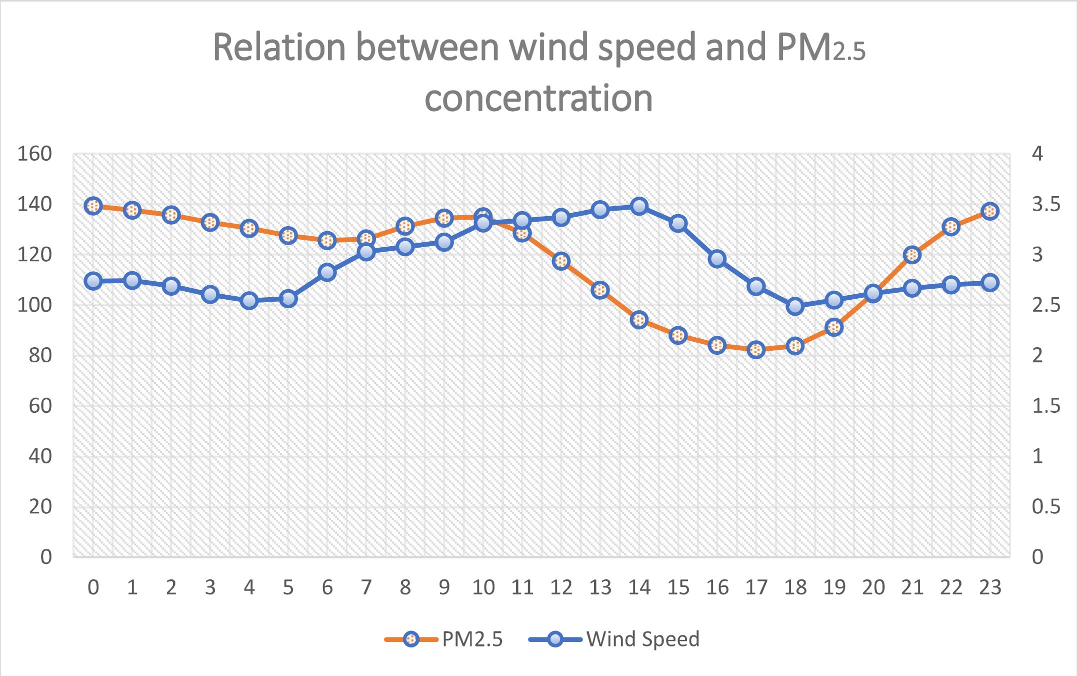

Figure 4.3.3: Graphical relationship between wind speed and $PM_{2.5}$ concentrations

As we can observe from the above graph, we can see that both the parameter tends to rise from 5 AM and 6 AM in the morning and shows a positive relationship while as er see a sudden spike in wind speed after 11 AM there is a sudden drop in the $PM_{2.5}$ concentration. According to [25] the haze formation in the night hours was caused by decreased temperature and lower wind with more relative humidity leading to condensation. The morning haze episode occurs due to the upward movement of moisture from the surface and tree leaves, which causes the particles to combine through mixing. The semi-diurnal variation, with the main peak occurring in the morning between 09:00 and 10:00 IST, also indicates a strong relationship between $PM_{2.5}$, pressure, and solar radiation. Additionally, a second peak is observed during the night-time, around 21:00 to 24:00 IST.

In the figure 4.3.3 relation between temperature and $PM_{2.5}$ is shown we can see that from the time of sunrise (5:00 AM) the temperature rises and $PM_{2.5}$ concentration continues to rise till 10:00 AM at this point the. This observation is quite similar to the study by [25] in which he stated that during early morning temperatures ranges in between 15 and 17 °C, which were relatively close to the dew point and caused haze development, which facilitated in a steady rise of $PM_{2.5}$ concentration for the next few hours in his study of hourly variation of daily concentration. During the peaking hours of $PM_{2.5}$ the wind speed and the temperature rises at the same time leading to evaporation of haze and moisture in the environment and the increasing wind speed leads to dispersion with intensified solar radiation at the time of noon.

