EFFECT OF TRAFFIC VOLUME ON AMBIENT AIR QUALITY ON MULTILANE DIVIDED URBAN ROADS AND SIGNALIZED INTERSECTIONS

Submitted in partial fulfilment of the requirements for the award of the degree of

DOCTOR OF PHILOSOPHY

by

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CERTIFICATE

This is to certify that the thesis entitled "**EFFECT OF TRAFFIC VOLUME ON AMBIENT AIR QUALITY ON MULTILANE DIVIDED URBAN ROADS AND SIGNALIZED INTERSECTIONS**" being submitted by **RAMA KANTH ANGATHA** for the award of the degree of **DOCTOR OF PHILOSOPHY** to the Department of Civil Engineering, **NATIONAL INSTITUTE OF TECHNOLOGY, WARANGAL** is a record of bonafide research work carried out by her under my supervision and it has not been submitted elsewhere for award of any degree.

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Dedicated to

My

Esteemed parents

&

Beloved wife

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ABSTRACT

Road traffic emissions are one of the major sources of air pollution in urban areas. Various hazardous gases, including Carbon Monoxide (CO), Nitrogen Oxides (NOx), Hydrocarbons (HC), Particulate Matter ($PM_{2.5}$ and PM_{10}), Sulphur Dioxide (SO_2), Carbon Dioxide (CO_2), Formaldehyde (HCHO), Volatile Organic Compounds (VOC), Lead (Pb), Ammonia (NH_3), and others, are present in the air across any urban roadway network. The concentration of air pollutants close to the main traffic routes is much higher than the regional background levels, putting the local people in danger and exposing them disproportionately to air pollution caused by traffic. The efficient investigation of the status of air quality in urban areas on both road mid-block sections and signalized intersections needs to be performed for better planning and designing of roadway network considering traffic volume growth. The present study deals with measuring, analysing, and modelling of concentrations of different pollutants observed in three medium scaled cities namely Warangal, Tirupathi and Vijayawada.

The present study measures the concentration of six different pollutants namely Carbon Monoxide (CO), Carbon Dioxide (CO_2), Formaldehyde (HCHO), Total Volatile Compounds (TVOC), Particulate Matter ($PM_{2.5}$), and Particulate Matter (PM_{10}) using portable equipment. The study also obtains field data related to traffic volume, temperature, signals, queuing, proportional share of different types of vehicles and Air Quality Index (AQI) at road mid-block sections and signalized intersections. The study carries out a detailed analysis on pollution data, volume data and AQI data obtained from different locations. The study also analyses the variation of concentration of different pollutants and AQI with respect to traffic volume and time of the day.

The present study proposed concentration model with respect to different pollutants (CO, CO_2, HCHO, TVOC, $PM_{2.5}$, and PM_{10}) considering traffic flow observed at road mid-block sections and signalised intersections. The other variables such as proportion of vehicle types, temperature and signal control parameters are also included in the model development for predicting test estimate of concentration and AQI index. The present study also developed an emission model to estimate CO, CO_2 and O_2 emissions using age of the vehicle, emission norms and vehicle type as independent variables. The study also implemented different machine learning tools like Support Vector Regression (SVR) and Artificial Neural Networks

(ANN) to develop air concentration and AQI models. The validation of models was performed successfully with different set of data collected in the field indicate their suitability under mixed traffic condition. The sensitivity analysis is performed with different combinations of model input variables namely traffic volume and percentage of 3W. The status of air quality is defined based on AQI values obtained when there is incremental change in the traffic volume from 0 to 7000 PCU/hr and percentage of 3W from 0 to 30%.

The concentration models developed in the study indicate that the variation in variables such as traffic volume, proportional share of vehicle types and signal control parameters would have a significant change in the concentration of pollutants. The study also identified from the emission model that age of the vehicle, emission norms and vehicle types are responsible factors for emissions. The study also signifies that the percentage of three wheelers could interpret the change in AQI. The findings of the study also illustrate the status of air quality is in moderate level in some regions and in satisfactory condition in some locations of the study areas according to Indian Air Quality Index (IND-AQI) standards. The study also infers that ANN models performed better in predicting the concentration of pollutants and AQI compared to MLR and SVM models. The results of the study provide insights to develop empirical guide for urban transportation planners and policy makers and traffic system designers to predict the level of pollution and AQI at various busy traffic facilities in the cities with similar characteristics.

Key Words: traffic volume, air quality, concentration of pollutants, emissions, measuring, modelling, AQI

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GLOSSARY OF TERMS

2W	Two wheeler
3W	Three Wheeler
API	Air Pollution Index
AQI	Air Quality Index
ARAI	Automotive Research Association of India
C	Car
CL	Cycle length
CNG	Compressed Natural Gas
CO	Carbon Monoxide
CO_2	Carbon Dioxide
CPCB	Central Pollution Control Board
GHG	Greenhouse gas
GIS	Geographical Information Systems
GPS	Global Positioning System
HC	Hydro Carbons
HCHO	Formaldehyde
HV	Heavy Vehicle
LCV	Light Commercial Vehicle
LPG	Liquid Petroleum Gas
MLR	Multiple Linear Regression
NAAQS	National Ambient Air Quality Standards
NH_3	Ammonia
NO	Nitric Oxide
NOx	Nitrogen Oxides
N_q	Average queued vehicles
P_{2W}	Percentage of two wheelers
P_{3W}	Percentage of three wheelers
Pb	Lead
P_{cars}	Percentage of cars
PCU	Passenger Car Unit
PEMS	Portable Emission Monitoring System
P_{HV}	Percentage of Heavy Vehicles
P_{LCV}	Percentage of Light Commercial Vehicles
$PM_{2.5}$ and PM_{10}	Particulate Matter
ppm	Parts per million
RT	Red time
SI	Signalized intersections
SO_2	Sulphur Dioxide
TVOC	Total Volatile Organic Compounds

USEPA	United States Environmental Protection Agency
V	Traffic volume
VAPI	Vehicle Air Pollution Inventory
V_e	Entering traffic volume
VOC	Volatile Organic Compounds

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Amenities such as roads and highways contribute significantly to a country's growth in both its economy and society. However, unregulated and gradual advancement may result in multiple environmental and economic damages. Air pollution is wreaking havoc on the ecology in many developing countries, including India. One of the biggest contributors to pollution in the air in cities is road traffic emissions. The first result of transportation operations is the ejection of various gases into the atmosphere. According to the geographical characteristics of the area where emissions occur (e.g. wind patterns), ambient pollution levels are created. The composition of gases in the air in any urban roadway network comprises different types of hazardous gases such as Carbon Monoxide (CO), Nitrogen oxides (NO_x), Hydro Carbons (HC), Particulate Matter ($PM_{2.5}$ and PM_{10}), Sulphur Dioxide (SO_2), Carbon Dioxide (CO_2), Formaldehyde (HCHO), Volatile Organic Compounds (VOC), Lead (Pb), Ammonia (NH_3), etc. Reducing emissions from transportation is an essential task for urban planners as well as policymakers due to increased demand for transit. It is obvious that the level of pollutants in the air adjacent to major traffic routes is much higher than that seen in regional background levels, endangering communities nearby and exposing them disproportionately to traffic-related air pollution (Zhu et al., 2002).

Air pollution is currently ubiquitous in India's urban regions, with vehicles being the primary source. Also, vehicles contribute significantly to the total air pollution load in many urban areas. Hence there is a need for easy and effective method of continuously monitoring air quality to create a great awareness among the people. Based on such studies the concerned authorities would take necessary steps for reducing air pollution. The plans to reduce idling period of vehicles on roads and intersections are required with proper implementation of traffic control measures for improving air quality and reducing health related hazards in a developing country.

1.2 URBANIZATION AND ITS ILL EFFECTS ON ENVIRONMENT

Although urbanization has historically been associated with social growth and advancement, new research has revealed that metropolitan environments can also result in significant disparities and health problems. Cities are understood to provide a variety of purposes in all societies. Many countries are hubs of technological advancement and economic expansion, but they are also breeding grounds for inequalities, poverty, risk to the environment, and infectious illnesses. (Michael, 2000). This effect grows and assumes a global character as more and more of the world's inhabitants are impacted as the trend toward urbanization continues (Alirol et al., 2011). Uncontrolled urbanization in India has resulted in substantial degradation of the environment, resulting in a variety of concerns such as land insecurity, poor water quality, excess pollution of the air, noise, and trash disposal issues.

Most of the significant environmental issues of the twenty-first century will likely be caused by the persistence and escalation of current issues that are not receiving enough political attention at the moment. In many nations, the issues may not be observed at all, or they may be noticed but nothing is done. The most recent issues are rising temperatures, freshwater shortage, destruction of forests, contamination of freshwater and expanding populations (Bhuvandas and Agarwal, 2012). These issues are extremely complicated, and it is challenging to specify how they interact. Examining issues through the lens of the social, economic, and cultural system is crucial. Even while the linkages between environmental challenges are more understood now, it lacks precise information about how the emerges problems to what extent they interact, and what the best solutions are available for mitigating environmental hazards.

1.3 IMPACT OF URBANIZATION ON TRANSPORTATION

Global urban mobility has seen a significant change from walking to using public transportation to driving as a result of economic growth, urbanization, and the success of the automobile industry. Private transportation is now a significant component of inhabitant’s daily excursions. Cities, particularly those that rely heavily on automobiles, suffer from a variety of negative consequences, including longer commutes, increased costs connected with congested roadways, crashes, pollution from traffic, including global warming, and so on. The main challenge that cities around the world face is balancing the connections between people's rising need for private motorization and the growth of urbanization, modernization, and motorization, alongside the essential social, environmental, and economic costs that these processes entail.

Public transportation, private transportation, and cargo transportation are the three main types of urban transportation. Karl Benz's Benz Motorwagen is thought to have given rise to the automobile industry in 1886, and it went into mass manufacturing in the 1920s. Private motor vehicles offer on-demand, prompt, and private transportation in addition to mobility and convenience. They are also seen as status and wealth symbols. Generally speaking, urban development, economic growth (including per capita income), urban shape, public policies, the health of the automotive industry, the availability of public transportation services, culture, etc. are all tied with private motor vehicle ownership. Analyzing the contributors is beneficial for estimating future private automobile ownership and use as well as social and environmental issues connected to private cars, such as energy use and greenhouse gas (GHG) emissions (Gao and Zhu, 2022).

1.4 TRANSPORTATION AND ENVIRONMENT

There are a variety of ways that transportation affects the environment. The effects of roads and other infrastructure, as well as the effects of cars and other transportation vehicles, can be loosely classified as having an impact on the environment. Environmental damage (air and noise pollution), the well-being of people, and other, broader phenomena such as acidification, photochemical reactions pollution of the air, and the effect of greenhouse gases are all adverse effects of transportation (Puscacu et al., 2014). Although the atmosphere is more affected by transportation than the ground, infrastructure upkeep has the biggest impact there. This is broken down into the development of linear routes like canals, trains, and highways, as well as facilities like ports, stations, and airports. Since transportation lines must be continuous, it is impossible to segregate natural areas from land usage.

Transportation enriches our civilization, but it also has a severe impact on our surroundings. One of the key contributors to increase in the pollution percentage ratio is transportation sector. Carbon monoxide (CO) and carbon dioxide (CO_2), oxides of nitrogen (NOx), particularly nitric oxide (NO) and nitrogen dioxide (NO_2), particulate matter (PM_{10}), and volatile organic compounds (VOCs), including hydrocarbons (HCs) like benzene, are the most significant atmospheric pollutants released by motor vehicles (Margarat et al. 2000). These poisonous gases, which are released from vehicles daily in large quantities, are to blame for a number of serious issues, including acid rain, effects on human health, and global warming. The atmospheric concentration of these greenhouse gases is rising because of the burning of fossil fuels, which also raise the planet's average temperature (Abraham et al. 2012). The most significant manmade gas influencing the climate is carbon dioxide. The largest source of nitrogen oxides and volatile organic compounds is transportation sector. Ozone and other oxidants are produced in the atmosphere because of the interaction between nitrogen oxides (NOx) and volatile organic compounds (VOC), particularly specific types of hydrocarbons, which are released into the atmosphere. High amounts of ground-level ozone harm materials and plants, have an adverse effect on human health, and can shorten the useful life of equipment or prevent crop harvests. These dangerous gases also affect the human body more severely. These harmful fumes contain some heavy metals that can lead to skin allergies and asthma. At least half of the particle emissions in modern cities are considered to be caused by road traffic, and up to 90% of those that occur at street level. Studies on causes, impacts, formation, and techniques of measurement of the small inhalable particles (PM_{10}, $PM_{2.5}$) that are present in diesel exhaust emissions are now being conducted in several countries (EPA, 2002).

By connecting cities, the transportation network, such as motorways and roads, is vital to the growth of any nation's economy. Due to the alteration in traffic modes, these infrastructures are quickly growing, causing congested highways. As a result, air quality on roads, and intersections is being negatively impacted by rising vehicle traffic emissions. Vehicle exhausts are the main source of traffic emissions, which include carbon monoxide (CO), carbon dioxide (CO_2), and particulate matter etc.

High levels of noise and high quantities of gaseous pollutants are just two of the detrimental effects that excessive traffic can have (Oftedal et al. 2015, Arcona et al. 2017). People who are exposed to high quantities of vehicular emissions are more likely to acquire cardiovascular disease, cancer, breathing issues, and premature births. It may be expensive, unsafe, and time-consuming to test vehicle emissions on roads and at intersections. Additionally, during the design phase, the designers are unable to determine the vehicle emissions. Traffic emission models are usually required in the most recent planning approaches for developing highways and road networks to encourage healthy mobility and a decrease of emissions from traffic owing to recurring delays and tollgates.

1.5 PROBLEM STATEMENT

Air pollution is currently ubiquitous in India, particularly in metropolitan areas where automobiles are the biggest contributors, as well as in a few other places with a large concentration of manufacturing and thermal energy facilities. Increasing trends in the population and vehicles in urban cities result in deterioration of the air quality affecting the public health. According to recent studies, vehicle emissions are responsible for over two-thirds of urban air pollution. Automobile pollution is one of the world's biggest issues in most countries. Automobiles are an important contributor of pollution to the environment in urban areas (Dev et al., 2018a). Unplanned transportation, inadequate roadway facilities and poor traffic management lead to increase in exhaust gases emission from motor vehicles. The emissions from vehicles at the surface would have the biggest impact on people in general. Furthermore, automobiles contribute substantially to the overall level of air pollution in several urban areas. The research lacks in analysing the impact of traffic volume and vehicle composition on air quality. The models with latest machine learning tools like Support Vector Regression and Artificial Neural Networks that provide the relationship between the pollutants and traffic volume are necessary to ascertain the complexity and non-linear relationships of the data. The analysis of air quality index is also a major concern for the transportation planners. The way to define the status of air quality with a concern of traffic volume will provide a solution to regulate the deterioration of air quality.

1.6 OBJECTIVES & SCOPE OF THE STUDY

The primary objective of this research is to analyze the quality of air with respect to the change in traffic volume on road mid-block sections and signalized intersections under mixed traffic conditions. The specific objectives of the research are as follows:

- To determine and analyze the concentration of various pollutants with respect to traffic volume observed at sections of multi-lane divided road mid-blocks and approaches of signalized intersections.
- To develop models for predicting concentration of major air pollutants on multi-lane divided roadway mid-blocks and signalized intersections under mixed traffic conditions.
- To define the status of air quality by developing a model for predicting Air Quality Index (AQI) on selected urban roads and signalized intersections.

A comprehensive traffic related pollution analysis is necessary to understand the situation of air quality in the urban areas. Given this, the present study attempts to measure the concentrations of different pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10} using low-cost portable equipment in road mid-block sections and at signalized intersections. The study also tries to develop models describing the relationship between traffic volume and concentration of pollutants using three different modelling techniques such as MLR, SVM and ANN. The study also focusses on defining the status of air quality with respect to different pollutants. To this end, the study also ascertains the relationship between Air Quality Index and percentage share of different types of vehicles. The study also defines the status of air quality based on IND-AQI standards. The status of air quality reveals the intensity of air pollution in the study areas that is categorized as good, satisfactory, moderate, poor, very poor and severe according to IND-AQI. The empirical study in this research is limited to the selected road mid-block sections and signalized intersections of three cities. The study is also confined to divided urban road and signalized intersection approaches.

1.7 OUTLINE OF THE THESIS

This report comprises seven chapters. A brief introduction and general description of the concepts made in this thesis are described in ***Chapter 1***. A brief description of urbanization and its ill effects on environment, the relation between transportation and urbanization, transportation and environment, the problem statement, and the study's objectives are also presented in this chapter. ***Chapter 2*** provides review on the past studies related to measuring and modelling the traffic related air pollution, studies describing the impact of traffic on air quality in road mid-block sections and at signalized intersections. This chapter also discusses various control strategies to reduce traffic induced air pollution suggested by various authors. Based on the inputs obtained from the critical literature review, a methodology has been developed to carry out the research. ***Chapter 3*** focuses on the overall methodology followed to attain the required objectives of the research work. ***Chapter 4*** presents the details of the study area and types of field data collected. ***Chapter 5*** describes the analysis of different types of data collected namely traffic data, signal data, queuing data and pollution data on the study sections and discusses the results obtained from them. ***Chapter 6*** provides different models to obtain the relation between the traffic variables and pollutant concentrations. This chapter also provides the model for air quality index with traffic flow. ***Chapter 7*** specifies the conclusions drawn from the study after summarizing the essential findings of the study. Moreover, limitations and future directions are also presented in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

In the past, numerous studies have drawn attention to the need to comprehend how traffic flow impacts the environment in the urban areas. The methods for measuring, analyzing and modelling the effect of traffic on air quality with respect to different pollutants have been explored. A thorough overview of studies on the influence of traffic volume and traffic flow variables on air quality in road mid-block sections and signalized intersections is described.

2.2 EVOLUTION OF TRAFFIC POLLUTION STUDIES

The causes of high emissions from automobiles have been the subject of several investigations. Organizations like the Indian Ambient Air Quality guidelines proposed by CPCB (1984), National Ambient Air Quality Standards (NAAQS) proposed by US Environmental Protection Agency (1970), and Air Quality Standards proposed by WHO have developed air quality standards for the various land uses (1995). Organizations like the Indian Institute of Petroleum (IIP) in 1985 and the Automotive Research Association (ARAI) of India have also developed vehicle emission factors.

Gaussian Dispersion Plume models, which took into consideration the dispersion properties of the pollutants, were used to model air pollution. In air dispersion models, vehicular emission is typically regarded as a line source. To evaluate the consequences of roadside emissions, line source models are employed (Venkatram and Horst, 2006). The Gaussian plume diffusion equation serves as the foundation for many of the air quality models created by research institutions to represent the temporal and spatial distribution of vehicle exhaust emissions on roads (Nagendra and Khare, 2002). In 1992, Source Emission Factor Model (MOBILE6) was developed by USEPA (United States Environmental Protection Agency) and by CARB (California Air Resources Board) in 2002. Some of the dispersion models developed include California Line Source Dispersion Model (CALINE 4 in, 1989), Line Source Model (IITLS) was developed by

Indian Institute of Technology Delhi, considering traffic conditions of Delhi (Goyal and Ramakrishan, 1999), and General Finite Line Source Model developed by Luhar and Patil in 1989. Later, Ditty (1995) attempted to develop time series based regression models for each pollutant using zone wise collected pollution data. The evolution of suspended particulate matters and carbon monoxide concentrations was done using traffic simulation and traffic-induced air pollution (Zia and Shao, 2005). Using CALINE 4 and spatial data analysis, an integrated land use and transportation for environmental analysis model was created, and found pollution hotspots using a GIS framework (Potogolu and Kanarogolu, 2004).

Different methods and models were used to analyze the traffic emitted air pollution. The methods used for measuring the concentration of different pollutants, the parameters influencing the traffic emissions and the models developed to understand the impact of the traffic on air quality in various Indian cities and cities across the globe are discussed.

2.3 STUDIES RELATED TO MONITORING OF AIR POLLUTANTS

Various studies have been carried out to explore different ways in measuring the vehicular emissions. The studies indicated that there are different equipment, tools and methods adapted by the researchers to measure the air pollutants in various forms. The detailed description of the monitoring equipment and the way they were adapted to measure different air pollutants is given below.

Denis et al. (1999) indicated that many organizations have tried to address the problem to categorize the emissions of vehicles. The emission factors obtained from chassis dynamometer tests through typical drive cycles demonstrated to be not always an accurate representation of real-world emissions. So, onboard monitoring equipment, also referred to as Portable Emission Monitoring System (PEMS) was developed. The PEMS is shown in Figure 2.1.The study found number of other variables affect pollution levels, including driver aggression (Vlieger, 1997 and Nam et al., 2003), road gradient, and auxiliary engine loads like air conditioning (Fernandez et al., (1997), as well as overall driving style (Holmen and Niemeier, 1998). According to these investigations, on-board measurements rather than dynamometer testing can be used to characterize emissions inventories more accurately.

Figure 2.1 Portable Emission Monitoring System
(Source: Nam et al., 2003)

North et al. (2005) described the design and development of a Vehicle Performance and Emissions Monitoring System (VPEMS) installed on test diesel vehicles with and without an engine management system interface. The study concluded that the monitoring system readings and standard readings have good correlation between them. Noland et al. (2004) carried out a study with an objective to measure emissions using a low-cost on board tail pipe emissions monitoring system such as Vehicle Performance and Emissions Monitoring System (VPEMS). VPEMS combines on-board emissions and vehicle/driver performance monitoring with location and communication methods to deliver an integrated environments-temporally referenced dataset to a central base station in near real time. These findings also relates on the connections of CO, CO_2, NOx, tail pipe emission with speed and acceleration. The architecture of VPEMS is shown in Figure 2.2.

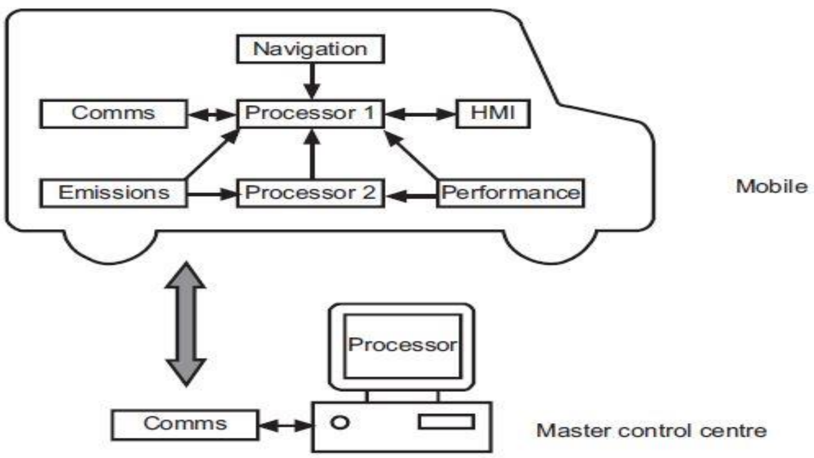


Figure 2.2 VPEMS High level architecture

Source: Noland et al., 2004

Ghose et al. (2004) found detrimental effects of air pollution in the mega cities in India. At busy crossroads in the vicinity, air quality monitoring stations were chosen for data collection. Field data such as wind direction, wind velocity, humidity, and temperature was collected during the air monitoring period. High volume samplers (HVS) and respirable dust samplers (RDS) are used to collect samples of suspended particulate matter (SPM) and respirable dust particulate matter (PM_{10}), respectively (Ghose, 1989; Ghose and Majee, 2000b). Anusha et al. (2008) measured that pollution concentrations emitted by the test vehicles while they are moving along a road using on-road vehicular emissions (OEM). With the aid of these data, it is possible to assess how emissions change depending on the kind of driving and the flow of traffic, which in turn aids in the identification of specific emission-reducing controls. The study also described a method for estimating on-road emissions using a portable gas analyzer in conjunction with other tools and accessories. Neesamani (2010) stated that it is important to continue to develop scientific methodology for emission inventories. In order to figure out emission levels (operating and starting) from vehicles on roads in Chennai, the IVE model was applied. Driving patterns were gathered using GPS. The findings of the study showed that Chennai's air quality has been deteriorated.

Partheeban (2012) discussed the real-time monitoring of air pollutants utilizing solid state gas sensors and GPS (Global Positioning systems) with a processor that links the observed air pollution levels to GIS (Geographical Information Systems) and to the internet so that the pollution levels may be quickly determined for any location. Chi-man et al. (2013) proposed a novel vehicle exhaust assessment as well as reporting system to help with everyday motor maintenance using the Internet of Things. Given the abundance of traffic lights in urban areas, the proposed system makes use of them to play a significant role. Because all vehicles are required to stop in front of red lights, RFID (Radio Frequency Identification) technology that is reasonably priced can be used to wirelessly query a vehicle's air ratio, which displays the engine emission status. Government authorities can efficiently manage car emissions by monitoring the air ratio in real-time. The study also discussed a number of implementation-related concerns examined to choose the right traffic signals on which RFID monitoring devices should be mounted.

Kiran and Dakshayani (2014) suggested a method that uses chemical sensors to continuously monitor and maintain the ideal emission level to lessen pollution caused by vehicle carbon emissions. The simulation findings demonstrated that dynamic carbon emission monitoring can be used to effectively reduce vehicle pollution. Raparthi et al. (2021) discussed on various on-road vehicular emission monitoring equipment to analyze various gaseous pollutants release from road-way tunnels in Greater Mumbai. Alves et al., (2015); Blanco-Alegre et al., (2020) used GrayWolf-IQ610 which is an air quality probe to monitor CO_2, CO, NO_2, VOCs, temperature, and relative humidity in real-time. With the help of non-dispersive infrared (NDIR), photo ionization detector, electrochemical, and CO_2 sensors, respectively, CO_2, VOCs, CO, and NO_2 were passively detected.

The Micro-Aeth AE51 (Magee Scientific, Berkeley, CA, USA) actively monitored black carbon (Anand and Phuleria, 2020; Liang et al., 2017).Particle Size Distribution (PSDs of 16 size bins from 0.3 m to 10 m) and Particle Number Concentrations (PNCs, 10 nm to >1 m) were actively sampled by CPC 3007 (TSI Inc., USA) and OPS 3330 (TSI Inc., USA), respectively (Cong et al., 2017; Khan et al., 2019; Kwon et al., 2015).Using a hot-wire anemometer, the tunnel's wind speed was monitored (GM8903, Bentech, China). Averaging for hourly variance, each real-time measurement was performed with a 1-min resolution. The findings were varied because there were currently no real-time instruments available, so the days on which the instruments were set up at both ends of the tunnel were alternated.

To make sure that emissions models accurately reflect the current in-use traffic flow and its operation, new emissions data will be required over time as the traffic composition and age of vehicle changes. Data from several different vehicles that operating in a wide range of circumstances will probably be needed for this. Using existing PEMS technology, a program of this kind will be labor-intensive and consequently expensive to administer. Therefore, various device that are affordable and durable enough to measure and monitor the air pollutants are used for extended periods of time.

2.4 STUDIES RELATED TO MODELLING THE VEHICULAR EMISSIONS

According to the US Environmental Protection Agency (EPA), mobile sources in the US supply 58% of carbon monoxide (CO), 56% of nitrogen oxide (NOx), and 33% of volatile organic compounds (VOC) in 2010 (EPA, 2011). Vehicles continue to account for sizable portions of air pollutant emissions despite strict exhaust emission limits due to increases in vehicle usage and a corresponding rise in vehicle miles travelled (VMT). To help with estimating vehicle exhaust emissions, air quality and transportation experts are developing a variety of transportation models at the state and regional levels. For determining the effects of sources and creating emissions management plans, emissions estimation is crucial (Gunsler 1993, Frey et al., 2001, Yi et al., 2004). Models for predicting emissions from mobile sources are becoming more and more important due to growing worries about climate change.

The United States Environmental Protection Agency (EPA) has created pollutant dispersion models to estimate the roadside pollutant concentration. The CALINE series models (CALINE3, CALINE4, CAL3QHC), as well as AERMOD (American Meteorological Society/Environmental Protection Agency Regulatory Model) use the Gaussian dispersion technique to simulate and forecast the geographic dispersion of various contaminants (Chen et al. 2009). Specifically, CALINE3 and CALINE4 simulate the dispersion of pollutants along open road segments. Based on CALINE3, the improved model CAL3QHC primarily predicts the amount and spread of major contaminants at signalized junctions (Jung et al. 2019). The vehicular pollution dispersion models classification is shown in Figure 2.3. The accuracy is decreased because of the microscopic emission model's undesirable simplification of the driving cycle of automobiles through signal crossings as cruise-and-idle portions without any transitions from acceleration to deceleration. Other models, like AERMOD, incorporate the effects of meteorological and topographic elements to primarily focus on the atmospheric pollution dispersion at district levels. In contrast, the Operational Street Pollution Model (OSPM) was mostly used to model the dispersion of pollutants in metropolitan streets by taking into account the impact of topographic features, such as street height and breadth of buildings (Murena et al. 2009).

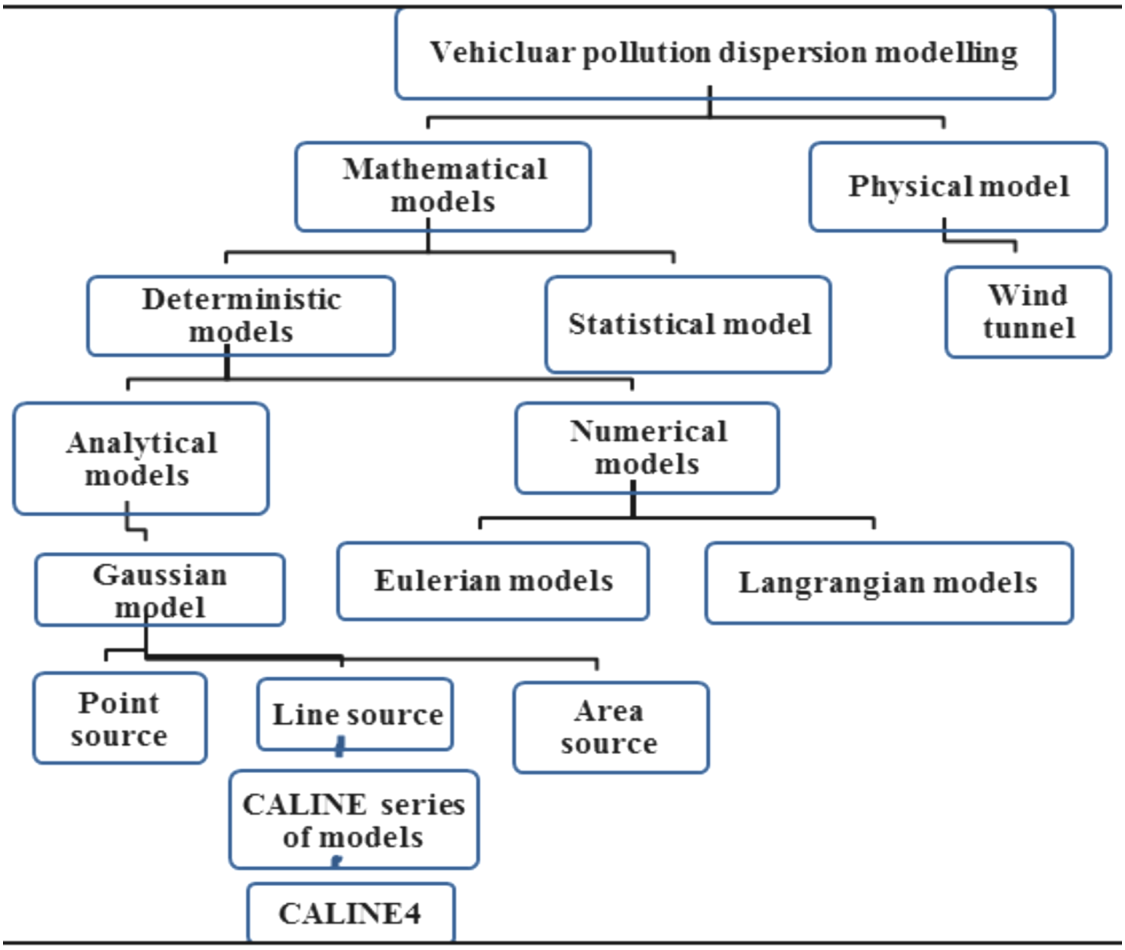


Figure 2.3 Vehicular pollution dispersion models

(Source: Dhyani and Sharma, 2018)

Furthermore, due to various localized vehicle emission limits in use, the EPA dispersion models are not appropriate to use with motor vehicles in other countries for approximating the motorized emissions at signalized intersections. As a result, the models must be adjusted when applied to cities of other countries, where the International Vehicle Emission (IVE) model may be added as a localization model.All models presuppose that motor vehicle traffic across the intersection moves through cruise and idle phases without accelerating or decelerating. The models and advancements for pollution dispersal have undergone a lot of work.

The Georgia Institute of Technology created the MEASURE (Mobile Emission Assessment System for Urban and Regional Evaluation) to calculate CO, NOx, and VOC emissions. Instead of estimating exhaust emissions as a function of average vehicle speed.It acts as a function of vehicle operating modes like cruising, acceleration, deceleration, and idling. The model uses lot of data because it has over 30 variables and does not estimate CO_2 emissions (Fomunung et al., 2000, Barth et al., 2000).

A micro-scale model CORSIM estimates emissions based on dynamometer data by applying default emission rates to each vehicle for each second it travels on the given link, based on speed and acceleration, CORSIM calculates the total emissions on each link. However, CORSIM's emission factors have not been updated (Lederer, 2001).

A trip-based model for microscopic traffic assignment, modelling, and optimization is analyzed using a model named INTEGRATION. As a function of velocity and acceleration learned through a dynamometer test, it can forecast emissions from composite fuel usage (Lederer, 2001).

The EMIT (Emissions from Traffic) model calculates CO_2, CO, HC, and NOx using dynamometer data for 344 light-duty cars and a regression equation with speed and acceleration as explanatory factors (Cappiello et al. 2002).

Using second-by-second emissions data from dynamometer testing, the Comprehensive Modal Emissions Model (CMEM) was created. The relationship between physical elements (vehicle mass, engine size, and aerodynamic drag coefficient) and vehicle operating parameters is used to simulate emissions of CO_2, CO, hydrocarbons (HC), and NO (speed, acceleration). For a wide range of light-duty cars, emissions can be approximated. However, 55 parameters of the model make it a data-intensive tool to utilize (Hung et al. 2005).

The MOBILE model was replaced by the US EPA's Motor Vehicle Emission Simulator (MOVES) model in 2010. On a project- or regional-level, MOVES2010 calculates the CO, NOx, VOCs, PM, and greenhouse gas emissions from light-duty vehicles (US EPA, 2010).

VT-Micro is an instantaneous emission model developed in Virginia-Tech – The Transportation Infrastructure and Systems Engineering program (TISE). It is a microscopic vehicle fuel consumption and emission modelling tool that allows users to estimate the vehicle instantaneous fuel consumption an emission levels. The VT-micro model was developed based on the chassis dynamometer data collected at the Oak ridge international laboratory from 60 light-duty vehicles and trucks. It was developed as a regression model from experimentation with polynomial combinations of speed and acceleration levels. The immediate acceleration and velocity levels are a collection of measurable distinct variables that the VT-micro model uses to tie the dependent variables to (Ahn et al. 2004).

According to Christopher et al. (2001), tail pipe gas emissions, including oxides of carbon (CO), oxides of nitrogen (NO), hydrocarbons (HC), and carbon dioxide (CO_2), are usually detected via the handheld OEM-2100TM on a second-by-second basis while operating a variety of light duty petrol vehicles. Compared to emissions when a vehicle is accelerating, idling emissions are typically modest. Based on the current speed and average acceleration, Kyounghoet al. (2002) created a computational framework to forecast the fuel usage and emissions of moving vehicles. Ahn et al. (2002) created regression models based on instantaneous speed and acceleration levels, to predict light-duty vehicle CO, HC, and NOx emissions. Although a fuel consumption model may be used as a substitute, a model for CO_2 emissions wasn't created. In order to estimate CO concentrations, Tippichai et al. (2005) employed site features, traffic data, meteorological data, and exhaust data obtained at signalized crossings as variables for the CAL3QHC algorithm. Hung et al. (2005), based on the gathering of on-road data from 4 automobiles in Hong Kong, created a micro-scale vehicle emissions model for HC, CO, and NOx. Although a model for CO_2 emissions wasn't developed, a substitute may be made using the fuel consumption model. The projected emissions for acceleration, deceleration, and cruising modes are factors of vehicle speed. It is not necessarily representative of automobiles with US emission restrictions, though, as it was created for Hong Kong. Additionally, the model does not distinguish between the various accelerations that can result in significantly varied emissions within the acceleration mode category.Toth-Nagy et al., (2006) developed an artificial neural network-based model for predicting CO and emissions of NOx from heavy-duty diesel conventional and hybrid cars. The approach seemed promising, but it does not account for CO_2 or apply to power by gasoline automobiles.

The use of spatial models of prediction as a decision-support tool for forecasting and simulating emissions from traffic on roadways has been successful (Bastien et al. 2015, Borge et al. 2016). Jazcilevich et al. (2007) developed a methodology for calculating automotive emissions of HC, CO, CO_2, and NOx was created by using a car simulator, a fundamental traffic model, and a Geographic Information System. Using data from 17 automobiles' on-board measuring systems (Semtech) and lab testing, experimental data for the car simulator was obtained. Measurements of the Fourier transform infrared (FTIR) with a dynamometer after normal driving cycles.Farzaneh et al. (2010),used three gasoline automobiles portable emissions measuring systems (PEMS) developed for calculating CO_2 emissions at varied speeds and acceleration rates. Rakha et al. (2011) established a CO_2 emissions model based on instantaneous vehicle power was created by and is computed using total resistance force, vehicle mass, acceleration, velocity, and driveline efficiency. Nagpure and Gurjar (2012) indicated that although the majority of the emission models were created in nations with established economies, there are many other vehicle emission models that are readily available worldwide. The implementation of these models in emerging nations like India may be deceptive due to the significant disparities in conditions and available datasets. The authors developed Vehicular Air Pollution Emission Inventory (VAPI) model which has been designed and tested to close the gap between the models that are now available and the tools that are required in developing nations. The suggested VAPI model is built on a straightforward methodology that incorporates emission variables and correction factors. In Indian cities, this model can be used to estimate emissions under exhaust, evaporative, and non-exhaust circumstances.

The VAPI model's temporal trend of emission estimations is in a fair amount of agreement with ambient air concentrations measured at places with high levels of vehicular activity.

Using data mining and GIS, a hybrid model was created to predict vehicular Carbon Monoxide (CO) emissions from traffic. The enhanced Artificial Neural Network (ANN) algorithm and GIS were combined to create the hybrid model. To estimate daily vehicular CO emissions, GIS and ANN approaches were integrated with the Correlation-based Feature Selection (CFS) algorithm. The proposed neural network architecture to predict CO is given in Figure 2.4. As a result, prediction maps at a small-scale level across a small urban region were developed, which is a recent advancement in traffic pollution modelling (Saud et al., 2019).

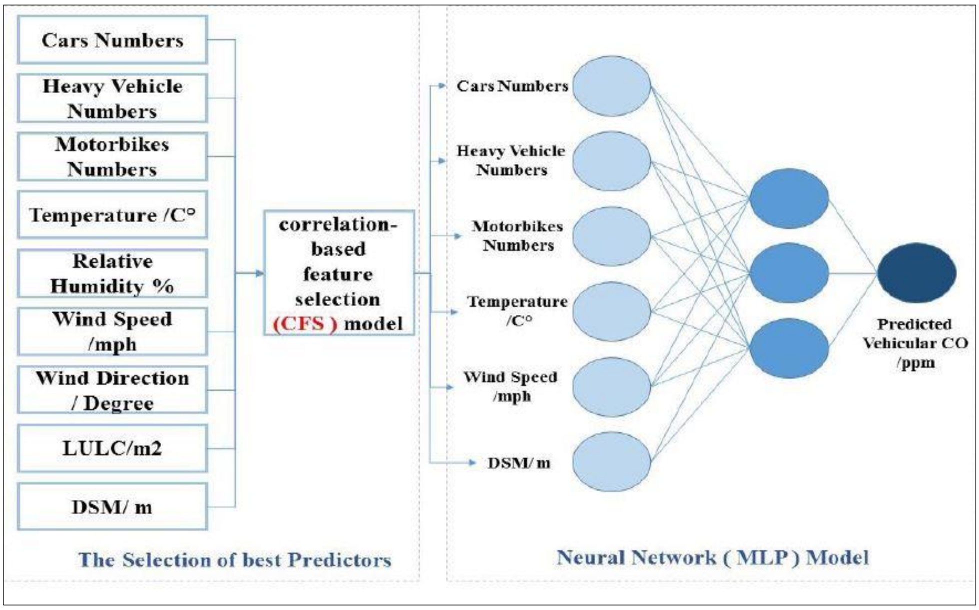


Figure 2.4 A proposed Neural Network architecture for traffic CO prediction
(Source: Saud et al., 2019)

Sun et al.(2020) used International Vehicle Emission (IVE) model in order to acquire the localized emission factors. As a result, the dispersion model CAL3QHC was introduced and modified to include vehicle acceleration and deceleration states. The Green Light Optimal Speed Advisory (GLOSA) system and the no-obstacle driveway design are two emission reduction strategies for urban signalized junctions that were developed for the study area. Using the upgraded CAL3QHC model, the overall performance and roadside emission dispersion were simulated using the VISSIM software program. Illari et al., (2022) developed a traffic modelling approach to estimate and predict the amount of traffic at each road segment and every hour by combining historical measurements of actual vehicular traffic with the use of the SUMO (Simulation of Urban Mobility) software, as well as the trajectory generation strategy. A pollution modelling approach offers to estimate the impact of traffic on airborne pollutants. Using the Vehicular Emissions Inventories (VEIN) R package, the amount of NOx produced by traffic is estimated while accounting for the composition of the area's vehicular fleet (i.e., the types of vehicles, their sizes, and the fuels they run on).Finally, in light of this NOx estimation, a service uses Graz Lagrangian Model (GRAL) using meteorological conditions and urban morphology has been established. It is capable of providing maps with the prediction of the dispersion of these atmospheric pollutants in the air. In order to increase awareness and assist residents in making better decisions the results of the study are helpful.

2.5 STUDIES ON AIR QUALITY ON ROAD MID-BLOCK SECTIONS

Bogo et al. (1999) measured the concentration of pollutants such as CO, NO, NO_2 and O_3 in Buenos Aires city with the help of continuous monitoring station. The study indicated that CO, NOx are mainly released from vehicular traffic. The concentration of O_3 mainly comes from mixing of clean air masses with exhaust gases released from the vehicles having the high concentrations of NO.

Fu et al. (2001) studied on the emission factors of vehicles with respect to CO, HC, and NOx in China cities. MOBILE 5 model has been used to find emission of pollutants from motor vehicles. The study concluded that the pollution is majorly concentrated in metropolitan cities even though China has less number of motor vehicles and the urban air quality is poorer than the national ambient air quality standard. Zhu et al. (2002) studied on the ultra-fine particles released from heavy-duty diesel vehicles near a major highway in Los- Angeles using a particle-measuring device. The devices measured the concentrations of CO and Black Carbon (BC) near the highway. It was observed that concentrations of CO and BC have been decreased exponentially as one moved away from the highway. Goyal et al. (2005) investigated on the air pollution problem coming from transport vehicles in Delhi, India. The study stated, the 72% of the pollution is emitted from motor vehicles in Delhi, city of India. Nelson et al. (1998) tried to analyze the air pollutant emissions with a tunable diode laser system. For measuring of air-pollutant emissions from on-road motor vehicles, a tunable infrared laser differential absorption spectrometer (TILDAS) has been established. The system consists of monostatic source detector platform and a reflector. By using this instrument, the pollutants of NO, N_2O and NO_2have been estimated with a very high sensitivity under real world conditions. In addition to this, pollutants of CO, NH_3, H_2CO, CH_3OH and other small molecules in vehicle exhaust can also be measured with this system. Comrie and Diem (1999) attempted to analyze the relationship between climatology and ambient Carbon Monoxide concentrations in phoenix city, Arizona. A multi-variate regression model was develop to describe the relationship between meteorology, traffic patterns and CO at seasonal, weekly, and diurnal time scales has been checked out and future predictions of CO concentrations were made. Xia and Shao (2004) worked on modeling of traffic flow and emissions of CO, NO_x and PM_{10} with the help of Lagrangian model and simulation of traffic flow has been done on a complicated road network in Hong Kong city.

Anjaneyulu et al. (2008) worked on the monitoring of Carbon Monoxide (CO) concentrations due to road traffic in Calicut city, Kerala, India. Air quality at each link was figured out and supervising of carbon monoxide at 15 links has been observed. The comparison of CO pollutant concentrations with National Ambient Air Quality Standards (NAAQS) has been done and CALINE4, IITLS and Linear regression models have been used to anticipate the CO concentrations. The study concluded that linear regression model executed better than CALINE4 and IITLS models. Ho et al. (2009) stated that Vehicular emissions are one of the major sources of volatile organic compounds (VOCs) in the urban areas. They analyzed vehicular emission of VOC’s inside and outside the tunnel. Bonsu et al. (2010) indicated that emissions from vehicles are mainly divided into two categories namely exhaust (tailpipe) emissions and evaporative (vapor)emissions. The conceptual diagram of vehicle emission stages is shown in Figure 2.5.The study described on traffic data driven modeling of vehicular emissions using COPERT III model in Ghana. Data on vehicular speed, mileage, fleet population, fuel consumption and quality, temperature have been used as inputs for COPERT III model. The study indicated that, conventional passenger vehicles contribute to increase in pollutant emissions.

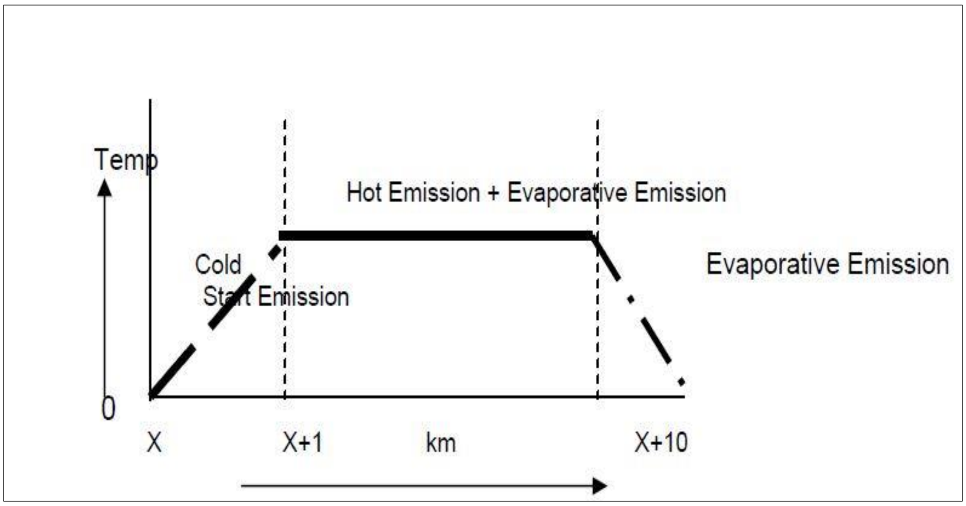


Figure 2.5 Conceptual diagram of a vehicle emission

Source: Bonsu et al., 2010

Rodrigues et al. (2011) tried to correlate the emission of formaldehyde and acetaldehyde with the kind of fuel used by Heavy Duty vehicles. Principal Component analysis (PCA) was used to analyze the correlation. Christopher et al. (2012) used a portable instrument for the calculation on-road tailpipe emissions from vehicles. For a selected highway vehicles fueled by gasoline and E85 (a blend of 85% ethanol and 15% gasoline), a design procedure was established for the deployment of portable onboard tailpipe emissions. The study developed the ability of stable modal emission rates for idle, acceleration, cruise, and deceleration even for uncontrollable external factors. Alhindawi et al. (2012) worked on greenhouse gas (GHG) emission for a road sector using a multivariate regression model. The ratio between vehicle-kilometers and number of transportation vehicles for six transportation modes has been used for the development of the model. The study indicated that multivariate regression model was suitable to model GHG emissions and the results will be useful for the planning of GHG emissions policies. Elkafoury et al. (2014) worked on vehicular CO emissions modeling for time headway-based environmental traffic management system. The study dealt with the relationship between time headway of vehicles and CO emissions. Calculation of emissions factors of separate type of vehicles in different traffic situation has been done with the help of instantaneous vehicular emission model (VT-Micro) where speed and acceleration are used as input variables. Nagpure et al (2016) analyzed formaldehyde emissions released from vehicles in Delhi city using Vehicular Air Pollution Inventory (VAPI) model. The study indicated that 23-44% of formaldehyde is released from private cars in the study area. Masood et al. (2017) worked on Carbon Monoxide emissions monitoring, modeling and mapping of air pollution with the use of CALINE4 model in New Delhi, India. The study also integrated the CO emission with ArcGIS to show the data in the form of digital maps. The study indicated that the maps would be helpful to the transport planners for identifying the hot spots around the city and to implement proper strategies and decision making.Akinyemi et al. (2018) worked on Carbon Monoxide emission modeling from diesel engine generators in Nigeria city. A model was developed using four input variables, such as installed capacity, purchase time, operating time and last serviced. Multiple Linear regression model was used to estimate the risk level of emission. According to Dabek-Zlotorzynska et al. (2019), the contribution of major highways to close-road $PM_{2.5}$ is a current study topic. According to a study of three Canadian cities, pollutants caused by traffic generated between 15 and 35% of $PM_{2.5}$, mostly from vehicle exhaust (diesel and petrol), re-suspended road dust, and brake wear.

