

MODELING OF CARBON MONOXIDE CONCENTRATIONS AT URBAN SIGNALIZED INTERSECTIONS USING MULTIPLE LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORKS

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Abstract

Increase in the use of personnel vehicles is evidently decreasing the quality of air in recent days. Pollutants released from vehicles are the major source for air pollution in urban cities. Carbon Monoxide (CO) is one of the dominant pollutants emitted from the transportation which affect the environment unfavorably. The present study attempts to determine the impact of traffic flow parameters such as approach volume (ATV), red time length (RT), cycle time length (CT), average vehicle count stopping during the red time length (AVCR) on Carbon Monoxide Concentrations (COC) at signalized intersections (SI) with a symbolic case study of Tirupathi and Warangal cities of India. The study proposes two models in order to predict CO at SI using Multiple Linear Regression (MLR) and Artificial Neural Networks (ANN) methods. It has been seen that the CO levels would range in between 12-35 ppm at signalized intersections. The linear increase in COC with increase of RT, CT, ATV, and AVCR was observed due to the changes in acceleration and deceleration of the vehicles at the intersections. The models validation illustrates that the estimated COC are constantly following the observed COC under the same sets of traffic and roadway conditions. The results of the study depicted that ANN model had performed well than MLR model in predicting the CO values with an MAPE value of 0.09%. The results recommend Pollution Control Board (PCB) officials and traffic control authorities to implement necessary actions for improving the air quality within city under consideration.

Keywords: Vehicles, Carbon Monoxide, traffic dynamics, signalized intersections, MLR, ANN

Introduction

Infrastructure like roads and highways are the significant source for economic and social development of a country. However, incremental and unchecked development may lead to innumerable environmental and economic losses. In many urban cities of developing countries like India,

Air pollution is damaging the environment continuously. Road traffic emissions are one of the major sources of air pollution in urban areas. Carbon Monoxide (CO) is the major pollutant emitted by motor vehicles when hydrocarbon fuels (natural gas, petrol, and diesel) are burned.

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The composition of air in any urban roadway network comprises of different types of hazardous gasses such as Carbon Monoxide (CO), Nitrogen oxides (NO_x), Hydro Carbons (HC) and Particulate Matter (PM). Due to increasing demand for transportation, reducing traffic emissions remains as a great challenge to the urban planners and policy makers. Zhu *et al.* (2002) indicated in a study that, air pollutant concentrations adjacent to the major traffic routes are significantly higher than the regional background levels which endangers nearby populations and disproportionately exposes them to traffic related air pollution. In most developing countries of the world, vehicular growth has not been checked properly by environmental regulating authorities leading to increasing levels of pollution. In this context, there is a need to study of the impact of vehicles growth on air quality in the cities. Pandian *et al.* (2009) and Zito (2009) stated that the amount of pollution released by transportation is much higher at signalized intersections rather than the other locations because of the changes in the vehicle speeds at the intersections. The objective of this study is to develop models to estimate and predict the Carbon Monoxide (CO) concentration released by vehicles at signalized intersections. The study also aims to compare the results obtained from MLR and ANN models adopted in the study.

Literature Review

Many studies indicated that, CO is emitted due to incomplete fuel combustion in motor vehicles and therefore it has been used as an important indicator contributing to air pollution (Law *et al.*, 1997; Comrie and Diem, 1999). In most of the studies related to traffic pollution modeling, the pollutant CO has been the focus of research (Moseholm *et al.*, 1996; Bogo *et al.*, 1999). Many studies indicated that, in urban areas, motor vehicles contribute over 90% of the CO emission (Hassan *et al.*, 2000; Schitfater *et al.*, 2003). Traffic emissions contribute about 50-80% of NO₂ and CO concentration in developing countries (Fu *et al.*, 2001; Goyal *et al.*, 2006).

Christopher *et al.* (2001) stated that, tail pipe gas emissions such as Carbon Monoxide (CO), Nitric Oxide (NO), Hydrocarbons (HC), and Carbon Dioxide (CO₂) are generally measured using a portable instrument OEM-2100TM on a second-by-second basis during actual driving of several light duty gasoline vehicles. Emissions during idling of vehicles are generally low compared to emissions during acceleration of vehicles. Kyoungcho *et al.* (2002) has developed a mathematical model to