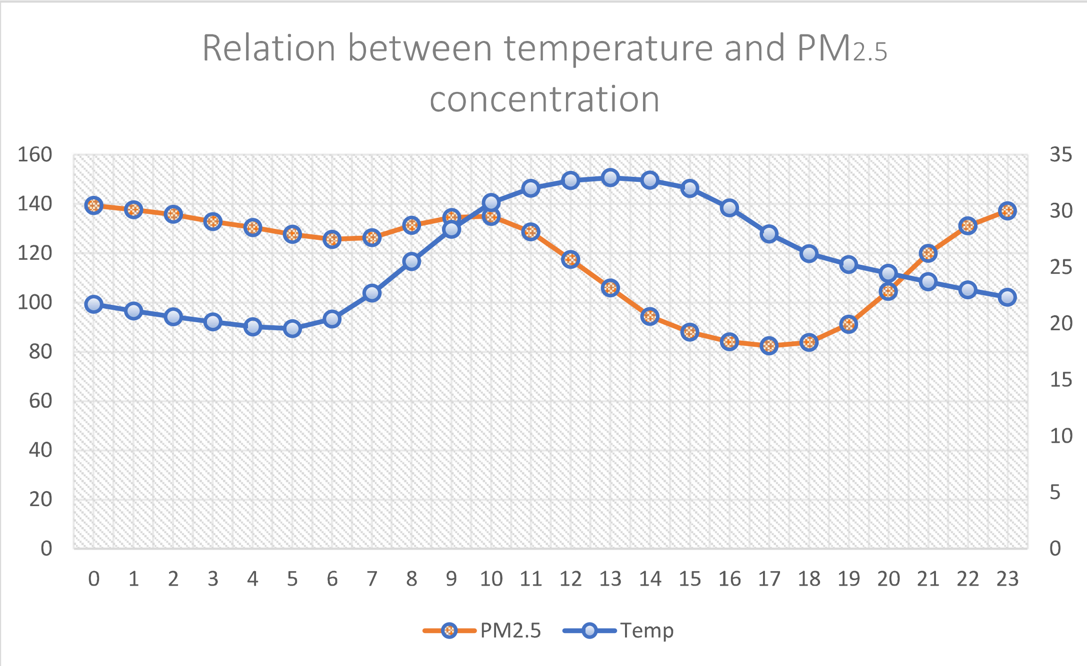

Figure 4.3.4: Graphical relationship between Temperature and $PM_{2.5}$ concentrations

If we look at the relation of wind and $PM_{2.5}$ concentrations independently increased wind speed leads to more dispersion of particles that should significantly lead to lower pollutant concentration in environment.

4.4 Health Impact assessment

To assess the impact on health, the average annual concentration of $PM_{2.5}$ and population data for the years 2015, 2016, 2017, 2018, and 2019 were considered. The Baseline Incidence (BI) and Relative Risk (RR) values were obtained from a relevant table based on WHO guidelines. By applying these values, the Excess Number of Cases (ENCs) for mortality due to all natural causes among adults aged 30 years and above was determined in the study period is given in figure 4.4:

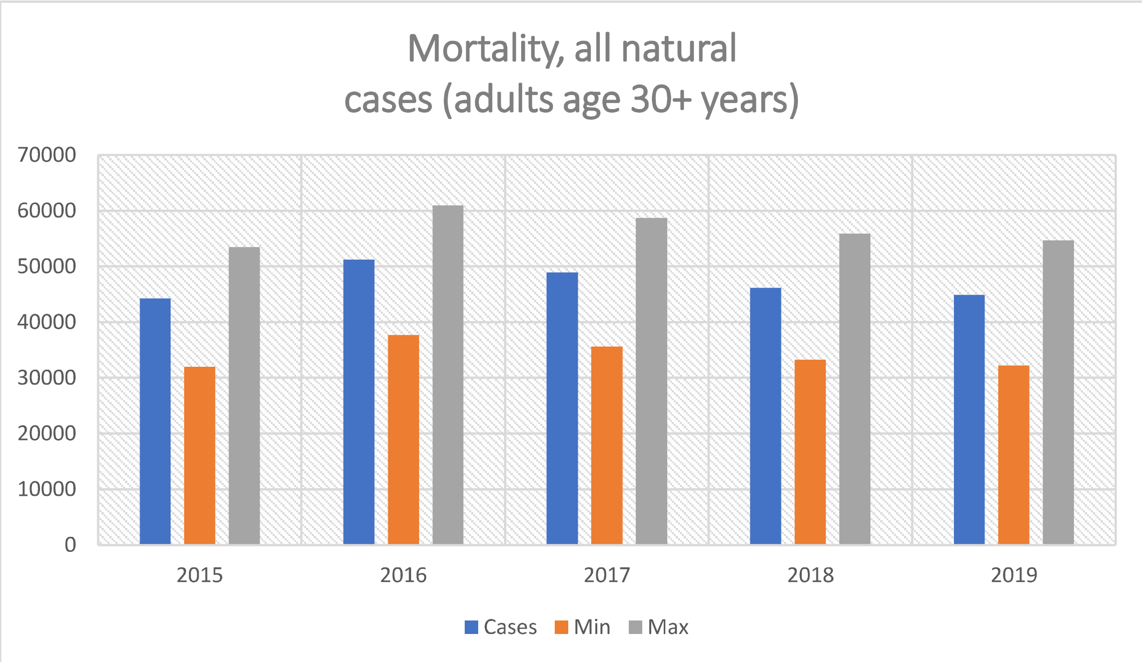

Figure 4.4.1: Plot showing mortality, all natural cases (adults age 30+) for 5 years

The highest value for the maximum no of cases occurs in 2016 resulting in 51228 cases (95% confidence limit of 37690 and 60972) followed by year 2017 having 48937 cases (95% confidence limit of 35649 and 58734), 2018 showing 46159 cases (95% confidence limit of 33275 and 55900), 2019 having 44920 cases (95% confidence limit of 32198 and 54665) and the least cases are for year 2015 having 44265 cases (95% confidence limit of 31974 and 53512)

In the figure 4.4.2 shows the plot of mortality of adults due to lung cancer (age 25+) the maximum number of cases of coming for 2019 having 5311 cases (95% confidence limit of 3949 and 6509), followed by 2018 having 5250 cases (95% confidence limit of 3889 and 6430), 2017 showing 5207 cases (95% confidence limit of 3846 and 6371), 2016 having 5145 cases (95% confidence limit of 3785 and 6292) and the least number of cases was in 2015 showing 4988 cases (95% confidence limit of 3691 and 6100)