2.6 STUDIES ON AIR QUALITY AT SIGNALIZED INTERSECTIONS

Moseholm et al. (1996) forecasted Carbon Monoxide concentrations near an intersection. In this study, the relationship between traffic and carbon monoxide concentrations has been examined and analyzed using Artificial Neural Network. Lane specific traffic information and on-site wind parameters were the inputs for neural network and 1-min average CO concentrations were predicted. The study also indicated that standard linear regression models and dispersion models (CAL3QHC and OSPM) could not be useful to predict CO for the same data set. Kyoungho (1998) worked on vehicle fuel consumption and emissions field data with the development of microscopic energy and emission models using nonlinear multiple regression and neural network techniques. The data collection has been done by the Oak Ridge National Laboratory which include emission measurements (CO, HC and NO_x) and microscopic fuel consumption for eight light duty vehicles with speed and acceleration as functional variables. For future application and relevance to traffic engineering studies, the models developed in this study have been incorporated into a microscopic traffic simulation tool called INTEGRATION. The study indicated that signalization techniques would be helpful in reducing fuel consumption and emissions significantly. Kyoungho et al. (2002) worked on many hybrid regression models which can anticipate the emission rates and hot stabilized vehicle fuel consumption rates of light-duty trucks and light-duty vehicles. Acceleration and instantaneous speed were the key input variables for these models. For future application and implementation to transport profession, these models have been incorporated within the INTEGRATION of microscopic traffic simulation and associated with Global Positioning System (GPS) for calculation of energy and environmental impacts. Tippichai et al. (2005) used a CAL3QHC model for the prediction of Carbon Monoxide (CO) concentrations at signalized road intersections in Thailand city. At each intersection, some data parameters have been collected like site parameters, traffic parameters, meteorological parameters and emission parameters and these data variables have been used as input variables. In Southern Italy, Zito (2009) investigated the influence of synchronised traffic light characteristics on roadside pollution concentrations. Using DRACULA traffic micro simulator software, the study explores the effect of integrated traffic signals on CO and C6H6 levels in a Southern Italian urban region. Traffic loop detection devices and one smog-monitoring device were utilized to collect data. The neural network was used to model CO and C6H6 ambient levels in conjunction with variable cycle and offset times of traffic lights. Pandian et al. (2009) worked on impacts of traffic flow, vehicle characteristics and road characteristics on vehicular emissions near an intersection. The relationships of traffic, vehicle and intersection characteristics with vehicular exhaust emissions have been illustrated and analyze the traffic flow and emission models. Wee and Ling (2014) explored on Carbon Monoxide emissions at a signalized intersection in Malaysia city. The study predicted the present and future CO concentrations using CAL3QHC dispersion model. The study identified that there is no increment in CO level from 2006 to 2014 even there is a gradual increase in number of vehicles. It also indicated that CO level was below the Malaysian Ambient Air Quality standards. Wang et al. (2020) investigated VOC’s from various types of vehicles using Portable Emission Measurement System (PEMS).The study stated that road conditions at intersections had great impacts on tailpipe emissions. Chun et al. (2020) estimated the effects of both land cover and transportation on $PM_{2.5}$ concentration. Spatial regression models were developed using GIS to examine the spatially correlated effects on $PM_{2.5}$ at intersections.

2.7 STUDIES ON AIR QUALITY INDEX (AQI)

An index with no dimensions that quantitatively describes the quality of the air is called the Air Quality Index (Lida, 2009). Individual contaminants are also given their own air quality sub-index. Fine particles, respirable particulate matter, sulphur dioxide, nitrogen dioxide, ozone, and carbon monoxide are the principal pollutants included in the assessment of air quality.

In the early stage of research on air quality index, Air Pollution Index (API) system was introduced in 2000. The Air Quality Index (AQI) system was introduced to replace the original Air Pollution Index in the first half of 2012. In general, the air quality index is divided into six levels with respect to the pollution namely good, fair, mild, moderate, heavy and serious respectively. The severity of the pollution problem increases with level of AQI and the threat to human health is larger for higher levels of AQI (Jiang, 2020). Partheeban (2012) indicated that four air pollutants, SPM, CO, SO_2, and NO_2, have been recognized under the National Ambient Air Quality Monitoring (NAAQM) network for routine monitoring at all 290 sites dispersed around the nation. SPM seems to be the most common types of air pollution, however there are several sites where CO, SO_2, and NO_2 levels are over legal limits. The problem of air pollution has been caused by a high influx of people to metropolitan areas, an increase in consumption patterns, unplanned urban and industrial expansion, and a lackluster enforcement system. The government has taken a number of actions, including laws, industry emission regulations, and guidelines for the establishment of industries, environmental audits, EIAs, and standards for vehicle emissions, among others.

Zhang and Batterman (2013) provided a system for categorizing traffic dangers for those who live on and near roads. Simulation modelling was used to determine on- and near-road NO_2 concentrations as well as health risks for highway and arterial scenarios with varying traffic loads during rush hour. According to the modelling analysis, incremental hazards for on-road populations on the motorway case study have a "U" shaped pattern with rising traffic volume, but incremental risks for arterial road have a different pattern, with dramatic rises at high traffic volumes. The study also indicated that numerous variables such as traffic volume, vehicle mix, kind of route, and weather, affect risk levels. Bagieński (2015) proposed a helpful tool for assessing air quality close to roads which is named as Traffic Air Quality Index (TAQI). The TAQI links human factors like street (roadway) structure and equivalent pollution from traffic sources to air quality. The study outlines a method for calculating the TAQI and identifies the levels of pollution emissions that are detrimental. It offers a classification system based on the TAQI value that identifies potential risks to human health and provides an illustration of how to determine the TAQI value for actual urban streets.

Singh and Sharma (2017), attempted to calculate AQI taking into account various parameters such as NO, NO_2, NOx, SO_2, ambient temperature, relative humidity, bar pressure, sun radiation, wind speed, wind direction, benzene, toluene, xylene, $PM_{2.5}$, and rack temperature. A multivariate regression model is used to depict the variance of the Air Quality Index (AQI) in Hyderabad city in order to analyze and represent the status of air quality. The model can be used for better short- and long-term forecasting of air quality indicators in major metropolitan areas where many types of activity, such as industrial, commercial, and residential, are ongoing. Clean, Moderate, Poor, Bad, and Extremely Poor are the five separate categories used to define the air quality status in order to make the index more helpful.

Ganesh et al. (2017) provided various regression models for the purpose of predicting the air quality index (AQI) in specific interest areas. Implemented models included support vector regression (SVR), multiple linear regression with gradient descent, stochastic gradient descent, and mini-batch gradient descent. These models depend on pollutant concentrations of NO_2, CO, O_3, $PM_{2.5}$, PM_{10}, and SO_2 to calculate the air quality index (AQI). The study indicated that, Support vector regression (SVR) performed exceptionally well when quality measures were taken into consideration.

Jiang (2020) used actual data on air quality in Shanghai, and six different parameters, including $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO concentration, are employed as potential AQI-affecting factors. Each of these six variables, Pearson correlation coefficients with the air quality index was determined independently, and the relationship between the variables was examined. Then, performed a multiple linear regression analysis using the SPSS software, considering AQI as the dependent variable and the other components as the independent variables.

Mani et al. (2021) indicated that the accumulation of NO_2, CO, O_3, $PM_{2.5}$, SO_2, and PM_{10} is one such element that affects the Air Quality Index (AQI), which measures air quality. The study used machine learning (ML) methods including linear regression and time series analysis to anticipate and predict the AQI. The data of different pollutants was considered as input and optimized AQI as the target for the model. Multiple Linear regression and Auto-Regressive Integrated Moving Average (ARIMA) time series model was applied to predict the AQI in the study area. Zhang et al. (2021) indicated that the fine-scale spatial variation of air pollutants is now predicted using land use regression (LUR) models. However, the majority of earlier studies fitted LUR models using linear regression techniques such as generalized linear models (GLM), which have limited application. This study used generalized additive models (GAM) to generate LUR models of air pollutants (including $PM_{2.5}$, PM_{10}, CO, NO_2, SO_2, and O_3) and air quality index (AQI) in Beijing with annual resolution, taking into account the potential nonlinear interaction between predictor variables.

Tian and Yao (2021) used a spatiotemporal stratified method to analyze how urban form, traffic volume, and air quality are related. The procedure extracts and preprocesses traffic volume data in both the spatial (zones with pollution and those without) and temporal (vacation and weekday times) dimensions. The correlations were examined using three decision tree models (random forest, random tree, and M5 model tree) and two comparison models (multiple linear regression, artificial neural network). The results of the study indicated that, particularly, heavily trafficked highways and industrial sectors are more frequently seen in polluted environments. The study also concluded that, between workdays and holidays, there are also notable differences in the strength of the relationship.

Comert et al. (2020) investigated on different models such as linear regression model (LM), linear mixed-effect regression model (LMER), Grey Systems (GM), error corrected GM (EGM), Grey Verhulst (GV), error corrected GV (EGV), and LMER + EGM to relate Air Quality Index (AQI) to traffic volume for selected study areas in South Carolina. According to their predictions, the AADT will continue to rise in South Carolina, worsening the air quality in the entire state. The results of the study also implies that AADT is not the only factor affecting the air quality in these counties and schools.

2.8 STUDIES ON MITIGATION MEASURES REDUCING TRAFFIC INDUCED AIR POLLUTION

Many studies in the past have suggested some mitigation measures to reduce the traffic related air pollution. The studies tried to provide some alternative means to prevent the degrading of air quality because of the traffic. However, it has been a challenge for the transportation planners to implement the mitigation measures in a proper manner. The following studies provide some insights on mitigation measures those are applied for improving the air quality in the areas.

Partheeban (2012) stated that that the concentrations of Air pollutants are to be monitored regularly to take appropriate decisions on adapting mitigation measures. According to the Policy guidelines for reducing vehicle emissions in Asia, staff of Asian Development Bank, (2003),improvements in emissions standards and technology; improved inspection and maintenance; cleaner fuels; and improved transport planning and traffic demand management are some of the solutions needed to be adopted to address pollution from mobile sources. Ghose et al. (2004) suggested some of the measures like replacement of old vehicles, reformulating diesel fuel, introduction of liquid petroleum gas (LPG) and compressed natural gas (CNG), massive improvements in infrastructure and radical traffic management measures are some of the measures to reduce the traffic induced air pollution. Takeuchi (2007) indicated that the potential of converting diesel buses to compressed natural gas (CNG) is one of most important mitigation measures to reduce the traffic related air pollution. However, this would need a rise in bus rates to pay for the expense of pollution controls. In order to slow the expansion of car ownership, boosting the price of gasoline, have an impact on the vehicle ownership, as well as imposing a license fee on cars are some of the beneficial strategies. Anusha et al. (2008) indicated that the suitable traffic control measures such as lane restrictions and signal synchronization could be adopted to improve vehicular flow conditions and thereby reducing the on road vehicular emissions. According to Nesamani (2010), advanced automotive technology and enhanced public transport would have a substantial impact on lowering vehicular emissions. According to Manohar et al. (2014), enforcing quality standards for automobiles, encouraging public transportation, and expanding roads are all effective ways to greatly reduce transportation pollution. Chambliss and Bandivadekar (2014) provided some local level actions such as cleaner burning fuels, stringent emission standards for new vehicles sold or operated within a jurisdiction and programs to clean up existing vehicles or remove them from service to control the motor vehicle emission. Kodjack (2015) indicated that clean, low-sulfur fuel standards; tailpipe emissions standards for new vehicles; fuel economy and CO_2 standards for new vehicles; and voluntary green freight programs are the strategies that can be implemented to reduce emissions from heavy-duty vehicles, including commercial freight trucks and buses.

The different policies or strategies are available to reduce or control the emissions from transportation in different studies. The effect of each policy on emissions should be influenced by changes in other modes of transportation as well as how it impacts the mode is subject to regulation.

2.9 SUMMARY OF LITERATURE

This chapter reviewed the literature on traffic related air pollution under different sections such as monitoring (or) measuring the air pollution, modelling the traffic related air pollution, impact of traffic on air quality in road mid-block sections and signalized intersections, air quality index and control measures for mitigating the traffic induced air pollution. Many studies indicate that the automobiles are one of the major sources for the release of various pollutants such as CO, CO_2, NO_x, SO_2, HC, HCHO, TVOC, $PM_{2.5}$, PM_{10}, Lead, Benzene, etc. Literature emphasized that the level of air quality is found to be low in the areas very adjacent to the roads. CO and CO_2 gases are released majorly form the vehicles is one of the key reasons for the global warming and greenhouse gas emissions. Many studies describes methods for measurement and analysis of exhaust emissions released from tail pipe of different types of vehicles. Different dispersion models were used like CALINE 3, CALINE 4, and CAL3QHC etc., to analyze the emissions at intersections. The idling of vehicles, acceleration and deceleration of vehicles at intersections are identified as the major reasons for more dispersion of pollutant concentrations at intersections. Literature also indicated that the types of vehicles stopped during a particular red time will also influence the release of pollutants in the air.

Although, there are several studies done to investigate the effect of traffic on air quality but they either are limited to the specific road mid-block sections or signalized intersections. The focus lacks in analyzing the impact of traffic volume and vehicle composition on concentration of different pollutants on both mid-blocks and signalized intersections in the same study area. The past studies were admitted to analyze one or two pollutants with only few modes of vehicles. Many studies were unable to define the status of air quality with respect to different pollutants in the study area. The research also lacks defining the quality of air in terms of Air Quality Index (AQI) for a particular mid-block section or signalized intersection.

The literature is limited in measuring the impact of traffic composition and the important congestion parameter like length of the queue that forms at signalized intersections on different pollutants concentration under highly mixed traffic conditions. The literature survey also indicates that there is very limited numbers of models were developed to explain the impact of vehicle composition and traffic volume on Air Quality Index. Most of the studies in the past have focused on measuring and analyzing the tail-pipe emissions of vehicles that may not explicitly illustrate the impact of traffic on ambient air quality. The studies were also found limited on modeling the pollutants based on traffic volume using latest machine learning tools.

A detailed analysis and models are presented in the subsequent chapters to describe the connection of air quality with traffic volume in road mid-block sections and signalized intersections.

CHAPTER 3

METHODOLOGY

3.1 GENERAL

The present chapter deals with the methodology adopted for carrying out the study with respect to air quality measurement in urban area. It involves various phases, including site investigation, data collection, data analysis and prediction of major pollutants and determination of Air Quality Index (AQI). The detailed framework for the analysis and methods used for prediction of concentration of different pollutants on urban roads is presented in this chapter.

3.2 STUDY METHODOLOGY

A detailed methodology is proposed to study the impact of traffic flow on air quality in urban areas in various phases. The first phase of the study involves a critical literature review to identify the objectives of the study. The second phase of the study deals with the selection of study areas such as urban road mid-block sections and signalized intersections in selected cities. The third phase of the study involves collection of data on sections of multilane divided road-ways and signalized intersections. The field data collected at roadway mid-blocks includes traffic flow data (traffic volume, vehicle composition data, speed etc.), temperature and concentration of pollutants. Moreover, signal data (red time length, cycle time length), and average length of vehicles at signalized intersection were also obtained from field. The concentrations of different pollutants and temperature were measured at specific intervals at different approaches of intersections. The AQI values were also observed in the field at both road mid-blocks and signalized intersections separately. The fourth phase of the study involves the detailed pollution data analysis, volume data analysis and AQI data analysis and defining the status of air quality. In fifth phase of the study, different models are studied to predict the concentration of major pollutants and AQI at junctions and roads with respect to different variables. The status of air quality in different cities is defined base on the observed and modelled AQI values according to IND-AQI standards. A procedure followed to carry out the present study is presented in Figure 3.1.

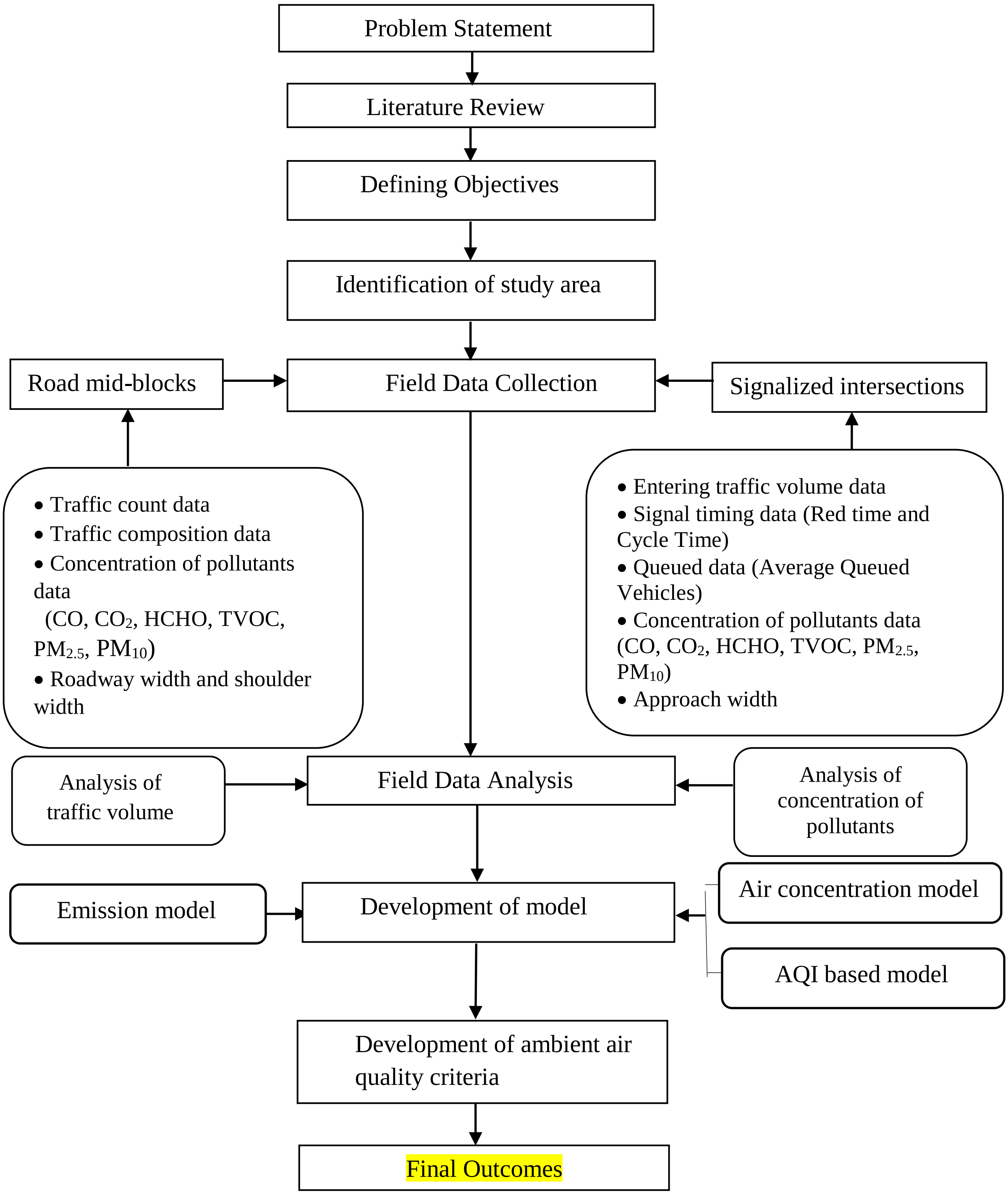


Figure 3.1 Flow chart showing study methodology

3.3 SITE INVESTIGATION

Three cities namely Vijayawada, Warangal, and Tirupathi have been chosen for the study. Road sections on multilane divided roads and signalized intersections for the present study are identified at different locations in these cities. Tirupathi city has a population of 2, 87,035, Warangal city has a population of 6, 15,998 and Vijayawada city has a population of 10, 21,896 as per 2011 census. The study locations identified in the study are away from vicinity of the industries, factories and food cooking stalls. The roadway midblock sections and signalized intersections selected for study cater high to low traffic volume.

3.4 DATA COLLECTION

The traffic flow data was collected on selected locations using videography method. Field inventory survey was performed by visiting selected locations. The field data acquired that includes road mid-block sections and intersection type, temperature, traffic volume and vehicle composition data at urban road mid-blocks and signal data such as red time length, cycle time length, and average queued vehicles. The concentration of pollutants with AQI data was observed at both mid-block of roadways and signalized intersections. The types of vehicle at selected sites are identified as 2-wheeler (2W), Car (C), 3-wheeler (3W), Light Commercial Vehicle (LCV), and Heavy vehicle (HV). The signal data include red time, cycle time and queued vehicles are obtained from the videography method and field observations. Six major pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$, and PM_{10} are observed at the study locations. The concentration of pollutants and AQI data is collected using portable equipment such as CO meter, laser-particle multi-functional detector and air quality detector. AQI data is collected at different roadway mid-blocks and signalized intersections using a portable Air Quality Index meter. Emission data of CO and CO_2 was also collected for the different categories of the vehicles along with emission norms, average age of the vehicle, registration number, model of the vehicle, vehicle class, type of the engine, and fuel type etc. from PUC's (Pollution Control Unit).

The concentrations of pollutants are observed by holding three different equipments in hand and recording the values for every 5 minutes interval. The pollutants were recorded using the equipments at the edge of the carriageway on road mid-block sections. Similarly, the concentrations of pollutants in the air were recorded at the median approach at signalized intersections. Pollutant concentrations and AQI data are obtained utilizing portable instruments such as a CO meter, laser-particle multi-functional detector, and air quality detector. The temperature of the study locations is also obtained using the equipment air quality meter.

3.5 DATA ANALYSIS

This phase of the study deals with the detailed analysis of the pollution data, volume data and AQI data as obtained from different road locations. The volume data analysis includes conversion of traffic volume into PCU and investigating the variation of traffic volume over time. The traffic volume data is converted to PCU based on the PCU factors provided in INDO-HCM 2017. The pollution data analysis involves variation of concentration of different air pollutants with time, estimation of total pollutants concentration and analysis of total pollution concentration with time. The analysis of AQI data includes the variation of AQI values with time.

3.6 MODELS CALIBRATION AND VALIDATION

Correlation analysis have been carried out to analyze the variation of concentration of each pollutant with respect to traffic volume observed at road mid-block sections and signalized intersections. The change in total pollution with respect to the change in traffic volume has been analyzed.

Models are developed to predict different pollutants (CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10}) at road mid-block sections and signalized intersections using different independent variables. Emission models were also developed for CO and CO_2 using age of vehicles, emission norms and vehicle type as variables. A model to predict the AQI with respect to traffic volume is also developed which can be used to estimate AQI at section of mid-block or signalized intersection with known values of traffic volume and vehicle composition. Three different modelling techniques namely Multiple Linear Regression, Support Vector Regression and Artificial Neural Networks are used for prediction of concentration of different pollutants and AQI at selected location. Each modelling technique is explained in detail as follows.

3.6.1 MULTIPLE LINEAR REGRESSION (MLR) ANALYSIS

Using various independent variables, MLR models are created to predict various pollutants (CO, CO_2, HCHO, TVOC, $PM_{2.5}$, and PM_{10}) at road mid-block sections and signalized intersections. The proportion of different type of vehicles, temperature and fuel type are considered as independent variables and concentration of pollutants are taken as dependent variables for models developed to mid-block sections.

Multiple Linear Regression (MLR) analysis is the method used in the study for developing the relationship between different variables. A multiple linear regression analysis is carried out to predict the values of a dependent variable, Y, given a set of p explanatory variables (x1, x2,… xp). MLR allows studying how a group of explanatory variables is related to a specific dependent variable. The general form of the regression equation is given by Equation (3.1)

$$Y = a + b_1X_1 + b_2X_2 + \dots\dots\dots\dots\dots b_nX_n \qquad (3.1)$$

where, Y represents the dependent variable, X (X_1, X_2…) represents the independent variable, b_1, b2,…, bn represents regression co-efficient and a represents the standard error and any other error which is unexplained by the linear regression model. The basic task of multiple regression analysis is to develop the prediction equation. This prediction model indicates that the error in predicting the dependent variable is minimized, if we weight each of the predictors as the statistical analysis has revealed.

3.6.2 SUPPORT VECTOR REGRESSION (SVR) MODELLING

For classification and regression applications, Support Vector Machine (SVM) modeling is a potent supervised learning technique. Fundamentally, SVM looks for the best hyperplane to divide data points into distinct classes with the largest possible margin in order to improve its generalization capacity. The present study attempted to perform SVM models using R-studio software in order to predict the concentration of pollutants at different mid-block sections and signalized intersections. In R, the support vector regression (SVR) model is typically implemented using the e1071 package, which provides functions for support vector machines (SVM) including support vector regression. SVR aims to find the function that best fits a set of training data while minimizing deviations within a specified margin. SVR uses a kernel function to map input variables into a higher-dimensional feature space where a linear relationship might exist. Common kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid kernels. In R, svm () function from the “e1071” package is used to train an SVR model. A basic expression for using SVR in R is given as:

```
# Load the e1071 package

library (e1071)

# Train SVR model

svm_model <- svm(formula = y ~ ., data = training_data, kernel = "radial", cost = C, epsilon = epsilon)

# Make predictions

predictions <- predict(svm_model, newdata = test_data)
```

In the above code:

- y represents the response variable.
- ‘.’represents all other predictor variables.
- training_data is the training dataset.
- kernel specifies the type of kernel function (e.g., "linear", "polynomial", "radial").
- cost (C) and epsilon are parameters controlling the margin of tolerance and regularization.

3.6.3 ARTIFICIAL NEURAL NETWORKS MODELLING

Modeling with artificial neural networks (ANNs) is a potent machine learning technique that draws inspiration from the composition and operation of the human brain. An input layer, one or more hidden layers, and an output layer are among the layers that make up an artificial neural network (ANN). Every node in the network converts input data into an output signal by processing it through an activation function. ANNs are trained to minimize the discrepancy between expected and actual outputs by learning how to modify the weights of connections between nodes using an iterative optimization procedure like backpropagation. The current study aimed to use neural network fitting tool in MATLAB software to develop ANN models. The neural network-fitting tool allows users to design and customize the architecture of artificial neural networks. This includes specifying the number of layers, the number of neurons in each layer, and the type of activation functions used in the neurons. The tool implements feedforward propagation, where input data is passed through the network layer by layer, with weighted connections between neurons. The output of each neuron is computed using an activation function, and the outputs of one layer serve as inputs to the next layer. The fitting tool allows partitioning the dataset into training, validation, and testing subsets. This enables the evaluation of the network's performance on unseen data and helps prevent overfitting. The general architecture of neural network mode is shown in Figure 3.2.

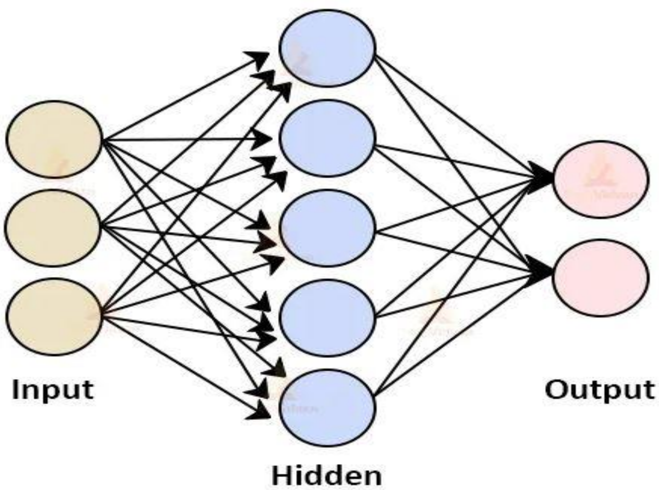


Figure 3.2 Neural network architecture

3.6.4 MODELS VALIDATION

The models developed in the study are validates by using the plots drawn between the observed values and modelled values obtained with a reference line of 45 degrees. Chi-square test was performed to obtain the p-value for model validation. The p-value is the probability estimated on basis of Chi-square test to match the predicted and observed data sets. For a 95% confidence interval, p-value should be greater than 0.05 to accept the null hypothesis in the comparative analysis.

The study also implemented different statistical and accuracy measures such as R^2 value, and Mean Absolute Percentage Error (MAPE) to validate the results obtained from different modelling techniques. The R^2 value is the statistical measure used to describe how close the data is to the fitted regression line. It is also called as Coefficient of determination. R^2 is the proportion of variance in the dependent variable that is predictable from the independent variable. When the R^2 value obtained between the data sets is closer to 1, it indicates the model's good performance. MAPE is a method of statistics that measures the prediction accuracy for a forecasting technique. It is generally used in model evaluation. MAPE value is obtained from Eq. 3.2.

$$\text{MAPE} = \frac{\Sigma \frac{|A-F|}{A} \times 100}{N} \tag{3.2}$$

where, A= actual value, F = forecast value and N = number of observations

The good fit of the model is understood by comparing the MAPE values of training data set (data considered for model development) and testing data set (data considered for model validation). If the MAPE values of both training and testing data sets are similar, then the model is said to be a good fit for the data. If the MAPE values of testing data are greater than the values of training data set, then the model is said to be over fitted and vice-versa.

3.7 DEFINING CRITERIA AND STATUS OF AIR QUALITY

In the later stage of the study, a model is developed to predict AQI for defining the pollution level in the study locations. The impact of traffic volume on ambient air quality index has been investigated. The status of air quality is defined based on the observed and predicted AQI values in reference to the IND-AQI standards. The description of AQI categories and range as prescribed by the equipment is given in Table 3.1.

Table 3.1 IND-AQI standards for measuring air quality

AQI range	AQI category	Health impacts
0-50	Good	Minimal Impact
51-100	Satisfactory	May cause minor breathing discomfort to sensitive people.
101-200	Moderate	May cause breathing discomfort to people with lung disease such as asthma, and discomfort to people with heart disease, children and older adults.
201-300	Poor	May cause breathing discomfort to people on prolonged exposure, and discomfort to people with heart disease
301-400	Very Poor	May cause respiratory illness to the people on prolonged exposure. Effect may be more pronounced in people with lung and heart diseases.
401-500	Severe	May cause respiratory impact even on healthy people, and serious health impacts on people with lung/heart disease. The health impacts may be experienced even during light physical activity.

Source: Central Pollution Control Board (CPCB, 2014)

3.8 SUMMARY

In this chapter, a detailed research methodology is presented. The detailed methodology is explained to analyze the variation of concentration of different pollutants with respect to time and traffic volume. The chapter also explained the methods used for the development of models in the study. The details of the study area and the procedure adapted for data collection is presented in the subsequent chapter.

CHAPTER 4

SITE SELECTION AND DATA COLLECTION

4.1 GENERAL

The present chapter describes the field survey locations and data collection methods adapted for the study. This chapter also describes the location's characteristics, and data requirements to carry out the study. The details of the equipment used for measuring concentration of pollutants are given with their working principle. The chapter also discusses the summary of the data collected in the field.

4.2 SITE SELECTION

The road mid-block sections with flat terrain and straight alignment are considered for the current study. Three legged and four-legged signalized intersections are chosen for the study. Field data is collected in three cities in India namely Warangal, Vijayawada and Tirupati. Six different mid-block sections and three signalized intersections have been identified for data collection from each city chosen. The region or map of the cities chosen for the study is shown in Figure 4.1.

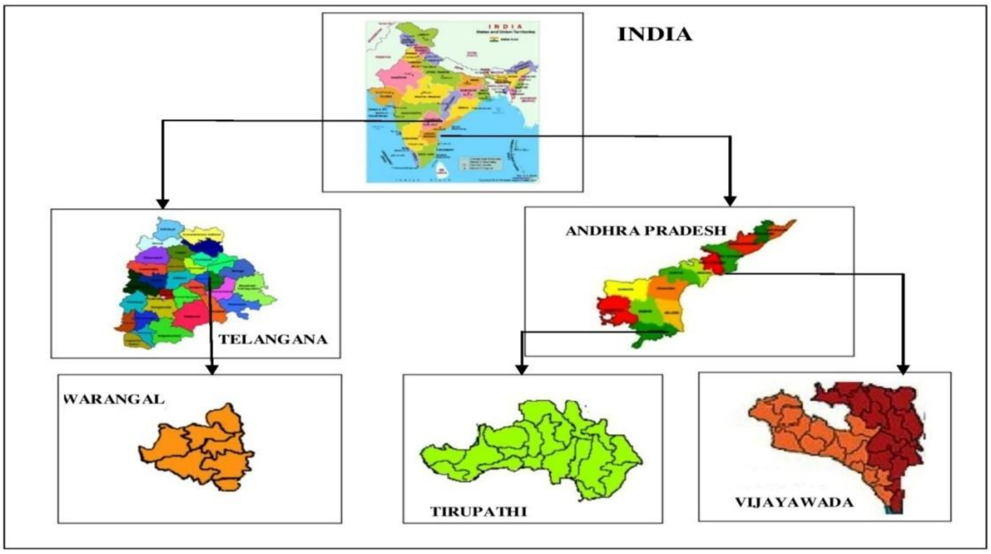


Figure 4.1 Region of the cities chosen for the study

The details of the different mid-block sections and signalized intersections chosen for the study are given in Table 4.1 and Table 4.2 respectively. Table 4.1 presents the names of the different mid-block sections and the location of the data collected. Table 4.2 presents the names of different signalized intersections chosen from each city.

Table 4.1 Urban road mid-block sections chosen for the study

Name of the city	RMB ID	Notation for the road sections	Road name	Location
Warangal	I	HNK	Asoka theater road	Geetha Bhavan
	II	SB	Collector office road	Near Hotel
	III	MGM	MGM Hospital road	Near MGM
	IV	DM	Hunter road	Near D-Mart
	V	BK	Central Jail road	Bhadrakali Temple
	VI	SBH	NIT Warangal road	Near SBH
Tirupati	VII	LP	Bus stand road	Near Meenakshi
	VIII	LM	Kapilatheertham road	Near Aroma
	IX	MR	Gandhi road	Near an apartment
	X	NTR	SV University road	Near a School
	XI	TT	Renigunta road	Near Dhruvathara
	XII	RC	RC road	Near a Boys hostel
Vijayawada	XIII	AP	Elluru road	Near Apsara
	XIV	PT	MG Road	Near an apartment
	XV	PR	Poranki road	Near Balaji Cine
	XVI	RV	Ramarappadu road	Near Novotel hotel
	XVII	PL	Pantakaluva road	Near a coffee day
	XVIII	BG	PrakasamBarraige	Near Sweet magic

Figure 4.2 Hunter road section in Warangal city (RMB IV)

Figure 4.3 SV University road section in Tirupati city (RMB X)

Figure 4.4 Elluru roadway mid-block in Vijayawada city (RMB XIII)

Table 4.2 Signalized intersections chosen for the study

Name of the city	SI ID	Notation of the intersection	Name of the intersection
Warangal	I	KZP	Kazipet railway station junction
	II	SRS	Spencors circle
	III	GB	GeethaBhavan Circle
Tirupati	IV	CP	Central Park intersection
	V	LM	Leela Mahal circle
	VI	AN	Annamayya circle
Vijayawada	VII	BRTS	BRTS junction
	VIII	KV	Kothavanthena junction
	IX	RH	Ramesh hospital intersection

Snapshots of some of the midblock sections and signalized intersections are shown in Figures 4.2 to 4.7.

Figure 4.5 Spencors intersection in Warangal city (SI II)

Figure 4.6 Annamayya circle intersection in Tirupati city (SI VI)

Figure 4.7 Kothavanthena junction in Vijayawada city (SI VIII)

4.3 FIELD DATA COLLECTION

The present study is required to collect different types of data such as roadway data and intersection approach data, traffic volume and vehicle composition data at road mid-block sections, traffic volume and signal data at signalized intersections, pollutant data at mid-blocks and signalized intersections and air quality index data. The traffic volume data was collected for eight hours in each mid-block section and different approaches of signalized intersection using video cameras. The classified traffic volume data was extracted from the video by playing the videos on wide screen display. The Red time, and Cycle length are observed in the field for different intersections. The queued vehicles in each approach of different intersections are also extracted from the recorded video and manual counting.

The field data in the present study was collected during weekdays and for a duration of 8 hours (4 hours in the morning and 4 hours in the evening) at each location. The details of the time frame providing the specific dates and period of the data collection are shown in Tables 4.3 and Table 4.4 for mid-block sections and signalized intersections respectively.

Table 4.3 Details of data collection on road mid-block section

Name of the city	RMB ID	Dates of data collection	Periods of the day
Warangal	I	07.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	II	08.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	III	09.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	IV	10.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	V	11.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	VI	14.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
Tirupati	VII	04.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	VIII	05.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	IX	06.01.2021	7:00 AM to 11:00 AM &

			5.00 PM to 9:00 PM
	X	07.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XI	08.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XII	11.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
Vijayawada	XIII	08.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XIV	09.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XV	10.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XVI	11.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XVII	12.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	XVIII	15.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM

Table 4.4 Details of data collection at signalized intersections

Name of the city	SI ID	Dates of data collection	Periods of the day
Warangal	I	21.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	II	22.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	III	23.12.2020	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM

Tirupati	IV	18.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	V	19.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	VI	20.01.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
Vijayawada	VII	16.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	VIII	17.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM
	IX	18.02.2021	7:00 AM to 11:00 AM & 5.00 PM to 9:00 PM

4.3.1 ROADWAY DATA

The road geometric details such as width of the roadway, the width of the median and the width of the shoulders are all carefully measured using a tape in the study locations. The selected road mid-block sections are straight roads with negligible gradient. The details of each selected roadway section and roadway at signalized intersections are given in Tables 4.5 and 4.6 respectively.

Table 4.5 Details of the road geometry at mid-block sections

RMB ID	Road name	Type of road	Carriage way width (m)	Shoulder width(m)	Median width(m)
I	Asoka theater road	Four lane divided	7.0	0.5	0.5
II	Collector office road	Four lane divided	8.5	1.0	1.2
III	MGM Hospital road	Six lane divided	7.0	1.5	1.2

IV	Hunter road	Six lane divided	10.5	0.5	1.2
V	Central Jail road	Six lane divided	10.5	1.0	1.2
VI	NIT Warangal road	Four lane divided	7.0	1.5	1.2
VII	Bus stand road	Four lane divided	7.0	1.5	1.2
VIII	Kapilatheertham road	Six lane divided	10.5	0.5	1.2
IX	Gandhi road	Four lane divided	7.0	0.5	0.5
X	SV University road	Four lane divided	8.5	1.0	1.2
XI	Renigunta road	Four lane divided	7.0	1.5	1.2
XII	RC road	Four lane divided	7.0	1.5	1.2
XIII	Elluru road	Four lane divided	7.0	0.5	0.5
XIV	MG Road	Six lane divided	10.5	0.5	1.2
XV	Poranki road	Four lane divided	7.0	0.5	0.5
XVI	Ramarappadu road	Six lane divided	10.5	0.5	1.2
XVII	Pantakaluva road	Four lane divided	7.0	1.5	1.2
XVIII	PrakasamBarraige road	Four lane divided	7.0	1.5	1.2

Table 4.6 Details of signalized intersections selected in the study

SI ID	Name of the intersection	Characteristics	Type of road	Approach width (m)	Median width (m)
I	Kazipet railway station junction	4-legged intersection	Six lane divided	21	2.5
II	Spencors circle	4-legged intersection	Six lane divided	22.5	2.5

III	GeethaBhavan Circle	4-legged intersection	Six lane divided	23	2.0
IV	Central Park intersection	3- legged intersection	Four lane divided	14.8	1.2
V	Leela Mahal circle	4-legged intersection	Six lane divided	21.5	2.5
VI	Annamayya circle	4-legged intersection	Six lane divided	22	2.2
VII	BRTS junction	4-legged intersection	Six lane divided	21	2.5
VIII	Kothavanthena junction	4-legged intersection	Six lane divided	23.5	2.75
IX	Ramesh hospital intersection	4-legged intersection	Six lane divided	22.5	2.5

4.4 VEHICLE TYPES AND TRAFFIC COMPOSITION

Various types of vehicles are observed on selected road sections and signalized intersections. The present study considered five types of vehicles as identified in the recorded video, counted for obtaining volume in 5 min time interval. The hourly traffic volume data was calculated by aggregating traffic counts taken on various roadway sections. In the present study several vehicle categories are merged into five vehicle types for simplifying the data analysis. The details of the vehicle types are given in Table 4.7.

Table 4.7 Details of the vehicle types observed in the field

Vehicle type	Notation	Vehicle groups	Length (m)	Width (m)	Power Performance (cc)	Fuel type
Two	2W	Motorized two wheeler i.e.	1.80	0.69	125	Petrol

wheeler		motor bike				
Passenger car	Car	Minivan, jeep, SUV, Sedan, Hatchback	3.5	1.70	1200	Petrol
Three wheeler	3W	Motorized three wheeler i.e. Auto rickshaw	2.91	1.34	145	Diesel
Light Commercial Vehicle	LCV	Light commercial vehicle i.e. tempo, Mini trucks	3.35	1.60	395	Diesel
Heavy Vehicle	HV	Passenger bus, truck, multi-axle	12.00	2.60	5675	Diesel

The vehicle composition in each road mid-block section is computed from the observed vehicle count on both road mid-block and signalized intersections. The average vehicle composition observed in a day during 7:00 AM to 11:00 AM in the morning and 5:00 PM to 9:00 PM in the evening is considered. The vehicle composition obtained in each roadway mid-block section is given in Table 4.8.

Table 4.8 Vehicle composition in road mid-block sections

RMB ID	**Percentage of vehicle types (%)**				
	2W	**Car**	**3W**	**LCV**	**HV**
I	64	8	26	1	2
II	54	18	24	2	3
III	50	8	38	2	3
IV	52	15	29	1	3
V	54	10	30	4	2
VI	60	13	23	2	2

VII	55	19	18	3	5
VIII	60	19	9	5	8
IX	77	7	14	1	1
X	71	5	21	1	2
XI	53	12	26	4	6
XII	81	4	15	0	0
XIII	70	9	17	2	2
XIV	65	16	13	1	5
XV	70	15	11	2	2
XVI	31	51	7	1	10
XVII	77	15	6	2	1
XVIII	60	21	17	2	0

High percentage of 2W dominates the traffic flow at all the selected mid-block sections. RMB XVI (RV) has higher percentage of Car than 2W. RMB XII (RC) has the lowest percentage of Car, which is approximately 4% and highest percentage of 2W which is 81%.

The composition of different types of vehicles at each signalized intersection was quantified by calculating the percentage of each vehicle types. The vehicle composition obtained at signalized intersections is given in Table 4.9.

Table 4.9 Vehicle composition at signalized intersections

SI ID	**Percentage of vehicle types (%)**				
	2W	**Car**	**3W**	**LCV**	**HV**
I	41	24	23	7	4
II	48	24	21	6	2
III	42	22	20	8	8
IV	54	15	21	8	0
V	47	19	21	8	4
VI	47	19	22	10	2

VII	69	13	14	3	1
VIII	72	12	14	1	1
IX	62	21	10	1	6

It is observed that a vehicle type 2W has a predominant share in the traffic flow at all signalized intersections. The traffic composition of Car and 3W are nearly same at all the intersections. The highest percentage of 2W and lowest percentage of Car is observed at SI VIII (KV).

4.5 SIGNAL TIME DATA

The red time length and cycle length were observed on each approach at different intersections from the field. Red time is defined as the actual duration the red light of a traffic signal is turned on. Cycle length is the time in seconds that it takes a signal to complete one full cycle of indications. It indicates the time interval between the starting of green for one approach till the next time the green starts. The average of red times and cycle lengths at intersections are obtained from entire data collection. The mean red time and cycle time lengths observed at each signalized intersection is given in Table 4.10.

Table 4.10 Signal data of intersections

SI ID	Red Time (sec)	Cycle Length (sec)
I	90	112
II	104	159
III	135	153
IV	50	100
V	65	93
VI	80	114
VII	150	180
VIII	135	195
IX	180	225

4.6 QUEUED VEHICLE DATA

The vehicles stopped in the queue are counted to estimate queue size and length from the video recording played on wide-screen display. The number of vehicles stopped during red time is counted as queued vehicles data. The queued vehicles data is collected for 8 hours in specified time of a day. The data is collected with the help of video cameras placed at different approaches of the intersections. The number of vehicles stopped during the red time on each approach of the intersection is counted form the video graphic data. The average value of all the approaches is computed to obtain the queued vehicles of the intersection. The minimum, maximum and average of the vehicles stopped during the red time per hour at each intersection is given in Table 4.11.

Table 4.11 Queued Vehicle Data at intersections

SI ID	**Queued Vehicles (veh)**		
	Minimum	Maximum	Average
I	38	88	60
II	49	154	102
III	45	185	97
IV	34	78	55
V	55	167	112
VI	21	80	53
VII	40	59	50
VIII	56	66	60
IX	59	71	64

4.7 MEASUREMENT OF AIR POLLUTION DATA

Six major pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10} are observed at road mid-block sections and signalized intersections. The concentration of pollutants was measured using handheld equipment. The data obtained for all the pollutant concentrations at every 5 min and aggregated for every 1 hour to measure average and total concentration. The present study used different portable equipment such as CO meter, laser particle multi-functional detector and air quality detector. The details of the equipment used in the study are given as follows.

4.7.1 CARBON MONOXIDE

The CO meter is used in the present study to measure the CO concentrations. It is made up of stabilized-electro-specific gas sensor. The range of measurement is 0-1000 ppm. The accuracy obtained from this equipment is 5%±10PPM. The measurement resolution of the equipment is 1ppm. The CO meter is shown in Figure 4.8.

Figure 4.8 Carbon Monoxide (CO) meter

The CO sensor present in the CO meter detects the CO value in the air when it is held properly. The CO meter displays the existing CO value on the LCD display at a particular time in a location. In the present study, the CO values are recorded for every 5 min and aggregated to 1 hour for different mid-block sections and signalized intersections.

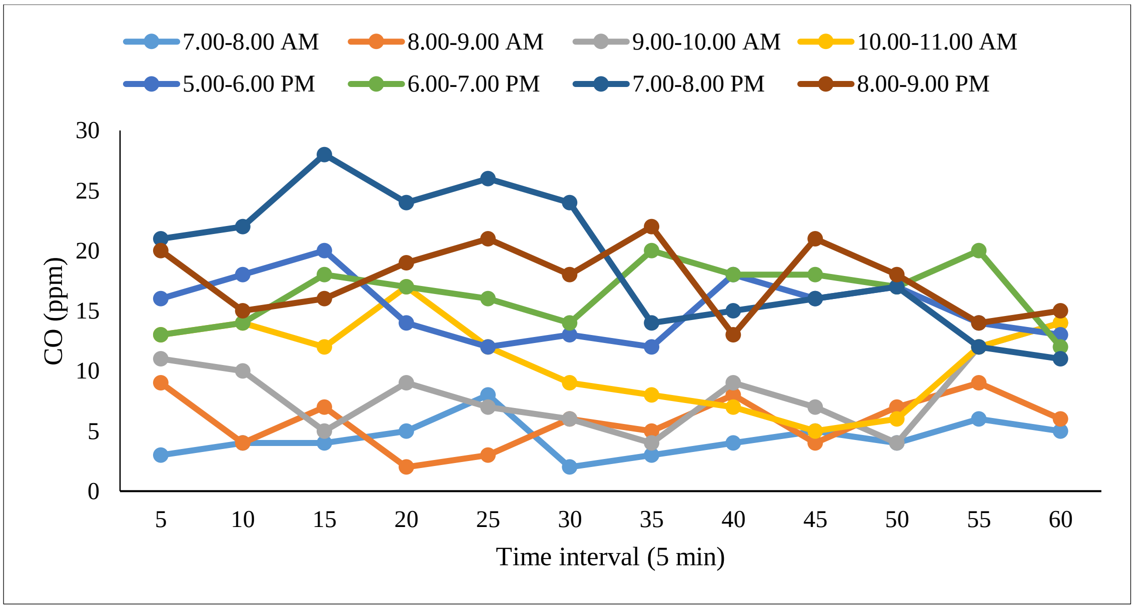


Figure 4.9 CO concentrations observed in field at RMB VIII (LM)

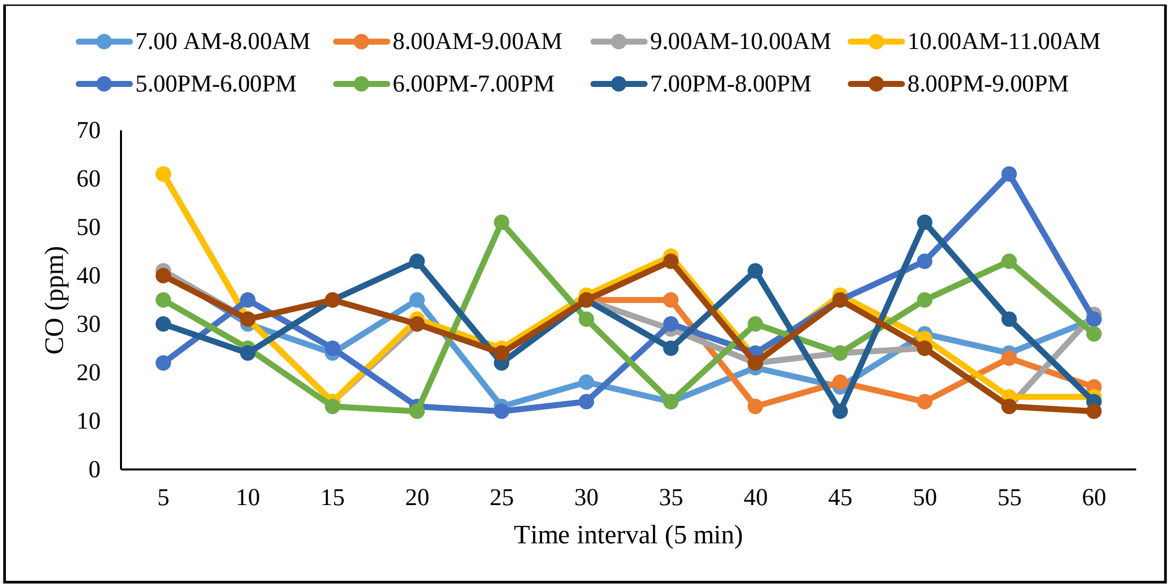


Figure 4.10 CO concentrations observed in field at SI II (SRS)

The CO values recorded for every 5 min at RMB VIII (LM) and SI II (SRS) are shown as a sample in Figures 4.9 and 4.10 respectively. Similarly, the concentration of all pollutants is recorded for every 5 min at all selected sections and signalized intersections. The data recorded is analyzed and aggregated to 1 hour for different sections and intersections. The standard deviation of observed CO data for mid-block sections and signalized intersections is found in the range as 1 PPM to 6 PPM, and 2 PPM to 5 PPM respectively. The details of the CO concentrations measured using CO meter at road mid-block sections and signalized intersections are given in Table 4.12 and Table 4.13 respectively.

