A Prediction Method for Estimating Exposure of Sedentary Workers to Carbon Monoxide along an Urban Traffic Corridor

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by

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CERTIFICATE

This is to certify that **Nongthombam Premananda Singh** has been working under my supervision since July, 2012 as a PhD student under QIP scheme. His thesis entitled **"A Prediction Method for Estimating Exposure of Sedentary Workers to Carbon Monoxide in an Urban Traffic Corridor"** is an authentic record of the results obtained from the research work carried out under my supervision in the Civil Engineering Department, Indian Institute of Technology Guwahati, Assam, India. I certify that he has fulfilled all the requirements according to the rules of this institute regarding the investigations embodied in his thesis and this work has not been submitted elsewhere for a degree.

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Dedicated

to

my mentor and supervisor

Prof. Sharad Gokhale

&

my dear

Parents

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ABSTRACT

Outdoor air pollution is one of the major health issues, Air Pollution in urban areas caused by vehicular traffic is of major concern. Rapid urbanization and unprecedented growth of vehicles have resulted into poor urban air quality, in particular, traffic corridors. People living or working close to the trafficked roads are often exposed to higher pollutant concentrations and often for longer time. As a result, exposure to air pollutants related to vehicular traffic in urban areas is of major concern.

Personal exposure to air pollutant may be assessed by monitoring with a portable instrument, which is carried along by the individuals during their normal duties. It is, however, unfavorable to carry for long time, costly and tedious in application. In another approach, the spatiotemporal air quality is combined with the time-activity of the individual to quantify exposure. In this approach, the spatiotemporal air quality is either estimated using dispersion models, or by using a network of large number of monitoring stations. While dispersion models are often subjected to errors in accuracy of inputs data and model assumptions, whereas, monitoring with large number of fixed stations is not feasible due to time and cost. Therefore, exposure quantification in a mixed urban environments is a challenging task.

In this research, a simple prediction method comprising of spatiotemporal model and exposure model for carbon monoxide exposure has been developed. The spatiotemporal model is developed by combining CALINE4 air quality dispersion model with lognormal probability distribution model improved with a calibration factor of data from one fixed monitoring station. The exposure model has been developed by combining the estimates of the spatiotemporal model and time-activity pattern of individuals. The prediction method estimates the spatiotemporal air quality and exposure in terms of probability of

exceedance over the NAAQS (National Ambient Air Quality Standard) India, respectively. Also the method has been applied (a) to estimate the required reduction in emission to maintain healthy air quality, (b) to estimate the probability of exposure in different times of the day, and (c) to established relationship between probability of exposure and annoyance by air pollution of a target population.

The results show that the developed prediction method estimated the spatiotemporal air quality and exposure reliably in an urban traffic corridor. The results of application of the prediction method also demonstrates the usefulness for developing various emission reduction strategies as well as exposure management related to air pollution health-risks.

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SYMBOLS AND ABBREVIATIONS

Symbol	*Description*
E_i	Integrated exposure of person i^{th} person
$E_{i(avg)}$	Average exposure of person i^{th} person
$E_i\ (t)$	Integrated exposure of person i^{th} person for a time t
PBM	Proximity based models
GM	Geostatistical models
LRM	Land-use regression models
DM	Dispersion models
IEM	Integrated emission-meteorological models
HM	Hybrid models
CO	Carbon monoxide
$PM_{2.5}$	Particulate matter of size 2.5 µ
PM_{10}	Particulate matter of size 10 µ
NO_2	Nitrogen dioxide
AERMOD	American Meteorological Society/Environmental Protection Agency Regulatory Model
CALINE	California Line Source Model
CAL3QC	California Line Source for Queuing and Hot Spot Calculations model
M-GFLSM	Modified General Finite Line Source Model
RLINE	A Research Line source dispersion model for near-surface releases
MOBILE	Mobile source emission factor model
MOVES	Motor Vehicle Emission Simulator
EMFAC	EMission FACtors (Emission inventory model)
COPERT	COmputer Programme for calculation of Emissions from Road Transport
TAD	Time-Activity Diary
PDA	Personal Digital Assistant
GPS	Global Positioning System
Calfit	California family Fitness (mobile apps)
2WH	Two wheelers

3WH	Three wheelers
PC-MUV	Passenger Cars and Multi Utility Vehicles
HCV	Heavy Commercial Vehicles
$P(C)$	Probability of occurrences of a CO concentration level
$P(T)$	Probability of time-spent
$P(E)$	Probability of exposure to a CO concentration level
KS	Kolmogorov-Smirnov statistics
AD	Anderson-Darlington statistics
PCC, r	Pearson Correlation Coefficient
NMSE	Normalised mean squared error
FB	Fractional bias
FS	Fractional variance
d	Index of agreement
CPCB	Central Pollution Control Board
L1	Monitoring location - 1
L2	Monitoring location-2
L3	Monitoring location-3
R_b	Richardson number
g	Acceleration due to gravity (m/s^2)
WS, u	Wind speed (m/s)
WD	Wind direction
SR	Solar Radiation
RH	Relative Humidity
Temp	Temperature
UHM	Uncensored Hybrid Model
CHM	Censored Hybrid Model
CCHM	Censored and Calibrated Hybrid model

CHAPTER - 1

INTRODUCTION

1.1 GENERAL

Outdoor air pollution is identified as a public health issue around the world (Clifford et al., 2016). Of which, the major source of air pollution in urban area is vehicular traffic (Shekarrizfard et al., 2016). Health issue related to vehicular traffic pollution is of major concern for many researchers (Gasana et al., 2012; Slezakova et al., 2013; Padula et al., 2014; Shekarrizfard et al., 2015). The studies have shown that short-term or long-term exposure to air pollution has been associated with several respiratory, cardiovascular diseases and mortality (Brunekreef and Holgate, 2002; Le Tertre et al., 2002; Bell et al., 2004; Miller et al., 2007; Katsoulis et al., 2014; Buteau and Goldberg, 2016). The rapidly urbanizing cities with an unprecedented growth of vehicular traffic have poor urban air quality, and thus traffic corridors are often heavily polluted (Pérez et al., 2010; Sharma et al., 2010). People using these corridors for various purposes are often exposed to high level of pollutants (Chan et al., 2002; Wu et al., 2010; Quiros et al., 2013; Amegah and Jaakkola, 2014). It is estimated that many people live or work, near or within a short distance from the high trafficked roads (Boehmer et al., 2013). Also usually a large number of schools and child care centers are located close to traffic corridors, especially in urban areas (Houston et al., 2006). Those children and older adults and with existing heart diseases are amongst the group with higher risk in terms of health impacts near traffic corridor (Balmes et al., 2009). Moreover, people spend longer time in travel due to heavy traffic in urban traffic corridors and exposed to poor air quality more (Schrank et al., 2012). De Nazelle et al. (2012) reported that significant difference in exposure levels of individuals using different types of travel modes (i.e. walk, bike, bus and car) and concluded that higher concentrations are experienced by modes which are closest to traffic source. Kingham et al. (2013) found that on-road cyclists are exposed to higher pollutant concentrations as compared to off-road cyclists but commuters using car and bus are exposed to higher concentrations as compared to cyclists. Similarly, MacNaughton et al. (2014) reported that exposure level of cyclists using routes, which are just adjacent to traffic are about 33% higher than routes, which are separated from traffic source. Ryan et al. (2015) found that children's exposure to ultrafine particles during transit to school and home by car and walking is 1.4 (95% Cl 1.33-1.99) and 2.5 (95% Cl 2.44-2.57), respectively, higher as compared to exposure at home. These studies are based on measurements from mobile monitoring devices. While such a method of measurements is convenient, it is limited in terms of cost of implementation (and hence sample size) and practicality (limitations with respect to children and certain activities). There is a growing concern about exposure quantification and better understanding of pollution phenomenon in urban centers where people are normally exposed to high pollutant concentrations.

While, air quality is usually monitored from a single or network of fixed monitoring stations, the pollutant concentrations so obtained are assumed to represent the human exposure (Laden et al., 2006; Winters et al., 2015). Several research findings have indicated that exposure depends on time and space, because pollutant concentrations vary with time and space (Nerriere et al., 2005b; Violante et al., 2006). For example, pedestrians commuting through the traffic corridor must have different exposure levels when compared to shopkeepers who remain at fixed locations. Therefore, concentrations obtained from a single fixed monitoring station are far more different than the level of concentrations to which people are normally exposed (Ott, 1982; Kousa et al., 2002; Wu et al., 2005; Brinkman et al., 2009).

The actual measurements of pollutant concentrations at a location represent the best temporal levels of pollutant concentrations. Kanaroglou et al. (2005) developed a method for establishing network of monitoring locations for assessing population exposure at intra-urban scale. Quantification of exposure is also possible by using ambient air dispersion modeling, or combination of dispersion modeling and fixed monitoring (Liu and Frey, 2011; Beevers et al., 2013). However, quantifying exposure to traffic-related air pollution needs a high spatial resolution estimates of air quality (Batterman et al., 2014a), whereas dispersion modeling approaches are often subjected to errors in accuracy of inputs data and algorithms of relevant processes (Pratt et al., 2014). Several studies have reported that the common sources of errors in ambient air dispersion modeling is often caused by input data on emission rates (Holmes and Morawska, 2006; Smit et al., 2010; Beevers et al., 2012b; Borge et al., 2012).

In recent years, several approaches have been developed to estimate traffic-related spatial air quality such as land-use regression model (Marshall et al., 2008; Venkatram et al., 2009; Aggarwal et al., 2012; Habermann et al., 2015), geo-statistical methods (kriging) (Janssen et al., 2008; Beelen et al., 2009; Pearce et al., 2009; O'Leary and Lemke, 2014), and hierarchical modeling (Li et al., 2013). These approaches require concentrations data from large numbers of monitoring stations but have the ability to produce higher spatial resolution of air quality estimates (Hoek et al., 2008; Isakov et al., 2012). Gilbert et al. (2005) utilized concentrations data from 67 monitoring locations to assess exposure to NO_2 using land-use regression model, while, Sampson et al. (2011) utilized data from 247 monitoring stations to resolve spatiotemporal air quality.

1.2 EXPOSURE ASSESSMENT APPROACHES

Air pollution exposure is defined as the amount of pollutant reaching the target (individual or population) with specific frequency for a specific period (Duan, 1981; Ott, 1982). Its assessment is the evaluation of exposure of such individual or the population to air population (WHO, 2004). In the studies of exposure assessment to air pollution, the major concern of air pollutants are particulate matter, carbon monoxide, nitrogen dioxide, ozone, and volatile organic compounds (Han and Naeher, 2006). The development of methods for quantifying the human exposure to air pollutants is still in progress. At the current development, three types of approaches are found in literatures (Duan, 1981; Ott, 1982; Lioy, 1995; Nieuwenhuijsen et al., 2006), i) Direct method ii) Indirect method, and iii) Bio-monitoring.

Direct method means personal exposure monitoring, which involves concentration measurements at breathing level at which the person is exposed. This is an accurate method of exposure measurement (Lioy, 1995; Zou et al., 2009). This method requires a portable monitoring instrument to be carried along with the person during their normal daily duties for exposure quantification. Several studies have used such a method of estimating exposure for a variety of population groups (Adams et al., 2001; Greaves et al., 2008; Berghmans et al., 2009; Braniš and Kolomazníková, 2010). In all these studies, it is observed that the main drawback of direct method is its limitations in applications. It is unfavorable for the volunteers to carry personal monitoring devices along during their normal duties and eventually increase study cost since it require a monitoring device for each volunteer (Zou et al., 2009).

On the other hand, indirect method involves deriving exposure level indirectly using concentrations and time-spent at locations of interest. This method is also known as 'micro-environment approach' (Duan, 1981). Few studies have utilized indirect method in estimating exposure to air pollution (Ott et al., 1988; Bell, 2006; Beckx et al., 2009a; Physick et al., 2011). The SHAPE model developed by Ott et al., (1988) uses hourly CO concentrations from 22 different micro-environments and time-activity data. Beckx et al. (2009a) estimated exposure using an activity-based transport model and air quality model. Bell (2006) demonstrated the use of air quality models for estimating exposure and concluded that air quality models along with measured data may provide better exposure estimates, which still requires model validation. Physick et al. (2011) demonstrated estimation of personal exposure, using blending technique, in which, air quality modeled concentrations are improved by using the measured concentration at different locations. While, indirect method requires accurately measured or estimated spatiotemporal concentrations and demands accurate time-activity pattern to arrive at reliable exposure estimation, it has some advantages like flexibility in selecting study area and most importantly the sample size (Zou et al., 2009). The method also promises a reliable approach in exposure estimation if the two required components are estimated with accuracy (Ozkaynak et al., 2013). These advantages have drawn the attention of researchers around the world to focus on estimating spatiotemporal concentrations more accurately. Several methods to estimate spatiotemporal concentrations are presented by researchers such as spatial interpolation, land-use regression, hierarchical and spatial proximity (Crouse et al., 2009; Chen et al., 2010; McAdam et al., 2011; Both et al., 2013; O'Leary and Lemke, 2014).

During the last decade, measurement of spatiotemporal concentrations by bio-magnetic monitoring of moss bags or biological samples of plants or trees such as leaves are demonstrated (Moreno et al., 2003; Mitchell and Maher, 2009; Vuković et al., 2015). These studies have reported strong correlation between magnetic susceptibility of samples and traffic-related air pollution. The Bio-monitoring approach associates human health to exposure (WHO, 1993). This approach utilizes biomarkers to quantitatively estimate exposure and to predict health-risks (Wallace et al., 1985; Talaska et al., 1996; Ayi Fanou et al., 2006; Brucker et al., 2013; Li et al., 2016). In bio-monitoring approach, detection is done using biologic tissue samples such as hair, nails, and blood, related to concentration of substances at which the person is exposed (Rodrigues et al., 2008; Slotnick, 2011; Rückerl et al., 2014). It, however, fails to relate internal dose with exposure concentrations (Barbosa et al., 2005). This is because parameters needed to link dose and exposure, such as kinetic, half-life and metabolic transformations of pollutants are complex and need more understanding (Zou et al., 2009). Assessing dose is important for active commuters (such as cyclists), who experience increased inhalation due to high respiration rate (Bigazzi and Figliozzi, 2014), and, exposure is important for sedentary people working in the shops and offices located along the corridor. In case of naturally ventilated shops or offices located close to the road in the traffic corridor, the exposure of them would be to the level of air pollutants that is in the outdoor. According to a study of Ke Zhong et. al. (2013), for naturally ventilated rooms, the indoor to outdoor ratio of CO concentrations is less than but close to 1.

1.3 AIR POLLUTION ANNOYANCE

The effects of increase in air pollution on health such as cardiovascular, respiratory diseases and mortality are widely evident (Brunekreef and Holgate, 2002) but the psychological effects such as annoyance due to air pollution are not widely validated (Llop et al., 2008). However, there are increasing number of studies examining the relationships of air pollution annoyance and pollutants level (Amundsen et al., 2008; Klæboe et al., 2008; Oglesby et al., 2000a; Rotko et al., 2002). These studies have concluded that there exist a significant relationship of air pollution annoyance with pollutants level (Amundsen et al., 2008; Llop et al., 2008)), but these studies do not adequately indicate as how air pollution level is perceived by the people (Klæboe et al., 2008). These, however, does not mean that people are not annoyed by air pollution. In these studies, the association is studied from the annual or periodic average concentrations (Amundsen et al., 2000; Llop et al., 2008; Rotko et al., 2002) or high exposure levels or 98-percentiles in the case of annoyance to odor (Miedma et al., 2000). Amundsen et al. (2000) have utilized the average of mean and maximum concentrations.

1.4 SUMMARY

The development of a quantification method which is simple, feasible and accurate has several challenges. The direct method is accurate but impractical and difficult in application (Branco et al., 2014), particularly to young children (Jones et al., 2007). It is also possible that personal monitoring may be influenced by other sources of pollution which may affect the source-effects relationship (Monn, 2001). The Bio-monitoring approach lacks in relating exposure to internal dose (Barbosa et al., 2005). The indirect methods require spatiotemporal concentration, mostly estimated from a large number of monitoring stations. Indirect method may be better in some ways as compared to others but needs to be simple in application without the need of many fixed stations data. With the use of air quality models and a few fixed station measurements, indirect method may be made easy and simple, particularly in mixed urban environment.

1.5 RESEARCH AIM

The foregoing introduction on exposure quantification warrants a method that is based on mathematical approaches and demands less number of fixed stations considering the problems of urban traffic corridor exposure. The indirect method offers opportunity for the modification in which spatiotemporal data can be produced by air quality modeling. It is possible at least within the urban traffic corridor where the source of pollution is same. The indirect method needs a precise estimations of spatiotemporal and time-activity pattern to produce exposure estimations. **Thus, the aim of the proposed research is to develop a prediction method for estimating exposure of sedentary workers (i.e. offices or shopkeepers) in terms of probability exceedances, which comprises of a spatiotemporal air quality model to be developed from a data of one fixed monitoring station and an air quality model in an urban traffic corridor.**

1.5.1 Objectives

i. Field work involving the measurements of air pollutant concentrations, collection of local meteorological parameters, traffic count and questionnaire survey of target population about health, annoyance to air pollution, and commuting behaviors within the corridor.

ii. Development of a model to estimate spatiotemporal concentrations of CO in an urban traffic corridor.

iii. Verification and validation of the model.

iv. Development of a time-activity pattern of the target population in the urban traffic corridor.

v. Development of an exposure model and estimation of exposure of sedentary workers in businesses located in the road traffic corridor.

vi. Validation and application of the exposure model to determine exposure at different times of the day and exposure-annoyance by air pollution relationship.

1.6 NOVELTY STATEMENT

i. Emphasis on the development of a prediction method for spatiotemporal concentration and exposure using minimal number of fixed station data – is one of its kind.

ii. The statistical association between the probability of exposure and the level of the annoyance of the target population using the traffic corridor.

iii. The prediction method is developed and applied in the urban traffic corridor having heterogeneous traffic condition and therefore maybe useful in urban environments of developing countries.

iv. Estimation of exposure of sedentary workers to air pollutant in terms of probability using indirect method is first of its kind in Indian urban mixed environment.

1.7 RESEARCH CONTRIBUTION

i. The traffic corridors in urban centers are highly congested, attract more people and a large volume of traffic, making it practically difficult to evaluate human exposure by direct methods. In this research, a simple prediction method using indirect approaches and minimum data has been developed to evaluate exposure of sedentary workers in businesses to CO.

ii. The prediction method comprising of air quality model and exposure model is one of its kind for the Indian traffic (mixed/heterogeneous) conditions.

iii. The hybrid model is developed by combining CALINE4 dispersion model and lognormal distribution model with a calibration factor which improves the prediction considerably.

iv. The prediction method when applied provides important information in terms of probability which can be used for various emission reduction strategies as well as to develop sedentary workers exposure management plan.
v. The prediction method is flexible and can be applied for a specific time of the day, thus, can help regulate traffic in the corridor with an aim to reduce sedentary workers exposure to air pollutants.
vi. The relationship of the probability of exposure with the degree of air pollution annoyance has also been developed, which may be useful for traffic management and planning policy related to air pollution health-risks.

1.8 THESIS OUTLINE

Chapter 1: Introduction — briefly introduces the topic and the overview of its related problems including the approaches to quantify exposure to air pollution. It highlights the key state-of-the-art and limitations of the existing methods. It describes the main aim of research to develop a prediction method comprising of a spatiotemporal air quality model and exposure model in an urban traffic corridor, the detailed research objectives, novelty statement, research contributions, and organization of the thesis.

Chapter 2: Literature review — provides the review of the concepts and methods of human exposure and assessment with a critical review on the various approaches of exposure assessment with thorough literature including exposure models and techniques. It begins with a background concepts of human exposure assessment including various definitions related to exposure. Subsequently, it covers the various methodologies of each approaches. It, further, provides the advantages, problems and shortcomings of the each methods of exposure assessment. Further, the chapter also includes discussion on estimation of spatiotemporal air quality and relationship between exposure and annoyance to air pollution.

Chapter 3: Field work and research methodology — provides a detailed methodologies for estimating human exposure in an urban traffic corridor has been described. The chapter includes about the site selection, monitoring locations, data collection procedure which is later utilized in estimating the exposure. The proposed research methodology to achieve the aim of the research has been presented.

Chapter 4: Data analysis and interpretation — provides a detailed analysis of the data is presented and discussed briefly. It consists of the pollutant concentrations, traffic and meteorological characteristics. Further, the statistical relationship of pollutant concentration with traffic and meteorological characteristics has been presented. It discussed the extent of relationship of traffic and meteorology with pollutant concentrations using statistical methods like regression and Pearson correlation analysis.

Chapter 5: Development of the spatiotemporal model — covers the development of a prediction method. As a part of it, the development of a probability distribution model and the development of a spatiotemporal air quality model have been separately discussed. The detailed step-by-step methodology of the development of prediction method has been presented in which a dispersion and probability distribution models are combined and calibrated to produce the spatiotemporal concentrations within the traffic corridor.

Chapter 6: Validation and application — presents the validation of spatiotemporal model and its application to estimate the spatiotemporal air quality in the same urban traffic corridor. The chapter also presents the calculation on the reduction of traffic emissions to meet the national ambient air quality standard of India.

Chapter 7: Development of exposure model and application — demonstrates the development of exposure model in which the predicted spatiotemporal concentration is combined with time-activity data to estimate the exposure of target population. The chapter also includes the comparison of estimated and measured exposure of target population and also the comparison of exposure in three time slots of the day. The analysis and discussion on relationship between estimated exposure and air pollution annoyance has been presented using logistic regression model. Further, the chapter demonstrates the application of the developed logistic model to calculate the degree of air pollution annoyance based on pollution concentrations exceedances.

Chapter 8: Discussion — provides a brief overview of the study including the development of the prediction method and its applications. The chapter compares the findings of the study with other studies.

Finally, Chapter 9: Conclusion and future scope — provides the summary of the findings from the research work, conclusions, limitations and scope of future work.

CHAPTER 2

LITERATURE REVIEW

The literature has been reviewed on the topics relevant to the objectives of the research including the background of the exposure evaluations and various methodologies such as direct and indirect methods of exposure estimations, spatiotemporal air quality and finally exposure assessment.

2.1 GENERAL

Due to rapid urbanization and unprecedented growth in road traffic urban traffic corridors have turned into traffic and pollution centers. People use traffic corridors for different purposes, thus, are exposed to a variety of air pollutants. Therefore, knowing exposure levels of air pollutants of the general population in urban traffic corridors is important to minimize the health impacts. Exposure levels vary for an individual with time and a space because pollutant distribution and the amount of time an individual spends vary spatially and temporally. This literature review has been focused mainly on the theoretical and mathematical approaches.

2.2 BACKGROUND CONCEPT FOR EXPOSURE ASSESSMENT

According to Ott (1982), the term e*xposure* is a contact between human and pollutant concentration for a period of time but when the pollutant crosses a physical boundary such as skin, lungs membrane then it is termed as *dose*. This literature review is restricted to exposure studies to vehicular emission, however, *dose* depends on respiration rate, the time of exposure and commuting mode (Grange et al., 2014) and is important for active commuter who experience increased inhalation due to high respiration rate (Bigazzi and Figliozzi, 2014). If the exposure occurs for *'T'* period of time at a particular location, then the *integrated exposure* is obtained by integrating the pollutant concentration of the location during the time of exposure (Georgopoulos et al., 1996). Mathematically, it is expressed by equation 2.1(Lioy, 1990).

$$E_i = \int_0^T C(t)dt \qquad (2.1)$$

where, $i = 1,2,3 \ldots$, E_i is the *integrated exposure* of i^{th} person; $C(t)$, the concentration of the pollutant at specified particular location, and dt is the increment in time from 0 to T.

If $C(t)$ remains same during the duration of exposure 'T' (e.g. $C(t)$ is constant for $0 \leq t \leq T$), then exposure can be expressed by multiplying concentration of pollutant and duration of exposure which is expressed by equation 2.2 (Ott, 1982).

$$E_i = C(t) \cdot T \qquad (2.2)$$

The *average exposure* (E_{avg}) of a person is estimated as the integrated exposure divided by the duration of exposure *(T)*, expressed by equation 2.3 (Ott, 1982).

$$E_{i(avg)} = \frac{E_i}{T} = \frac{1}{T}\int_0^T C(t)dt \qquad (2.3)$$

Since a person moves from one location (point of space) to another, the concentration $C(t)$ in equation 2.1 may be replaced by $C(s,t)$ (concentration for each point of space visited by the i^{th} person), which is a function of space (s) and time (t), then the equation 2.1 is reduced to equation 2.4 (Louie and Pierce, 1988).

$$E_i(t_1) = \int_0^{t_1} C(s,t)dt \qquad (2.4)$$

where, $E_i(t_1)$ provides the *integrated exposure* (E_i) of a person for time ($t=t_1$) at each point of space (s).

Since the exposure estimate as given in by equation 2.4 depends on $C(s,t)$, which is complicated, makes the accurate assessment of $E_i(t_1)$ difficult. Duan (1981) introduced a simplified version of exposure assessment method, which is based on the fact that there are certain locations visited by the person, where spatial variation of concentration is uniform during a specific time period. Such locations with uniform concentration are the termed as *microenvironment* (Ott, 1982). If a person moves through such a microenvironment *(j)*, then exposure *(E_i)* of i^{th} person can be estimated by multiplying the concentration and the time spent in each microenvironment by the person, expressed by equation 2.5 (Duan, 1981; Ott, 1982).

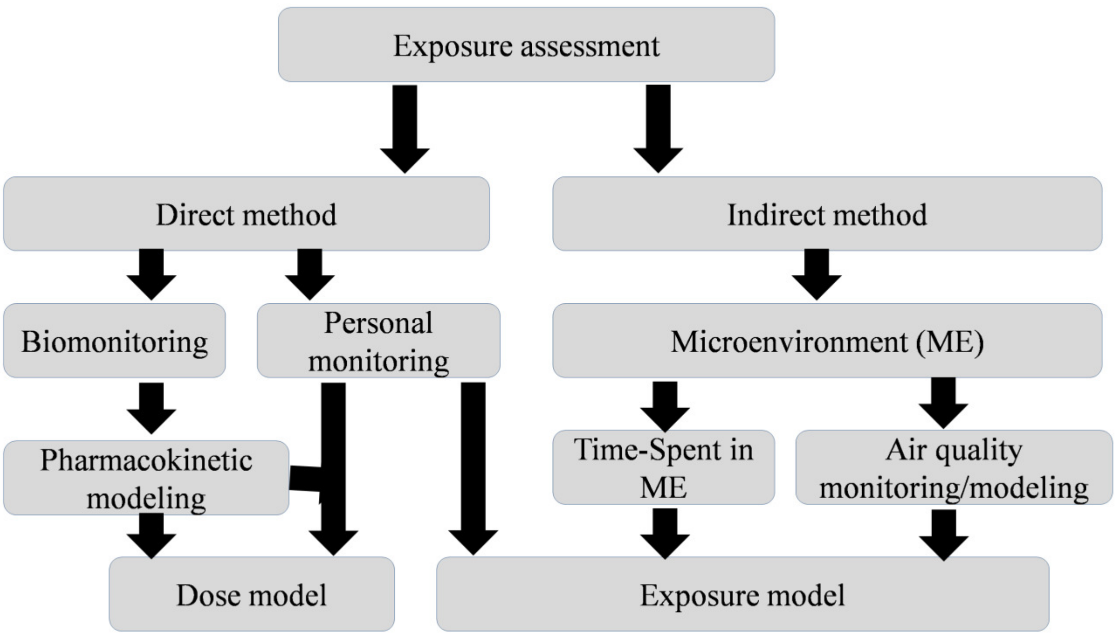
$$E_i = \sum_{j=1}^{n} C_j \cdot t_{ij} \tag{2.5}$$

where, $j = 1, 2 \ldots \ldots n$, E_i is the *integrated exposure* of i^{th} person in a given time period; C_j the concentration of micro-environment *(j)* as experienced by the person *(i)* and t_{ij} is the time spent by the person *(i)* in the micro-environment *(j)*. The accuracy depends on the types of micro-environment considered by the analyst and tend to be more accurate when smaller in sizes. It, however, increases the number of micro-environments (Duan, 1981).

2.3 METHODS OF HUMAN EXPOSURE ASSESSMENT

Two approaches are commonly used for quantifying human exposure to air pollution (Ott, 1982) i) direct measurement of exposure, in which personal sampler is used or wore by the individuals during their routine activities (Rojas-Bracho et al., 2002; Scapellato et al., 2009). The personal sampler (i.e. portable devices) provides the pollutant concentrations encountered by a person, near the point of contact between the individual and the pollutant (Dons et al., 2012) and some of the portable devices record time series (e.g. up to 1 second resolution) while other devices are designed to give one value based on cumulative exposure over the period of deployment. ii) indirect estimation of exposure, in which the pollutant concentrations recorded at several fixed monitoring stations in the area are used along with the diary-based time-activity data into some mathematical methods (Ott, 1982; Macintosh and Spengler, 2000).

Another approach in which biomarkers are used, which reflect the interactions between the chemical species and personal biological system, known as *biological monitoring* (Lioy, 1995; Nieuwenhuijsen et al., 2006). In this type of approach, the measure of biomaker and the exposure to pollutant are related by estimating the concentration backward by using the pharmacokinetic of the chemical species (Moschandreas and Saksena, 2002). Biomarkers are associated with the dose (mass of pollutants entering the body and reaching the body organs) but it cannot identify the source of pollutant, duration of exposure and the pathways (Lioy, 1990). Therefore, more focus is given on the *field study and modeling based approach* which are also termed as the *personal monitoring* and *indirect method,* respectively. The *personal monitoring* and the *biological monitoring* are *direct methods* (Branco et al., 2014) as shown in Figure 2.1, which represents the different approaches used in quantifying the human exposure to air pollution. The methods are discussed briefly in the subsequent sections.



(Source: Modified from Nieuwenhuijsen et al. (2006))

Figure 2.1: Approaches to quantify human exposure to air pollutants

Several models exist for estimating the exposure (Williams et al., 2010). Jerrett et al. (2004) reviewed the models for exposure and categorized them as *proximity based*, *geostatistical*, *land use regression*, *dispersion*, *integrated emission-meteorological,* and *hybrid models*. These models provide the environmental quality (in terms of pollutants concentration) of the location, where human and pollutants possibly come in contact. Of these models, hybrid models are relatively better (Jerrett et al., 2004). Usually, hybrid models are combination of direct measurements and modeling results or combination of two different models. The important features of these models are discussed briefly (Jerrett et al., 2004; Zou et al., 2009).

i) *Proximity based models* (PBM) assume that the person nearer to the pollution source is exposed more than the one farther away from it. These models relate exposure and health effect but do not consider the dispersion of pollutants or its physiochemical activities in the environment (Ryan et al., 2007). ii) *Geostatistical models* (GM) use multiple fixed-site pollutant concentrations measurements and estimate the concentration of the locations where the fixed station data are not available (Lee et al., 2012). The disadvantage, however, is that the applicability is limited to the monitoring area and specific time period, and further, cost factor is another disadvantage as number of monitoring instruments are needed (O'Leary and Lemke, 2014). iii) *Land use regression models* (LRM) estimate the concentration of a pollutant based on land-use pattern and traffic-related parameters in which the pollutant concentration is treated as the response variable and the land-use pattern in the study area as the predictor variable (Gilliland et al., 2005). The LRM can predict the temporal variation in air pollution if developed from long-term measurements (Mölter et al., 2010; Wang et al., 2013) and also spatial variation (Rivera et al., 2012). iv) *Dispersion models* (DM) — these models generally employ Gaussian plume equations using emission, meteorology, and topological features to estimate spatiotemporal concentrations (Holmes and Morawska, 2006). These models are flexible as compared to other models in terms of linking source and effects (Jerrett et al., 2004). v) *Integrated emission-meteorological models* (IEM) — In these models the meteorology and emissions rates are integrated together at every time step to estimate the dynamic pollutants concentration (Hertel et al., 2007). These models are generally used for long-range transport of air pollution, which requires high implementation cost and input data requirements (Brandt et al., 2012). Hence, it is not used in studies related to exposure (Jerrett et al., 2004). vi) *Hybrid models* (HM) — HM are those models which are formed by combination of certain tools and methods or models (Jerrett et al., 2004). The advantage of HM is that the exposure estimation is more accurate when compared to other models (Zou et al., 2009). The HM related to exposure studies include combination of dispersion with land use regression model (Di et al., 2016; Michanowicz et al., 2016), measured data with models (Batterman et al., 2014b; Isakov et al., 2014b), regional with local dispersion models (Beevers et al., 2012a). However, these models are intensive in computations and require large inputs data for intra-urban study (Yu and Stuart, 2016). Nevertheless, the HM are better than other models for smaller area such as traffic corridors.

Estimation of indoor exposure on the basis of outdoor concentrations have limitations (Gall et al., 2015), for example, a factor such as ventilation influences the infiltrations of outdoor air pollutants (Chen and Zhao, 2011). However, naturally ventilated indoor environments may have the same air quality as of immediate outdoor environments.

2.3.1 Direct method of exposure quantification

In these studies, personal exposure to a specific pollutant or multiple pollutants is measured during the routine activity or while commuting or while using a specific type of transportation facility (Adams et al., 2001; Quintana et al., 2001; Greaves et al., 2008; Braniš and Kolomazníková, 2010; Lim et al., 2012). A few devices for personal exposure measurement are commonly used — AM 510 SidePak personal aerosol monitor (Greaves et al., 2008; Lim et al., 2012), Aerodynamic Particle Sizer, Model 3021, TSI Inc (Gupta et al., 2011), and Personal Cascade Impactor Sampler (PCIS) (Singh et al., 2003).

In a study on personal exposure, the measurements of CO and $PM_{2.5}$ while commuting by a two-wheeler was done in Bangalore, India (Sabapathy et al., 2012) by stripping devices based on an electrochemical sensor (Langan T15d personal sampler) for CO and a light scattering (MIE pDRAM 1100 nephelometer pDR) for $PM_{2.5}$. An active monitoring device is needed for monitoring short-term temporal variation in concentration to study the temporal exposure (Chakrabarti et al., 2004), thus the accuracy of the exposure estimation depends upon the type of equipment used (Brauer et al., 2003). Most of the present days monitoring devices are capable for such measurements (Koehler and Peters, 2015). In a comparison study of three different commuting modes (taxi, bus, and bicycle), the exposure was estimated by a CO monitor (T15n, Langan Inc., San Francisco) and $PM_{2.5}$ monitor (aerosol spectrometer, model LD-6S, Beijing Green Technology Digital Co., Ltd, China). It revealed that the exposure of taxi commuters to $PM_{2.5}$ is less than bus commuters and cyclists and exposure to CO is higher for taxi commuters than the other two (Huang et al., 2012). In similar study, the pedestrian exposure to $PM_{2.5}$, ultrafine particles and CO while commuting through a busy carriageway in UK found variations in exposure with time, pavement position and side of a roadway used by the subjects (Kaur et al., 2005). Thus, exposure level depends upon the person's behavior, the choice of timing and position while commuting through a busy roadway. Also, direct method is good for capturing indoor concentration levels whereas outdoor sites can be a poor representation.

The direct approach reflects the true personal exposure level when compared to other methods (Lioy, 1995). In epidemiological studies, a large number of individuals is needed to draw a reliable conclusion on health-risk to air pollution (Branco et al., 2014). For number of individuals, direct method would require equal number of personal monitoring devices. Moreover, collecting data from such groups of individuals is expensive and time consuming (Monn, 2001). Table 2.1 shows the relevant studies carried out by direct methods. These studies have measured the exposure levels for different pollutants, target population and locations. Most of the studies are done in traffic environment. In all these studies, the monitored individuals is less in number ranging from 1 to 62 individuals.

Table 2.1: List of some recent exposure studies using direct method

Sl. no.	Study Area	Types of pollutant.	Target population	Sampler	Key findings	References
1.	Roadway	BC	Commuter	MicroAeth BC monitor	-Walking mode experience lower exposure but higher dose than other mode.	Li et al. (2015)
2.	Roadway	BC, UFP	Cyclist	TSI P-Trak, and MicroAeth BC Monitor	-Significant impact on cyclist exposure occurs during peaks.	Peters et al. (2014)
3.	Roadway	CO, $PM_{2.5}$, UFP	Commuter	Particle counter , P and Q-Trak TSI, Inc.	-Active mode experience seven times higher dose than non-active mode.	Quiros et al. (2013)
4.	Roadway	CO, CO_2, BC, $PM_{2.5}$, UFP,	Commuter	MicroAeth, CPC , P and Q-Trak TSI, Inc.	-In-car exposure are 2/3 times higher than active modes.	De Nazelle et al. (2012)
5.	Roadway	CO, $PM_{2.5}$	Commuter	Aerosol spectrometer, and T15n CO monitor	-Cyclists experience highest exposure than other modes.	Huang et al. (2012)
6.	All ME	NO_2, $PM_{2.5}$	Commute	MicroAeth BC monitor	-Exposure level between couples differs by 30%	Dons et al. (2011)
7.	All ME	$PM_{2.5}$	An Individual	P-trak TSI Inc.	-Highest exposure in restaurants than other ME.	Braniš and Kolomazník ová (2010)
8.	Roadway	PM_1, $PM_{2.5}$, PM_{10}, UFP	Cyclist	P-trak TSI Inc., GRIMM spectrometer	-Exposure level higher during morning peaks.	Berghmans et al. (2009)
9.	Roadway	$PM_{2.5}$	Pedestrian	AM510 SidePak™ aerosol monitor	-Two time increase in traffic volume results in 26% increase in exposure level.	Greaves et al. (2008)

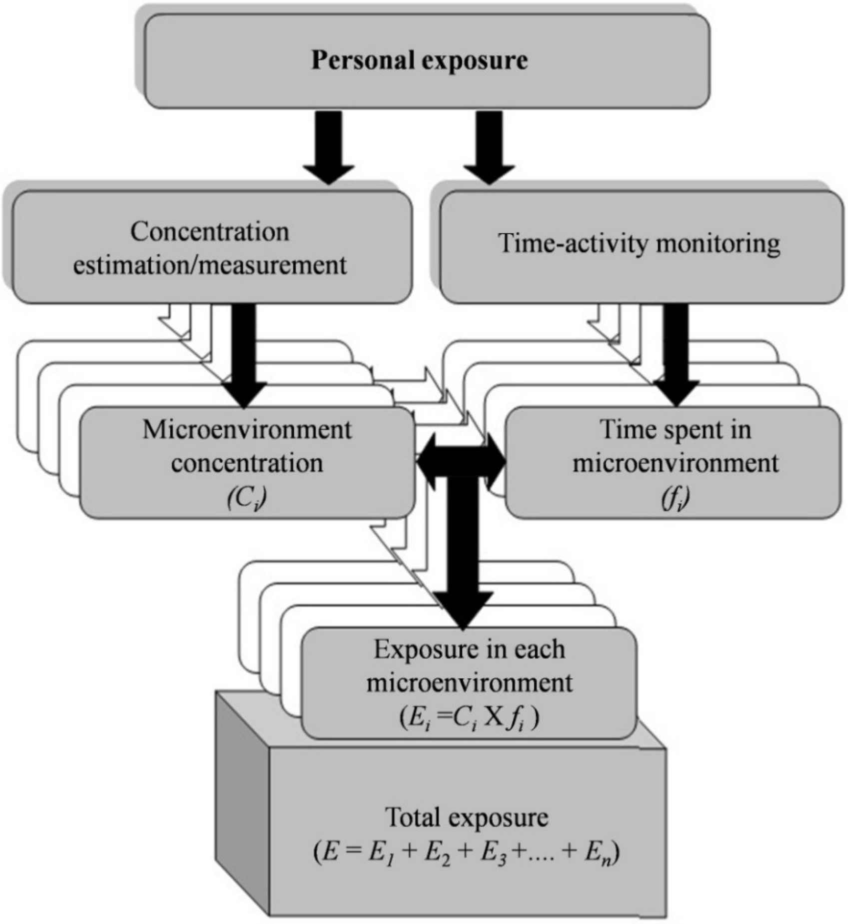
Note: ME: Micro-environment, BC: Black carbon, CO: Carbon monoxide, CO_2: Carbon dioxide, NO_2: Nitrogen dioxide, PM_1: Particulate matter (1 micron), $PM_{2.5}$: Particulate matter (2.5 micron), PM_1: Particulate matter (10 micron), UFP: Ultra fine particle, Couples: husband and wife (living in same location)

2.3.2 Indirect method of exposure quantification

In indirect method, the exposure is estimated using a *modeling approach* (Ott, 1982). In this section, more emphasis is given on modeling approach used in various studies of exposure assessment. In this approach, the exposure is estimated as the sum of the product of time-averaged concentration of each visited microenvironment and the time spent in it by the individual (Ott, 1982; Macintosh and Spengler, 2000), which is suitable for both individual and large population exposure assessment (Zou et al., 2009), and also for various exposure conditions (Klepeis, 1999). It is the most suitable method to determine the source-effect relationship to minimize exposure-related activities (Weisel, 2002) and to inspect probable outcome of future environmental conditions and policies (Miller et al., 2007).

The accuracy of exposure estimation by this method depends on input data supplied to the model (Hanninen et al., 2003; Branco et al., 2014), such as higher spatiotemporal resolved concentrations, especially for near-field traffic-related exposure estimation (Batterman et al., 2014a) and/or enhanced time-activity data (Chang et al., 2003). Time-activity pattern is an important parameters for exposure estimation not only for time spent in a location but also due to exposure scenario which depends largely on movements across each microenvironment (Dons et al., 2011).

Pollutants concentrations, either on-road or near the traffic source, shows high spatiotemporally variation (Barzyk et al., 2009; Hagler et al., 2009; Batterman et al., 2015a). Such variations arise difficulty in exposure estimation at locations near the source (Health Effects Institute, 2010), due to limitations and criterion on number of fixed monitoring stations (Wilson et al., 2005). In such an environment, indirect method may prove to be the appropriate approach of exposure estimation. Figure 2.2 shows the elements of the indirect method of exposure.



(Source: Modified from Louie and Pierce (1988))

Figure 2.2: Indirect method to estimate the personal exposure

2.3.2.1 Determination of pollutant concentration

The concentrations of pollutants mainly in road traffic environment depends on emissions from the source, local meteorology and, fate and transport of the pollutants (Field, 1988). The parameters related to traffic characteristics and wind-flow pattern are important to predict pollutant concentrations (Cassidy et al., 2007). These factors bring variation in concentrations in the traffic corridor (Baldauf et al., 2008). In the absence of direct measurements on the pollutant concentrations, air quality models can be used to estimate the pollutant concentrations attributed to the specific source at the point of interest (Batterman et al., 2015b). Air quality dispersion based models incorporate emission and meteorology to estimate pollutant concentrations at the desired locations

(Nagendra and Khare, 2002), but need to be calibrated to suit the local conditions (Jerrett et al., 2004). Several dispersion models exist for evaluating roadside air quality (Sharma and Khare, 2001; Gokhale and Khare, 2004). A few, which have gained wide popularity, are AERMOD, CALINE, CAL3QHC models (Levitin et al., 2005; Kenty et al., 2007; Yura et al., 2007; Gokhale and Raokhande, 2008; Chen et al., 2009). Gokhale and Raokhande (2008) have applied three different models at traffic intersection and inter-compared the results i.e. Modified General Finite Line Source Model (M-GFLSM), California Line Source (CALINE3), California Line Source for Queuing and Hot Spot Calculations (CAL3QHC). Among these dispersion models, CALINE4 is most used and well validated for Indian roadside air quality (Majumdar et al., 2010; Dhyani et al., 2013). Such dispersion models are based on Gaussian dispersion equation as shown in equation 2.6 (Chen et al., 2009, Ganguly et al., 2009).

$$C(x,y,z) = \frac{q}{2\cdot\pi\cdot u\cdot\sigma_y\cdot\sigma_z}\left\{exp\left(\frac{-(z-H)^2}{2\cdot\sigma_z^2}\right) + exp\left(\frac{-(z+H)^2}{2\cdot\sigma_z^2}\right)\right\}\int_{y_1}^{y_2} exp\left(\frac{-y^2}{2\cdot\sigma_y^2}\right)dy \qquad (2.6)$$

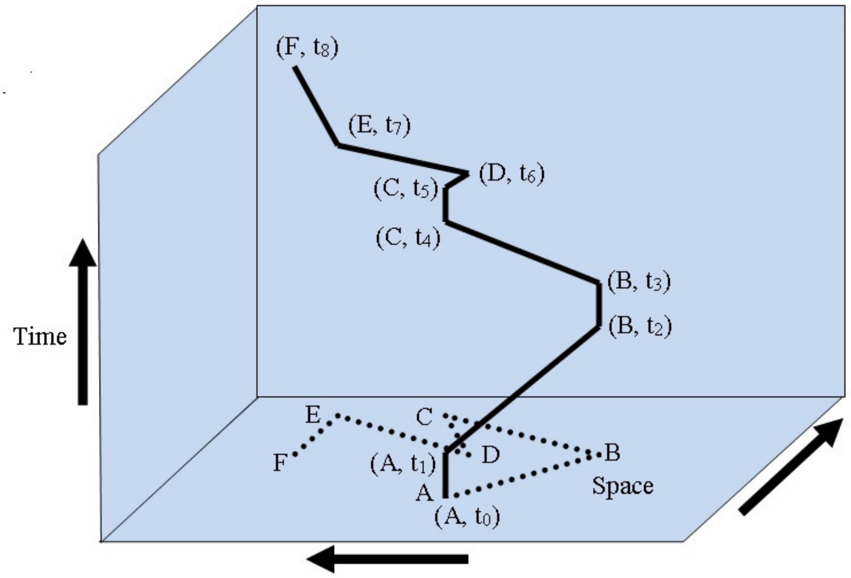
where, $C(x,y,z)$ represents the concentration at any receptor point (µgm^{-3}), q the line source strength (µ$gm^{-1}s^{-1}$), u the wind speed (ms^{-1}), z the height of receptor (m), H the effective height of source in (m), σ_y and σ_z the dispersion coefficients along perpendicular to wind direction and vertical direction, respectively, $y_1$and y_2 the beginning and end of line source, and dy the infinitesimally small section along line source length.

Several detailed reviews on air quality models, particularly, related to roadside air quality are presented elsewhere (Sharma and Khare, 2001; Nagendra and Khare, 2002; Holmes and Morawska, 2006). Recently developed dispersion model, RLINE (a Research LINE source model), is developed for estimation of human exposure to traffic-related air pollution (Snyder et al., 2013). Several studies have used this model to evaluate near-road exposure and air quality (Heist et al., 2013; Isakov et al., 2014a; Chang et al., 2015; Pachón et al., 2016), but it is under development phase and is not validated widely (Snyder et al., 2013; Venkatram et al., 2013).