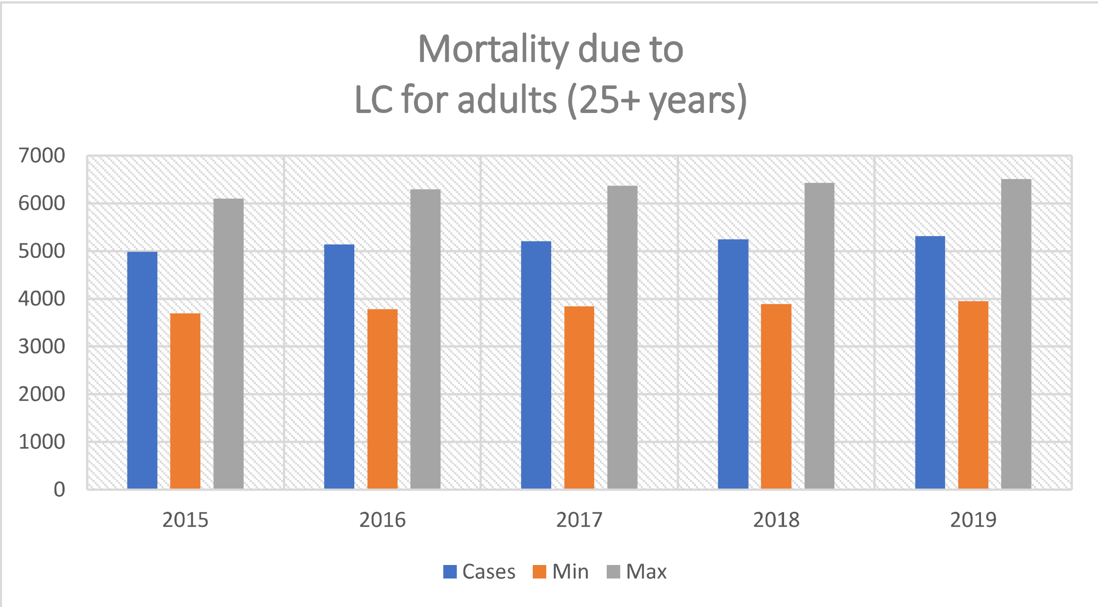

Figure 4.4.2: Plot showing mortality due to lung cancer (adults age 25+) for 5 years

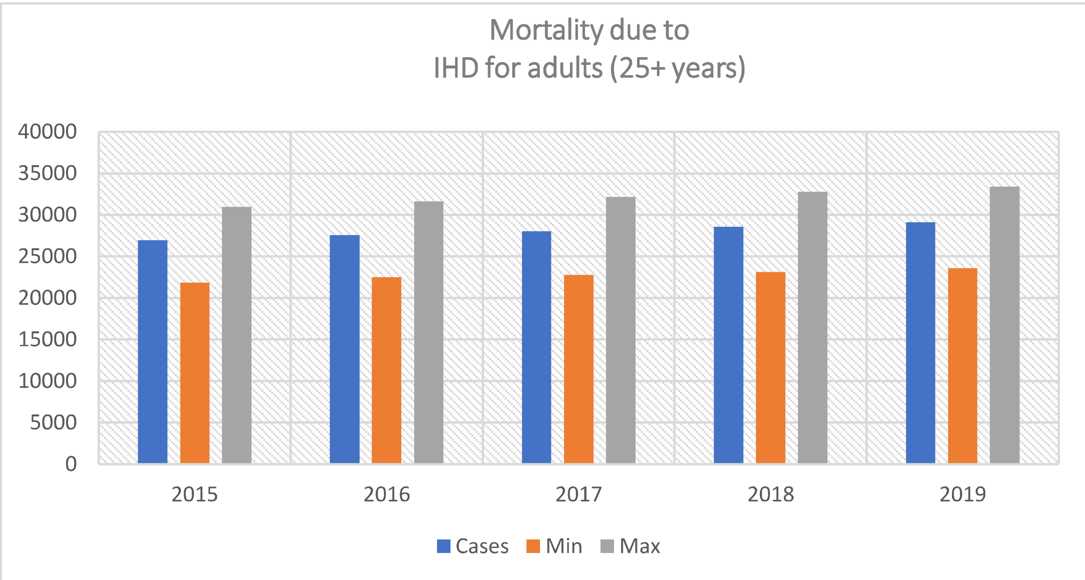

Figure 4.4.3: Plot showing mortality due to IHD for adults (adults age 25+) for 5 years

In the figure 4.4.3 shows the plot of mortality due to IHD for adults (adults age 25+) the maximum number of cases of coming for 2019 having 29077 cases (95% confidence limit of 23575 and 33405), followed by 2018 having 28546 cases (95% confidence limit of 23135 and 32783), 2017 showing 28045 cases (95% confidence limit of 22797 and 32184), 2016 having 27550 cases (95% confidence limit of 22472 and 31617) and the least number of cases was in 2015 showing 26953cases (95% confidence limit of 21841and 30947)