Table 4.12 Carbon Monoxide values observed in different road mid-block sections

RMB ID	CO (ppm)		
	Minimum	Maximum	Average
I	5	18	12
II	4	17	12
III	4	15	9
IV	6	16	13
V	4	19	12
VI	5	13	10
VII	4	19	12
VIII	5	17	11

IX	3	6	5
X	4	18	11
XI	5	15	11
XII	4	12	8
XIII	5	11	8
XIV	7	22	13
XV	7	16	11
XVI	6	11	8
XVII	6	15	9
XVIII	9	17	13

Table 4.13 Carbon Monoxide values observed at different signalized intersections

SI ID	CO (ppm)		
	Minimum	Maximum	Average
I	24	35	28
II	25	30	28
III	28	35	31
IV	12	17	14
V	30	35	32
VI	19	26	22
VII	18	32	28
VIII	20	35	29
IX	22	33	25

4.7.2 HCHO AND TVOC

The laser-particle multi-functional detector is used to measure HCHO and TVOC concentrations. It consists of a high precision electrochemical formaldehyde sensor and laser particle sensor. The equipment may be operated at a temperature of 0°C to 50°C. The measurement range and resolution given by the equipment is 0 to 5mg/m^3 and 0.01mg/m^3 respectively. The Laser-particle multi-functional detector is shown in Figure 4.11.

Figure 4.11 Laser-particle multi-functional detector used to measure HCHO and TVOC concentrations

The laser-particle multi-functional detector is a hand-held sensor to detect HCHO and TVOC values in the air. The sensor detects the concentration of HCHO and TVOC when HCHO button is pressed. Then the values of HCHO and TVOC are displayed on the LCD screen. The HCHO and TVOC values obtained from the equipment are noted for every 5 minutes interval in each location. The standard deviation of observed HCHO data for mid-block sections and signalized intersections is found in the range between 0.01 mg/m^3 to 0.07 mg/m^3 and 0.005 mg/m^3 to 0.06 mg/m^3 respectively. Similarly, it is also observed that the range of standard deviation of TVOC lies in between 0.01 mg/m^3 to 0.10 mg/m^3 and 0.01 mg/m^3 to 0.07 mg/m^3. The minimum, maximum and average values of HCHO and TVOC measured in different road mid-block sections and signalized intersections using the laser-particle multi-functional detector are given in Table 4.14 and Table 4.15, respectively.

Table 4.14 HCHO and TVOC values observed in road mid-block sections

RMB ID	HCHO (mg/m^3)			TVOC (mg/m^3)		
	Minimum	Maximum	Average	Minimum	Maximum	Average
I	0.05	0.17	0.09	0.08	0.28	0.17
II	0.05	0.12	0.08	0.11	0.25	0.22
III	0.05	0.09	0.06	0.07	0.25	0.15
IV	0.06	0.10	0.08	0.13	0.25	0.21
V	0.04	0.10	0.08	0.08	0.23	0.15
VI	0.05	0.08	0.07	0.07	0.22	0.15
VII	0.04	0.18	0.09	0.08	0.29	0.19
VIII	0.05	0.10	0.07	0.11	0.26	0.18
IX	0.01	0.05	0.03	0.04	0.09	0.06
X	0.02	0.17	0.09	0.06	0.27	0.16
XI	0.05	0.08	0.07	0.12	0.18	0.15
XII	0.05	0.09	0.06	0.06	0.11	0.08
XIII	0.01	0.03	0.02	0.01	0.05	0.03
XIV	0.01	0.20	0.08	0.02	0.29	0.14
XV	0.02	0.09	0.05	0.03	0.32	0.15
XVI	0.01	0.05	0.03	0.03	0.16	0.06
XVII	0.06	0.11	0.08	0.08	0.14	0.11
XVIII	0.05	0.09	0.07	0.17	0.22	0.19

Table 4.15 HCHO and TVOC values observed at different signalized intersections

SI ID	HCHO (mg/m^3)			TVOC (mg/m^3)		
	Minimum	Maximum	Average	Minimum	Maximum	Average
I	0.09	0.13	0.12	0.15	0.24	0.20
II	0.08	0.12	0.10	0.12	0.25	0.16
III	0.13	0.21	0.16	0.09	0.32	0.25
IV	0.01	0.03	0.02	0.05	0.08	0.06
V	0.08	0.13	0.11	0.07	0.20	0.15
VI	0.03	0.08	0.06	0.09	0.16	0.13
VII	0.04	0.18	0.11	0.08	0.25	0.17
VIII	0.04	0.20	0.14	0.06	0.28	0.14
IX	0.02	0.08	0.05	0.13	0.21	0.17

4.7.3 CO_2, $PM_{2.5}$ and PM_{10}

The air quality detector is used to measure concentrations of CO_2, $PM_{2.5}$ and PM_{10}. It consists of a Laser particle sensor and carbon dioxide sensor based on Non-dispersive infra-red (NDIR) detection theory. The equipment may be operated at a maximum temperature 50°Cand minimum temperature of 0°C. The measurement range and resolution given by the equipment for measuring $PM_{2.5}$ and $PM_{10}$is 0 to 999µg/m^3 and 0.1 µg/m^3 respectively. Similarly, the measurement range and resolution given by the equipment for measuring CO_2 is 0 to 5000 ppm and 1ppm respectively. The air quality detector is shown in Figure 4.12.

Figure 4.12 Air quality detector used to measure concentrations of CO_2, $PM_{2.5}$ and PM_{10}.

The portable air quality detector displays the values of different pollutants and AQI on the screen. For every 5 minutes interval, the values are noted from the equipment, in the required locations and analyzed. The standard deviation of observed CO_2 is found in the range of 29 ppm to 189 ppm at mid-block sections and 22 ppm to 92 ppm at signalized intersections. The range of standard deviation is observed as 1 μg/m^3 to 21 μg/m^3 at mid-block sections and 5 μg/m^3 to 30 μg/m^3 at signalized intersections for $PM_{2.5}$. Likewise, standard deviation of PM_{10} data is observed in the range of 5 μg/m^3 to 39 μg/m^3 at mid-block sections and 3 μg/m^3 to 46 μg/m^3 at signalized intersections.

Table 4.16 CO_2, $PM_{2.5}$ and PM_{10} values observed on different road mid-block sections

RMB ID	CO_2(ppm)			$PM_{2.5}$(μg/m^3)			PM_{10}(μg/m^3)		
	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum	Average
I	718	1015	874	17	38	27	42	97	62
II	712	973	926	16	60	30	36	71	55
III	658	968	819	14	29	22	27	65	46
IV	883	990	951	22	38	29	48	70	57
V	735	1067	897	16	40	28	31	100	64
VI	701	952	802	16	27	24	36	58	49
VII	689	1098	900	15	67	35	31	107	66
VIII	702	1002	867	16	36	24	36	95	57
IX	588	718	664	12	16	15	21	36	30
X	665	1098	881	14	39	26	27	98	58
XI	721	880	822	15	28	23	37	59	50
XII	664	873	799	14	27	20	35	53	44
XIII	558	885	710	13	40	27	20	46	30
XIV	656	1158	895	23	75	51	23	120	63
XV	712	1000	867	33	68	51	31	72	53
XVI	603	898	735	28	48	36	26	54	36
XVII	753	895	825	15	39	28	39	65	53
XVIII	925	1002	960	39	59	48	55	74	66

Table 4.17 CO_2, $PM_{2.5}$ and PM_{10} values observed at signalized intersections

SI ID	CO_2 (ppm)			$PM_{2.5}$ (μg/m^3)			PM_{10} (μg/m^3)		
	Minimum	Maximum	Average	Minimum	Maximum	Average	Minimum	Maximum	Average
I	958	1098	1025	56	95	72	102	109	105
II	907	984	939	58	120	87	94	101	98
III	1033	1267	1151	66	79	71	111	124	116
IV	688	857	762	14	42	30	19	63	47
V	1010	1075	1040	53	67	60	100	109	104
VI	798	900	847	41	69	52	59	88	75
VII	775	912	849	36	103	85	42	158	106

VIII	735	1007	882	40	120	94	49	166	122
IX	687	831	769	99	122	113	56	120	91

4.8 AIR QUALITY INDEX (AQI)

AQI values are measured using the Laser particle multi-functional detector. AQI values are observed for every 5 min interval for eight hours (4 hours in the morning and 4 hours in the evening) on different mid-blocks and signalized intersections. The mean values of AQI observed are aggregated for every 1 hour and AQI values are computed. The equipment used to measure the AQI values in the field is shown in Figure 4.13.

Figure 4.13 Laser particle multi-functional detector used to measure AQI

The details of the AQI values observed in different road mid-block sections and signalized intersections are given in Tables 4.18 and 4.19 respectively.

Table 4.18 Details of the AQI values observed on road mid-block sections

RMB ID	Range of AQI values		Average AQI
	Minimum	Maximum	
I	75	138	105
II	72	124	106
III	59	115	89
IV	96	122	109
V	69	153	108
VI	71	110	98
VII	70	155	110
VIII	78	131	102
IX	54	73	66
X	63	146	101
XI	72	110	98
XII	62	106	84
XIII	55	112	85
XIV	85	190	132
XV	97	158	128
XVI	92	124	107
XVII	61	105	89
XVIII	110	150	132

The higher average AQI value is observed in RMBs XIV and XVIII of Vijayawada because of the higher traffic volumes recorded in that sections. The lowest average AQI value is noticed in RMB IX of Tirupati because of the lower mean traffic volume recorded on road.

Table 4.19 Details of the AQI values observed at signalized intersections

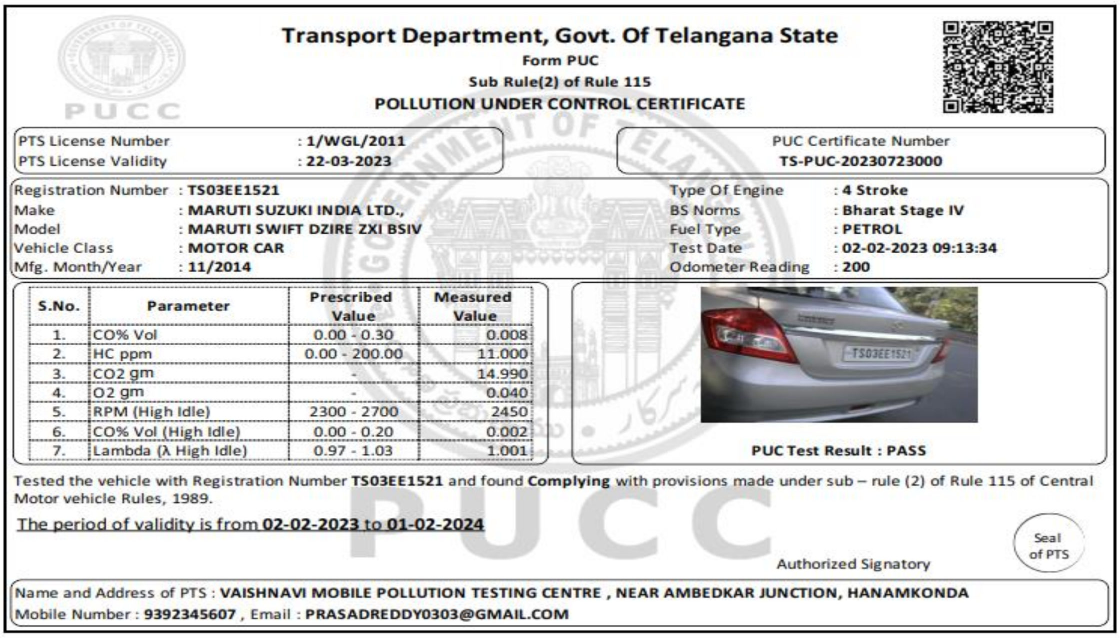
SI ID	Range of AQI values		Average AQI values
	Minimum	Maximum	
I	132	141	136
II	121	139	130
III	144	184	164
IV	53	81	67
V	133	147	138
VI	75	121	97
VII	85	172	140
VIII	98	198	159
IX	72	128	108

The higher average AQI value of AQI is noticed in SI III of Warangal and lowest AQI value is observed in SI IV of Tirupati because of their highest and lowest traffic volumes recorded at those intersections.

4.9 EMISSION DATA

A total of 1127 emission data points were obtained from the pollution control center in order to determine the emissions of the real running car in the field. To determine the emission of the real field cars, the emission of samples obtained at the PUC center was extracted, together with the other parameters listed in the certificate.

A sample, shown in Figure 4.14, was obtained from the pollution certificate center. It offers a pollution certificate with information on the car, such as the registration date (from which the vehicle's age was determined), engine type, Bharat stage norms, vehicle class, and model name.



PUCC

Transport Department, Govt. Of Telangana State
Form PUC
Sub Rule(2) of Rule 115
POLLUTION UNDER CONTROL CERTIFICATE

PTS License Number : **1/WGL/2011**
PTS License Validity : **22-03-2023**

PUC Certificate Number
TS-PUC-20230723000

Registration Number : **TS03EE1521**
Make : **MARUTI SUZUKI INDIA LTD.,**
Model : **MARUTI SWIFT DZIRE ZXI BSIV**
Vehicle Class : **MOTOR CAR**
Mfg. Month/Year : **11/2014**

Type Of Engine : **4 Stroke**
BS Norms : **Bharat Stage IV**
Fuel Type : **PETROL**
Test Date : **02-02-2023 09:13:34**
Odometer Reading : **200**

S.No.	Parameter	Prescribed Value	Measured Value
1.	CO% Vol	0.00 - 0.30	0.008
2.	HC ppm	0.00 - 200.00	11.000
3.	CO2 gm	-	14.990
4.	O2 gm	-	0.040
5.	RPM (High Idle)	2300 - 2700	2450
6.	CO% Vol (High Idle)	0.00 - 0.20	0.002
7.	Lambda (λ High Idle)	0.97 - 1.03	1.001

PUC Test Result : PASS

Tested the vehicle with Registration Number **TS03EE1521** and found **Complying** with provisions made under sub – rule (2) of Rule 115 of Central Motor vehicle Rules, 1989.

The period of validity is from **02-02-2023 to 01-02-2024**

Seal of PTS

Authorized Signatory

Name and Address of PTS : **VAISHNAVI MOBILE POLLUTION TESTING CENTRE , NEAR AMBEDKAR JUNCTION, HANAMKONDA**
Mobile Number : **9392345607** , Email : **PRASADREDDY0303@GMAIL.COM**

Figure 4.14 PUC Certificate format sample

Using the Pollution under Control Certificate issued by the RTO department, emission data in the form of CO_2, O_2, and CO, as well as emission norms, vehicle class, and vehicle age, were retrieved for modeling purposes. 1127 PUC certificates were collected. Table 4.20 shows the data from five such pollution certifications as a sample.

Table 4.20 PUC data sample of few vehicles

Registration No	**Maker**	**Fuel type**	**Registration Date**	**Vehicle class**	**Emission Norm**	**CO_2 (gm)**	**O_2 (gm)**	**CO (%v)**
TS03EZ6563	ACTIVA	PETROL	Mar-15	MOTOR CYCLE	BS-VI	6.100	0.6100	0.04
TS03FA6655	HYUNDAI	PETROL	Nov-20	MOTOR CAR	BS-VI	34.750	0.0112	0.002
AP36TB1026	BAJAJ	DIESEL	Jan-13	AUTO	BS-III	4..460	0.0446	0.755
TS03UC85	MARUTI	PETROL	Jan-21	AMBULANCE	BS-VI	14.510	0.0355	0.001
TS03EE1521	SWIFT	PETROL	Nov-14	PETROL	BS-IV	14.990	0.0159	0.008

4.10 CALIBRATION

The concentration of pollutants observed using the equipment and a Continuous Ambient Air Quality Monitoring Station (CAAQMS) present at the study locations are compared. The sample display board of CAAQMS located at Tirupati is given in Figure 4.15. The CAAQMS setup of the monitoring station located at Tirupati is shown in Figure 4.16.

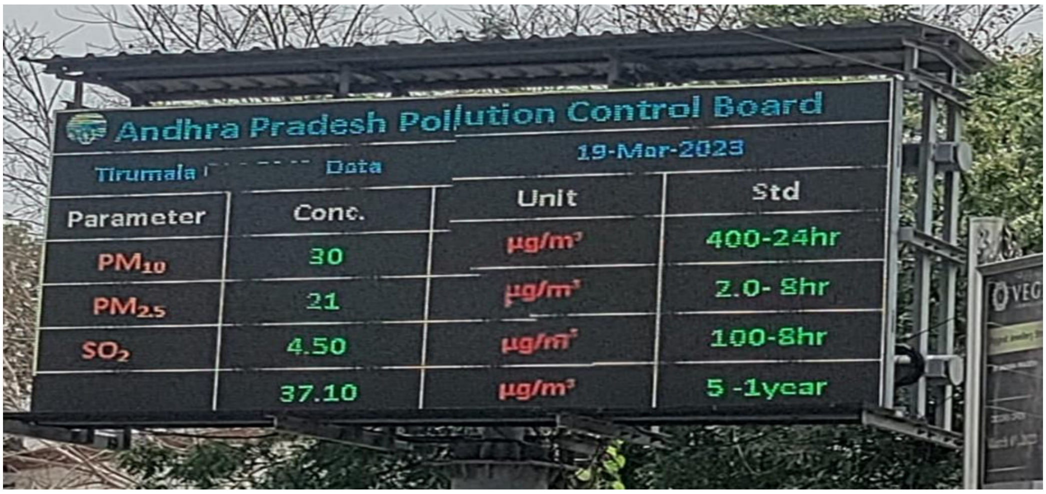


Figure 4.15 Sample display board of CAAQMS located at Tirupati

Figure 4.16 CAAQMS setup located at Tirupati

The concentration of three pollutants namely CO, $PM_{2.5}$ and PM_{10} are compared and shown in Figures 4.17, 4.18 and 4.19 respectively. The result indicates that the concentration of different pollutants measured using the equipment in the field and the CAAQMS located in the study locations are almost the same. It is also observed that the percentage error between the equipment based reading and CAAQMS reading should not be more than 15% for reasonable accuracy.

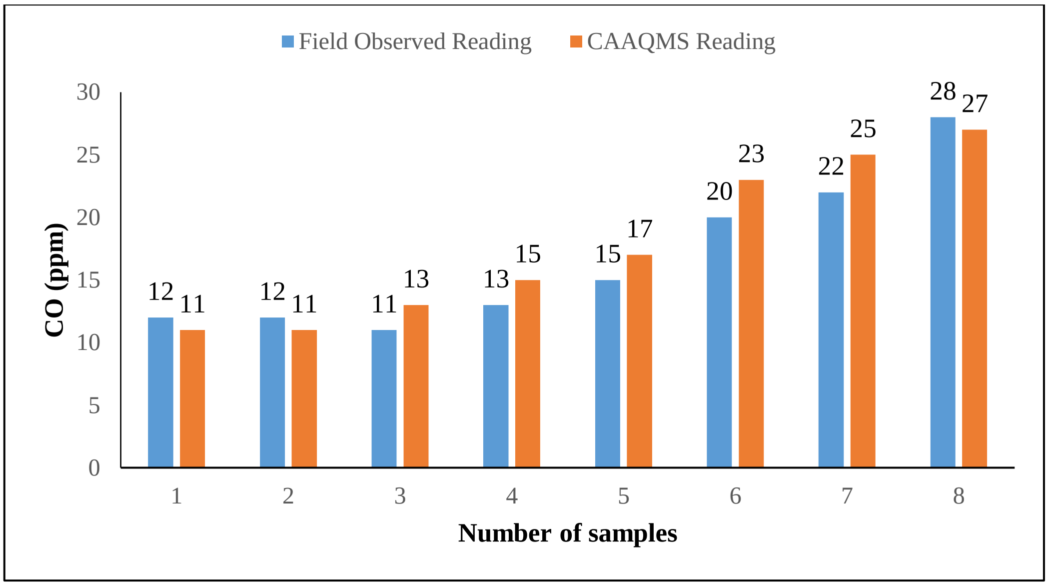


Figure 4.17 Comparison of CO concentrations

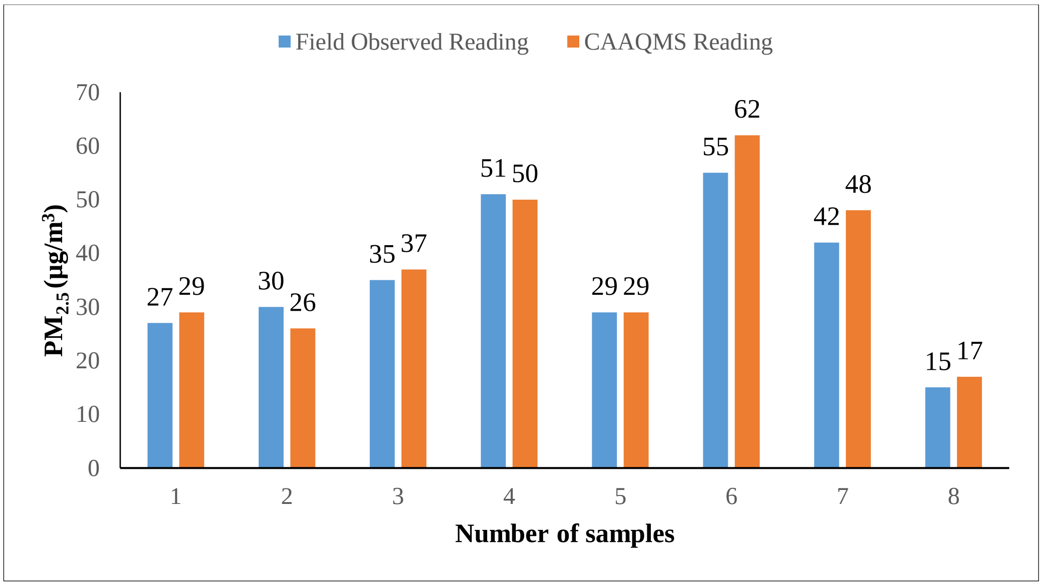


Figure 4.18 Comparison of $PM_{2.5}$ concentrations

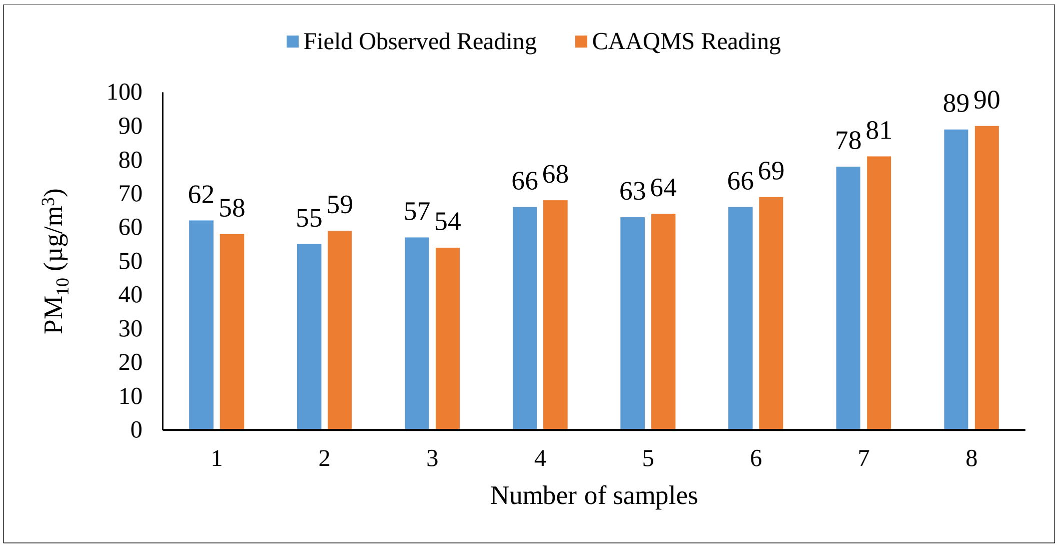


Figure 4.19 Comparison of PM_{10} concentrations

The percentage error estimated between the equipment and CAAQMS readings is given for each interval in Table 4.21

Table 4.21 Percentage error between equipment-based data and CAAQMS data for CO

Sample	Field observed reading (ppm)	CAAQMS reading (ppm)	Percentage Error CO (%)
1	12	11	9
2	12	11	9
3	11	13	15
4	13	15	13
5	15	17	12
6	20	23	13
7	22	25	12
8	28	27	4

Table 4.22 Percentage error between equipment-based data and CAAQMS data for $PM_{2.5}$

Sample	Field observed reading ($\mu g/m^3$)	CAAQMS reading ($\mu g/m^3$)	Percentage Error $PM_{2.5}$ (%)
1	27	29	7
2	30	26	15

3	35	37	5
4	51	50	2
5	29	29	0
6	55	62	11
7	42	48	13
8	15	17	12

Table 4.24 Percentage error between equipment-based data and CAAQMS data for PM_{10}

Sample	Field observed reading (µg/m^3)	CAAQMS reading (µg/m^3)	Percentage Error PM_{10} (%)
1	62	58	7
2	55	59	7
3	57	54	6
4	66	68	3
5	63	64	2
6	66	69	4
7	78	81	4
8	89	90	1

4.11 SUMMARY

The field data collection and extraction procedures as used in the study have been described in detail. The equipment used to measure concentration of different pollutants are provided with details along with their uses and specifications. The summary of the types of data observed in the field is also given in this chapter.

CHAPTER 5

FIELD DATA ANALYSIS

5.1 GENERAL

Field data analysis is performed to understand the concentration behavior of pollutants with respect to time of the day and traffic volume. This chapter covers analysis of pollution data, traffic volume estimation, and Air Quality Index data obtained at mid-blocks and signalized intersections. The traffic volume observed for the study sections are analyzed and converted in to passenger car units for further examination. For each study location, concentration of pollutants data and AQI data has been analyzed.

5.2 ANALYSIS OF DATA ON ROAD MID-BLOCK SECTIONS

The concentration of pollutants, traffic volume data and Air Quality Index (AQI) data as observed in the field are analyzed. Different pollutants such as CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10} analyzed at different time of the day under different traffic volumes is also discussed in this section.

5.2.1 TRAFFIC VOLUME

The classified traffic count obtained from the field was converted into PCU using appropriate PCU factors. Five types of vehicles namely 2W, Car, 3W, LCV and HV are considered for conversion of traffic volume. The heterogeneous traffic volume was converted to homogeneous one by using Passenger Car Unit (PCU) pertaining to each vehicle type. The PCU values as suggested by Indo-HCM (2017) have been used in the present study. The PCU factors used in the study as per INDO-HCM are given in Table 5.1.

Table 5.1 PCU factors for mid-block sections (INDO HCM 2017)

Vehicle type	2W	Car	3W	LCV	HCV
PCU factors	0.2	1	0.8	2.2	4.6

The descriptive analysis of traffic volume is performed to extract useful information such as minimum, maximum and average values. The result of analysis with respect to each roadway section are given in Table5.2. It is observed that the average traffic volume is higher in RMBs XIV (PT), XV (PR), XVI (RV) and XVIII (BG) in Vijayawada city as compared to other cities.

Table 5.2 Details of the traffic volume in road mid-block sections

RMB ID	Range of Traffic volume (PCU/hr/direction)		Average traffic volume (PCU/hr/direction)
	Minimum	Maximum	
I	452	1360	859
II	485	1324	930
III	344	1292	821
IV	622	1605	1200
V	311	1449	938
VI	393	1194	871
VII	360	1836	1045
VIII	482	1826	1206
IX	60	317	206
X	207	994	596
XI	691	1987	1463
XII	109	399	287
XIII	447	1313	878
XIV	769	2793	1739
XV	892	2136	1561
XVI	1302	2058	1695
XVII	483	1124	862
XVIII	1111	1914	1559

The vehicle count obtained at each mid-block section for every 5 minutes interval was aggregated to hourly vehicle count. Then it was converted to PCU using PCU factors and the total traffic volume was computed. The total traffic volume (PCU/hr) in each mid-block section during the period of data collection is given in Table 5.3.

Table 5.3 Total traffic volume in road mid-block sections

RMB ID	7.00 AM-8.00AM	8.00AM-9.00AM	9.00AM-10.00AM	10.00AM-11.00AM	5.00PM-6.00PM	6.00PM-7.00PM	7.00PM-8.00PM	8.00PM-9.00PM
I	903	1147	1398	1353	1597	2123	2720	2498
II	971	1234	1685	2018	1774	2163	2647	2384
III	689	958	1251	1649	1695	2117	2583	2193
IV	689	958	1251	1649	1695	2117	2583	2193
V	623	977	1461	1904	2044	2385	2898	2713
VI	785	1124	1557	2023	1958	2031	2387	2071
VII	720	994	1461	1804	1929	2565	3568	3673
VIII	964	1304	1655	2190	2716	3286	3653	3525
IX	121	249	339	412	443	508	635	586
X	414	548	949	1088	1275	1548	1988	1731
XI	1382	1788	2511	3342	3141	3589	3973	3686
XII	217	366	540	630	630	696	797	711
XIII	894	1124	1476	1713	1707	1971	2532	2625
XIV	1538	2038	2446	3192	3595	4522	5586	4914
XV	1784	2207	2662	3290	3046	4126	4271	3591
XVI	2604	2691	3408	3748	3366	3760	4116	3430
XVII	967	1250	1491	1910	1864	2058	2248	2009
XVIII	2222	2489	2874	3436	3216	3499	3828	3372

The traffic volume is analyzed to understand the change in volume of traffic at different times of the day. The variation of traffic volume in different mid-block sections with respect to time of the day is shown in Figure 5.1. The highest traffic volume as 5586 PCU/hr is observed at RMB XIV (PT) during 7:00 PM to 8:00 PM. This section connects two major roads in Vijayawada city namely Eluru road and Bandar road that carries intercity traffic. Higher traffic volume is observed at this particular section. It is also noticed that the lowest traffic volume of 121 PCU/hr is observed at RMB IX (MR) during 7:00 AM to 8:00AM. It is due to this section connects a residential street with less traffic flow.

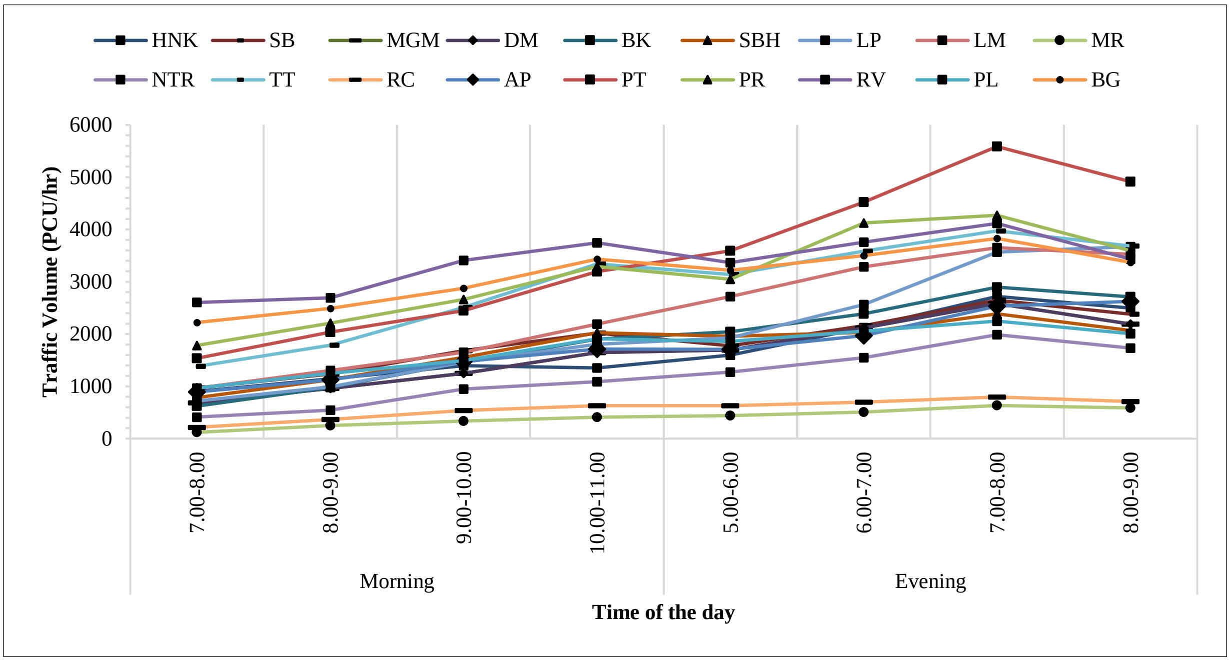


Figure 5.1 Variation of traffic volume with time

5.2.2 ANALYSIS OF POLLUTION CONCENTRATION

The variation of concentration of different air pollutants over time, has been analyzed. Six major pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10} are observed at the study locations at different time of the day. The concentration of pollutants are collected in the field for 8 hours (4 hours in the morning and 4 hours in the evening). The concentration of pollutants was noted for every 5 minutes and is aggregated for every 1 hour for each section as average value. The variation of CO, CO_2 and HCHO concentrations at different times in a day on selected mid-block sections is shown in Figures 5.2, 5.3 and 5.4. Similarly, the variation of TVOC, $PM_{2.5}$ and PM_{10} concentrations with respect to time were also analyzed.

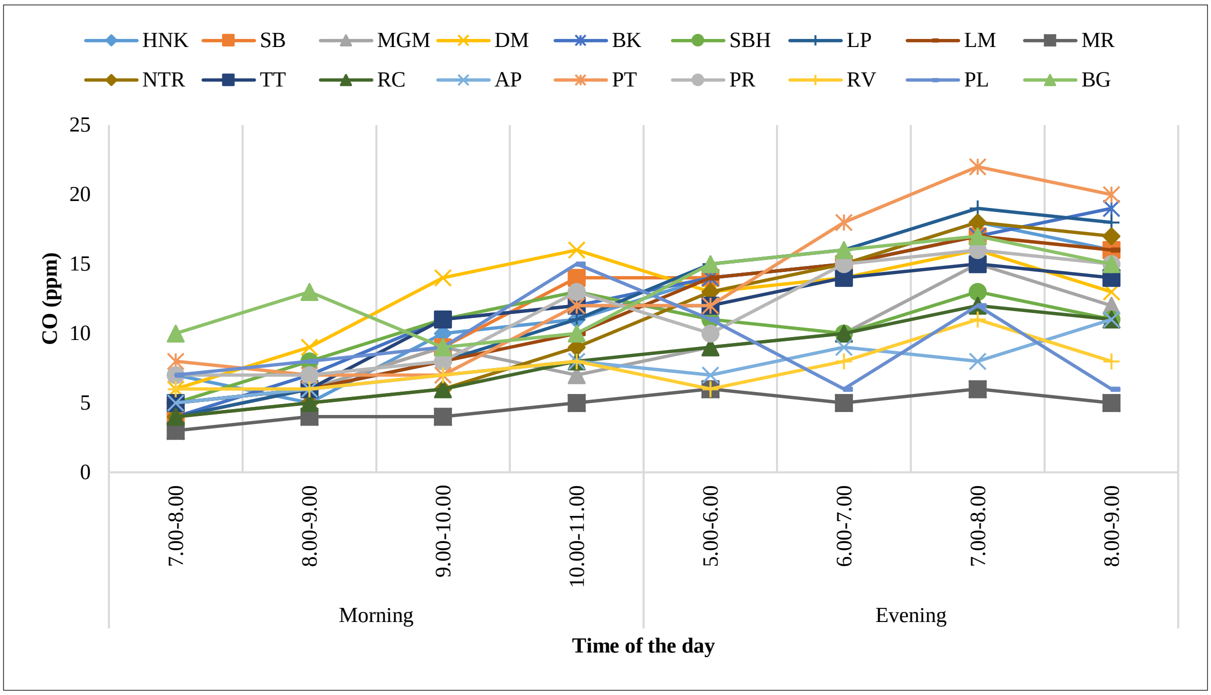


Figure 5.2 Variation of CO concentrations with time of the day

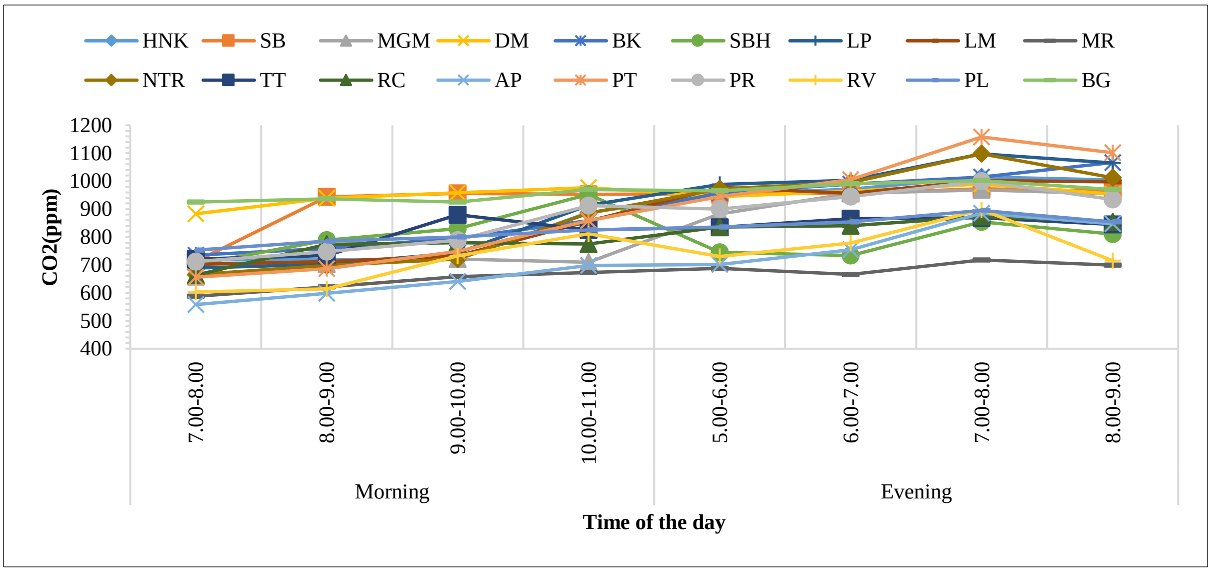


Figure 5.3 Variation of CO_2 concentrations with time of the day

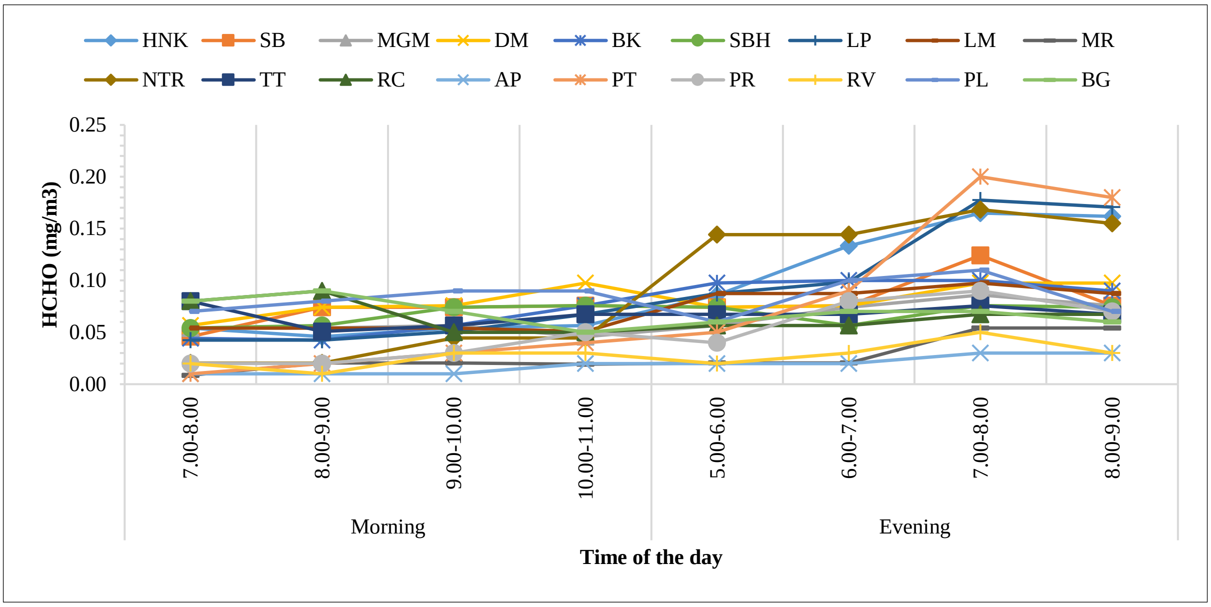


Figure 5.4 Variation of HCHO concentrations with time of the day

Figures 5.2 to 5.4 represents the variation in concentration of different pollutants with respect to time of the day. It is observed that higher values in concentration of pollutants is observed in between 6:00 PM to 9:00 PM in almost all the mid-block sections. It is also observed that the concentration of pollutants is higher in the day peak hours and evening peak hours of traffic volume mainly during 10:00 AM- 11:00 AM and 7:00 PM to 8:00 PM.

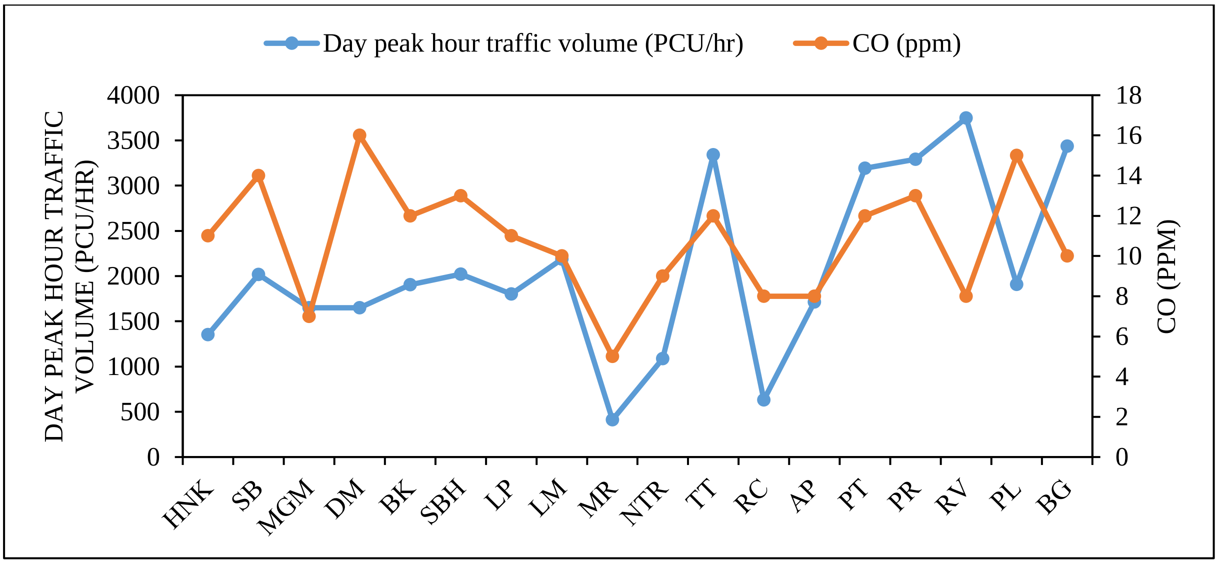


Figure 5.5 Variation of CO concentrations with traffic volume in morning peak hour

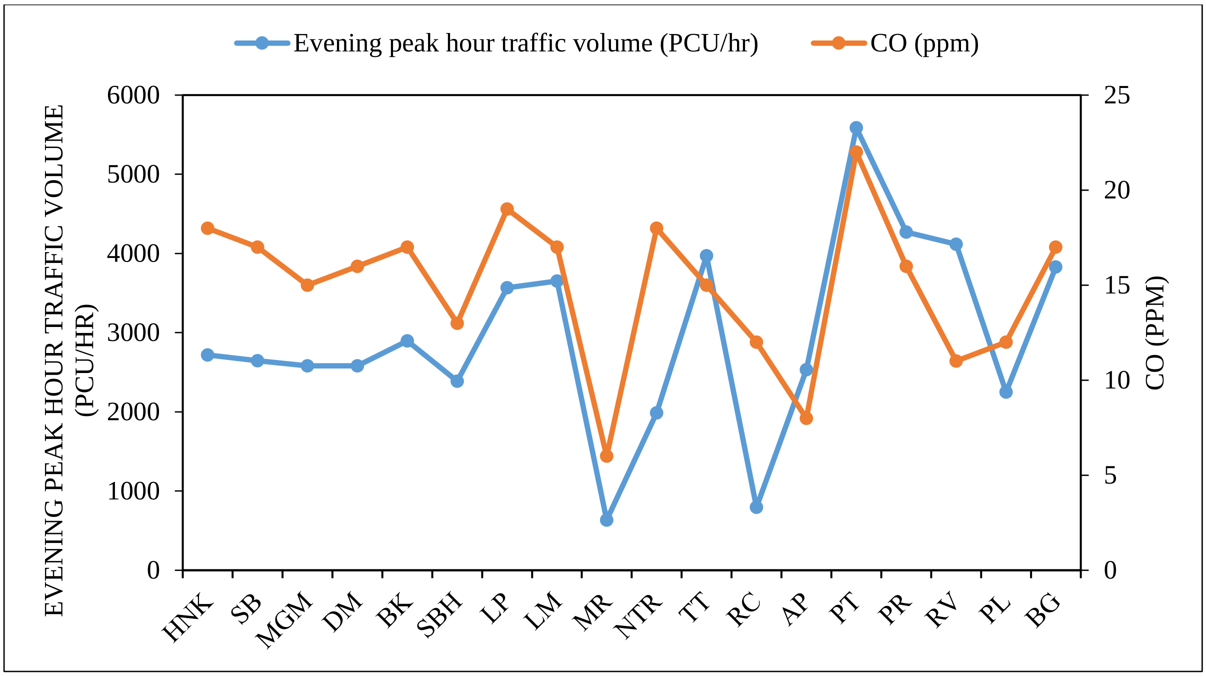


Figure 5.6 Variation of CO concentrations with traffic volume in evening peak hour

The variation of concentration of CO pollutant during day peak hour and evening peak hour traffic volume is presented in Figures 5.5 and 5.6 respectively. Similarly, the variation of other pollutants during day peak hour and evening peak hour traffic volume is given in Appendix 2.

The total pollution considering all mid-block sections data obtained for each hours has been computed. Total pollution is the sum of all six pollutants converted to same unit ppm. HCHO and TVOC concentrations are converted into ppm using Eq. (5.1). Similarly, $PM_{2.5}$ and PM_{10} concentrations are converted into ppm using Eq. (5.2).

$$\text{Concentration (ppm)} = 24.45 \times \text{concentration (mg/m}^3) \div \text{molecular weight} \quad (5.1)$$

$$\text{Concentration (ppm)} = \text{concentration } (\mu g/m^3) * 10^{-3} \quad (5.2)$$

The variation of total pollution observed at different mid-block sections with respect to time is shown in Figure 5.7. It indicates that highest pollution of 1180 ppm is observed at RMB XIV (PT) during 7:00 PM -8:00 PM. It correlates with the highest traffic volume as 5586 PCU/hr observed at section. The lowest pollution level as 671 ppm is observed at RMB IX (MR) during 7:00 AM – 8:00 AM. It also relates with lowest traffic volume.

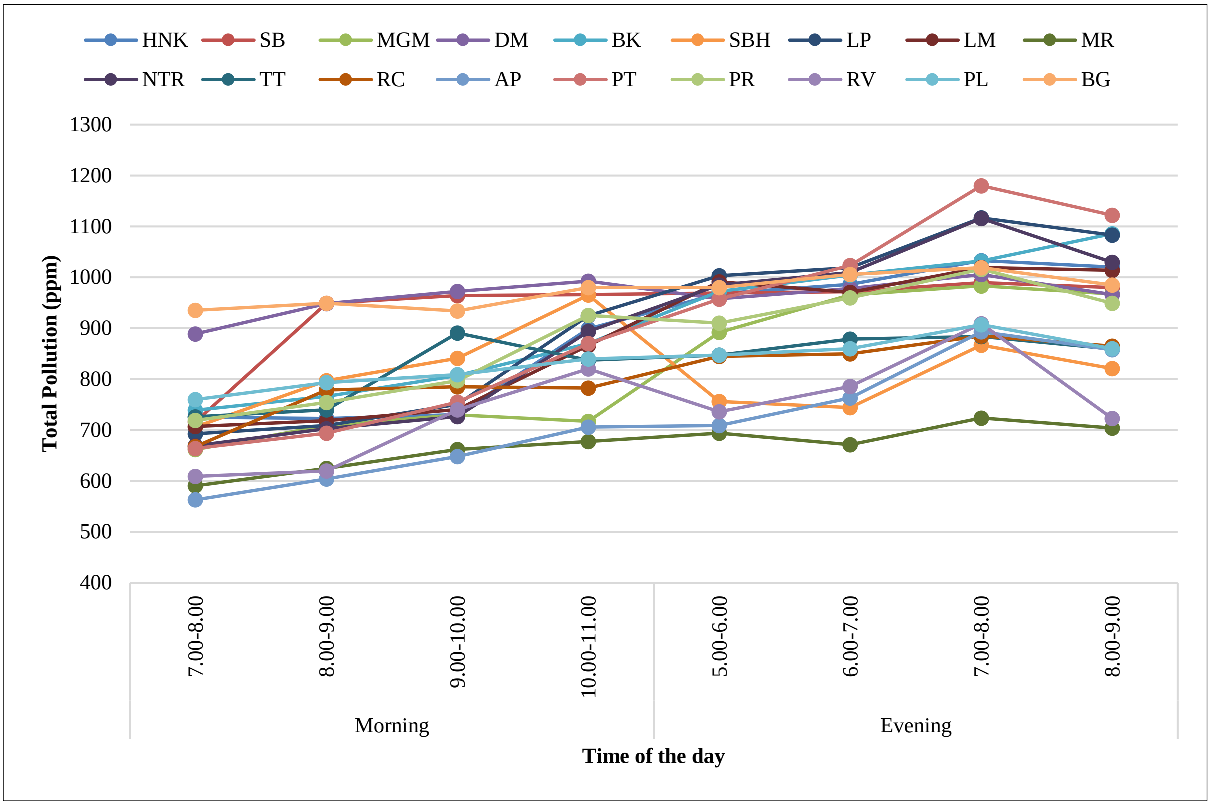


Figure 5.7 Total pollution on mid-block sections

5.2.3. SUMMARY OF CONCENTRATION OF POLLUTANTS

The distribution of concentration of pollutants data at different mid-block sections are shown in the box plots. The graphs summarizes the concentration of pollutants data observed in the field. The summary of the CO, CO2 and HCHO concentrations are shown in Figures 5.8, 5.9 and 5.10.