The emission rate from traffic may be calculated using vehicular emission models (Liu et al., 2013), For example, MOBILE, MOVES (USEPA, 2010), EMFAC (California Air Resources Board, 1986), COPERT (Eggleston et al., 1993) are often used to estimate emission rate of pollutants depending on the type, age, weight and operational frequencies of the vehicles (Moschandreas and Saksena, 2002; Zou et al., 2009; Liu, 2015). A number of characteristics related to vehicle and traffic affects the emission rate (Pandian et al., 2009). Dirks et al., (2003) and Gokhale and Pandian (2007) have developed a semi-empirical box modeling, in which, the emissions rate are derived using empirical relationships between traffic flow and driving cycle. Traffic intersection having high rise buildings, the free airflow is obstructed, which leads to pattern needing attention to estimate the variation of pollutant concentration in urban environments (Tiwary et al., 2011; Wang et al., 2011; Pirjola et al., 2012). Due to complex airflow pattern, the pollutant concentration varies substantially inside urban traffic microenvironment and hence nested dispersion models estimates should be used (Kousa et al., 2002; Greco et al., 2007). In the case of pollutant concentration estimation using dispersion models, there may arise the uncertainty of the estimated values (Vardoulakis et al., 2003). Studies have shown that the accuracy can be increased by reducing the bias/uncertainty in predicted values. Such a study is demonstrated by Physick et al. (2006) in which concentrations measured from network of monitoring stations are blended with modeled values; the technique is termed as blending technique. The same technique is later applied in modeling personal exposure to nitrogen dioxide (NO_2) by Physick et al. (2011) in which the exposure is estimated based on the hourly average NO_2 concentrations, estimated by an air quality model and blended with hourly-average monitored data to produce the refined estimates of pollutant concentrations and later combined with time-activity pattern.

2.3.2.2 Determination of time activity in microenvironment

The time spent by a person in some activity at a location is important in exposure quantification (Dons et al., 2011). Figure 2.3 shows the space-time diagram (Shaw et al., 2008). The spatial dimension indicates the change in locations and the temporal dimension indicates the sequence of the activities and time taken by each activity in each location (Shaw et al., 2008).



(Source: Modified from Shaw et al. (2008))

Figure 2.3: Space-Time diagram. A, B, C, D, E, F represent different locations and t_0, t_1, t_2, t_3, t_4, t_5, t_6, t_7, t_8 represent time. Dotted lines indicate spatial position and solid lines indicate spatiotemporal position.

The time components express the time-spent in a particular activity. Each activity may be expressed as stationary and movement from one location to another (Shaw et al., 2008). Referring to the Figure 2.3, the vertical lines in time dimension shows the stationary activity e.g. activity (A, t_0) to (A, t_1), whereas the inclined lines indicate the movement from one location to another e.g. (A, t_1), (B, t_2). There are different approaches used in estimating the time-activity patterns of individuals (Steinle et al., 2013b). For example, Rönmark et al. (2009) extracted time-activity patterns from survey and questionnaire data. Lioy et al., (1988) and Freeman et al., (1991) used time-activity diary (TAD), while others utilized the global positioning system (GPS) and other tracking system (Gulliver and Briggs, 2011; Houston et al., 2011). In many studies, TAD are used by the volunteers to record the activities and time spent in it (Leech et al., 1995; Jantunen et al., 1998; Rotko et al., 2000; Schweizer et al., 2007; Hänninen et al., 2009; Wheeler et al., 2011). The information that is recorded in TAD includes time of start and end of the activities, location of the activities, features or attributes of activities, particulars of the volunteers (Harrison et al., 2002). This diary may be in the form of electronic device like PDA (Personal Digital Assistant) (Dons et al., 2013). In other studies, a device such as GPS is used to monitor the location and time-spent by individuals during the study period (Freeman and Saenz de Tejada, 2002; Gerharz et al., 2009; Houston et al., 2011; Buonanno et al., 2014; Neatt et al., 2016). Other studies utilized smart-phones equipped with GPS to monitor the time-activity pattern of individuals during the study period (Glasgow et al., 2014; Su et al., 2015; Byrnes et al., 2016). This type of method promises the real-time monitoring of the time-activity data (Phillips et al., 2001). In one of such studies, Calfit Smartphone technology, an android based mobile-phone software, is used to track the persons geographical location, physical activity pattern and the time spent during the activity and then it is linked with the space-time air pollution maps to estimate the personal exposure to air pollution (Nieuwenhuijsen et al., 2015). Calfit also provides the location based on the network-triangulation method when there is weak or unavailable satellite signals but the accuracy as compared to the satellite based position is less (De Nazelle et al., 2012). Many a times volunteers forget to enter records (TAD), resulting in missing some of the locations visited, which is reduced with GPS devices (Steinle et al., 2013a). In a study carried out by Houston et al. (2011) with 47 residents in Los Angeles as participants, both TAD as well as GPS tracking system used and compared. It revealed that half of the locations or trips log in GPS devices are not reported in the TAD.

Recently, a study carried out by Schlink and Ragas (2011) developed and used human mobility models to determine human mobility pattern for estimating the personal exposure. The human mobility models are i) Lévy-modulated correlated random walk (LMCRW[1]) (Bartumeus et al., 2005), ii) truncated Lévy flights (TLF[2]) (Chechkin et al., 2008), iii) reference point mobility (RPM[3]) (Bai and Helmy, 2004), and iv) agenda-based walk (RPMA[4]) . It is reported that TLF and RPMA algorithms have the properties to predict the human mobility movement for estimation of human exposure to air pollutant (Beckx et al., 2009b).

2.4 SPATIOTEMPORAL AIR QUALITY

The human exposure studies have mostly used concentrations from a few fixed monitoring stations, in which, the measurements at each location are assumed to represent the air quality of that microenvironment (Oglesby et al., 2000b; Nerriere et al., 2005a; Van Roosbroeck et al., 2006; Brown et al., 2008; Boogaard et al., 2010). Such approach may provide information of spatial and temporal variability between the larger areas but it does not take into account the individuals variation in exposure (Violante et al., 2006; Delgado-Saborit et al., 2011). The variation in air pollution level within cities or areas are higher than the variation between cities or areas (Crouse et al., 2015). For instance, traffic related air pollutant such as NO_x shows influence of traffic density and diesel exhaust particulate matter to buses and trucks share in the traffic (Kinney et al., 2000; Sayegh et

[1] LMRW: mobility model based on correlation between successive steps.
[2] TLF: mobility model which consider choice of direction on uniform distribution of turning angles.
[3] RPM: mobility model based on reference point.
[4] RPMA: mobility model based on predefined agenda.

al., 2016). This argument suggests that exposure studies based on fixed location concentrations for all individuals in the area could result in weak assessment of exposure levels (Violante et al., 2006). Further, it is not practically feasible to locate many numbers of fixed monitoring station due to time and cost, so estimation of spatiotemporal air quality based on models is cheaper (Wilson et al., 2005).

The spatiotemporal variability of air pollutant concentration, especially in urban areas, depends on sources of pollution, traffic conditions, local climate and surrounding building environment (Hoek et al., 2008). The estimation of local spatiotemporal variability of pollutants in an area should be as accurate as possible for prediction of exposure levels (Batterman et al., 2014a). Due to such importance of spatial air quality, exposure assessment studies are these days mostly focused on spatiotemporal variability of pollutions and relationship with human health (Dadvand et al., 2011; Sampson et al., 2011; Nonnemacher et al., 2014; Wang et al., 2015).

The spatial variability of concentrations is most commonly estimated by dispersion models, Land-use regression models (LUR) and geo-statistical interpolation technique (i.e. kriging) (Beevers et al., 2013; Dons et al., 2013; Batterman et al., 2014b; O'Leary and Lemke, 2014; Chang et al., 2015). The prediction accuracy of dispersion models depends upon the accurate emission inventories and meteorology (Beelen et al., 2010). The LUR and kriging techniques require data from a large number of monitoring locations and do not take readily the variation in meteorology but are capable of producing spatial variability of concentrations to higher spatial resolution (Wang et al., 2013; O'Leary and Lemke, 2014).

2.5 EXPOSURE AND AIR POLLUTION ANNOYANCE

Humans have the ability to perceive air pollutants through senses, mainly, odor and irritation senses (such as eye irritation, coughing and responses to allergies) (Amundsen et al., 2008). These two human senses are often sensitive to most chemicals (Klæboe et al., 2008). Studies have demonstrated the effectiveness of such senses in perceiving poor air quality (Miedema et al., 2000; Jacquemin et al., 2007), through the use of questionnaire survey data and by examining its statistical relationship with air quality data. Therefore, the level of perceptions (i.e. annoyance) indicates warning of poor air quality (Jantunen, 1997) and may be used to assess health effects of air pollution (Baird et al., 1990). Annoyance due to environmental pollution, mostly in urban areas, could have psychological effects (stress, negative health effects due to air pollution) and impair quality of life (Jacquemin et al., 2007; Llop et al., 2008; Andersson et al., 2009).

Few studies have estimated the relationship of exposure-response considering the level of pollutants and degree of annoyance. The level of pollutants may be annual or periodic average concentrations (Amundsen et al., 2000; Llop et al., 2008; Rotko et al., 2002) or high exposure values (maximum) concentrations or 98-percentiles (Miedema et al., 2000). Jacquemin et al. (2007) studied the variation in annoyance related to air pollution in Europe through self-reported questionnaire of 11 point scale (where, 0: no disturbance at all, 10: intolerable disturbance), which concludes that 15% of the population in Europe is highly annoyed by air pollution and about 50% feel the annoyance. Another study of Norway indicated that people are annoyed by air pollution even though concentration levels are within limits (Amundsen et al., 2008). The high number of pregnant women in a study perceived medium to high annoyance due to air pollution and also noise (Llop et al., 2008). Also, according to another study, exposure-response relationship studied in different European countries are roughly similar although exposure and annoyance level differs between, which suggest that common exposure-response relationships may be established so that the relationships may be useful to as a proxy for air pollution exposure and for planning policy related to air pollution health-risks (Klæboe et al., 2008).

2.6 SUMMARY AND DISCUSSION

The advantages and disadvantages of the methods used in the exposure assessments are shown in table 2.2. The methods for quantification of human exposure to air pollution have been reviewed. The main focus of the researchers around the world is on the accuracy and limitations of the methods. It has been found that both direct and indirect methods are used by researchers depending upon the resources availability. While direct methods seem resources extensive, indirect methods offer scope for modification of existing approaches, development of exposure models, making use of mathematical models to estimate exposure levels or at least to provide necessary information, or even integrate the fixed monitoring data with the modeling data and so on. It may also be important to investigate whether the annoyance by air pollution is associated with extreme concentrations.

Table 2.1: Comparison of exposure assessment methods

Sl. No.	Methods	Advantages	Disadvantages	References
1.	Direct method (Personal monitoring method)	- Easy in application - Ability to measure accurate exposure	- High cost and time-consuming process - Not feasible for large population	Both et al. (2013), Huang et al. (2012), Li et al. (2015)
2.	Indirect method.	- Simple in conceptual approach - Large sampled data. Cost effective in acquiring sampled data. - Cost effective and rapid to estimate exposure over various environment and conditions - An appropriate way for prediction of possible outcomes	- Expected uncertainty due to model assumptions - Demands large input data for intra-urban exposure estimation	Moschandreas and Saksena (2002), Mölter et al. (2012), (Physick et al., 2011), Batterman et al. (2014b)

CHAPTER 3

FIELD WORK AND RESEARCH METHODOLOGY

3.1 GENERAL

The main aim of proposed research has been achieved by developing a prediction method based on indirect approach, in which, from one fixed sampling location, a spatiotemporal model is developed, and validated at other locations within the urban traffic corridor. The model has been used to determine the probability of occurrence of exposure level. The research works involve field measurements of pollutant concentration in the urban traffic corridor, traffic volume, meteorological parameters, and determine emission rates and estimate spatiotemporal pollutant concentration by CALINE4 model and improve its prediction by hybridizing it with the probability distribution models over the entire corridor. The so developed model from one fixed monitored data has also verified and validated at two other locations within the same corridor, influenced by the same source.

3.2 SELECTION OF SITE AND MONITORING LOCATIONS

A highly trafficked corridor was selected in the urban center of Guwahati (a largest city in Assam, India) with a population of about 1.84 million. The corridor is a part of Guwahati-Shillong road, which is an important commercial area with retail, wholesale and commercial offices. The atmospheric temperature during March (the sampling month) generally reached around 30^0 centigrade during daytimes and around 16^0 centigrade during nighttimes, relative humidity reached around 63% and average wind speed of 4 km/h. The corridor is situated between Ulubari and Bhangagarh area, which attracts a large volume of traffic due to its highly urbanized activities. The average daily traffic volume is about 100,000. The height of buildings around the area ranges from 4 m to 18 m. Figure 3.1 shows the location of the urban traffic corridor. Three monitoring locations were identified for carrying out the pollutant concentration measurement i.e. L1, L2 and L3 as shown in the figure. The basis of locating the monitoring stations are (i) density of shops and offices, (ii) meteorological effects with respect to locations. It is more or less like an uneven street canyon where both sides meteorology would be difficult to capture the this effect.

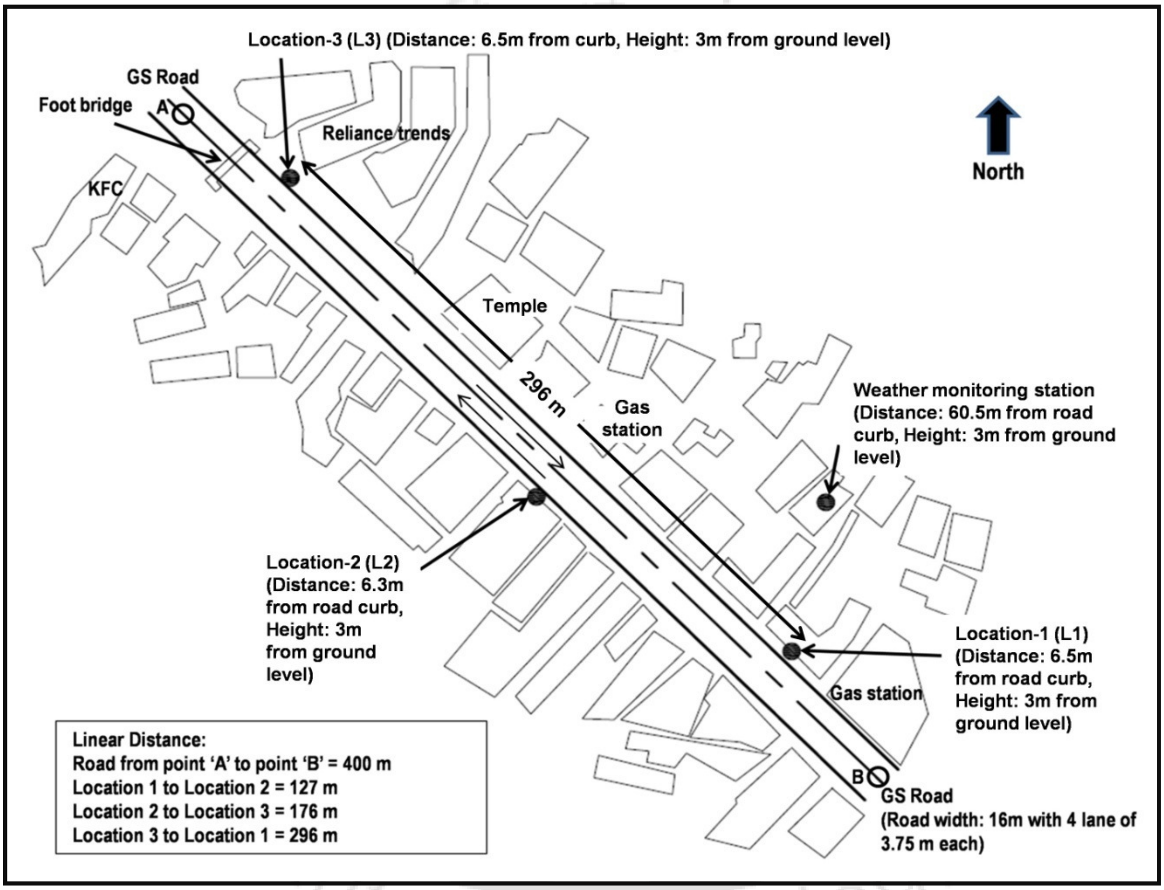


Figure 3.1: The details of the study area with monitoring locations

The distance between L1 and L2 is 127 m, between L2 and L3 is 176 m, and between L1 and L3, it is 296 m. The total length of the corridor is 400 m. It is 16 m wide double lane road with a separator of 1m with each lane 3.75 m wide. The road is at 136 degree to north. A number of commercials, office buildings are housed along roadside and residential buildings at an average distance of 5 m from the curb of the road, due to which, a large number of people living and working in the corridor are exposed to higher levels of traffic-related air pollutants. Besides three locations for pollutant measurements, another one was selected for recording meteorological parameters in the corridor, at 60.5 m from the curb on rooftop of tallest building in the area (18 m).

3.3 FIELD MONITORING

The monitoring has been carried out to collect the primary data on pollutant concentrations, meteorology and traffic characteristics for a period of one month. The pollutant concentration measurements were done for one week at each location due to availability of one monitoring device. The traffic volume study was carried out for one week, which was assumed to be same every week and meteorological monitoring was carried out for three weeks.

3.3.1. Ambient air quality monitoring

The CO concentrations have been measured from 7am to 7 pm daily for one full week, covering all weekdays and weekends during March 2014, at each location by a CO analyzer (Delta ohm, model no. HD37B17D). This analyzer has a measuring range of 0-500 ppm of CO concentration with a least count of 1 ppm. Figure 3.2 shows the traffic corridor with monitoring locations and a normal traffic flow and an image of the CO analyzer in the inset. It works on electrochemical method to detect CO concentrations, which are recorded every three seconds. The CO analyzer was placed at a height of 3 m at each monitoring location and at a distance of about 6.5 m from the curb of the road.

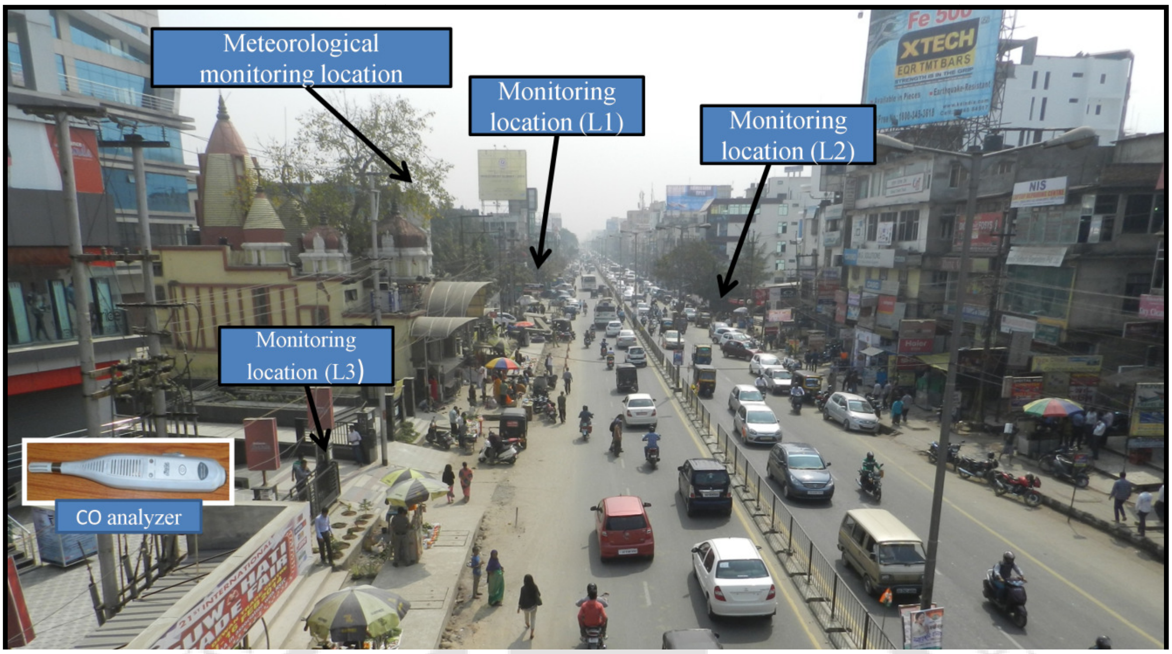


Figure 3.2 : Picture of the study site showing monitoring locations. Inset picture shows the CO analyzer

3.3.2 Meteorological monitoring

Meteorological parameters such as wind speed, wind direction, ambient temperature, relative humidity and solar radiation have been recorded simultaneously with the air quality monitoring by a weather station (Wireless Vantage Pro2, model no:6152). It records every second data of meteorological parameters. Ground level temperature was also measured at each location. Figure 3.3 shows the meteorological monitoring instrument at the site.

Figure 3.3: Picture shows the meteorological monitoring instrument (Wireless Vantage Pro2, model no: 6152) at the installed location

3.3.3 Monitoring of traffic characteristic

Traffic volume survey has been carried out during the air quality monitoring by videotapes for a period of one week. The video camera was installed on the foot over-bridge (as shown in fig 3.4). The videotapes were later analyzed in the laboratory to determine various traffic characteristics such as hourly traffic-flow rate, average daily traffic volume, traffic volume in different composition, fleet speed, and percentage share of heavy vehicles. For composition, the vehicles were classified into four categories (Ntziachristos and Samaras, 2010), e.g. (i) two-wheelers (2WH) (mopeds, scooters, and motorcycles), (ii) three-wheelers (3WH) (auto-rickshaws), (iii) passenger cars and multi-utility vehicles, (PC-MUV) (cars, jeeps. MUV's, SUV's), and (iv) heavy commercial vehicles, (HCV) (minibus, bus, trucks).

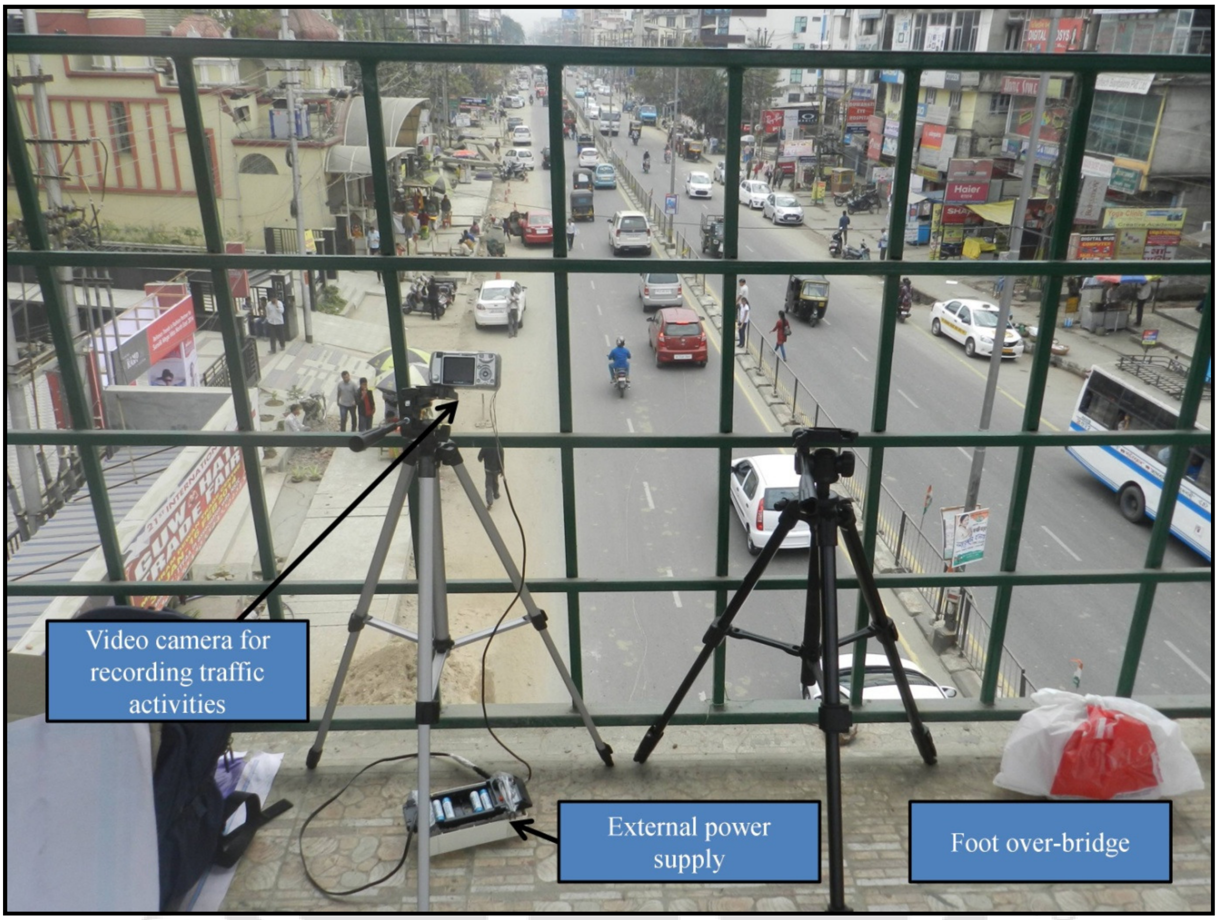


Figure 3.4 : Video camera installed at foot over-bridge for recording traffic activity

3.3.4 Questionnaire survey

A questionnaire was designed and developed to determine the people's perception using the traffic corridor on the menace of traffic and the pollution caused by it. The main aim was to determine the time-activity pattern of the sedentary people working along the traffic corridor. This survey was carried out on these target population during the air quality monitoring period. They were visited at their business offices and the questions were asked. The people who are smokers but do not smoke at workplaces were also included in the study. The questionnaire is enclosed in Appendix-I (Freeman and Saenz de Tejada, 2002). The questionnaire includes the details of the target population such as their age, gender, time of arrival and departure from workplace, health-related questions, and number of months in the workplace. Annoyance caused by air pollution was recorded as "yes" or "no" through the question. The question for the annoyance was "Are you annoyed by traffic air pollution while working at the workplace? ". Other important questions were also included in the questionnaire such as, "Whether you suffered from cough apart from general", and others such as "Whether you have breathing problems", "headache", "chest tightness", "stress due to traffic", and "habits to smoking".

3.4 PROPOSED METHODOLOGY FOR THE DEVELOPEMNT OF PREDICTION METHOD

The proposed methodology has been developed from the indirect approach in which spatiotemporal concentrations and time-activity patterns of target population are required. Using this approach a prediction method comprising of spatiotemporal air quality and exposure model that can reduce dependency on several fixed monitoring stations and also instead of quantifying just the exposure level, probability of exposure is proposed to be calculated as it will directly be influenced by the probability of the person using the corridor, time-spent by the person, amount of traffic, pollutant concentration and also local meteorology. Figure 3.5 shows the proposed methodology of the exposure estimation method. The prediction method includes development of a model to estimate spatiotemporal concentrations in terms of probability and then estimate the probability of exposure when concentration exceeds the national ambient air quality standards. The development of the model includes the use of CALINE4 model for estimating pollutant concentration at one location and improvement of its performance (prediction ability) by combining its output with the probability distribution model (i.e. hybrid model) and a calibration factor.

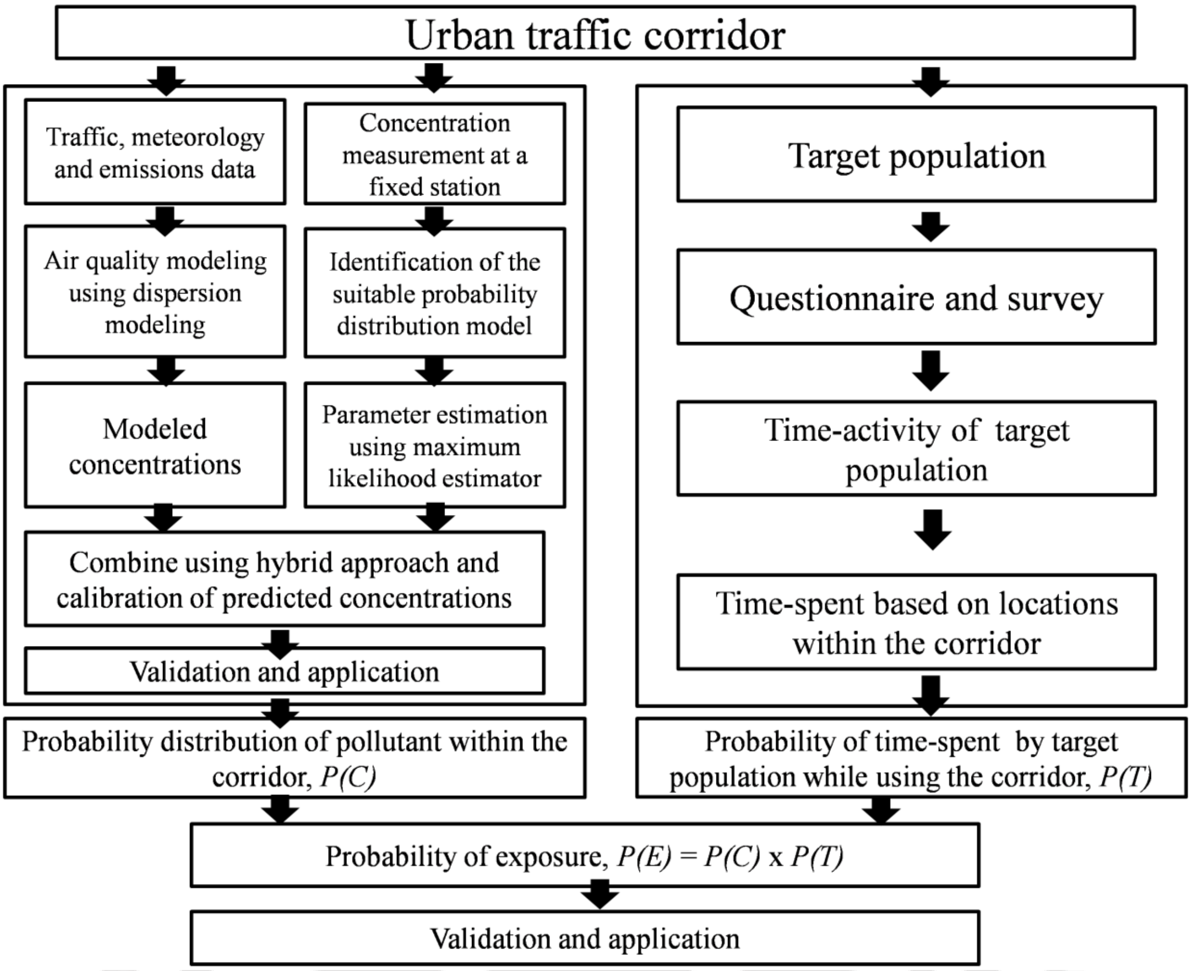


Figure 3.5: Proposed methodology for the development of prediction method

The probability distribution model has been identified using the pollutant concentrations observed at three monitoring locations to ensure that its statistical behavior is similar throughout the corridor. This has been done using goodness-of-fit statistics test, involving Kolmogorov-Smirnov (KS) test, Anderson-Darling (AD) test, and Pearson correlation coefficient (PCC). And the parameters of the probability distribution model have been estimated by method of maximum likelihood (MLE) (Mage and Ott, 1984; Myung, 2003).

The KS test is used to decide if the random variables follow a specific statistical distribution (Lu, 2002; Sharma et al., 2013a). It is a nonparametric test, which compares, the empirical and hypothetical cumulative distribution function (cdf) (Kottegoda and

Rosso, 1997). It is based upon the maximum vertical distance between the two cdf (Massey, 1951; Wilcox, 2005) and is more sensitive near the center compared to the tail of the distribution (Wilcox, 2005). The AD test is a modified KS test. Unlike KS test, it gives more weights to the tail of the distribution (Kottegoda and Rosso, 1997). The PCC is based upon the linear relationship between empirical and hypothetical probability distribution functions (pdf) (Snedecor and Cochran, 1989). The PCC statistics has a value between 0 and 1, 0 indicates no relationship between the two pdf and 1 indicates prefect relationship (Brown and Benedetti, 1977; Snedecor and Cochran, 1989; Gokhale and Khare, 2007). The KS statistics is given by equation 3.1

$$D_n = \max_n |F_n(x) - F_0(x)| \tag{3.1}$$

where, $F_n(x)$ and $F_0(x)$ represents the empirical and hypothetical continuous cdf, respectively. D_n represents the maximum vertical distance between empirical and hypothetical cdf, and x represents the random variable.

The AD statistics is defined by equation 3.2

$$A^2 = -n - \sum_{i=1}^{n} \frac{(2 \cdot i - 1)}{n} [\ln F_0(x_i) + \ln\{1 - F_0(x_{n+1-i})\}] \tag{3.2}$$

where, x_i represents the random variable at i^{th} term in increasing order, and n the number of observations.

The PCC is defined by equation 3.3

$$r = \frac{\sum_{i=1}^{n} x_i \cdot y_i - \frac{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n}}{\sqrt{\left(\sum_{i=1}^{n} x_i^2 - \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n}\right)\left(\left(\sum_{i=1}^{n} y_i^2 - \frac{\left(\sum_{i=1}^{n} y_i\right)^2}{n}\right)\right)}} \tag{3.3}$$

where, x_i represents the empirical pdf, and y_i represents the hypothetical pdf.

The performance of the method was evaluated using the commonly used statistical measures such as Pearson correlation coefficient (r), normalized mean square error

(*NMSE*), fractional bias (*FB*), fractional variance (*FS*) and index of agreement (*d*). The numerical value of *r* ranges from 1 to -1, where 1 and -1 represents perfect correlation and 0 indicates no correlation. The *NMSE* ranges from 0 to ∞, where 0 represents perfect agreement. The *FB* and *FS* ranges from -2 to 2, where, -2 represents extreme under-prediction and +2 extreme over-prediction, and *d* value ranges from 0 to 1, where, 1 represents perfect agreement and 0 represents no agreement (Cox and Tikvart, 1990; Marmur and Mamane, 2003). Further details on these statistical measures are given in Appendix-IX.

The so developed prediction method has been validated at two other locations within the corridor. And, the method is applied to calculate spatiotemporal concentration within the corridor and also to get the probability of the occurrence of the concentrations exceeding over the national ambient air quality standards (CPCB, 2009) and to estimate the required emission reduction to maintain the air quality. Further, the probability of concentrations obtained from the spatiotemporal model have been combined with the time-activity patterns to obtain the probability of exposure of target population and validated with the measured probability of exposure. It is also applied to establish exposure-response relationship based on the estimated probability of exposure and response of target population on annoyance to air pollution collected through questionnaire survey.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

4.1 GENERAL

In this chapter, the data collected during the field work have been organized for meaningful interpretation and discussed in detail. The process of data description and interpretation helps to transform the data into crucial evidence.

4.2 AMBIENT AIR QUALITY

The CO concentrations observed at each monitoring location (Appendix–II) i.e. L1, L2, and L3 were averaged for 1-h across the working days and non-working days separately. Figure 4.1 and 4.2 shows the hourly variation of the mean CO concentrations on working and non-workings days, respectively. In a traffic corridor of 400 m length, the CO concentration observed at three different locations represent the air quality of the corridor as the source of pollution is same. There is not much variation in the working days and non-working days mean values at location to location but significantly a large variation has been observed in hourly concentrations particularly at L1. On working days, the highest variation was observed at L2 during 6-7 pm (0-4.75 ppm) and L3 (0.28-3.61 ppm). At L1, it was observed during 1-2 pm (0.2-2.91 ppm).

On non-working days, the highest variation was observed at L1 during 1-2 pm (0.2-4.36 ppm), 12-1 pm (0.05-3.59 ppm) and 2-3 pm (0-2.65 ppm). At L2, it was observed during 2-3 pm (0.04-1.69), whereas at L3, it was observed during morning hours i.e. 7-8 am (0.01-1 ppm) and 8-9 am (0.01-1 ppm). For some hours, higher concentration were observed at L1 than L2 and L3. The average working day concentration was 0.48±0.64 ppm in the corridor and 0.42±0.76 ppm was on non-working days. If traffic (the main source of CO concentration) remains same from week to week, the changes in CO is only due to meteorology which is also not observed to be significant.

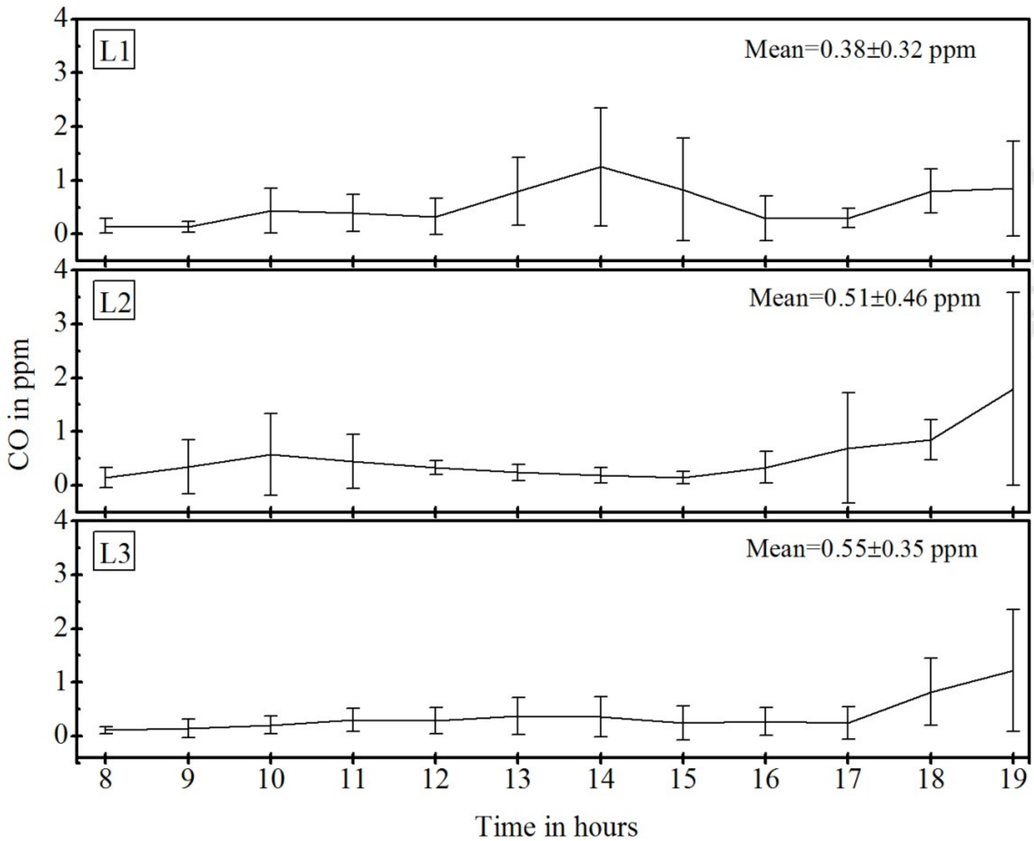


Figure 4.1: Hourly variation of mean CO concentrations observed at the monitoring locations during working days (Monday to Friday) with error bars (±SD)

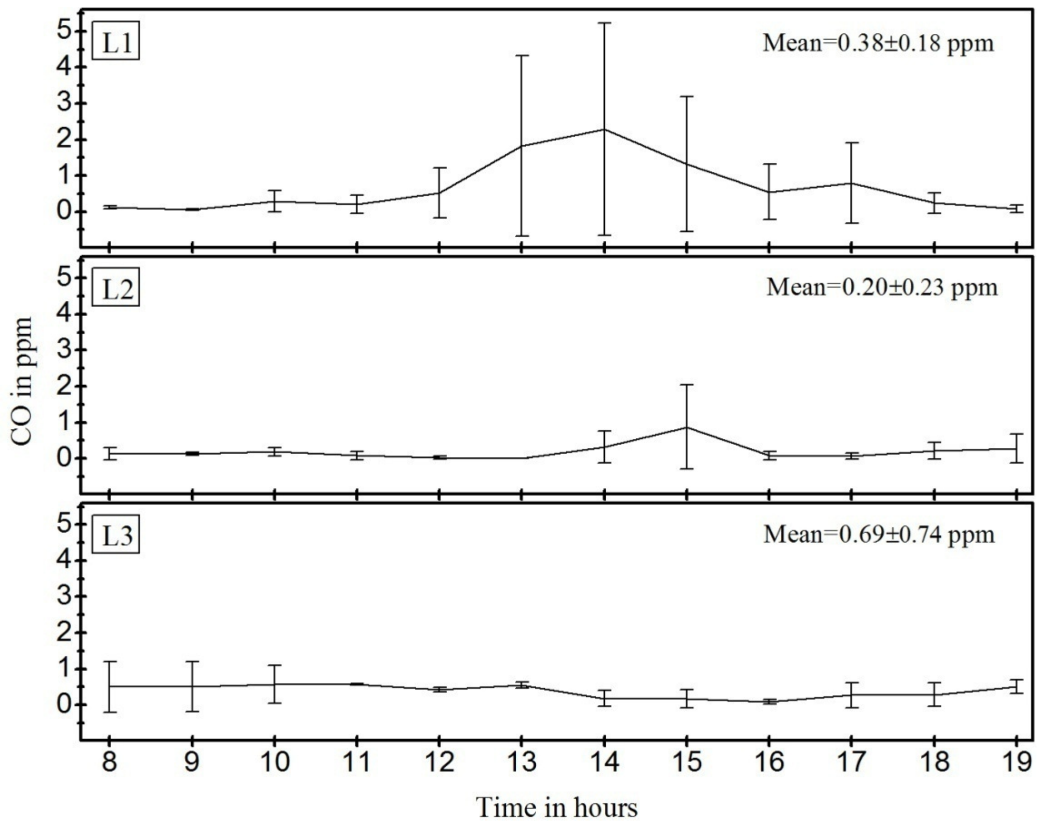


Figure 4.2 : Hourly variation of mean CO concentrations observed at the monitoring locations during non-working days with error bars (±SD) (Saturday to Sunday)

Figure 4.3, 4.4 and 4.5 shows the hourly variation of CO concentrations from Monday to Sunday at L1, L2 and L3. The concentrations were observed to be highest on weekend (Saturday) during afternoon hours (i.e. 13-14 hours) at L1, while at L2 and L3 the concentrations were highest on weekday (Thursday) during evening hours (i.e. 18-19 hours).

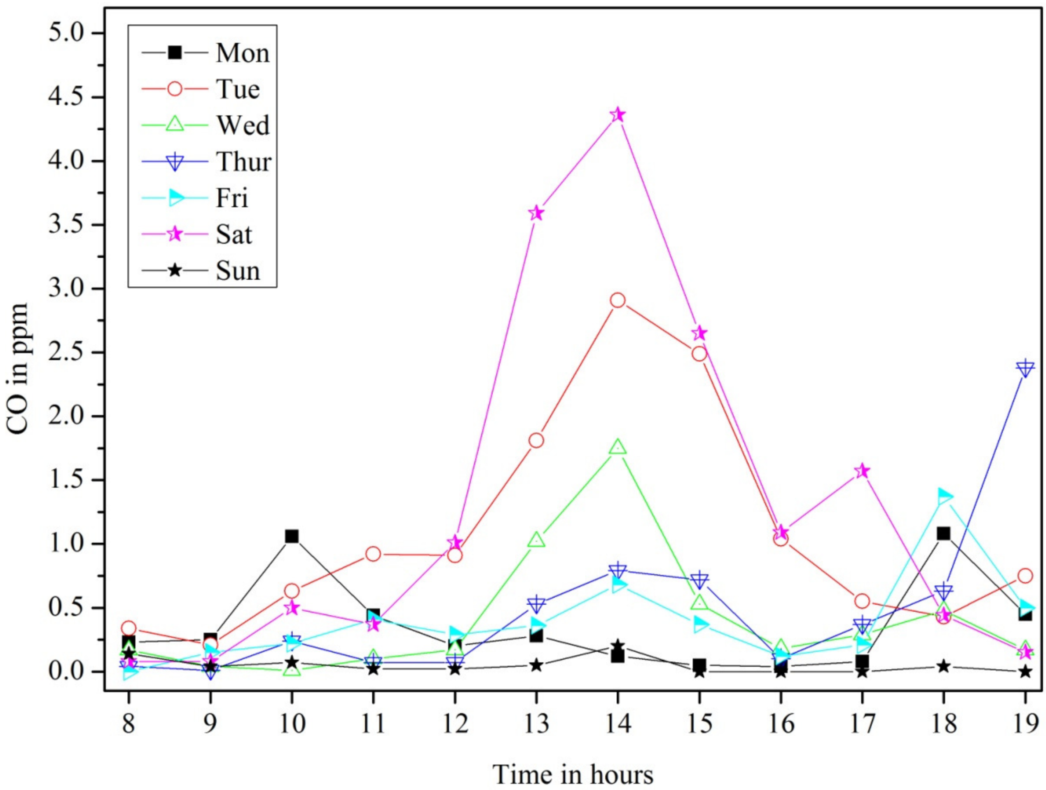


Figure 4.3: Diurnal variation of hourly CO concentrations at L1

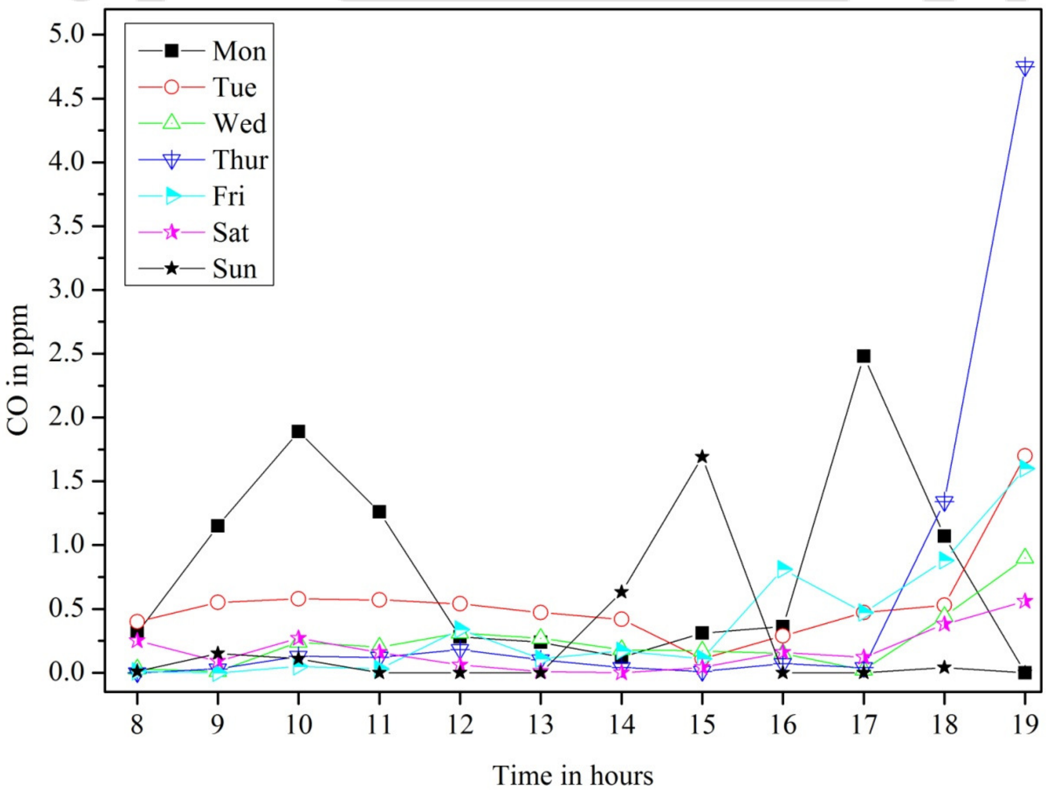


Figure 4.4: Diurnal variation of hourly CO concentrations at L2

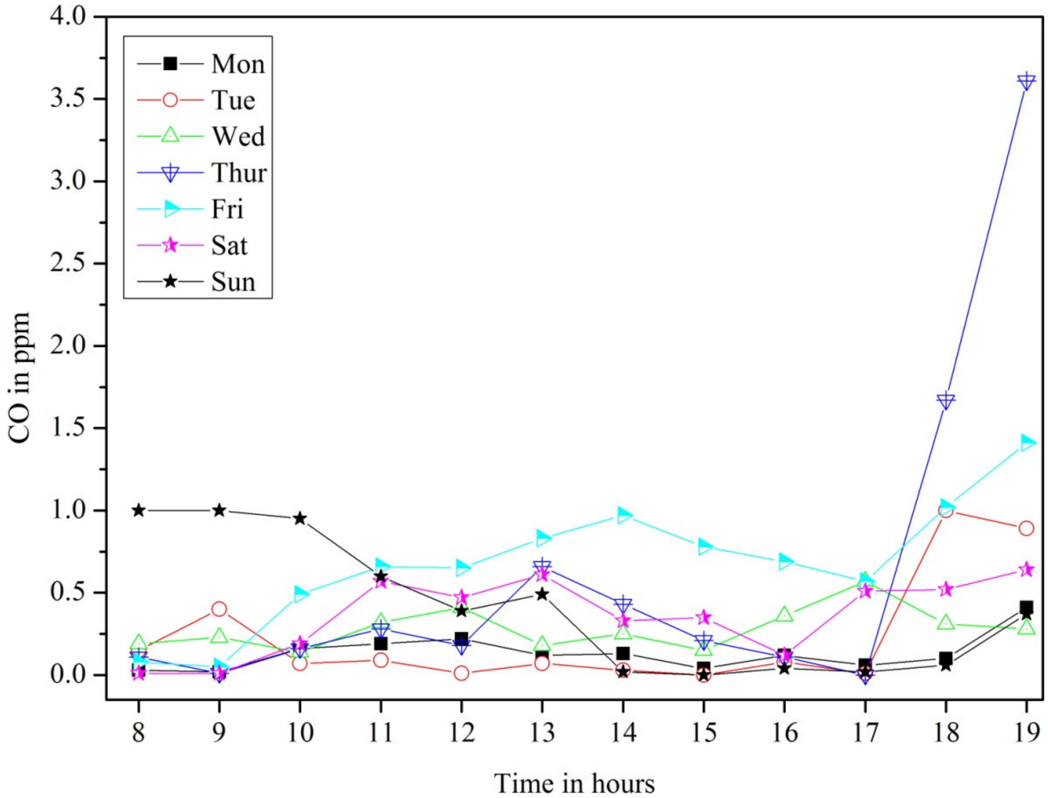


Figure 4.5: Diurnal variation of hourly CO concentrations at L3

4.3 TRAFFIC CHARACTERISTICS

The videotapes were analyze for hourly traffic-flow, average daily traffic volume, traffic volume for different composition, fleet speed, and percentage share of light and heavy vehicles (Appendix–IV). Figure 4.6 and 4.7 shows the hourly variation of traffic volume on working days and non-working averaged across the working and non-working days, respectively. Similarly, hourly variations of traffic composition is shown in Figure 4.8 and 4.9 during working days and non-working days, respectively. The traffic volume was lowest on working days during 7-8 am and highest during 10-12 am and also 5-7 pm, whereas, on non-working days, lowest and highest volume was observed during 7-8 am and 11-1 pm, respectively. Traffic flow is assumed to be same from week to week and hourly trend remains same day to day and week to week.