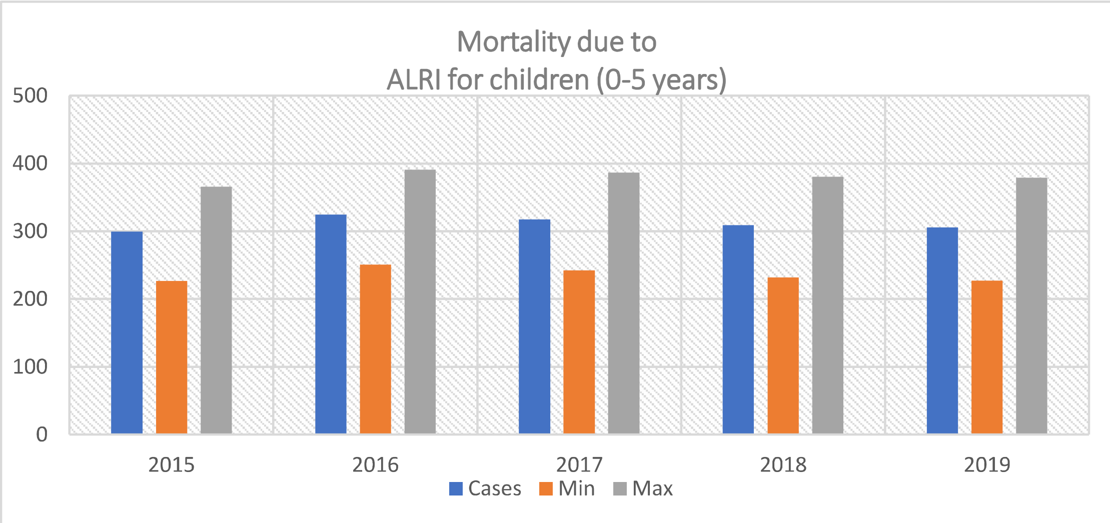

Figure 4.4.4: Plot showing mortality due to ALRI for children (0-5 years) for 5 years

Figure 4.4.4 shows the mortality cases due to ALRI for children (0-5 rears) highest value for the maximum no of cases occurs in 2016 resulting in 325 cases (95% confidence limit of 251 and 391) followed by year 2017 having 318 cases (95% confidence limit of 242 and 386), 2018 showing 309 cases (95% confidence limit of 232and 380), 2019 having 306 cases (95% confidence limit of 227 and 379) and the least cases are for year 2015 having 299 cases (95% confidence limit of 227 and 366).