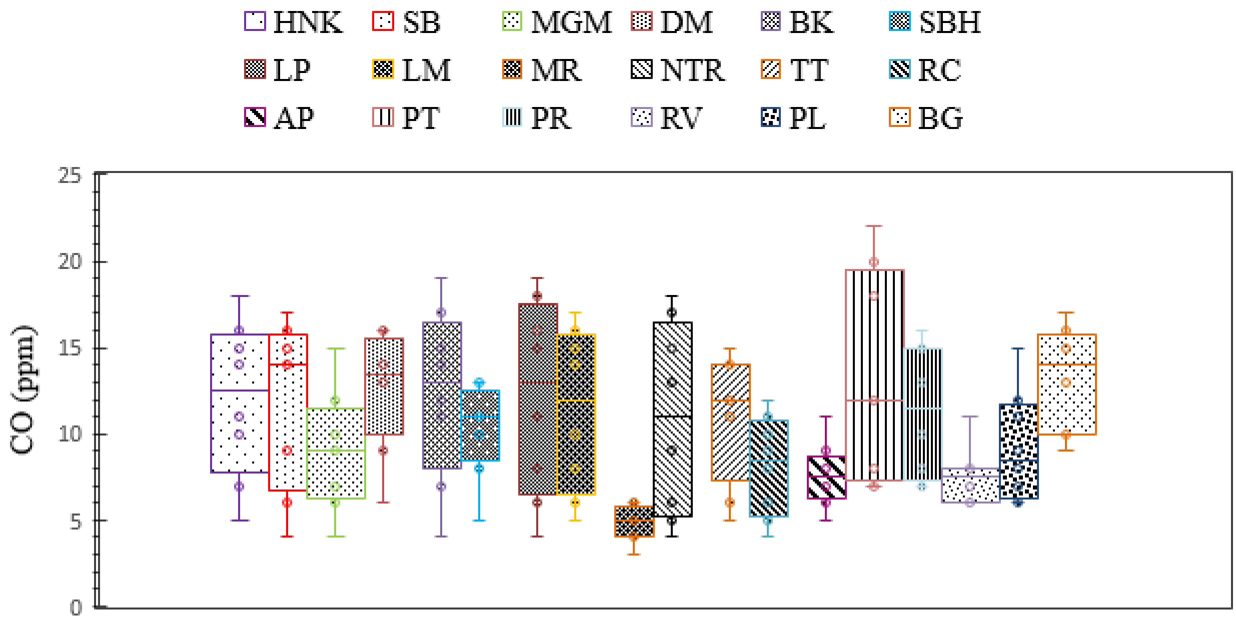


Figure 5.8 CO concentrations on mid-block sections

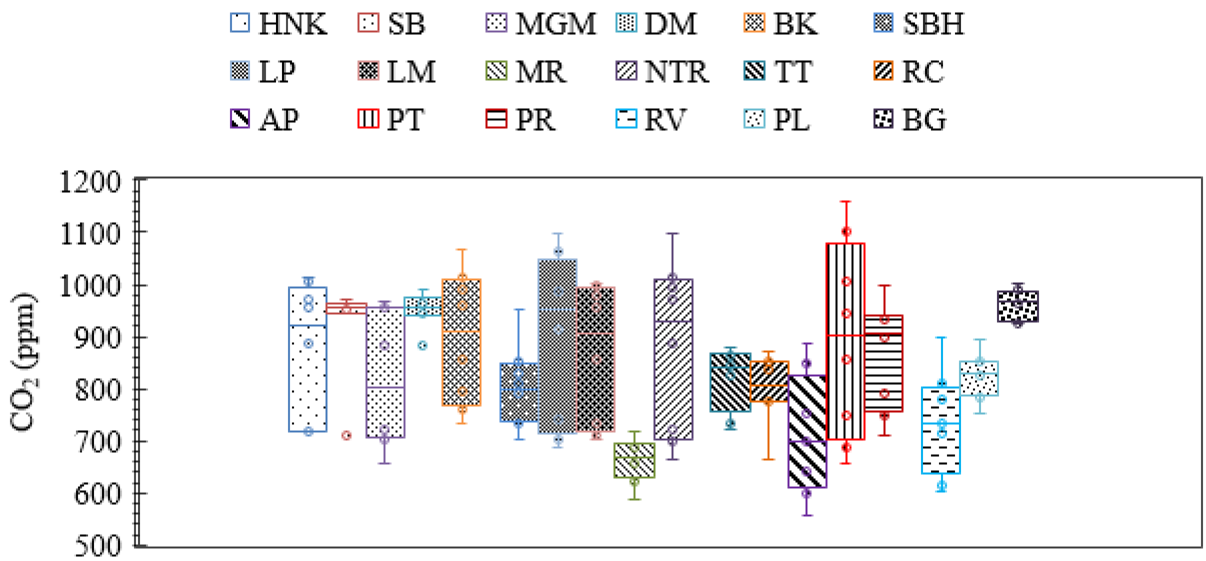


Figure 5.9 CO_2 concentrations on mid-block sections

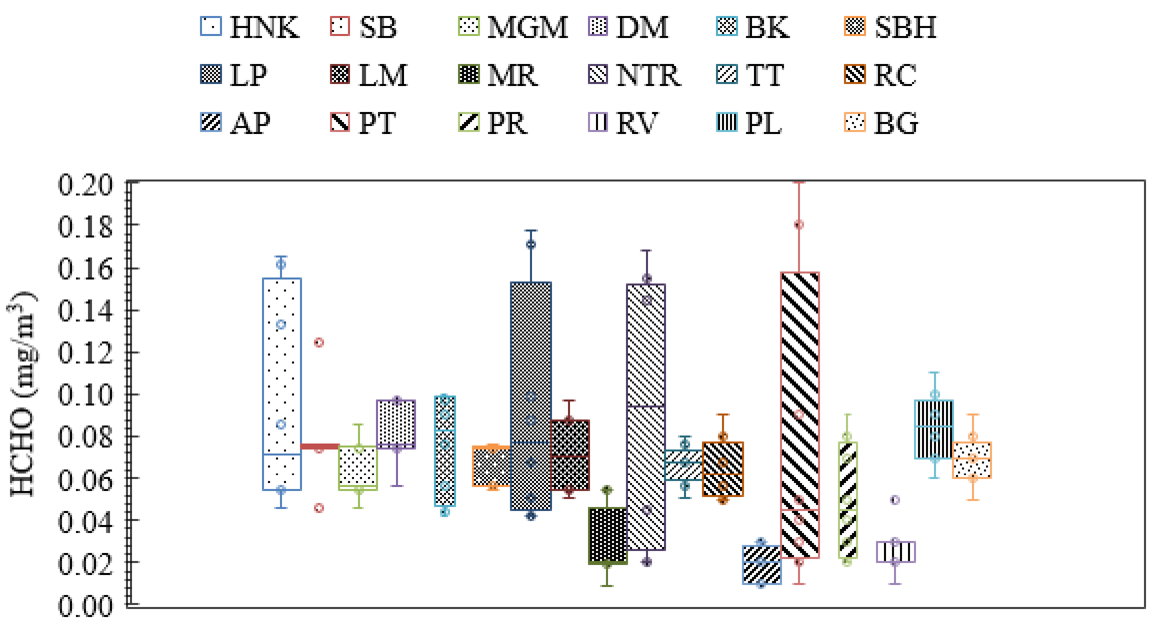


Figure 5.10 HCHO concentrations on mid-block sections

5.3 ANALYSIS OF DATA ON SIGNALIZED INTERSECTIONS

The concentration of pollutants data, traffic volume data, signal data, queued vehicles data and Air Quality Index data as observed in the field are analyzed over time of the day under varying traffic volume. The entering traffic volume, signal data, queued vehicles data was collected on each approach of the intersection. The data collected on each approach is averaged to obtain the values for whole junction.

5.3.1 ANALYSIS OF TRAFFIC VOLUME DATA

The classified traffic count collected from the field was converted to PCU using the necessary PCU factors. The conversion of traffic volume takes into account five types of vehicles: 2W, Car, 3W, LCV, and HV. The heterogeneous traffic volume was converted to a homogeneous one by employing a Passenger Car Unit (PCU) specific to each vehicle type. The PCU values provided by Indo-HCM (2017) were employed in the current investigation. The PCU factors used for the conversion of volume are given in Table 5.4.

Table 5.4 PCU factors for signalized intersections (INDO HCM 2017)

Vehicle type	2W	Car	3W	LCV	HCV
PCU factors	0.5	1	4	3.5	4.5

A descriptive analysis of entering traffic volume is performed, and useful information such as minimum, maximum, and average values are obtained at each signalized intersection as given in Table 5.5. The average entering traffic volume is observed to be higher at signalized intersections of Vijayawada city because of the higher traffic volume observed on all important intersections.

Table 5.5 Details of the entering traffic volume at signalized intersections

SI ID	Range of Entering Traffic Volume (PCU/hr)		Average Entering Traffic volume (PCU/hr)
	Minimum	Maximum	
I	3780	4597	4205
II	2906	3512	3180
III	4718	5599	5117
IV	1088	1904	1435
V	3284	4753	4032
VI	1778	2608	2173
VII	2298	5817	4535
VIII	2698	6081	4982
IX	1813	3581	3085

The entering traffic volume in PCU/hr computed at signalized intersections is given in Table 5.6.

Table 5.6 Entering traffic volume at signalized intersections in PCU/hr

SI ID	7.00 AM-8.00AM	8.00AM-9.00AM	9.00AM-10.00AM	10.00AM-11.00AM	5.00PM-6.00PM	6.00PM-7.00PM	7.00PM-8.00PM	8.00PM-9.00PM
I	3780	3875	4099	4267	4215	4392	4597	4415
II	2906	3006	3130	3333	2984	3159	3512	3406
III	4718	4743	4887	5001	5184	5320	5599	5480

IV	1088	1165	1224	1374	1575	1712	1904	1865
V	3284	3438	4018	4321	4018	4392	4753	4638
VI	1778	1905	2042	2167	2184	2215	2608	2487
VII	2298	3557	4554	5323	4775	5280	5817	4673
VIII	2698	3793	4930	5921	5291	5882	6081	5262
IX	1813	2573	3110	3637	3360	3581	3462	3142

The variation of traffic volume at time of the day is analyzed to understand the behavior of traffic volume at selected junctions. Figure 5.11 shows the variation of total traffic volume at different signalized intersections with respect to time. It indicates that highest traffic volume of 5921 PCU/hr is observed at SI III (GB) during 6:00 PM to 7:00 PM. This intersection involves many commercial activities going on in the evening time, so more traffic flow is noticed. The lowest traffic volume of 1088 PCU/hr is observed at SI IV (CP) during 7:00 AM to 8:00AM.

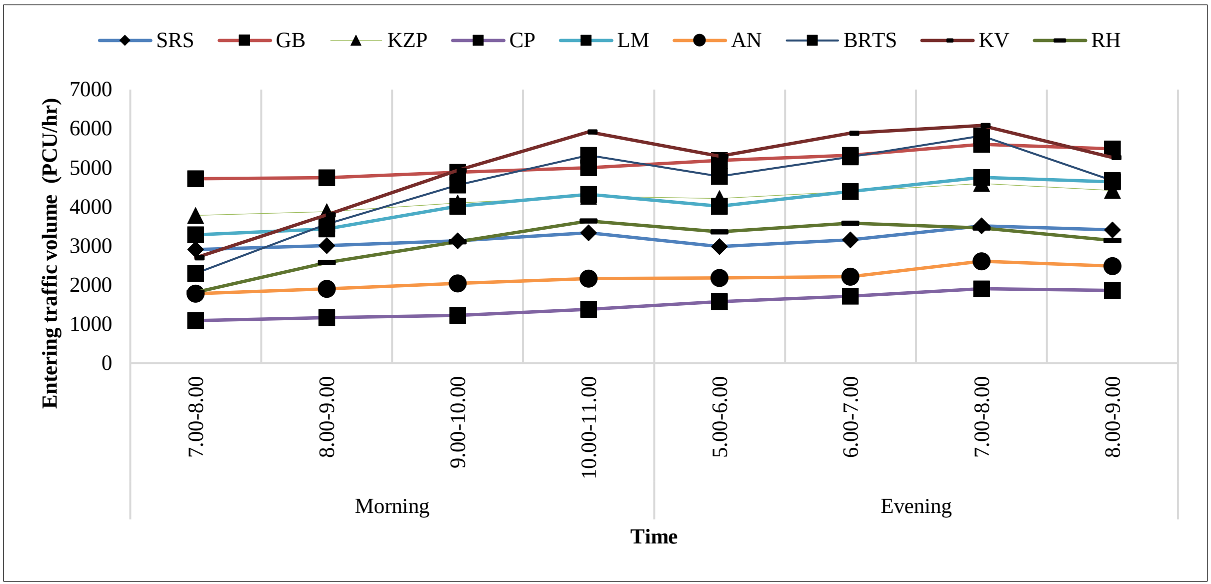


Figure 5.11 Variation of entering traffic volume with time of the day

5.3.2 ANALYSIS OF POLLUTION CONCENTRATION

The pollution data analysis involves variation of concentration of different air pollutants over time, estimation of total concentration of pollutants in the air and its analysis observed over time. At the study sites, six major pollutants are detected namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10}.The variation of TVOC, $PM_{2.5}$ and PM_{10} with respect to time in a day is analyzed and shown as sample in Figures 5.12, 5.13 and 5.14. Similarly, the variation of CO, CO_2 and HCHO concentrations over time are also analyzed.

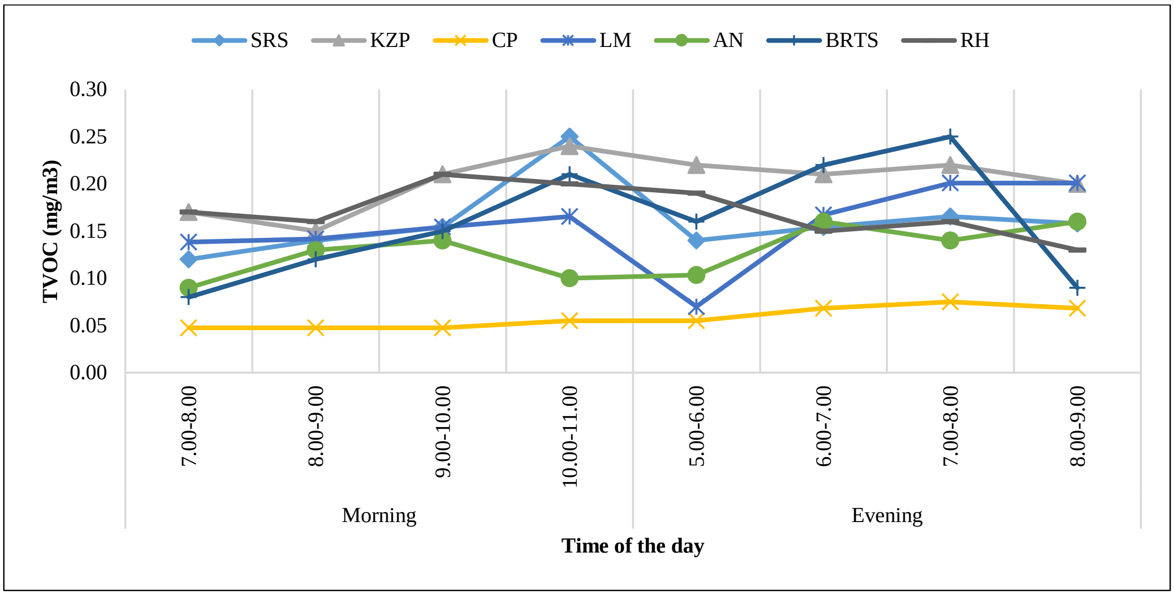


Figure 5.12 Variation of TVOC concentrations with time of the day

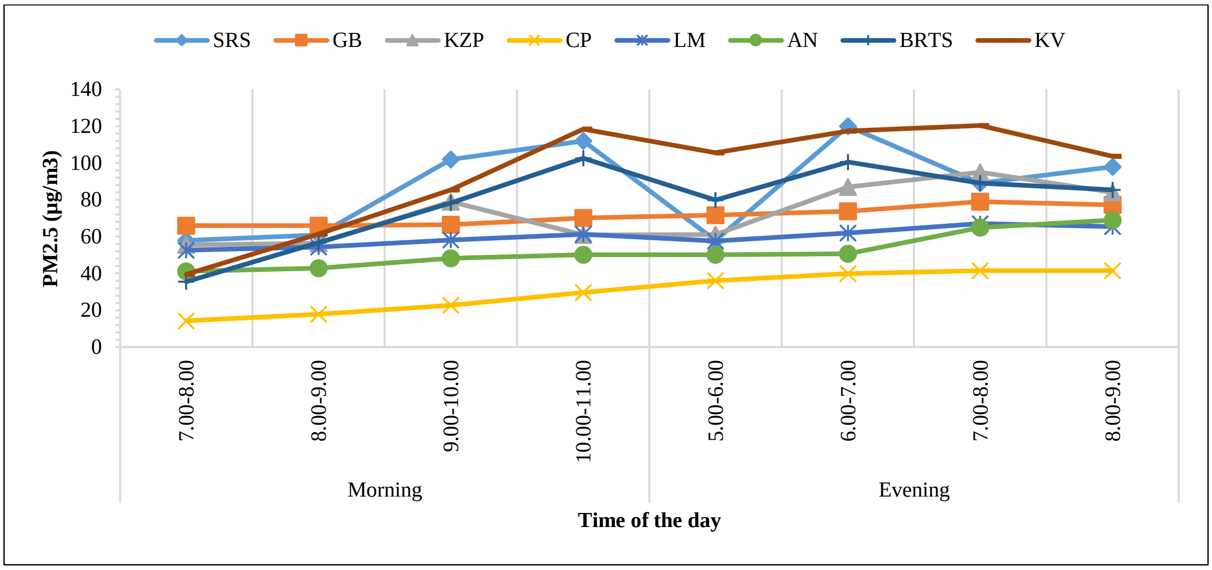


Figure 5.13 Variation of $PM_{2.5}$ concentrations with time of the day

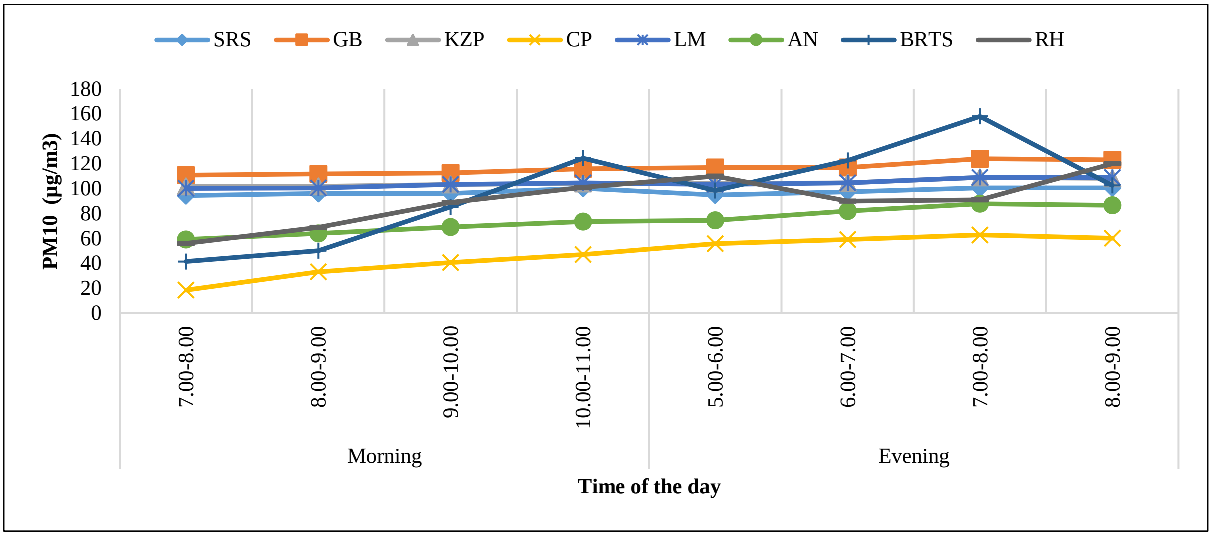


Figure 5.14 Variation of PM_{10} concentrations with time of the day

Figures 5.10 to 5.12 depict how different concentration of pollutants change in a day. Higher levels of concentration of pollutants are observed between 6:00 PM and 9:00 PM at selected signalized intersections. Concentration of pollutants are also higher during peak traffic hours, particularly between 10:00 AM and 11:00 AM and 7:00 PM and 8:00 PM. The variation of CO_2 concentrations during morning and evening peak hour traffic volume is shown in Figures 5.15 and 5.16 respectively. Similarly, the variation of other pollutants in morning and evening peak hour traffic volume is shown in Appendix 3.

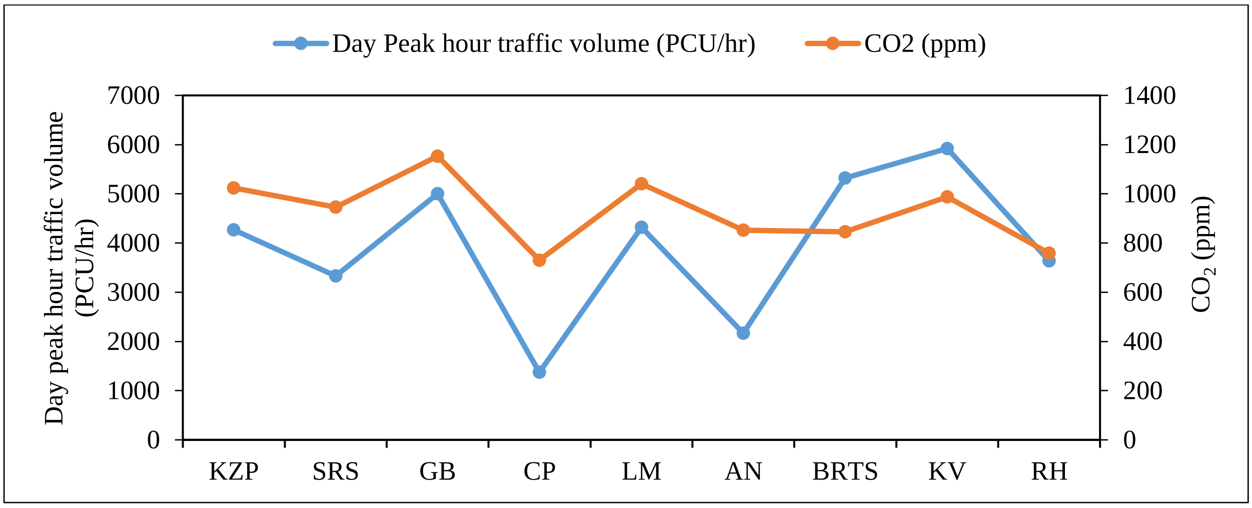


Figure 5.15 Variation of CO_2 concentrations with morning peak hour traffic volume

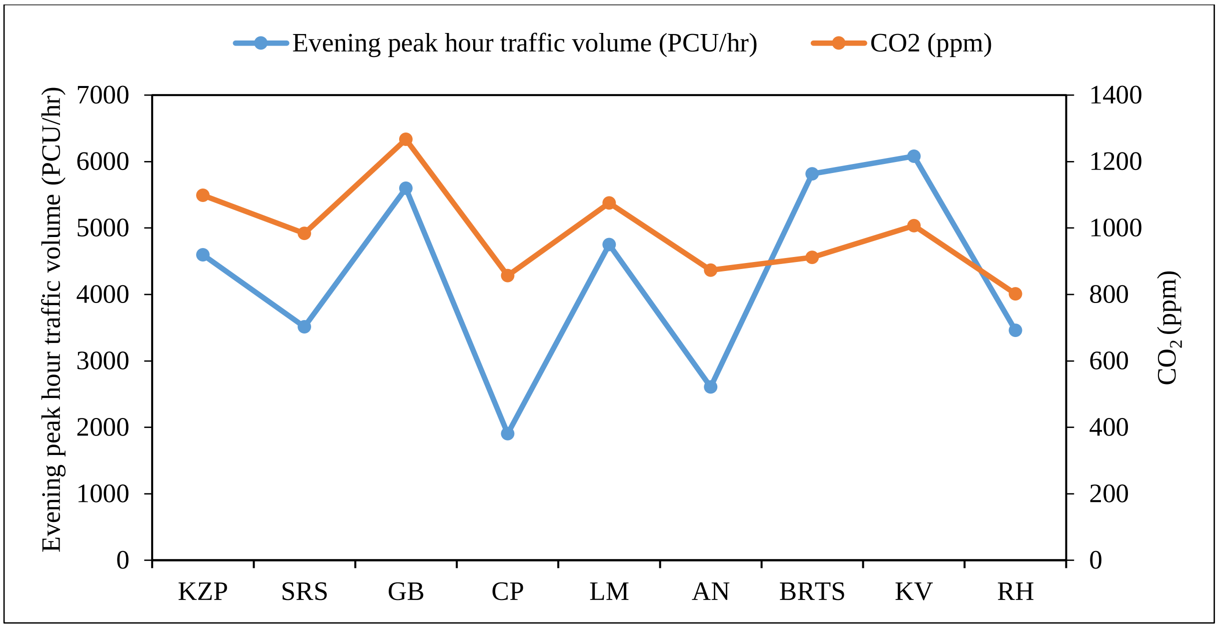


Figure 5.16 Variation of CO_2 concentrations with evening peak hour traffic volume

5.3.3 SUMMARY OF CONCENTRATION OF POLLUTANTS

The summary of concentration of pollutants data observed at signalized intersections is for HCHO, TVOC and PM2.5 are shown in Figures 5.17 to 5.19.

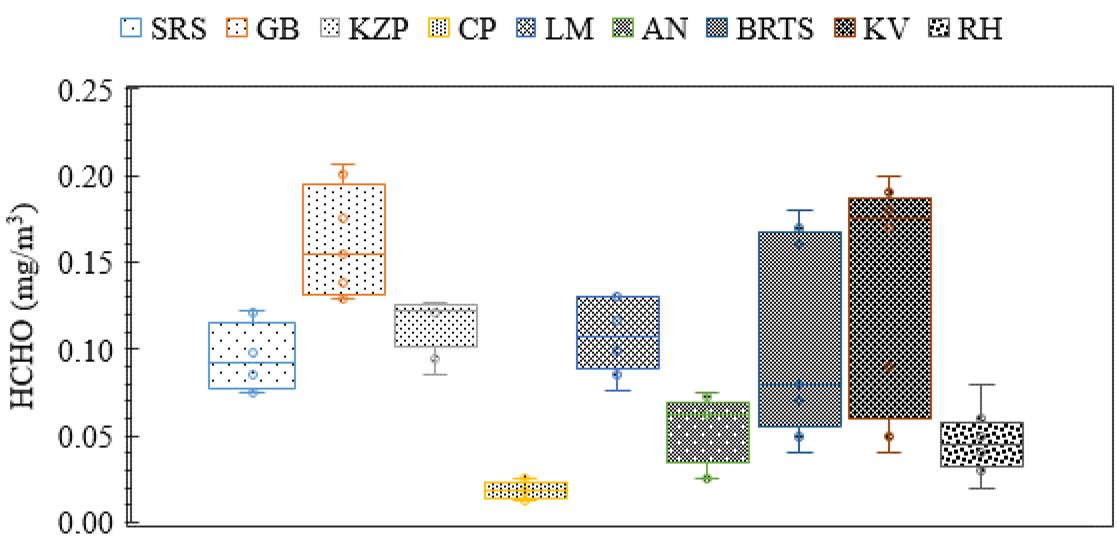


Figure 5.17 Summary of HCHO concentrations

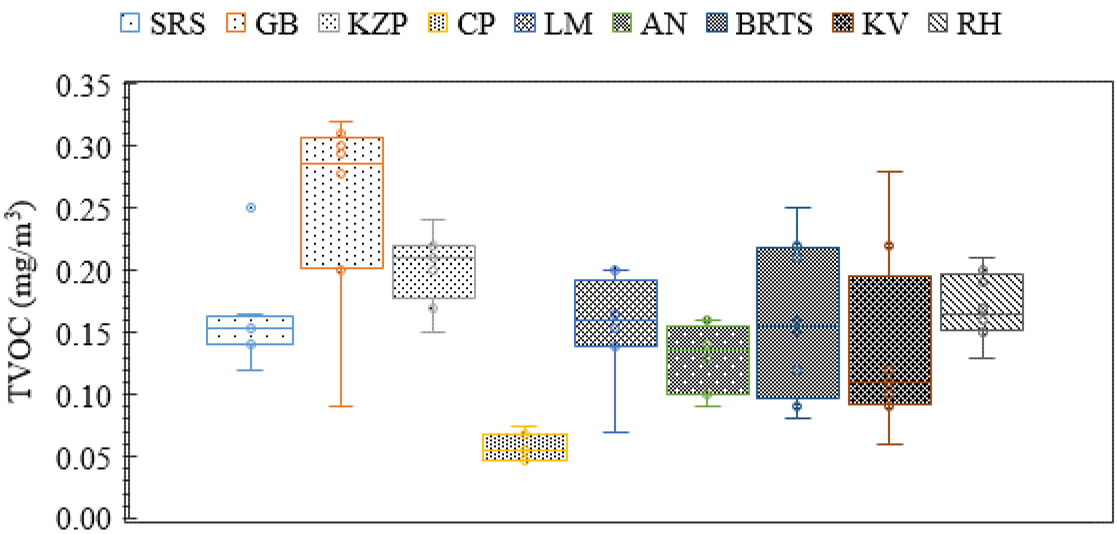


Figure 5.18 Summary of TVOC concentrations

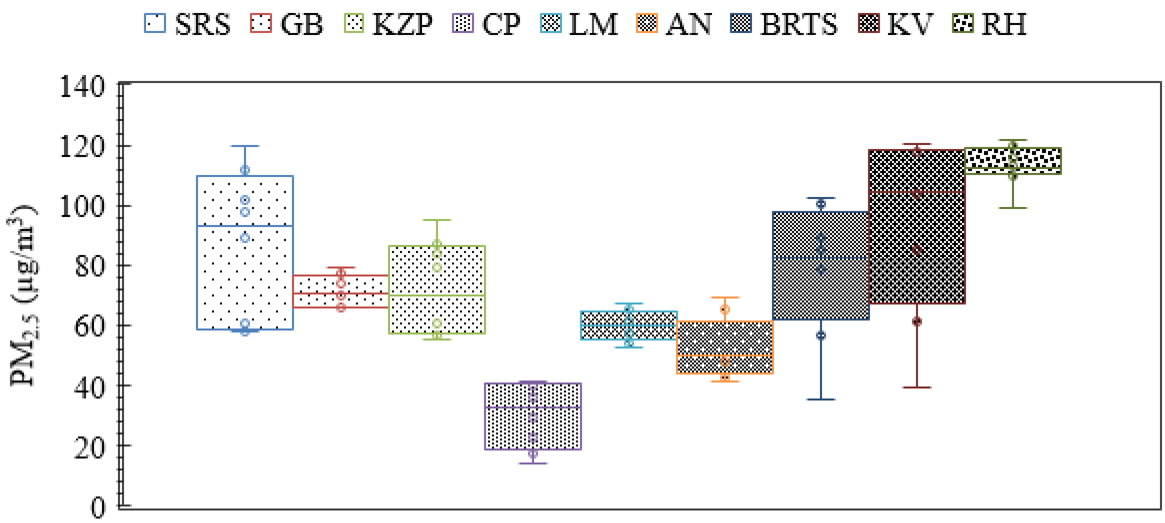


Figure 5.19 Summary of $PM_{2.5}$concentrations

5.3.4 TOTAL POLLUTION VARIATION WITH TIME

The total pollution at each signalized intersection for different hours is computed. The concentrations of different pollutants are converted into single unit ppm (as described in Section 5.2.2). The variation of total pollution observed at different signalized intersections with respect to time is shown in Figure 5.20. It indicates that the highest pollution of 1294 ppm is observed at SI III (GB) during 6:00 PM -7:00 PM. The highest traffic volume is also observed at this particular signalized intersection compared to other intersections. It is also noticed that lowest pollution of 700 ppm is obtained in SI IV (CP) during 7:00 AM – 8:00 AM.

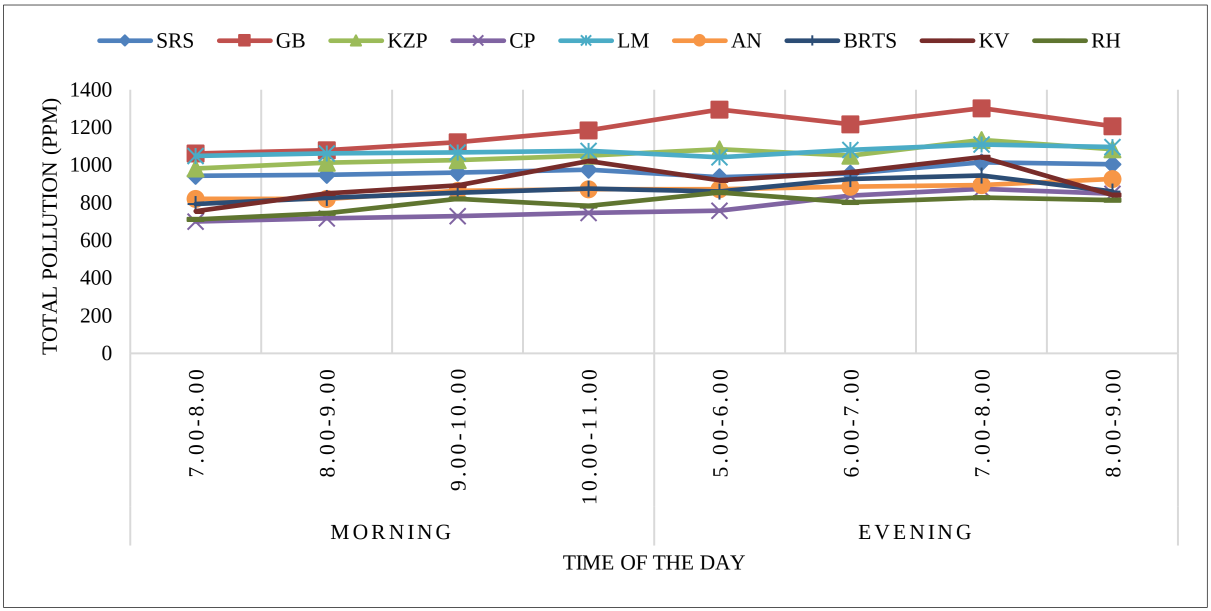


Figure 5.20 Total pollution with time at signalized intersections

5.4 ANALYSIS OF AQI DATA

AQI values are measured using the Laser particle multi-functional detector. The AQI in each mid-block section and signalized intersection for different hours is computed as average value for selected sections. The variation of AQI observed in different mid-block sections and signalized intersections, with respect to time is shown in Figures 5.21 and 5.22 respectively. Figure 5.17 indicates that the highest AQI value as 190 as observed on RMB XIV (PT) of Vijayawada during 7:00 PM – 8:00 PM. The lowest AQI value as 55 observed on RMB XIII (AP) of Vijayawada during 7:00AM – 8:00AM. Figure 5.18 indicates that the highest AQI value as 185 observed in SI VIII (GB) of Vijayawada during 10:00AM – 11:00 AM. The lowest AQI value as 53 is noticed in SI IV (CP) during 7:00 AM – 8:00 AM because of the lower traffic volume recorded at the intersection.

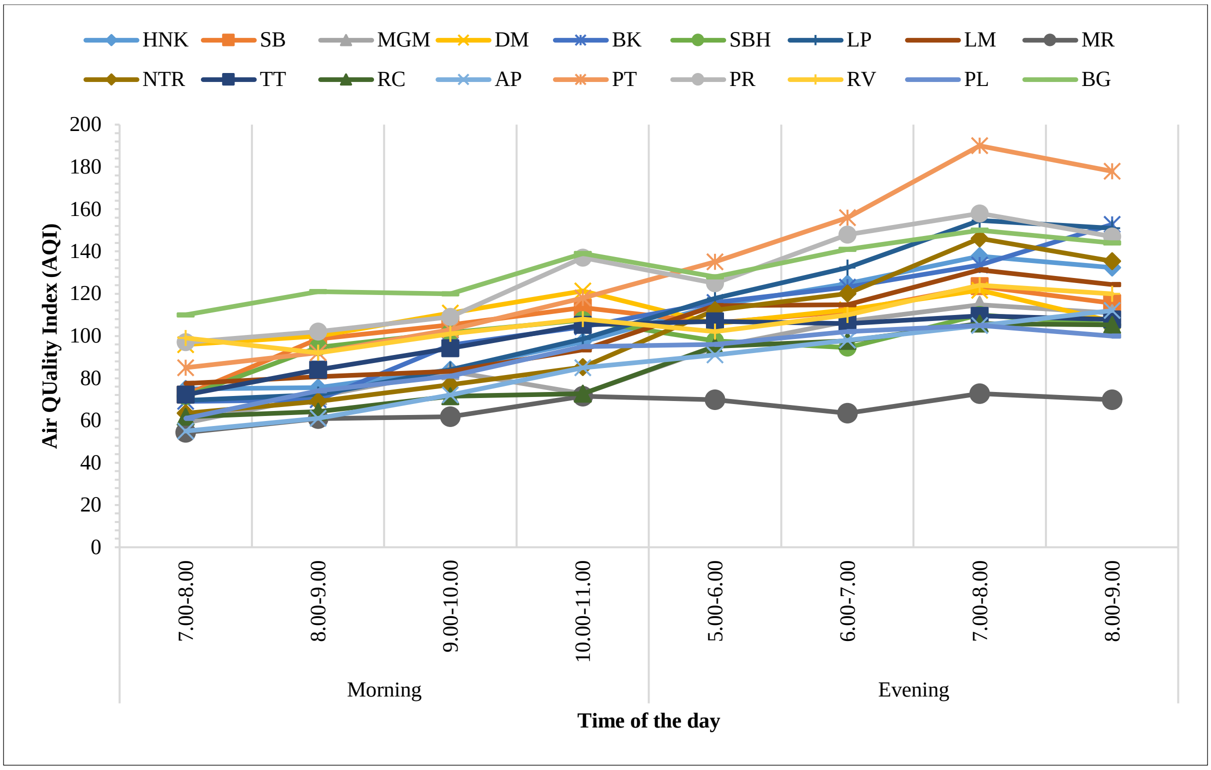


Figure 5.21 Variation of AQI over time at mid-block sections

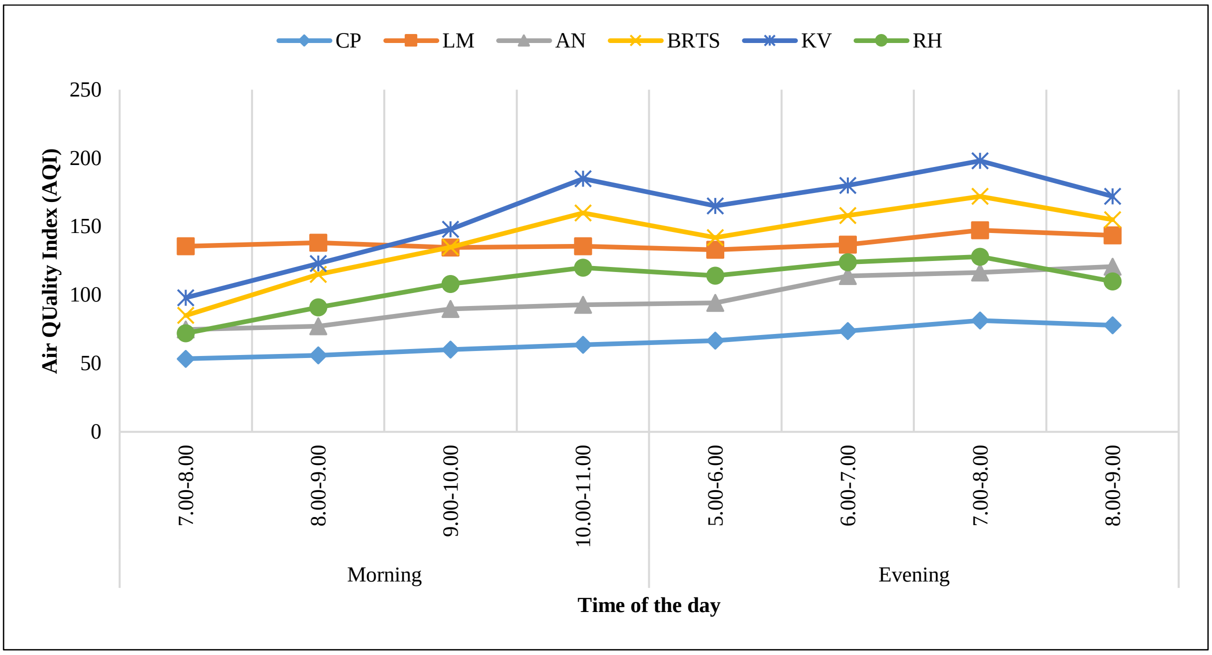


Figure 5.22 Variation of AQI over time at signalized intersections

5.5 SUMMARY

The present chapter explained the detailed analysis of different data such as traffic volume, concentration of pollutants and AQI. The results of the analysis were described in the chapter. The analysis on variation of concentration of pollutants over time and summary of the data collected are illustrated in detail in the present chapter. The models developed in the study to predict the concentration of different pollutants are explained in the subsequent chapter.

CHAPTER 6

DEVELOPMENT OF MODELS FOR MEASURING AIR QUALITY AND EMISSIONS

6.1 GENERAL

The present chapter discusses the variables influencing the observed concentration of pollutants and AQI on road mid-block sections and signalized intersections. Modeling with emission data is also performed using secondary data obtained from PUC center at study locations. It also covers the validation of different prediction models for road mid-block sections and signalized intersections separately. This chapter also analyzes the status of air quality based on AQI measured at different locations in different cities.

6.2 CONCENTRATION OF POLLUTANTS MODELS FOR ROAD MID-BLOCK SECTIONS

The relationship between different variables can be analyzed using various modelling techniques. The present study implemented three different modelling techniques namely Multiple Linear Regression (MLR), Support Vector Regression (SVR) and Artificial Neural Networks (ANN) to predict the concentration of different pollutants on road mid-block sections. The concentration of pollutants is taken as dependent variable and proportional share of different type of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV}, traffic volume (V) and temperature (T) are considered as independent variables for all the models. The trend of traffic volume with concentration of each pollutant is analyzed on scatter plot. The plots for each pollutant are shown in Figures 6.1 to 6.6.

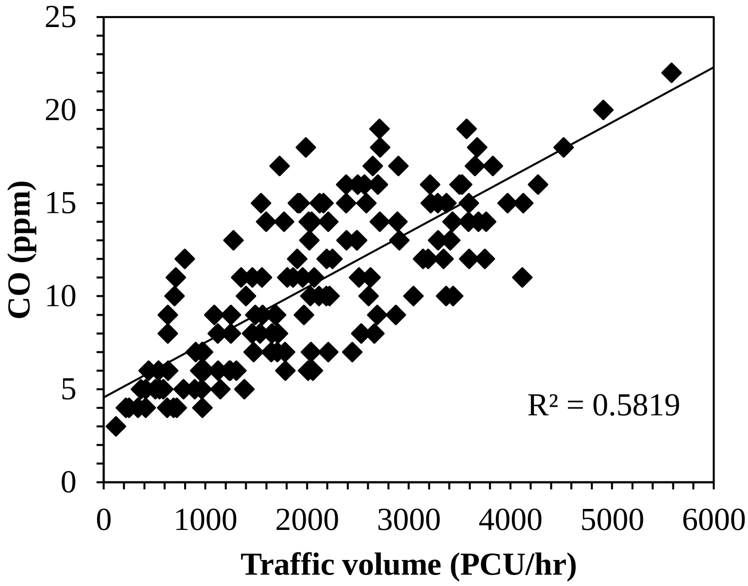


Figure 6.1Variation of CO with traffic volume

The range of CO values observed at different locations is found between 3ppm to 22ppm. The higher CO value of 22ppm is noticed at the maximum traffic volume of 5586 PCU/hr during 7:00 PM to 8:00 PM (RMB IV - DM) in Vijayawada city. The lower CO value of 3ppm is recorded at a traffic volume of 121 PCU/hr during 7:00 AM to 8:00 AM (RMB IX - MR) in Tirupathi city. The plot also indicates traffic volume and time of the day are two major factors responsible for varying CO concentration values on road mid-block sections.

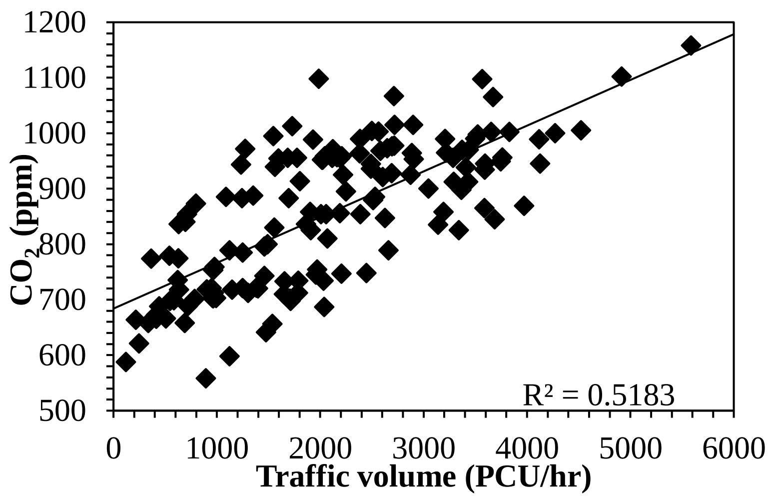


Figure 6.2 Variation of CO_2 with traffic volume

The CO_2 observed in field also increased highly with increase in traffic volume. The results indicates that the maximum value of CO_2 concentration observed as 1158ppm during 7:00 PM to 8:00 PM (RMB IV - DM) in Vijayawada city falls under the group of "unhealthy for sensitive groups" as per the standards given for the CO_2 equipment. It shows any further increase in CO_2 value may cause serious damage to the health of the people in the roadway vicinity.

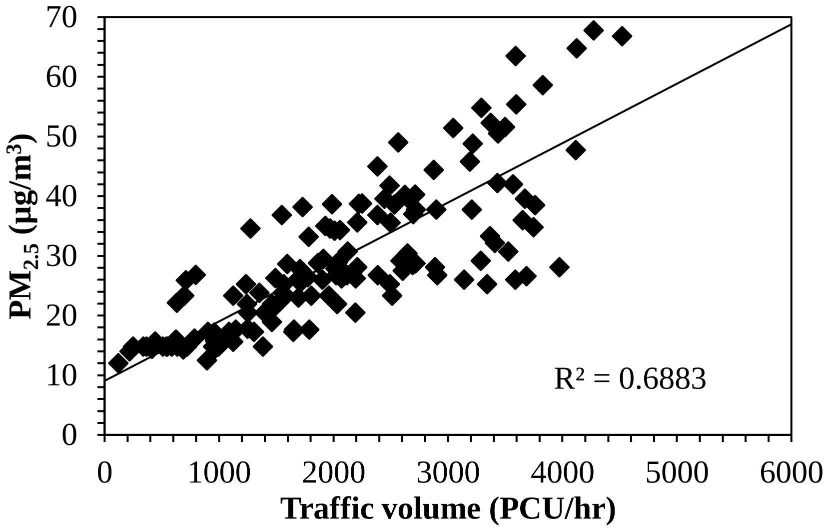


Figure 6.3 Variation of $PM_{2.5}$ with traffic volume

A relation between traffic volume and $PM_{2.5}$ showed a rise in $PM_{2.5}$ values with the increase in traffic volume. When the traffic volume is 4522 PCU/hr, the maximum value of $PM_{2.5}$as 67 µg/$m^3$is observed under the category of "unhealthy". The increase in traffic volume on road mid-block is responsible for rising of $PM_{2.5}$ values. Therefore, more the vehicle flow, more will be the release of particulate matter into the air.

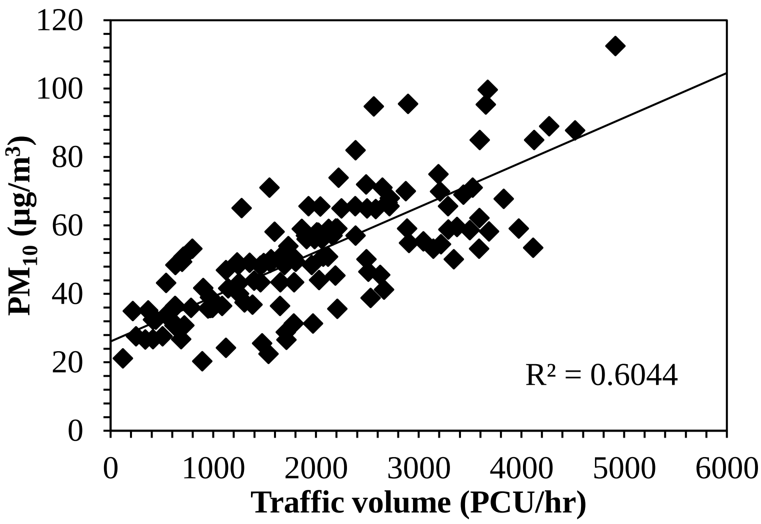


Figure 6.4 Variation of PM_{10} with traffic volume

The range of PM_{10} values is found between 21µg/m^3 to 113 µg/m^3. The maximum value of 113µg/m^3 observed in the field when the traffic volume reaches 4914 PCU/hr. PM_{10}concentrations falls under moderate level as per standards given for the PM_{10} equipment (details as given in Section 5.4). It is observed from the analysis that the increase in traffic volume causing an increase in PM_{10} values. Therefore, if there is further increase in traffic volume, it is expected to have a rise in PM_{10} concentrations.