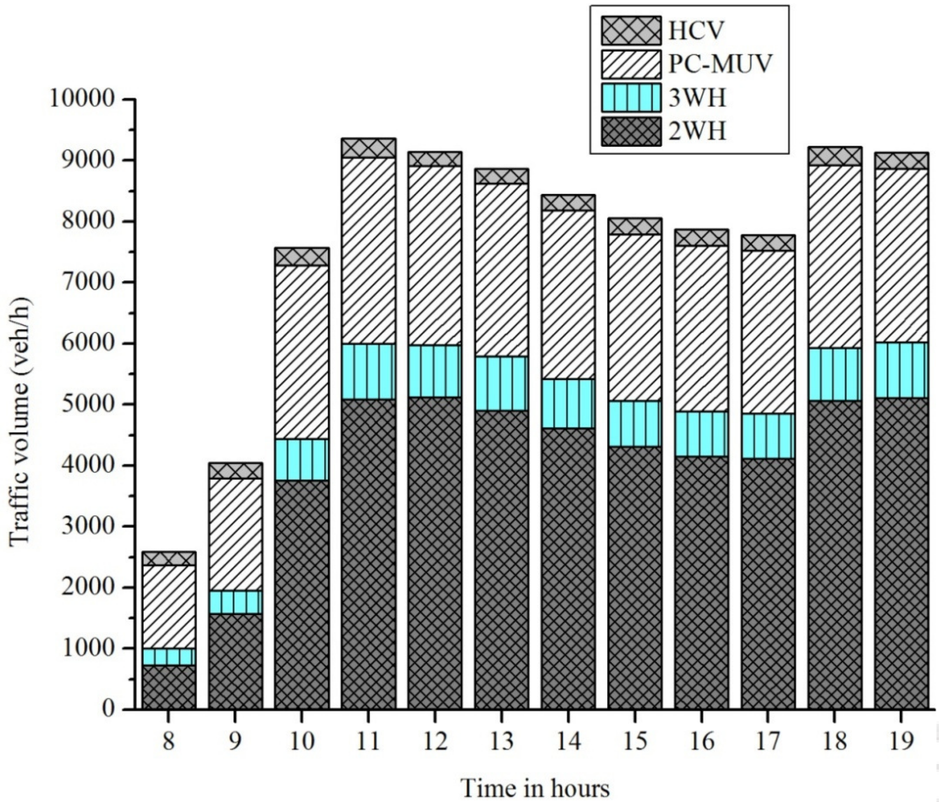


Figure 4.6: Hourly variation of mean traffic volume on working days (averaged across Monday-Friday).

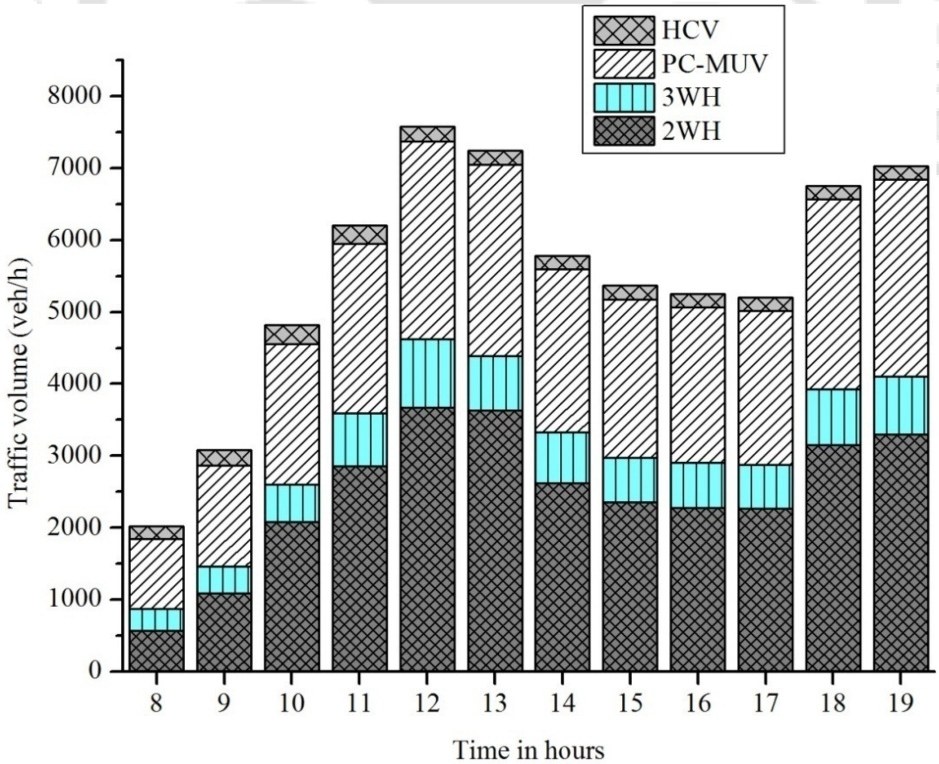


Figure 4.7: Hourly variation of mean traffic volume on non-working days (averaged across Saturday-Sunday)

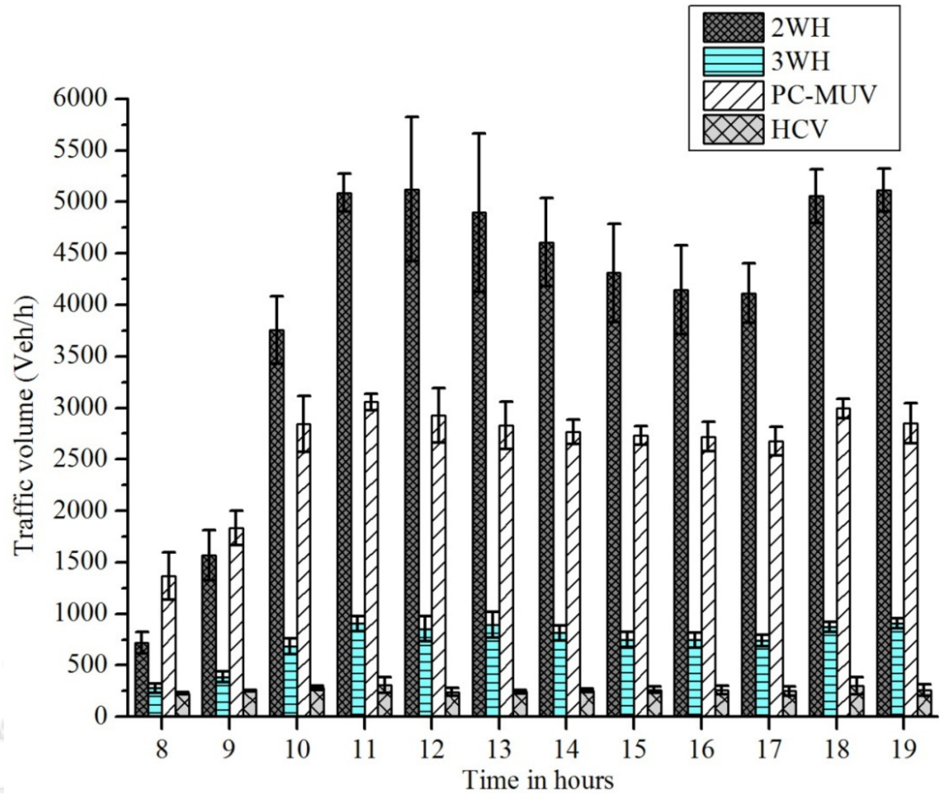


Figure 4.8: Hourly variation of mean traffic composition on working days with error bars (±SD) (averaged across Monday-Friday).

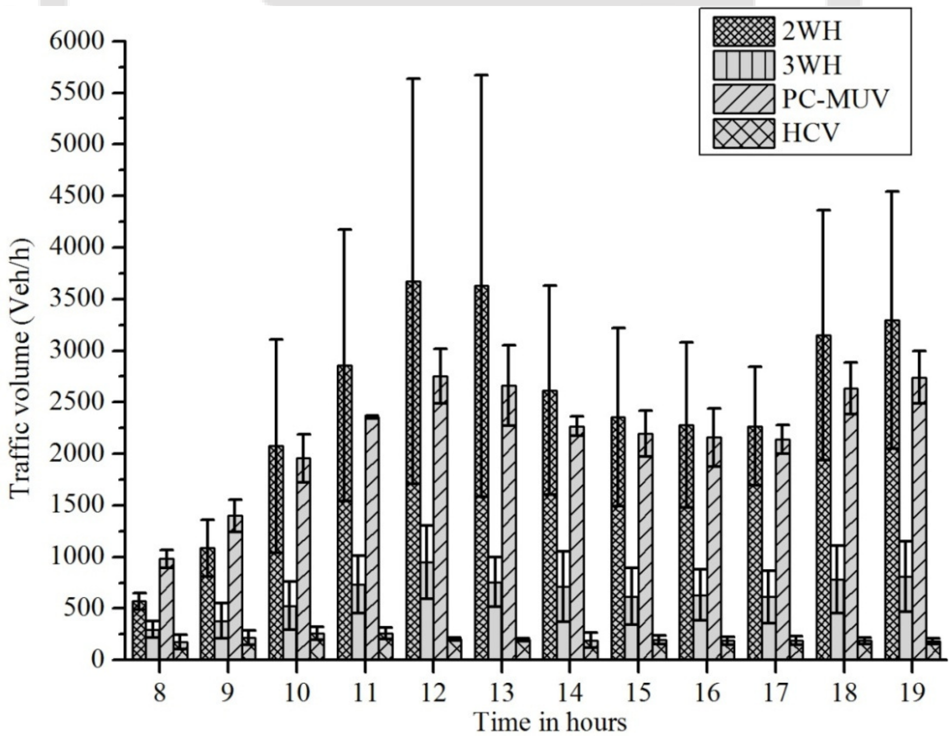
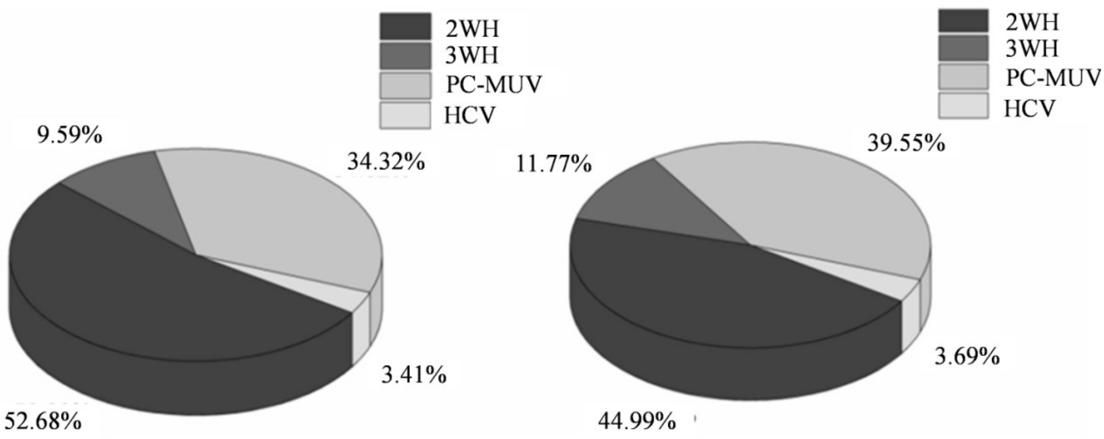


Figure 4.9: Hourly variation of mean traffic composition on non-working days with error bars (±SD) (averaged across Saturday-Sunday).

Figure 4.10 and 4.11 shows the percentage share of vehicle category in the traffic fleet and the percentage share of light-vehicles[5] and heavy-vehicles[6] during workings and non-working days. The share of two-wheelers (2WH) has been the highest in the traffic fleet, i.e. about 53% and 45% on working days and non-workings days. It has been observed that about 87% of the traffic was comprised of 2WH and four-wheelers (PC-MUV) followed by 9-10% of three-wheeler (3WH) and mere 3-4% of heavy vehicles (HCV) on working days, while, on non-working days about 85% comprised of 2WH and PC-MUV, 11-12% of 3WH and 3-4% of HCV. During the off-peak hours, PC-MUV and 2WH composition were 52% and 28%, respectively, while during the peak hours the composition changed to 34% and 53%, respectively.

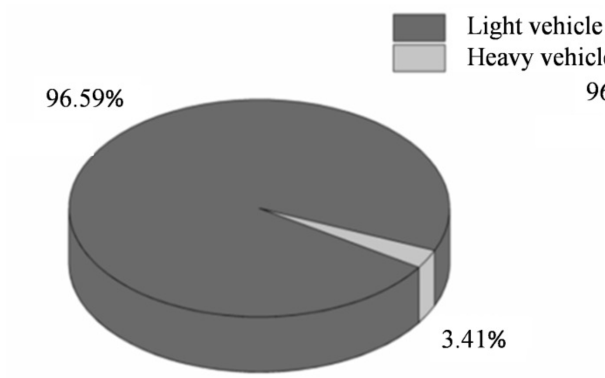


(a) (b)

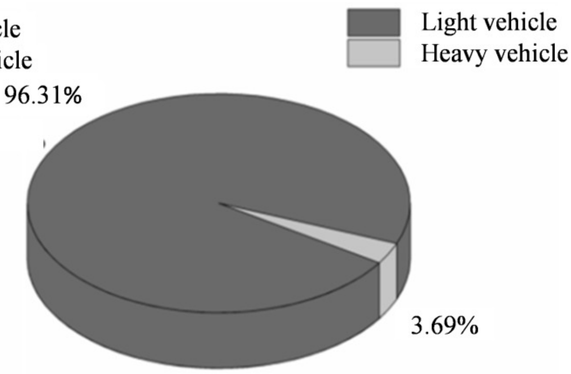
Figure 4.10: Share of vehicles category in the traffic fleet on (a) working days, and (b) non-working days

[5] Light vehicles comprises of two-wheelers (2WH), three-wheelers (3WH), and passenger cars and multi-utility vehicle (PC-MUV).

[6] Heavy vehicles refers to heavy commercial vehicles (HCV) i.e. minibus, truck, and bus



(a)



(b)

Figure 4.11: Share of light and heavy vehicles in the traffic fleet on (a) working days, and (b) non-working days

The running speed averaged for every one hour for each vehicle category was estimated from the videotapes. This was done with the help of a two reference lines of known distance taken on the videotape and time instance at which a particular vehicle passes the two references lines. Using the details, the hourly vehicle speed was estimated. Figure 4.12 and 4.13 shows the hourly variations in speed of different vehicles category and the traffic fleet, respectively. The traffic fleet speed was calculated using the hourly average speed of each vehicle category. The maximum speed was observed during off-peak hour i.e. 7-8 am of about 55 km/hr was for 2WH, 50 km/hr for 3WH, 58 km/hr for PC-MUV and 48 km/hr for HCV.

The minimum speed was observed during evening peak hour (6-7 pm) about 24 km/hr for 2WH, 19 km/hr for 3WH, 18 km/hr for PC-MUV and 20 km/hr for HCV. It has been observed that the speed of PC-MUV during off-peak hour (i.e. 7-8 am) was highest amongst the vehicle category, while that of 2WH was highest in the other hours of the day.

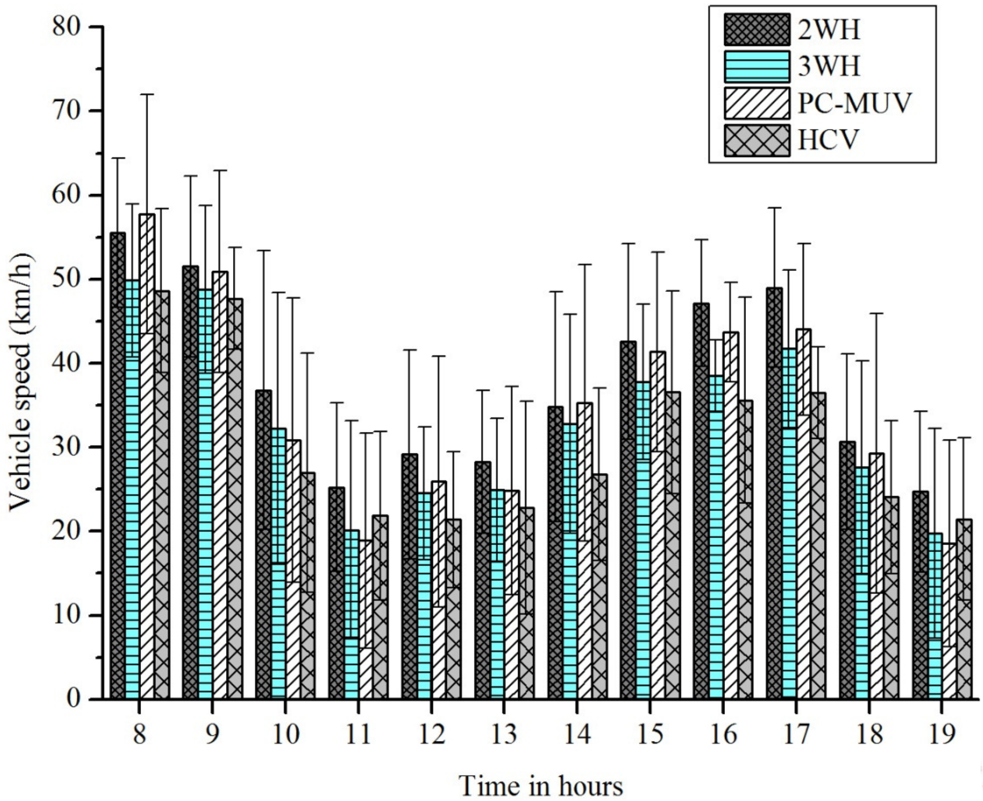


Figure 4.12: Hourly variation in speed for each vehicle category with error bars (±SD).

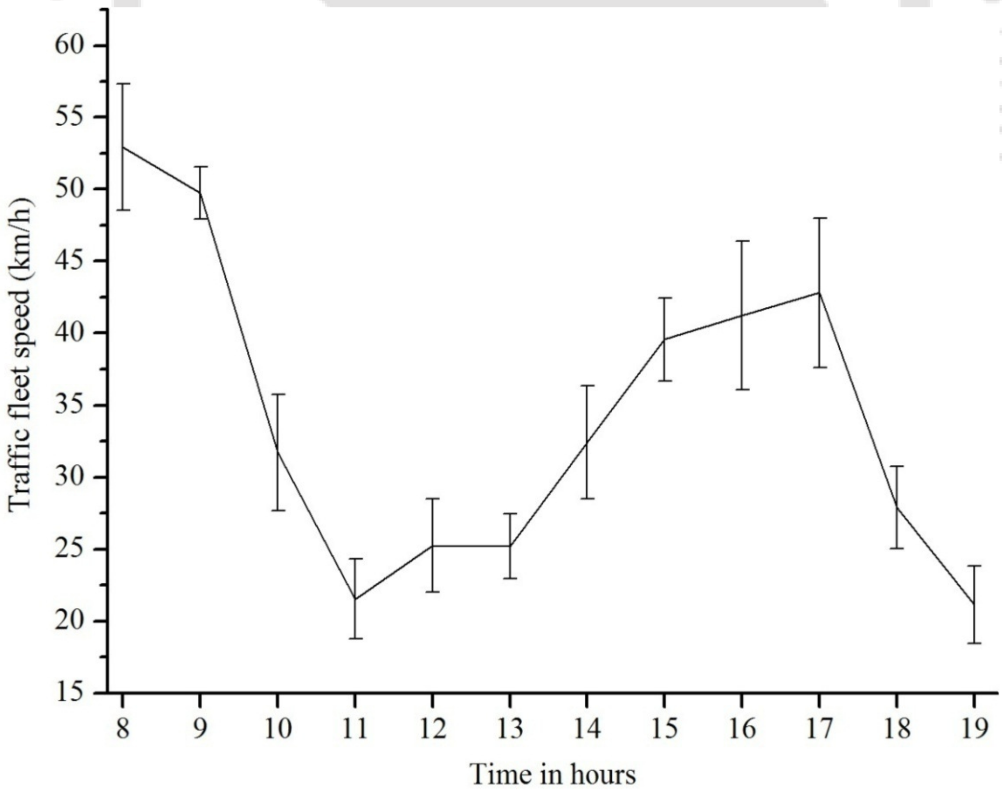


Figure 4.13: Hourly variation in speed for traffic fleet with error bars (±SD).

4.4 METEOROLOGICAL CHARACTERISTICS

The meteorological parameters monitored for three weeks in month (Appendix–III) of March 2014 have been analyzed weekly since air quality monitoring was done at each location for a period of one week so that air quality at three different locations can be interpreted as an effect of meteorology.

4.4.1 Wind flow distribution pattern

Figure 4.14 shows the wind rose diagram each for the period of a week corresponds to the air quality monitoring done at three locations on March 1-7, 2014 at L1, March 8-16, 2014 at L2, and March 17-23, 2014 at L3. As observed, the prevailing wind direction has changed a bit from week to week, i.e. northwest for L1, north for L2 and northeast for L3. The calm-condition[7] was observed for about 37%, 31.3% and 17.1% for each week, respectively.

[7] Calm-condition is regarded as the state of meteorology when wind speed is below a threshold limit which is generally taken as 0.5 m/s Jeong, H., Park, M., Hwang, W., Kim, E., Han, M. (2013) The effect of calm conditions and wind intervals in low wind speed on atmospheric dispersion factors. Annals of Nuclear Energy 55, 230-237.

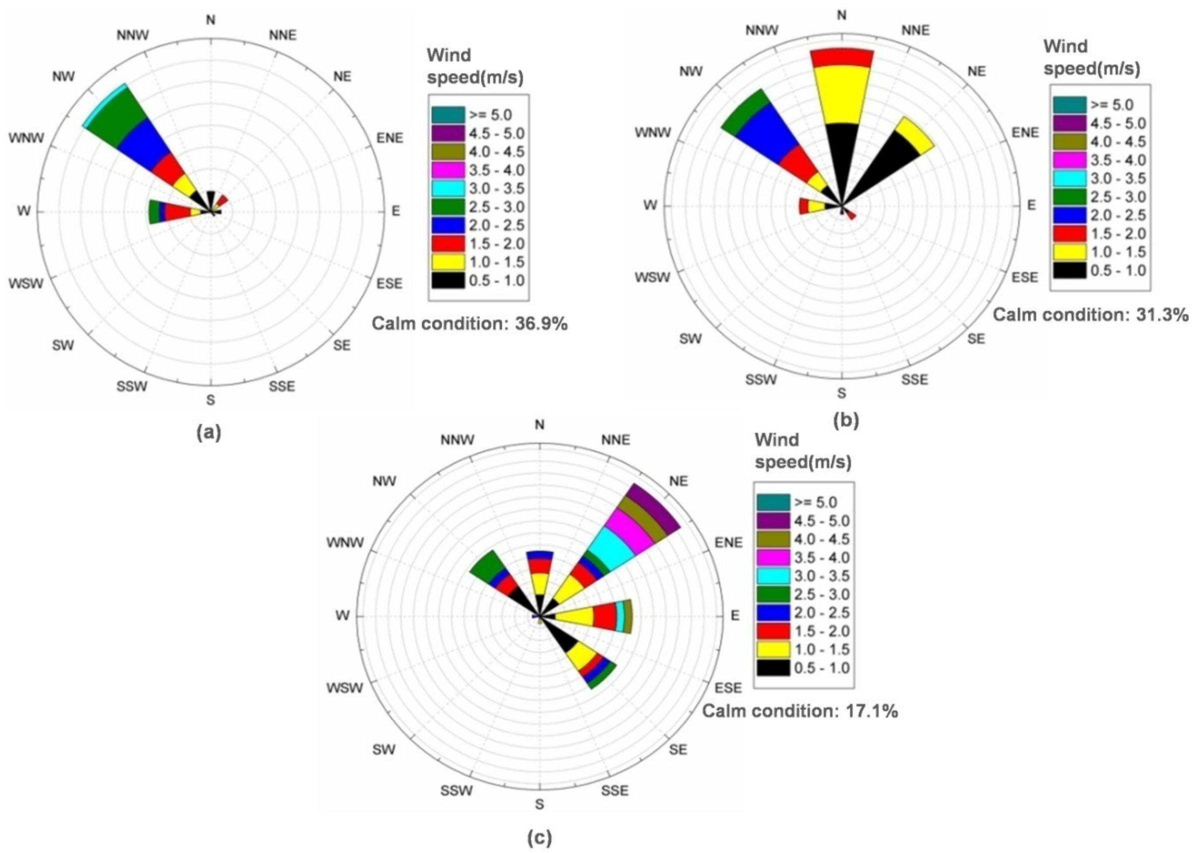


Figure 4.14 Wind-roses during the air monitoring period (a) Week 1 (March-1 to March-7) (b) Week 2 (March-8 to March-14) (c) Week 3 (March-15 to 21)

4.4.2 Temperature, humidity and solar radiation

Temperature was measured at two altitudes of 3m and 18m, which is required for estimation of atmospheric stability class (details in subsequent section). At 3m, the temperature was recorded along with CO concentration at all the locations (i.e. L1, L2 and L3). Figure 4.15(a) shows the hourly averaged temperature observed at 3m during week-1 (March 1-7) at L1, week-2 (March 8-14) at L2, and week-3 (March 15-21). Significant differences in temperature were observed between the weeks, i.e. especially during afternoon (12-4 pm). The highest difference in hourly averaged temperature of about 12.7 ^{0}C was observed between week-1 and week-2 during 1-2 pm. The average temperature of week-1 during the morning hours (i.e. 8-12 am) was lower as compared to that of week-2 and week-3 but highest during 12-4 pm.

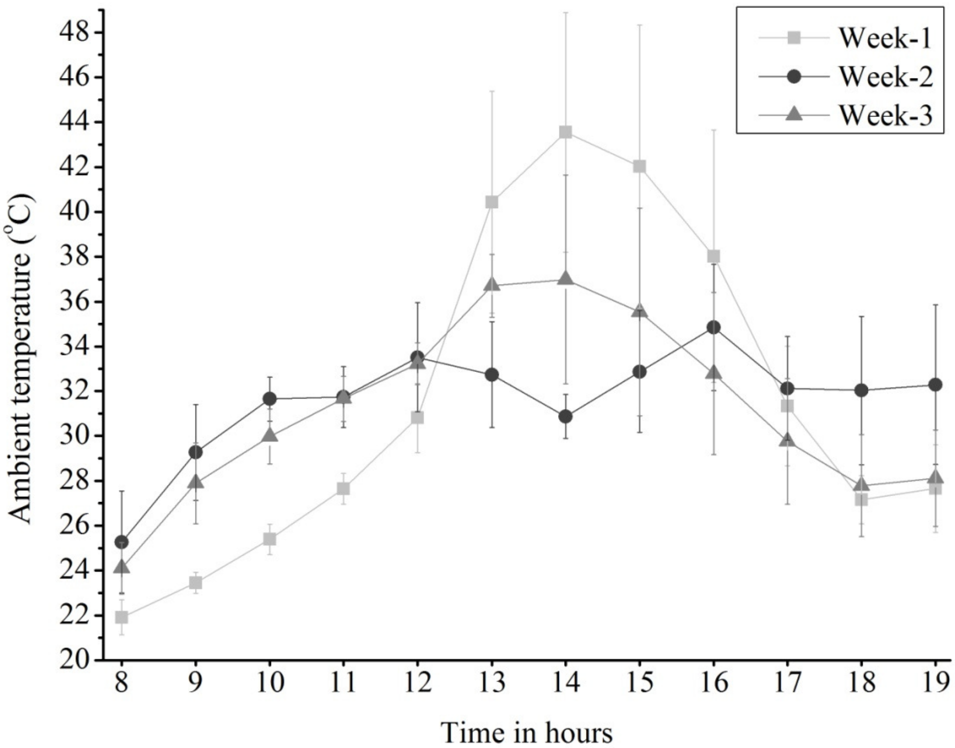


Figure 4.15(a): Hourly averaged ambient temperature observed at 3m from ground level with error bars (±SD).

Figure 4.15(b) shows the hourly averaged temperature observed at 18 m during the weeks. The temperature trends between the weeks at this altitude were quite similar with little difference of about 2^0C between week-1 and week-2. Figure 4.15(c) shows the comparison of the temperatures observed at both altitude during the weeks. Significant large difference in temperature between the altitudes was observed during week-1 (1-4 pm) while difference were lesser during week-2 and week-3.

It has been, therefore, evident that thermal turbulence was dominant during the air quality monitoring at L1, indicating strongly unstable atmospheric condition from 12 noon to 5 pm . This has been verified by the stability class using the bulk Richardson number, which also takes into account wind speed.

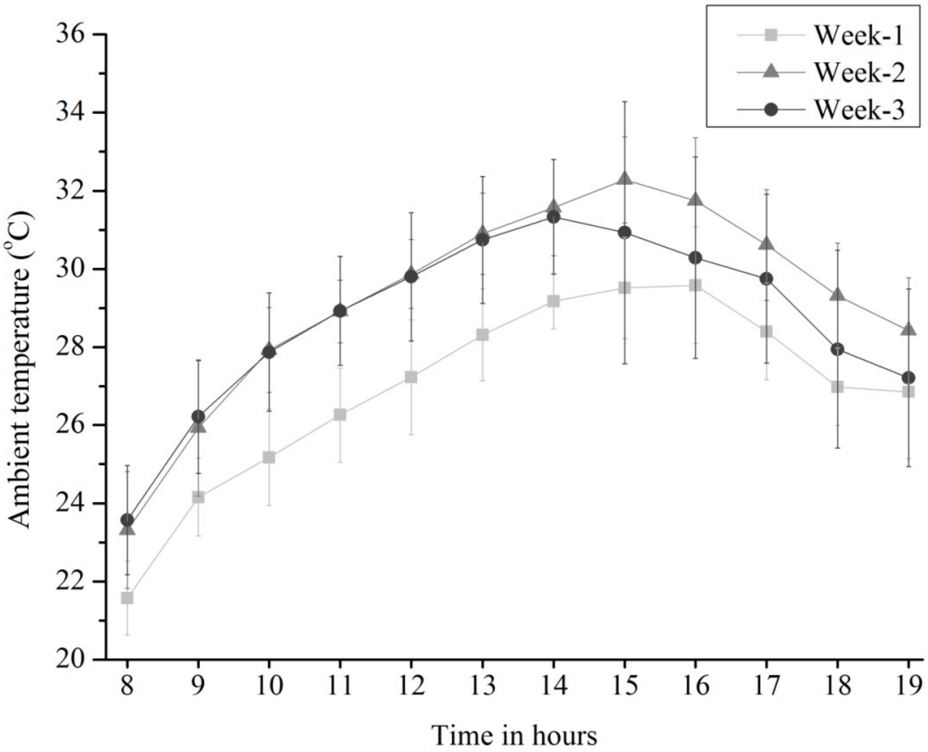


Figure 4.15(b): Hourly averaged ambient temperature observed at 18m from ground level with error bars (±SD).

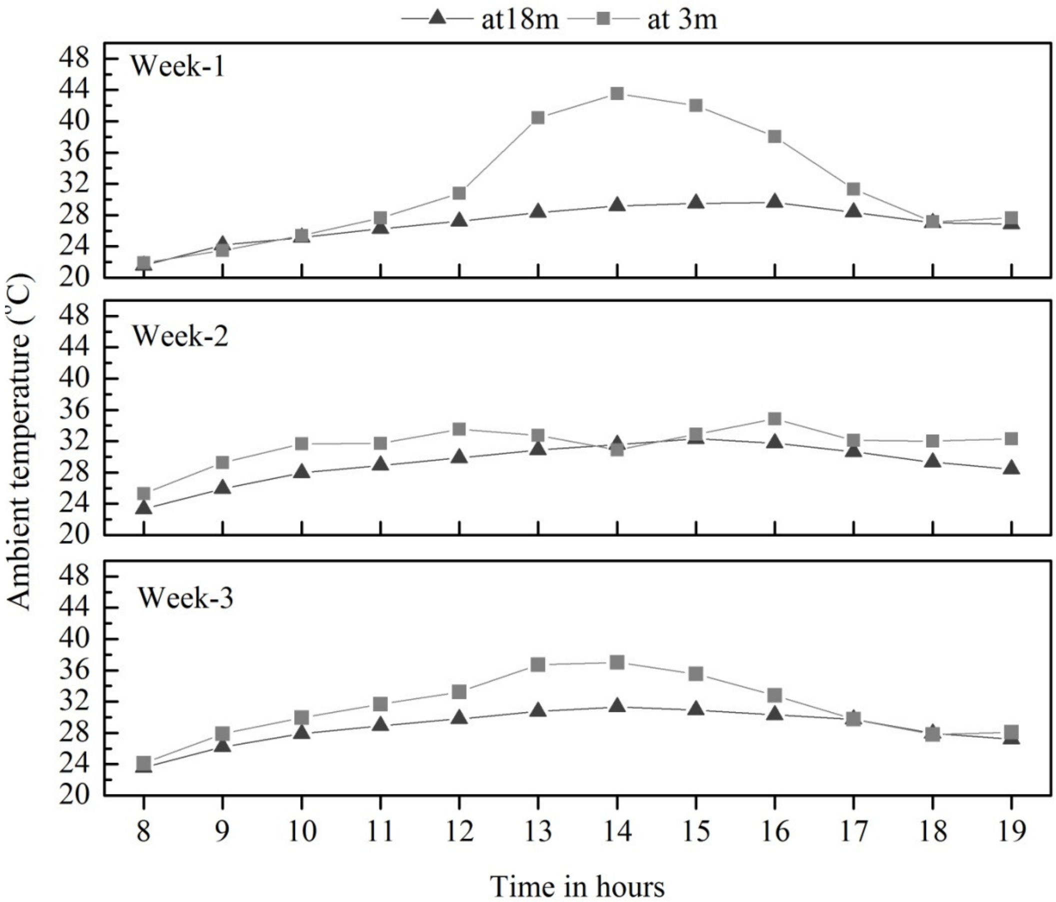


Figure 4.15(c): Comparison of hourly temperature at 18m and 3m.

Bulk Richardson number provides a reasonable estimate of stability class (Mohan and Siddiqui, 1998). This method takes into account the change in temperature with altitude and wind speed to classify the atmospheric stability. When thermal turbulence dominates it create unstable atmospheric condition. This condition is changed to neutral when wind induced turbulence increases and thermal turbulence decreases. Further, change leads to stable condition when both turbulence decreases and attend highly stable conditions if both are absent. Bulk Richardson number, (R_b) is defined by equation 4.1.

$$R_b = \frac{gH_z(T_z - T_o)}{\{U_z{}^2(T_b + 273)\}} \tag{4.1}$$

where, g is the acceleration due to gravity (m/s^2); H_z the height of meteorological station (m); T_z the temperature at meteorological station height; T_o the ground level temperature (^{0}C); T_b the ambient background temperature (^{0}C); and U_z is the wind speed at meteorological station height (m/s). The criteria for stability based on bulk Richardson number is given in table 4.1. Hourly atmospheric stability during monitoring weeks has been estimated using equation 4.1 and table 4.1.

Table 4.1: Stability criteria based on bulk Richardson number

Stability Class	Richardson number (R_b)
A	$R_b < -0.023$
B	$-0.023 < R_b < -0.011$
C	$-0.011 < R_b < -0.036$
D	$-0.036 < R_b < 0.007$
E	$0.007 < R_b < 0.042$
F	$0.042 < R_b < 0.084$
G	$R_b > 0.084$

Source: (Mohan and Siddiqui, 1998)

Figure 4.16 shows the frequency of occurrence of each stability class. During week-1, 83% of the time, the atmospheric conditions was unstable with 50% of the time was extremely unstable. During week-2, unstable conditions were observed for 77% with 56% of the time was extremely unstable. The lowest occurrence of unstable conditions was observed during week-3 with about 71% of the time of which about 37% was extremely unstable.

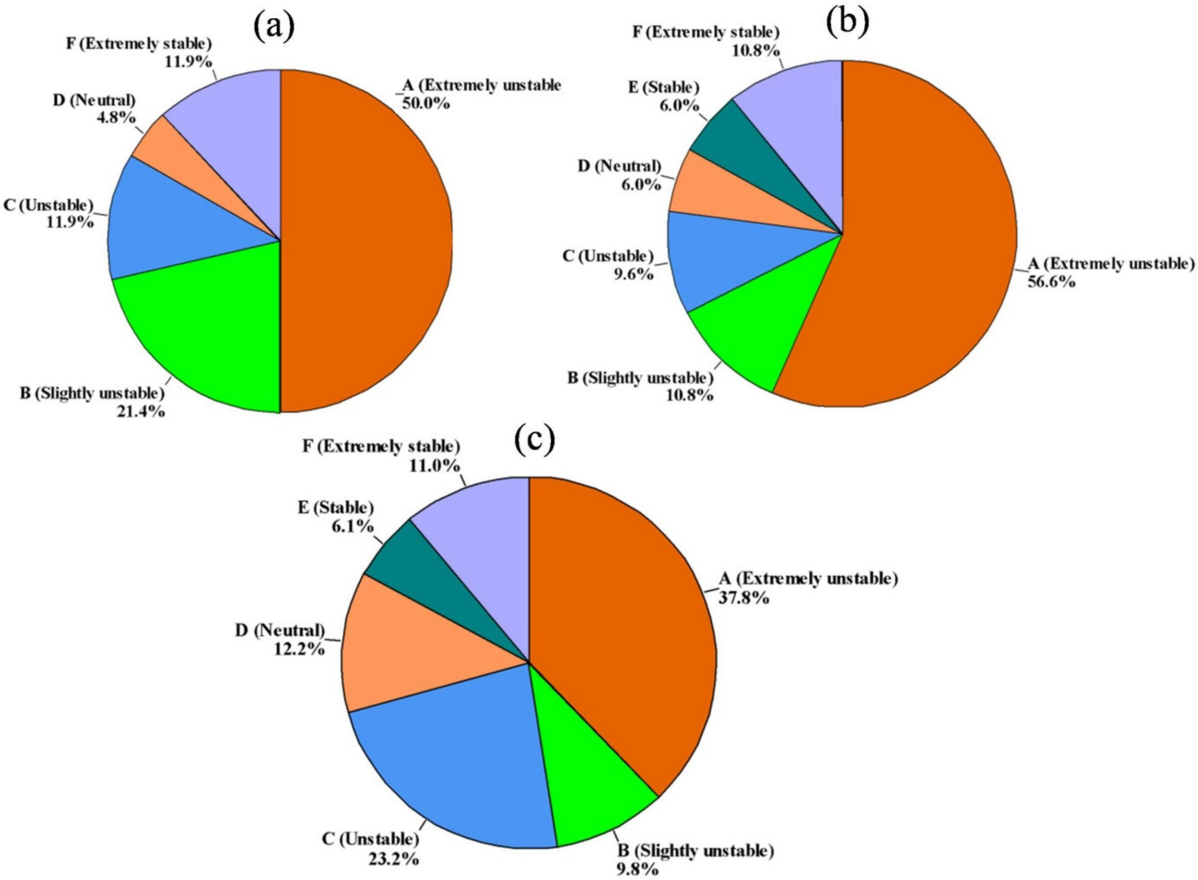


Figure 4.16 Frequency of atmospheric stability during the monitoring period (a) Week 1 (March-1 to March-7) (b) Week 2 (March-8 to March-14) (c) Week 3 (March-15 to 21)

It has been observed that extremely unstable condition occurred more frequently during week-1 and week-2. The huge variations in temperature suggest that unstable condition during week-1 may have been contributed by thermal turbulence whereas during week-2 due to wind-speed induced turbulence.

Figure 4.17 shows the solar radiation observed in the corridor during air quality monitoring at each location. The hourly variations in solar radiation during three weeks were quite similar with slightly higher during week-3 morning hours (8-12 am) as compared to other weeks. However, radiations were nil at all the weeks after 5 pm.

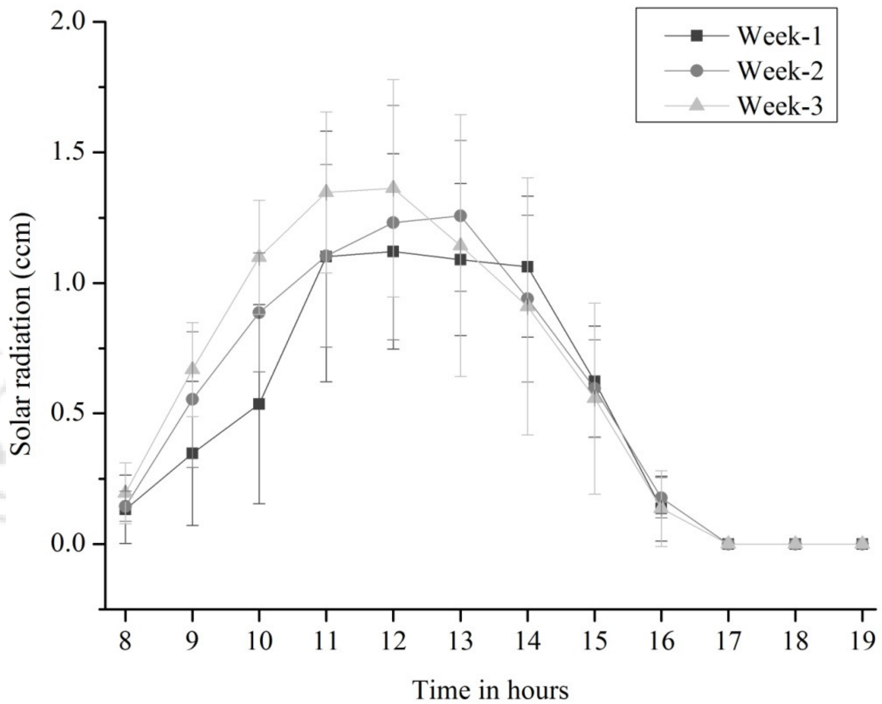


Figure 4.17: Hourly solar radiation observed during the monitoring period at L1, L2 and L3 with error bars (±SD).

Figure 4.18 shows relatively humidity observed. The variation was higher by 5-10% during week-1 (8 am-1 pm) as compared to others week, but the variation during 1-7 pm was higher in week-3 and almost same between week-1 and week-2.

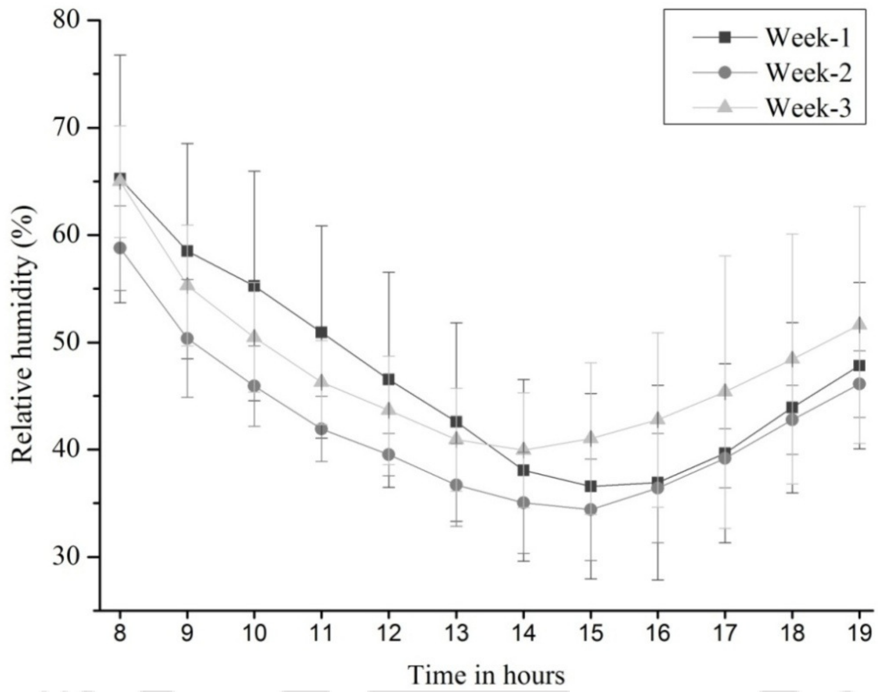


Figure 4.18: Hourly relative humidity observed during the monitoring period at L1, L2, L3 with error bars (±SD).

4.5 CO VS TRAFFIC VS METEOROLOGY

Figure 4.19, 4.20 and 4.21 shows the hourly variation of concentrations along with the meteorological parameters during monitoring periods at L1, L2 and L3.