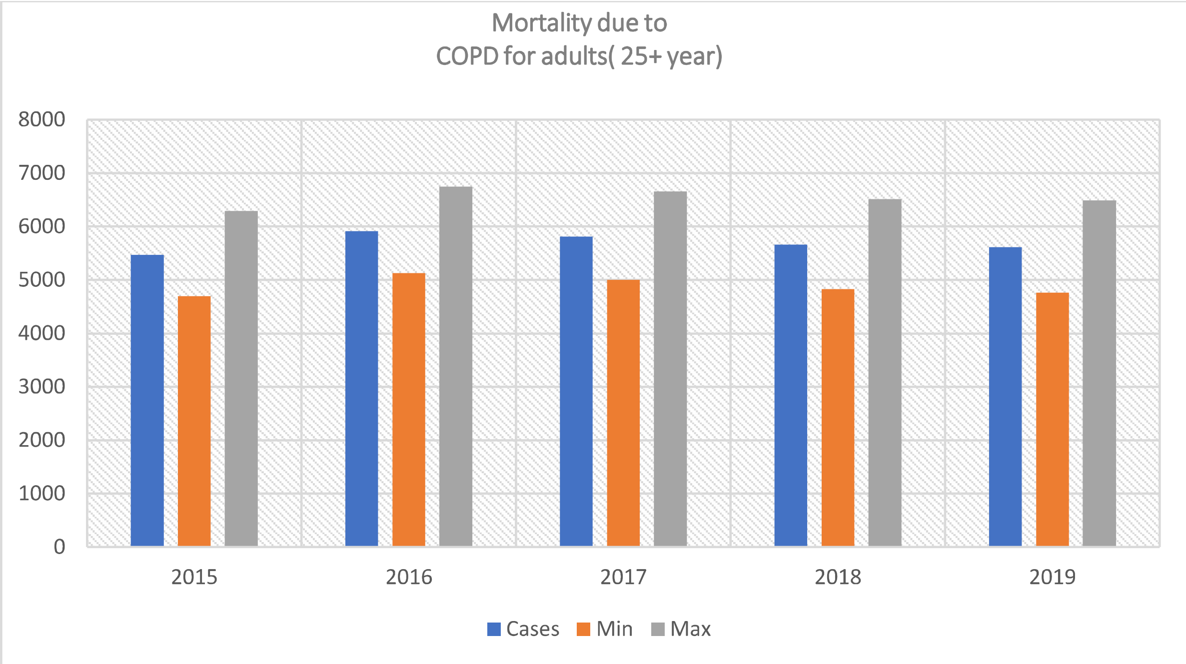

Figure 4.4.5: Plot showing mortality due to COPD for adults (25+ years) for 5 years

Figure 4.4.5 shows the mortality due to COPD for adults (25+ years) it show trend similar to that of mortality due to ALRI and all natural cases showing highest value for the maximum no of cases occurring in 2016 resulting in 5915 cases (95% confidence limit of 5127 and 6746) followed by year 2017 having 5808 cases (95% confidence limit of 5000 and 6654), 2018 showing 5657 cases (95% confidence limit of 4828 and 6514), 2019 having 5612 cases (95% confidence limit of 4760 and 6483) and the least cases are for year 2015 having 5475 cases (95% confidence limit of 4697 and 6286).

For the mortality due to stroke in adults for age 25+ is shown in figure 4.4.6 and it also follows a totally different trend unlike we have seen in the previous cases it shows the maximum no of cases occurring in 2015 resulting in 5915 cases (95% confidence limit of 5127 and 6746) followed by year 2017 having 5808 cases (95% confidence limit of 5000 and 6654), 2018 showing 5657 cases (95% confidence limit of 4828 and 6514), 2019 having 5612 cases (95% confidence limit of 4760 and 6483) and the least cases are for year 2015 having 5475 cases (95% confidence limit of 4697 and 6286).