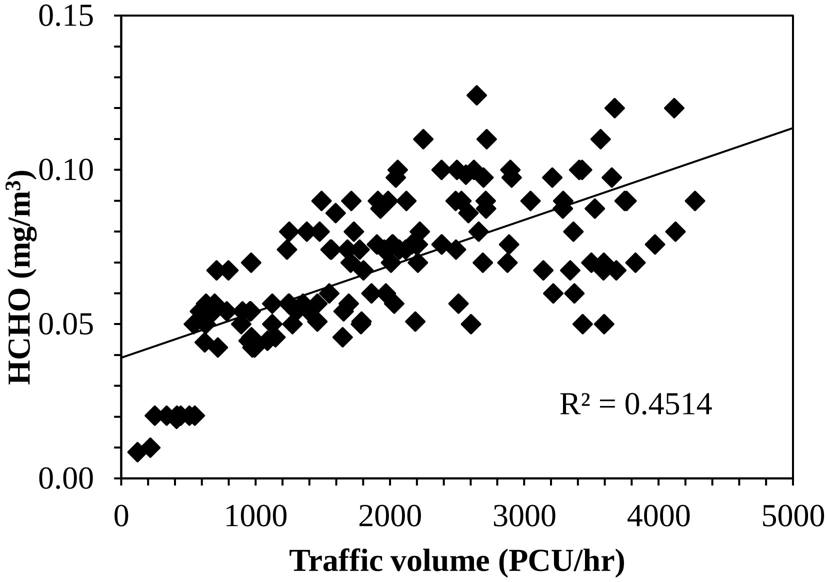


Figure 6.5 Variation of traffic volume with HCHO

In most of the cases there is an increase in HCHO values by 0.01 mg/m^3. It is also observed that there is an increase in HCHO values when there is rise in traffic volume. There are some cases where the HCHO values are greater than 0.1 which is unsafe condition as per the standards prescribed for the equipment.

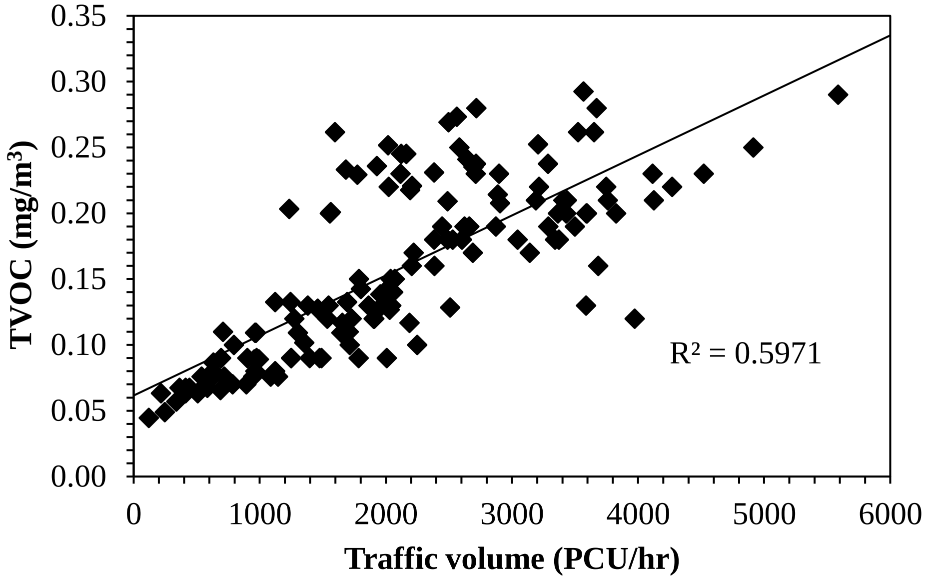


Figure 6.6 Variation of traffic volume with TVOC

According to the results, there is typically a 0.01 mg/m^3 increase in TVOC levels. Additionally, it has been noted that when traffic volume rises, TVOC values climb as well. It is also observed that, the range of TVOC values are in safe level as per the equipment standards.

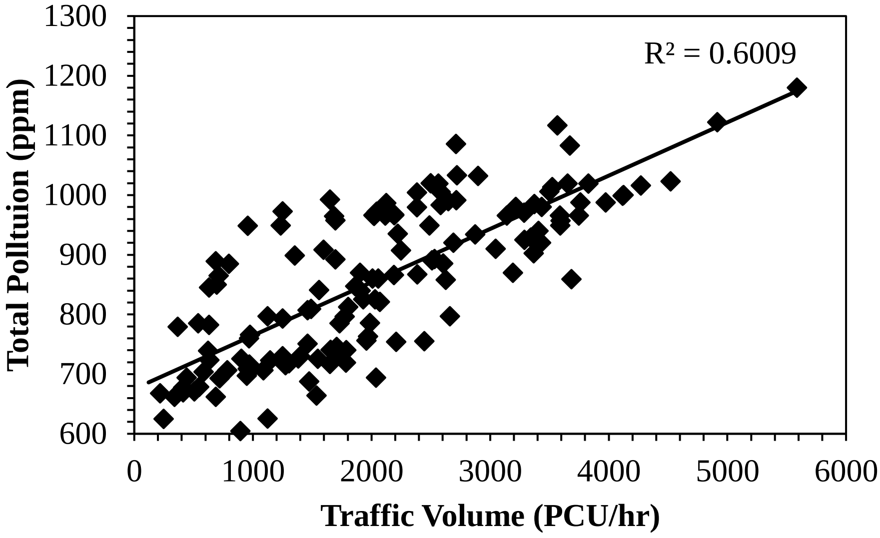


Figure 6.7 Variation of total pollution with traffic volume on road mid-block sections

The relation between observed traffic volume and total pollution estimated is examined. The relationship is shown in Figure 6.7. The total pollution at each location for different hours is computed. Total pollution is the sum of all six pollutants concentration by converting into same unit as ppm. The result indicates that there is a positive linear relationship between traffic volume and total pollution. The maximum pollution of 1180ppm is observed at a traffic volume of 5586 PCU/hr which is the maximum traffic volume recorded in the field.

6.2.1 DEVELOPMENT OF MLR MODELS

Correlation analysis has been performed between the proportional share of different type of vehicles, temperature, traffic volume and concentration of pollutants. The R-values obtained from the correlation analysis is shown in Table 6.1.

Table 6.1 Correlation values for concentration of pollutants and traffic variables

	P_{2W}	P_{Car}	P_{3W}	P_{LCV}	P_{HV}	T	V
CO	0.35	0.42	0.43	0.52	0.45	0.32	0.58

CO_2	0.35	0.45	0.53	0.35	0.41	0.51	0.52
HCHO	0.35	0.32	0.56	0.41	0.31	0.52	0.46
TVOC	0.38	0.42	0.49	0.52	0.23	0.50	0.59
$PM_{2.5}$	0.31	0.41	0.46	0.42	0.52	0.41	0.68
PM_{10}	0.32	0.41	0.52	0.43	0.44	0.49	0.60

Models were developed to predict concentration of different pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10} using MLR analysis. The field data collected at 12 road mid-block sections are considered for model development. The data obtained on four road mid-block sections from each city with RMB ID's I, II, III, and IV from Warangal city, VII, VIII, IX, and X from Tirupathi city, XIII, XIV, XV, and XVI from Vijayawada city is considered for model development. The concentrations of pollutants are taken as dependent variables and proportional share of different types of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV}, traffic volume and temperature are considered as independent variables. The models developed to predict the concentration of pollutants obtained the R^2 value as about 0.6. The MLR models for each pollutant are developed as given in Eq. (6.1) to (6.6). The outputs of the MLR analysis is given in Table 6.2. The results of the regression analysis indicate that percentage of 3W, percentage of LCV and traffic volume are the parameters influencing the concentration of different pollutants.

$$CO = 0.49 + 137.31 \times P_{LCV} + 0.002 \times V \tag{6.1}$$

$$CO_2 = 418.45 + 1437.03 \times P_{3W} - 4.80 \times T + 0.04 \times V \tag{6.2}$$

$$HCHO = 0.01 + 0.36 \times P_{3W} - 0.02 \times T + 0.0007 \times V \tag{6.3}$$

$$TVOC = 0.03 + 0.55 \times P_{3W} - 0.005 \times T + 1.71 \times P_{LCV} \tag{6.4}$$

$$PM_{2.5} = 7.38 + 166.32 \times P_{HV} + 0.01 \times V \tag{6.5}$$

$$PM_{10} = 28.54 + 183.17 \times P_{3W} - 1.12 \times T + 0.007 \times V \tag{6.6}$$

Table 6.2 Regression outputs of the MLR models developed at road mid-block sections

Dependent variable	Independent variables	p-value	t-stat value	R^2	Adjusted R^2
CO (ppm)	Intercept	0.004	2.92	0.68	0.67
	P_{LCV}	0.000	11.68		
	Traffic volume	0.000	9.41		
CO_2 (ppm)	Intercept	0.000	8.10	0.70	0.71
	P_{3W}	0.000	9.52		
	Temperature	0.020	-2.35		
	Traffic volume	0.000	6.34		
HCHO (mg/m^3)	Intercept	0.001	2.15	0.61	0.61
	P_{3W}	0.000	6.00		
	Temperature	0.003	-3.04		
	Traffic volume	0.006	2.76		
TVOC (mg/m^3)	Intercept	0.041	1.98	0.80	0.79
	P_{3W}	0.000	3.58		
	Temperature	0.000	-4.07		
	P_{LCV}	0.022	2.32		
$PM_{2.5}$ ($\mu g/m^3$)	Intercept	0.000	6.11	0.74	0.73
	P_{HV}	0.000	4.81		
	Traffic volume	0.000	16.13		
PM_{10} ($\mu g/m^3$)	Intercept	0.033	2.16	0.66	0.65
	P_{3W}	0.000	7.21		
	Temperature	0.005	-2.85		
	Traffic volume	0.000	7.03		

6.2.2 VALIDATION OF CONCENTRATION MODELS

The models developed to predict the concentration of each pollutant are validated. The data of 6 road mid-block sections with RMB ID's V, VI, XI, XII, XVII and XVIII is considered for models' validation. The RMB V and VI are in Warangal, XI and XII are in Tirupathi, XVII and XVIII are in Vijayawada city. The plots between the observed values and modelled values were obtained with a reference line of 45 degrees. The Chi-square test was performed to obtain the p-value for model validation. The p-values shown in the validation plots represent the results obtained from the Chi-square test and the value greater than 0.05 indicates that there is no significant difference between the observed and predicted values of concentrations. The validation plots for different pollutants are shown in Figures 6.8 to 6.13.

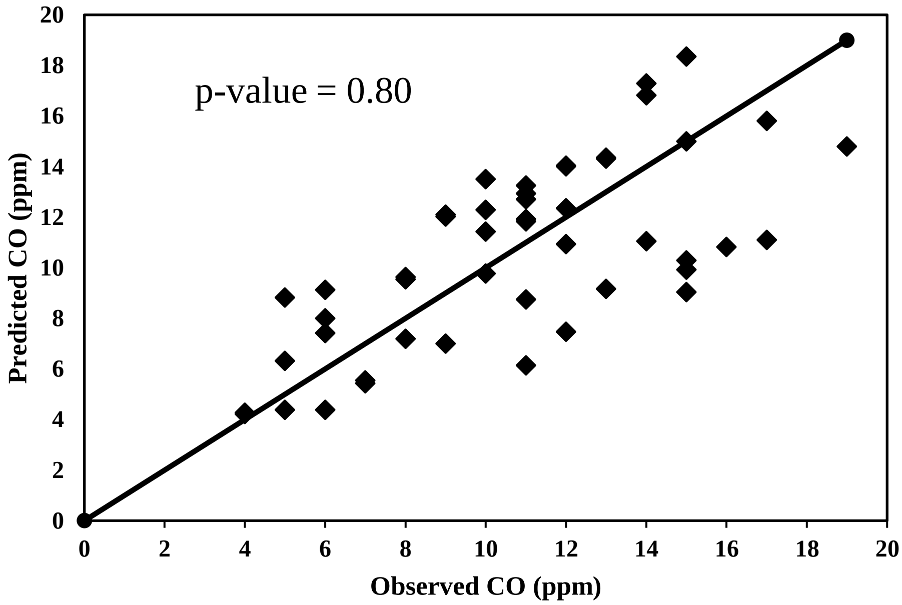


Figure 6.8 Validation plot for CO concentrations

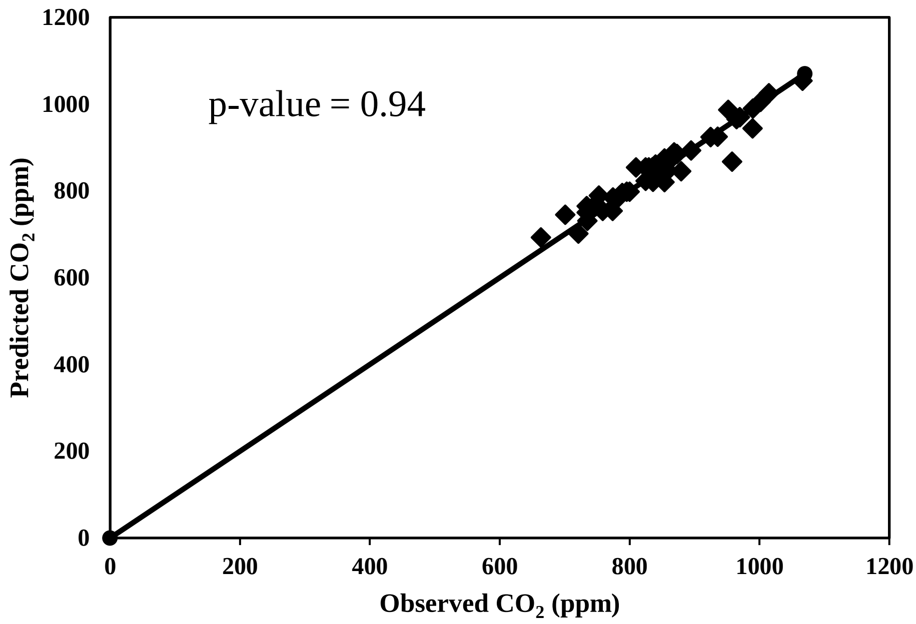


Figure 6.9 Validation plot for CO_2 concentrations

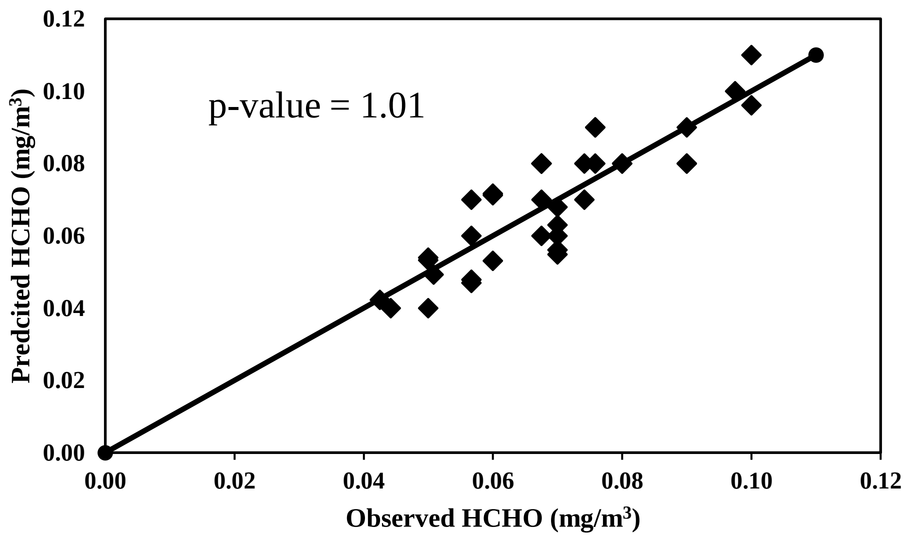


Figure 6.10 Validation plot for HCHO concentrations

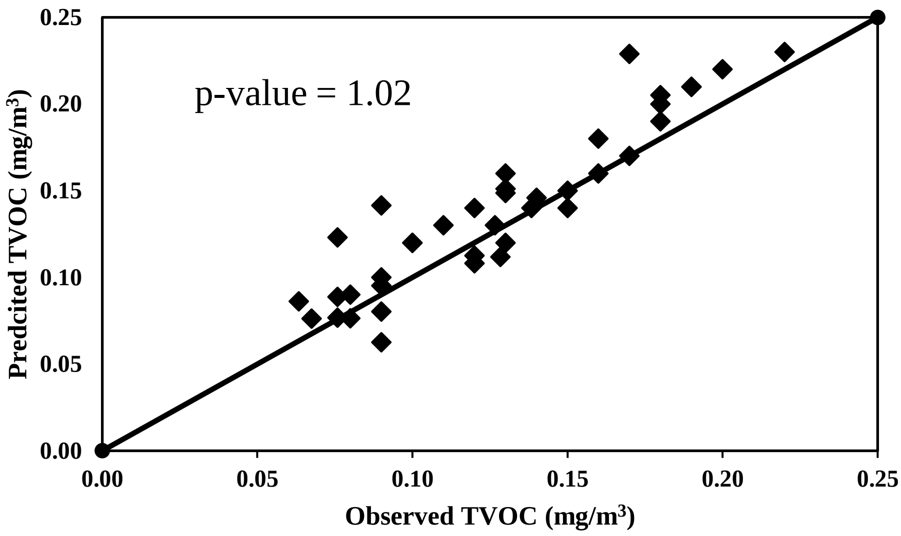


Figure 6.11 Validation plot for TVOC concentrations

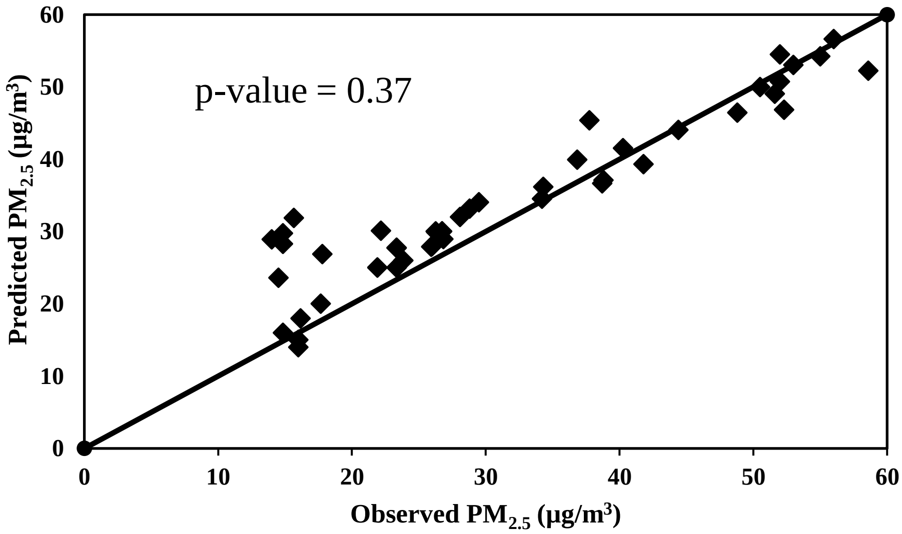


Figure 6.12 Validation plot for $PM_{2.5}$concentrations

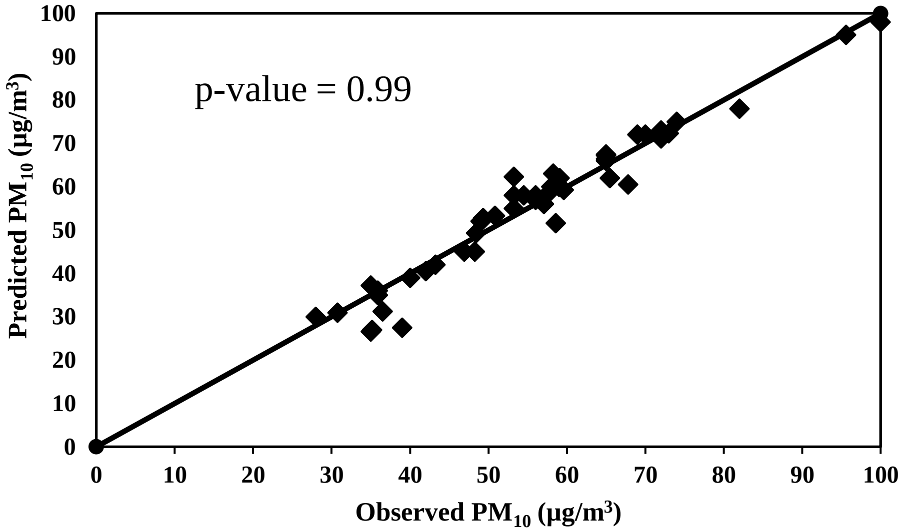


Figure 6.13 Validation plot for PM_{10} concentrations

6.2.3 DEVELOPMENT OF EMISSION MODEL

The emission model is generated utilizing a sample of pollution under control certificates (PUCs) obtained from the pollution center. These certificates comprise various vehicle specification parameters, including but not limited to the following: registration date, class, make, model, cylinder capacity, vehicle number, registration date, age, body type, fuel type, manufacturing date, cylinder capacity and CO_2, and CO emissions. To ascertain the true field emission, models have been developed with emissions serving as the dependent variable and emission norms (E_n), vehicle type (Veh_t), and age of vehicle (A_g) as independent variables. The MLR models developed for predicting the CO and CO_2 emissions are given in Eq. (6.7) and (6.8) The regression outputs are shown in Table 6.3.

$$CO = 2.677 + \left(0.00087 * A_g\right) - (3.2188 * Veh_t) + (0.00036 * E_n) \tag{6.7}$$

$$CO_2 = 18.52 + \left(0.086 * A_g\right) + (1.549 * Veh_t) - (0.263 * E_n) \tag{6.8}$$

Table 6.3 Regression outputs of emission models

		p-value	t-stat	R^2	Adjusted
CO	Intercept	0.001	18.293	0.73	0.72
	A_g	0.002	3.780		
	V_{eht}	0.001	-3.929		
	E_n	0.003	-0.595		
CO_2	Intercept	0.001	21.450	0.83	0.82
	A_g	0.001	-6.335		
	V_{eht}	0.005	1.673		
	E_n	0.011	-1.587		

The emission models developed are validated using 30% of the data collected in the field. The validation plots are drawn between observed emission values and predicted emission values. The validation is described using p-value obtained from Chi-square test. The results of the validation are shown in Figure 6.14 and 6.15.

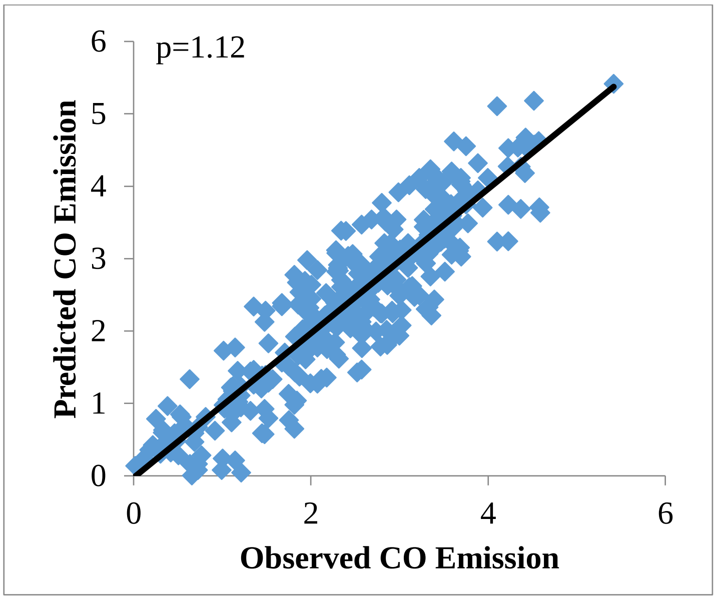


Figure 6.14 Validation plot for CO (% vol) emission

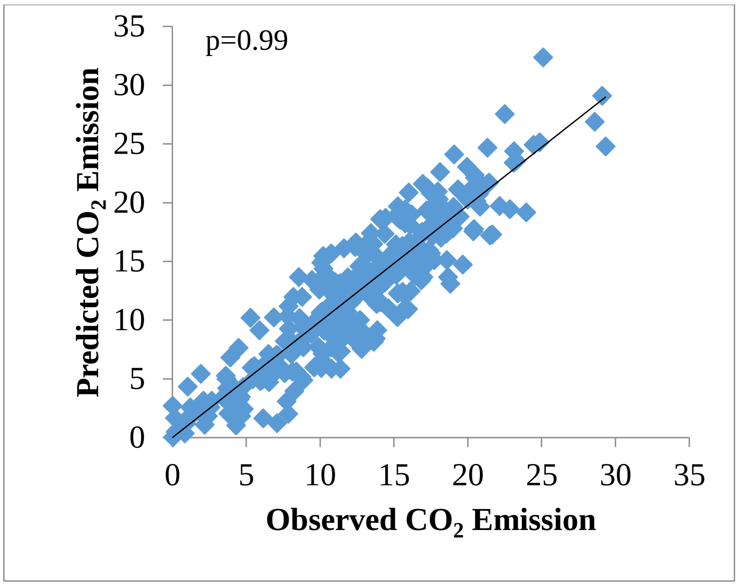


Figure 6.15 Validation plot for CO_2 (gm) emission

6.2.4 DEVELOPMENT OF SVR MODELS

The Support Vector Regression (SVR) modeling approach provides a robust framework for regression tasks. SVM technique is efficient in handling high-dimensional data and non-linear relationships. The present study implemented SVR in R-software to predict the concentration of different pollutants on road mid-block sections. SVR modelling considers 70% of the data for training and 30% of the data for testing. The SVM type taken for the regression is eps-regression. The SVM Kernel function used for the regression is radial. The confidence interval used for the regression is 95%. The libraries, functions and data assumptions used to develop the model is given as a sample in Figure 6.16.

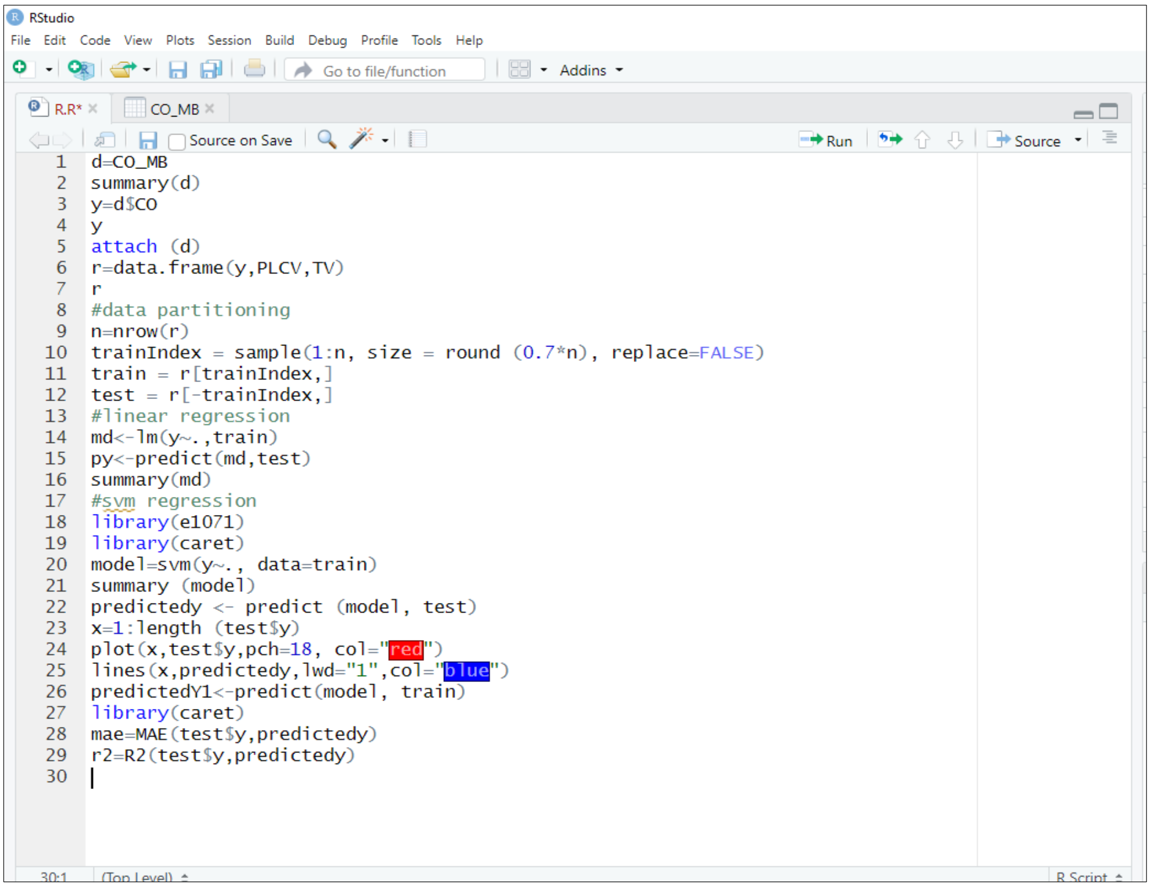


Figure 6.16 Sample data input for SVR model developed for mid-block sections

The proportional share of different type of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV}, traffic volume (V) and temperature (T) are considered explanatory variables and concentration of pollutants as dependent variables for all the models. The statistical outputs of support vector regression models developed in the study are given in Table 6.4.

Table 6.4 Regression outputs of the SVM models developed at road mid-block sections

Dependent variable	Independent variables	Co-efficient	p-value	t-stat value	R^2	Adjusted R^2
CO (ppm)	Intercept	1.75	0.002	3.12	0.72	0.71
	P_{LCV}	143.9	0.000	11.33		
	Traffic volume	0.001	0.000	9.49		

CO_2 (ppm)	Intercept	425.45	0.000	7.21	0.75	0.75
	P_{3W}	762.34	0.000	3.96		
	Temperature	-3.81	0.015	-2.22		
	Traffic volume	0.06	0.000	8.19		
HCHO (mg/m^3)	Intercept	0.004	0.001	2.24	0.65	0.66
	P_{3W}	0.028	0.000	4.42		
	Temperature	-0.002	0.004	-2.89		
	Traffic volume	0.0006	0.003	2.92		
TVOC (mg/m^3)	Intercept	0.001	0.041	2.01	0.85	0.86
	P_{3W}	0.42	0.021	2.92		
	Temperature	-0.003	0.042	-2.00		
	P_{LCV}	1.40	0.022	2.12		
$PM_{2.5}$ ($\mu g/m^3$)	Intercept	5.42	0.000	5.37	0.81	0.80
	P_{HV}	92.69	0.000	2.49		
	Traffic volume	0.02	0.000	14.29		
PM_{10} ($\mu g/m^3$)	Intercept	24.97	0.033	2.60	0.70	0.71
	P_{3W}	135.49	0.000	4.45		
	Temperature	-0.58	0.005	-2.15		
	Traffic volume	0.007	0.000	5.99		

The plots were generated for each SVM model showing the predicted concentration of pollutants. These plots represent the number of test samples on X-axis and the predicted values of concentration of pollutants on Y-axis. Each point in the plots represents the predicted values of various pollutant concentrations generated by SVR model. The trend line visualizes the pattern of the predicted values obtained. The results of the models indicate that the predicted values closely following the trend line representing the performance of each model. The plot for predicted values of TVOC is given as a sample in Figures 6.17.

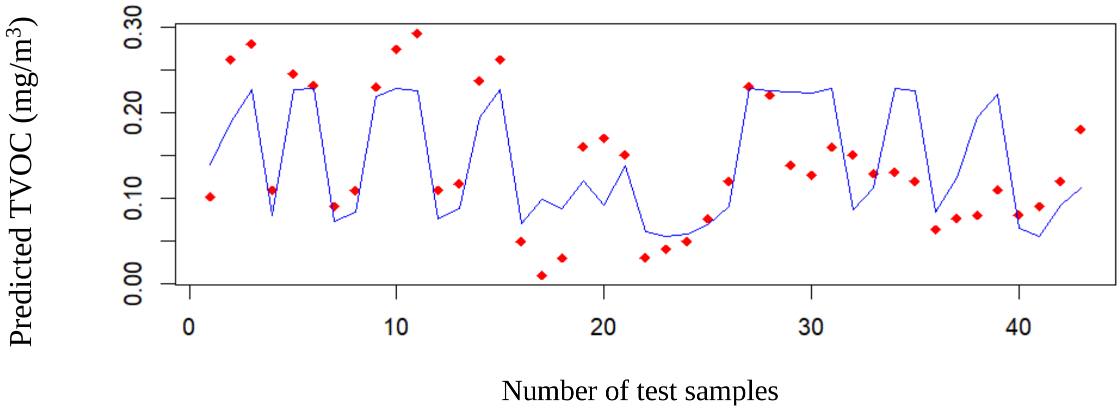


Figure 6.17 SVR model predicted TVOC concentrations

6.2.5 DEVELOPMENT OF ANN MODELS

The present study also used the ANN technique to predict concentration of pollutants based on proportional share of different type of vehicles. Multi-layered feed-forward ANN is used by considering concentration of pollutants as the output layer in this study, and proportional share of different type of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV}, traffic volume (V) and temperature (T) as input layers.

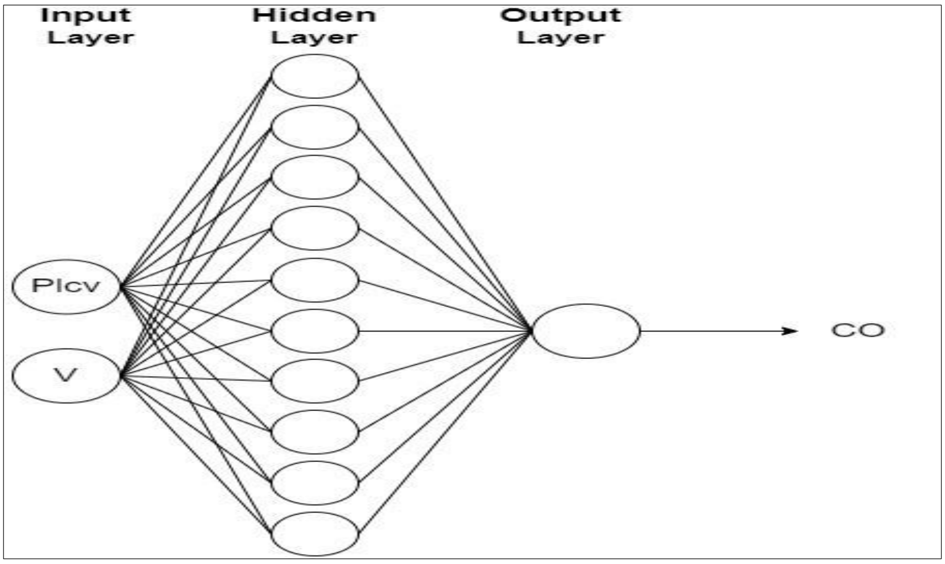
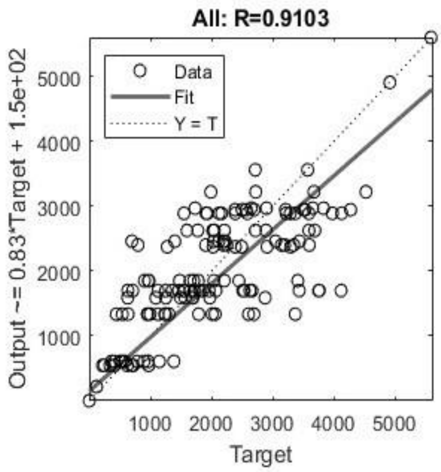
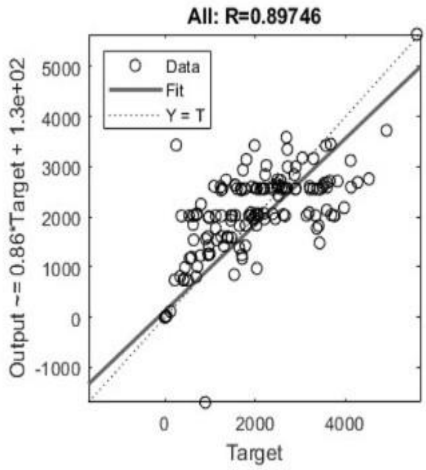


Figure 6.18 Neural network architecture for CO model

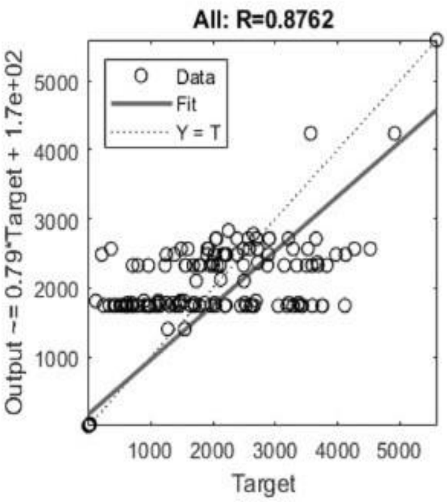
Different iterations were carried out by changing the number of hidden layers and neurons to obtain the optimal network structure. The network structure with less error between the measured and ANN modelled values is the optimal structure. The neural network structure (one input layer, one hidden layer with ten neurons and one output layer) obtained for CO model is shown as a sample in Figure 6.18. Similar neural network structures are obtained for all the pollutants. The output of ANN models is given in Figures 6.19.



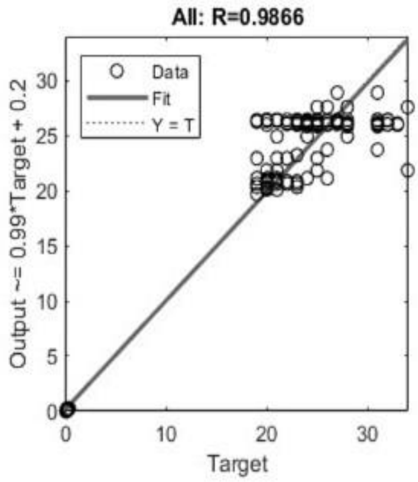
(a)



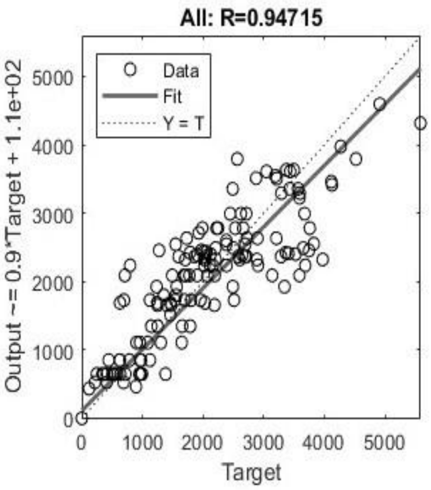
(b)

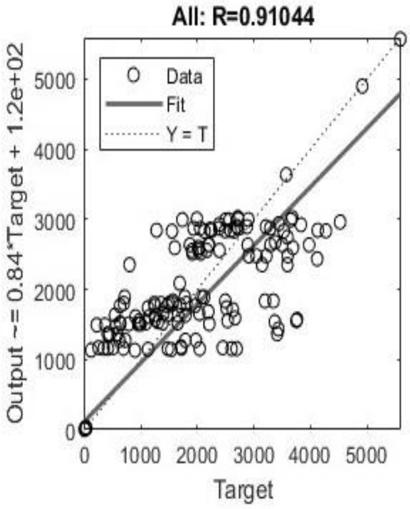


(c)



(d)





(e) (f)

Figure 6.19 Output of ANN models (a) CO, (b) CO_2, (c) HCHO, (d) TVOC, (e)$PM_{2.5}$, (f) PM_{10}

The output of the ANN model obtained for different pollutants on road mid-block sections is presented in the Figures 6.19. The ANN models developed in present study represents the graphs between the observed pollutant values, and ANN predicted pollutant values. The horizontal axis values displays the field observed values. The vertical axis values are the forecasted values produced by the neural network model. The R-value represents the correlation between the observed and ANN predicted values.

6.2.6 COMPARISION OF MLR, SVM AND ANN MODELS DEVELOPED FOR ROAD MID-BLOCK SECTIONS

In this section, a comparison has been made between the developed models of MLR, SVM, and ANN to understand the accuracy of the prediction of concentration of pollutants corresponding to the traffic volume. The error between the measured and modelled values is quantified to examine different methods' performance in predicting concentration of pollutants. The statistical estimates such as R^2value and Mean Absolute Percentage Error (MAPE) are used for measuring accuracy and determining the error. The MAPE value is the error percentage between the observed and predicted values obtained for each model.

The model with high R^2value and low MAPE values gives the best-predicted values. The R^2 values and MAPE values obtained for the models are shown in Figures 6.20 and 6.21 respectively.

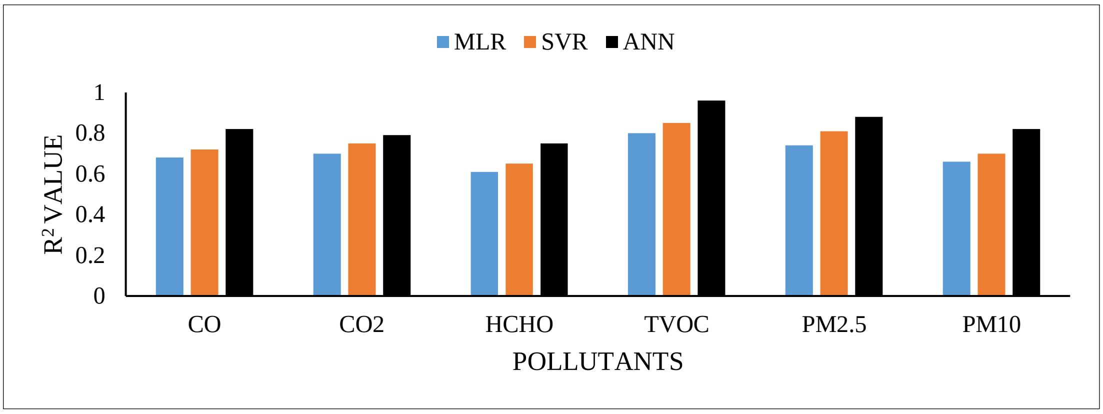


Figure 6.20 Comparison of R^2 values for different models

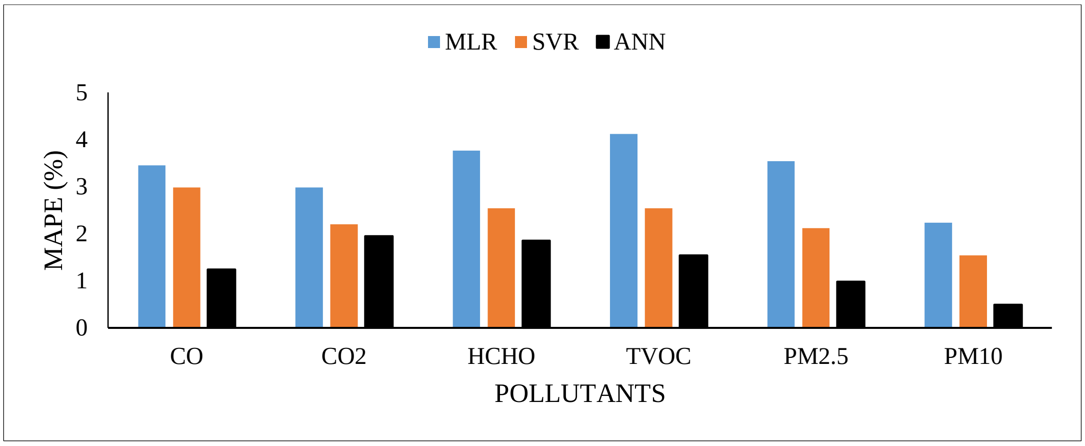


Figure 6.21 Comparison of MAPE values for different models

The results of Figure 6.20 and Figure 6.21 indicate that high R^2value and low MAPE values are obtained when the ANN method is used to predict concentration of pollutants on road mid-block sections compared to the other methods. It represents that the ANN method could better predict the concentration of pollutants values regarding the rather than MLR and SVR methods.

6.3 MODELS FOR SIGNALIZED INTERSECTIONS

The change in concentration of each pollutant with the traffic entering the intersection is estimated using correlation analysis. The correlation analysis was performed to understand the relation between different pollutants concentration and entering traffic volume at different intersections. Different models are developed to predict concentration of different pollutants using Multiple Linear Regression (MLR), Support Vector Regression and Artificial Neural Networks methods. The concentration of each pollutant are the output variables and red time length (RT), cycle time length (CL), average queued vehicles (Nq) and entering traffic volume (Ve) are the explanatory variables used in the model.

The trend of each pollutant with respect to observed traffic volume at signalized intersections is examined. The analysis reveals a positive linear trend for traffic volume with CO, CO_2, HCHO, TVOC, $PM_{2.5}$, and PM_{10}. The variation of each pollutant with traffic volume is shown in Figures 6.22 to 6.27.

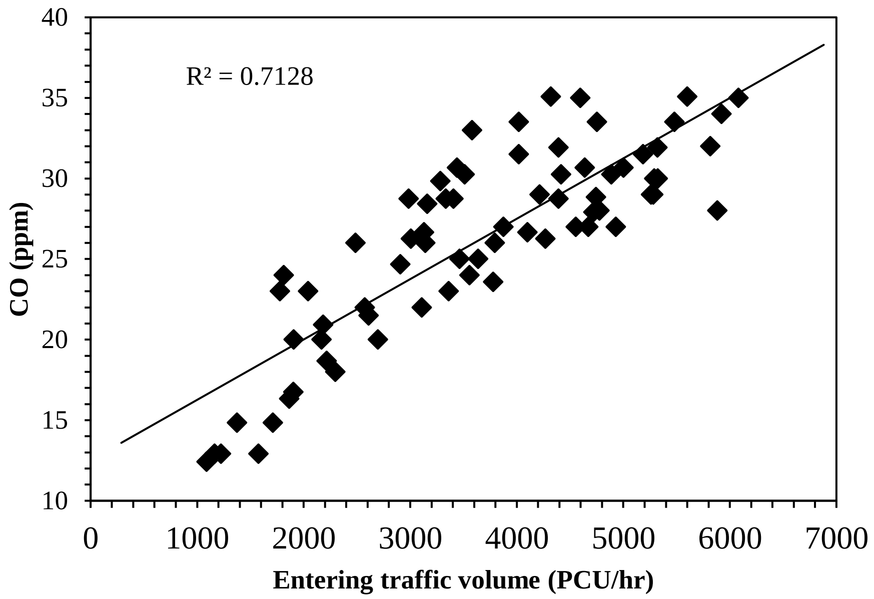


Figure 6.22 Variation of CO with entering traffic volume

The analysis indicates that the CO values significantly rise when higher traffic volume approaches at signalized intersections. The concentration of CO found to be varied from 12 ppm to 35 ppm. It is also observed that the CO values are increasing approximately at a rate of 8% from the minimum value. When traffic volume reaches its maximum value as of 6081 PCU/hr at SI VIII – KV (Vijayawada city) between 7:00 PM and 8:00 PM, a higher CO value of 35 ppm is detected. The value of 35 ppm is the maximum safe limit for the CO values as prescribed by the equipment. Beyond the value of 35ppm, the level of CO is said to be unsafe. Therefore, future increase in traffic volume at the intersections may rise the CO value to unsafe level.

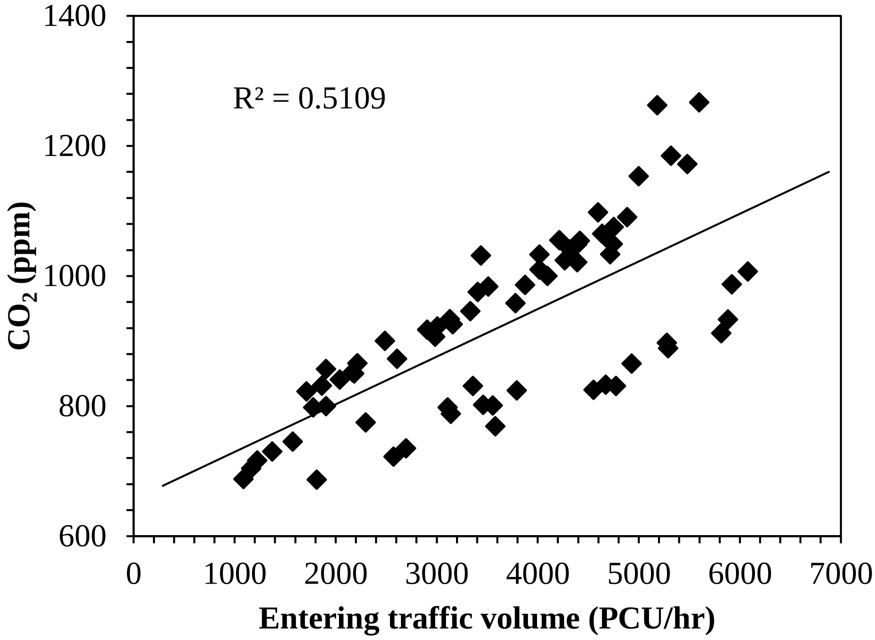


Figure 6.23 Variation of CO_2 with entering traffic volume

The results indicate that the rate of increase of CO_2 values is approximately 2.5% as traffic volume changes low to high. It is also observed that the maximum concentration value of CO_2 which is found to be 1267 ppm, falls under the category of "unhealthy for sensitive groups" according to the requirements for CO_2 equipment as given in Table 5.5. This suggests that a further rise in CO_2 levels could seriously harm the health of the people. It is also observed that higher CO_2 value of 1267ppm is noticed at intersection III (Warangal city) during 7:00 PM to 8:00 PM. It may be due to the highest queue length observed at the intersection. The value of maximum queue length observed at intersection III is 185 veh (details as given in Table 4.11).