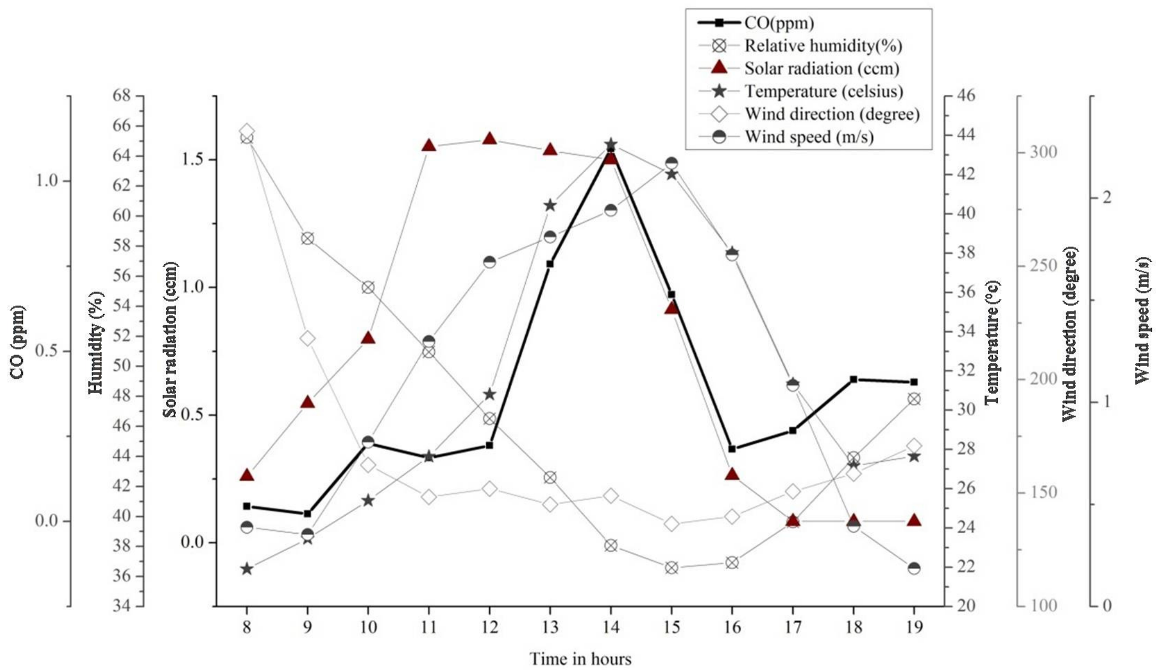


Figure 4.19: Hourly variation of CO with the meteorological parameters during week-1

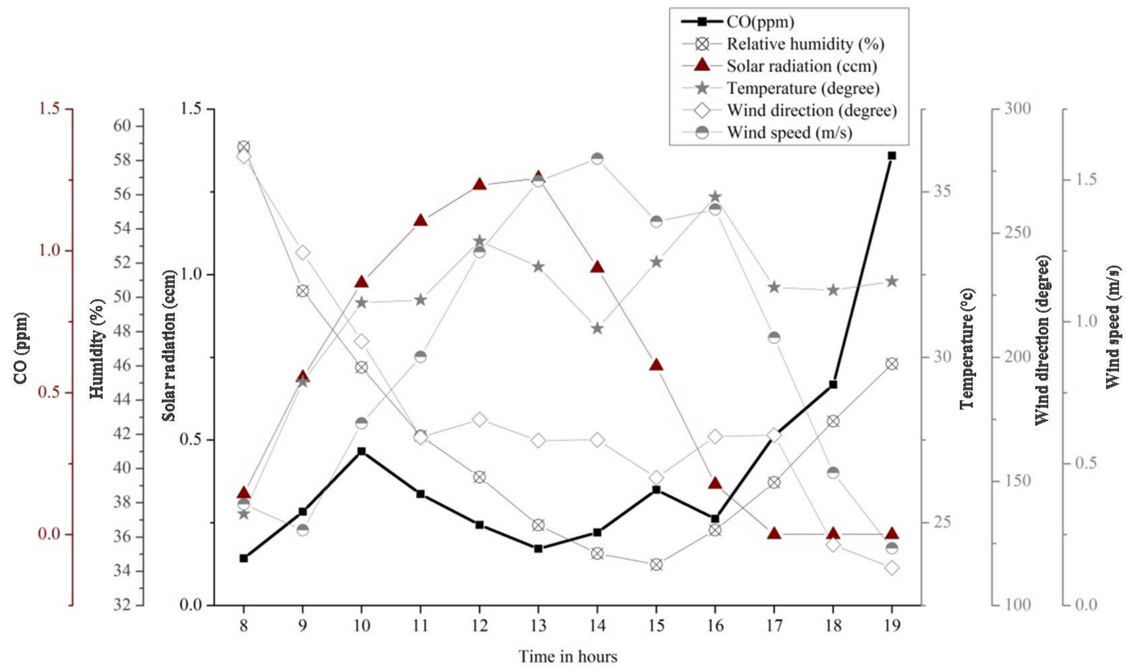


Figure 4.20: Hourly variation of CO with the meteorological parameters during week-2

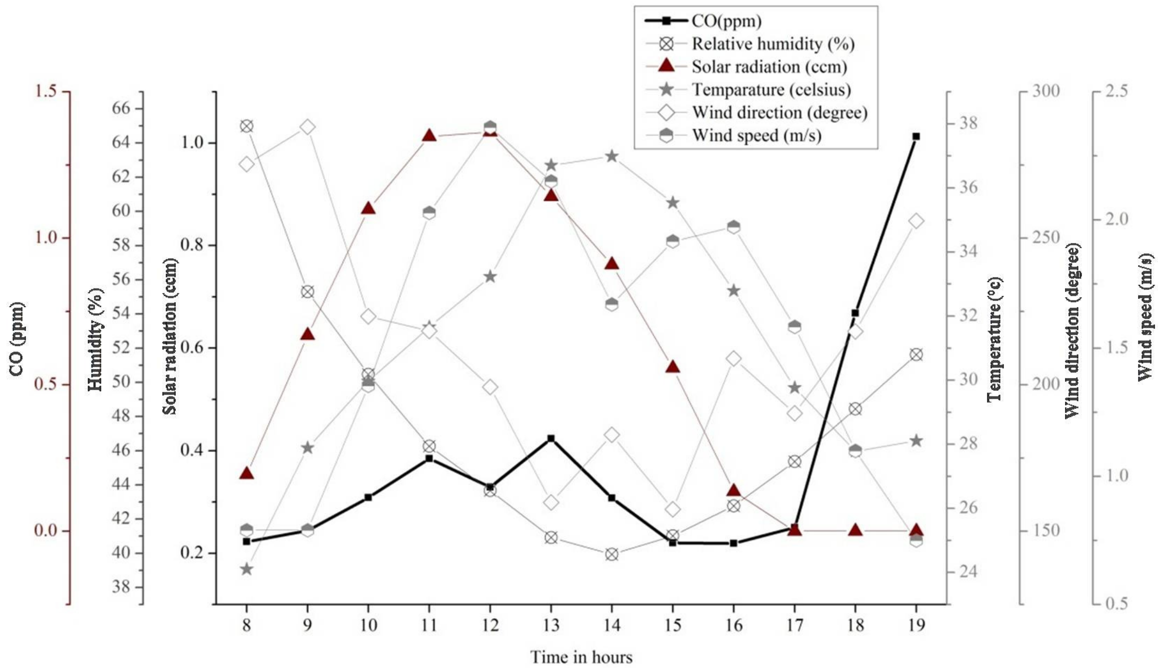


Figure 4.21: Hourly variation of CO with the meteorological parameters during week-3

Figure 4.22, Figure 4.23 and 4.24 shows the scatter plots of hourly averaged CO concentrations along with the hourly averaged meteorological parameters and hourly traffic volume during monitoring periods at L1, L2 and L3, respectively.

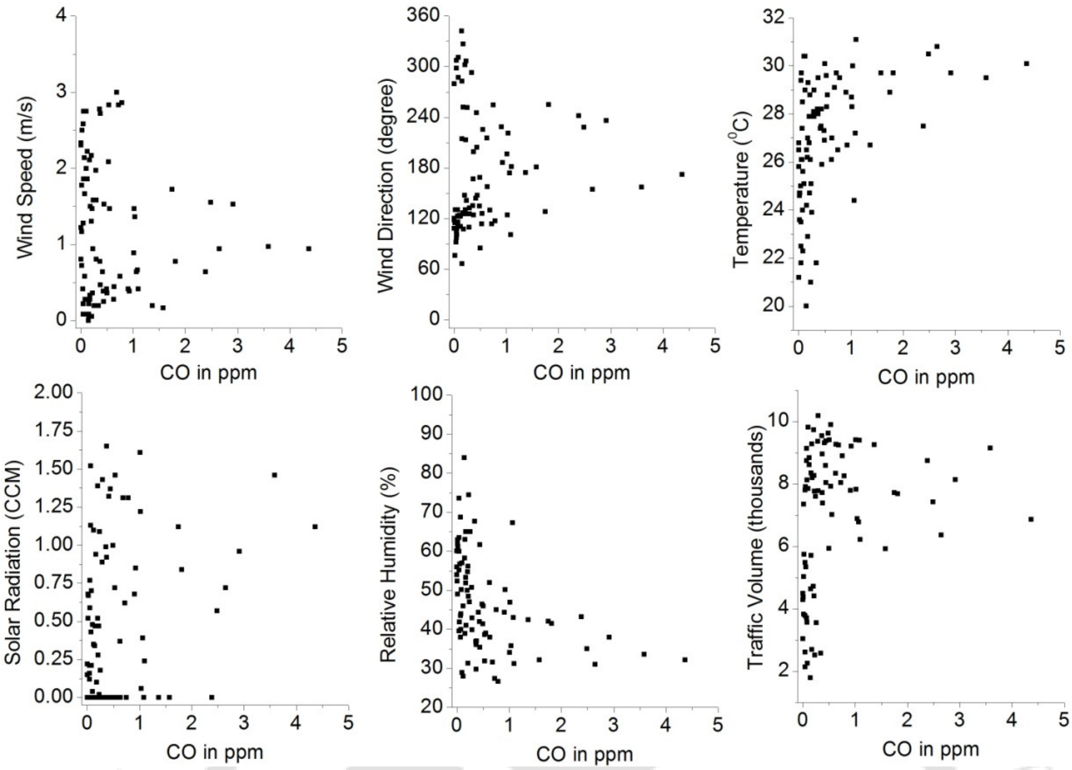


Figure 4.22 : Scatter plots of hourly averaged CO with the meteorological parameters and traffic volume during week-1

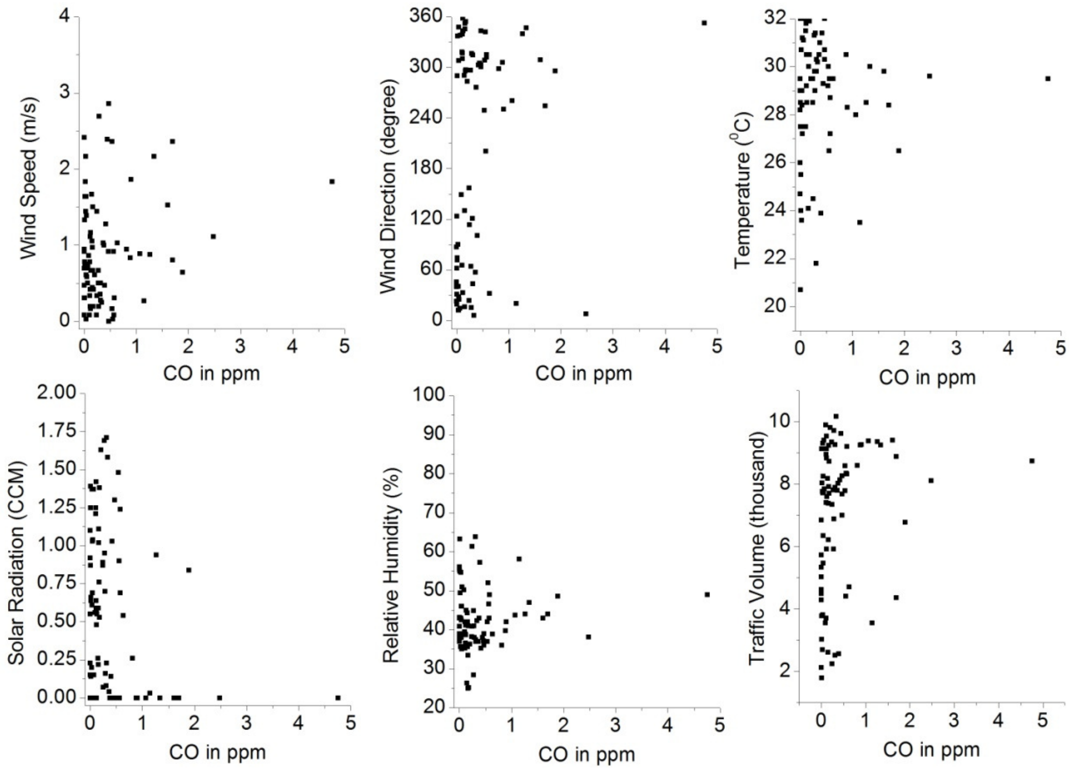


Figure 4.23 : Scatter plots of hourly averaged CO with the meteorological parameters and traffic volume during week-2

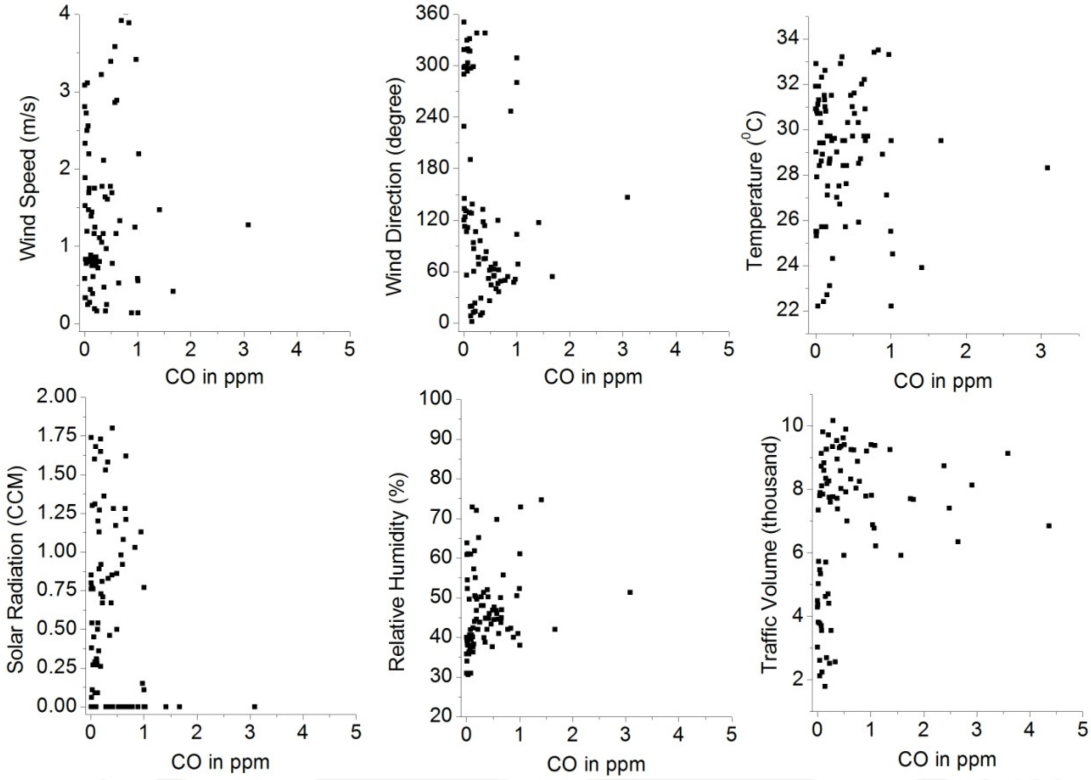


Figure 4.24 : Scatter plots of hourly averaged CO with the meteorological parameters and traffic volume during week-3

Figure 4.25 shows the wind roses in three different weeks with pollution rose at L1, L2 and L3. It has been observed that frequencies of CO concentrations (0-1 ppm) were dominant at all the locations, i.e. 76% of time at L1, 83% at L2, and 92% at L3. The maximum concentration was observed for just about 1.2% of the time at each location when the wind direction was from north at L1 and L2 and from south-east (i.e. parallel to road) at L3. This indicates that maximum concentrations occurred when the monitoring location was at upwind direction at L1 and downwind direction at L2. The frequency of higher CO concentrations (i.e. >2 ppm) at L2 was low as compared to other two locations. It occurs for 7% of the time at L2 whereas, in L1 and L3, for about 24% and 17%.

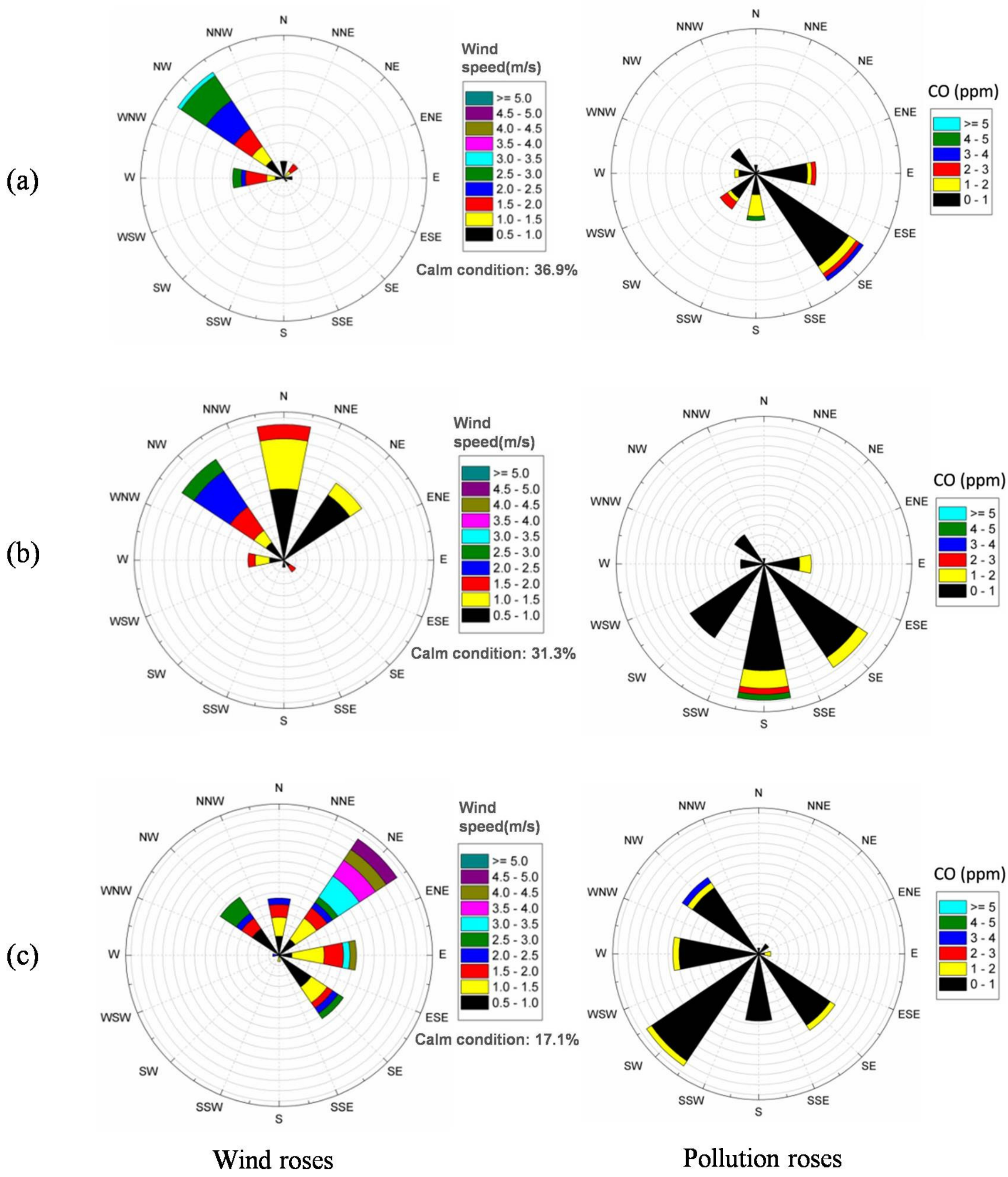


Figure 4.25: Wind roses in three different weeks and pollution roses (a) at L1, (b) at L2, and (c) at L3

The relationships of CO with traffic characteristics and meteorological parameters was studied to investigate to what extent CO concentration is influenced by traffic flow and various meteorological characteristics. The multi-linear regression (MLR) is commonly used to establish the relationship between input variables (independent) and output variables (dependent) without detailing the causes of relationships (Cardelino et al., 2001; Paschalidou et al., 2009). Moreover, Pearson correlation analysis (PCA) is often used in conjunction with regression because correlation analysis is used to determine the strength of association between two variables (Kottegoda and Rosso, 1997). Therefore, the PCA and MLR methods were employed to study the relationships of CO concentration with traffic and meteorological parameters (temperature, wind-speed, relative humidity, solar radiation, and wind direction). The general MLR model consists of 'm' independent variables and an a dependent variable which can be written as equation 4.1 (Kottegoda and Rosso, 1997).

$$Y = \beta_o + \beta_1 x_1 + \ldots\ldots\ldots\ldots + \beta_m x_m + \varepsilon \tag{4.1}$$

where, Y is the dependent variable; $\beta_o, \beta_1, \ldots, \beta_m$ are the regression coefficients; x_1, $x_2, \ldots, x_m$ are independent variables and ε is the error associated with the regression.

The Pearson correlation (r) is used to find a correlation between at least two continuous variables (Zou et al., 2003). The general formula of the r is shown in equation 4.2

$$r = \frac{\sum XY - \frac{\sum X \sum Y}{N}}{\sqrt{\left(\sqrt{\sum X^2} - \frac{(\sum X)^2}{N}\right)\left(\sqrt{\sum Y^2} - \frac{(\sum Y)^2}{N}\right)}} \tag{4.2}$$

where, N is the sample size; X, the value of the independent variable, and Y is the value of the dependent variable. The r value ranges between -1 and +1 indicating perfect negative and positive correlation between the two variables, respectively whereas, 0 represents lack of correlation (Zou et al., 2003).

The measured hourly CO concentration was treated as dependent variable whereas, hourly traffic volume and meteorological parameters as the independent variables. The meteorological parameters used as independent variables were wind-direction, wind-speed, temperature, solar radiation, and humidity. In MLR analysis, independent variables are entered into the regression equations based on selection criteria such as significant correlation with dependent variable and its contribution to regression equations with respect to *F*-test or *t*-test (Witz and Moore Jr, 1981). After the variable is entered, variables satisfying the criteria were retained, otherwise it is removed from the equation (Thomas and Jacko, 2007). The model performance was assessed using standard errors of the estimated slopes and *p*-values (Lin et al., 2012).

4.5.1 Pearson correlation matrix

The correlation matrix is shown in table for 4.2 for L1, L2 and L3. It has been observed that correlation between traffic and CO was poor but significant ($p<0.05$) at all three monitoring locations. Further in the case of meteorological parameters and CO, correlation was found to be different. For example, temperature has a good correlation with CO at L1 and significantly not at L2 and L3. The solar radiation was positively correlated with CO at L1 and negatively at L2 and L3, whereas, relative humidity was negatively correlated at L1 and positively at L2 and L3. The wind-speed was negatively correlated with CO at all the three locations but was statistically significant only at L2. The CO was significantly correlated with wind direction at L1 and L3 but not in L2. The wind directions were divided into four according to wind relative to orientation of road, (i.e. $0 \leq WD1 < 45$, $45 \leq WD2 < 90$, $180 \leq WD3 < 225$ and $225 \leq WD4 < 270$). It was found that WD4 were significantly correlated with CO at L1, and WD2 at L3. During the monitoring period at L1, no wind was observed from the direction of WD1.

Table 4.2: Pearson correlation analysis

Monitoring Locations	Variables	CO	WS	WD1	WD2	WD3	WD4	Temp	SR	RH	Traffic
L1	CO	1									
	WS	-0.10	1								
	WD1	-	-	-							
	WD2	-0.09	-0.16	-	1						
	WD3	0.07	-0.29*	-	-0.07	1					
	WD4	0.31*	-0.16	-	-0.07	-0.14	1				
	Temp	0.45*	0.37*	-	0.01	0.13	0.15	1			
	SR	0.25*	0.43*	-	-0.11	0.04	-0.14	0.26*	1		
	RH	-0.40*	-0.34*	-	0.09	-0.16	-0.07	-0.65*	-0.14*	1	
	Traffic	0.24*	0.35*	-	-0.06	0.05	0.10	0.66*	0.36*	-0.55*	1
Monitoring Locations	**Variables**	**CO**	**WS**	**WD1**	**WD2**	**WD3**	**WD4**	**Temp**	**SR**	**RH**	**Traffic**
L2	CO	1									
	WS	-0.28*	1								
	WD1	-0.11	-0.12	1							
	WD2	-0.16	-0.21	-0.20	1						
	WD3	0.03	-0.13	-0.06	-0.04	1					
	WD4	0.21	-0.23	-0.15	-0.09	-0.03	1				
	Temp	-0.04	0.55*	0.06	-0.25	0.01	-0.08	1			
	SR	-0.27*	0.44*	0.12	-0.01	-0.12	-0.28	0.24*	1		
	RH	0.12	-0.66*	-0.02	0.20	0.06	0.05	-0.85*	-0.34*	1	
	Traffic	0.21*	0.3*	-0.04	-0.36*	0.06	0.22*	0.68*	0.24*	-0.59*	1
Monitoring Locations	**Variables**	**CO**	**WS**	**WD1**	**WD2**	**WD3**	**WD4**	**Temp**	**SR**	**RH**	**Traffic**
L3	CO	1									
	WS	-0.18	1								
	WD1	-0.07	-0.14	1							
	WD2	0.23*	0.43*	-0.32	1						
	WD3	-0.11	0.05	-0.07	-0.11	1					
	WD4	0.12	-0.13	-0.05	-0.08	-0.02	1				
	Temp	-0.06	0.43*	0.19	0.17	0.14	-0.01	1			
	SR	-0.21	0.14	0.22*	-0.10	0.01	-0.12	0.08	1		
	RH	0.19	-0.19	-0.10	0.01	-0.17	-0.08	-0.85*	-0.14	1	
	Traffic	0.25*	0.31*	0.12	0.19	-0.02	0.09	0.49*	0.20	-0.37*	1

* Correlation is significant at the 0.05 level

Notation: CO: Carbon dioxide (ppm), WS: Wind speed (m/s), WD1: Wind direction ($0\text{-}45^0$), WD2: Wind direction ($45\text{-}90^0$), WD3: Wind direction ($180\text{-}225^0$), WD4: Wind direction ($225\text{-}227^0$), Temp: Temperature (C^0) at 18m, SR: Solar radiation (ccm), RH: Relative humidity(%), Traffic: Traffic volume (count)

4.5.2 Regression analysis

Table 4.3 shows the descriptive statistics of the observed the CO concentrations at L1, L2 and L3. It has been observed that the CO concentrations were non-normally distributed (CV=1.22 at L1, 1.32 at L2 and 1.04 at L3). The CO concentrations were log-transformed to normalize and treated as the dependent variables for the regressions models. It is also observed in a study that regression model performance improves substantially by logarithmic-transformation of dependent variable (Abdul-Wahab et al., 2005). Since the normality criterion applies only to dependent variable, the independent variables were not transformed therefore, the regression analysis was performed over the significantly correlated independent variables of all the locations, as shown in table 4.4.

Table 4.3: Descriptive statistics of CO observed at L1, L2 and L3

Statistics	L1	L2	L3
N	70	61	69
Mean (ppm)	0.70	0.57	0.46
Standard error	0.86	0.10	0.06
Median (ppm)	0.37	0.31	0.35
Standard deviation	0.86	0.75	0.47
Sample variance	0.75	0.56	0.22
Kurtosis coefficient	5.81	15.83	13.86
Skewness coefficient	2.34	3.47	3.03
Range (ppm)	4.31	4.70	3.56
Minimum (ppm)	0.05	0.05	0.05
Maximum (ppm)	4.36	4.75	3.61
Coefficient of variation (CV)	1.22	1.32	1.04
Shapiro-Wilk test	1.71×10^{-10}	1.82×10^{-10}	4.56×10^{-10}
1st Quartile (ppm)	0.17	0.16	0.15
3rd Quartile (ppm)	0.90	0.57	0.61
95% of Confidence Interval about mean			
Lower (ppm)	0.50	0.38	0.35
Upper (ppm)	0.91	0.76	0.57

Table 4.4: Results of regression analysis

Monitoring location	Model variables	Coefficients	Standard error	*p*-value	R-square
L1	Intercept	-4.328	0.535	0.00	0.54
	Temp	0.147	0.021	0.00	
	WS	-0.330	0.065	0.00	
	SR	0.317	0.103	0.00	
	WD2	-0.618	0.253	0.02	
	WD4	0.311	0.150	0.04	
L2	Intercept	0.361	0.772	0.04	0.22
	Traffic	0.157	0.040	0.00	
	SR	-0.309	0.125	0.02	
	Temp	-0.069	0.032	0.04	
L3	Intercept	-2.314	0.414	0.00	0.29
	Traffic	0.105	0.027	0.00	
	WD4	0.335	0.118	0.01	
	RH	0.016	0.006	0.01	

The independent variables which were not statistically significant after entering the equations were removed. The results show temperature, wind speed, solar radiation, wind directions were the important independent variables at L1. While for L2 and L3, traffic volume with solar-radiation, temperature and relative-humidity were the independent variables which explain the variations in CO, though with low R^2 values but statistically significant ($p<0.05$). Figure 4.26, 4.27 and 4.28 shows the measured and predicted hourly CO concentrations at L1, L2 and L3, respectively. It can be seen that the model failed to predict the higher concentration at all three locations.

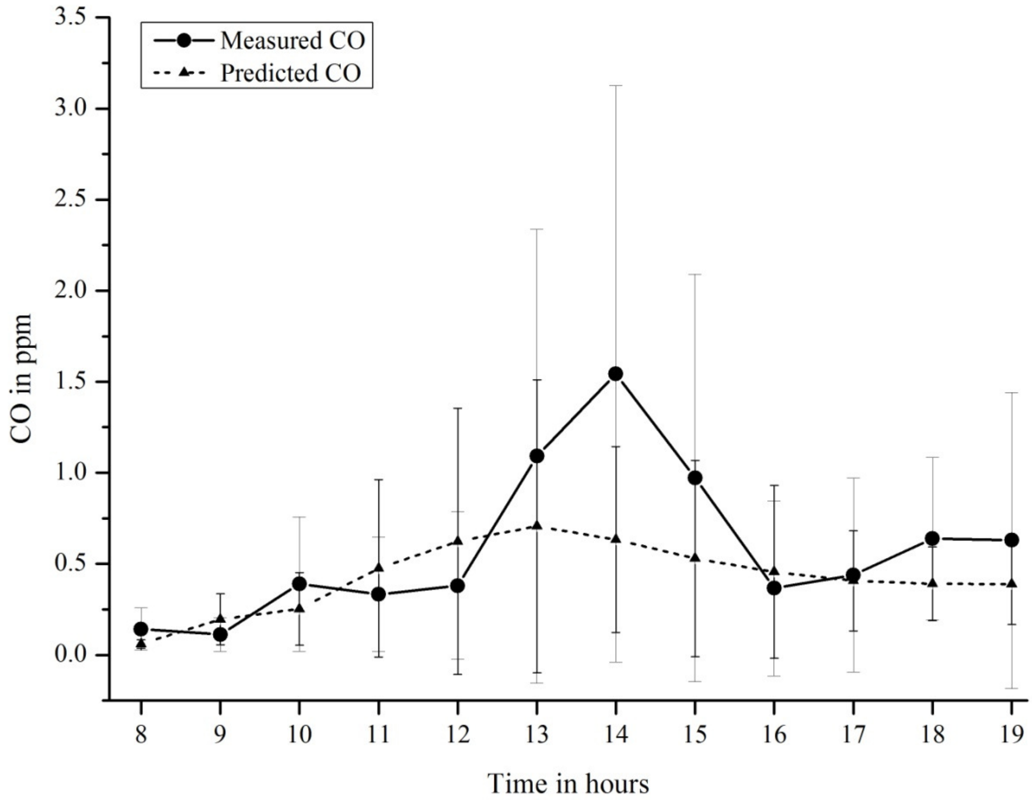


Figure 4.26: Time-series plot of measured and predicted hourly CO concentrations at L1 with error bars (±SD).

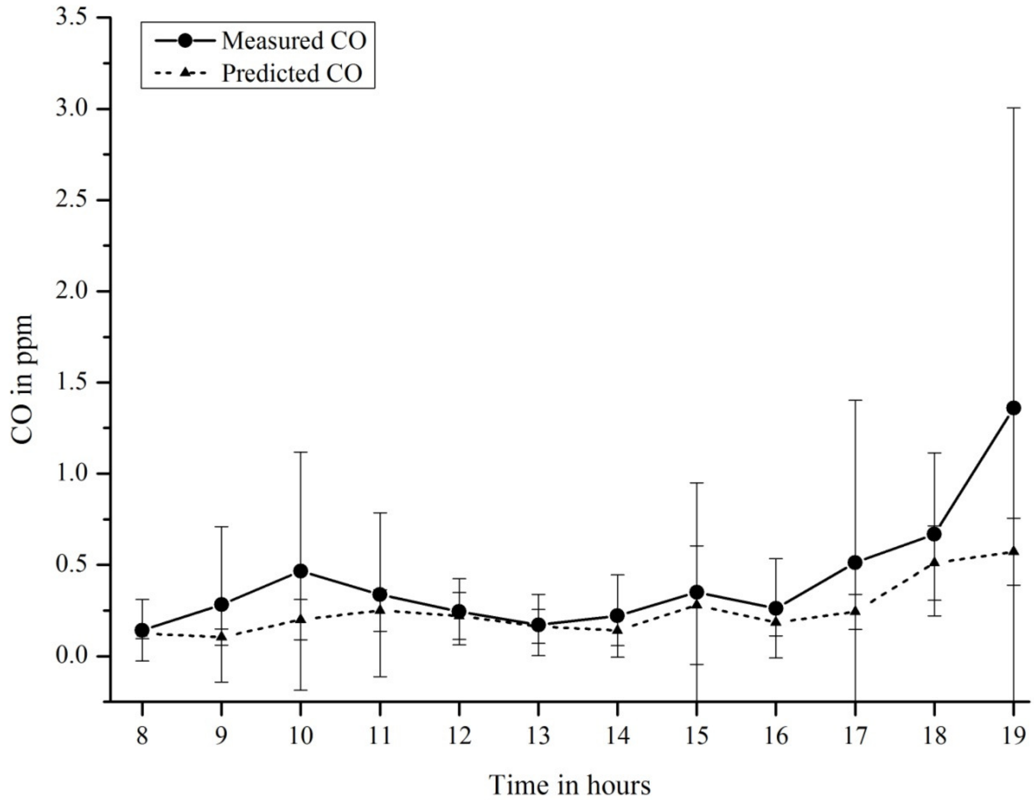


Figure 4.27: Time-series plot of measured and predicted hourly CO concentrations at L2 with error bars (±SD).

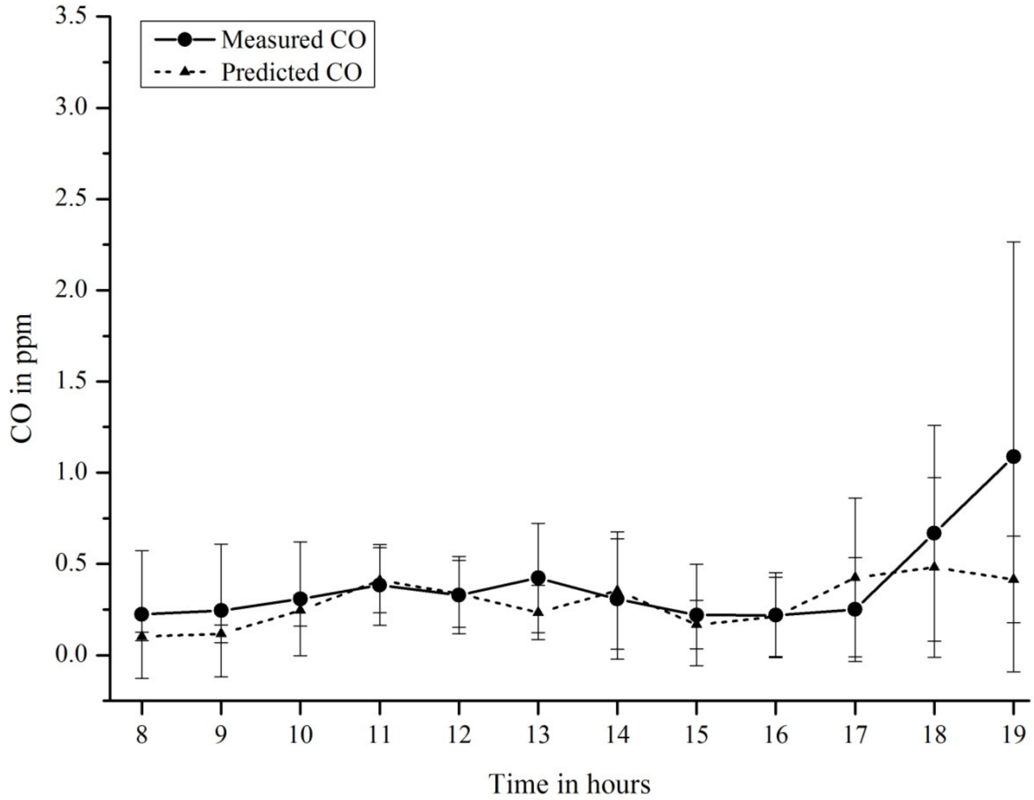


Figure 4.28: Time-series plot of measured and predicted (Regression model) hourly CO concentrations at L3 with error bars (±SD).

4.6 QUESTIONNAIRE RESPONSE

The total number of responses obtained in questionnaire survey was 52 (fifty two) with response rate of 30%. Out of the total responses, 44 (forty four) were male and 8 (eight) were female, whose age ranges from 19-61 years. From the group, 66% were in the ages between 19 and 30 years, 21% between 30 and 40 years, 8% between 40 and 50 years, and 5% above 50 years, as shown in Figure 4.29.

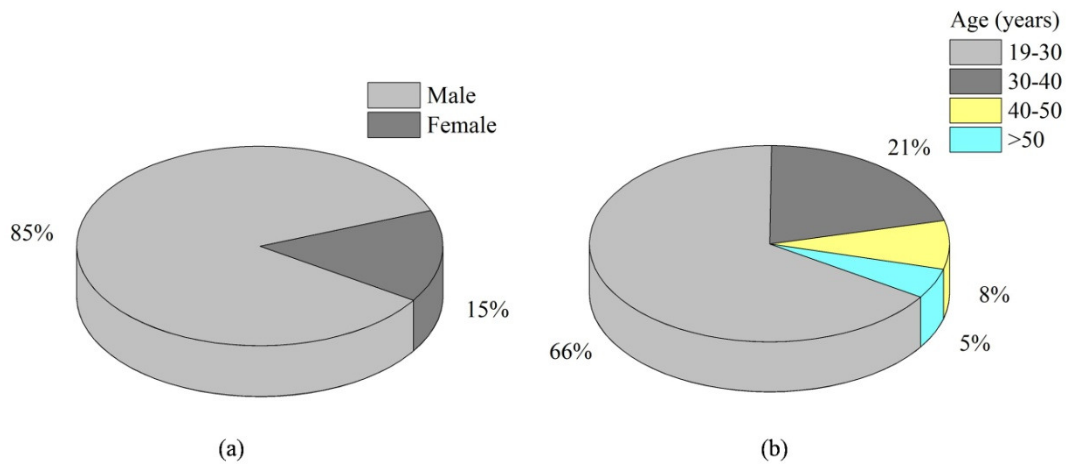


Figure 4.29: Percentage share of responses from target population (a) male and female, and (b) age group

About 50% of the study group reported to having chronic coughing, 23% of breathing problems and 27% of chest tightness, whereas 65% and 25% experience headache and skin allergy during their working hours, respectively. Amongst the study group, 17% reported of not having any of the above health problems as shown in Figure 4.30. When the study group was asked if traffic causes any stress, 77% answered positively, which includes individuals without health problem. About 58% also reported that materials inside the shop were affected in short-time. The 34% of the study group reported that they were exposed to cigarette smoking but those are the people who do not smoke at workplace. Only 3% of the study group reported other source of air pollution were also present around them such as diesel generator. Each of the responses were analyzed. It is found that those 92% of respondents having breathing problems and all those who are exposed to cigarette smoke were significantly annoyed by air pollution ($p<0.01$). They all feel stress due to traffic as well. While, 62% of respondents without breathing problems and 68% of non smokers were also significantly annoyed by air pollution and feel the traffic stress.

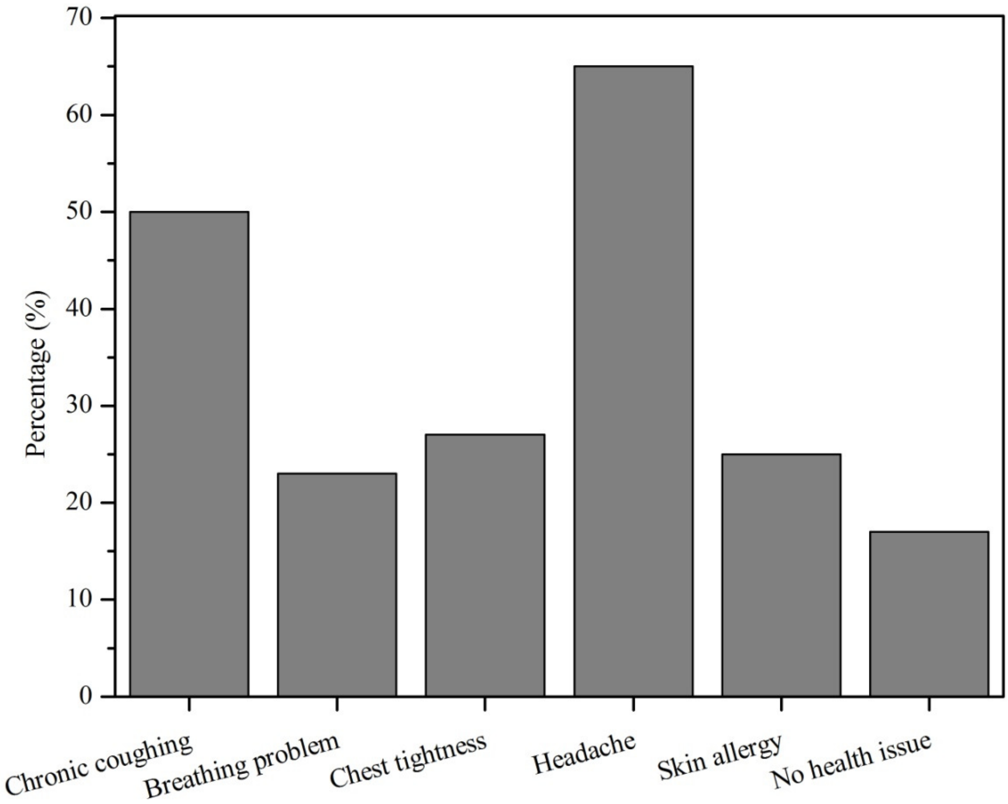


Figure 4.30: The percentage of responses with health issues

4.7 SUMMARY AND DISCUSSIONS

The variation of hourly averaged CO concentration does not vary much from location to location even under different meteorological conditions but large variations in hourly concentrations were observed. This may suggest the presence of same traffic characteristics from week to week and higher variations from hour to hour. Further, the higher variation in temperature observed at two altitude i.e. 3m and 18m may be the contributing factor since thermal turbulence create extremely unstable atmospheric conditions, which was observed for about 70-80% of the time from week to week. The correlation and regression analysis shows that the variation of CO concentrations were associated with traffic volume and wind direction as compared to other parameters but not strongly. This suggest that some other influencing factors were present which are affecting the CO variations. It may be variation in traffic emissions based on vehicles category, wind turbulence due to vehicular movements and the role of surrounding features on dispersion.

From the descriptive statistics (table 4.2), the CO concentration data observed at L1 were comparatively better than L2 and L3 since skewness and kurtosis coefficient are much less, suggesting that the data are more evenly spread and lack outliers. Also, L1 data show higher variations and range of concentrations as given by standard deviation and sample variation. In the subsequent section, the development of spatiotemporal model has been developed at L1 and the remaining two locations have been used for validation of the model.

CHAPTER 5

DEVELOPMENT OF SPATIOTEMPORAL MODEL

5.1 GENERAL

There are several methods to estimate spatiotemporal concentrations, such as land-use regression (LUR), hierarchical, geo-statistical interpolation (kriging) and dispersion models (Wheeler et al., 2008; Crouse et al., 2009; Chen et al., 2010; McAdam et al., 2011; Both et al., 2013; Dons et al., 2013; O'Leary and Lemke, 2014). Most of these methods, except dispersion models, used statistical approaches which do not represent the changes in source and meteorological characteristic. For example, LUR models are usually developed based on observed concentrations as dependent variables with surrounding land features and traffic characteristics as independent variables (Ryan and LeMasters, 2007). It is limited to a specific area and tends to produce poor predictions when used at other location with different features (Hoek et al., 2008). Also LURs are intended for estimating long-term averages and are not designed to account for short-term changes in concentration due to meteorology (Wang et al., 2013). While, hierarchical and geo-statistical interpolation methods requires highly resolved observed concentrations (Sampson et al., 2011; Li et al., 2013). In such environment, dispersion models are more feasible as compared to other models in estimating spatiotemporal concentrations but its accuracy depends upon input data such as emissions, meteorology and model assumptions.

In this research, a method to estimate hourly-average spatiotemporal concentrations has been developed with the help of one fixed station data to estimate hourly average spatiotemporal concentrations. The method involves the use of dispersion model for estimating spatiotemporal concentration, improve its prediction by hybridizing it with a probability distribution model, calibration of model using the observed data from the fixed station and estimating spatiotemporal concentration in terms of probability and probability of exceedance at various location within the traffic corridor. The model has also been validated at two spatial locations within the traffic corridor. Further, the prediction method has been then used to determine the concentration contour to identify the areas of higher probability of occurrences of concentrations that exceeds NAAQS within the traffic corridor.

5.2 DISPERSION MODELING

The CALINE4 (California line source dispersion model, version4) (Benson, 1984) is well evaluated and validated air quality model for modeling pollutant concentrations from vehicular sources and is invariably used (Levitin et al., 2005; Du et al., 2011; Heist et al., 2013). The CALINE4 has been applied to estimate the CO concentration at the fixed locations, L1. The meteorology and traffic characteristics observed during the monitoring period in the traffic corridor were processed and used as inputs. The emission rate were calculated using COPERT IV which is a software program for calculation of emissions from the road transport using average speed dependent equations based on different vehicle category (COPERT IV, 2012). The calculated emission is based on the assumption that the hot emission factors only corresponds to average speed of the vehicles (COPERT IV, 2012). The hourly mixing height was estimated from the data taken from Indian Meteorological Department (Attri et al., 2008) situated at international airport (Guwahati) which is about 15 km from the study site. The background concentration was assumed as nil since the traffic is the major source of pollution in the traffic corridor and also due to the limitations of CO monitoring device which has least count of 1 ppm.