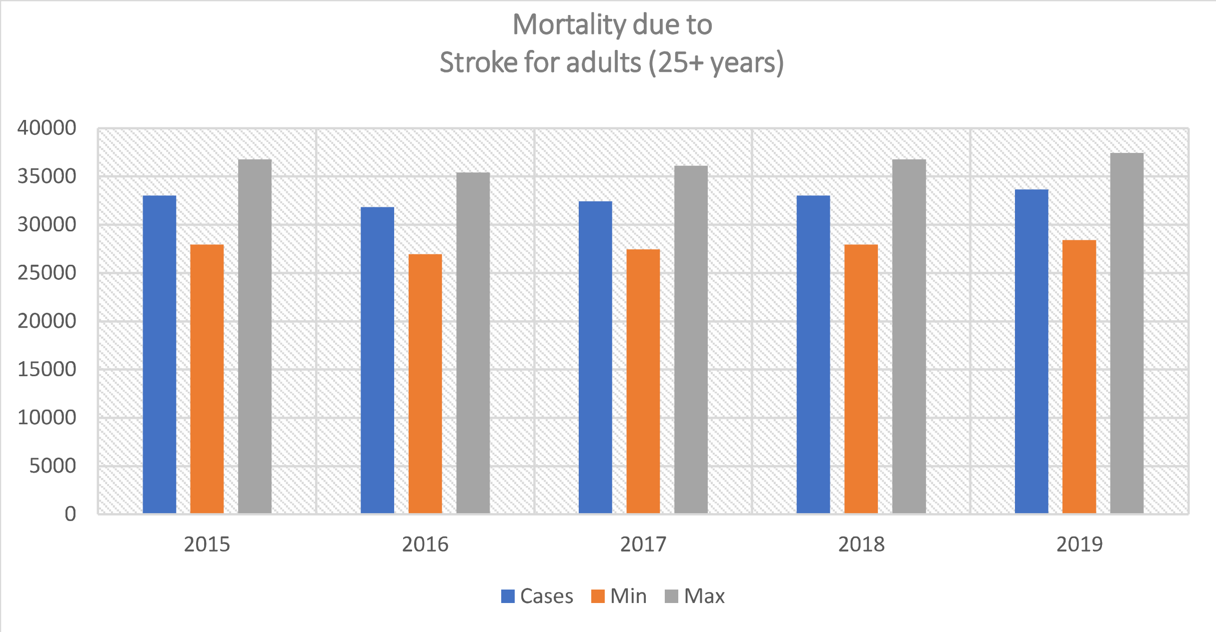

Figure 4.4.6: Mortality due to Stroke for adults (25+ years)

CHAPTER 5

CONCLUSION

In conclusion, using the WHO AirQ+ programme from 2015 to 2019, for 5 years, we estimated the long-term health impacts of the crucial marker of air pollution, $PM_{2.5}$, in Delhi by analysing the temporal trends of this pollutant. The results demonstrated that since 2016, annual $PM_{2.5}$ values had decreased by about 22% till 2019. Its year 2015 the mean $PM_{2.5}$ concentrations was 117.3665 and in 2016 it was 139.1395 and in 2019 it lowered down to 108.5015 which is nearly 22% higher that of 2016. Such finding reveals that Delhi is suffering a very high burden of $PM_{2.5}$ concentration which goes beyond the standards prescribed by many authorities such as WHO, EPA and NAAQS standards by many folds. It was noticed that the concentration of the $PM_{2.5}$ concentration used to dominate during winters season especially during November and December, but usually the concentration of $PM_{2.5}$ remains way beyond standards throughout the year. And our dial fluctuation study shows that the concentration of $PM_{2.5}$ follows a fluctuating trend throughout the day with respect to wind speed, temperature, and relative humidity but the main points are that it follows an increasing trend in the morning rush hours and eventually reaching its peak by noon and then it tends to show a declining trend and further increases during night times.

Regarding the health impacts it was observed that mortality due to all natural cases (30+ age) is responsible for the greatest fraction of mortality associated with long-term exposure to $PM_{2.5}$. We strongly encourage the implementation of green belts and the planting of native trees as effective measures to address the issue of elevated $PM_{2.5}$ concentration. It is also crucial for the government to rigorously enforce the existing laws and regulations for ensuring optimal air quality. Additionally, here are some more additional suggestions to combat $PM_{2.5}$ pollution:

- Promoting the use of more cleaner and efficient transportation methods, such as electric vehicles and a well-planned public transportation system.

- Reduce reliance on fossil fuels for power generation and encourage more and more renewable energy sources.
- Impose stricter industrial emissions standards and promote the use of advanced pollution control technologies and admission of more and more green technologies.
- Improve urban planning to reduce pollution hotspots and enhance green spaces in residential and commercial areas.
- Enhance monitoring and data collection systems to accurately assess air quality and identify pollution sources.
- Invest in research and innovation for the development of advanced air pollution mitigation technologies and solutions. And volunteer for transborder research and innovation in order to address the pollution issues related to neighbouring countries.

By adopting a comprehensive approach that combines these strategies, we can make significant progress in mitigating the problem of $PM_{2.5}$ concentration and improving overall air quality.

Chapter 6

LIMITATIONS

The RR values used in this analysis are established based on US standards. However, there may be uncertainties if these values are applied to other countries like India due to differences in atmospheric conditions and economy. The degree of indoor pollution can also vary and affect exposure values. While 80% of the population may be susceptible to emissions, it is important to note that this number may vary depending on factors such as indoor pollution levels. In 2020, lockdowns were imposed in India due to high pollution levels. As a result, population exposure to PM might have been below average. It is also important to note that there are potential pitfalls in the precision of data given by CPCB due to factors such as power loss, labour unavailability, human error, error in control and inadequacy of air quality monitoring infrastructure.

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