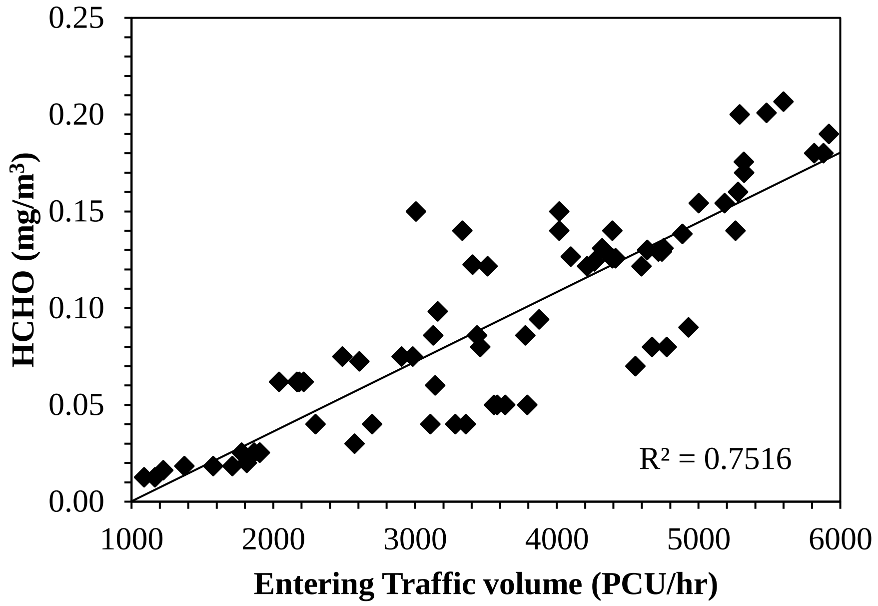


Figure 6.24 Variation of HCHO with entering traffic volume

The analysis indicates that when traffic volume rises, HCHO values increases linearly. The HCHO values at signalized intersections are varying between 0.01mg/m^{3}to 0.21mg/m^3. It is noticed that there is a 1% increase in HCHO concentration at every 10% increase in traffic volume. The values greater than 0.1 mg/m^3 indicates the unsafe level of HCHO level at various signalized intersections according to the standards given for the equipment.

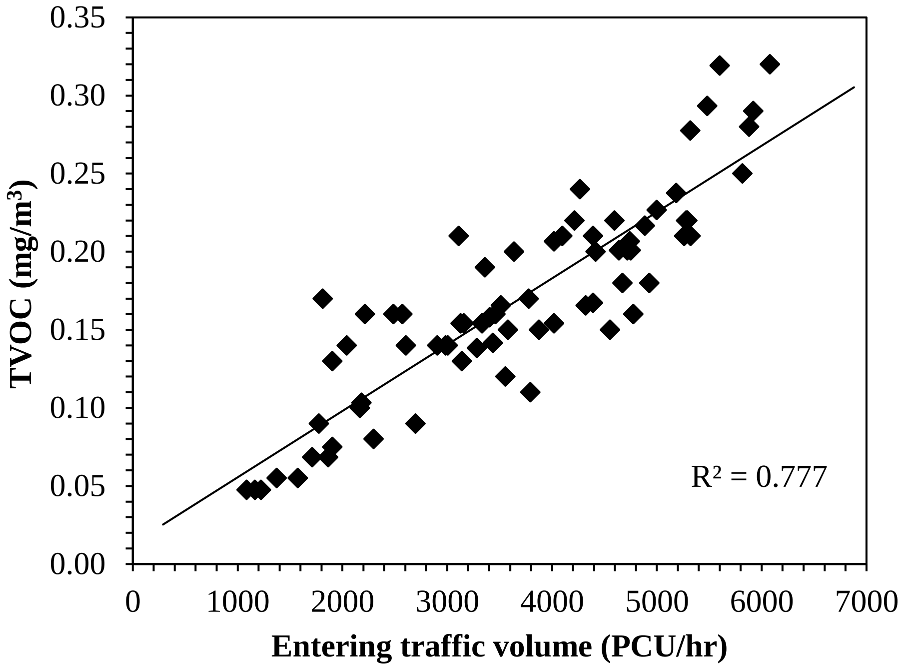


Figure 6.25 Variation of TVOC with entering traffic volume

A plot between traffic volume and TVOC indicates that the higher value of 0.32 mg/m^3 lies within the safe limits as per equipment standards. The higher value of TVOC is noticed at the maximum traffic volume of 5599 PCU/hr at intersection VIII (Vijayawada city). It indicates that the TVOC values increase linearly with the increase in traffic volume.

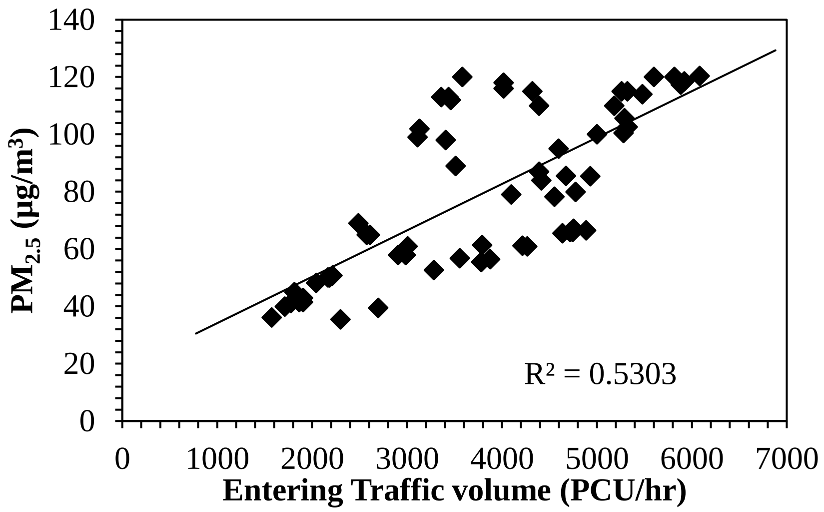


Figure 6.26 Variation of traffic volume with $PM_{2.5}$

The higher value of $PM_{2.5}$ is observed as of 120 μg/m^3 when the traffic volume reaches to 3581 PCU/hr (SI IX). It is also observed that the $PM_{2.5}$ values are being increased by nearly 8% with the variation in traffic volume. This may be because this intersection has average red time length of 180 seconds which is comparatively higher than other intersections.

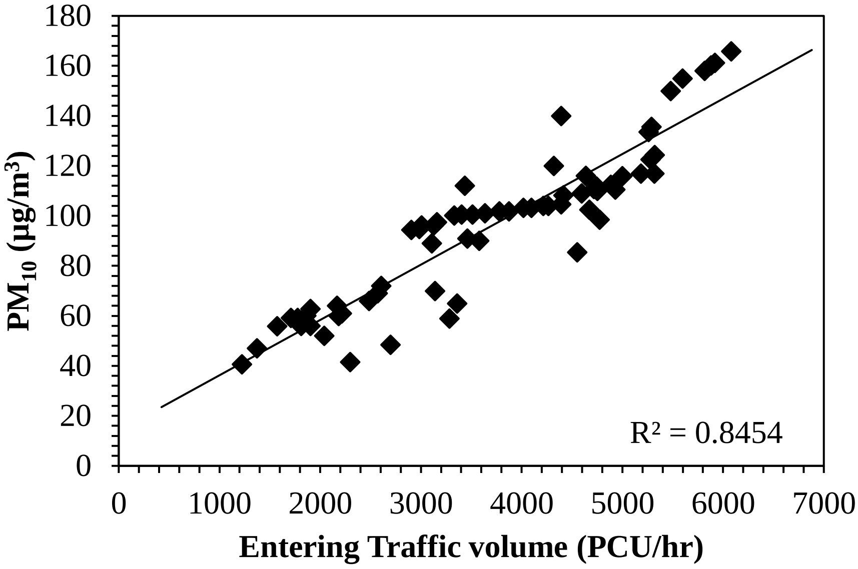


Figure 6.27 Plot between traffic volume and PM_{10}

It is known that the queuing of vehicles, acceleration and deceleration of vehicles will release more particulate matter into the air. It is noticed that the PM_{10} concentration is increasing at a rate of nearly 17% with increase in traffic volume. The results of the analysis shows that the higher PM_{10} value of 166µg/m^3 is observed at maximum traffic volume. It indicates that when the traffic approaching the intersection is increasing, the PM_{10} values are also significantly increasing.

The dependency of pollution on traffic volume has been analyzed and is presented in Figure 6.28.

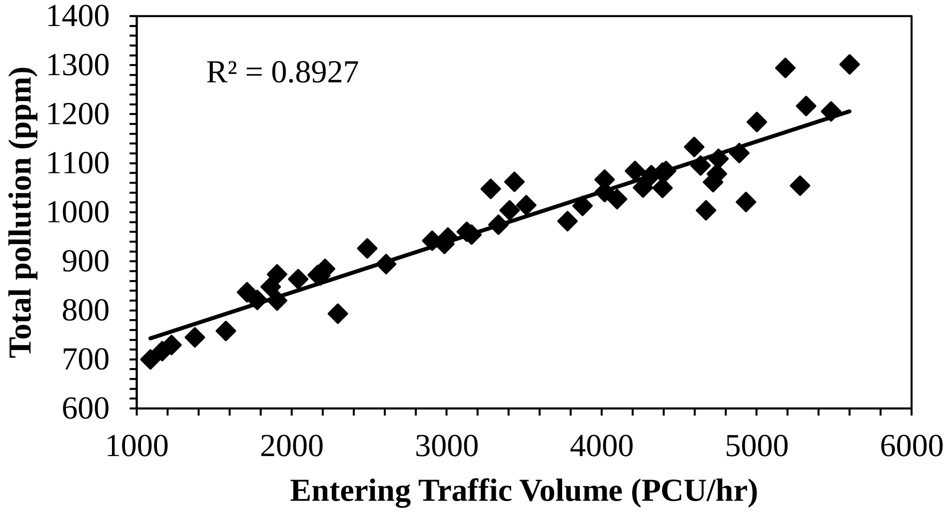


Figure 6.28 Variation of total pollution with entering traffic volume

The results indicates that the level of pollution at signalized intersections is being increased by nearly 2.5% with the increase in entering traffic volume. The total pollution computed at each signalized intersection for different hours is converted to same unit ppm. It is evident from the results that the pollution reaches a maximum level when the traffic approaching the intersection is higher.

6.3.1 DEVELOPMENT OF MLR MODELS

The strength of relation between concentration of pollutants and signal parameters is analyzed using correlation analysis. The R - values obtained from the correlation analysis is shown in Table 6.5.

Table 6.5 Correlation values between concentration of pollutants and signal parameters

	RT	CL	N_q	T	V_e
CO	0.39	0.42	0.65	0.43	0.71
CO_2	0.52	0.41	0.58	0.54	0.51
HCHO	0.35	-0.51	0.36	0.41	0.75
TVOC	0.41	0.52	0.39	0.43	0.77
$PM_{2.5}$	0.32	0.35	0.41	0.35	0.84
PM_{10}	0.41	0.42	0.42	0.39	0.82

MLR is performed for predicting concentration of pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10}. Models are developed based on the field data observed at 6 intersections with SI ID's I, II, IV, V, VII and VIII. The intersections SI I and SI II are located in Warangal, SI IV and SI V are located in Tirupathi. Similarly, the intersections SI VII and SI VIII are in Vijayawada city. The dependent variable considered in the model is concentration of each pollutant. Red time length (RT), cycle time length (CL), average queued vehicles (N_q), temperature (T) and entering traffic volume (V_e) are the explanatory variables taken as inputs for the model. The average queued vehicles (N_q) is defined as the mean of the number of vehicles stopped during the every red time in different approaches of the intersection. The entering traffic volume (V_e) is the total number of vehicles approaching towards the intersections from different legs in a particular time. The MLR models developed for each pollutant is given in Eq. (6.9) to (6.14). The regression outputs of the models developed are given in Table 6.6.

$$CO = 4.64 + 0.05 \times N_q + 0.02 \times V_e \tag{6.9}$$

$$CO_2 = 853.3 - 0.56 \times RT + 1.53 \times N_q - 10.13 \times T + 0.06 \times V_e \tag{6.10}$$

$$HCHO = -0.027 - 0.0001 \times CL + 0.0005 \times V_e \tag{6.11}$$

$$TVOC = 0.01 + 0.0003 \times CL + 0.0003 \times V_e \tag{6.12}$$

$$PM_{2.5} = 8.97 + 0.01 \times V_e \tag{6.13}$$

$$PM_{10} = 13.77 + 0.02 \times V_e \tag{6.14}$$

Table 6.6 Regression outputs of the MLR models

Dependent variable	**Independent variable**	**p-value**	**t-stat value**	**R^2**	**Adjusted R^2 value**
CO (ppm)	Intercept	0.000	5.95	0.87	0.87
	Average queued vehicles	0.000	6.99		
	Entering traffic volume	0.000	14.90		

CO_2 (ppm)	Intercept	0.000	8.69	0.83	0.81
	Red time length	0.001	-3.50		
	Average queued vehicles	0.006	2.85		
	Temperature	0.023	-2.35		
	Entering traffic volume	0.000	8.09		
HCHO (mg/m^3)	Intercept	0.000	-4.81	0.87	0.88
	Cycle length	0.007	-2.79		
	Entering traffic volume	0.000	14.38		
TVOC (mg/m^3)	Intercept	0.001	2.98	0.78	0.77
	Cycle length	0.000	3.48		
	Entering traffic volume	0.000	5.99		
$PM_{2.5}$ ($\mu g/m^3$)	Intercept	0.018	2.44	0.79	0.78
	Entering traffic volume	0.000	4.07		
PM_{10} ($\mu g/m^3$)	Intercept	0.036	2.15	0.80	0.80
	Entering traffic volume	0.000	13.92		

The combined effect of the explanatory variables on concentration of each pollutant is examined. It is noticed from the MLR analysis that an R^2 values of about 0.6 is obtained for the models developed for predicting the concentration of pollutants at signalized intersections. It is also observed that entering traffic volume, average queued vehicles and cycle length are significantly influencing the concentration of pollutants. It is also observed from the results that temperature has a significant impact on the CO_2 concentrations.

6.3.2 MODELS VALIDATION

Models developed are validated considering the field data of three intersections represented with Intersection ID's SI III (Warangal), SI VI (Tirupathi) and SI IX (Vijayawada). Chi-square test was performed to compare the results based on p-value. The p-values shown in the validation plots are greater than 0.05 indicating that there is no significant difference between the observed and predicted values of concentration of pollutants. The validation plots for different pollutants are shown in Figures 6.29 to 6.34.

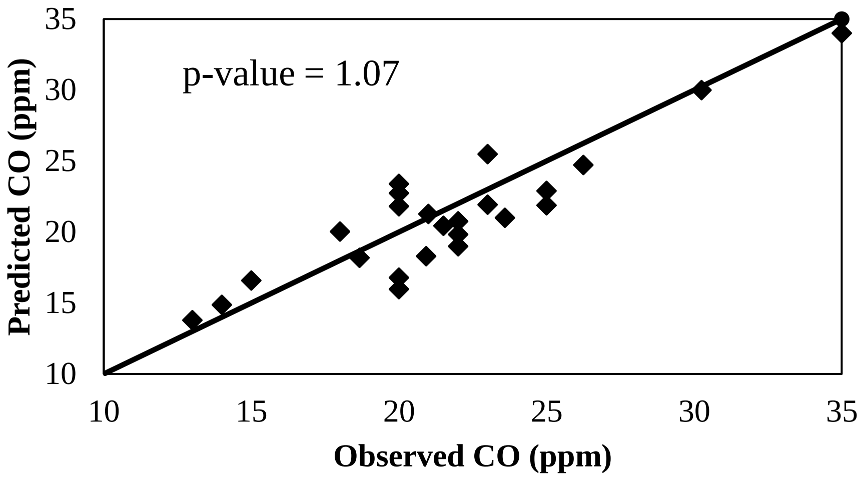


Figure 6.29 Validation plot for CO concentrations

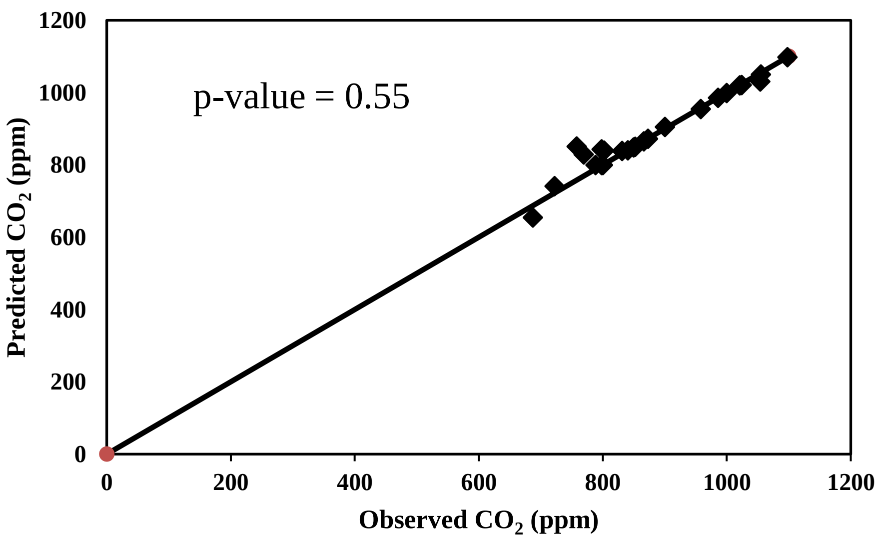


Figure 6.30 Validation plot for CO_2 concentrations

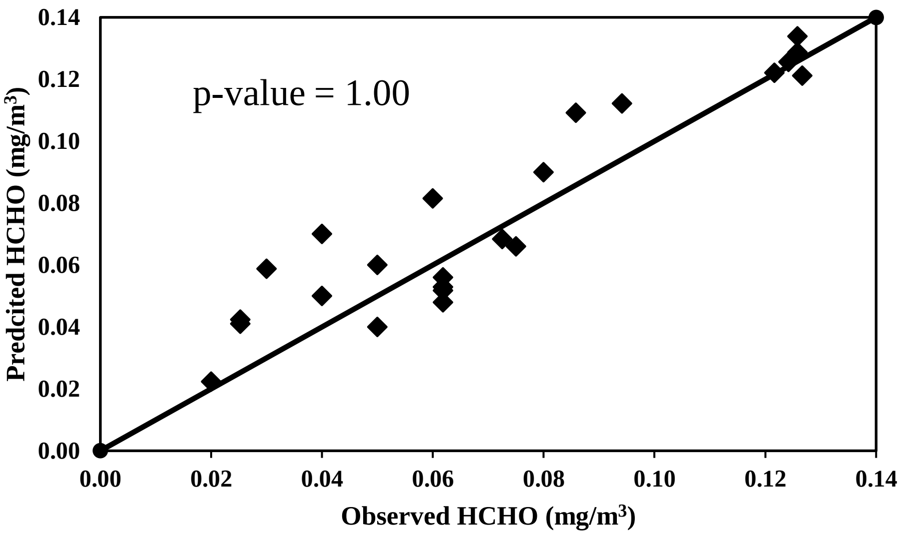


Figure 6.31 Validation plot for HCHO concentrations

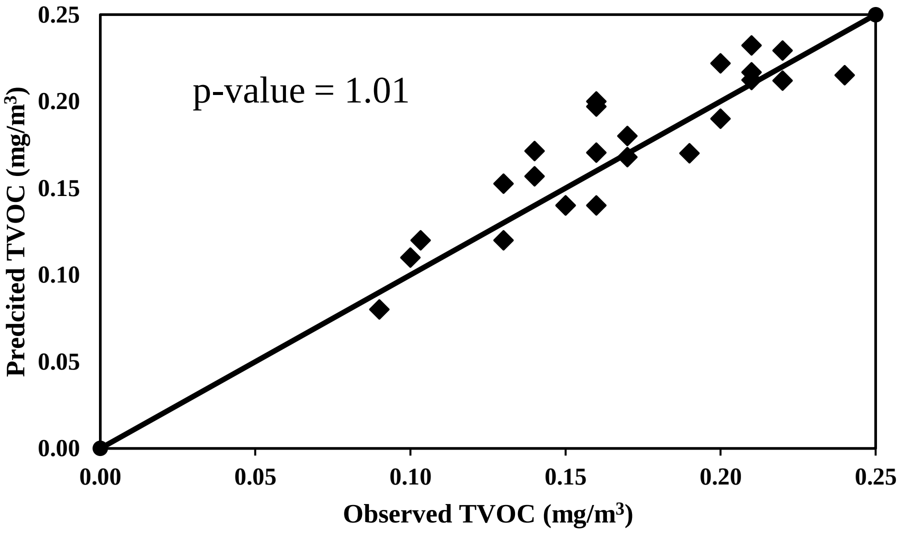


Figure 6.32 Validation plot for TVOC concentrations

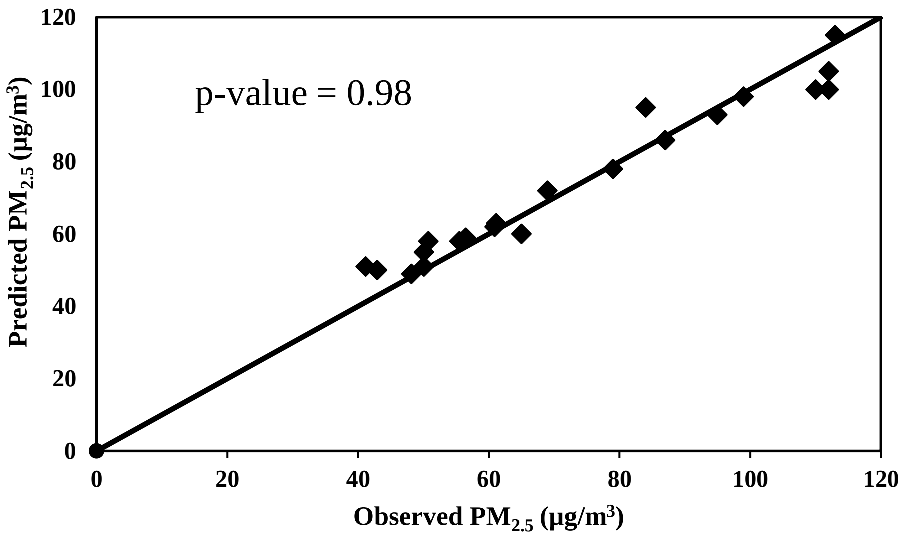


Figure 6.33 Validation plot for $PM_{2.5}$concentrations

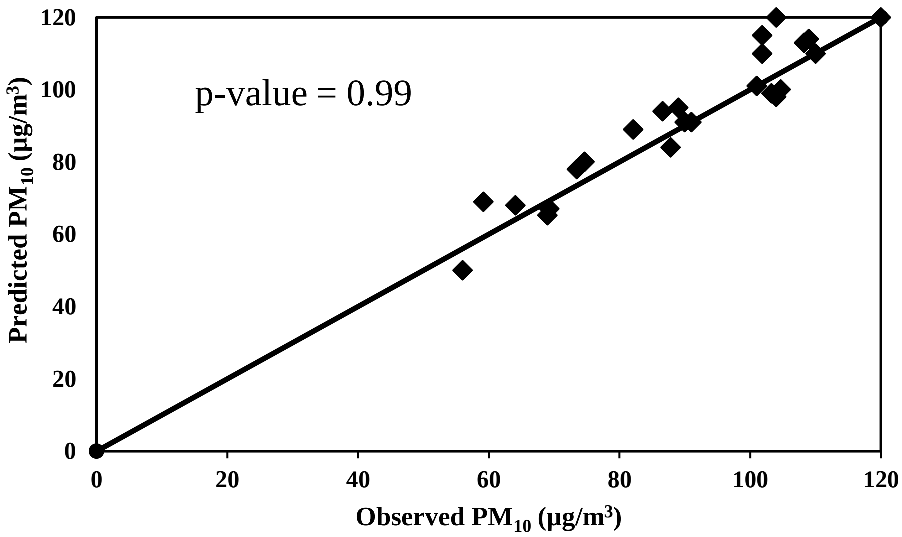


Figure 6.34 Validation plot for PM_{10} concentrations

6.3.3 DEVELOPMENT OF SVR MODELS

The current study utilizes the Support Vector Regression (SVR) modeling approach, which offers a strong and reliable framework for regression tasks. The SVM technique is highly effective at managing datasets with a large number of dimensions and complex, non-linear connections. The current study utilized Support Vector Regression (SVR) in the R-software to forecast the levels of various contaminants on road mid-block sections. The SVR modelling technique utilizes 70% of the available data for training purposes, while the remaining 30% is used for testing. The regression is performed using the SVM type called eps-regression. The regression in this case utilizes a radial SVM kernel function. The regression uses a 95% confidence interval. The model's development includes a sample of the libraries, functions, and data assumptions, which are provided in Figure 6.35.

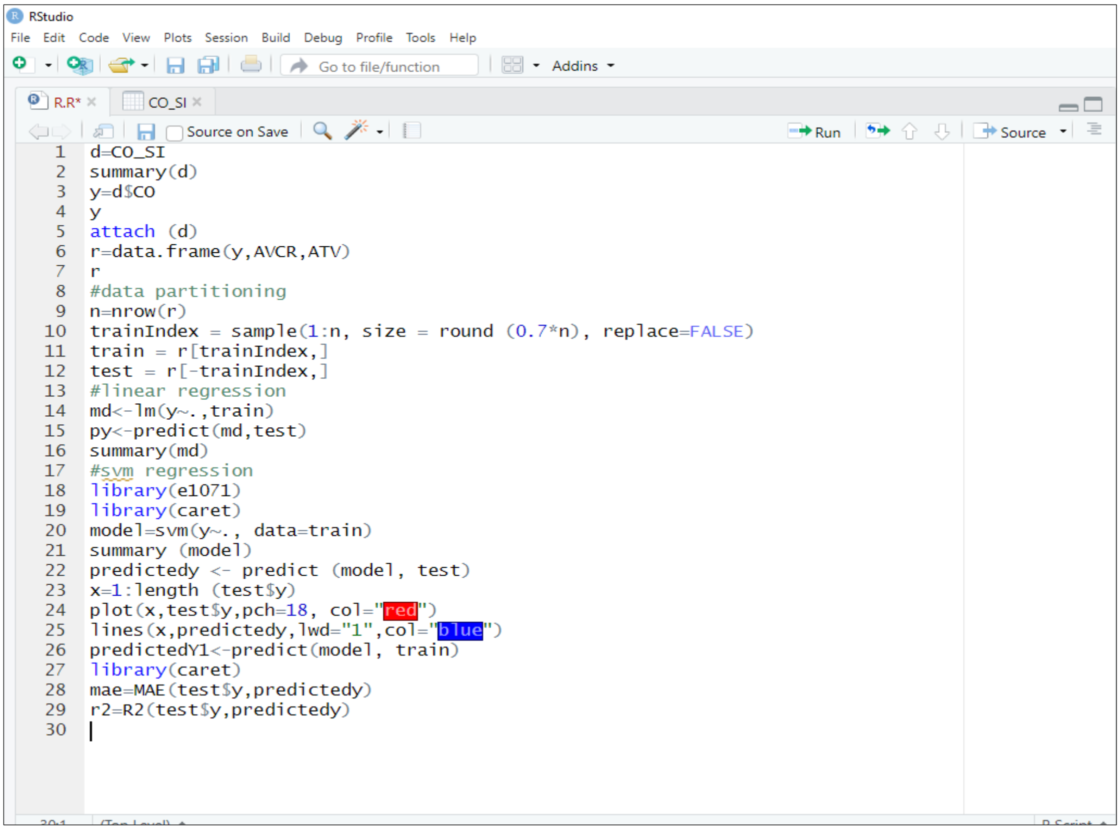


Figure 6.35 Sample data input for SVM model of signalized intersections

The explanatory factors in all the models are the red time length (RT), cycle time length (CL), average queued vehicles (Nq), and entering traffic volume (Ve). The dependent variables are the concentration of pollutants. The statistical results of the support vector regression models constructed in the study are presented in Table 6.7.

Table 6.7 Regression outputs of the SVR models developed at signalized intersections

Dependent variable	**Independent variables**	**Co-efficient**	**p-value**	**t-stat value**	**R^2**	**Adjusted R^2**
CO (ppm)	Intercept	3.98	0.000	8.97	0.90	0.89
	Average queued vehicles	0.05	0.000	4.09		
	Entering traffic volume	0.02	0.000	9.34		
CO_2 (ppm)	Intercept	754.3	0.000	9.73	0.85	0.86
	Red time length	-1.22	0.002	-4.33		
	Average queued vehicles	1.20	0.005	3.74		
	Temperature	-9.03	0.021	-2.56		
	Entering traffic volume	0.07	0.000	8.45		
HCHO (mg/m^3)	Intercept	0.001	0.000	-2.98	0.91	0.92
	Cycle length	-2.62	0.005	-3.64		
	Entering traffic volume	3.94	0.001	17.15		
TVOC (mg/m^3)	Intercept	0.001	0.001	2.96	0.81	0.81
	Cycle length	0.0003	0.000	3.67		
	Entering traffic volume	0.0002	0.000	4.03		
PM2.5 ($\mu g/m^3$)	Intercept	7.59	0.018	3.26	0.84	0.85
	Entering traffic volume	0.01	0.000	4.07		
PM10 ($\mu g/m^3$)	Intercept	12.54	0.000	3.36	0.85	0.84
	Entering traffic volume	0.02	0.000	13.03		

Plots were created for each Support Vector Machine (SVM) model, displaying the forecasted levels of contaminants. The X-axis of these plots represents the number of test samples, while the Y-axis represents the expected values of pollutant concentration. Each data point in the graphs corresponds to the anticipated values of different pollutant concentrations provided by the Support Vector Regression (SVR) model. The trend line illustrates the pattern of the projected values acquired. The model results demonstrate that the anticipated values closely adhere to the trend line that represents the performance of each model. The projected values for HCHO is shown as a sample in Figure 6.36.

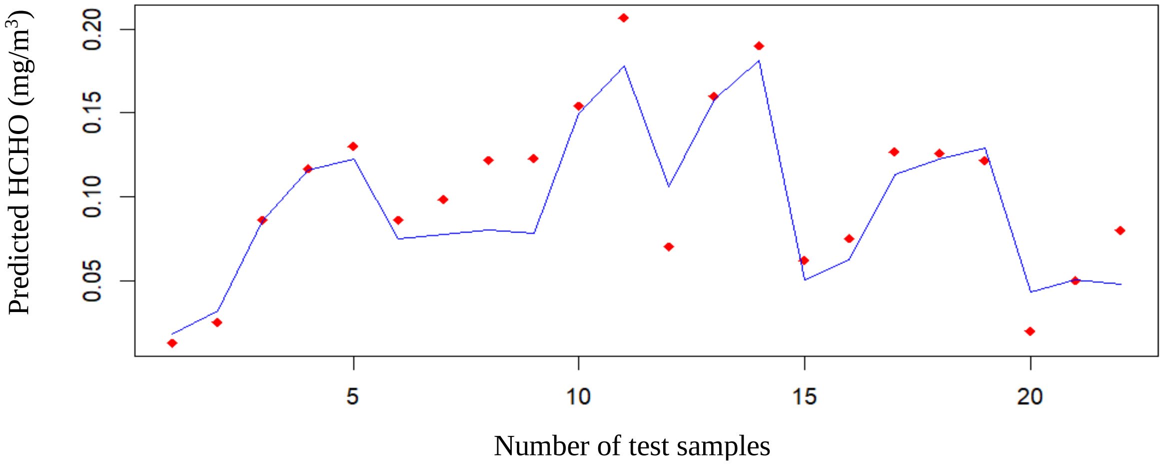


Figure 6.36 SVR model predicted HCHO concentrations

6.3.4 DEVELOPMENT OF ANN MODELS

In addition, the current investigation employed the ANN methodology to forecast pollutant concentrations by considering different signal parameters. In this study, ANN is implemented with signal parameters including entering traffic volume (Ve), temperature (T), and concentration of pollutants (RT), cycle time length (CL), average queued vehicles (Nq), and temperature (T), serving as input layers. The neural network architecture for models developed at signalized intersections are optimized at two layers- ten neurons (one input layer, one hidden layer) and an output layer. The neural network structure obtained for CO model is shown as a sample in Figure 6.37. Similarly, the network structures are obtained for all the pollutants.

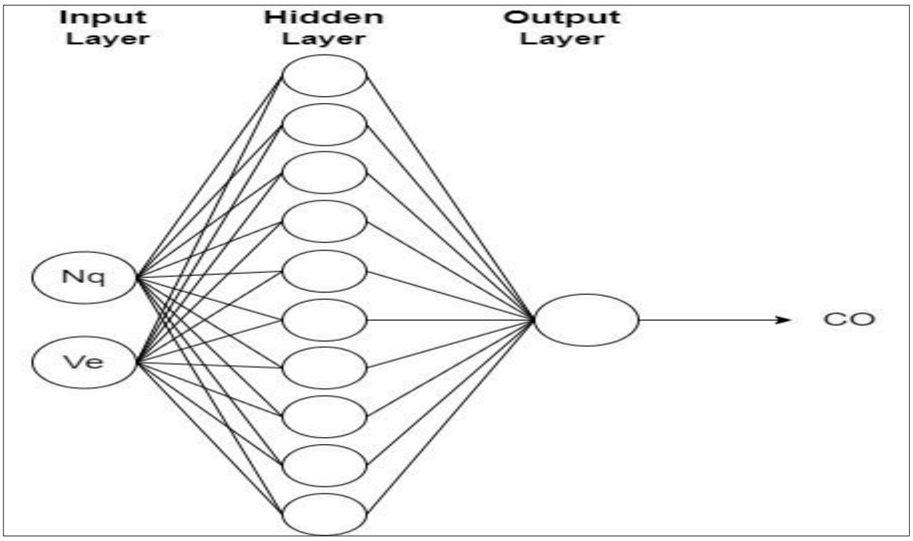
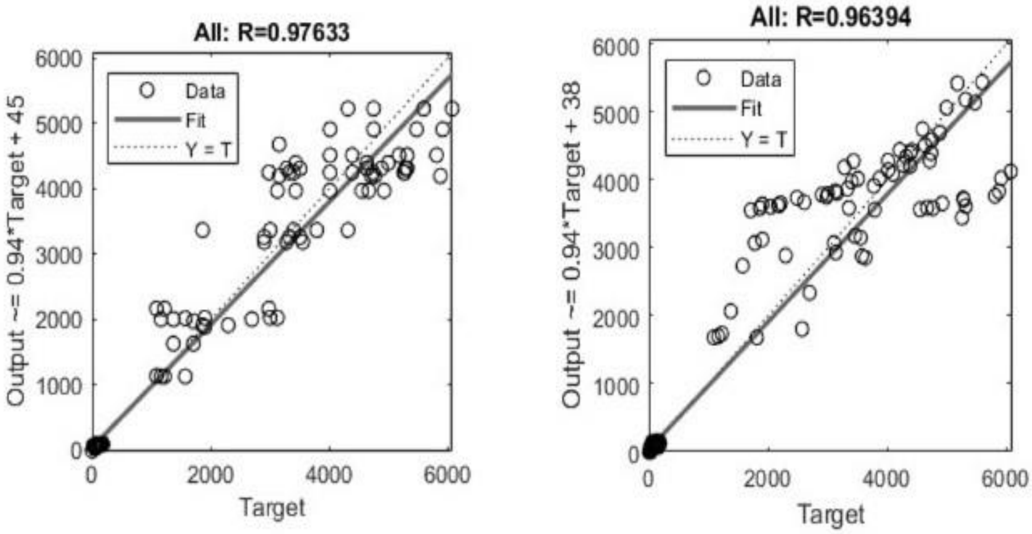
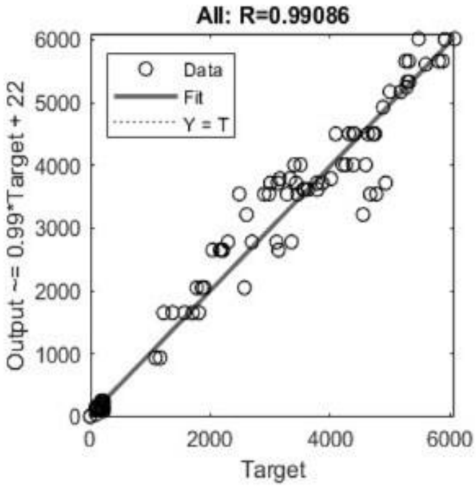


Figure 6.37 Neural network architecture obtained for CO model

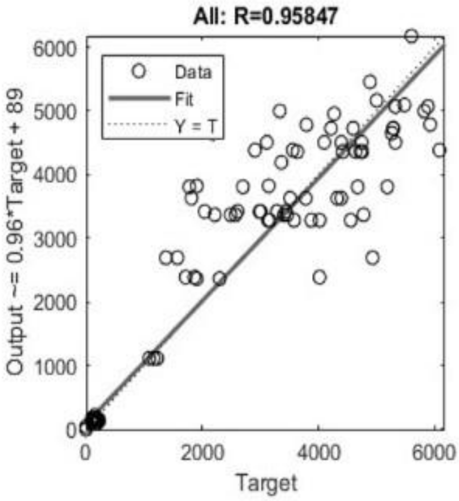
Variations in the quantity of hidden layers and neurons were implemented across multiple iterations in order to determine the most effective network architecture. The optimal network structure is the one in which the discrepancy between the measured and ANN-modeled values is minimized. The results produced by ANN models are illustrated in Figure 6.38.



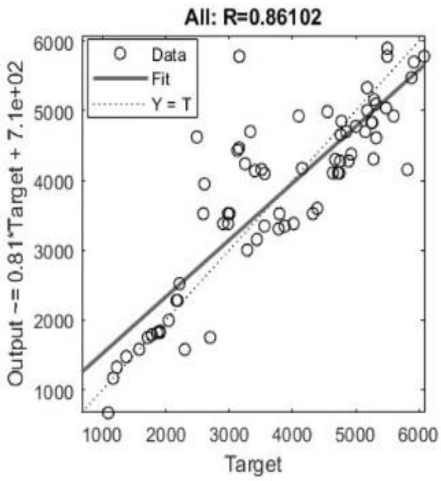
(a) (b)



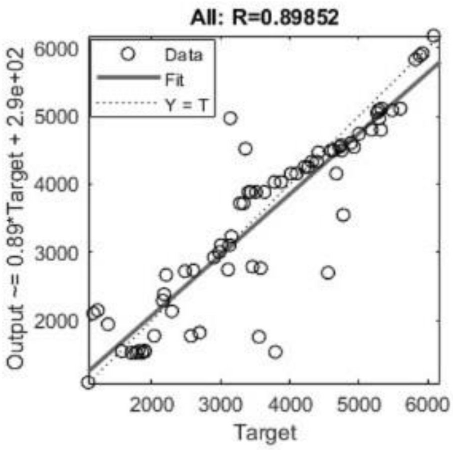
(c)



(d)



(e)



(f)

Figure 6.38 Output of ANN models (a) CO, (b) CO_2, (c) HCHO, (d) TVOC, (e) PM2.5, (f) PM_{10}

The ANN diagrams depict the relationships between the observed and predicted pollutant concentrations. The horizontal axis represents the observed values. The vertical axis represents the predicted values generated by the neural network model. The relation between the observed and ANN predicted values is denoted by the R-value. Higher R-values indicate that the difference between the predicted and observed values is not statistically significant. A significant discrepancy between the predicted and observed values does not exist if the obtained data points approach the Y=T reference line. There is never a substantial disparity observed between predicted and observed values.

6.3.5 COMPARISION OF MLR, SVM AND ANN MODELS DEVELOPED FOR SIGNALIZED INTERSECTIONS

This section presents a comparative analysis of the developed MLR, SVM, and ANN models in order to assess the accuracy of their predictions regarding the concentration of pollutants in relation to traffic volume. By quantifying the discrepancy between the estimated and measured values, the performance of various methods in forecasting. For measuring precision and identifying error, statistical estimates such as R^2value and Mean Absolute Percentage Error (MAPE) are applied. The model exhibiting a high R^2 value and low MAPE values provides the most accurate predictions. The R^2 and MAPE values that were computed for the models are respectively displayed in Figures 6.39 and 6.40.

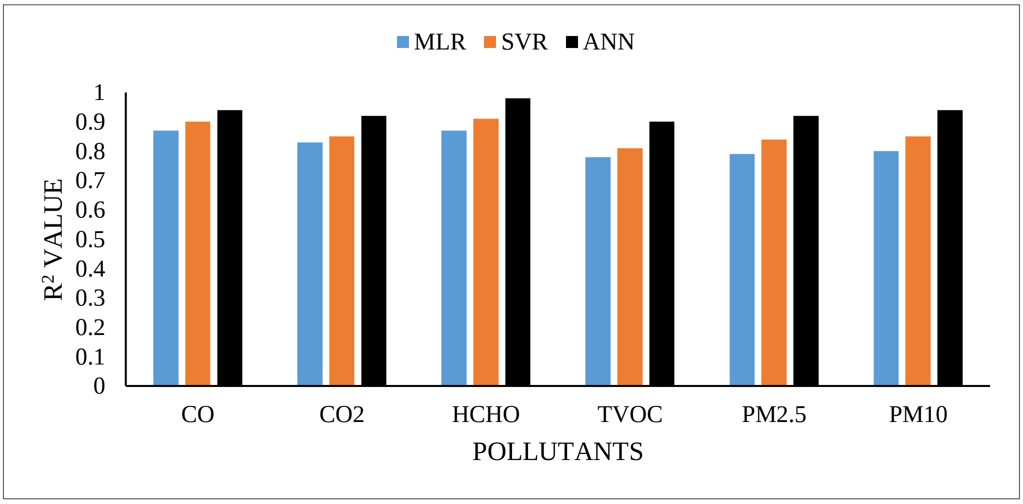


Figure 6.39 Comparison of R^2 values for different models

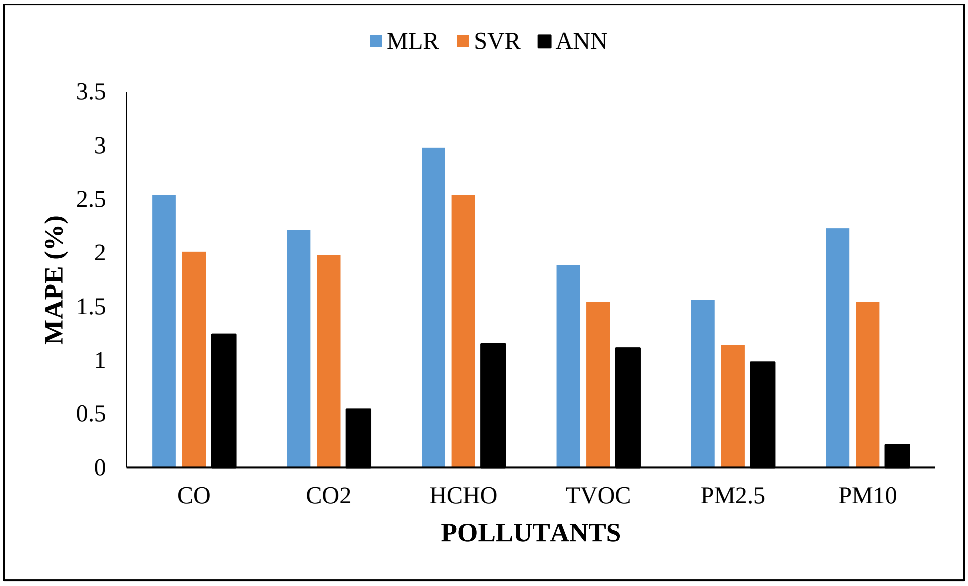


Figure 6.40 Comparison of MAPE values for different models

The results indicate that high R^2value and low MAPE values are obtained when the ANN method is used for prediction on road mid-block sections. It represents that the ANN method could better predict the concentration of pollutants values as compared to MLR and SVR methods. ANN models performed better because of the incorporation of hidden layers in the network structure. These hidden layers provide the complex relationship between the signal parameters, traffic volume and concentration of pollutants.

6.4 PREDICTION OF AIR QUALITY INDEX

A simple model is developed to predict AQI at different road mid-block sections and signalized intersections with respect to traffic volume and percentage of different types of vehicles using MLR method. The impact of traffic volume on ambient air quality index has been investigated. The status of air quality is defined based on the observed and predicted AQI values in reference to the IND-AQI standards (details as given in Table 3.1).

6.4.1 CORRELATION ANALYSIS

The statistical dependency of AQI on traffic volume has been examined. It is noticed that the change in traffic volume has a significant impact on the AQI values. The variation of traffic volume with AQI at urban road mid-block sections and signalized intersections is shown in Figures 6.41 and 6.42. The correlation analysis indicates that an increase in traffic volume leads to increase in the AQI values.

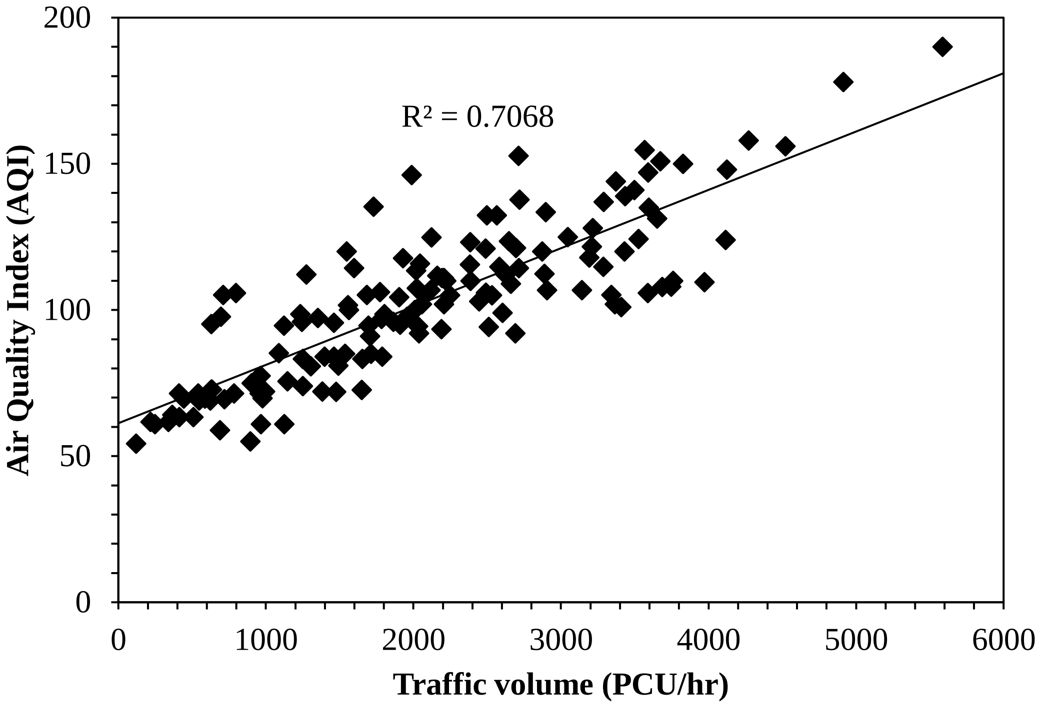


Figure 6.41 Variation of AQI with traffic volume on road mid-block sections

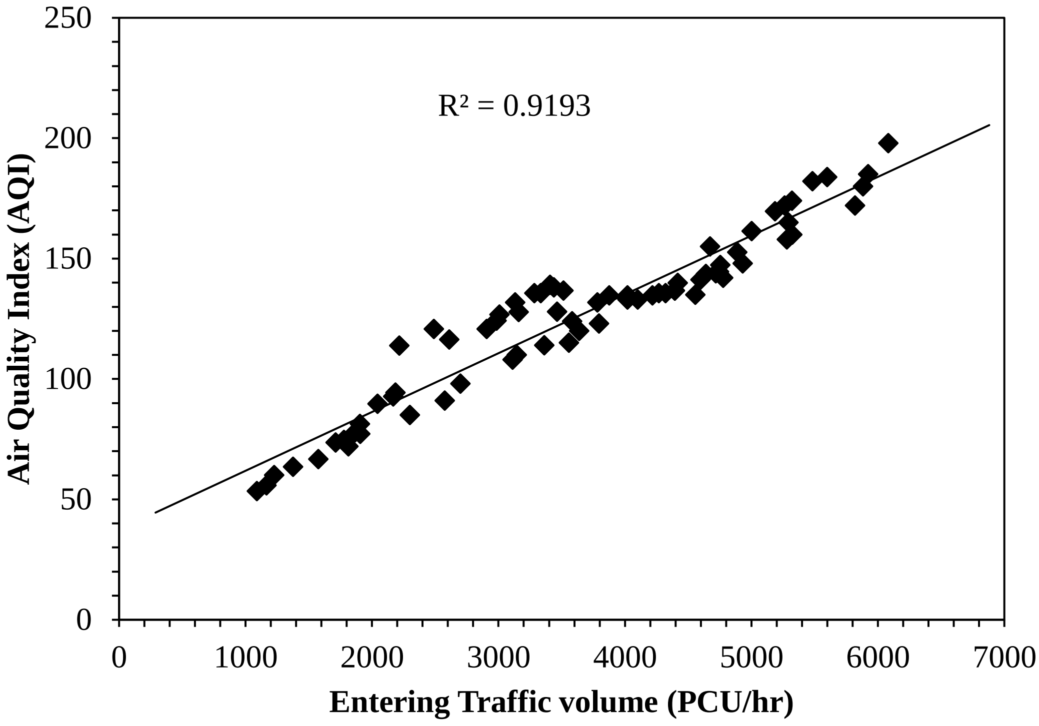


Figure 6.42 Variation of AQI with traffic volume at signalized intersections

The results indicate that the AQI values are increasing at a rate of about 13% when there is increase in traffic volume on road mid-block sections. It is also noticed that that there is approximately 21% rise in AQI values with increase in traffic volume at signalized intersections. The analysis also indicates that the AQI values are found to be higher at signalized intersections than road mid-block sections.