Figure 5.1(a) and Figure 5.1(b) shows the comparison of CALINE4 modeled and measured hourly averaged CO concentrations at location L1. The weekly average of modeled and measured CO were 0.60±0.21 ppm and 0.56±0.42 ppm, respectively.The adjusted R^2, Pearson correlation coefficient (r), $NMSE$, FB, and d values were 0.06, 0.27, 1.50, 0.89, and 0.53, respectively indicating a large deviation between the modeled and measured concentrations and are highly scattered. For this, the presence of several extreme concentration on lower as well as higher side might be the reasons. The dispersion models particularly Gaussian based are poor in estimating extreme concentration adequately (Gokhale and Khare, 2005). When the modeling was carried out at other two locations, the model's performance was even poor (d at L2 = 0.49 and d at L3 = 0.19). The poor performance of CALINE4 may be because of existing features of the study site which is similar to a street canyons having irregular gaps between the buildings (refer Figure 3.1).

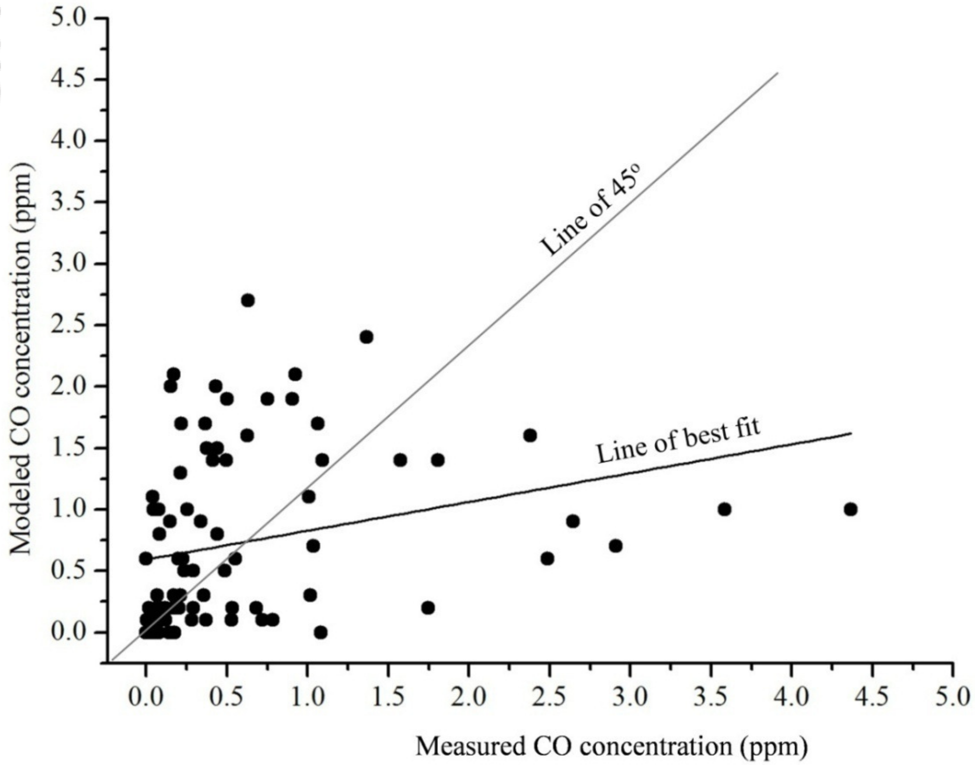


Figure 5.1(a): Comparison of hourly measured and modeled CALINE4 CO concentrations at L1

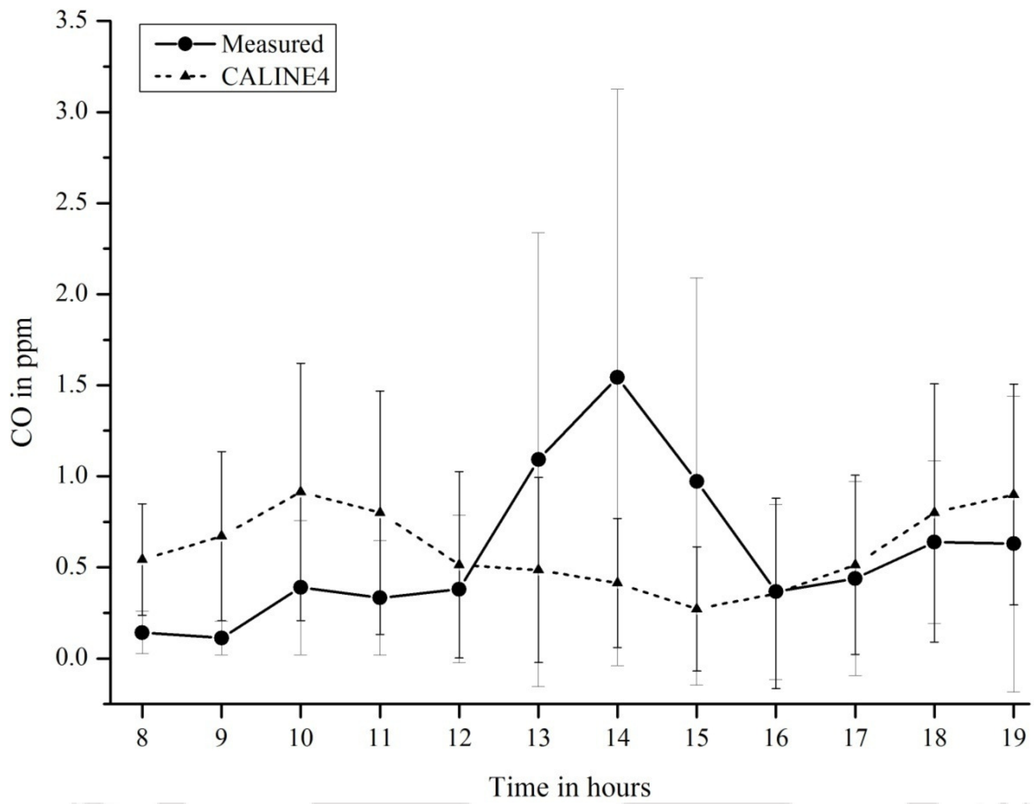


Figure 5.1(b): Time-series plot of measured and CALINE4 predicted hourly CO concentrations at L1 with error bars (±SD)

The poor performance of the CALINE4 model, therefore, entails to improve its predictions with some other method. For this reason, several studies have used hybrid model (a combination of dispersion and probability distribution models) to estimate air quality (Taylor et al., 1985; Jakeman et al., 1988; Gokhale and Khare, 2005; Sharma et al., 2013b). Dispersion models predict average concentrations reasonably well, while probability distribution models represent extreme concentrations well as they capture stochastic variability (Marani et al., 1986; Ott, 1995; Burkhardt et al., 1998). This attribute of the probability distribution models eliminates large deviations between estimated and measured concentrations. Therefore, a suitable probability distribution model has been identified and as a part of hybridizing, combined with the CALINE4 to check whether the performance is improved at L1.

5.3 STATISTICAL DISTRIBUTION MODELING

The goodness-of-fit test comprising three statistics, i.e. KD, AD, and PCC, has been applied to the hourly-average CO concentrations observed at L1, L2, L3. This is done to find out whether the CO concentrations observed at any location within the corridor follow same or different distributional forms. CO concentrations at each location had higher coefficient-of-variation (>1) and differed marginally location to location. This implied that temporal variation was higher as compared to spatial variation within the corridor. Table 5.1, 5.2 and 5.3 shows the results of goodness-of-fit tests at L1, L2 and L3, respectively. The CO concentration data of each location fits well to lognormal distribution (LND) model based on KS statistic (0.059, 0.089, 0.0663), AD statistic(0.229, 0.402, 0.427), and PCC(0.99) with the highest p-value of 0.97, 0.73, 0.81, corresponding to L1, L2, L3 respectively. The result show that CO concentrations follows log-normal distribution at all the locations. Further, the log-normal distribution parameters particularly scale were close indicating that the statistical distribution of concentration remains same at any locations within the traffic corridor despite the significant temporal variation. This may have been because of having same traffic characteristics in the corridor. Figure 5.2, 5.3 and 5.4 shows the probability distribution of CO concentrations with a lognormal model.

Table 5.1 The Goodness-of-fit test statistics of the CO concentration at L1

Probability distributional Forms	KS-test		AD-test		PCC
	KS	*p*-value	AD	*p*-value	
Normal	0.225	0.00	6.716	0.00	0.92
Lognormal	**0.059**	**0.96**	**0.229**	**0.97**	**0.99**
Exponential	0.129	0.18	1.382	0.04	0.92
Gamma	0.109	0.36	1.296	0.03	0.99
Weibull	0.093	0.56	1.034	0.01	0.98
Logistic	0.223	0.00	4.609	0.01	0.96
Loglogistic	0.106	0.40	0.314	0.25	0.97

Table 5.2 The Goodness-of-fit test statistics of the CO concentration at L2

Probability distributional forms	KS-test		AD-test		PCC
	KS	*p*-value	AD	*p*-value	
Normal	0.236	0.00	6.57	0.00	0.94
Lognormal	**0.089**	**0.62**	**0.402**	**0.73**	**0.99**
Exponential	0.125	0.22	1.523	0.05	0.92
Gamma	-	-	1.619	0.00	0.99
Weibull	0.104	0.43	1.438	0.30	0.97
Logistic	0.208	0.00	4.206	0.00	0.98
Loglogistic	0.361	0.00	0.428	0.25	0.96

Table 5.3 The Goodness-of-fit test statistics of the CO concentration at L3

Probability distributional forms	KS-test		AD-test		PCC
	KS	*p*-value	AD	*p*-value	
Normal	0.191	0.01	3.893	0.01	0.97
Lognormal	**0.066**	**0.91**	**0.427**	**0.81**	**0.99**
Exponential	0.072	0.84	0.360	0.89	0.85
Gamma	-	-	0.542	0.20	0.99
Weibull	0.074	0.82	0.581	0.66	0.96
Logistic	0.167	0.04	2.083	0.00	0.99
Loglogistic	0.380	0.00	0.579	0.09	0.95

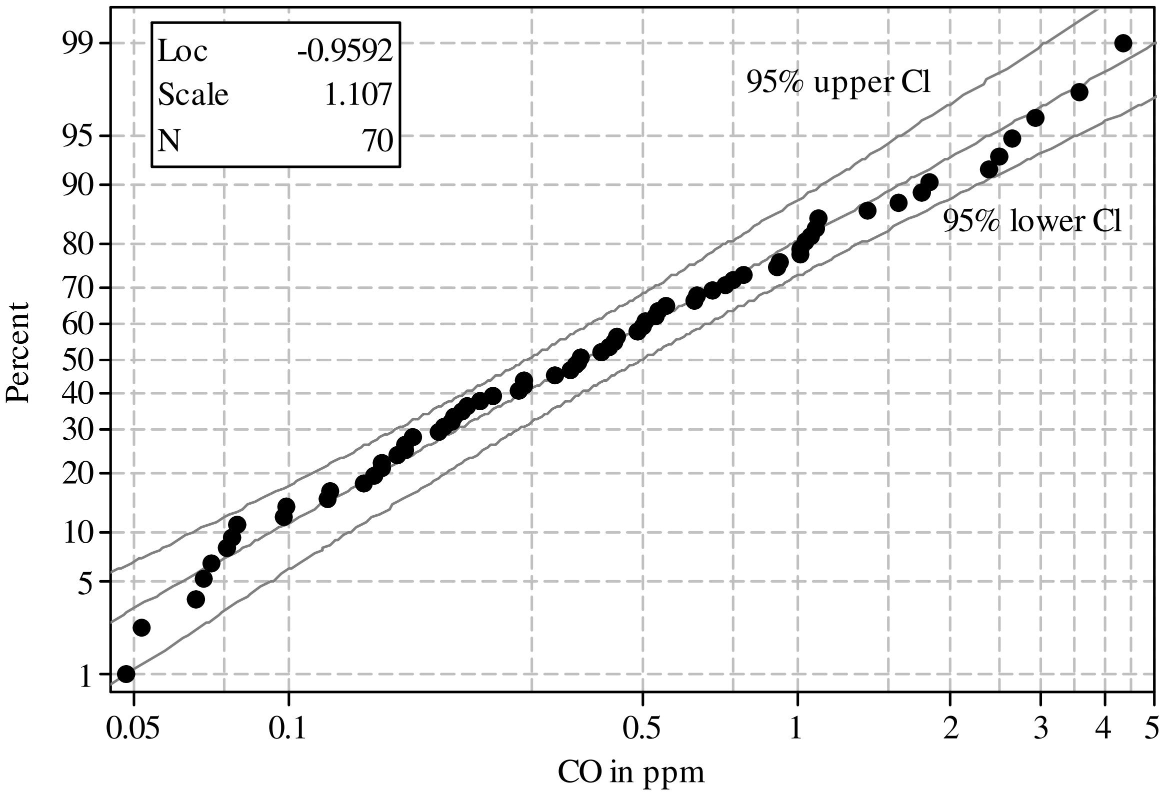


Figure 5.2 Probability distribution of CO concentrations with a lognormal model at L1

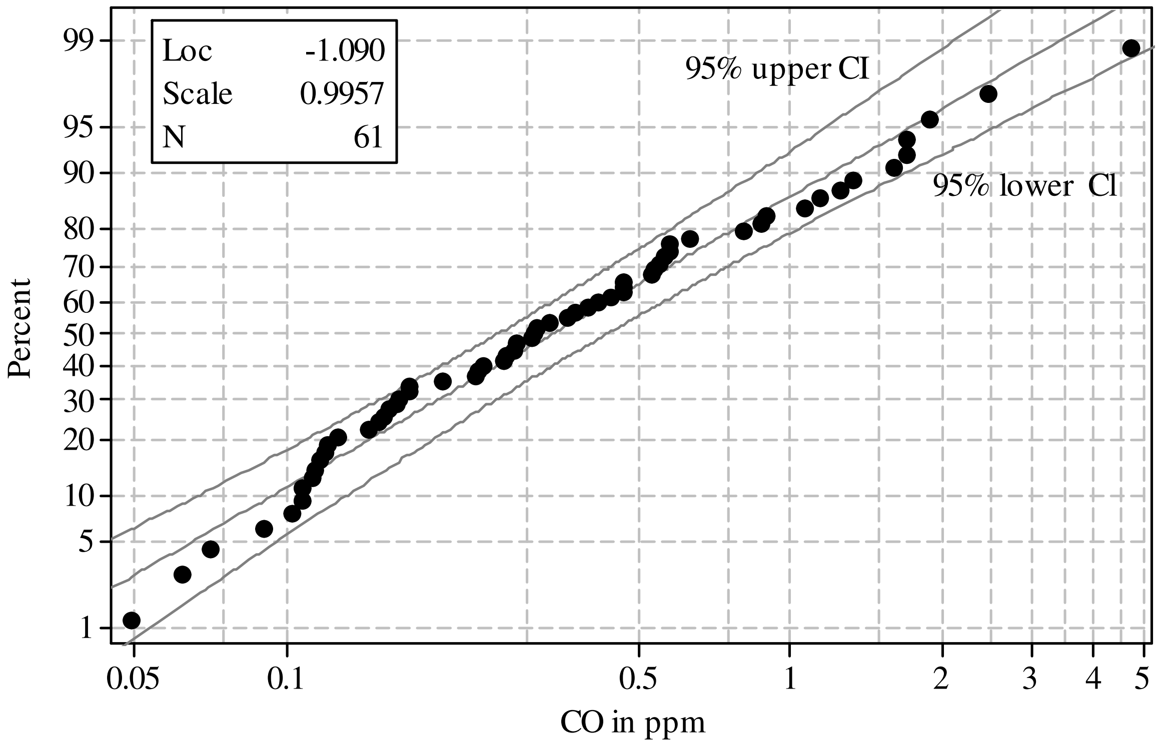


Figure 5.3 Probability distribution of CO concentrations with a lognormal model at L2

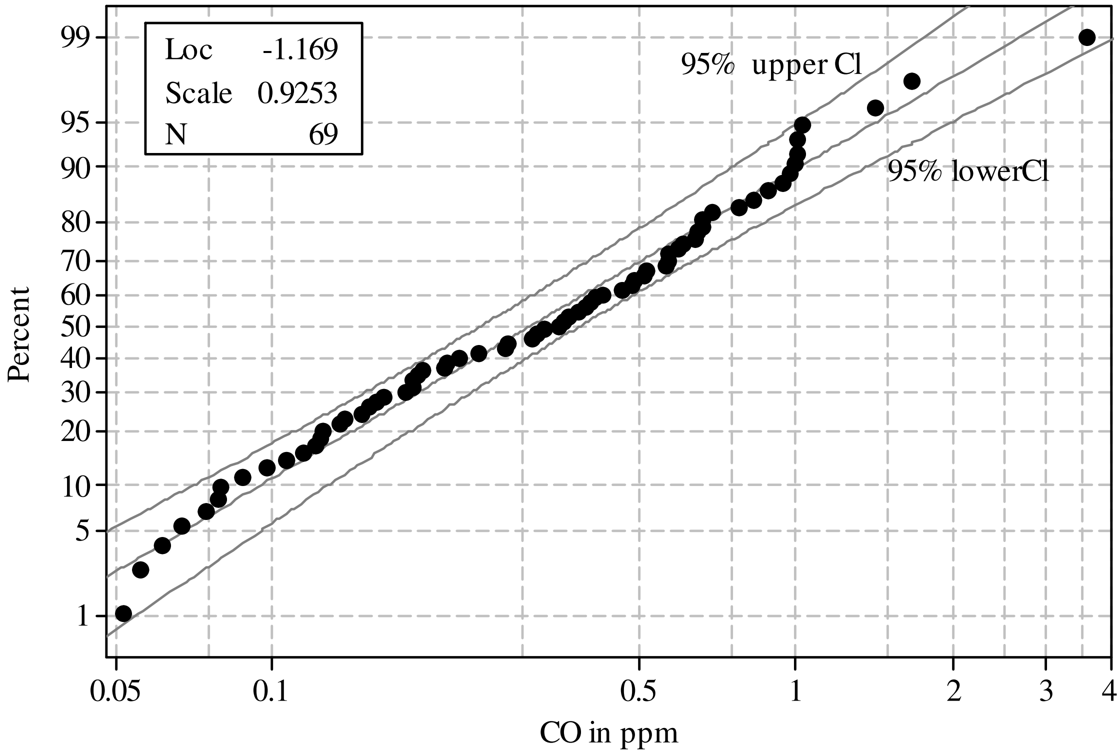


Figure 5.4: Probability distribution of CO concentrations with a lognormal model at L3

5.4 HYBRID MODELING

Hybrid modeling is an approach in which the best features (i.e. causality) of deterministic models and stochastic variability of statistical distribution models are combined to predict the entire range of distribution of pollutant concentrations (Jakeman et al., 1988). This approach is applied by Taylor et al. (1985) and Gokhale and Khare (2005) to predict the entire range of concentrations resulting from vehicular exhausts. Generally, four steps are involved in the formulation of hybrid model (Jakeman et al., 1988) – (i) choose an appropriate deterministic model for prediction of reliable range of concentrations using emission, meteorological and site data, (ii) identify a statistical distribution model from the historical pollutant concentrations (iii) develop hybrid model by estimating the parameters of statistical distribution model identified in the above step from the reliable range of concentrations predicted by deterministic model, (iv) incorporate concentration values after censoring from percentiles using distributional properties of the hybrid model. Hybrid model in the literature is developed by combining a suitable range of output by trimming upper and lower extreme concentrations (30-70), which is because dispersion models predict middle range well than extreme concentrations (Gokhale and Khare, 2005; Sharma et al., 2013b). However, the results of those studies show significant improvement in the extreme regions though, a large deviations are observed in the middle range, which reduces the overall performance of the hybrid models. This might be attributed to the range (30-70%). Therefore, in this study, the suitable range of the CALINE4 output was determined by evaluating the statistical performance using the index of agreement and the Pearson correlation coefficient between the measured and the CALINE4 modeled concentrations.

The Figure 5.5 shows the comparison of the uncensored hybrid model (obtained by combining CALINE4 modeled CO (uncensored) with lognormal distribution model) with the measured CO concentrations. The model shows considerable deviation from the measured concentrations in the lower and upper ranges. There was a deviation in the middle range as well but was relatively less. The statistical indicators such as *d*, *r*, *NMSE*, *FB*, and *FS* were found to be 0.68, 0.44, 0.87, 0.03, and -0.30, respectively.

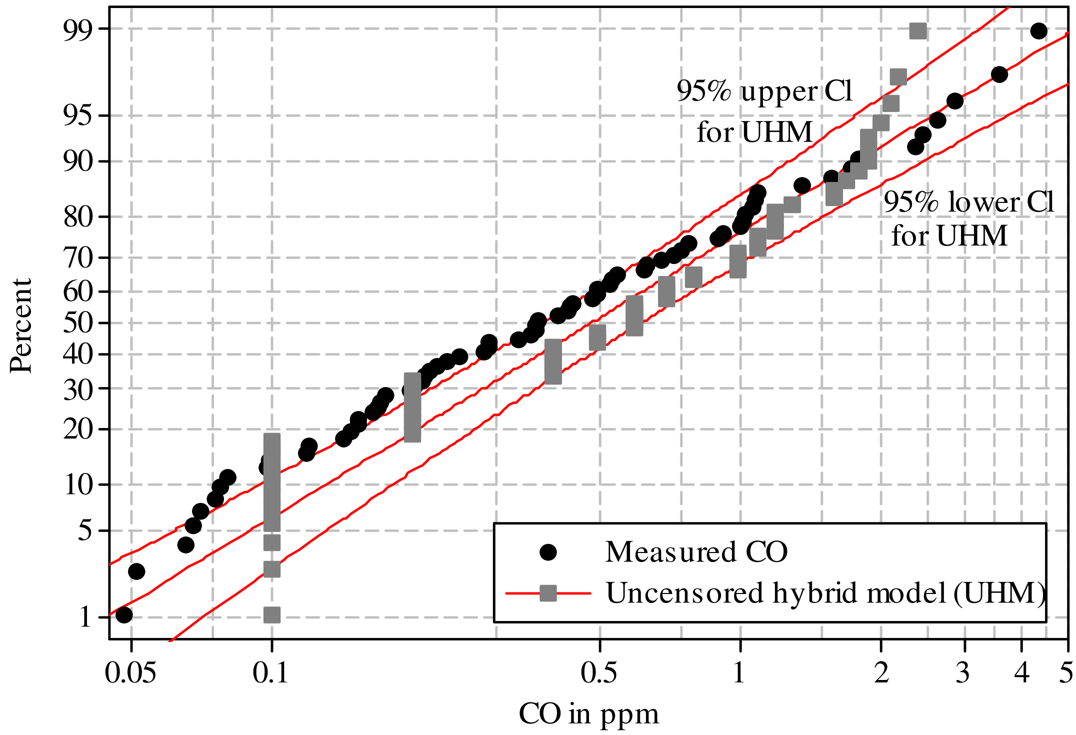


Figure 5.5: Comparison of the measured and the uncensored hybrid modeled CO concentration

In order to identify the area of deviations, the model's performance was tested by censoring the extreme ranges of its output at different percentiles and comparing with the measured concentrations so that the deviation can be minimized. Figure 5.6(a) and 5.6(b) show the *d* and *r* for different percentile ranges of measured and modeled concentrations. It has been observed that for the range of about 5 to 90 percentiles the concentrations are in good agreement. the statistics has been improved, i.e. d>0.9 from 0.68 and r>0.8 from 0.44. Therefore, the percentile range of 5 - 90 was selected as the reliable range to develop the hybrid model and the concentrations below 5 and above 90 percentiles were censored.

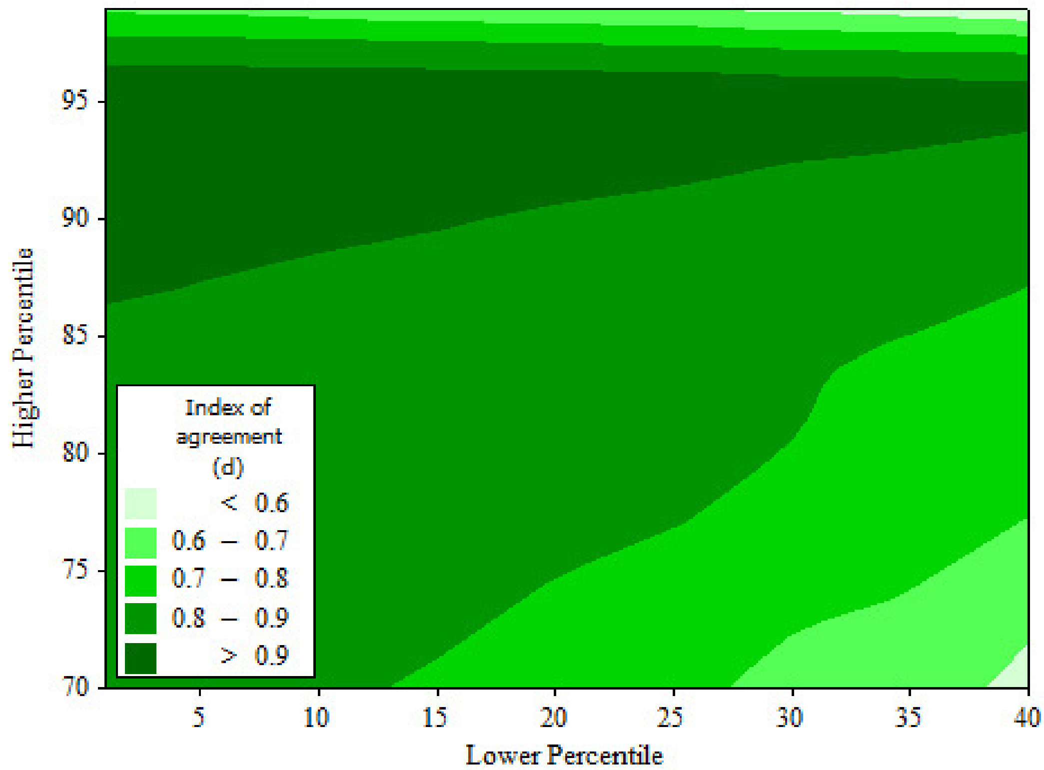


Figure 5.6(a): Index of agreement (*d*), for different percentile ranges of the measured and uncensored hybrid model

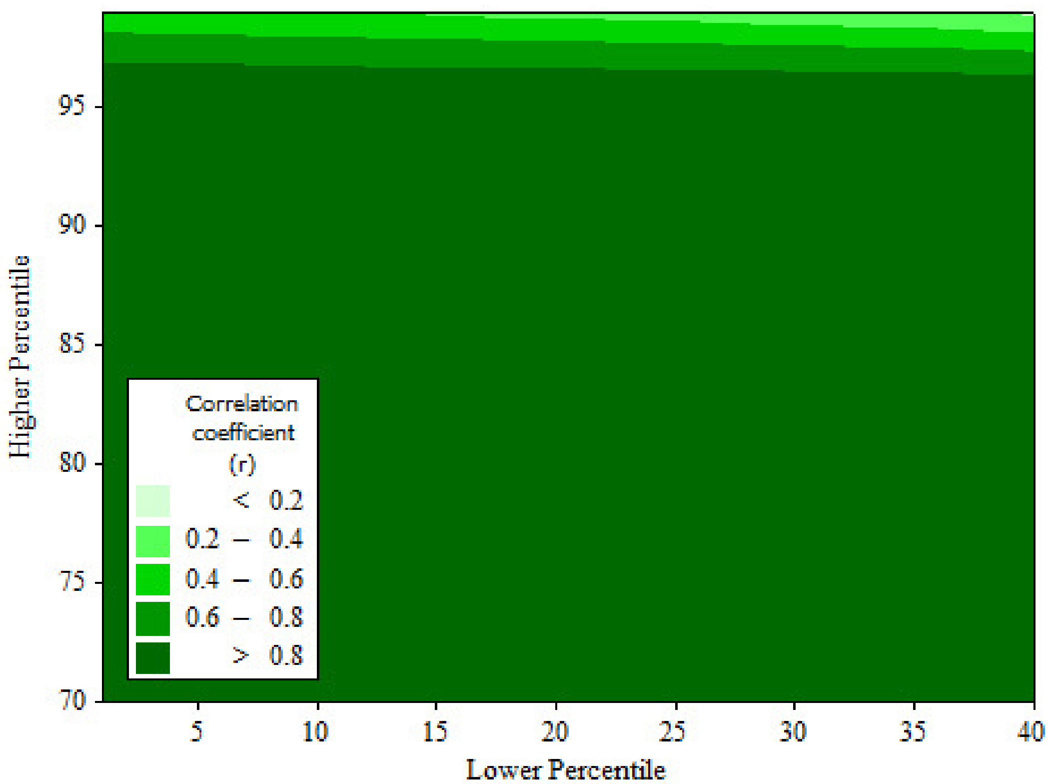


Figure 5.6(b): Correlation coefficient (*r*), for different percentile ranges of the measured and uncensored hybrid model

Figure 5.7 shows the comparison of censored hybrid model (i.e. 5-90 range combined with lognormal distribution model) with measured CO concentrations. The deviations in the extreme CO concentration range are considerably reduced. However, slight deviations in the middle range is still observed.

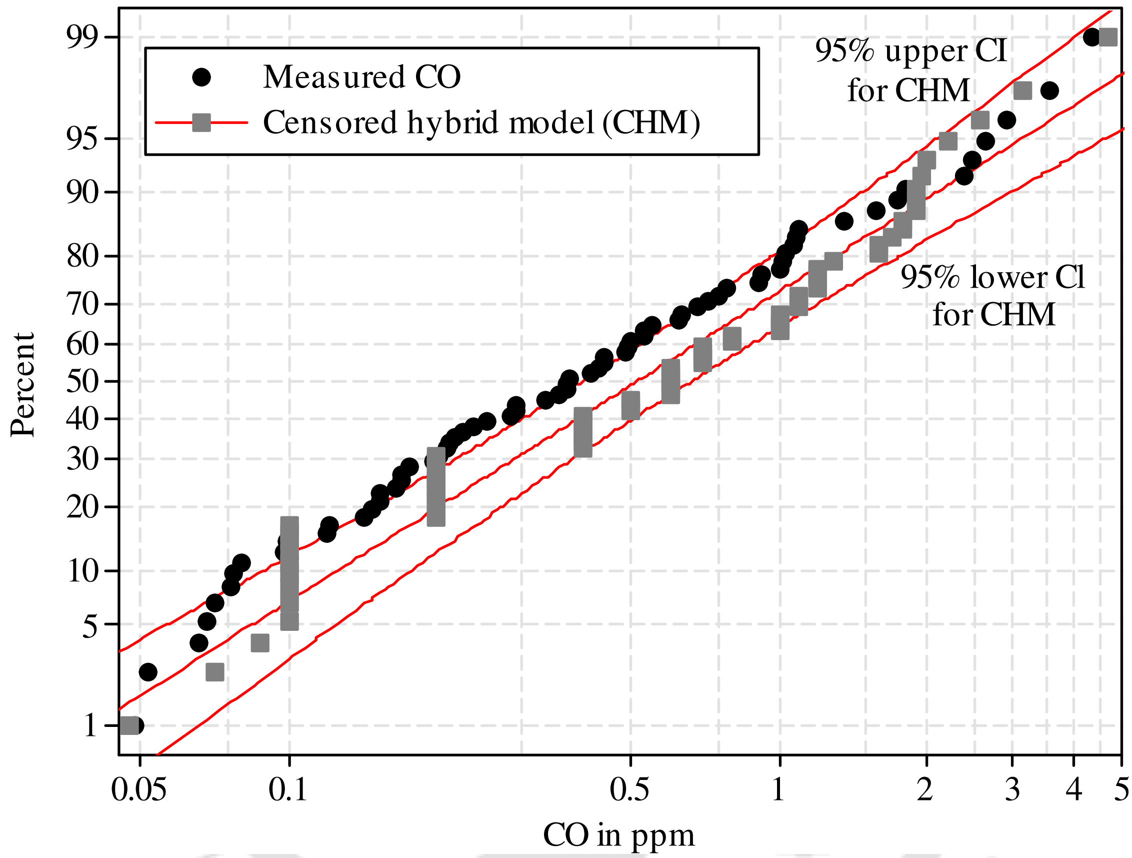


Figure 5.7: Comparison of the measured and the censored hybrid modeled CO concentration

In order to reduce that further, a calibration factor has been estimated and applied to improve the hybrid model's estimates. The calibration factor was estimated by comparing the respective distribution parameters of the modeled and measured concentrations. The modeled concentrations were divided by this factor to re-estimate the concentrations. This factor is the ratio between distribution parameters of the modeled and measured concentrations, given by equation 5.1.

$$\frac{P_{mo}}{P_{me}} = C_f \qquad (5.1)$$

where, P_{mo} and P_{me} are the parameters of modeled and measured concentrations, respectively; and C_f is the calibration factor. The $P_{mo}=exp(L_{mo})$ and $P_{me}=exp(L_{me})$, where L_{mo} and L_{me} are the location parameters of modeled and measured concentrations, respectively. This method has been explain in the following steps:

i) As found out, the range (i.e. 5-90 percentiles) of concentrations of the CALINE4 model has been utilized to estimate the parameters of the LND (i.e. location and scale parameters) using MLE. The location and scale parameters were found to be -0.7497and 0.9380, respectively.

ii) The LND with these parameters was applied back to estimate extreme CO concentrations for the censored percentiles ranges of less than 5 and greater than 90, which reduced the deviations at extreme ranges to minimal. .

iii) The calibration factor was calculated by comparing the ratio of the respective distribution parameters (location) of the modeled entire range (including the 5-90 percentiles and the revised extreme concentrations for ranges less than 5 and more than 90) and the entire range of measured concentrations. The factor was found to be about 1.3.

iv) The 5-90 percentile range of the modeled concentrations was corrected by the calibration factor to get a new entire range of the modeled concentrations. Thus in this method, the middle as well as the extreme ranges were improved.

v) Figure 5.8 shows the comparison of the measured concentrations, uncensored hybrid, and the censored-calibrated hybrid modeled. Figure 5.9 shows the comparison of the absolute concentrations modeled by CALINE4, censored hybrid model, and censored-calibrated hybrid method. These concentrations have been studied in respect of the line of 45^0 at which the predicted and the measured are same. The results have been significantly improved.

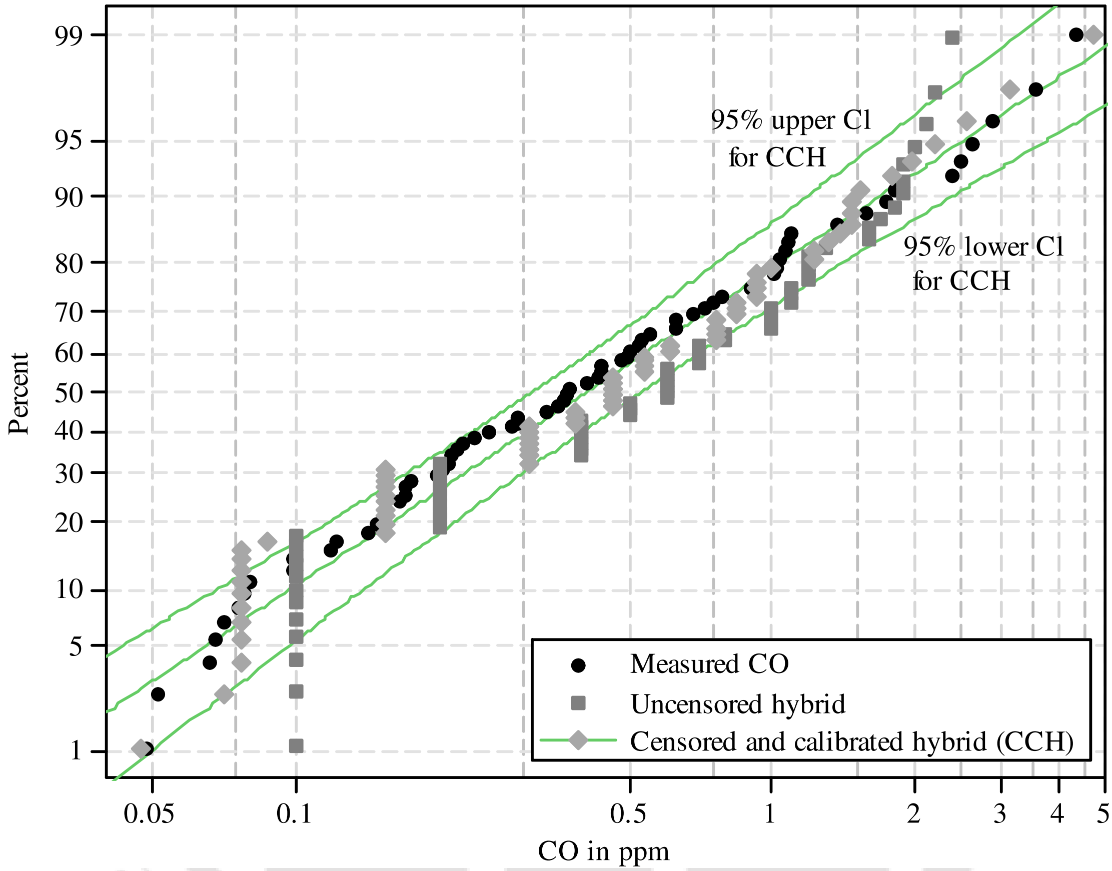


Figure 5.8: Comparison of the CO concentrations modeled of uncensored hybrid and the censored-calibrated hybrid with measured concentration at L1

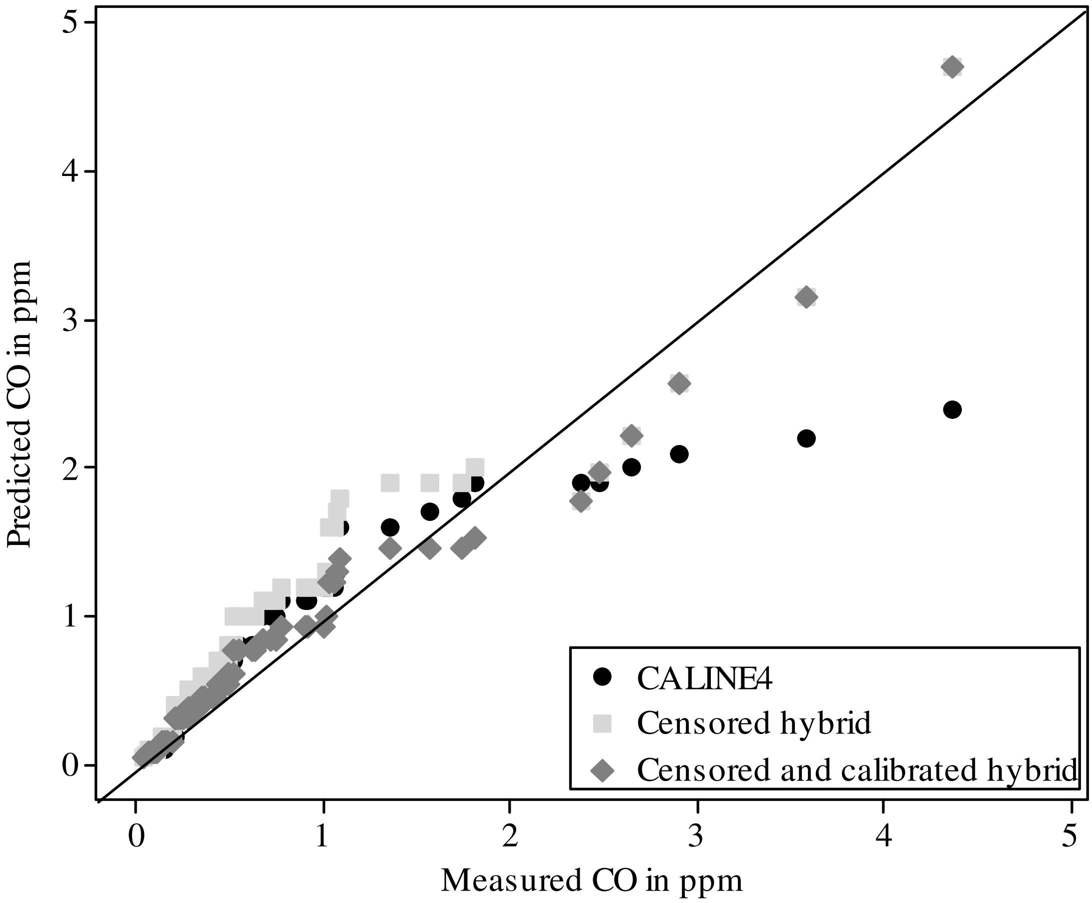


Figure 5.9: Comparison of the CO concentrations modeled of CALINE4, censored hybrid model and censored-calibrated hybrid model with measured concentration at L1

The procedure developed and adopted in this research produced considerably better estimates of the concentrations than CALINE4 alone. The statistical indicators between the measured and the developed censored-calibrated hybrid modeled concentrations ascertained good match for the entire range, i.e. *d*(0.99), *r*(0.97), *NMSE*(0.02), *FB*(0.02), and *FS*(-0.07). These statistics indicate that the developed model minimized the error to about 1%. Figure 5.10 shows the distribution of measured, CALINE4 and censored-calibrated hybrid modeled estimated concentrations at L1. It can be seen that the statistics of measured and developed hybrid model are quite similar as compared to CALINE4.

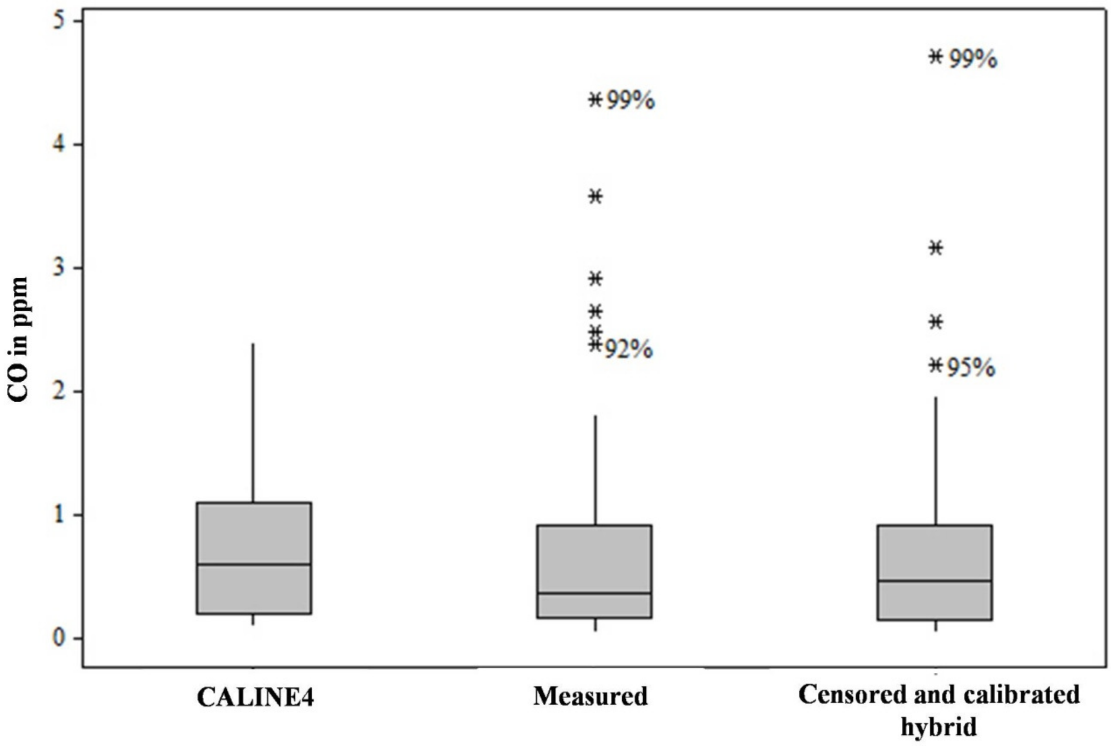


Figure 5.10: The comparison of the distributions of the hourly CO concentrations obtained by measured, CALINE4 and censored-calibrated hybrid model at L1

5.5 SUMMARY AND DISCUSSION

In this research, a censored-calibrated hybrid model for predicting spatiotemporal concentrations in traffic corridors has been presented. The model has been developed in which CALINE4 has been hybridized with probability distribution model and calibrated using a calibration factor. The model has been developed based on one fixed monitoring station data. It has been observed that a simple hybrid modeling technique improves the prediction ability of lower and higher concentrations range but lacks in improving the middle concentrations range i.e. *d*(0.94), *r*(0.93), *NMSE*(0.06), *FB*(-0.20), and *FS*(0.10). With the use of a calibration factor in the hybrid modeling technique, a considerable improvement in all range of concentrations was observed i.e. *d*(0.99), *r*(0.97), *NMSE*(0.02), *FB*(0.02), and *FS*(-0.07). The results have, therefore, demonstrated that the newly developed censored-calibrated hybrid model considerably improves the prediction ability as compared to CALINE4.

In general, the probability distribution of a pollutant in a contained environment remains same and, therefore, the model may be useful for developing spatiotemporal concentration contours for various probabilities of exceedances in similar traffic corridors of the mixed urban environment. And even with one fixed station data on pollutant concentrations, meteorology, and traffic it can be applied.

5.6 CONCLUSION

The developed spatiotemporal model has been simple, needs less number of pollutant monitoring stations to produce a reliable estimate of concentrations in traffic corridors. Since the important component of the method is probability distribution model and the calibration factor, it incorporates spatial distribution of concentrations, which may arise due to local wind flow, urban feature, changes in traffic-flow pattern within urban traffic corridor.

CHAPTER 6

VALIDATION AND APPLICATION

6.1 GENERAL

This chapter includes the validation study of the developed censored-calibrated hybrid (CCH) model and its application to produce the spatiotemporal concentrations in the entire traffic corridor. The CCH model has also been used to estimate the amount of reduction in emission necessary to maintain healthy air quality within the traffic corridor.

6.2 VALIDATION

The model has been validated at L2 and L3 against the measured hourly averaged CO concentrations. Figure 6.1 and Figure 6.2 shows the results of the validations of CCH model at L2 and L3, respectively. The uncensored hybrid modeled concentrations have also been shown. It was evident that dispersion modeling to produce spatiotemporal concentrations of entire range satisfactorily was not enough since it produced a huge deviation in various part of the range. The CCH model, however, provided the best estimates of the hourly averaged concentrations for the entire range. The statistics *d*, *r*, *NMSE*, *FB*, and *FS* were found to be 0.98, 0.96, 0.05, 0.23, 0.05 at L2 and 0.91, 0.96, 0.22, 0.33, 0.49 at L3, respectively indicating that the CCH model estimates the concentrations with more accuracy even at far spatial locations within the corridor, which validates the model which can be applied within the traffic corridor to estimate spatial and temporal concentrations. However, the validation were carried out with limited data (i.e. one week data) but the results are promising and with a large data set, the model may produce far accurate results.

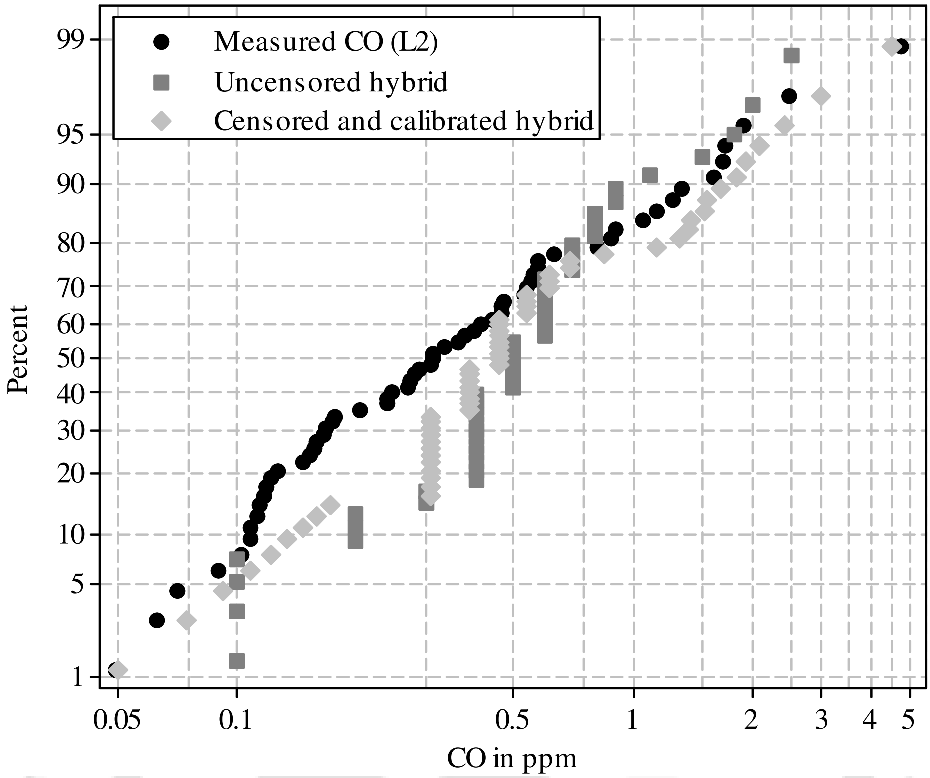


Figure 6.1: The validation results of the censored-calibrated hybrid, and comparison with the uncensored hybrid modeled and measured hourly averaged CO concentrations at L2

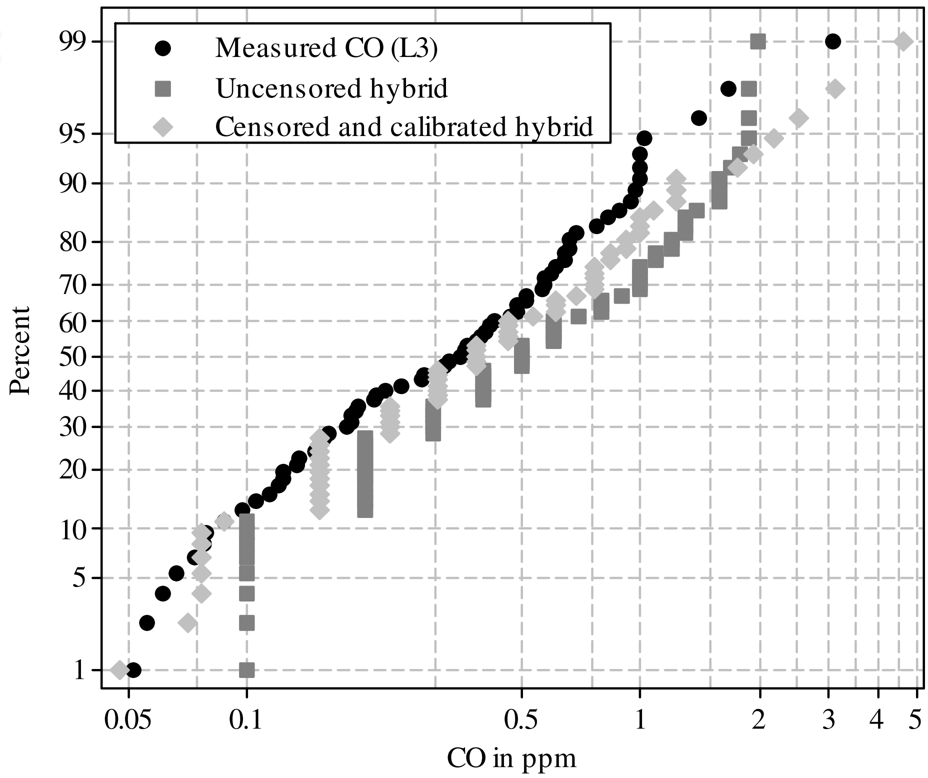


Figure 6.2: The validation results of the censored-calibrated hybrid and comparison with the uncensored hybrid modeled and measured hourly averaged CO concentrations at L3

6.3 SPATIOTEMPORAL AIR QUALITY

Receptors were selected at 10m and 20m from the center of the road on both sides for every 10m along the corridor (Figure 3.1). The CCH model was applied to estimate hourly concentrations at those receptors. The probability of occurrences greater than a specified concentration value (3.5 ppm, hourly NAAQS) was estimated at each receptor (CPCB, 2009). For convenience in identification of locations, two sides of the road were named as north-east side (NES) and south-west side (SWS). NES is where L1 and L3 are located and SWS is where L2 is located.

Figure 6.3 shows the contours of the probability of occurrence of hourly concentrations >3.5 ppm.

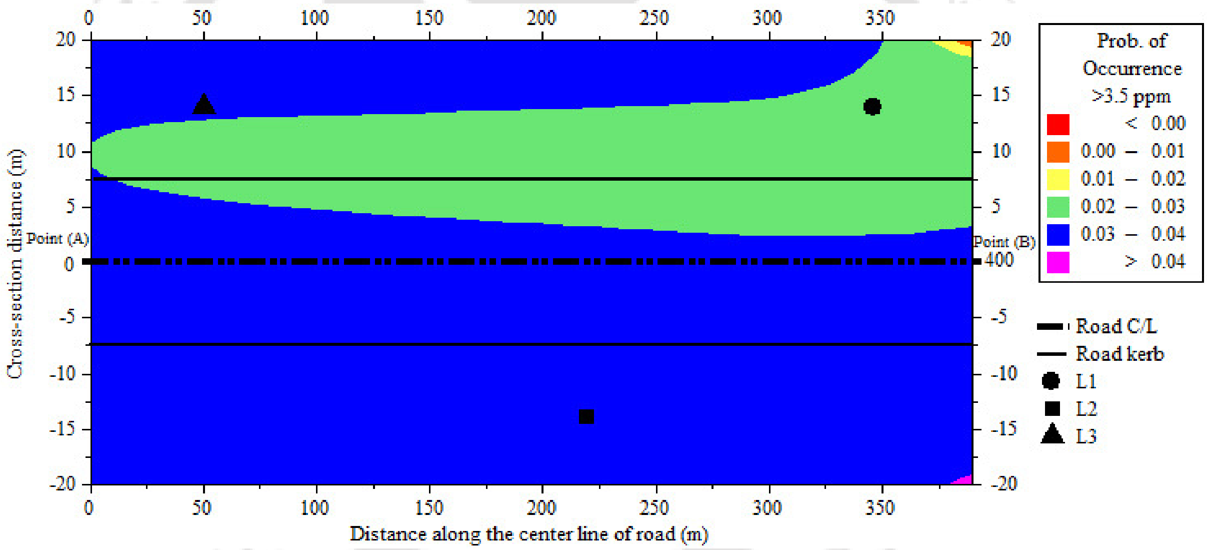


Figure 6.3: Contours showing probability of exceedances of CO concentration over 3.5 ppm (NAAQS) in the traffic corridor

The 2% to 3% probability of occurrence indicates that at least once a week the concentrations exceeded the NAAQS value (i.e. 12 samples each day for a week, 12 x 7 = 84 samples, therefore 0.02 % of 84 samples = 1.68), while 3% to 4% means it exceeded at least twice a week (i.e. 0.03 x 84 = 2.52). Similarly, Figure 6.4 shows the probability of occurrence of CO concentration exceeding 1 ppm. At about 10m from the road center, it was 12% to 15% at NES and 18% to 21% at SWS, whereas, 15% to 18% at other locations. This means the likelihood of concentrations exceeding 1 ppm was for 10 h in a week at about 10m from road center on SWS and at least 15 hours in a week at NES and at other locations it occurs for at least 12 hours in a week.

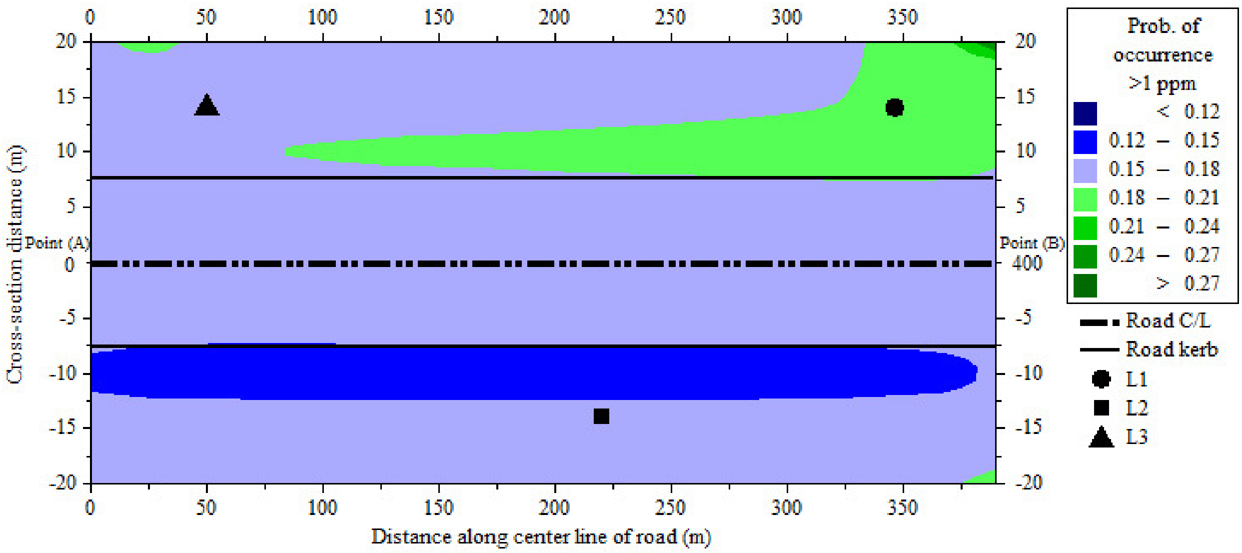


Figure 6.4: Contours showing probability of exceedances of CO concentration over 1 ppm in the traffic corridor

Such a CCH model may be useful for human exposure assessment in which spatiotemporal concentrations are essential. The model can further be extended to estimate the probability of exposure by the probability of occurrence of a specific concentration and the probability of time spent by a person in a location in a traffic corridor.

6.4 EMISSION REDUCTION

The Rollback model is used to determine concentrations before and after emission-control, which is particularly developed to estimate the required reduction in emissions to comply with air quality standards (Ott, 1995). But the model have limitations, such as, the model assumes a linear relationship between emission and concentration which might not be the case. Nevertheless, the model is simple and requires less data for estimation of required reduction in emissions. The probabilistic version of this model was also developed (Georgopoulos and Seinfeld, 1982). Several studies have estimated the required reduction in emissions based on the probability distribution of measured concentrations (Lu, 2004; Perišić et al., 2014).

In this study, the CCH model has been applied to estimate the required reduction in emissions within the traffic corridor as per the national ambient air quality standard (NAAQS) (CPCB, 2009). The rollback model is given in equation 6.1, (Georgopoulos and Seinfeld, 1982; Ott, 1995):

$$R = \frac{E[C_p]-E[C_s]}{E[C_p]-C_b} \tag{6.1}$$

where, R is the required reduction in emission; $E[C_p]$ the average concentration in the area; $E[C_s]$ the average concentration corresponding to probability of exceeding the air quality standard, and C_b is the background concentration. In this study, C_b was neglected since traffic is the main source of emissions within the selected study corridor.

Figure 6.5 shows the weekly averaged hourly concentrations estimated by CCH model. The highest CO concentration was found to be 0.38 ppm.

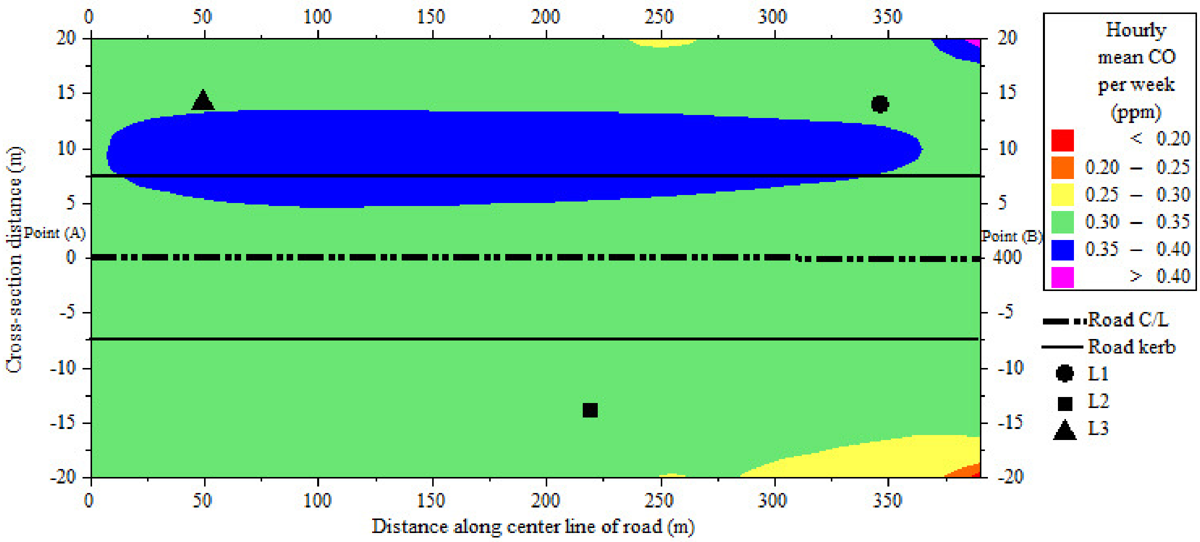


Figure 6.5: Weekly averaged hourly CO concentrations in the corridor

Further, to maintain healthy air quality in the traffic corridor it was assumed that the hourly CO concentration should not exceed more than once a week. Figure 6.6, shows the relationship between the probability of exceedance (>3.5 ppm) and the corresponding CO concentrations using the CCH model based on locations with highest weekly averaged hourly CO concentrations. At these locations the probability of exceedance was found to be 0.023 (i.e. it exceeds the NAAQS (>3.5 ppm) twice a week).

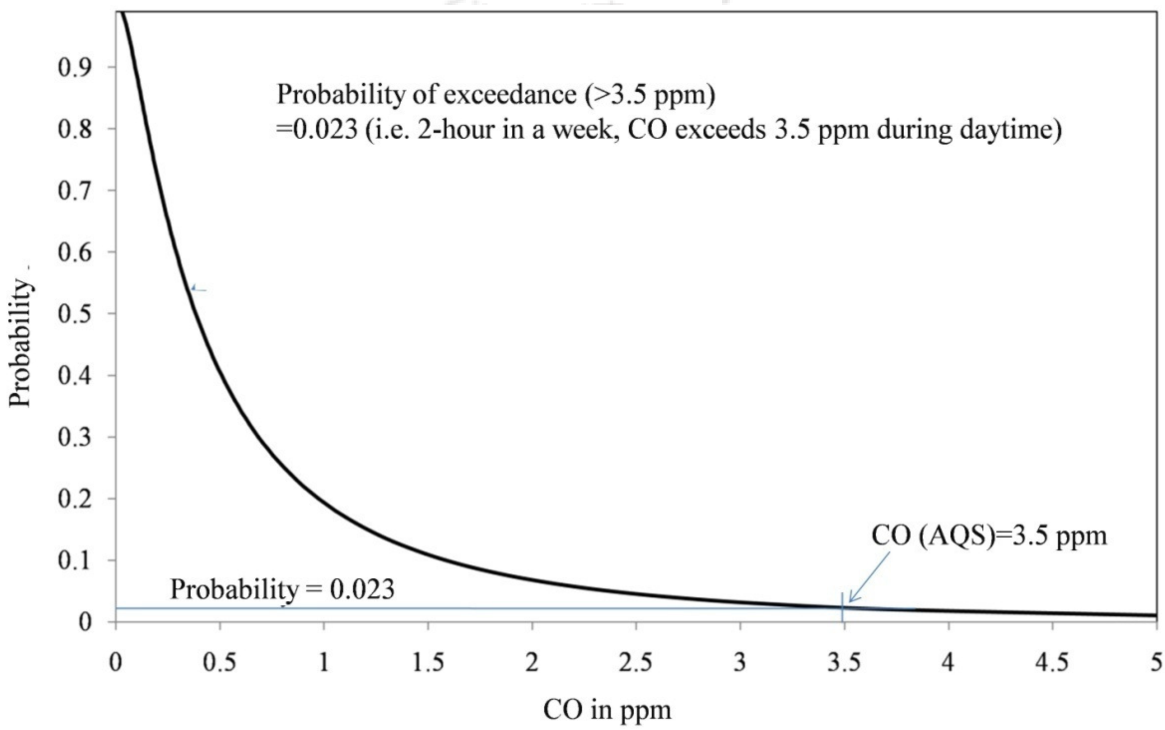


Figure 6.6: Relationship of the probability of exceedances and the CO concentration

Figure 6.7 shows the relationship of probability of exceedance (>3.5 ppm) and the expected average of CO concentrations. The corresponding average concentration for the probability of exceedance of 0.012 (i.e. probability of exceeding 3.5 ppm once a week) was found to be 0.29 ppm. Thus, the required emission reduction was 0.24 (as per equation 6.1).

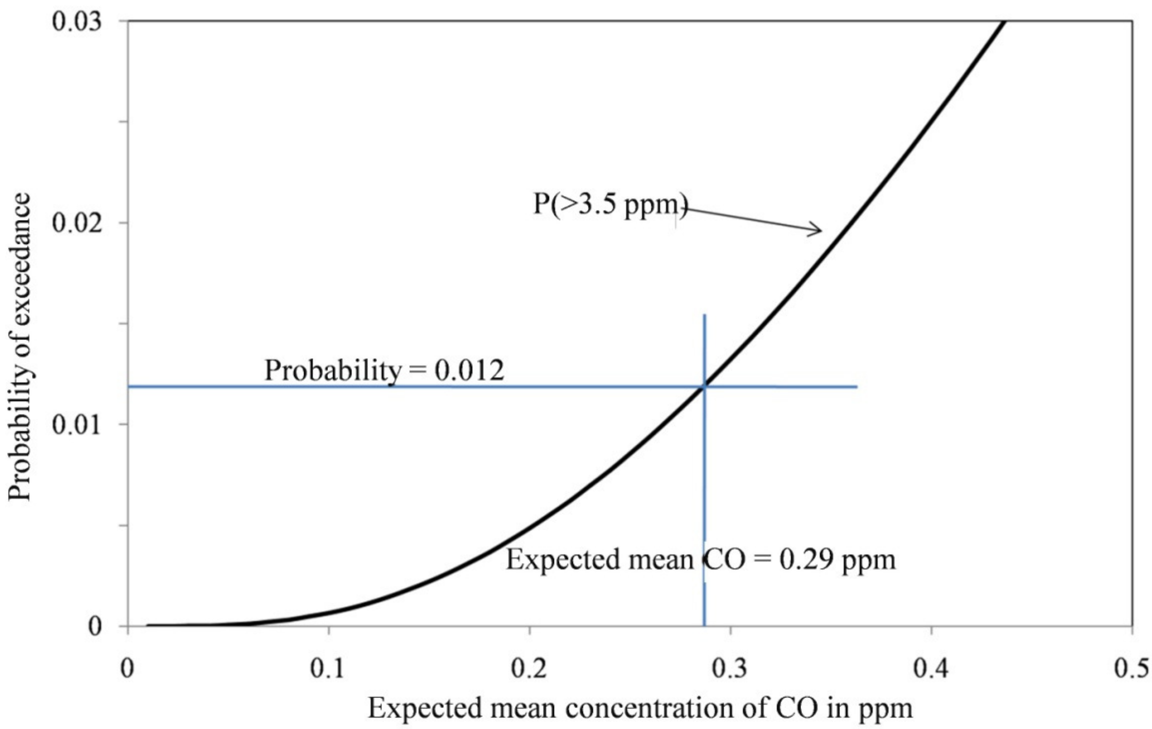


Figure 6.7: Relationship of the probability of exceedance and expected average of CO concentrations using the censored-calibrated hybrid model

6.5 CONCLUSION

The censored-calibrated hybrid model has been validated against the measured concentrations at other spatial locations in the corridor. The model has been applied to estimate concentration distributions at several spatial locations and another interesting application has been demonstrated by estimating the required reduction in emission so that CO concentration does not exceed NAAQS more than once a week. Thus, it is evident that the censored-calibrated hybrid model developed in this research may also be applied to estimate the human exposure within the traffic corridor in terms of probability. However, the model might not produce accurate exposure probabilities since it is validated on a one week data. The model would, however, produce more accurate predictions if validated on a large data set of several weeks.

CHAPTER 7

DEVELOPMENT OF EXPOSURE MODEL AND APPLICATION

7.1 GENERAL

The developed censored-calibrated hybrid model provides the estimates of the spatiotemporal probability of occurrences of concentration in the traffic corridor. This in combination with the probability of the time-spent by individual, produces the probability of exposure of the individual. To develop such a human exposure prediction method, people who are regularly using the traffic corridor and get exposed to traffic-related pollution on daily basis and whose location can be easily and accurately tracked have been selected as a target population. Therefore, shopkeepers having shops along the corridor next to the roadway have been selected as the target population. The shopkeepers whose building enclosure are partly or fully open were only selected for the study. This is done in order to assume that they are exposed to the outdoor concentration during their stay at their workplace. Questionnaire survey of such group were carried out, from which the time-spent at their location has been calculated and the probability of time-spent has been estimated. Three shopkeepers from the group were identified whose locations are near to the monitoring locations (i.e. L1, L2 and L3). The measured concentrations at each location during their time of stay at the workplace were assumed to be the level an individual was exposed to (personal exposure), which was later compared to validate with the estimated exposure. Further, the prediction method has been applied to estimate probability of exposure in three time slots (i.e. morning, afternoon, and evening hours) and relationships of exposure with annoyance to air pollution has been established.

7.2 AMOUNT OF TIME SPENT BY INDIVIDUALS

Figure 7.1 shows the time-spent by the shopkeepers in the traffic corridor from questionnaire survey. The probability of daily time-spent in the traffic corridor during the monitoring hours (i.e. 7 am to 7 pm) has been calculated as given in Figure 7.2.

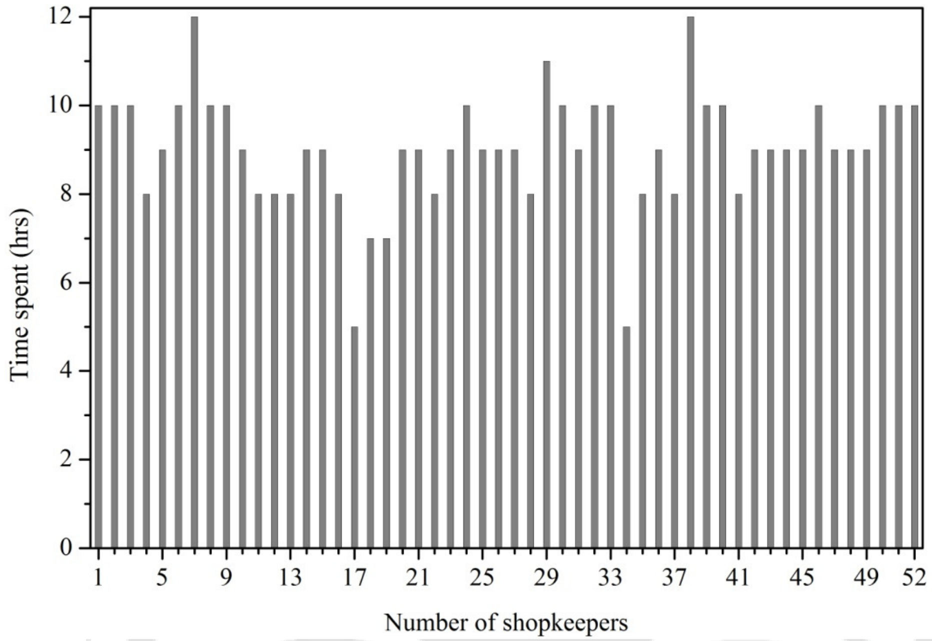


Figure 7.1: Daily time-spent by shopkeepers during 7 am to 7 pm in the traffic corridor

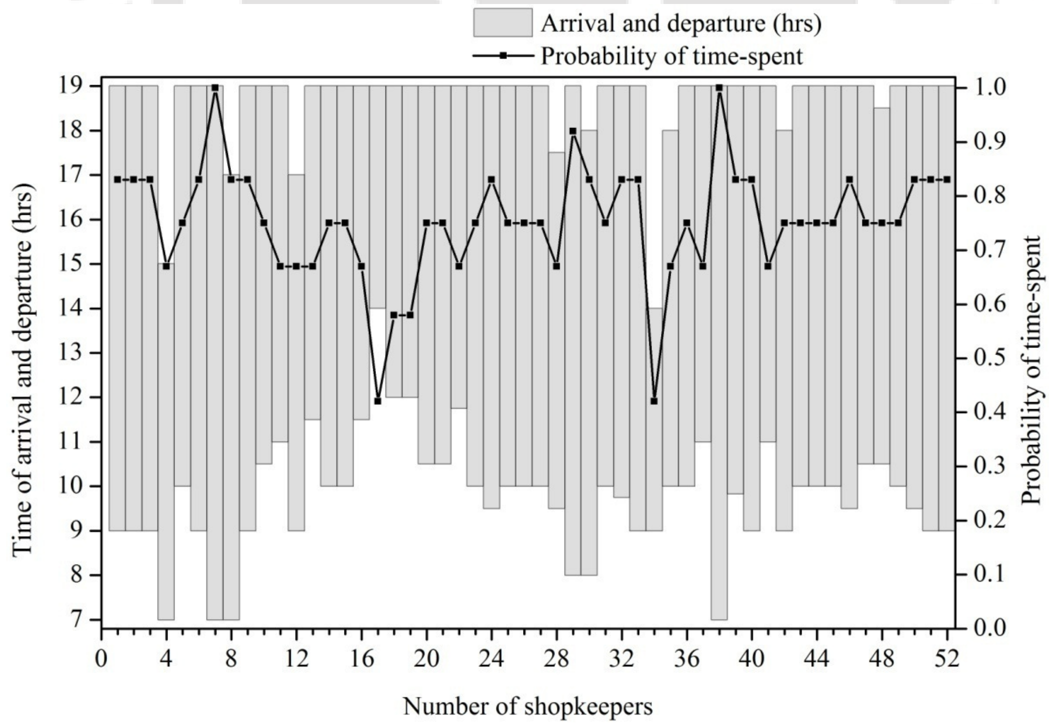


Figure 7.2: Time of arrival and departure of shopkeepers and probability of time-spent in the traffic corridor

From Figure 7.1, it has been observed that 4% of the target population spent 12 hours daily, 30% spent 10 hours, 31% about 9 hours, 19% about 8 hours, and 8% below 6 hours. The minimum time-spent observed was 5 hours. The higher probability of time-spent was for those who spent longer time in the corridor. The lowest probability of time-spent was observed to be about 0.42.

7.3 PROBABILITY OF EXCEEDANCE

The locations of the shopkeeper's workplaces have been geo-coded and referred thereafter as per Figure 3.1 (chapter 3). The probabilities of exceedance, *P(*≥3.5 ppm*)* at each shopkeeper's location has been estimated using the developed spatiotemporal model, as shown in Figure 7.3 and the detailed data is included as Appendix-VI.

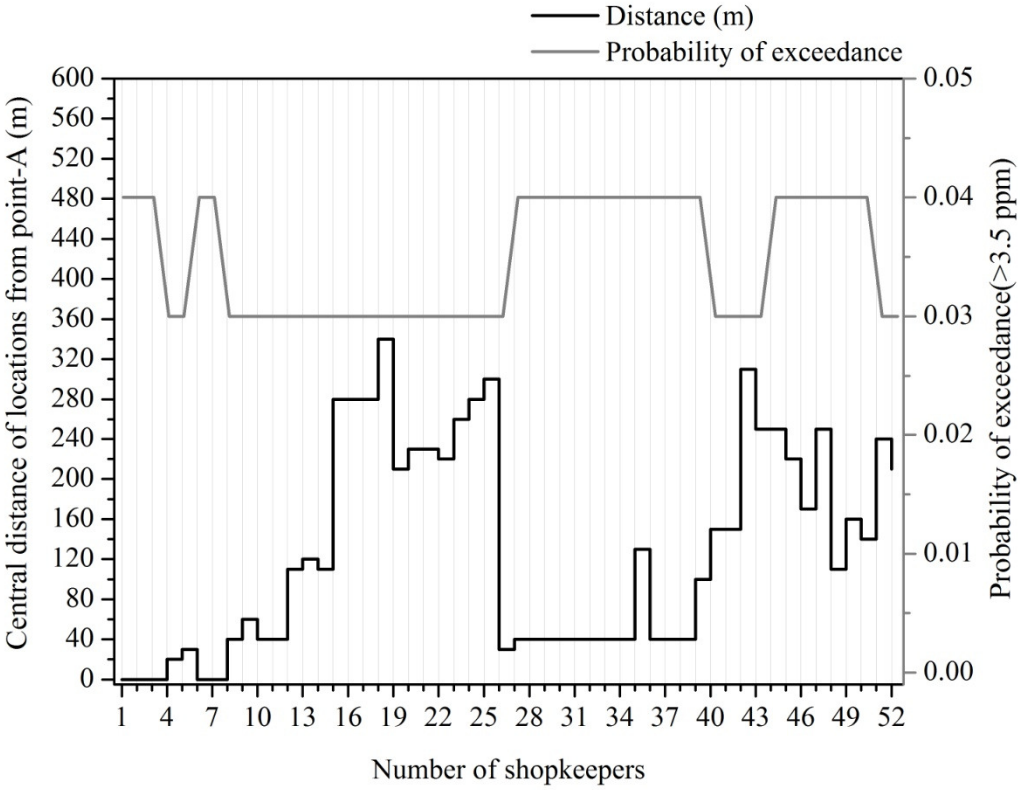


Figure 7.3: Probability of exceedance (> 3.5 ppm) of shopkeepers with locations in the traffic corridor

From Figure 7.3, it has been observed that the probability of exceedance (>3.5 ppm) at the shopkeepers locations vary between 0.03-0.04, which indicates that the hourly CO concentration exceeds 3-4 times a week at the shopkeeper's locations.

7.4 PROBABILITY OF EXPOSURE

The probability of exposure of the shopkeepers, $P(E \geq 3.5$ ppm), was estimated by combining probability of time-spent (Figure 7.2) and probability of exceedance (Figure 7.3) as shown in Figure 7.4.

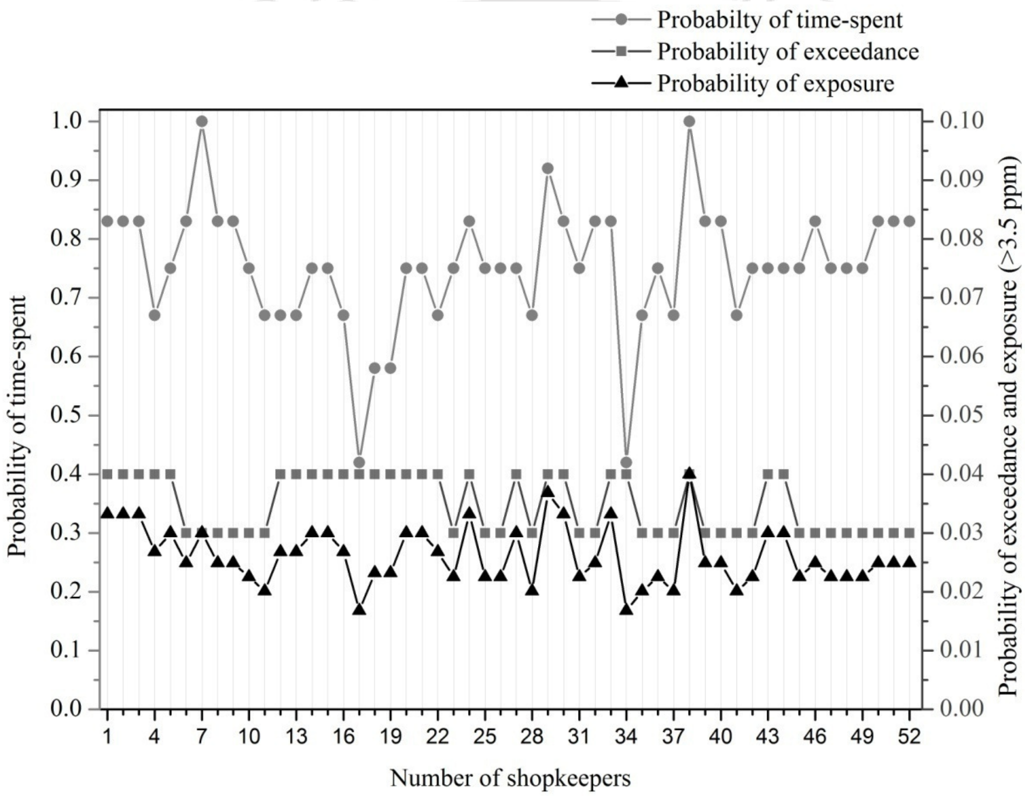


Figure 7.4: Probability of time-spent, exceedance (> 3.5 ppm) and exposure (> 3.5 ppm) of the shopkeepers

The probability of exposure was observed to be higher for those who spent longer time with higher probability of exceedance at the location. About 15% of the target population experiences higher probability of exposure (i.e. >0.03) since they spend longer time as well as concentrations exceeds 3.5 ppm about 4 times a week at their locations.

Whereas, about 4% experiences the least probability of exposure because of their least time-spent among the population.

7.5 VALIDATION

The estimated probability of exposure, $P(E_p)$, of shopkeepers has been compared with the probability of measured personal exposure, $P(E_o)$. Those shopkeepers whose workplaces are closest to the CO monitoring locations (i.e. L1, L2 and L3) were identified. Such shopkeepers are given in serial number 52, 37, 9 for L1, L2, L3, respectively in Figure 7.4. The respective measured hourly-average CO concentrations during their working hours at each location are given in Figure 7.5, Figure 7.6, and Figure 7.7.

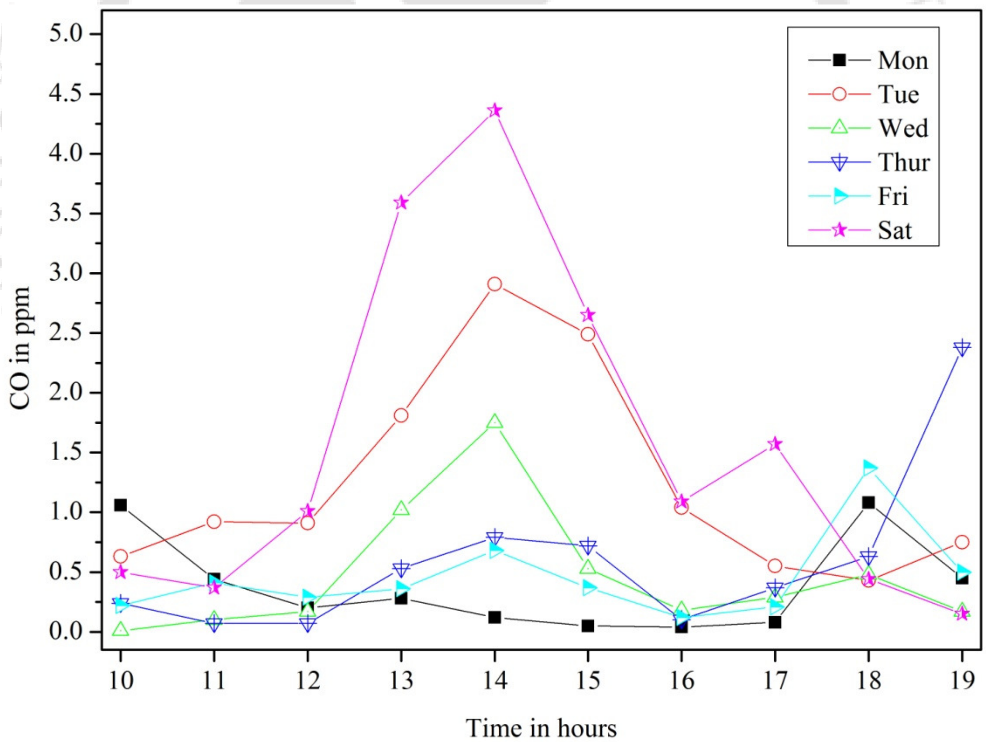


Figure 7.5: Measured CO experienced by shopkeeper (number 52 in Figure 7.4) near monitoring location (L1)

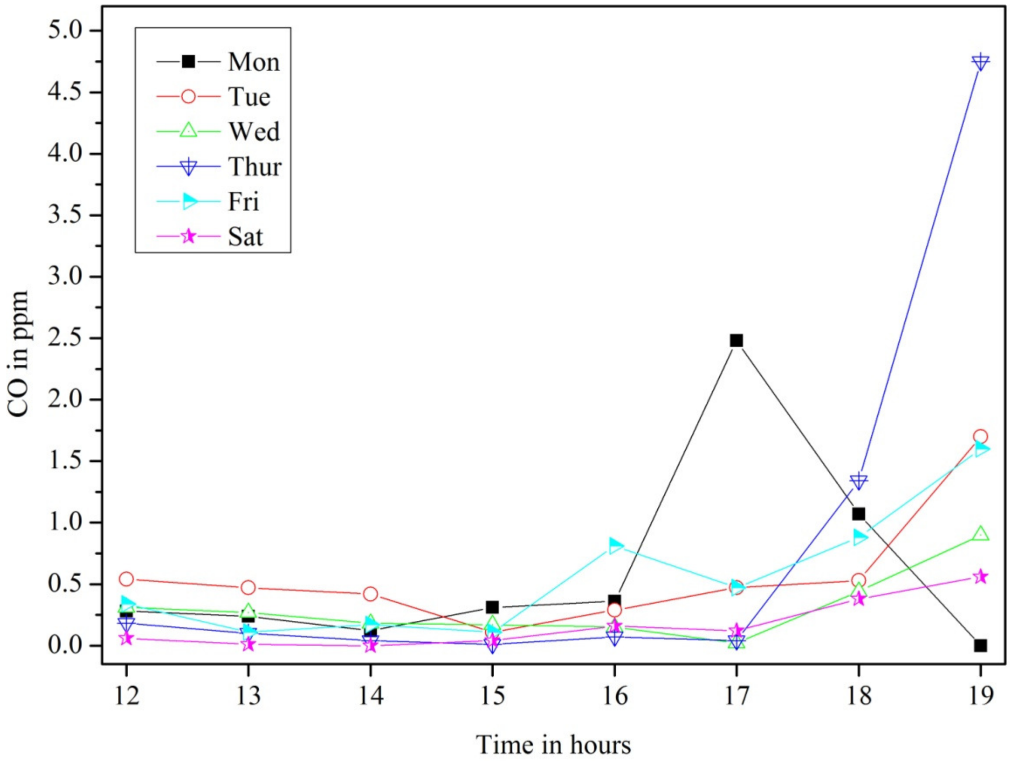


Figure 7.6: Measured CO experienced by shopkeeper (number 37 in Figure 7.4) near monitoring location (L2)

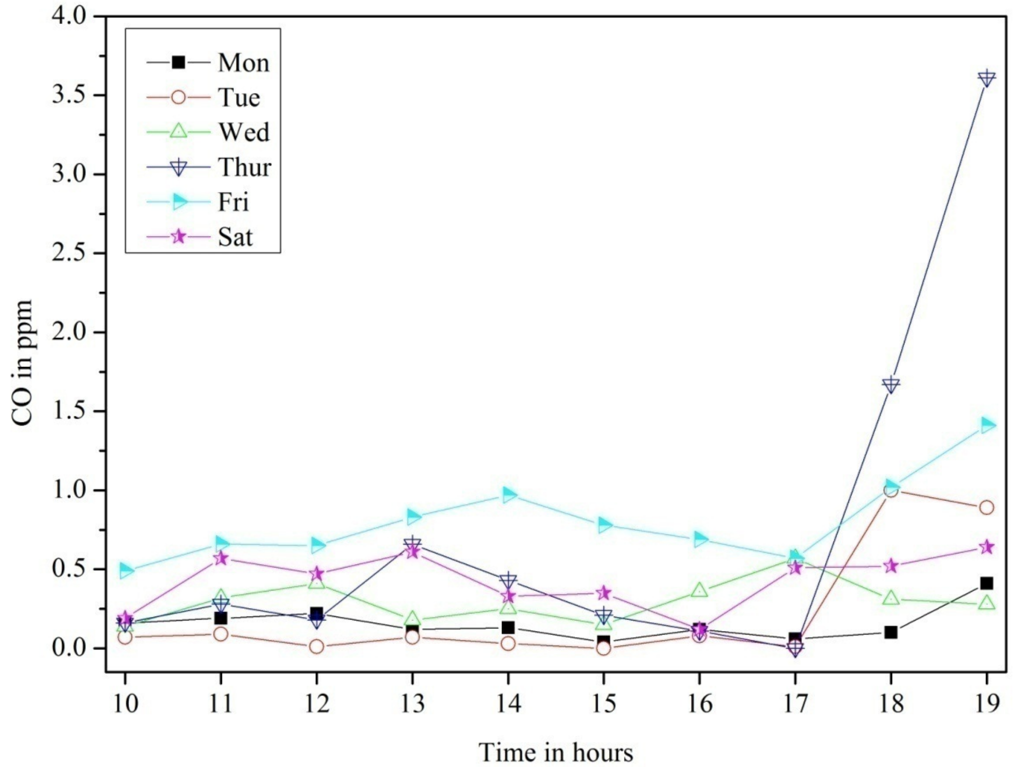


Figure 7.7: Measured CO experienced by shopkeeper (number 9 in Figure 7.4) near monitoring location (L3)

The probability of exposure $P(E_o)$ of measured concentrations exceeding the NAAQS (i.e. 3.5 ppm), has been calculated by rearranging the observed CO concentrations experienced by the shopkeepers in ascending order and by assigning rank to each value from highest to lowest, using equation 7.1.

$$P\ (E_o) = m/(n+1) \qquad (7.1)$$

where, $P(E_0)$ is the probability of exposure above the standard limit. m is the ranking, from highest to lowest values, and n is the total number of the dataset. Figure 7.8, 7.9, and 7.10 show the rank ordered concentrations and the observed probability of exposure by the shopkeeper at each location.

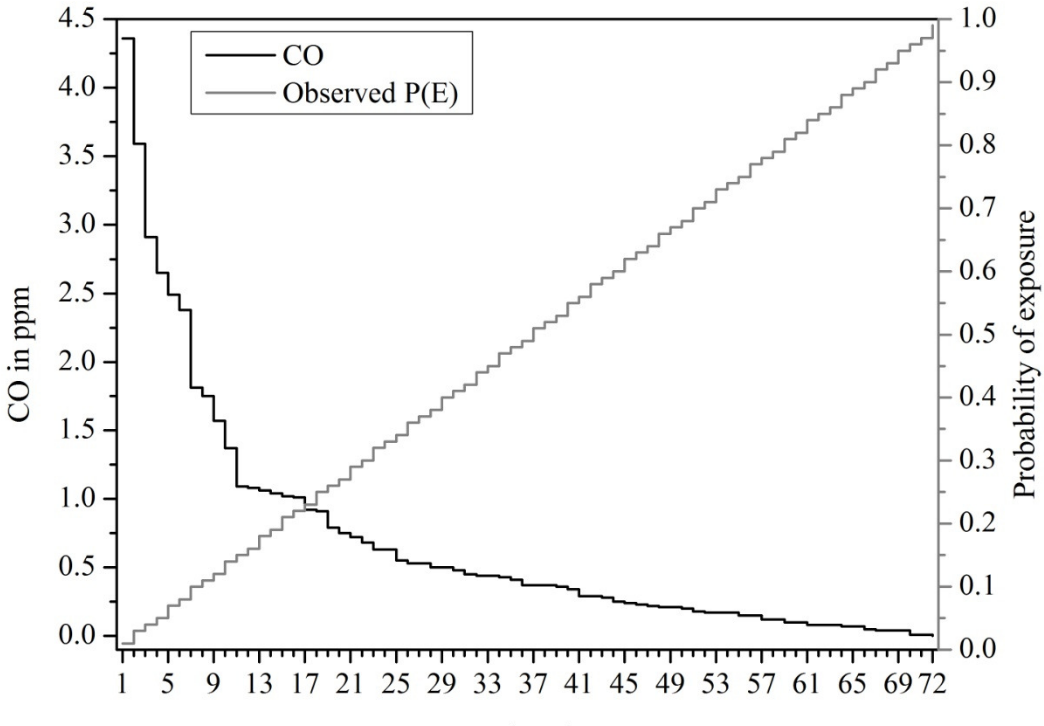


Figure 7.8: Rank order of concentration experience by shopkeeper (number 52 in Figure 7.4) near monitoring location L1 and the corresponding probability of exposure

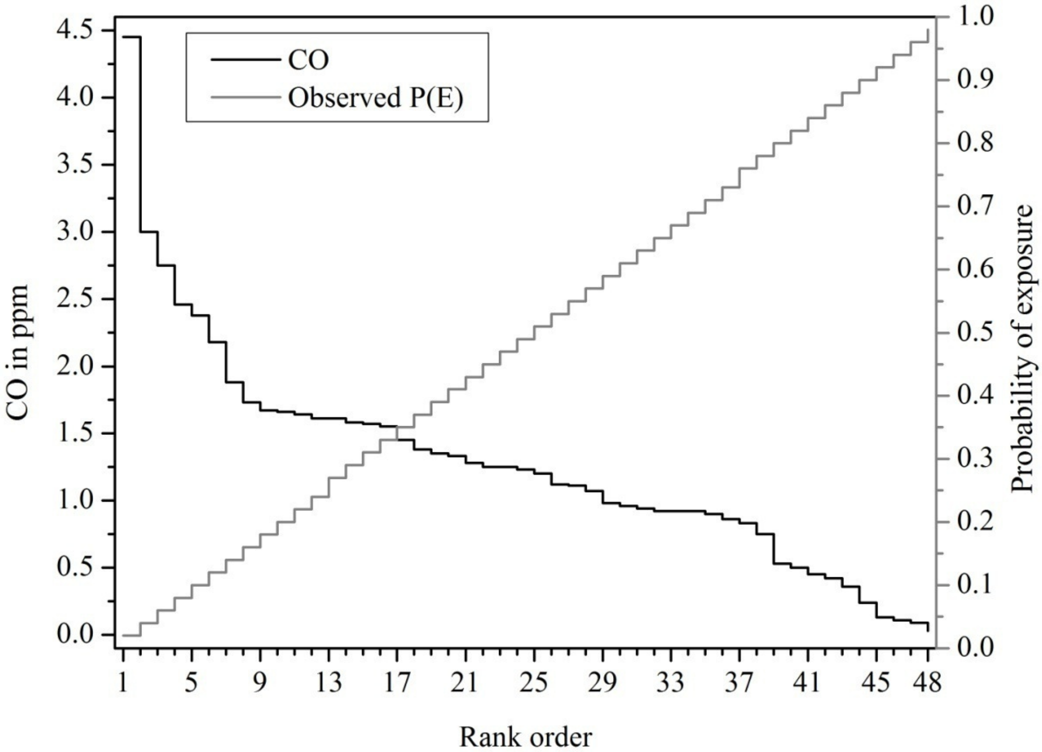


Figure 7.9: Rank order of concentration experience by shopkeeper (number 37 in Figure 7.4) near monitoring location L2 and the corresponding probability of exposure

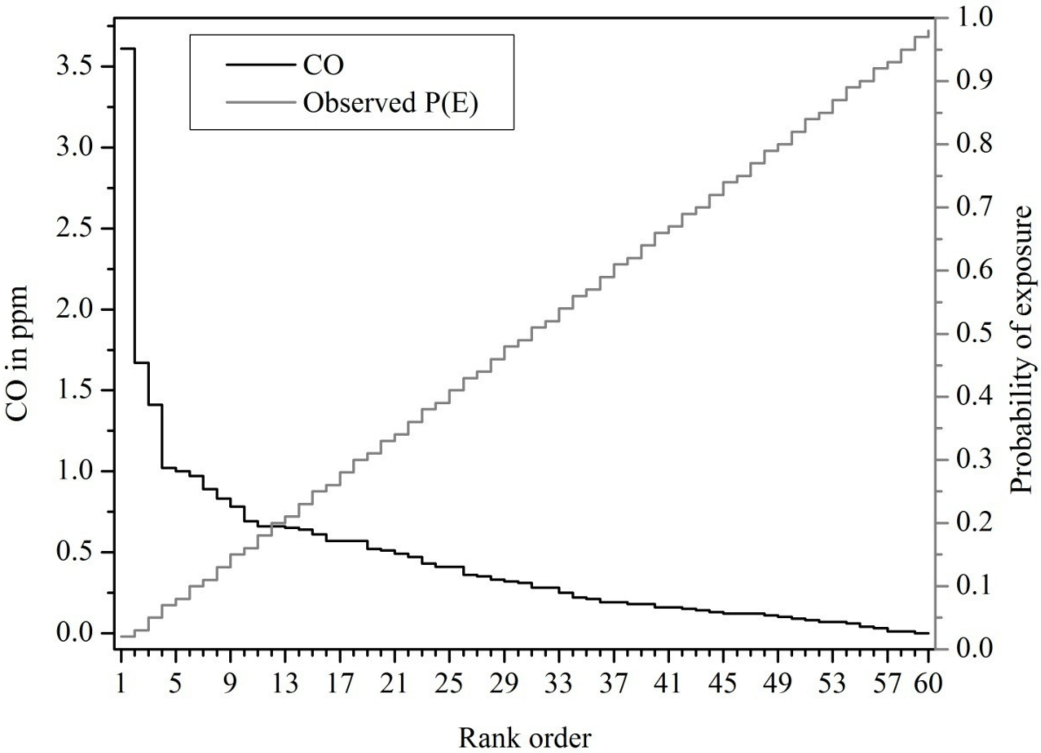


Figure 7.10: Rank order of concentration experience by shopkeeper (number 9 in Figure 7.4) near monitoring location (L3) and the corresponding probability of exposure

It has been observed that the probability of exposure from the measured data was about 0.03, 0.02, 0.02 for shopkeepers near monitoring locations L1, L2, L3, respectively. The observed and estimated probabilities of exposures were found to be in exact agreement for shopkeepers whose workplaces were near to L1 and L2 whereas, for L3 the estimated value was 0.03 against the measured value of 0.02. This might be due to the reason in which the measured concentration exceeded 3.5 ppm over once a week, where the estimated concentration exceed over twice a week. Thus, the findings suggest that the developed prediction method to estimate probability of exposure produces reliable results.