6.4.2 DEVELOPMENT OF AQI MODEL

A model has been developed to predict AQI considering traffic volume and percentage of different type of vehicles using MLR method. The output variable considered in the model is AQI value observed in the field. The traffic volume (V) and percentage of different type of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV} are the explanatory variables in the model. The data obtained on twelve road mid-block sections (four from each city) and six signalized intersections (two from each city) is used for developing the model. The model developed to predict AQI is given in Eq. (6.15).

$$\text{AQI} = 44.74 + 0.02 \times V + 0.57 \times P_{3W} \qquad (6.15)$$

The regression equation explains the combined effect of percentage of different types of vehicles and traffic volume on ambient air quality. It is note-worthy from Eq. 6.15 that the two explanatory variables namely traffic volume (V) and percentage of 3W (P_{3W}) have a significant impact on AQI. It is observed from that the t-stat values obtained for traffic volume and percentage of 3W are 28.92 and 3.91 respectively at 95% confidence interval. The results indicates that the independent variables traffic volume and percentage of 3W could explain the variance in AQI.

6.4.3 MODEL VALIDATION

The AQI model developed in the study is validated with the data of six road mid-block sections (two from each city) and 3 signalized intersections (one from each city).The p-value based on chi-square test is used for checking difference at 5% significant level. Result of model validation indicates that the developed model is predicting AQI reasonably well there is no significant difference between the observed and predicted AQI values. The validation plot for AQI model is shown in Figure 6.43.

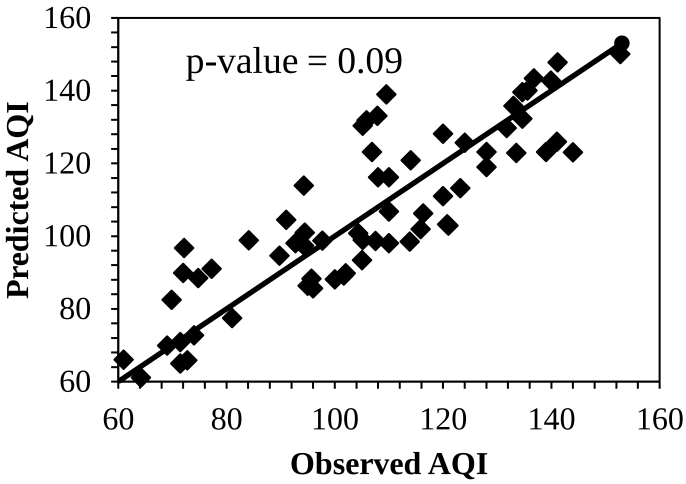


Figure 6.43 Validation chart comparing predicted and observed AQI

6.4.4 MODEL APPLICATION

Sensitivity analysis was performed with developed AQI model to define the pollution level based on the variation in traffic volume and percentage of 3W. The AQI model is used to set the level of purity in the air in the selected cities according to the IND-AQI standards. The AQI based level of ambient air quality under different traffic volume and mix of 3W in the vehicle composition is analyzed. The levels of air quality when traffic volume reaches up to 7000 PCU/hr with 30% of 3W has been examined. It is noticed that when the traffic volume is about 1500 PCU/hr and mix of 3W in the vehicle composition is up to 25%, the AQI is in satisfactory condition. Similarly, when the traffic volume reaches about 5500 PCU/hr with a mix of 25% 3W and 30% 3W, the AQI reached to a very poor level. The results evidently indicate that with a constant increase in traffic volume and rise in percentage of 3W in the vehicle composition deteriorate the air quality levels and causing damage to the environment and health of the people. The level of purity at different traffic conditions according to IND-AQI standards is shown in Figure 6.44.

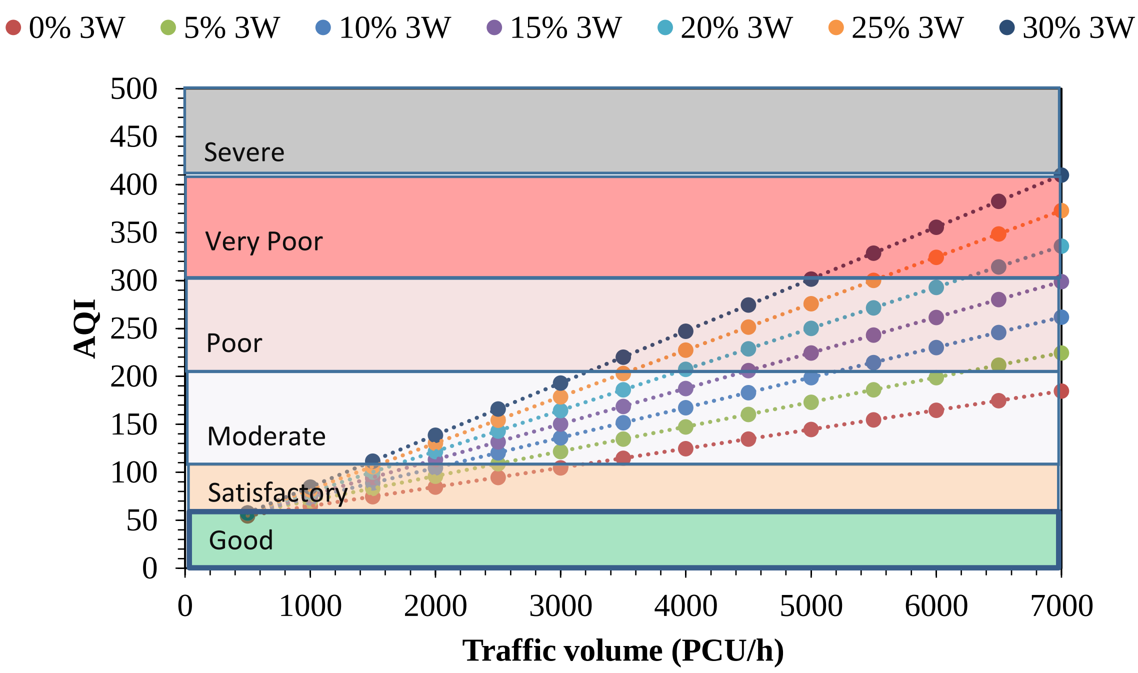
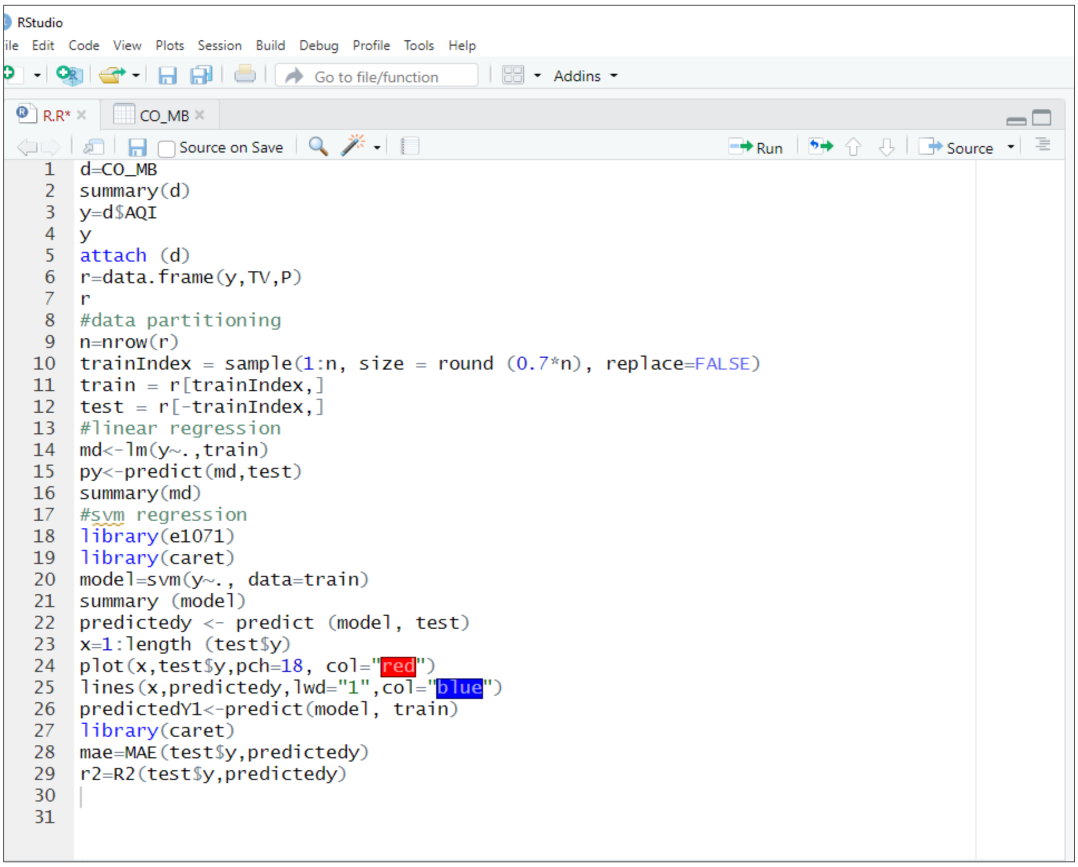


Figure 6.44 Level of purity at different traffic conditions

6.4.5 SVR MODEL FOR AQI PREDICTION

A SVR model has been developed to predict AQI in study locations based on traffic volume and percentage of different type of vehicles. The output variable considered in the model is AQI value observed in the field. The data assumptions given in R software to develop SVR model of AQI is shown in Figure 6.45.



```r
d=CO_MB
summary(d)
y=d$AQI
y
attach (d)
r=data.frame(y,TV,P)
r
#data partitioning
n=nrow(r)
trainIndex = sample(1:n, size = round (0.7*n), replace=FALSE)
train = r[trainIndex,]
test = r[-trainIndex,]
#linear regression
md<-lm(y~.,train)
py<-predict(md,test)
summary(md)
#svm regression
library(e1071)
library(caret)
model=svm(y~., data=train)
summary (model)
predictedy <- predict (model, test)
x=1:length (test$y)
plot(x,test$y,pch=18, col="red")
lines(x,predictedy,lwd="1",col="blue")
predictedY1<-predict(model, train)
library(caret)
mae=MAE(test$y,predictedy)
r2=R2(test$y,predictedy)
```

Figure 6.45 Data assumptions for SVR model of AQI

The traffic volume (V) and percentage of different types of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV} are the explanatory variables used in the model. The model developed to predict AQI from SVR model is given in Eq. (6.16).

$$AQI = 42.56 + 0.02 \times V + 0.51 \times P_{3W} \qquad \text{Eq. (6.16)}$$

where, AQI= Air Quality Index

V = Traffic volume (PCU/hr)

P_{3W}= Percentage of 3Wheeler

It is observed that the t-stat values obtained for traffic volume and percentage of 3W are 31.14 and 4.9 respectively at 95% confidence interval. The results indicates that the independent variables traffic volume and percentage of 3W could explain the variance in AQI. The plot obtained for SVR model predicted AQI values is given in Figure 6.46.

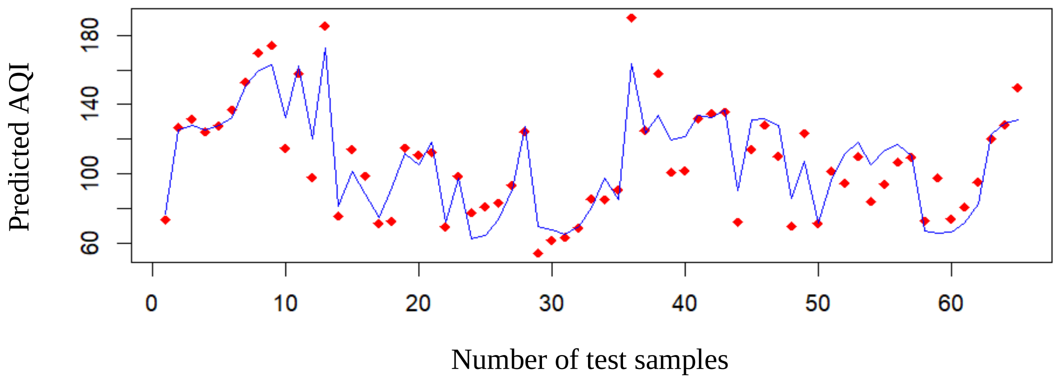


Figure 6.46 Plot for SVR model predicted values of AQI

6.4.6 ANN MODEL FOR AQI

ANN model is also developed for predicting the AQI values by considering AQI as the output variable and traffic volume (V) and percentage of different type of vehicles such as P_{2W}, P_{Car}, P_{3W}, P_{LCV} and P_{HV} as inputs to the model. The neural network structure is optimized at two layers and ten neurons. The output of ANN model is given in Figure 6.47. The R^2 values obtained for MLR, SVR and ANN models developed for AQI are 0.81, 0.81 and 0.84 respectively. The results of different models developed for AQI also indicted that ANN model is the best fit for the present data with an R^2 value of 0.84.

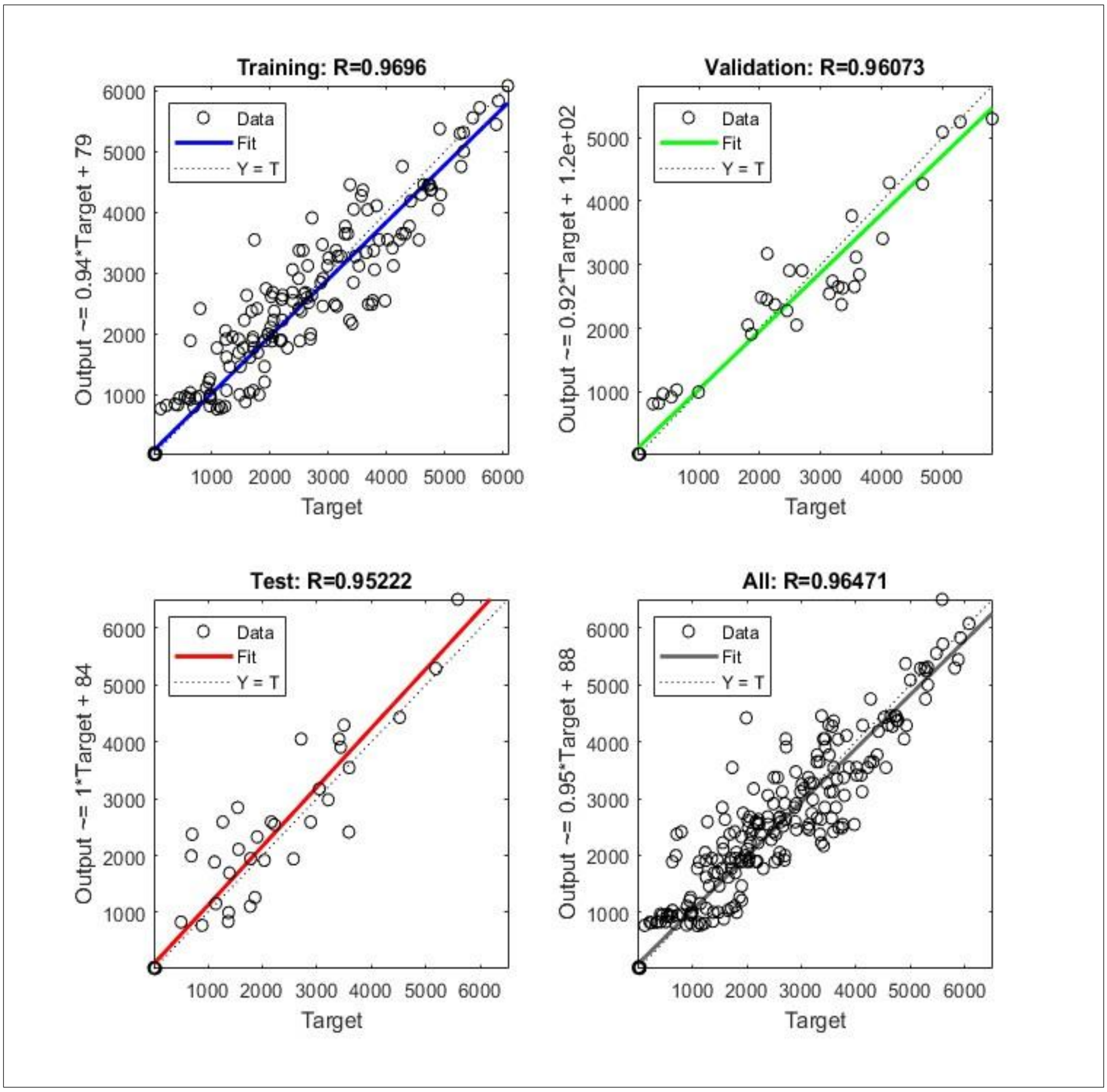


Figure 6.47 Output of ANN model

6.5 DEFINING AMBIENT AIR QUALITY STATUS

The status of the air quality in all study locations based on the observed and modelled AQI values is defined separately for road mid-block sections and signalized intersections. The status of the air quality is defined based on the IND-AQI standards. The ambient air quality status defined for each road mid-block section and signalized intersection is given in Tables 6.8 and 6.9 respectively.

Table 6.8 Ambient air quality status on road-mid-block sections

RMB	Observed AQI value	AQI category	Predicted AQI value	Predicted AQI Category
I	105	Moderate	103	Moderate
II	106	Moderate	109	Moderate
III	89	Satisfactory	100	Satisfactory
IV	109	Moderate	110	Moderate
V	109	Moderate	105	Moderate
VI	98	Satisfactory	93	Satisfactory
VII	110	Moderate	106	Moderate
VIII	102	Moderate	110	Moderate
IX	66	Satisfactory	61	Satisfactory
X	101	Moderate	103	Moderate
XI	98	Satisfactory	90	Satisfactory
XII	84	Satisfactory	79	Satisfactory
XIII	85	Satisfactory	90	Satisfactory
XIV	132	Moderate	112	Moderate
XV	128	Moderate	114	Moderate
XVI	107	Moderate	117	Moderate
XVII	89	Satisfactory	83	Satisfactory
XVIII	132	Moderate	117	Moderate

Table 6.9 Ambient air quality status at signalized intersections

SI	Observed AQI value	AQI category	Predicted AQI value	Predicted AQI Category
I	136	Moderate	139	Moderate
II	130	Moderate	117	Moderate
III	164	Moderate	157	Moderate
IV	67	Satisfactory	80	Satisfactory

V	136	Moderate	136	Moderate
VI	97	Moderate	98	Moderate
VII	140	Moderate	145	Moderate
VIII	159	Moderate	155	Moderate
IX	108	Moderate	116	Moderate

The status of air quality for different road mid-block sections and signalized intersections is defined based on observed and predicted AQI values. Observed values are obtained from the field measured using the air quality meter. Predicted values are computed using the regression equation developed for AQI.

It is observed that the air quality in the study locations is in *moderate* and *satisfactory* levels according to the IND AQI standards. As the results, clearly indicate that the rise in traffic volume is responsible for deteriorating air quality, further increase in traffic volume in the study locations would cause adverse effects to the environment.

According to the AQI standards of China, the air quality of the study locations fall in good and lightly polluted category. Similarly, as per the AQI standards of Mexico, the level of air quality falls in moderate and Unhealthy for sensitive groups. The AQI criteria for six different developing countries is given in Appendix 3.

6.6 SUMMARY

The present chapter describes the modelling and analysis of concentration of pollutants on road mid-block sections and signalized intersections. The validation of the model is also carried out using field data developed are discussed. The model developed for predicting AQI was explained in the chapter and its validation results are discussed. The application of the AQI model was explained in detail. The status of air quality based on the observed and modelled AQI values is defined and presented. The results obtained from various models indicated that increasing traffic volume is one of the major responsible parameters for rise in concentration of different pollutants and lowering the ambient air quality. The summary and important conclusions drawn from the study are explained in the subsequent Chapter.

CHAPTER 7

SUMMARY AND CONCLUSION

7.1 SUMMARY

The major source of air pollution in the urban regions is traffic induced emissions. This is one of the major concerns to be addressed before the effects of air pollution becomes hazardous. It is apparent that the concentration of air pollutants near a road corridor is substantially higher than the regional background values, placing residents in risk and exposing them excessively to traffic-related air pollution. The present study identified that traffic volume on roads is the major factor responsible for lowering the air quality in the study areas. The present study reviewed the literature on traffic resulted air pollution under different sections such as evolution of traffic pollution studies, monitoring of air pollutants, modelling the vehicular emissions, air quality on road mid-block sections and signalized intersections, air quality index, and mitigation measures reducing traffic induced air pollution. The proper methods to measure and monitor the concentration of pollutants released in the air due to the traffic are to be explored to prevent the lowering of air quality. The present study was carried out in different phases which includes a detailed description of the study area, field data collection, detailed analysis of the field data and modelling the concentration of different pollutants. The data such as road mid-block sections and intersection type, traffic volume, temperature, vehicle composition data, signal data, queued data, concertation of different pollutants (CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10}) and AQI data have been collected from the field.Emission data for the different categories of the vehicles along with emission norms, average age of the vehicle, registration number, model of the vehicle, vehicle class, type of the engine, and fuel type etc., are obtained from PUC centre in the study area.

A detailed analysis has been performed for the field data collected resulting in the variation of traffic volume and concertation of different pollutants with time. The analysis also involves the variation of AQI values with time and traffic volume. This part of the study also tried to define the status of concentration of different pollutants based on standards provided in the air quality parameter guide of each equipment used in the study.

The present study focused on determining the statistical dependency of concentration of each pollutant on traffic volume. Models were developed for prediction of concentration of different pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10} using Multiple Linear Regression analysis, Support Vector Regression analysis and Artificial Neural Networks. The concentration of different pollutants is considered as the dependent variable for development the models. The traffic volume, proportional share of different type of vehicles and temperature are the explanatory variables in the models developed for road mid-block sections. The study also attempted to develop an emission model for major pollutants CO and CO_2 and age of the vehicle, vehicle type and emission norms as independent variables to the model. The models developed for signalized intersection includes entering traffic volume, red time length, cycle length, temperature and average queued vehicles as independent variables. The models are validated successfully using different set of field data based on statistical evaluations. The results indicates that the ANN model preforms better for predicting the concentration of pollutants than SVR and MLR models at both mid-block and signalized intersection locations.

The result of the study is note-worthy that traffic volume and percentage of 3W identified as two explanatory variables which have a significant impact on air quality index values. The model evidently represent that the major percentage of diesel vehicles are responsible for the increase in AQI. The level of air quality in the study locations is defined based on the actual and anticipated AQI values with reference to the Indian AQI standards and indicated that the air quality in the study locations is in moderate and satisfactory conditions. The results clearly depict that the rise in the traffic volume is majorly responsible for the lowering of air quality and causing adverse effects to the environment. The present study acts as an empirical guide to understand the behavior of different pollutants released in the air with the traffic volume and thus provides insights to transportation planners and policy makers for controlling and managing a rise in traffic volume on all important roads and intersections in the cities.

7.2 CONCLUSIONS

The following are the specific conclusions drawn from the research work.

- The major pollutants such as CO, HCHO, TVOC and PM showed a greater increase in concentrations in the evening time between 6 PM to 9 PM, at various sections of multi-lane divided road mid-blocks. The traffic volume also found to be varying highly during these hours from 2500 to 4000 PCU/hr. However, there was no significant change in the level of CO_2 concentration.

- The total concentration of pollution estimated at mid-block road sections is found to be increased about 50% from morning 7 AM to evening 9 PM. The increase in the traffic volume is also found as 73% on these roads since morning hours of the day.
- The peak concentration of pollutants at mid-block road is found as 1180 ppm which happened during peak hour (7PM to 8PM) traffic observed as high as 4000 PCU/h.
- The observed CO, HCHO, TVOC and PM pollutants such as showed greater change in its values in the evening time between 6 PM to 9 PM at different signalized intersection approaches. The total entering traffic volume varying in this duration between 1200 to 6000 PCU/hr.
- The total concentration of pollution estimated at signalized intersection is found to be increased about 46% from morning 7 AM to evening 9 PM and entering traffic volume is found to increase as 80% on these intersections. The peak concentration of pollutants at signalized intersection is found as 1301 ppm happened during peak hour (7PM to 8PM) traffic observed as high as 6000 PCU/h.
- The pollution level at signalized intersection is significantly higher than mid-block roads. The average concentration of pollutants CO, $PM_{2.5,}$ HCHO, PM_{10}, TVOC and CO_2 is found to be increased by 160%, 143% 50%, 83%, 14%, and 9% respectively, from road mid-block sections to signalized intersections.
- The models developed for prediction of the various pollutants on road mid-block sections are best fitted with traffic volume and percentage share of vehicles type such as 3W and LCV. Similarly, entering traffic volume, cycle length and average queued vehicles are the variables influencing the concertation of different pollutants on signalized intersections.
- The emission models for pollutants such as CO and CO_2 are developed based on MRL analysis considering significant variables such as age of the vehicle, vehicle type and emission norms. It is observed that CO and CO_2 emissions are increased at a rate of 9.2% and 10.4% for increase in age of the vehicle. The model developed for air quality

index could be used for estimation of air quality index at any location with similar characteristics of study locations. The traffic volume and percentage of 3W could depict the variance of AQI. The sensitivity analysis reveals that the change in AQI values ranges between 56 to 356 due to change in percentage of 3W from 5% to 30%.

- The study concluded that ANN models are best fit for the prediction of concentration of pollutants and AQI that SVR and MLR models. ANN models developed in the study obtained high R^2 values and low MAPE values.

The study focussed on measuring, analysing and modelling the concentration of pollutants released in air using portable equipment. This allows the planners and policy makers to understand the type of vehicles and signal control parameters that are influencing the ambient air variations. The present study analyzed the the impact of traffic volume and vehicle composition on concentration of different pollutants on both mid-blocks and signalized intersections in the same study area which is not found in the past literature. Models were developed in the study considering the traffic volume, vehicle composition and queued vehicles as inputs to the model using machine learning techniques like ANN and SVR where specific research has not been found.

7.3 LIMITATIONS OF THE STUDY & SCOPE FOR FUTURE WORK

- The study is limited to measurement and analysis of only six pollutants namely CO, CO_2, HCHO, TVOC, $PM_{2.5}$ and PM_{10}. The impact of traffic flow behavior on pollutants like Hydrocarbons (HC), Nitrogen oxides (NO_x), Sulphur Dioxide (SO_2), etc, can also be analyzed as a part of the future research.

- As the study is carried out in mixed traffic conditions, the present work is limited in considering only different modes of vehicles for the analysis. The study may be extended by segregating the traffic with respect to different fuel types.

- Seasonal variation of the release of concentration of pollutants is not observed in the present study. Future studies may be carried out by analyzing the variation of pollutants concentration in different seasons.

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APPENDIX 1

Categorized vehicle volume and their count

Table A.1.1 Categorized vehicle count in the mid-block sections

RMB ID	Time	2W	Cars	3W	LCV	HCV
I	7.00 AM-8.00 AM	675	41	202	11	20
	8.00AM-9.00AM	722	112	230	14	23
	9.00AM-10.00AM	709	130	371	16	21
	10.00AM-11.00AM	869	97	347	21	18
	5.00PM-6.00PM	860	101	439	19	29
	6.00PM-7.00PM	1352	167	471	23	43
	7.00PM-8.00PM	1535	202	680	34	50
	8.00PM-9.00PM	1481	146	628	16	59
II	7.00 AM-8.00 AM	529	101	200	13	20
	8.00AM-9.00AM	587	142	268	20	22
	9.00AM-10.00AM	633	230	311	31	37
	10.00AM-11.00AM	731	281	401	34	41
	5.00PM-6.00PM	761	268	322	20	36
	6.00PM-7.00PM	830	320	400	22	50
	7.00PM-8.00PM	1010	371	448	32	70
	8.00PM-9.00PM	911	340	371	40	62
III	7.00 AM-8.00 AM	230	41	230	11	11
	8.00AM-9.00AM	311	57	272	20	22
	9.00AM-10.00AM	488	65	373	28	23
	10.00AM-11.00AM	590	86	448	34	41
	5.00PM-6.00PM	710	105	481	19	38
	6.00PM-7.00PM	890	140	581	16	52
	7.00PM-8.00PM	1011	176	682	32	65
	8.00PM-9.00PM	913	149	641	38	37
IV	7.00 AM-8.00 AM	592	111	281	11	32
	8.00AM-9.00AM	538	131	410	19	38
	9.00AM-10.00AM	808	230	538	23	50
	10.00AM-11.00AM	1012	311	586	20	70
	5.00PM-6.00PM	1130	320	551	22	46
	6.00PM-7.00PM	1181	350	641	29	61
	7.00PM-8.00PM	1270	401	659	34	76
	8.00PM-9.00PM	1121	371	592	26	71
V	7.00 AM-8.00 AM	230	94	101	13	24
	8.00AM-9.00AM	319	131	131	23	32
	9.00AM-10.00AM	592	168	160	34	52
	10.00AM-11.00AM	722	178	230	44	65
	5.00PM-6.00PM	770	212	222	52	67
	6.00PM-7.00PM	994	320	320	65	79
	7.00PM-8.00PM	1400	529	448	88	92

	8.00PM-9.00PM	1310	608	409	80	101
VI	7.00 AM-8.00 AM	322	101	61	13	52
	8.00AM-9.00AM	491	131	68	32	65
	9.00AM-10.00AM	605	178	88	41	80
	10.00AM-11.00AM	770	230	103	52	112
	5.00PM-6.00PM	911	311	140	88	122
	6.00PM-7.00PM	1338	400	178	112	128
	7.00PM-8.00PM	1400	461	191	131	140
	8.00PM-9.00PM	1330	440	221	122	133
VII	7.00 AM-8.00 AM	101	11	22	2	2
	8.00AM-9.00AM	230	22	41	4	4
	9.00AM-10.00AM	313	29	62	7	3
	10.00AM-11.00AM	371	34	67	11	5
	5.00PM-6.00PM	410	38	71	9	5
	6.00PM-7.00PM	461	47	80	8	7
	7.00PM-8.00PM	620	49	92	12	10
	8.00PM-9.00PM	581	42	107	7	7
VIII	7.00 AM-8.00 AM	268	19	101	2	11
	8.00AM-9.00AM	410	22	131	4	13
	9.00AM-10.00AM	680	41	221	8	23
	10.00AM-11.00AM	808	50	250	7	25
	5.00PM-6.00PM	1009	88	281	11	22
	6.00PM-7.00PM	1310	101	311	31	21
	7.00PM-8.00PM	1608	160	403	32	26
	8.00PM-9.00PM	1483	130	371	25	19
IX	7.00 AM-8.00 AM	780	52	112	24	21
	8.00AM-9.00AM	815	87	197	20	24
	9.00AM-10.00AM	898	112	244	41	35
	10.00AM-11.00AM	960	147	301	38	42
	5.00PM-6.00PM	1244	186	256	24	35
	6.00PM-7.00PM	1425	212	304	32	38
	7.00PM-8.00PM	1642	298	447	34	45
	8.00PM-9.00PM	1898	272	512	39	36
X	7.00 AM-8.00 AM	656	156	178	12	68
	8.00AM-9.00AM	1014	198	212	24	86
	9.00AM-10.00AM	1564	298	247	38	72
	10.00AM-11.00AM	1898	372	276	45	114
	5.00PM-6.00PM	1945	486	356	39	120
	6.00PM-7.00PM	2241	684	412	56	147
	7.00PM-8.00PM	2478	856	556	60	188
	8.00PM-9.00PM	2589	747	478	42	156
XI	7.00 AM-8.00 AM	1444	247	178	24	35
	8.00AM-9.00AM	1674	224	287	45	47
	9.00AM-10.00AM	1912	312	312	42	64

	10.00AM-11.00AM	2147	441	345	72	74
	5.00PM-6.00PM	1987	415	356	64	62
	6.00PM-7.00PM	2264	658	412	78	98
	7.00PM-8.00PM	2658	721	378	82	87
	8.00PM-9.00PM	2478	598	298	56	74
XII	7.00 AM-8.00 AM	387	645	56	9	112
	8.00AM-9.00AM	398	712	84	8	102
	9.00AM-10.00AM	412	887	112	11	135
	10.00AM-11.00AM	554	756	134	18	187
	5.00PM-6.00PM	512	719	128	19	156
	6.00PM-7.00PM	457	845	133	21	172
	7.00PM-8.00PM	589	898	145	28	188
	8.00PM-9.00PM	523	788	117	24	147
XIII	7.00 AM-8.00 AM	311	41	111	19	17
	8.00AM-9.00AM	371	61	229	38	19
	9.00AM-10.00AM	620	139	281	50	29
	10.00AM-11.00AM	731	155	448	56	37
	5.00PM-6.00PM	886	168	461	65	36
	6.00PM-7.00PM	911	194	680	50	35
	7.00PM-8.00PM	1129	230	808	78	38
	8.00PM-9.00PM	1411	268	668	58	32
XIV	7.00 AM-8.00 AM	509	101	140	9	13
	8.00AM-9.00AM	641	140	191	23	20
	9.00AM-10.00AM	808	160	311	29	32
	10.00AM-11.00AM	1129	191	430	37	37
	5.00PM-6.00PM	991	221	448	32	29
	6.00PM-7.00PM	911	250	461	28	33
	7.00PM-8.00PM	1130	281	499	41	43
	8.00PM-9.00PM	1011	298	397	35	31
XV	7.00 AM-8.00 AM	250	50	300	50	52
	8.00AM-9.00AM	371	178	311	43	65
	9.00AM-10.00AM	538	191	448	80	92
	10.00AM-11.00AM	722	221	581	110	131
	5.00PM-6.00PM	1011	268	551	89	101
	6.00PM-7.00PM	1219	272	628	101	121
	7.00PM-8.00PM	1262	311	641	121	140
	8.00PM-9.00PM	1258	291	608	92	133
XVI	7.00 AM-8.00 AM	281	11	52	0	0
	8.00AM-9.00AM	448	21	88	1	0
	9.00AM-10.00AM	632	25	131	3	2
	10.00AM-11.00AM	770	28	140	2	4
	5.00PM-6.00PM	808	32	132	4	2
	6.00PM-7.00PM	860	43	146	7	0
	7.00PM-8.00PM	921	46	160	11	4

	8.00PM-9.00PM	898	41	148	4	2
XVII	7.00 AM-8.00 AM	998	147	41	18	14
	8.00AM-9.00AM	1214	189	78	24	17
	9.00AM-10.00AM	1478	212	92	35	19
	10.00AM-11.00AM	1545	344	124	42	24
	5.00PM-6.00PM	1612	312	135	38	23
	6.00PM-7.00PM	1598	378	147	47	24
	7.00PM-8.00PM	1702	412	152	51	30
	8.00PM-9.00PM	1645	386	124	30	27
XVIII	7.00 AM-8.00 AM	1444	447	356	41	0
	8.00AM-9.00AM	1612	512	372	47	2
	9.00AM-10.00AM	1547	647	408	68	1
	10.00AM-11.00AM	1898	698	547	88	2
	5.00PM-6.00PM	1745	656	523	84	0
	6.00PM-7.00PM	1897	647	645	92	1
	7.00PM-8.00PM	2160	712	662	101	4
	8.00PM-9.00PM	1912	612	614	87	2

Table A.1.2 Categorized vehicle count in the signalized sections

SI ID	Time	2W	Cars	3W	LCV	HCV
I	7.00 AM-8.00 AM	775	112	299	76	48
	8.00AM-9.00AM	812	186	312	81	59
	9.00AM-10.00AM	798	218	454	97	67
	10.00AM-11.00AM	954	195	465	68	36
	5.00PM-6.00PM	990	211	515	53	88
	6.00PM-7.00PM	1465	234	568	105	98
	7.00PM-8.00PM	1632	298	778	108	126
	8.00PM-9.00PM	1567	237	702	119	134
II	7.00 AM-8.00 AM	611	225	295	85	68
	8.00AM-9.00AM	660	249	366	94	58
	9.00AM-10.00AM	704	356	414	118	79
	10.00AM-11.00AM	794	392	496	79	82
	5.00PM-6.00PM	838	354	429	96	117
	6.00PM-7.00PM	915	440	517	125	228
	7.00PM-8.00PM	1114	464	556	145	223
	8.00PM-9.00PM	1012	415	435	88	114
III	7.00 AM-8.00 AM	315	89	334	63	82
	8.00AM-9.00AM	408	126	389	90	94
	9.00AM-10.00AM	550	118	468	124	78
	10.00AM-11.00AM	675	174	567	118	118
	5.00PM-6.00PM	806	208	598	85	142
	6.00PM-7.00PM	986	263	652	93	113

	7.00PM-8.00PM	1158	256	774	78	112
	8.00PM-9.00PM	1053	278	758	95	98
IV	7.00 AM-8.00 AM	318	156	212	105	85
	8.00AM-9.00AM	398	195	231	85	125
	9.00AM-10.00AM	660	258	250	125	140
	10.00AM-11.00AM	798	252	328	91	145
	5.00PM-6.00PM	840	303	323	115	157
	6.00PM-7.00PM	1010	399	420	138	185
	7.00PM-8.00PM	1515	612	528	268	258
	8.00PM-9.00PM	1419	696	499	128	268
V	7.00 AM-8.00 AM	433	205	113	84	115
	8.00AM-9.00AM	586	213	128	131	119
	9.00AM-10.00AM	699	264	158	102	168
	10.00AM-11.00AM	860	284	198	116	222
	5.00PM-6.00PM	1018	392	239	138	208
	6.00PM-7.00PM	1458	501	268	198	198
	7.00PM-8.00PM	1514	536	285	205	205
	8.00PM-9.00PM	1404	540	301	195	218
VI	7.00 AM-8.00 AM	338	79	195	35	78
	8.00AM-9.00AM	496	88	216	45	80
	9.00AM-10.00AM	720	112	299	58	68
	10.00AM-11.00AM	915	97	333	66	98
	5.00PM-6.00PM	1112	158	382	85	105
	6.00PM-7.00PM	1408	215	412	112	88
	7.00PM-8.00PM	1717	239	489	115	78
	8.00PM-9.00PM	1522	281	465	85	83
VII	7.00 AM-8.00 AM	860	159	213	94	75
	8.00AM-9.00AM	887	179	290	118	81
	9.00AM-10.00AM	950	212	314	124	109
	10.00AM-11.00AM	1013	257	408	82	114
	5.00PM-6.00PM	1343	226	315	57	121
	6.00PM-7.00PM	1515	212	393	86	98
	7.00PM-8.00PM	1729	389	535	114	128
	8.00PM-9.00PM	1982	362	602	124	98
VIII	7.00 AM-8.00 AM	723	245	268	72	127
	8.00AM-9.00AM	1119	285	320	124	158
	9.00AM-10.00AM	1616	388	311	114	168
	10.00AM-11.00AM	1984	454	318	125	203
	5.00PM-6.00PM	2025	559	443	137	198
	6.00PM-7.00PM	2313	744	506	148	230
	7.00PM-8.00PM	2545	964	605	178	258
	8.00PM-9.00PM	2698	815	553	135	236
IX	7.00 AM-8.00 AM	1535	319	252	112	98
	8.00AM-9.00AM	1768	297	338	99	115

	9.00AM-10.00AM	2004	403	418	95	168
	10.00AM-11.00AM	2236	517	452	138	158
	5.00PM-6.00PM	2015	502	472	168	111
	6.00PM-7.00PM	2359	762	506	172	230
	7.00PM-8.00PM	2734	809	469	119	239
	8.00PM-9.00PM	2598	689	373	149	227

APPENDIX 2

Variation of concentration of pollutants during morning and evening peak hours

The variation of concentration of pollutants during morning and evening peak hour traffic volume is given in Figures A.2.1 to A.2.20.

Mid-block sections morning peak hours

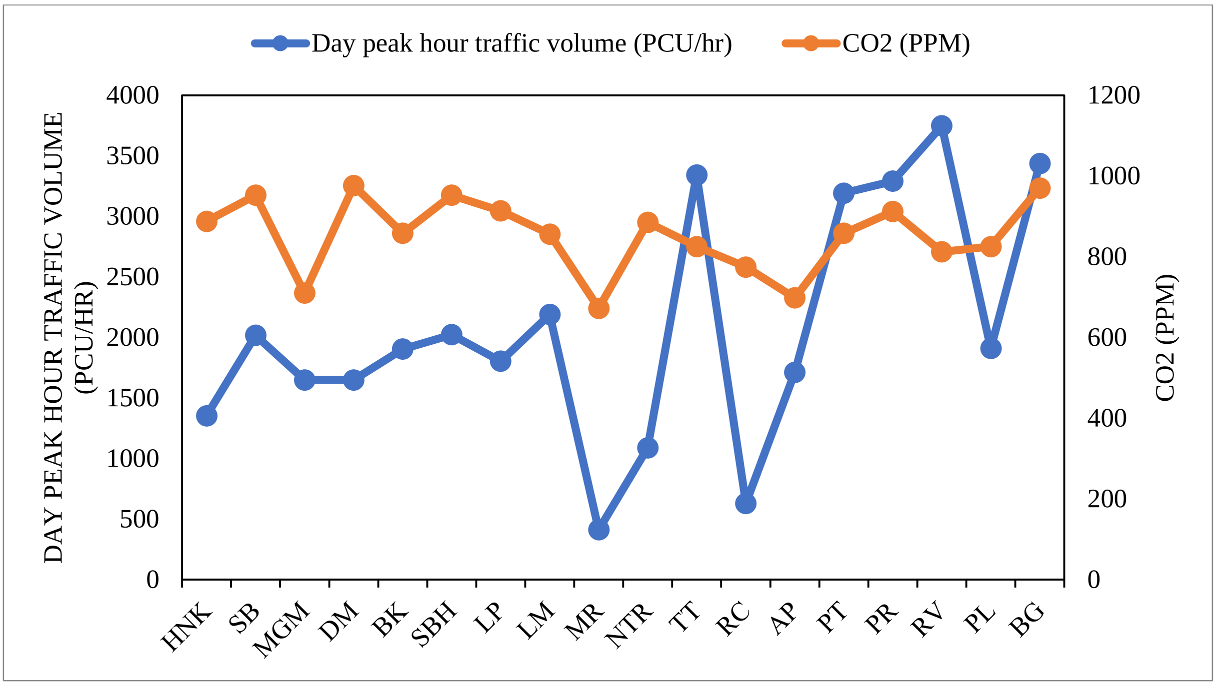

Figure A.2.1 Variation of CO_2 concentrations with morning peak hour traffic volume

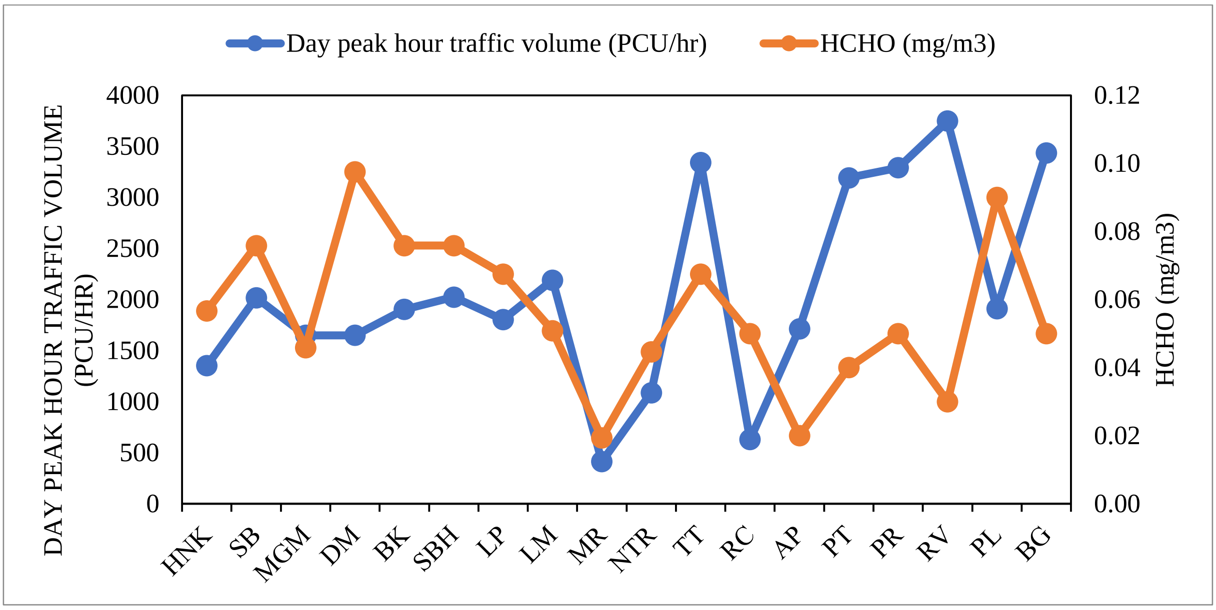

Figure A.2.2 Variation of HCHO concentrations with morning peak hour traffic volume

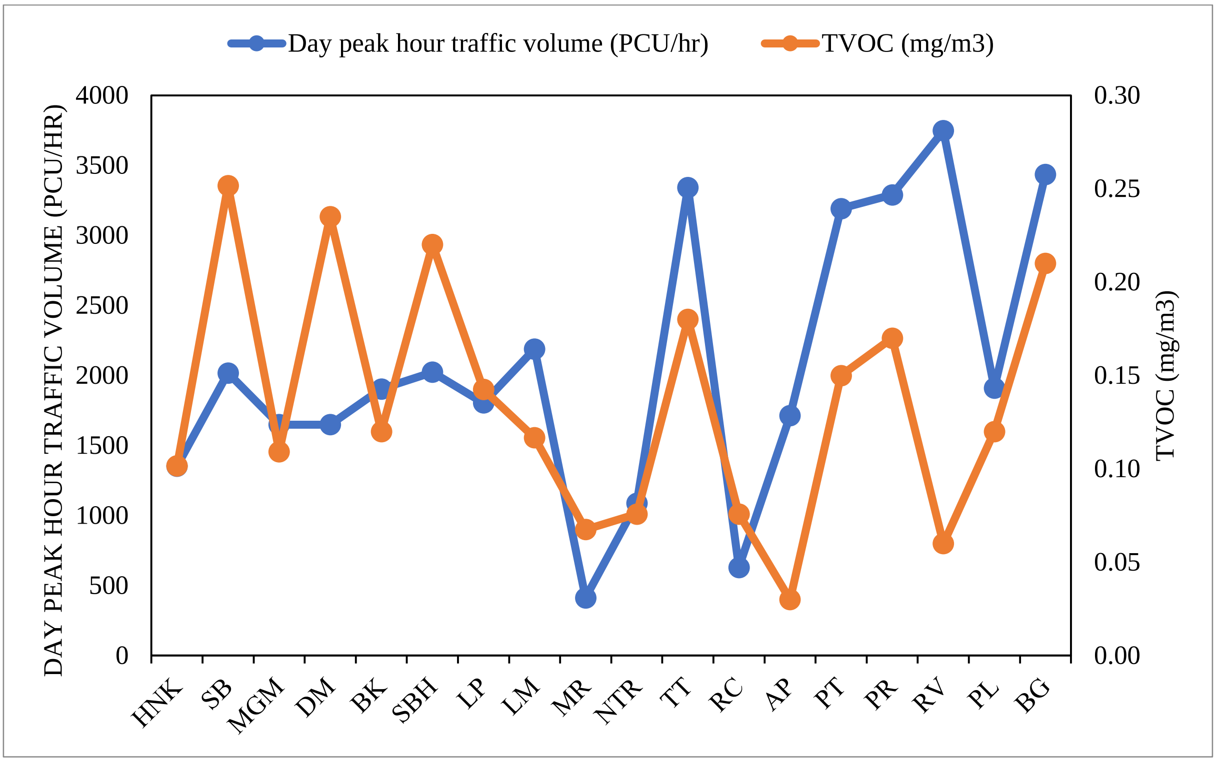

Figure A.2.3 Variation of TVOC concentrations with morning peak hour traffic volume

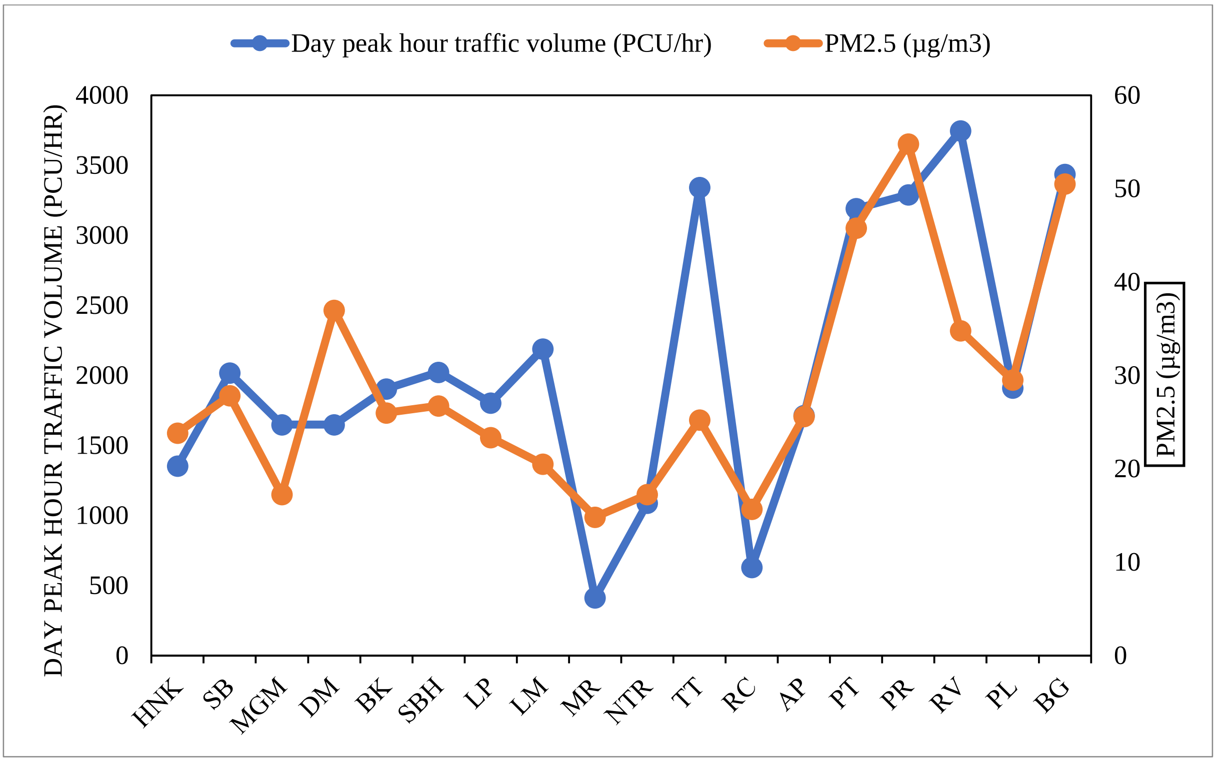

Figure A.2.4 Variation of $PM_{2.5}$ concentrations with morning peak hour traffic volume