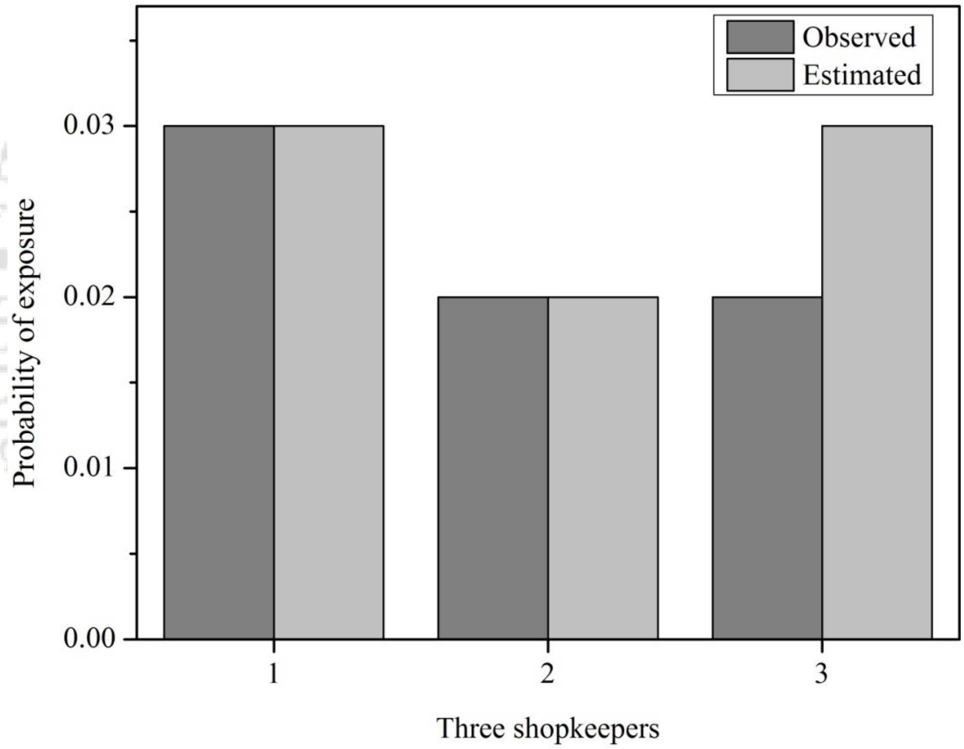


Figure 7.11: Comparison of observed and estimated probability of exposure

7.6 PROBABILITY OF EXPOSURE AT DIFFERENT TIME SLOTS

The probability of exposure at three time slots has been estimated. This is done to find out the exposure level of shopkeepers during morning, afternoon, and evening hours separately. This is because the traffic flow significantly varies in these time slots, which may cause different level of CO concentrations and also individual's exposure. Figure

7.12, 7.13, and 7.14 shows the mean of hourly-averaged measured concentrations in three different time slots i.e. morning hours (7 am to 1 pm), afternoon hours (1 pm to 3 pm), and evening hours (3 pm to 7 pm) at each monitoring location, L1, L2 and L3. The mean, minimum, and maximum concentrations of each time slot have been put back to the prediction method to estimate the probability of exposure during each time period at the location. It has been assumed the average concentration for a specific time period of a location is known, which, when given to the prediction method, produces the probability of occurrence of the concentration and hence may be treated as the probability of exposure of a person spending the same amount of time period in the corridor.

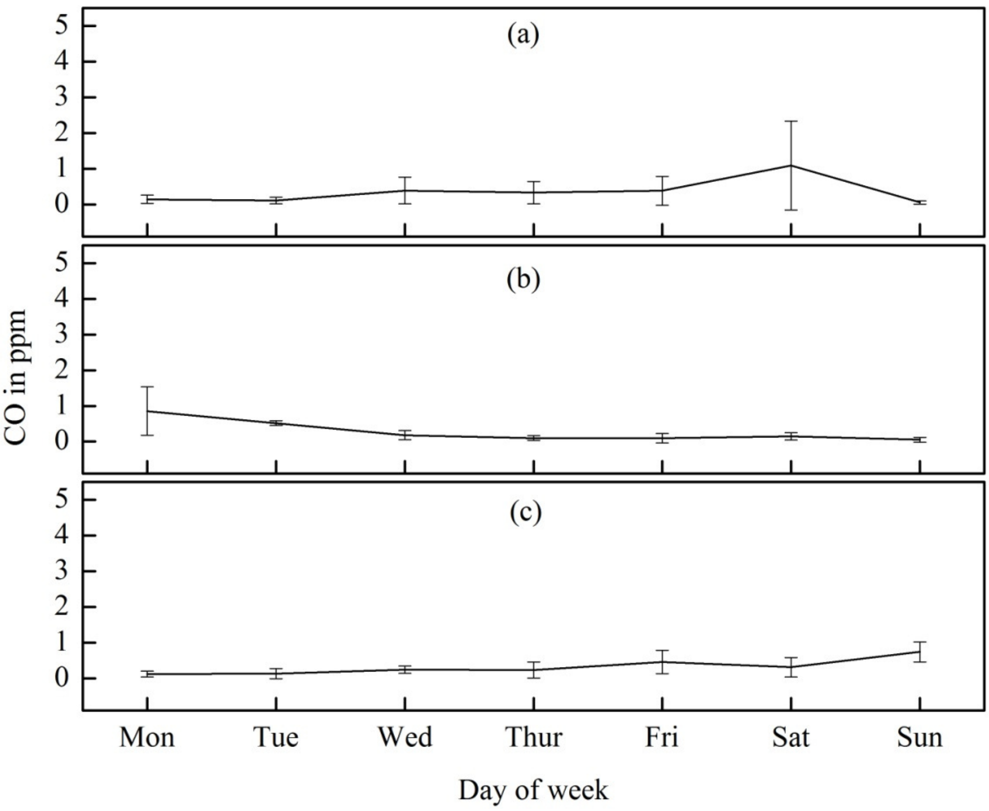


Figure 7.12: Measured CO concentration during morning hours (i.e. 7 am to 1pm) at monitoring locations (a) L1, (b) L2, (c) L3

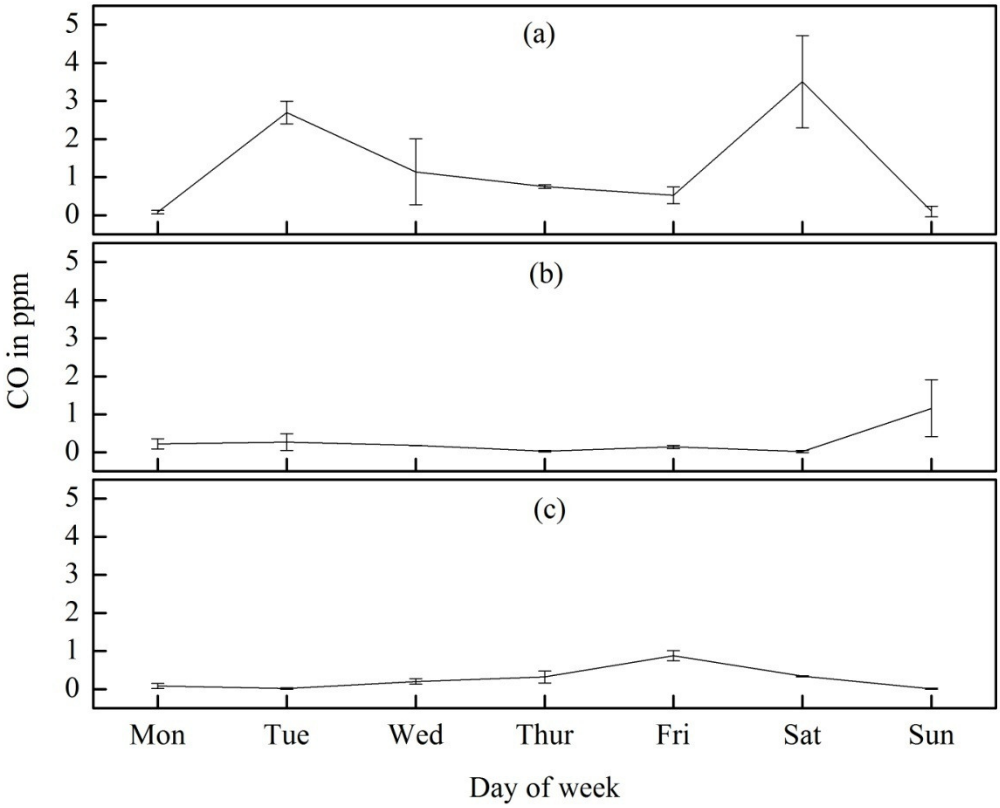


Figure 7.13: Measured CO concentration during afternoon hours (i.e. 1 pm to 3 pm) at monitoring locations (a) L1, (b) L2, (c) L3

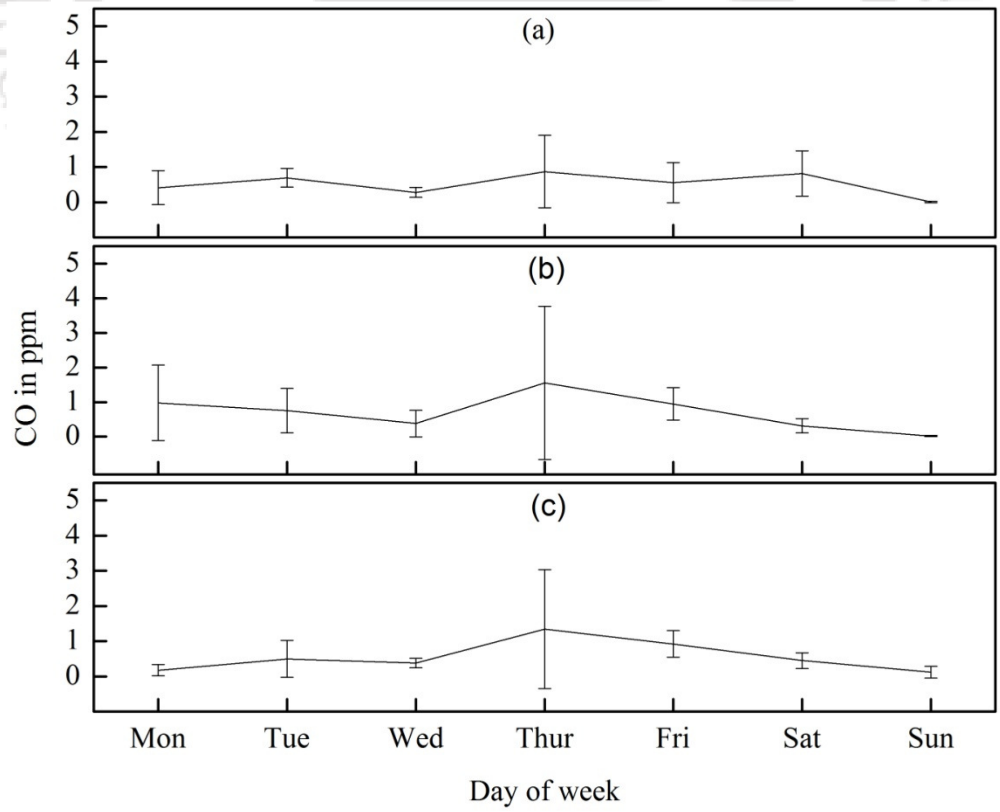


Figure 7.14: Measured CO concentration during evening hours (i.e. 3 pm to 7 pm) at monitoring locations (a) L1, (b) L2, (c) L3

The output of the prediction method in terms of the range (minimum-maximum) and average probability of exposure, $P(E \leq C)$, in the traffic corridor for each time slot has been shown in Figure 7.15, 7.16, 7.17.

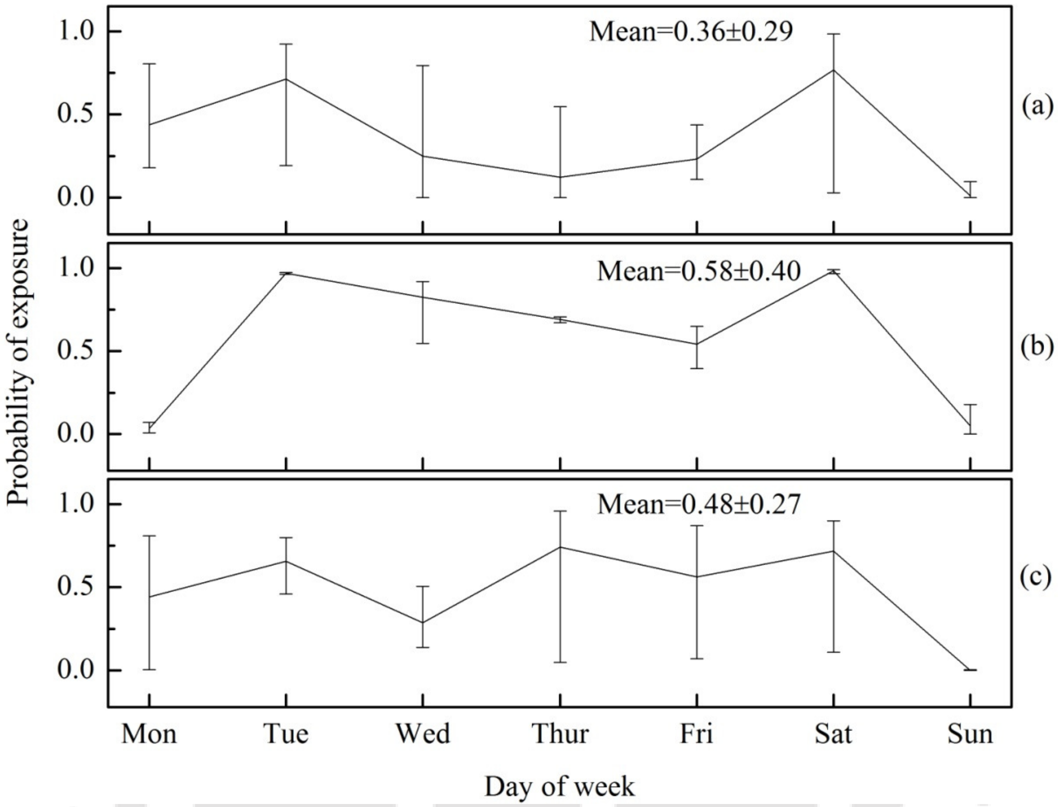


Figure 7.15: Probability of exposure (a) Morning (7 am to 1 pm) (b) Afternoon (1 pm to 3 pm) (c) Evening (3 pm to 7 pm) at monitoring location (L1)

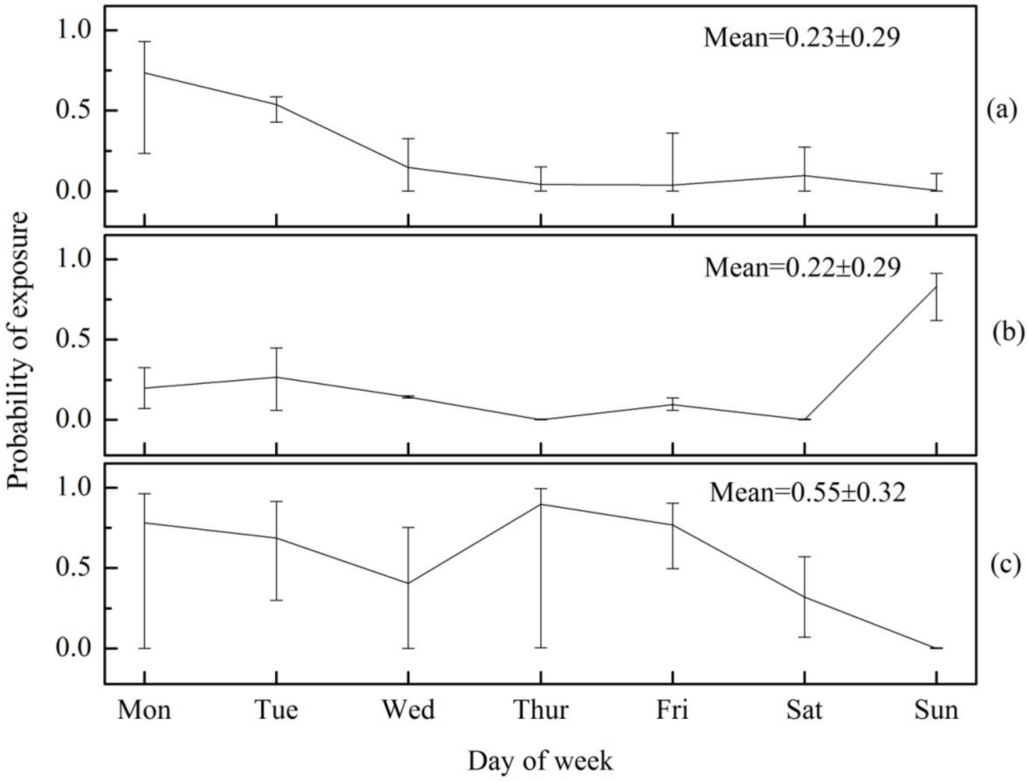


Figure 7.16: Probability of exposure (a) Morning (7 am to 1 pm) (b) Afternoon (1 pm to 3 pm) (c) Evening (3 pm to 7 pm) at monitoring location (L2)

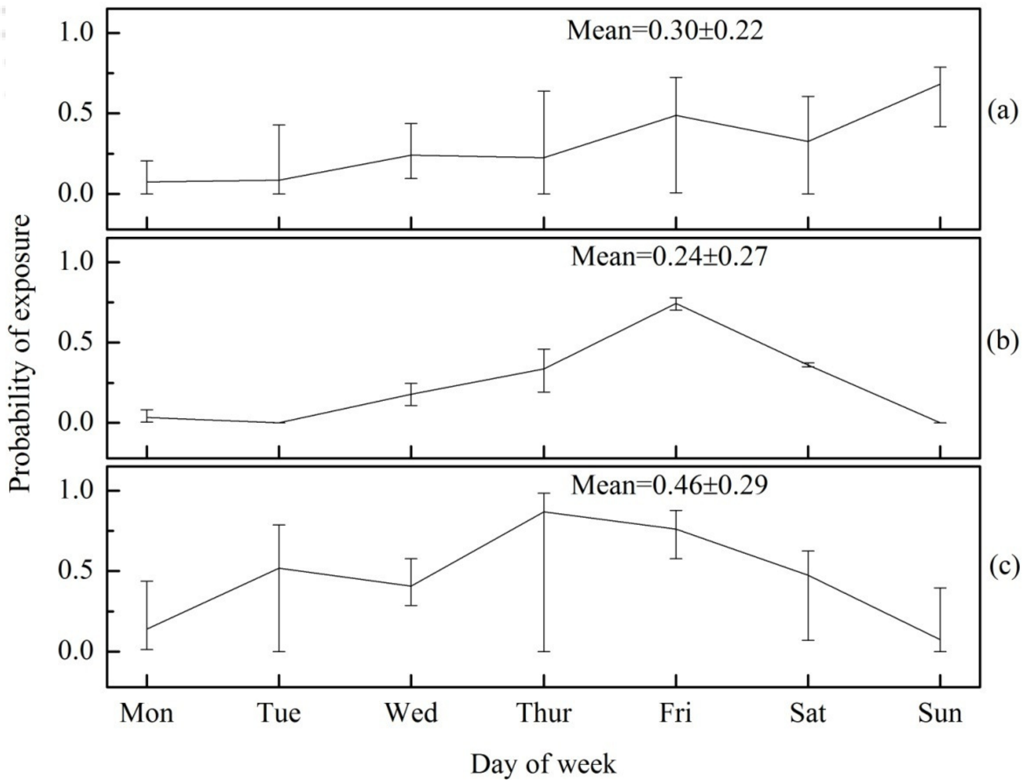


Figure 7.17: Probability of exposure (a) Morning (7 am to 1 pm) (b) Afternoon (1 pm to 3 pm) (c) Evening (3 pm to 7 pm) at monitoring location (L3)

It has been found that probability of exposure is the highest during afternoon hours at location L1 and during evening hours at location L2 and L3, indicating that there are different probability of exposure at different times of the day within the corridor. This is because the traffic flow and meteorology significantly varies over the day.

7.7 EXPOSURE-RESPONSE RELATIONSHIP

Further, the relationship between the probability of exposure and annoyance to traffic-related pollution has been established. It is reported in the literature that people become annoyed when exposed to common air pollution level and even when levels are below the specified standard limit (Amundsen et al., 2008). In this analysis, the estimated probability of exposure of shopkeepers and response to air pollution annoyance from questionnaire survey has been utilized to derive the relationship. In most of the exposure-response relationship studies, the established relationship are based on the estimation using concentrations observed at fixed monitoring location, or outputs of dispersion models, or spatial interpolation method (Oglesby et al., 2000a; Rotko et al., 2002; Amundsen et al., 2008). Therefore, the objective of this analysis has been to establish relationship between the probability of exposure and the responses from questionnaire survey.

The estimated $P(E_p)$ indicates the exposure level of shopkeepers to traffic-related pollutants while working in the traffic corridor. The higher value of $P(E_p)$ indicates higher chances of exposure to pollutant concentration exceeding the NAAQS. The logistic-regression (binary logit model) has been carried out for establishing the relationship of exposure-response. The annoyance has been treated as a dependent variable and the probability of exposure as independent variable. From the estimated parameters of the binary logit model (equation 7.2), it is possible to estimate the relationships.

The logit model indicates the probability of obtaining an annoyance response, "yes" or "no", depending upon the estimated probability of exposure, given by equation 7.2.

$$P(Y \geq \text{"Yes" or "No"} \mid x_i) = 1 - \frac{e^{\beta_0 + \beta_1 x_i}}{1 + e^{\beta_0 + \beta_1 x_i}} \tag{7.2}$$

where, β_0 and β_i are the parameters of the model and x_i is the probability of exposure (%), i.e. $P(E_p)$. The statistical analysis and estimation of parameters were carried out using SPSS ver. 20. The shopkeepers were exposed to different levels of probability of exposure, 33% were exposed to probability of exposure of 0.03, while 60% were exposed to 0.02 and 6% were exposed to 0.01. Table 7.1 shows the estimated parameters of the logit model.

Table 7.1: Parameters of logit model

Predictors	**Parameters**	***p*-value**	**Odds ratio**	**95% CI Lower**	**95% CI Upper**
Constant	$\beta_0 = 5.022$	0.005	-	-	-
P (E_p)	$\beta_i = -1.530$	0.027	0.22	0.06	0.84

* All results are statistically significant ($p = 0.018$); N =52

The estimated parameters were utilized in equation 7.2 with which the annoyance level was estimated based on probability of exposure. For example, probability of exposure of 0.04 (i.e. 0.04 x 100 = 4%), the level of annoyance is given by:

$$P(Y \geq \text{"Yes" or "No"} \mid x_i) = 1 - \frac{e^{5.022 - 1.530 \times 4}}{1 + e^{5.022 - 1.530 \times 4}} = 0.75$$

Therefore, approximately 75% of the respondents were annoyed when the level of probability of exposure (>3.5 ppm) was 0.04 (4%). Figure 7.18 shows the exposure-response relationships for the respondents while working in the traffic corridor. The curve is the cumulative, which indicates the percentage of the population who is annoyed to traffic-related pollution.

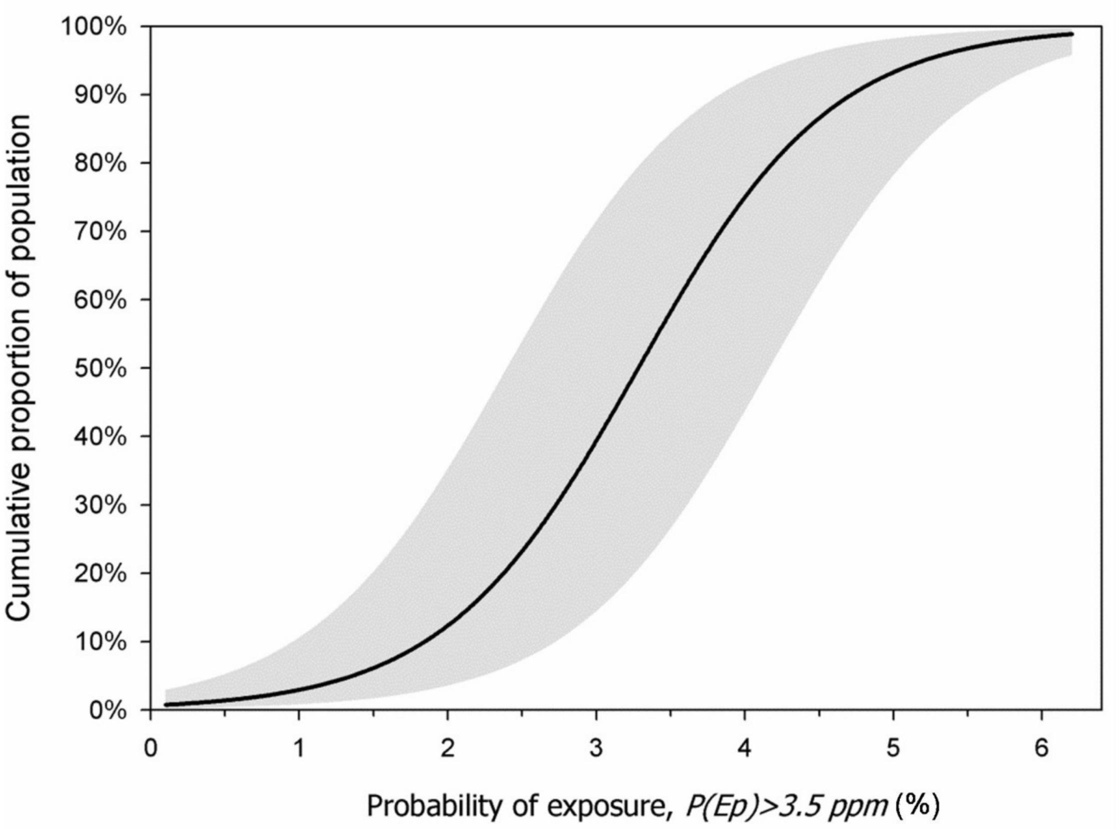


Figure 7.18: Probability of exposure and percentage of target population annoyance (the grey curve shows the 95% confidence limit of the relationship).

It has been observed that even at low probability of exposure, few people were still annoyed to air pollution. In this analysis, other factors such as sensitivity of people, age of people, working status were not taken into account while establishing the relationship. Such factors may affect the annoyance level of certain people, particularly, having health issues. However, estimated parameters of the model as shown in table 7.13 were statistically significant. This implies that the simple model using probability of exposure can provide insight into the exposure-response relationship. Incorporating the above factors may still improve the relationship, which might produce better results.

7.8 SUMMARY AND DISCUSSION

In this study, the probability of exposure (>3.5 ppm) of the target population (shopkeepers) has been estimated using the developed prediction method and validated with the probability calculated for personal monitoring. The estimated probability of exposure matched the observed probability for two shopkeepers with a slight difference for the third shopkeeper. This indicates that the prediction method is reliable to estimate probability of exposure.

Further, the prediction method has been applied to estimate the probability of exposure at different time slots of the day (i.e. morning, afternoon, and evening). The result shows variation of probability of exposure in different times of day indicating significant variation of traffic-flow and meteorology over the day. Moreover, exposure-response relationship between probability of exposure and annoyance due to air pollution was established. The results showed that the probability of exposure was significantly associated with annoyance due to air pollution. This may be true since the estimated probability of exposure takes into account the extreme concentrations as well as the duration of exposure but this needs to be validated. The relationship was statistically significant. However, the model may be improved by considering other factors, which may influence the annoyance level, such as other pollutants, health status, etc. Such exposure-annoyance relationships may be useful for planning policy related to health-risk due to various air pollutants.

CHAPTER 8

FINDINGS AND DISCUSSION

In this research, a prediction method has been developed for estimation of exposure of sedentary workers to carbon monoxide in an urban traffic corridor. The method includes censored-calibrated hybrid model (CCH), the output of which has been combined with the time-spent by the sedentary workers at the workplaces to estimate the probability of exposure. The CALINE4 and lognormal distribution model were combined to develop the CCH model, which is further calibrated using a calibration factor. These models have been combined using a hybrid technique (Gokhale and Khare, 2005; Sharma et al., 2013; Taylor et al., 1985). When the technique was applied in this research, it was observed that it improved the predictions in the lower and higher range of concentrations except in the middle range. The statistics were d = 0.94, r = 0.93, $NMSE$ = 0.06, FB = -0.20, and FS = 0.10. This technique was further improved with the use of a calibration factor (CCH model), the results showed a considerable improvement in the middle as well as in the extreme ranges, for which the statistics were d = 0.99, r = 0.97, $NMSE$ = 0.02, FB = 0.02, and FS = -0.07. The results have, therefore, demonstrated that the CCH model provides better estimates of the concentration distributions.

It has been observed that the statistical behavior of CO represented by the lognormal distribution remains same within the traffic corridor at different times and at different locations. The CCH model was validated at the other two spatial locations (L2 and L3) in the corridor for which the statistics were d = 0.98, r = 0.96, $NMSE$ = 0.05, FB = 0.23, FS = 0.05 and d = 0.91, r = 0.96, $NMSE$ = 0.22, FB = 0.33, FS = 0.49, respectively. The results of the validation show that the CCH model can provide reliable estimates of concentrations distribution at other spatial locations in the corridor. With the

CCH model contours of spatiotemporal probabilities of exceedances within the traffic corridor were plotted.

Using the CO concentrations predicted by the CCH model at spatial locations within the traffic corridor, the required reduction in emission was estimated. The emission reduction required to maintain the air quality (i.e. below hourly NAAQS) was found to be about 24%. The results of this research are promising and indicative, based on the limited amount of data. The model, therefore, needs validation in other traffic corridors with a large set of data.

Exposure model has been developed by combining the CCH model and the time spentby the sedentary workers (i.e. shopkeepers and office workers). The model estimates the exposure of such workers in terms of probability of exceedances (i.e. >3.5 ppm, hourly NAAQS). This method is different from the other methods, in which, generally the exposure is estimated with absolute concentrations and time-spent at the locations (Bell, 2006; Physick et al., 2011). In this study, the indoor exposure of sedentary workers was estimated on the basis of outdoor CO concentrations. This method, however, may be affected by a ventilation, which influences the infiltration of outdoor air pollutants into the indoors (Chen and Zhao, 2011; Gall et al., 2015). The results showed that the estimated probability of exposure matched reasonably well with the observed probability of exposure of the sedentary workers.

Further, the estimated probabilities of exposure of the sedentary workers were utilized to find if there exists any association with the air pollution annoyance. The results showed that the estimated probability of exposure was significantly associated with the annoyance to air pollution. Since the association was found on the basis of statistical analysis, this may need a validation. A few studies have demonstrated the association of annual or periodic average concentrations with the air pollution annoyance (Amundsen et al., 2000; Llop et al., 2008; Rotko et al., 2002) and Miedema at al. (2000) used 98-percentiles exposure values.

CHAPTER 9

CONCLUSION AND FUTURE SCOPE

9.1 GENERAL CONCLUSION

The prediction method, developed in this research, estimates the spatiotemporal air quality in terms of probability and probability of exceedance over national ambient air quality standards. The results of the research demonstrated that with one location data in a traffic corridor, the prediction method can be employed to produce spatiotemporal concentrations. One important features of this methodology is that its stepwise process of development progressively eliminated errors from the tails ends and the middle ranges of the CO concentrations. The ability of the prediction method to estimate the entire range of concentrations is important for the assessment of health-risk due to air pollution. With this method, the required emission reduction to maintain the healthy air quality and annoyance level in the traffic corridor can also be estimated. The method produces the spatiotemporal concentration in term of probability which can be easily combined with time-activity of a target population to estimate the probability of exposure.

9.2 KEY CONCLUSIONS

- The research demonstrated that at three distant locations in urban traffic corridor, CO concentrations followed lognormal distribution form indicating that in a roadside microenvironment, the statistical behavior of pollutant does not change spatially and temporally.
- The spatiotemporal concentrations estimated using a widely used dispersion model (CALINE4) in the traffic corridor were improved by combining them with the lognormal distributional form using a hybrid approach and by further

calibration. This method can be applied with any suitable dispersion model and thus forms an important part of the prediction method.

- The prediction method estimates the probability of exposure to CO concentrations depending upon the probability of time-spent by the individual and the probability of CO concentrations exceedances in the traffic corridor reasonably well.
- The prediction method was found to be simple, flexible and can be developed from one monitoring station data and can be applied to any roadside microenvironment where the source of pollution is traffic alone.
- The prediction method can be applied to determine the spatiotemporal concentration and probability of exposure at any desired hour of the day. Therefore, it can be used to suggest emission reduction or exposure at any specific time when required.
- Further, the relationship between the estimated exposure and the degree of annoyance due to air pollution was found to be statistically significant.

9.3 LIMITATIONS

- The prediction method may not produce equally good result if the corridor has a curved roadway, arterial links or a junction as it is demonstrated for a straight roadway having no junction or arterial link.
- The method may not be applicable where there are multiple sources of CO since the statistical distribution form may not be same throughout the corridor in such case.
- The method may not be feasible for secondary or reactive pollutants since the characteristics of such pollutants vary location to location, therefore, the pollutants may not have similar statistical behaviors.

- The features like the presence of trees and roadside parked cars, which may affect the distributional form and exposure levels, were not considered in the analysis.
- The prediction method is based on one week data from three different monitoring locations, hence the level of accuracy of the method could be improved with a large data sets.
- The relationship of air pollution annoyance and probability of exposure developed in the study is based on statistical association which needs to be validated.
- It is assumed that the day to day traffic volume and hourly trends remain same every week. Hence the model may not be reliable for a traffic corridor where traffic characteristics are considerably different.

9.4 FUTURE SCOPE

- The prediction method may be verified at spatial locations of similar characteristics but in another traffic corridor.
- The prediction method may be applied to estimate probability of exposure for other target population - pedestrians.
- The prediction method may be verified on other pollutants.

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APPENDIX-I
(QUESTIONNAIRE)

Sl. No.	OCCUPATION	GENDER (M or F)	AGE (Yrs)	Time spent at work (Hrs/day)	Number of months at work	Distance from traffic (meters)	Suffer from Cough apart from general (Yes=Y or No=N)	Breathing problems ? (Yes=Y or No=N)	Head-ache? (Yes=Y or No=N)	Any skin allergy ? (Yes=Y or No=N)	Suffer From Chest Tightness ? (Yes=Y or No=N)	Annoyance to air pollution (Yes=Y or No=N)	Traffic causes Stress? (Yes=Y or No=N)	Any Change In material in short-time? (Yes=Y or No=N)	Distance of work from home (Km)	Exposure to cigarette (Yes=Y or No=N)	Any other source of air pollution other than traffic (Yes=Y or No=N)
1	SALESMAN	M	21	13	2	5	N	Y	Y	N	N	N	Y	Y	5	Y	N
2	BUSINESSS	M	48	13	5	5	N	N	N	N	N	N	Y	N	2	Y	N
3	SALESMAN	M	21	13	2	2	N	N	N	N	N	N	N	N	2	N	Y
4	SALESMAN	M	37	13	24	3	N	N	N	N	N	N	Y	N	8	N	N
5	BUSINESS	M	61	14	936	10	N	N	N	N	N	Y	N		1	N	
6	SALESMAN	M	29	8	23	10	Y	N	Y	N	Y	Y		Y	1	Y	N
7	BUSINESS	M	21	12	24	10	Y	Y	N	N	N	Y	Y	N	1	N	N
8	SERVICE	M	41	8	36	6	N	Y	Y	N	Y	N	Y	Y	0.5	Y	N
9	SALESMAN	M	25	10	24	5	Y	N	Y	N	N	Y	Y	Y	2	Y	N
10	SALESMAN	F	22	9	12	5	Y	Y	Y	Y	N	Y	Y	Y	10	N	N
11	WORKER	F	21	8	4	1	Y	Y	N	N	Y	Y	Y		10	Y	
12	SALES MAN	M	19	12	12	10	Y	N	N	N	Y	Y	Y	Y	5	Y	N
13	SALESMAN	M	32	8	30	6	N	N	Y	N	N	Y	N	N	1.5	N	N
14	SALES MAN	M	23	12	24	10	Y	Y	Y	N	Y	Y	Y	Y	3	Y	N
15	SALESMAN	M	32	13	48	6	N	Y	Y	N	Y	Y	Y	Y	6	N	N
16	SALES SERVICE	M	24	9	12	6	N	N	N	N	N	N	Y	N	7	N	N
17	SALES EXECUTIVE	M	26	10	18	10	N	Y	Y	Y	Y	Y	Y	Y	12	Y	N
18	SERVICE	M	39	12	216	6	Y	Y	N	N	Y	Y	Y	Y	1	N	N
19	SALESMAN	M	29	8	36	6	N	N	Y	N	N	Y	Y	Y	3	N	N
20	SALESMAN	M	36	11	132	6	N	Y	Y	N	N	N	Y	Y	12	N	N

APPENDIX-I (Continued)
(QUESTIONNAIRE)

Sl. No.	OCCUPATION	GENDER (M or F)	AGE (Yrs)	Time spent at work (Hrs/day)	Number of months at work	Distance from traffic (meters)	Suffer from Cough apart from general (Yes=Y or No=N)	Breathing problems ? (Yes=Y or No=N)	Head-ache? (Yes=Y or No=N)	Any skin allergy ? (Yes=Y or No=N)	Suffer From Chest Tightness ? (Yes=Y or No=N)	Annoyance to air pollution (Yes=Y or No=N)	Traffic causes Stress? (Yes=Y or No=N	Any Change In material in short-time? (Yes=Y or No=N	Distance of work from home (Km)	Exposure to cigarette (Yes=Y or No=N	Any other source of air pollution other than traffic (Yes=Y or No=N
21	SALESMAN	M	22	11	12	6	N	Y	Y	N	N	N	Y	Y	7	N	N
22	BUSINESS	F	25	6	24	5	N	N	N	N	N	N	Y	N	3	N	N
23	SALESMAN	M	25	11	36	6	N	N	N	Y	N	Y	Y	N	5	Y	N
24	SALES MAN	M	39	11	77	6	Y	N	Y	N		N	Y	Y	3	Y	N
25	BUSINESS	M	36	10	36	6	Y	N	Y	N	N	N	Y	N	12	N	N
26	BUSINESS	M	36	10	12	0	Y	Y	Y	N	N	Y	Y	N	8	N	N
27	SALES MAN	M	21	8	12	10	Y	Y	Y	N	N	N	Y	N	2	Y	N
28	SALES MAN	M	22	8	17	10	Y	Y	Y	Y	Y	Y	Y	N	1	Y	N
29	SALES MAN	F	22	9	12	10	Y	Y	Y	Y	Y	Y	Y	Y	5	N	N
30	SALES MAN	F	25	9	24	10	Y	Y	Y	N	Y	Y	Y	Y	2	N	N
31	SALES MAN	M	25	9	4	10	Y	Y	Y	N	N	Y	Y	Y	5	N	N
32	SECURITY GUARD	M	24	8	12	10	Y	Y	Y	N	Y	Y	Y	N	3	N	N
33	BUSINESS	M	28	9	24	10	Y	Y	Y	N	N	N	Y	Y	7	Y	N
34	SALES MAN	M	27	9	6	10	N	N	N	N	N	Y	Y	Y	1	N	N
35	BUSINESS	M	55	12	12	6	Y	N	Y	Y	N	Y	N	N	1	N	N
36	SALES EXECUTIVE	F	21	9	36	10	Y	Y	Y	Y	N	N	Y	Y	10	N	N
37	SALES EXECUTIVE	F	24	9	24	10	Y	Y	Y	Y	N	N	Y	Y	6	N	N
38	SALES MAN	M	19	9	12	10	N	N	N	N	N	Y	Y	Y	48	N	N
39	SALES MAN	F	22	10	12	6	Y	Y	Y	Y	Y	Y	Y	N	4	Y	N
40	SALES MAN	M	20	10	4	6	N	N	N	N	N	N	N	Y	12	N	N

APPENDIX-I (Continued)
(QUESTIONNAIRE)

Sl. No.	OCCUPATION	GENDER (M or F)	AGE (Yrs)	Time spent at work (Hrs/day)	Number of months at work	Distance from traffic (meters)	Suffer from Cough apart from general (Yes=Y or No=N)	Breathing problems ? (Yes=Y or No=N)	Head-ache? (Yes=Y or No=N)	Any skin allergy ? (Yes=Y or No=N)	Suffer From Chest Tightness ? (Yes=Y or No=N)	Annoyance to air pollution (Yes=Y or No=N)	Traffic causes Stress? (Yes=Y or No=N)	Any Change In material in short-time? (Yes=Y or No=N)	Distance of work from home (Km)	Exposure to cigarette (Yes=Y or No=N)	Any other source of air pollution other than traffic (Yes=Y or No=N)
41	BUSINESS	M	25	10	2	6	N	N	N	N	N	N	Y	Y	6	N	N
42	BUSINESS	M	45	12	144	6	Y	Y	Y	Y	N	Y	Y	Y	2	Y	N
43	SERVICE	M	27	9	12	8	N	N	N	N	N	N	N	N	0	N	N
44	SERVICE	M	30	10	24	8	N	N	N	N	N	N	N	N	2	N	N
45	BUSINESS	M	49	14	240	10	Y	N	Y	N	N	Y	N	Y	12	N	N
46	BUSINESS	F	39	5	120	10	Y	Y	Y	N	N	Y	Y	Y	2	N	N
47	SERVICE	M	60	10	480	10	N	N	N	N	N	N	N	N	5	N	N
48	BUSINESS	M	30	9	48	8	N	Y	N	Y	N	N	Y	Y	5	Y	N
49	SALES MAN	M	25	8	6	8	N	Y	Y	Y	Y	N	Y	N	2	Y	N
50	SALES MAN	M	24	8	12	6	N	Y	Y	N	N	N	N	N	2	N	Y
51	BUSINESS	M	20	9	6	6	Y	Y	Y	N	N	N	Y	Y	8	N	N
52	SALES MAN	M	26	8	6	6	N	N	N	Y	N	Y	N	Y	1	N	N

APPENDIX-II
Hourly observed CO concentrations
*All units are in ppm

Monitoring location (L1)

Time of day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
7-8 AM	0.23	0.34	0.17	0.04	0.00	0.08	0.14
8-9 AM	0.25	0.21	0.04	0.01	0.15	0.08	0.04
9-10 AM	1.06	0.63	0.01	0.24	0.22	0.50	0.07
10-11 AM	0.44	0.92	0.10	0.07	0.41	0.37	0.02
11-12 PM	0.20	0.91	0.17	0.07	0.29	1.01	0.02
12-1 PM	0.28	1.81	1.02	0.53	0.36	3.59	0.05
1-2 PM	0.12	2.91	1.75	0.79	0.68	4.36	0.20
2-3 PM	0.05	2.49	0.53	0.72	0.37	2.65	0.00
3-4 PM	0.04	1.04	0.18	0.10	0.12	1.09	0.00
4-5 PM	0.08	0.55	0.29	0.37	0.21	1.57	0.00
5-6 PM	1.08	0.43	0.48	0.63	1.37	0.44	0.04
6-7 PM	0.45	0.75	0.17	2.38	0.50	0.15	0.00

Monitoring location (L2)

Time of day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
7-8 AM	0.31	0.40	0.03	0.00	0.01	0.25	0.01
8-9 AM	1.15	0.55	0.01	0.03	0.00	0.09	0.15
9-10 AM	1.89	0.58	0.24	0.13	0.05	0.27	0.11
10-11 AM	1.26	0.57	0.20	0.12	0.03	0.16	0.00
11-12 PM	0.28	0.54	0.31	0.18	0.34	0.06	0.00
12-1 PM	0.24	0.47	0.27	0.10	0.11	0.01	0.00
1-2 PM	0.12	0.42	0.18	0.04	0.17	0.00	0.63
2-3 PM	0.31	0.11	0.17	0.01	0.11	0.04	1.69
3-4 PM	0.36	0.29	0.15	0.07	0.81	0.16	0.00
4-5 PM	2.48	0.47	0.02	0.04	0.47	0.12	0.00
5-6 PM	1.07	0.53	0.44	1.34	0.88	0.38	0.04
6-7 PM	0.00	1.70	0.90	4.75	1.60	0.56	0.00

APPENDIX-II (Continued)
Hourly observed CO concentrations

Monitoring location (L-3)

Time of day	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
7-8 AM	0.03	0.15	0.19	0.11	0.08	0.01	1.00
8-9 AM	0.02	0.40	0.23	0.01	0.05	0.01	1.00
9-10 AM	0.16	0.07	0.14	0.16	0.49	0.19	0.95
10-11 AM	0.19	0.09	0.32	0.28	0.66	0.57	0.60
11-12 PM	0.22	0.01	0.41	0.18	0.65	0.47	0.39
12-1 PM	0.12	0.07	0.18	0.66	0.83	0.61	0.49
1-2 PM	0.13	0.03	0.25	0.43	0.97	0.33	0.02
2-3 PM	0.04	0.00	0.15	0.21	0.78	0.35	0.00
3-4 PM	0.12	0.08	0.36	0.11	0.69	0.12	0.04
4-5 PM	0.06	0.01	0.57	0.00	0.57	0.51	0.02
5-6 PM	0.10	1.00	0.31	1.67	1.02	0.52	0.06
6-7 PM	0.41	0.89	0.28	3.61	1.41	0.64	0.37

APPENDIX-III
METEOROLOGICAL DATA
(During Week-1)
Monday (3/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	306.6	17.7	3.4	21	74.5	0.02
8-9 AM	251.6	19.6	0.7	23.9	65	0.18
9-10 AM	174.1	17.2	2.3	24.4	67.3	0.39
10-11 AM	147.7	22.6	5.5	25.9	61.7	1.37
11-12 PM	125.4	26.5	7.8	26.8	54.7	1.39
12-1 PM	109.8	32.1	7.1	28.1	50.7	0.89
1-2 PM	110.5	31.7	8	29	46	1.1
2-3 PM	100.9	25.4	9.9	29.7	41.9	0.59
3-4 PM	103.9	20.8	9.3	29.4	39.6	0.16
4-5 PM	111.1	17.5	6	28.5	40	0
5-6 PM	101.1	13.3	2.4	27.2	43	0
6-7 PM	353.5	8.3	0.1	25.9	46.8	0

Tuesday (4/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	292.8	17.7	0.7	21.8	67.7	0
8-9 AM	302.2	23.8	0.2	24.7	56.2	0.28
9-10 AM	215.4	18.1	1	26.1	52	0.37
10-11 AM	186.2	23.1	1.4	26.7	50.2	0.85
11-12 PM	228.5	40.3	1.5	28.9	44.4	0.68
12-1 PM	255.1	28.7	2.8	29.7	41.5	0.84
1-2 PM	236.2	25.9	5.5	29.7	38	0.96
2-3 PM	228	20.4	5.6	30.5	35	0.57
3-4 PM	221.3	17.5	4.9	30	35.8	0.06
4-5 PM	225.6	16	5.3	28.8	39	0
5-6 PM	245.3	11.4	1.4	27.5	42	0
6-7 PM	265.4	10.2	1.2	27	45	0

APPENDIX-III (continued)
METEOROLOGICAL DATA

Wednesday (5/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	327	25.2	1	22.9	65	0
8-9 AM	97.5	21	4.6	23.5	63.5	0
9-10 AM	108.5	23.1	6.4	23.6	61.9	0
10-11 AM	123.6	22.7	9.9	25.1	57	0.48
11-12 PM	126.8	22.3	7.6	26.2	53.3	0.94
12-1 PM	124.1	31.4	5.3	28.3	46.9	1.22
1-2 PM	128	21.2	6.2	28.9	42.1	1.12
2-3 PM	113.8	22.2	7.5	29.6	38.6	0.72
3-4 PM	107.3	21.9	5.4	29.3	41	0.1
4-5 PM	132.4	17.5	2.9	29	42.9	0
5-6 PM	134.7	10.4	1.4	27.3	46.5	0
6-7 PM	61.3	12.6	1	26.4	51.9	0

Thursday (6/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	307.4	12.8	0.8	21.8	55.2	0.21
8-9 AM	76.2	19.1	2.6	24.7	49	0.68
9-10 AM	141.2	19.1	5.7	25.1	47	1.09
10-11 AM	122.7	22.9	7.7	26.1	43.5	1.52
11-12 PM	130.4	24.2	7.7	27.4	38	1.13
12-1 PM	125.8	23.8	10.2	28.3	31.9	1.46
1-2 PM	117.2	23.7	10.3	29.5	26.6	1.31
2-3 PM	113.5	24.8	10.2	29.7	27.4	0.62
3-4 PM	122.4	24.6	7.2	30.4	28.9	0.04
4-5 PM	166.9	12.8	2.8	28.2	36.1	0
5-6 PM	157.8	12.4	1.6	27	38	0
6-7 PM	81.2	14.9	1.2	25.9	43.2	0

APPENDIX-III (continued)
METEOROLOGICAL DATA

Friday (7/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	279.8	19.8	2.9	21.2	60.1	0.15
8-9 AM	214.7	16.3	0.2	24.2	58.3	0.47
9-10 AM	213.4	25	1.3	26.1	48.5	0.47
10-11 AM	144.2	26.8	2.3	27.4	44.4	1.32
11-12 PM	125.6	22.2	5.7	27.9	39.9	1.43
12-1 PM	135.4	20.8	10	28.2	36.8	0.99
1-2 PM	130.1	20.7	10.8	29.1	31.6	1.31
2-3 PM	124.3	22.3	9.8	29.5	29.8	0.92
3-4 PM	122.8	22.9	6.7	30.4	28	0.35
4-5 PM	130.2	17.8	5.3	28.8	31.3	0
5-6 PM	174.3	6.1	0.7	26.7	42.5	0
6-7 PM	85.3	9	0.1	25.8	46	0

Saturday (8/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	310.9	15.2	1	22.3	50.2	0.21
8-9 AM	287.1	24	0.3	25.6	44	0.7
9-10 AM	168.7	17.7	1.5	26.9	41.4	1
10-11 AM	198.9	15.7	1.7	28	37	1.65
11-12 PM	196.6	22.3	3.2	28.7	34.1	1.61
12-1 PM	157.2	29	3.5	29.5	33.6	1.46
1-2 PM	172.2	24.8	3.4	30.1	32.2	1.12
2-3 PM	154.6	19.7	3.4	30.8	31	0.72
3-4 PM	181.5	11.2	1.5	31.1	31.2	0.24
4-5 PM	181	11.1	0.6	29.7	32.2	0
5-6 PM	204.3	9.6	0.9	28.2	35.4	0
6-7 PM	282.8	13.5	0.3	26.5	38.9	0

APPENDIX-III (continued)
METEOROLOGICAL DATA

Sunday (2/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	342.4	0	0	20	84	0.34
8-9 AM	298.3	22.7	0.3	22.5	73.6	0.12
9-10 AM	116	32.1	2.1	24	68.7	0.43
10-11 AM	114.8	27.5	4.2	24.6	62.9	0.52
11-12 PM	130.2	18.1	9	24.7	61.2	0.67
12-1 PM	107.8	28.5	6.7	26.1	56.7	0.77
1-2 PM	147.8	28.1	4.7	27.9	50	0.52
2-3 PM	120.3	19.5	8.3	26.8	52.4	0.22
3-4 PM	118.2	20.7	8.4	26.5	54	0
4-5 PM	108.3	22.9	4.4	25.8	56	0
5-6 PM	92.3	20.4	1.5	25	60	0
6-7 PM	66.7	10.6	0.8	24.5	63	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-2)

Monday (10/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	301.1	13.1	0.7	21.8	63.8	0.08
8-9 AM	199.9	17.7	0.3	23.5	58.1	0.03
9-10 AM	115.6	17	0.7	26.5	48.6	0.84
10-11 AM	160	26.5	1.8	28.5	44	0.94
11-12 PM	195.2	22	3.7	29	41	0.7
12-1 PM	203.7	18.5	4	29.5	38.2	0.87
1-2 PM	212.7	23.2	3.2	30.5	36.6	0.48
2-3 PM	223.2	19.8	3.5	30.3	37	0.23
3-4 PM	236.9	17.7	1.7	30.5	37	0.04
4-5 PM	187.6	4.1	0.1	29.6	38.1	0
5-6 PM	80.5	10.5	1.1	28	43.7	0
6-7 PM	65.8	10.6	0.3	27.5	48.4	0

Tuesday (11/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	280.8	10.7	0.6	23.9	57.3	0.14
8-9 AM	162.1	0.8	0	26.5	52	0.9
9-10 AM	135.1	21.2	4.6	27.2	49	0.69
10-11 AM	132.2	22.7	4	28.7	43	1.24
11-12 PM	128.7	19.8	9.7	30	37	1.48
12-1 PM	122.9	26.2	10.3	30.7	36	1.3
1-2 PM	122.9	22.4	8.5	31.4	35.3	1.03
2-3 PM	130.5	23.6	8.5	31.9	36.1	0.59
3-4 PM	136.5	19.3	7.8	31.4	38	0.16
4-5 PM	120.7	16.1	5.9	30.3	39	0
5-6 PM	69	11.3	1.2	29.2	42	0
6-7 PM	74.5	16	2.2	28.4	44	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-2)

Wednesday (12/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	270	14.3	1	23.6	54.7	0.2
8-9 AM	254.3	20.2	1.8	25.5	49.5	0.64
9-10 AM	337	33.4	1.5	28.5	40.9	0.89
10-11 AM	103.6	27.1	5.4	29.5	36.3	1.63
11-12 PM	134.9	23.9	6	29.8	37.5	1.71
12-1 PM	116.8	31.4	6.6	31.3	28.4	1.69
1-2 PM	117	23.9	8.6	31.9	25.2	1.38
2-3 PM	116	28.2	6.7	32.5	25	0.76
3-4 PM	110.5	21.7	8.7	32.2	26.3	0.26
4-5 PM	157.2	16.2	5.2	30.7	35.6	0
5-6 PM	125.2	13	2.4	29.3	38	0
6-7 PM	70.5	13.4	0.6	28.3	42	0

Thursday (13/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	266.9	21.2	0.7	24.7	56.1	0.23
8-9 AM	220.4	14.8	0.3	28.4	43	0.61
9-10 AM	163.2	13.9	2.2	28.5	45	0.55
10-11 AM	178.5	22.1	2.7	29.2	41.2	0.57
11-12 PM	174.4	23.6	2.6	30.5	41	0.53
12-1 PM	138.2	25.8	5.9	31.5	39.5	1.21
1-2 PM	128	21.7	7.8	32	38	1.03
2-3 PM	110.2	26.4	6.6	32.5	37.9	0.66
3-4 PM	158.3	15.3	4.8	32.4	39	0.15
4-5 PM	167.9	15	3.4	31.2	42.5	0
5-6 PM	166.8	9.9	2.1	30	47	0
6-7 PM	172.5	3.7	0.1	29.5	49	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-2)

Friday (14/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	251.4	18.9	0.9	24	63.3	0.14
8-9 AM	219.7	21.3	1.5	26	55.5	0.55
9-10 AM	204.8	23.5	2.4	27.5	51	1.04
10-11 AM	192	17.8	2.8	29	46	1.37
11-12 PM	186	19.6	3.4	30.2	42.3	1.58
12-1 PM	159.2	27.5	3.3	31.8	38.9	1.42
1-2 PM	172.4	26.4	3	33	33.5	1.02
2-3 PM	136.8	23.6	5.5	33.1	35.3	0.64
3-4 PM	118.4	21.7	5.2	32.8	36	0.26
4-5 PM	163.3	13.9	3.1	32	37.2	0
5-6 PM	126.1	14	2.4	30.5	39.7	0
6-7 PM	129	13.1	1.6	29.8	43	0

Saturday (15/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	293.3	15.2	1.8	24.5	61.4	0.07
8-9 AM	329.1	24	1.1	27.5	50.2	0.56
9-10 AM	244	38.6	1.1	29.8	44.9	0.95
10-11 AM	165.7	30.6	2.5	30	42	1.11
11-12 PM	194.3	26	3.5	31.1	38.8	1.37
12-1 PM	199	19.1	4.2	32	38.9	1.39
1-2 PM	202.9	22.1	3.6	32.7	37.8	1.1
2-3 PM	192	18.7	3.3	33.4	35.1	0.69
3-4 PM	196.1	19.8	2.8	33.9	35.6	0.22
4-5 PM	163.2	13.4	3.8	32.3	38.7	0
5-6 PM	96.2	12	1.2	31	43	0
6-7 PM	20.8	6.7	0.3	29.5	46.6	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-2)

Sunday (9/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	303.4	19.2	3.3	20.7	55	0.15
8-9 AM	310.2	21.4	1.7	24.1	44.3	0.59
9-10 AM	245.6	12.3	3.7	27.5	42	1.25
10-11 AM	242.1	30.5	2.9	27.5	40.9	0.87
11-12 PM	211	22.6	2.5	28.5	39	1.25
12-1 PM	225.6	25.8	3.4	29.5	37	0.92
1-2 PM	211.9	19.5	5	29.5	38.9	0.54
2-3 PM	-	-	-	-	-	-
3-4 PM	220.2	17	4.2	29	43	0.15
4-5 PM	220.9	16	2.3	28.2	43.2	0
5-6 PM	208	10.3	1.4	27.2	46	0
6-7 PM	273	9.2	0	26	49.8	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-3)

Monday (24/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	303.7	18.1	2.8	22.2	61.1	0.11
8-9 AM	292.6	31.3	1.2	25.5	52.3	0.77
9-10 AM	181.5	31.1	2.2	27.1	50.5	1.13
10-11 AM	240.2	35.9	2.9	28.7	44.6	0.92
11-12 PM	193.4	23.8	3.1	29.5	42	0.67
12-1 PM	10.7	34.1	3.1	31	37.6	0.5
1-2 PM	117.1	24.8	5.2	30.8	38.3	0.54
2-3 PM	119.5	24.6	4.3	31.9	35.8	0.76
3-4 PM	137.1	24.1	5	31.3	36.3	0.27
4-5 PM	149.8	15.5	3	30.7	38	0
5-6 PM	137.2	9.6	1	29.4	40.6	0
6-7 PM	255.3	6.8	0.9	28.4	44.8	0

Tuesday (18/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	307.9	11.5	1.4	25.3	63.8	0.06
8-9 AM	293.3	13.1	0.6	27.9	54.5	0.38
9-10 AM	139.6	19.4	5.3	29.7	49.6	0.73
10-11 AM	117.1	21.6	6.3	30.3	46.8	0.98
11-12 PM	138.9	18	8.4	31.5	43.4	1.17
12-1 PM	113.4	23.7	9.2	32	41	1.08
1-2 PM	119.5	22.2	9.8	32.9	39.9	0.83
2-3 PM	109.9	22.3	10.1	33.2	38.8	0.46
3-4 PM	123.3	21.6	7.9	32.6	42.4	0.09
4-5 PM	118.2	16.2	5.5	31.6	44.5	0
5-6 PM	100.4	14.6	2	30.7	47.6	0
6-7 PM	66.8	12.7	0.5	29.7	50	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-3)

Wednesday (19/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	273.5	12.8	0.7	25.7	61	0.09
8-9 AM	286.2	18.7	0.6	28.4	49.6	0.45
9-10 AM	188.3	13.6	2.7	29.7	46.9	0.86
10-11 AM	189.2	23.1	3.8	30.9	45	1.21
11-12 PM	158.3	28.2	3.5	32.2	43.7	1.28
12-1 PM	118.9	28.8	6.3	33.5	42.3	1.03
1-2 PM	158.2	19.7	2.6	33.3	41	0.15
2-3 PM	199.7	19	1.4	33.4	42	0
3-4 PM	312.5	21.2	7.6	29.7	55.7	0
4-5 PM	243	25.8	10.3	25.9	69.7	0
5-6 PM	276	20.9	11.6	24.5	72.9	0
6-7 PM	248.6	19.2	4	23.9	74.7	0

Thursday (20/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	308.9	24.3	1.6	22.4	72.9	0.31
8-9 AM	299.9	30.3	1.2	25.5	60.9	0.8
9-10 AM	318.7	33.8	2.7	27.5	55.1	1.27
10-11 AM	256.6	33	2.9	29	50.2	1.53
11-12 PM	192.2	17.8	4.2	28.5	50.2	1.73
12-1 PM	216.5	23.3	4.8	29.5	47	1.62
1-2 PM	263.1	24.1	5.8	30.3	46	1.28
2-3 PM	203	22.6	2.7	31.5	42	0.81
3-4 PM	151.6	21.6	3.2	31.5	40.1	0.3
4-5 PM	170.9	14	2.1	30.9	40	0
5-6 PM	234.1	12.7	1.5	29.5	42	0
6-7 PM	326.5	23.1	4.6	28.3	51.4	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-3)

Friday (21/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	291.3	19.3	6.1	23.1	72	0.26
8-9 AM	235.8	24.2	11.2	24.3	65.2	0.71
9-10 AM	241.5	23.3	12.2	25.7	57.3	1.2
10-11 AM	242.1	20.4	15.6	26.7	51.4	1.58
11-12 PM	225.9	22	16.5	27.6	50.2	1.8
12-1 PM	233.8	22.1	14	28.6	46.8	1.65
1-2 PM	231	21.2	12.3	29.6	43.8	1.36
2-3 PM	229.5	21.8	14.5	29.7	44	0.89
3-4 PM	228.5	22.5	14.1	29.5	44.9	0
4-5 PM	235.2	21	12.9	28.5	46	0
5-6 PM	248.5	19.1	7.9	27.5	48	0
6-7 PM	297	16.1	5.3	27	48	0

Saturday (22/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	313.1	27	6.8	22.7	61.8	0.36
8-9 AM	325.1	24.5	3	25.7	52	0.85
9-10 AM	266.4	31.1	4.5	28.6	41.9	1.31
10-11 AM	234.6	21.3	15.4	28.9	39.5	1.68
11-12 PM	231.6	19.7	17.9	29	39.3	1.74
12-1 PM	219.8	22.2	10.4	30.3	36.9	1.6
1-2 PM	208.8	22.4	6.4	31.1	30.6	1.3
2-3 PM	191.8	28	4.2	32.9	31	0.85
3-4 PM	199.1	15.3	2.9	32.3	31	0.29
4-5 PM	224.4	18.3	6.1	30.9	34	0
5-6 PM	245	15	2.8	29.5	38	0
6-7 PM	299.6	14.2	1.9	28.9	40	0

APPENDIX-III (continued)
METEOROLOGICAL DATA
(Week-3)

Sunday (23/3/2014)

Time	Wind direction (deg)	Wind direction (standard deviation)	Wind speed (Km/hr)	Tempe-rature (Celsius)	Humidity (%)	Solar Radiation (CCM)
7-8 AM	129	26.7	0.5	23.6	62.3	0.17
8-9 AM	283.3	25	2.1	26.2	52.6	0.72
9-10 AM	227.5	22.3	4.5	26.8	52	1.19
10-11 AM	248.9	37.4	4.2	28	46.3	1.53
11-12 PM	254.5	35.3	5.9	30.3	36.9	1.15
12-1 PM	205.9	21.3	6.4	30.3	34.8	0.52
1-2 PM	-	-	-	-	-	-
2-3 PM	49.2	28.1	11.1	23.9	53.5	0.13
3-4 PM	310.7	26.5	9	25.1	49	0
4-5 PM	-	-	-	-	-	-
5-6 PM	286.3	16.7	0.9	24.5	50	0
6-7 PM	297.9	20.8	1.7	24.3	52.5	0

APPENDIX-IV

Hourly traffic volume

Monday (3/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	611	281	1407	217	2516
8-9 AM	1277	341	1693	244	3555
9-10 AM	3292	627	2603	255	6777
10-11 AM	5212	864	3065	227	9368
11-12 PM	5434	964	3101	225	9724
12-1 PM	5010	943	3188	219	9360
1-2 PM	4938	876	2756	271	8841
2-3 PM	4215	706	2685	301	7907
3-4 PM	3985	715	2780	326	7806
4-5 PM	4165	806	2820	328	8119
5-6 PM	5224	850	3064	254	9392
6-7 PM	5434	963	2659	256	9312

Tuesday (4/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	767	291	1274	239	2571
8-9 AM	1740	445	1965	259	4409
9-10 AM	3920	801	3306	308	8335
10-11 AM	4896	959	3066	286	9207
11-12 PM	4095	840	2692	194	7791
12-1 PM	4091	774	2581	238	7684
1-2 PM	4330	807	2785	226	8138
2-3 PM	3768	739	2665	247	7419
3-4 PM	3516	639	2505	224	6884
4-5 PM	3660	668	2480	206	7014
5-6 PM	4678	826	2881	209	8592
6-7 PM	4896	850	2944	203	8891

APPENDIX-IV (continued)
Hourly traffic volume

Wednesday (5/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	658	319	1493	229	2699
8-9 AM	1399	366	1762	251	3778
9-10 AM	3535	689	2853	272	7349
10-11 AM	5340	1003	3175	256	9814
11-12 PM	5142	880	2994	257	9273
12-1 PM	4128	745	2680	268	7821
1-2 PM	4125	718	2603	270	7716
2-3 PM	4106	681	2853	285	7925
3-4 PM	4321	786	2847	236	8190
4-5 PM	4170	738	2622	246	7776
5-6 PM	5367	881	3112	262	9624
6-7 PM	5142	870	2997	263	9272

Thursday (6/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	685	204	1023	221	2133
8-9 AM	1537	347	1688	250	3822
9-10 AM	3976	607	2729	290	7602
10-11 AM	4964	821	2957	396	9138
11-12 PM	4953	932	2619	232	8736
12-1 PM	5779	1023	2854	245	9901
1-2 PM	4488	767	2746	253	8254
2-3 PM	4398	756	2649	239	8042
3-4 PM	4221	746	2649	236	7852
4-5 PM	4116	698	2667	240	7721
5-6 PM	4964	953	2947	396	9260
6-7 PM	4953	942	2618	234	8747

APPENDIX-IV (continued)
Hourly traffic volume

Friday (7/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	881	296	1628	229	3034
8-9 AM	1876	438	2057	258	4629
9-10 AM	4047	694	2733	287	7761
10-11 AM	5027	886	3023	379	9315
11-12 PM	5995	656	3230	297	10178
12-1 PM	5470	983	2839	247	9539
1-2 PM	5160	898	2935	254	9247
2-3 PM	5060	868	2801	231	8960
3-4 PM	4683	834	2818	272	8607
4-5 PM	4458	783	2792	236	8269
5-6 PM	5046	865	2965	379	9255
6-7 PM	5135	901	3025	347	9408

Saturday (8/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	628	355	1044	225	2252
8-9 AM	1279	499	1509	270	3557
9-10 AM	2808	694	2121	305	5928
10-11 AM	3791	932	2366	300	7389
11-12 PM	5062	1198	2938	213	9411
12-1 PM	5074	928	2936	207	9145
1-2 PM	3331	952	2332	242	6857
2-3 PM	2966	812	2356	226	6360
3-4 PM	2843	806	2359	214	6222
4-5 PM	2672	793	2238	218	5921
5-6 PM	4004	1012	2812	207	8035
6-7 PM	4178	1051	2919	201	8349

APPENDIX-IV (continued)
Hourly traffic volume

Sunday (2/3/2014)

Time	2WH (Motorcycle, mopeds and scooters)	3WH (Auto-rickshaw)	PC-MUV (Cars, Van, Jeep)	LHCV (minibus, urban bus, truck)	Total (Composite traffic)
7-8 AM	511	240	918	125	1794
8-9 AM	892	259	1289	171	2611
9-10 AM	1345	360	1790	214	3709
10-11 AM	1929	534	2345	219	5027
11-12 PM	2281	698	2567	194	5740
12-1 PM	2183	586	2388	185	5342
1-2 PM	1902	473	2200	141	4716
2-3 PM	1745	422	2040	167	4367
3-4 PM	1711	457	1959	162	4289
4-5 PM	1861	433	2039	161	4494
5-6 PM	2292	550	2457	166	5475
6-7 PM	2412	569	2560	165	5706

APPENDIX-V (Probability of Time-Spent) Shopkeeper

Sl no.	GENDER	Age (yrs)	Height (cm)	Weight (kg)	Daily time of arrival at workplace	Daily time of departure from workplace	Time spent during (7am-7pm) (hr)	Time spent per week (hr)	Probability of daily time-spent, *P(T)*
1	M	21	165	55	9:00 AM	10:00 PM	10	60	**0.83**
2	M	48	160	52	9:00 AM	10:00 PM	10	60	**0.83**
3	M	21	157	50	9:00 AM	10:00 PM	10	60	**0.83**
4	M	29	170	65	7:00 AM	3:00 PM	8	48	**0.67**
5	M	21	155	51	10:00 AM	9:00 PM	9	54	**0.75**
6	M	37	168	57	9:00 AM	10:00 PM	10	60	**0.83**
7	M	61	168	72	7:00 AM	8:00 PM	12	72	**1.00**
8	M	36	170	65	7:00 AM	5:00 PM	10	60	**0.83**
9	M	41	170	61	9:00 AM	8:00 PM	10	60	**0.83**
10	F	22	157	41	10:30 AM	7:30 PM	9	54	**0.75**
11	F	21	168	45	11:00 AM	7:00 PM	8	48	**0.67**
12	M	21	170	51	9:00 AM	5:00 PM	8	48	**0.67**
13	M	22	160	50	11:30 AM	7:30 PM	8	48	**0.67**
14	F	22	155	51	10:00 AM	7:00 PM	9	54	**0.75**
15	F	25	165	55	10:00 AM	7:00 PM	9	54	**0.75**
16	M	25	168	59	11:30 AM	8:30 PM	8	48	**0.67**
17	M	24	163	53	2:00 PM	10:00 PM	5	30	**0.42**
18	M	28	170	75	12:00 PM	9:00 PM	7	42	**0.58**
19	M	27	157	53	12:00 PM	9:00 PM	7	42	**0.58**
20	F	21	157	48	10:30 AM	7:30 PM	9	54	**0.75**
21	F	24	163	45	10:30 AM	7:30 PM	9	54	**0.75**
22	M	19	168	49	11:45 AM	9:00 PM	8	48	**0.67**
23	M	25	175	58	10:00 AM	8:00 PM	9	54	**0.75**
24	F	22	160	56	9:30 AM	7:30 PM	10	60	**0.83**
25	M	19	152	48	10:00 AM	10:00 PM	9	54	**0.75**
26	M	23	183	60	10:00 AM	10:00 PM	9	54	**0.75**
27	M	30	155	50	10:00 AM	10:00 PM	9	54	**0.75**
28	M	32	157	60	9:30 AM	5:30 PM	8	48	**0.67**
29	M	55	173	62	8:00 AM	8:00 PM	11	66	**0.92**
30	M	24	152	55	8:00 AM	6:00 PM	10	60	**0.83**
31	M	20	160	57	10:00 AM	8:00 PM	9	54	**0.75**
32	M	25	165	58	9:45 AM	8:00 PM	10	60	**0.83**
33	M	25	168	70	9:00 AM	10:00 PM	10	60	**0.83**
34	F	39	152	45	9:00 AM	2:00 PM	5	30	**0.42**
35	M	29	160	50	10:00 AM	6:00 PM	8	48	**0.67**
36	M	26	157	53	10:00 AM	11:00 PM	9	54	**0.75**
37	M	30	165	75	11:00 AM	10:00 PM	8	48	**0.67**
38	M	49	157	45	7:00 AM	9:00 PM	12	72	**1.00**
39	M	36	172	67	9:50 AM	9:00 PM	10	60	**0.83**
40	M	22	172	65	9.00 AM	8:00 PM	10	60	**0.83**
41	M	20	155	50	11:00 AM	8:00 PM	8	48	**0.67**
42	M	27	157	55	9:00 AM	6:00 PM	9	54	**0.75**
43	M	30	157	59	10:00 AM	8:00 PM	9	54	**0.75**
44	M	60	157	60	10:00 AM	8:00 PM	9	54	**0.75**
45	M	25	160	49	10:00 AM	9:00 PM	9	54	**0.75**
46	M	32	185	78	9:30 AM	10:30 PM	10	60	**0.83**
47	M	24	157	55	10:30 AM	7:30 PM	9	54	**0.75**
48	M	26	155	68	10:30 AM	8:30 PM	9	54	**0.75**
49	M	39	160	49	10:00 AM	9:00 PM	9	54	**0.75**
50	M	36	168	62	9:30 AM	7:30 PM	10	60	**0.83**
51	M	45	170	61	9:00 AM	9:00 PM	10	60	**0.83**
52	M	39	155	69	9.00 AM	11:00 PM	10	60	**0.83**

APPENDIX-VI (Probability of Exceedance >3.5 ppm) Shopkeepers Location

SL No.	GENDER	Age (Yrs)	Height (CM)	Weight (KG)	Central distance of location from Point-A (Meter)	Distance of location from central line (left side) (Meter)	Distance of location from central line (right side) (Meter)	Probability of exceedance, P(>3.5 ppm)
1	M	21	165	55	0	10	0	**0.04**
2	M	48	160	52	0	10	0	**0.04**
3	M	21	157	50	0	10	0	**0.04**
4	M	37	168	57	20	10	0	**0.03**
5	M	61	168	72	30	10	0	**0.03**
6	M	29	170	65	0	10	0	**0.04**
7	M	21	155	51	0	10	0	**0.04**
8	M	41	170	61	40	10	0	**0.03**
9	M	25	175	58	60	10	0	**0.03**
10	F	22	157	41	40	20	0	**0.03**
11	F	21	168	45	40	20	0	**0.03**
12	M	19	152	48	110	20	0	**0.03**
13	M	32	157	60	120	20	0	**0.03**
14	M	23	183	60	110	20	0	**0.03**
15	M	32	185	78	280	20	0	**0.03**
16	M	24	157	55	280	20	0	**0.03**
17	M	26	155	68	280	20	0	**0.03**
18	M	39	155	69	340	10	0	**0.03**
19	M	29	160	50	210	10	0	**0.03**
20	M	36	172	67	230	10	0	**0.03**
21	M	22	172	65	230	10	0	**0.03**
22	F	25	157	46	220	10	0	**0.03**
23	M	25	160	49	260	10	0	**0.03**
24	M	39	160	49	280	10	0	**0.03**
25	M	36	168	62	300	10	0	**0.03**
26	M	36	170	65	30	5	0	**0.03**
27	M	21	170	51	40	0	20	**0.04**
28	M	22	160	50	40	0	20	**0.04**
29	F	22	155	51	40	0	20	**0.04**
30	F	25	165	55	40	0	20	**0.04**
31	M	25	168	59	40	0	20	**0.04**
32	M	24	163	53	40	0	20	**0.04**
33	M	28	170	75	40	0	20	**0.04**
34	M	27	157	53	40	0	20	**0.04**
35	M	55	173	62	130	0	20	**0.04**
36	F	21	157	48	40	0	20	**0.04**
37	F	24	163	45	40	0	20	**0.04**
38	M	19	168	49	40	0	20	**0.04**
39	F	22	160	56	100	0	20	**0.04**
40	M	20	160	57	150	0	20	**0.03**
41	M	25	165	58	150	0	20	**0.03**
42	M	45	170	61	310	0	10	**0.03**
43	M	27	157	55	250	0	20	**0.03**
44	M	30	157	59	250	0	10	**0.04**
45	M	49	157	45	220	0	20	**0.04**
46	F	39	152	45	170	0	10	**0.04**
47	M	60	157	60	250	0	20	**0.04**
48	M	30	155	50	110	0	10	**0.04**
49	M	25	168	70	160	0	10	**0.04**
50	M	24	152	55	140	0	10	**0.04**
51	M	20	155	50	240	0	20	**0.03**
52	M	26	157	53	210	0	20	**0.03**

APPENDIX-VII (Probability of Exposure >3.5 ppm) Shopkeepers

Sl no.	GENDER	Age (yrs)	Height (cm)	Weight (kg)	Central distance of location from point-A (meter)	Distance of location from central line (left side) (meter)	Distance of location from central line (right side) (meter)	Probability of exceedance, P(>3.5 ppm)
1	M	21	165	55	30	0	10	**0.04**
2	M	48	160	52	30	0	10	**0.04**
3	M	21	157	50	30	0	10	**0.04**
4	M	29	170	65	30	0	10	**0.04**
5	M	21	155	51	30	0	10	**0.04**
6	M	37	168	57	30	0	10	**0.03**
7	M	61	168	72	30	0	10	**0.03**
8	M	36	170	65	30	0	10	**0.03**
9	M	41	170	61	40	20	00	**0.03**
10	F	22	157	41	40	0	20	**0.03**
11	F	21	168	45	40	0	20	**0.03**
12	M	21	170	51	40	0	20	**0.04**
13	M	22	160	50	40	0	20	**0.04**
14	F	22	155	51	40	0	20	**0.04**
15	F	25	165	55	40	0	20	**0.04**
16	M	25	168	59	40	0	20	**0.04**
17	M	24	163	53	40	0	20	**0.04**
18	M	28	170	75	40	0	20	**0.04**
19	M	27	157	53	40	0	20	**0.04**
20	F	21	157	48	40	0	20	**0.04**
21	F	24	163	45	40	0	20	**0.04**
22	M	19	168	49	40	0	20	**0.04**
23	M	25	175	58	60	10	0	**0.03**
24	F	22	160	56	100	0	20	**0.04**
25	M	19	152	48	110	20	0	**0.03**
26	M	23	183	60	110	20	0	**0.03**
27	M	30	155	50	110	0	10	**0.04**
28	M	32	157	60	120	20	0	**0.03**
29	M	55	173	62	130	0	20	**0.04**
30	M	24	152	55	140	0	10	**0.04**
31	M	20	160	57	150	0	20	**0.03**
32	M	25	165	58	150	0	20	**0.03**
33	M	25	168	70	160	0	10	**0.04**
34	F	39	152	45	170	0	10	**0.04**
35	M	29	160	50	210	10	0	**0.03**
36	M	26	157	53	210	0	20	**0.03**
37	M	30	165	75	220	0	10	**0.03**
38	M	49	157	45	230	0	20	**0.04**
39	M	36	172	67	230	10	0	**0.03**
40	M	22	172	65	230	10	0	**0.03**
41	M	20	155	50	240	0	20	**0.03**
42	M	27	157	55	250	0	20	**0.03**
43	M	30	157	59	250	0	10	**0.04**
44	M	60	157	60	250	0	20	**0.04**
45	M	25	160	49	260	10	0	**0.03**
46	M	32	185	78	280	20	0	**0.03**
47	M	24	157	55	280	20	0	**0.03**
48	M	26	155	68	280	20	0	**0.03**
49	M	39	160	49	280	10	0	**0.03**
50	M	36	168	62	300	10	0	**0.03**
51	M	45	170	61	310	0	10	**0.03**
52	M	39	155	69	340	10	0	**0.03**

APPENDIX-VIII (Personal Monitoring Data)

Table: Observed CO concentration experience by shopkeeper near location 1

	MON	TUE	WED	THURS	FRI	SAT
7-8 am	0.23	0.34	0.17	0.04	0.00	0.08
8-9 am	0.25	0.21	0.04	0.01	0.15	0.08
9-10 am	1.06	0.63	0.01	0.24	0.22	0.50
10-11 am	0.44	0.92	0.10	0.07	0.41	0.37
11-12 am	0.20	0.91	0.17	0.07	0.29	1.01
12-13 pm	0.28	1.81	1.02	0.53	0.36	3.59
13-14 pm	0.12	2.91	1.75	0.79	0.68	4.36
14-15 pm	0.05	2.49	0.53	0.72	0.37	2.65
15-16 pm	0.04	1.04	0.18	0.10	0.12	1.09
16-17 pm	0.08	0.55	0.29	0.37	0.21	1.57
17-18 pm	1.08	0.43	0.48	0.63	1.37	0.44
18-19 pm	0.45	0.75	0.17	2.38	0.50	0.15

Table: Observed CO concentration experience by shopkeeper near location 2

	MON	TUE	WED	THURS	FRI	SAT
11-12 am	1.07	1.25	0.53	1.73	0.92	1.61
12-13 pm	4.45	1.35	1.58	2.18	0.98	1.57
13-14 pm	3.00	0.03	1.88	1.45	1.66	0.24
14-15 pm	1.67	0.09	1.61	0.92	0.96	2.75
15-16 pm	1.11	0.36	0.92	0.83	1.25	2.46
16-17 pm	0.42	1.28	1.33	0.94	1.20	1.55
17-18 pm	0.13	0.11	0.86	1.23	1.12	1.38
18-19 pm	0.45	0.75	0.90	2.38	0.50	1.64

Table: Observed CO concentration experience by shopkeeper near location 3

	MON	TUE	WED	THURS	FRI	SAT
9-10 am	0.16	0.07	0.14	0.16	0.49	0.19
10-11 am	0.19	0.09	0.32	0.28	0.66	0.57
11-12 am	0.22	0.01	0.41	0.18	0.65	0.47
12-13 pm	0.12	0.07	0.18	0.66	0.83	0.61
13-14 pm	0.13	0.03	0.25	0.43	0.97	0.33
14-15 pm	0.04	0.00	0.15	0.21	0.78	0.35
15-16 pm	0.12	0.08	0.36	0.11	0.69	0.12
16-17 pm	0.06	0.01	0.57	0.00	0.57	0.51
17-18 pm	0.10	1.00	0.31	1.67	1.02	0.52
18-19 pm	0.41	0.89	0.28	3.61	1.41	0.64

APPENDIX-VIII (A) (Observed probability of exposure at L1)
Ranked-Ordered concentrations of personal monitoring at location 1

Rank	Rank-ordered data (ppm)	Probability of exposure above each value (m/n+1)*	Rank	Rank-ordered observed concentration (ppm)	Probability of exposure above each value (m/n+1)*
1	4.36	0.01	43	0.28	0.59
2	3.59	0.03	44	0.25	0.60
3	2.91	0.04	45	0.24	0.62
4	2.65	0.05	46	0.23	0.63
5	2.49	0.07	47	0.22	0.64
6	2.38	0.08	48	0.21	0.66
7	1.81	0.10	49	0.21	0.67
8	1.75	0.11	50	0.20	0.68
9	1.57	0.12	51	0.18	0.70
10	1.37	0.14	52	0.17	0.71
11	1.09	0.15	53	0.17	0.73
12	1.08	0.16	54	0.17	0.74
13	1.06	0.18	55	0.15	0.75
14	1.04	0.19	56	0.15	0.77
15	1.02	0.21	57	0.12	0.78
16	1.01	0.22	58	0.12	0.79
17	0.92	0.23	59	0.10	0.81
18	0.91	0.25	60	0.10	0.82
19	0.79	0.26	61	0.08	0.84
20	0.75	0.27	62	0.08	0.85
21	0.72	0.29	63	0.08	0.86
22	0.68	0.30	64	0.07	0.88
23	0.63	0.32	65	0.07	0.89
24	0.63	0.33	66	0.05	0.90
25	0.55	0.34	67	0.04	0.92
26	0.53	0.36	68	0.04	0.93
27	0.53	0.37	69	0.04	0.95
28	0.50	0.38	70	0.01	0.96
29	0.50	0.40	71	0.01	0.97
30	0.48	0.41	72	0.00	0.99
31	0.45	0.42			
32	0.44	0.44			
33	0.44	0.45			
34	0.43	0.47			
35	0.41	0.48			
36	0.37	0.49			
37	0.37	0.51			
38	0.37	0.52			
39	0.36	0.53			
40	0.34	0.55			
41	0.29	0.56			
42	0.29	0.58			

Mean = 0.68 ppm
Standard deviation = 0.86 ppm
Skewness Coefficient = 2.36

$P(E_0) = 0.03$

* m = Rank of individual data point. n = Total number of points (n = 72 in this table)

APPENDIX-VIII (B) (Observed probability of exposure at L2)

Ranked-Ordered concentrations of personal monitoring at location 2

Rank	Rank-ordered data (ppm)	Probability of exposure above each value (m/n+1)*	Rank	Rank-ordered observed concentration (ppm)	Probability of exposure above each value (m/n+1)*
1	4.75	0.02	43	0.04	0.88
2	2.48	0.04	44	0.02	0.90
3	1.70	0.06	45	0.01	0.92
4	1.60	0.08	46	0.01	0.94
5	1.34	0.10	47	0.00	0.96
6	1.07	0.12	48	0.00	0.98
7	0.90	0.14			
8	0.88	0.16			
9	0.81	0.18			
10	0.56	0.20			
11	0.54	0.22			
12	0.53	0.24			
13	0.47	0.27			
14	0.47	0.29			
15	0.47	0.31			
16	0.44	0.33			
17	0.42	0.35			
18	0.38	0.37			
19	0.36	0.39			
20	0.34	0.41			
21	0.31	0.43			
22	0.31	0.45			
23	0.29	0.47			
24	0.28	0.49			
25	0.27	0.51			
26	0.24	0.53			
27	0.18	0.55			
28	0.18	0.57			
29	0.17	0.59			
30	0.17	0.61			
31	0.16	0.63			
32	0.15	0.65			
33	0.12	0.67			
34	0.12	0.69			
35	0.11	0.71			
36	0.11	0.73			
37	0.11	0.76			
38	0.10	0.78			
39	0.07	0.80			
40	0.06	0.82			
41	0.04	0.84			
42	0.04	0.86			

Mean = 1.26 ppm
Standard deviation = 0.82 ppm
Skewness Coefficient = 1.38

$P(E_0) = 0.02$

* m = Rank of individual data point. n = Total number of points (n = 48 in this table)

APPENDIX-VIII (C) (Observed probability of exposure at L3)
Ranked-Ordered concentrations of personal monitoring at location 3

Rank	Rank-ordered data (ppm)	Probability of exposure above each value (m/n+1)*	Rank	Rank-ordered observed concentration (ppm)	Probability of exposure above each value (m/n+1)*
1	3.61	0.02	43	0.14	0.70
2	1.67	0.03	44	0.13	0.72
3	1.41	0.05	45	0.12	0.74
4	1.02	0.07	46	0.12	0.75
5	1.00	0.08	47	0.12	0.77
6	0.97	0.10	48	0.11	0.79
7	0.89	0.11	49	0.1	0.80
8	0.83	0.13	50	0.09	0.82
9	0.78	0.15	51	0.08	0.84
10	0.69	0.16	52	0.07	0.85
11	0.66	0.18	53	0.07	0.87
12	0.66	0.20	54	0.06	0.89
13	0.65	0.21	55	0.04	0.90
14	0.64	0.23	56	0.03	0.92
15	0.61	0.25	57	0.01	0.93
16	0.57	0.26	58	0.01	0.95
17	0.57	0.28	59	0.00	0.97
18	0.57	0.30	60	0.00	0.98
19	0.52	0.31			
20	0.51	0.33			
21	0.49	0.34			
22	0.47	0.36			
23	0.43	0.38			
24	0.41	0.39			
25	0.41	0.41			
26	0.36	0.43			
27	0.35	0.44			
28	0.33	0.46			
29	0.32	0.48			
30	0.31	0.49			
31	0.28	0.51			
32	0.28	0.52			
33	0.25	0.54			
34	0.22	0.56			
35	0.21	0.57			
36	0.19	0.59			
37	0.19	0.61			
38	0.18	0.62			
39	0.18	0.64			
40	0.16	0.66			
41	0.16	0.67			
42	0.15	0.69			

Mean = 0.49 ppm
Standard deviation = 0.76 ppm
Skewness Coefficient = 3.65

$P(E_0>3.5ppm)$ = 0.02

* m = Rank of individual data point. n = Total number of points (n = 60 in this table)

APPENDIX IX

STATISTICAL MEASURES

Generally, model evaluation are carried out with the statistical measures such as Pearson correlation coefficient (*r*), normalized mean square error (*NMSE*), fractional bias (*FB*), fractional variance (*FV*) and the index of agreement (*d*). These statistical measures are further explained in details. The observed and estimated concentrations is denoted by O_c and P_c, and standard deviation by σ. The bar over the notation represents the average value.

The *r* is defined by equation 1. The numerical value of *r* ranges from 1 to -1, i.e.1 ≤ *r* ≤ -1 where ±1 represents perfect correlation and 0 represents no correlation between estimated and observed concentrations.

$$r = \frac{\overline{(O_c - \overline{O_c})(P_c - \overline{P_c})}}{\sigma_{O_c} . \sigma_{P_c}} \tag{1}$$

where, O_c, P_c represents observed and estimated concentration (ppm), $\overline{O_c}$, $\overline{P_c}$ the average observed and estimated concentration (ppm) ; and σ_{O_c}, σ_{P_c} the standard deviation of observed and estimated concentration (ppm), respectively.

The *NMSE* estimates the overall deviation of estimated concentration from observed concentration. Its value ranges from 0 to ∞, where 0 represents prefect agreement between estimated and observed concentrations. The larger the values of *NMSE* the more is the deviation. It is defined by equation 2.

$$NMSE = \frac{\overline{(P_c - O_c)^2}}{\overline{P_c . O_c}} \tag{2}$$

The *FB* is a measure of correlation between average of estimated concentrations and average of observed concentrations. Its value ranges from -2 to +2 (i.e. -2≤*FB*≤2). The value of -2 indicates extremes under-prediction of average values where +2 indicate over-prediction. The value equal to 0 indicates the prefect agreement between estimated and observed concentrations. It is defined by equation 3.

$$FB = 2\frac{\overline{P_c}-\overline{O_c}}{\overline{P_c}+\overline{O_c}} \tag{3}$$

The *FV* is a measure of correlation between variance of estimated concentrations and variance of observed concentrations. The value ranges from -2 to +2, where -2 indicate extreme under-prediction of variance and +2 indicates extreme over-prediction. *FV* value of 0 indicates the perfect agreement. *FV* is defined by equation 4.

$$FV = 2\frac{\sigma_{P_c}-\sigma_{O_c}}{\sigma_{P_c}+\sigma_{O_c}} \tag{4}$$

The *d* is the most preferred statistical measures in air quality and is used quite often. It determines the magnitude of agreement between the estimated and observed values taking into account the sensitivity of differences between the values. The value of d has a range of $0 \leq d \leq 1$, where value of 1 represents prefect agreement between predicted and observed concentrations, and 0 indicates complete disagreements between the values. It is defined by equation 5.

$$d = 1 - \frac{\sum(P_c-O_c)^2}{\sum\{|P_c-\overline{O_c}|+|O_c-\overline{O_c}|\}^2} \tag{5}$$

PUBLICATIONS FROM THE RESEARCH

Refereed International Journals:

I. Published

Singh, N.P., Gokhale, S. (2015) A method to estimate spatiotemporal air quality in an urban traffic corridor. *Science of The Total Environment* 538, 458-467.

II. Communicated

Singh, N.P., Gokhale, S. Human exposure to air pollutants in urban traffic corridor – a review of quantification methods and approaches. *Chemosphere*.

Singh, N.P., Choudhary, A., Sahu, M., Gokhale, S. On-road emission factors in urban traffic corridor and prediction of spatiotemporal air quality. *Urban Climate*.

Conference:

Singh, N. P. and Gokhale, S. (2015) Estimation of emission source reduction using best-fit statistical distribution of measured pollutants within an urban traffic corridor. *National Conference on Challenges in Environmental Research, Indian Institute of Technology Guwahati,* June 2015, India.