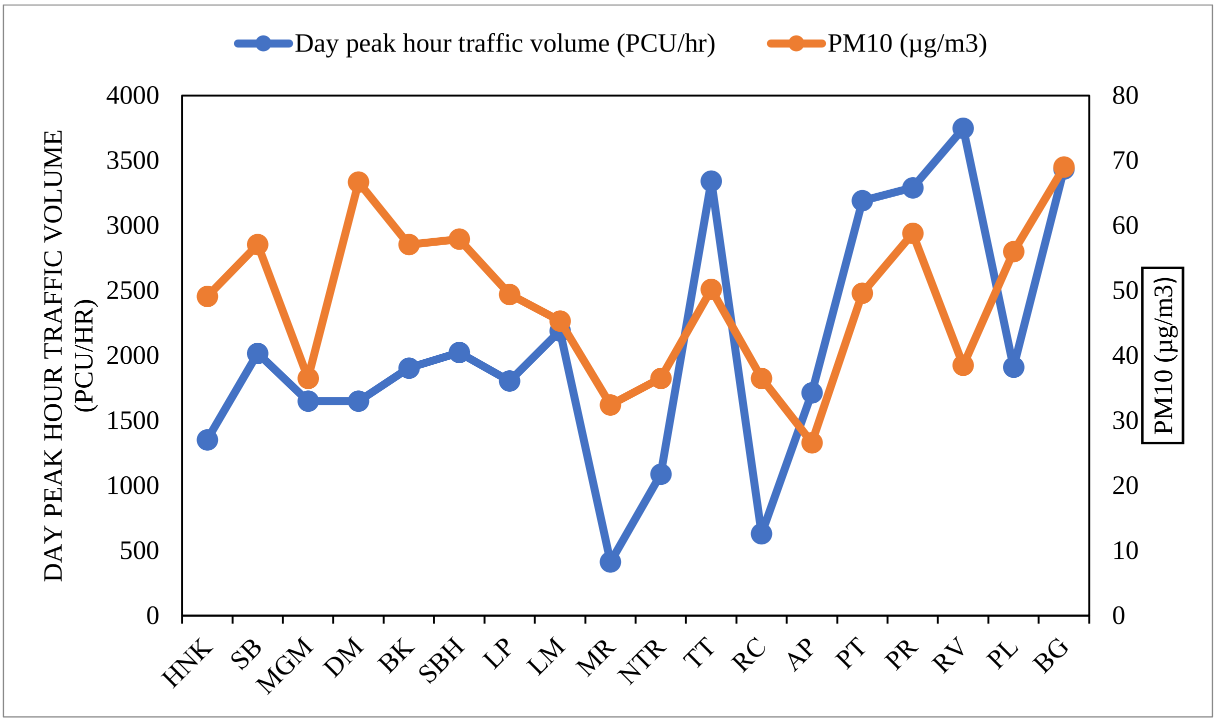

Figure A.2.5 Variation of PM_{10} concentrations with morning peak hour traffic volume

Mid-block sections evening peak hours

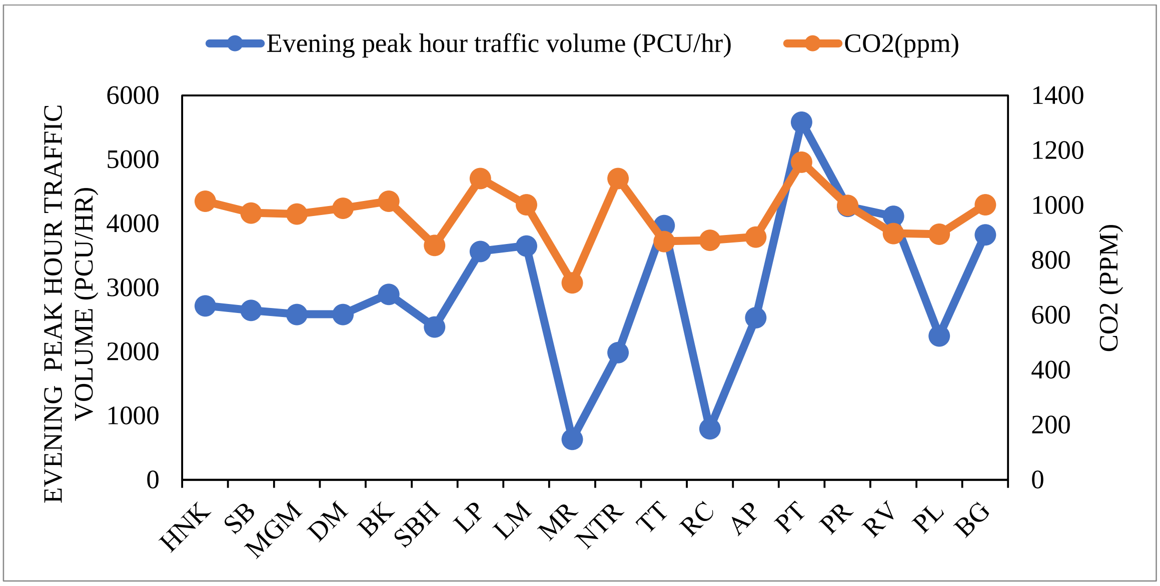

Figure A.2.6 Variation of CO_2 concentrations with evening peak hour traffic volume

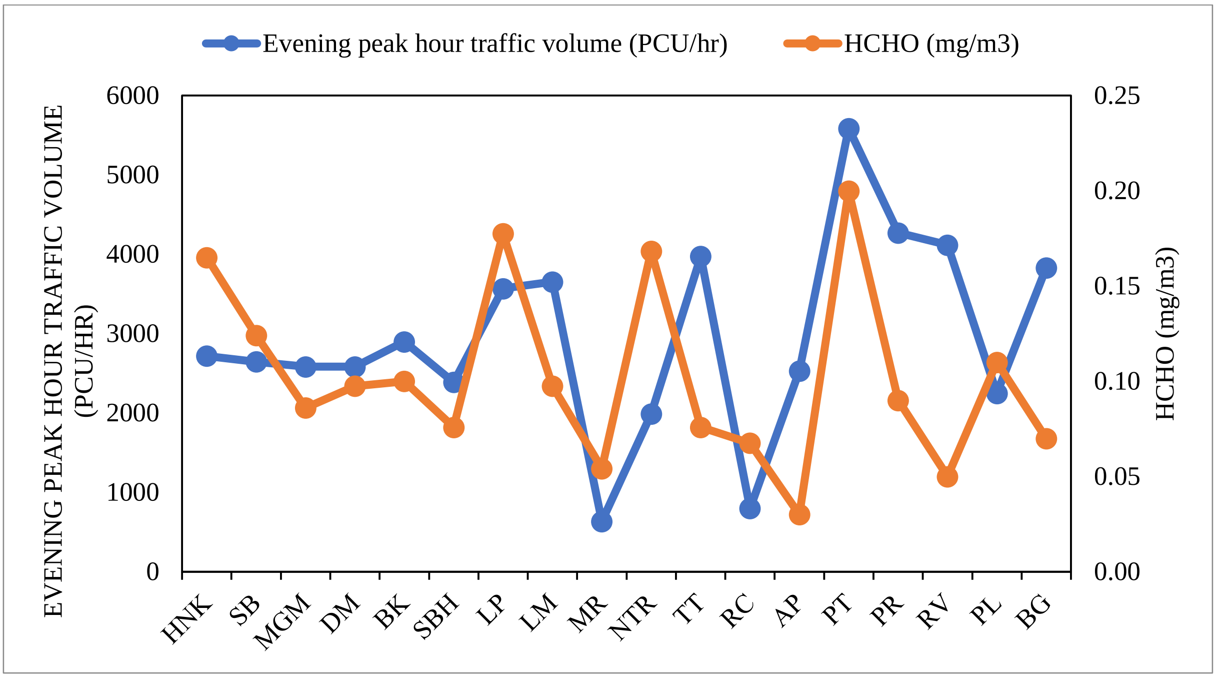

Figure A.2.7 Variation of HCHO concentrations with evening peak hour traffic volume

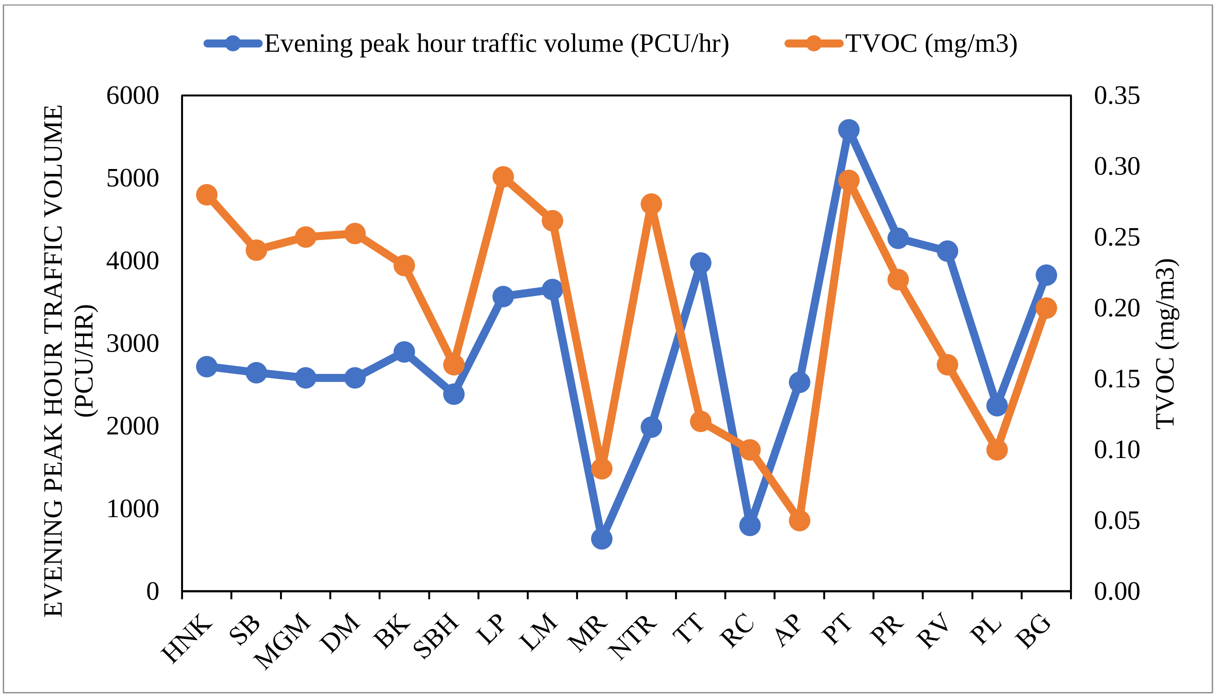

Figure A.2.8 Variation of TVOC concentrations with evening peak hour traffic volume

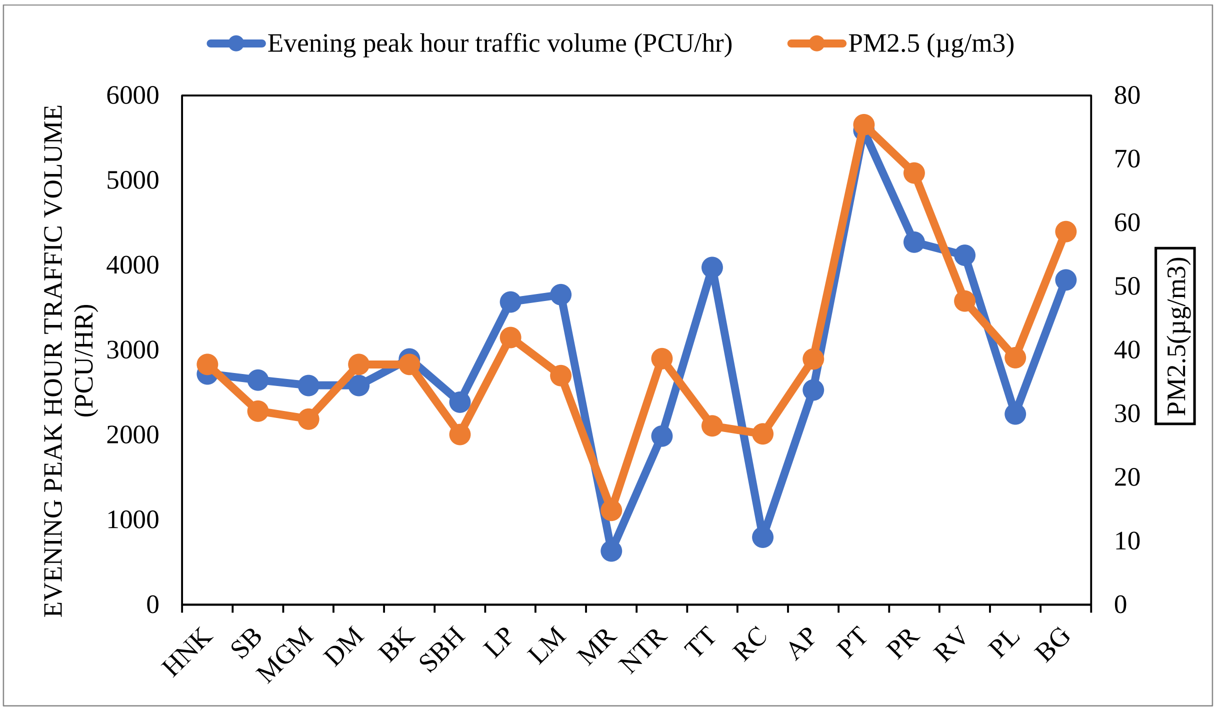

Figure A.2.9 Variation of $PM_{2.5}$ concentrations with morning peak hour traffic volume

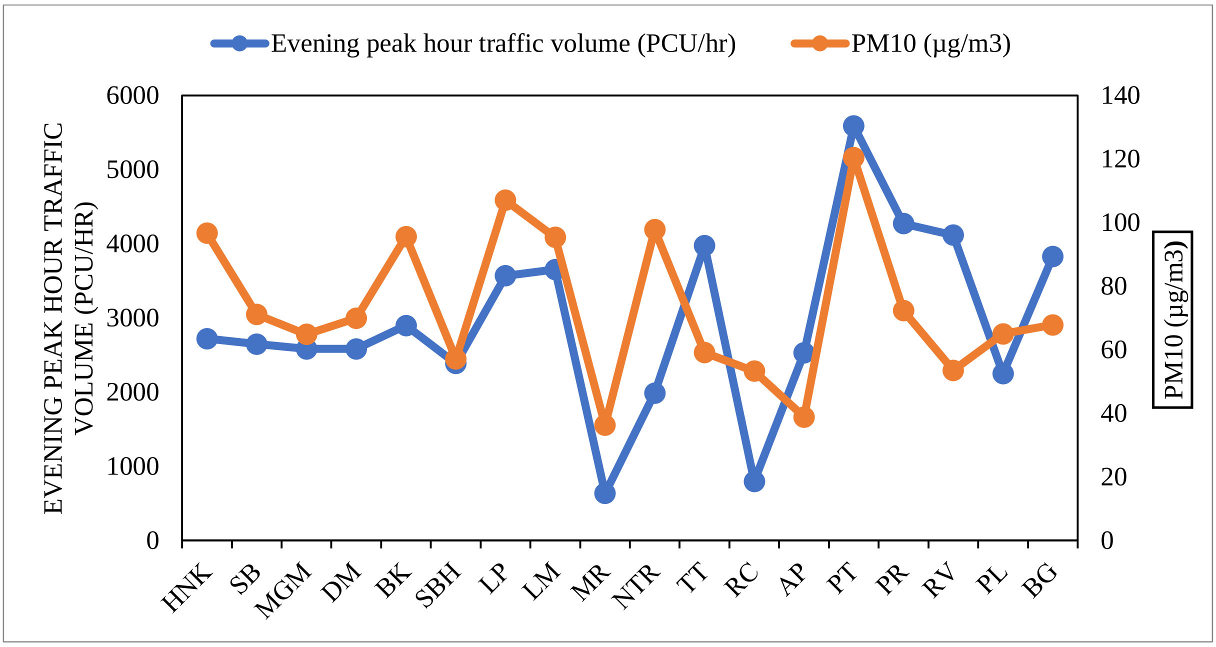

Figure A.2.10 Variation of PM_{10} concentrations with morning peak hour traffic volume

Signalized intersections morning peak hours

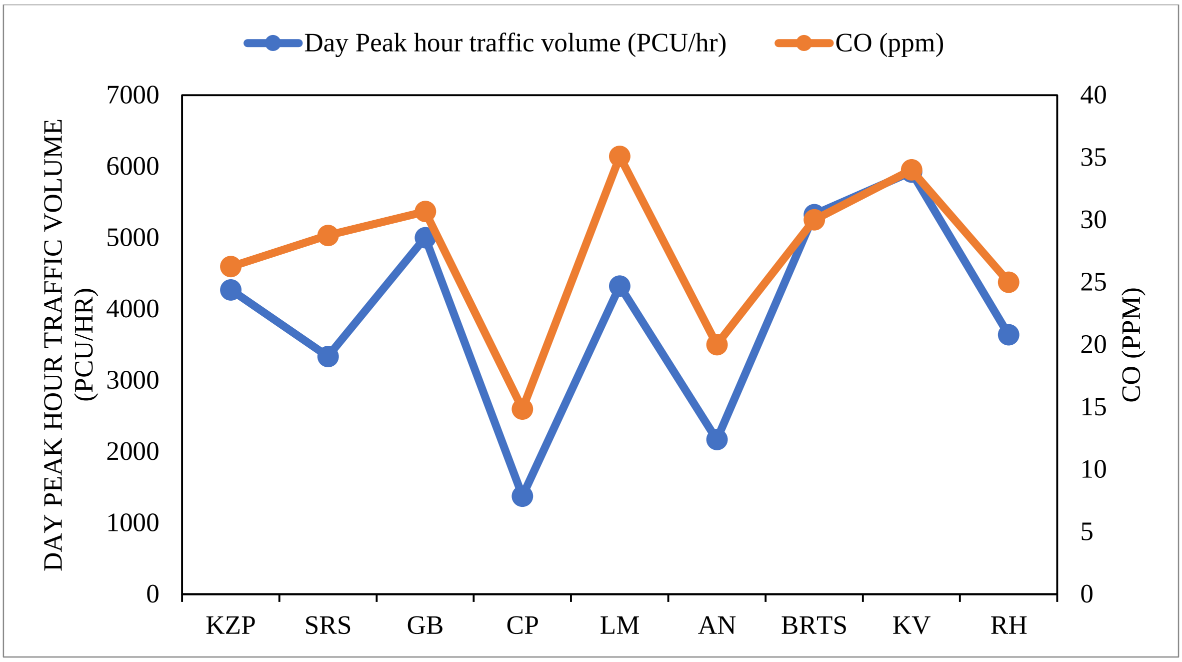

Figure A.2.11 Variation of CO concentrations with morning peak hour traffic volume

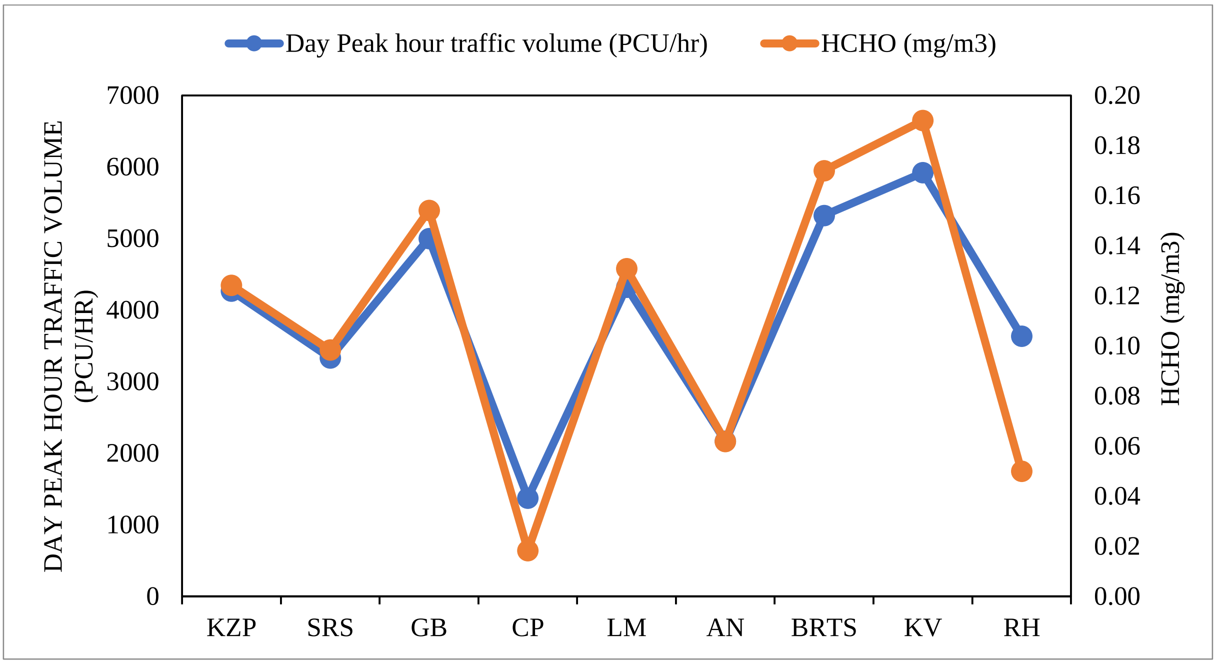

Figure A.2.12 Variation of HCHO concentrations with morning peak hour traffic volume

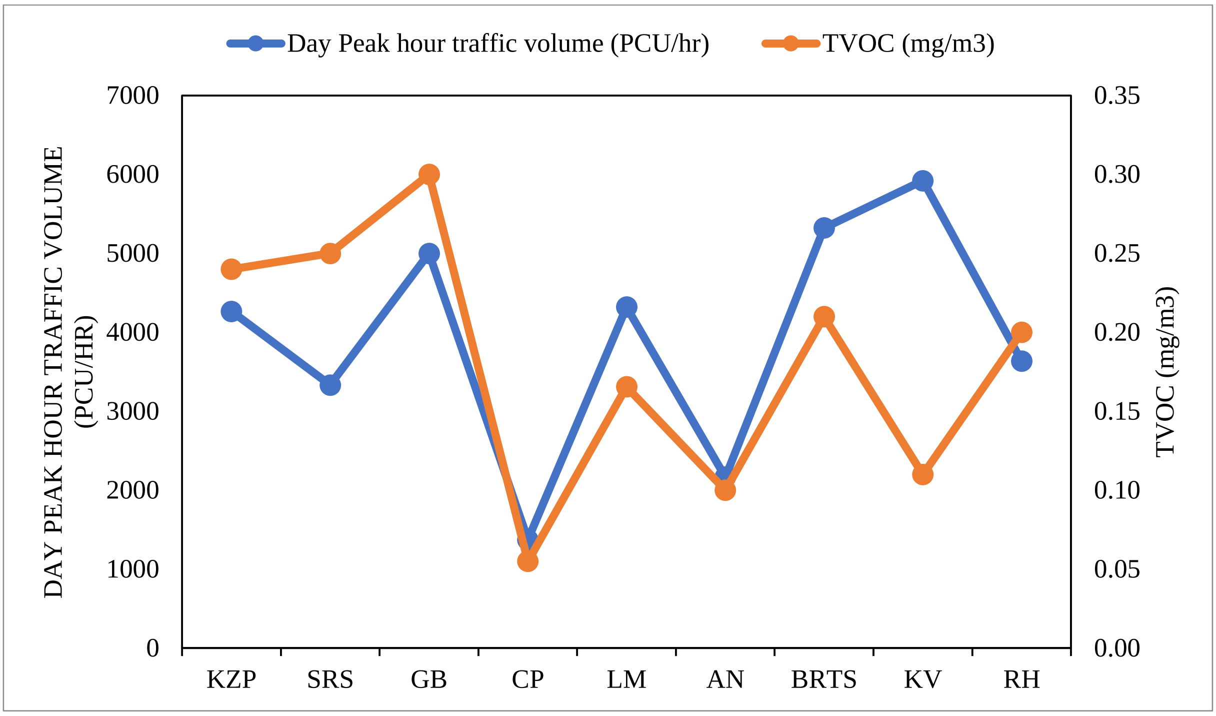

Figure A.2.13 Variation of TVOC concentrations with morning peak hour traffic volume

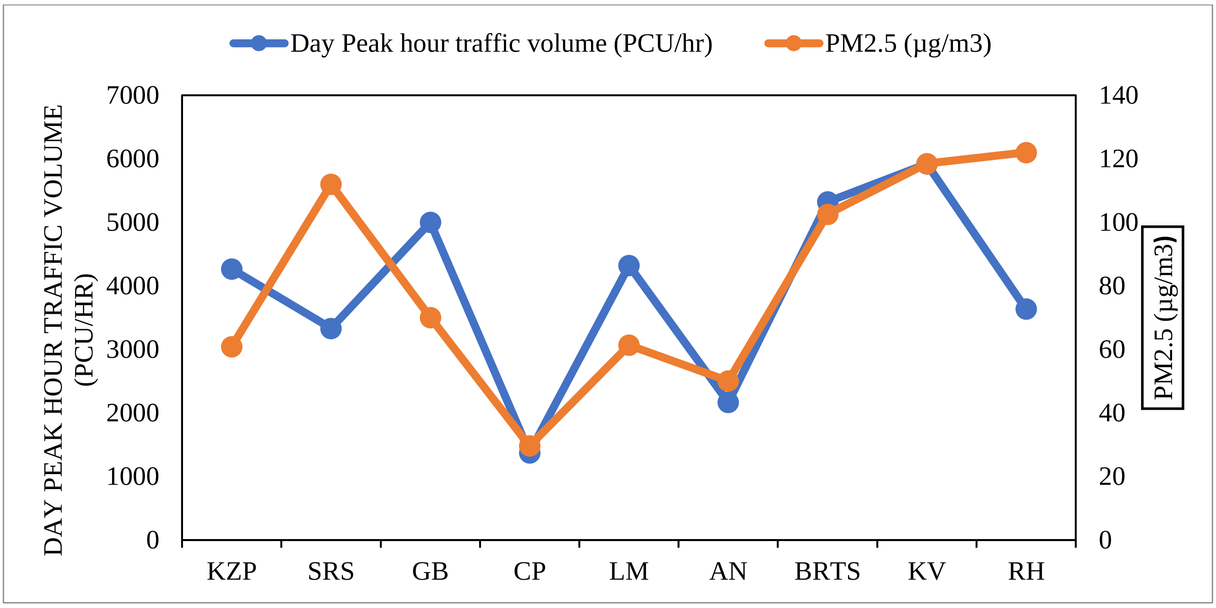

Figure A.2.14 Variation of $PM_{2.5}$ concentrations with morning peak hour traffic volume

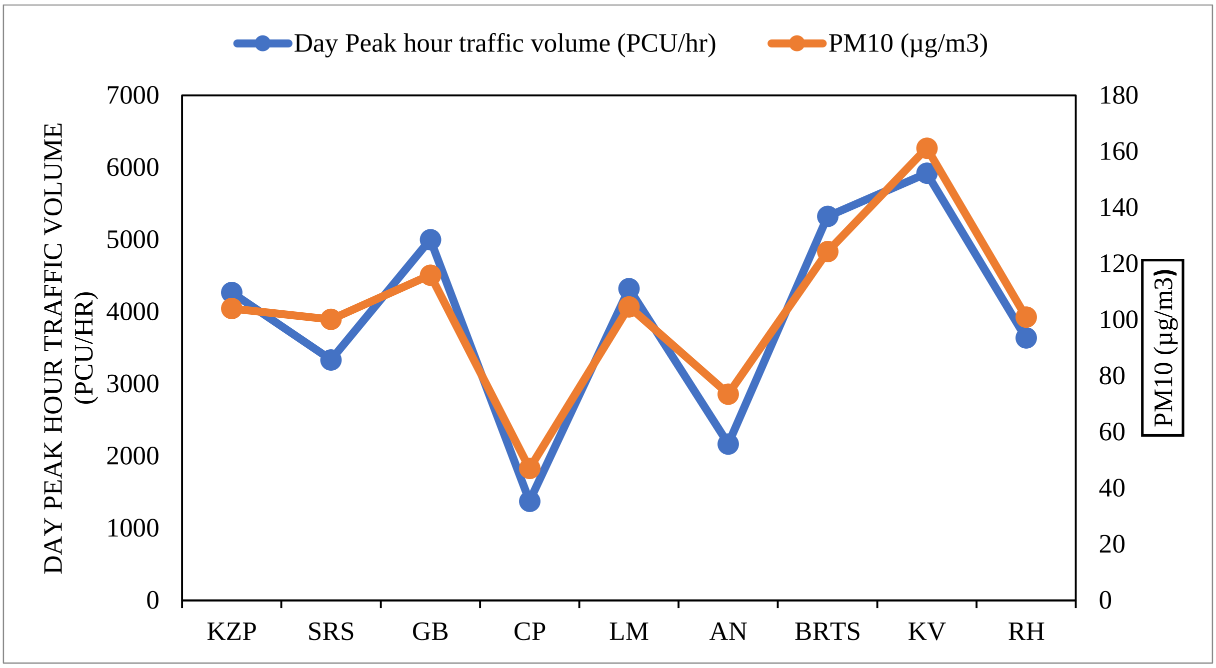

Figure A.2.15 Variation of PM_{10} concentrations with morning peak hour traffic volume

Signalized intersections evening peak hours

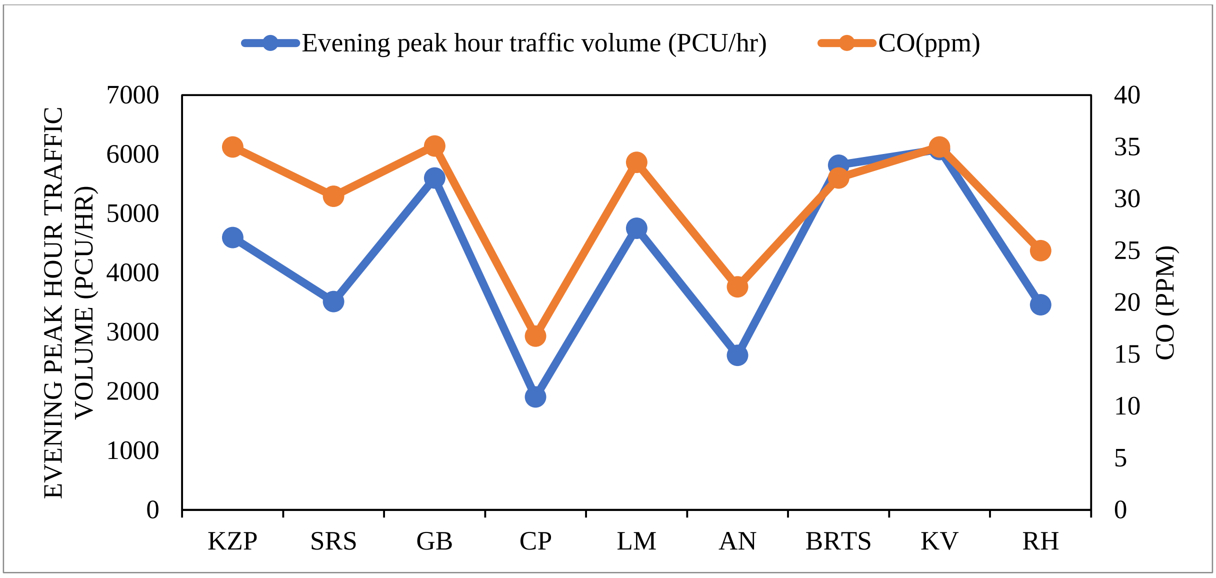

Figure A.2.16 Variation of CO concentrations with evening peak hour traffic volume

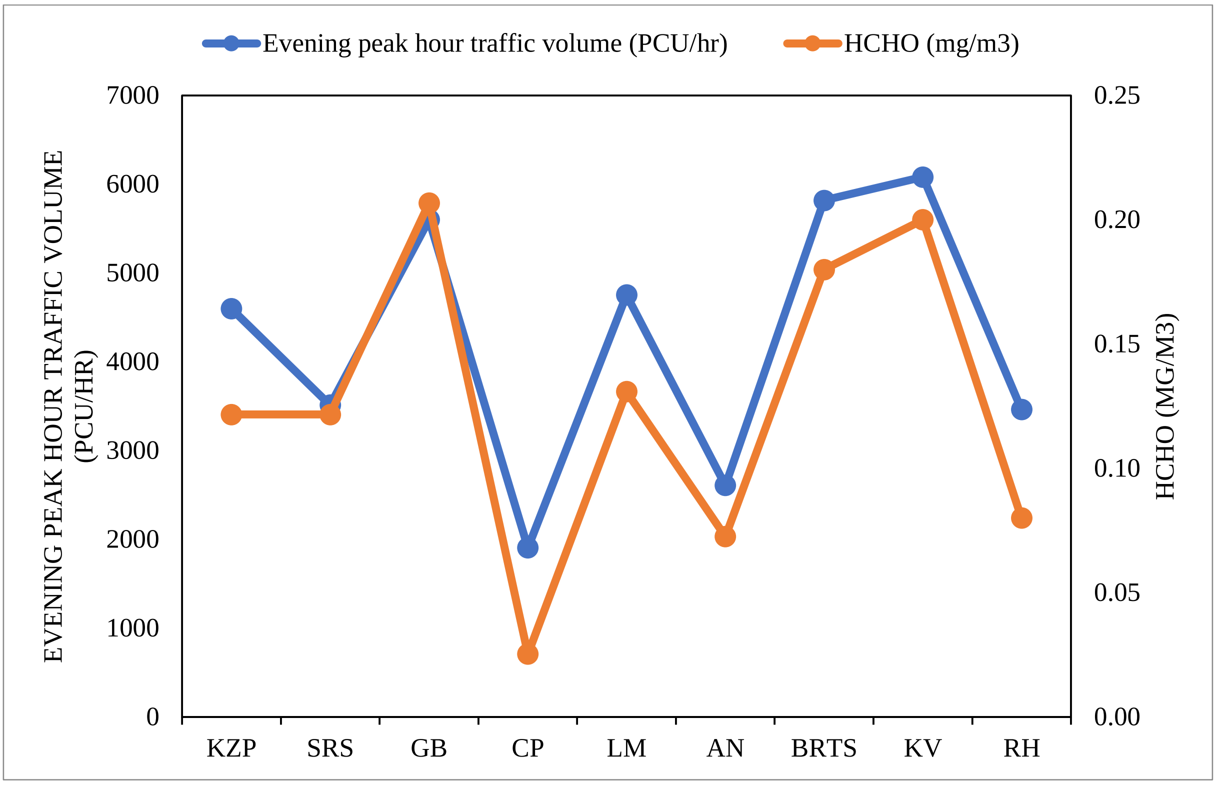

Figure A.2.17 Variation of HCHO concentrations with evening peak hour traffic volume

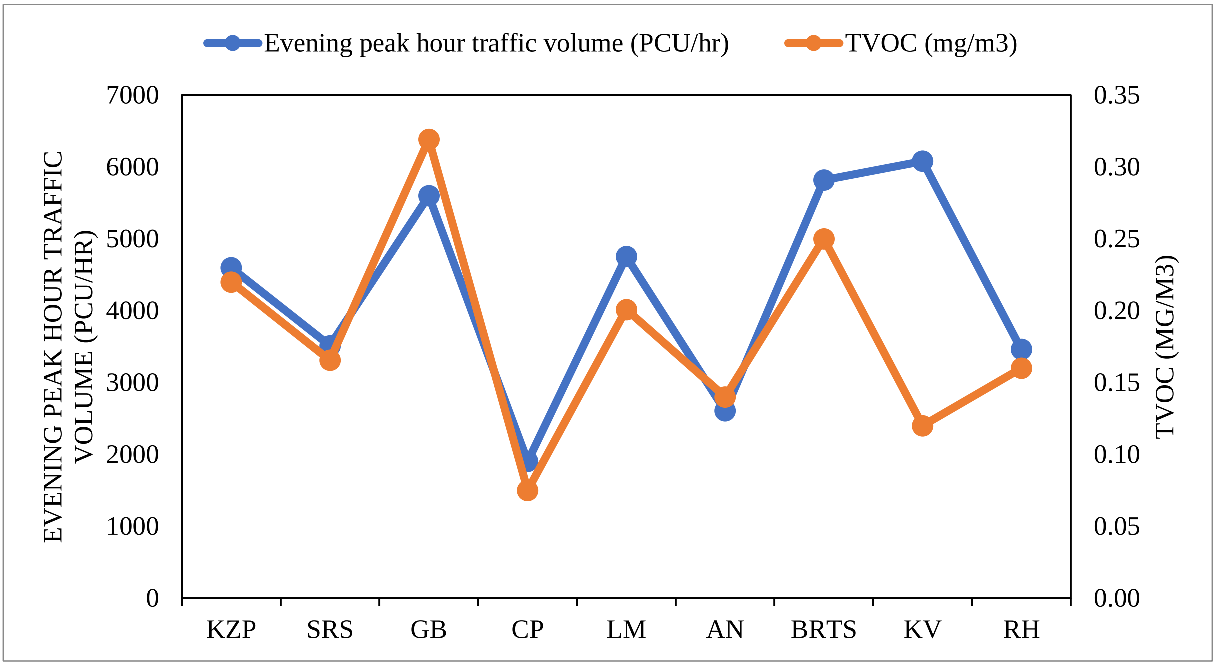

Figure A.2.18 Variation of TVOC concentrations with evening peak hour traffic volume

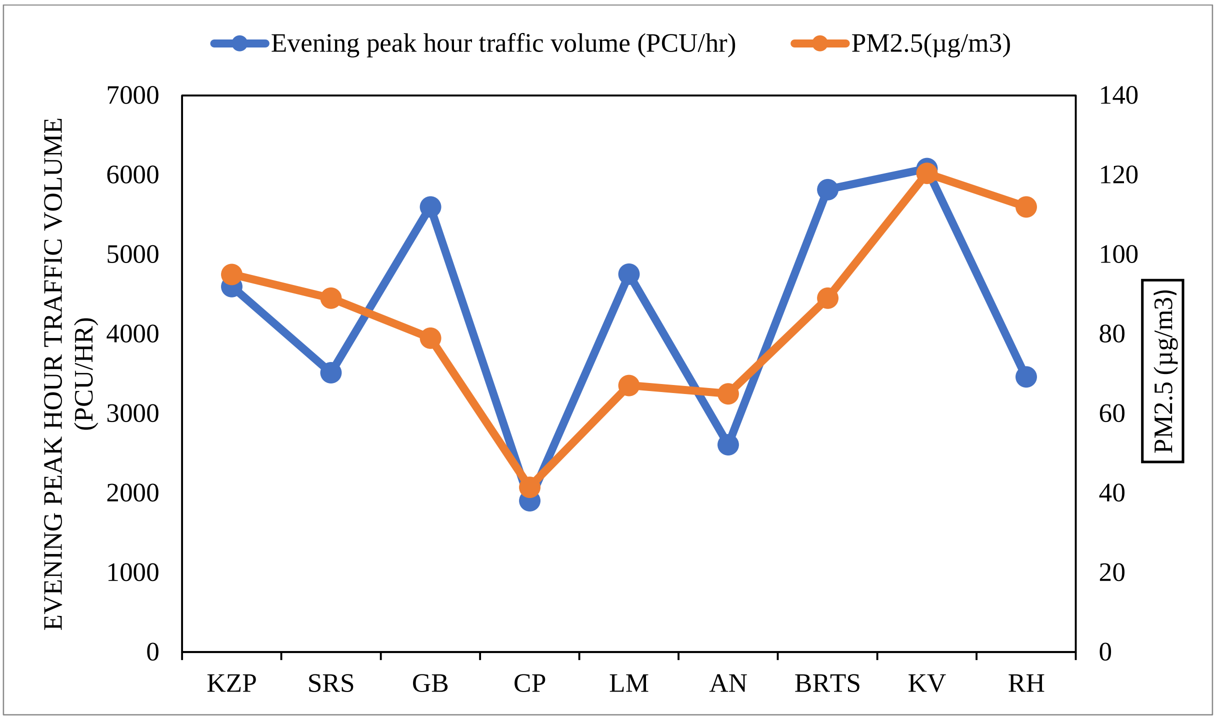

Figure A.2.19 Variation of $PM_{2.5}$ concentrations with evening peak hour traffic volume

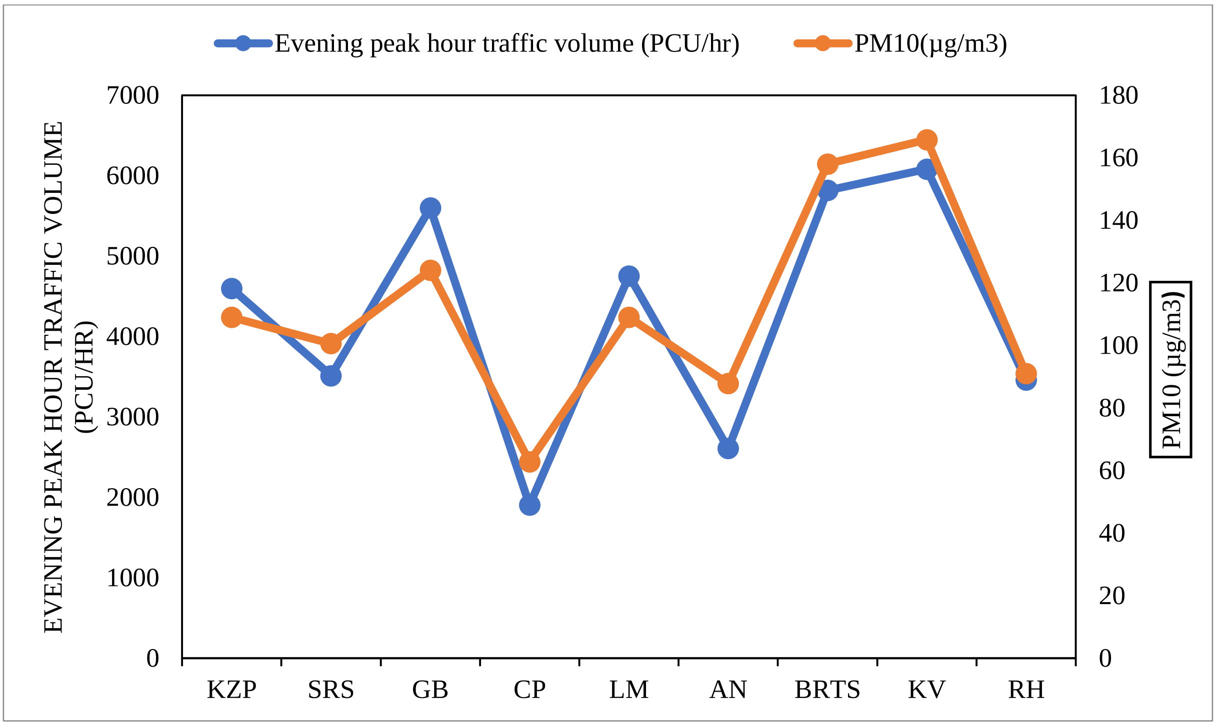

Figure A.2.20 Variation of PM_{10} concentrations with evening peak hour traffic volume

APPENDIX 3

Comparison of AQI standards

Air Quality Index (AQI) is a tool used worldwide to communicate how polluted the air currently is or how polluted it is forecast to become. Understanding AQI standards is crucial as they guide the public on health implications and necessary precautions. Different countries adopt different AQI standards based on their specific environmental policies, industrial activities, and public health priorities.

The Indian AQI standards are compared with AQI standards of six different developing countries namely China, Brazil, South Africa, Mexico, Thailand and Indonesia. All these countries use a six-category AQI system that progresses from good to hazardous, indicating increasing levels of health risk.

India

- **Good** (0-50): Minimal impact.
- **Satisfactory** (51-100): Minor breathing discomfort to sensitive people.
- **Moderate** (101-200): Breathing discomfort to people with lungs, asthma, and heart diseases.
- **Poor** (201-300): Breathing discomfort to most people on prolonged exposure.
- **Very Poor** (301-400): Respiratory illness on prolonged exposure.
- **Severe** (401-500): Affects healthy people and seriously impacts those with existing diseases.

China

- **Excellent** (0-50): No health implications.
- **Good** (51-100): Acceptable air quality but may have moderate health concern for sensitive groups.
- **Lightly Polluted** (101-150): Sensitive groups may experience health effects; the general public is not likely to be affected.
- **Moderately Polluted** (151-200): Everyone may begin to experience health effects; sensitive groups may experience more serious health effects.
- **Heavily Polluted** (201-300): Health alert; everyone may experience serious health effects.

- **Severely Polluted** (301-500): Health warnings of emergency conditions; the entire population is likely to be affected.

Brazil

- **Good** (0-50): No health implications.
- **Moderate** (51-100): Acceptable air quality; some pollutants may have moderate health concern for sensitive groups.
- **Unhealthy for Sensitive Groups** (101-150): Sensitive groups may experience health effects; the general public is not likely to be affected.
- **Unhealthy** (151-200): Everyone may begin to experience health effects; sensitive groups may experience more serious health effects.
- **Very Unhealthy** (201-300): Health alert; everyone may experience serious health effects.
- **Hazardous** (301-500): Health warnings of emergency conditions; the entire population is likely to be affected.

South Africa

- **Good** (0-50): Air quality is considered satisfactory, and air pollution poses little or no risk.
- **Moderate** (51-100): Air quality is acceptable; however, some pollutants may have moderate health concerns for sensitive groups.
- **Unhealthy for Sensitive Groups** (101-150): Sensitive groups may experience health effects; the general public is not likely to be affected.
- **Unhealthy** (151-200): Everyone may begin to experience health effects; sensitive groups may experience more serious health effects.
- **Very Unhealthy** (201-300): Health alert; everyone may experience serious health effects.
- **Hazardous** (301-500): Health warnings of emergency conditions; the entire population is likely to be affected.

Mexico

- **Good** (0-50): Air quality is satisfactory, and air pollution poses little or no risk.

- **Moderate** (51-100): Air quality is acceptable; however, some pollutants may have a moderate health concern for a very small number of people.
- **Unhealthy for Sensitive Groups** (101-150): Members of sensitive groups may experience health effects. The general public is not likely to be affected.
- **Unhealthy** (151-200): Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
- **Very Unhealthy** (201-300): Health alert: everyone may experience more serious health effects.
- **Hazardous** (301-500): Health warnings of emergency conditions. The entire population is likely to be affected.

Thailand

- **Good** (0-50): Air quality is considered satisfactory, and air pollution poses little or no risk.
- **Moderate** (51-100): Air quality is acceptable; however, some pollutants may pose a moderate health concern for a very small number of people.
- **Unhealthy for Sensitive Groups** (101-150): Members of sensitive groups may experience health effects. The general public is not likely to be affected.
- **Unhealthy** (151-200): Everyone may begin to experience health effects; sensitive groups may experience more serious health effects.
- **Very Unhealthy** (201-300): Health alert: everyone may experience more serious health effects.
- **Hazardous** (301-500): Health warnings of emergency conditions. The entire population is likely to be affected.

Indonesia

- **Good** (0-50): Air quality is satisfactory, and air pollution poses little or no risk.
- **Moderate** (51-100): Air quality is acceptable; however, some pollutants may pose a moderate health concern for a very small number of people.
- **Unhealthy for Sensitive Groups** (101-150): Members of sensitive groups may experience health effects. The general public is not likely to be affected.
- **Unhealthy** (151-200): Everyone may begin to experience health effects; sensitive groups may experience more serious health effects.

- **Very Unhealthy** (201-300): Health alert: everyone may experience more serious health effects.
- **Hazardous** (301-500): Health warnings of emergency conditions. The entire population is likely to be affected.

The thresholds for each category may differ slightly in different countries. For example, the threshold values for "Moderate" and "Unhealthy" levels can vary, reflecting different national air quality standards and public health policies. These differences may be due to varying industrial activities, environmental policies, public health priorities, and levels of pollution.

The AQI standards of China, Brazil, South Africa, Mexico, Thailand, and Indonesia with those of India, several similarities and differences emerge. All these countries employ a six-category system that ranges from "Good" to "Hazardous/Severe," indicating increasing levels of health risk. In India, the categories are "Good," "Satisfactory," "Moderate," "Poor," "Very Poor," and "Severe," with corresponding health impacts from minimal effects to severe health warnings for the entire population. China, Mexico, Thailand, Indonesia, Brazil, and South Africa have similar category names and health impact descriptions, emphasizing health risks for sensitive groups at moderate levels and escalating to warnings for the entire population at higher levels. The primary difference lies in the specific AQI thresholds for each category, which can vary slightly among these countries. For instance, while India's "Moderate" category ranges from 101-200, other countries might have slightly different ranges for equivalent categories. These variations reflect localized environmental policies, pollution sources, and public health priorities, underscoring the need for tailored approaches to air quality management while maintaining a broadly consistent framework for public communication.