predict vehicular fuel consumption and emission based on instantaneous speed and average acceleration. Tippichai *et al.* (2005) used site characteristics, traffic, meteorological data and emission data collected at three signalized intersections in Khon Kaen province as inputs for CAL3QHC model to predict CO concentrations. Potoglou and Kanaroglou (2005) estimated the vehicle-generated Carbon Monoxide Concentration using an urban model designed to simulate land-use and transportation interactions at the link level of urban transport network. Anjaneyulu *et al.* (2008) carried out a study to evaluate the Carbon Monoxide concentrations on selected links in Calicut city by using CALINE 4 model, (Indian Institute of Technology Line Source (IITLS), 2017) model and regression models. The association between traffic flow, type of vehicle, traffic stream speed and CO concentrations was also evaluated. Coelho *et al.* (2005) indicated that the air pollution released from traffic at signalized intersections is much higher because of the high traffic dynamics near the intersections. The study concluded that regression model performs better than CALINE 4 and IITLS models. Wee and Ling (2014) used CAL3QHC dispersion model to predict the present and future CO levels at a busy signalized intersection in Malaysia. This study identified CO concentration hot-spots during typical peak hours. Elkafoury *et al.* (2015) identified the relationship between time headway and Carbon Monoxide emission factors by conducting traffic characteristics field measurements on road link at the entrance of a city in Egypt. An instantaneous vehicular emission model VT-Micro was utilized to calculate CO emissions of passenger cars and heavy vehicle in different traffic situations. Ratanavaraha and Jomnonkwa (2015) tried to identify the amount of Carbon Dioxide (CO₂) emitted from transportation in Thailand. Population, Gross Domestic Product (GDP), number of different sized registered vehicles was the influencing factors considered in the study. The results of the study indicated that the factors considered have significant effect on CO₂ emission. The study was helpful in bringing out policies for reducing GHG emissions and its impacts. Alhindwai *et al.* (2016) developed a multivariate regression model using the ratio between vehicle-kilometers and number of transportation vehicles for six vehicle types in US such as light trucks, single-unit trucks, tractor and bus for forecasting the Green House Gas (GHG) emissions for road sector. This study illustrated the entire ratio between vehicle-kilometers and number of transportation vehicle for different vehicle types are having significant effect on GHG emission. Masood *et al.* (2017) modeled the CO emissions emanating from Mathura road

using CALINE4 model. A set of emission factors employing simplified vehicle classification methodology was utilized. A fair agreement has been observed between the predicted CO concentrations and actual monitored CO concentrations at the receptor locations. Rafiei and Sturm (2018) modeled the Carbon Monoxide dispersion around the Niayesh tunnel in Tehran using a Lagrangian model composed of Graz Lagrangian Model and Graz Mesoscale model. CO concentrations at the vicinity of portals are calculated using the proper dispersion simulation. Akinyemi *et al.* (2018) used Multiple Linear regression technique to develop the model estimating the risk level of Carbon Monoxide emitted from diesel engine generators. The input variables such as the installed capacity, purchase time, operating time and the time last serviced were used to explain the risk level of CO in Nigeria. Saud *et al.* (2019) designed a hybrid model with integration of Geographical Information Systems (GIS), Artificial Neural Networks (ANN) algorithm and Correlation based Feature Selection (CFS) algorithm to predict the daily vehicular CO emissions on an expressway in Malaysia. The results showed that the proposed model achieved validation accuracy of 80.6%. Lin *et al.* (2019) used MOVES (Motor Vehicle Emission Simulator) for estimating the emissions of traffic near signalized intersections at Changchun, China and provide necessary information for decision- making, planning and management.

Methodology

The main objective of this study is to predict the COC at signalized intersections. Two cities namely Warangal and Tirupathi were identified as study areas for the data collection. The field data was collected at different signalized intersections in two cities. The ATV, RT, CT, and AVCR data collected at different signalized intersections were analyzed. MLR analysis was performed to establish an equation for estimating COC. ANN model was also developed considering ATV, RT, CT and AVCR as inputs variables and COC as output variable. The models developed in the present study have

been validated for their adequacy. The flow chart explaining the methodology is shown in Figure 1.

Study Area and Data Collection

Signalized intersections for the present study were identified at different locations in two cities namely Warangal and Tirupathi. The selected cities are having similar characteristics such as same size, region and population. Based on the vehicle registration data obtained in Warangal and Tirupathi cities, from Road Transport Authority (RTA) office, there is 20 to 25 percent increase in vehicles from 2010 to 2018. The location of the cities chosen for the study is presented in Figure 2. Six typical signalized intersections were chosen for data collection. The locations selected for the study those are away from the vicinity of any plants and industries. Five types of vehicle are commonly observed on all the selected sections such as

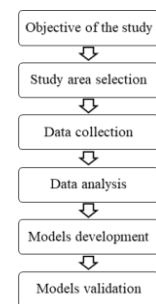


Figure 1. Flow chart showing the methodology of the study

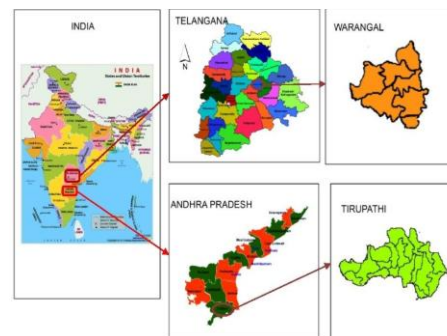


Figure 2. Location of the study area

Table 1. Signalized intersections locations and characteristics

Intersection	Name of the intersection	City	Remarks
I	Central Park	Tirupathi	3-legged intersection
II	LeelaMahal Circle	Tirupathi	4-legged intersection
III	Annamayya Circle	Tirupathi	4-legged intersection
IV	Spencors Circle	Warangal	4-legged intersection
V	GeethaBhavan Circle	Warangal	4-legged intersection
VI	Kazipet Intersection	Warangal	4-legged intersection

motorized two wheelers (2W), passenger cars (CARS), auto-rickshaws (3W), light commercial vehicles (LCV), Bus (BUS). The Table 1 provides the details for signalized intersections selected for present study.

The ATV, RT, CT, and AVCR data was collected for eight hours (four hours in the morning (7:00 AM to 11:00 AM) and four hours in the evening (5:00 PM to 9:00 PM) at each intersection using video-graphic method. The time taken in the day covers the peak and off-peak hours of traffic flow in the intersections. In the present study, the data collected was limited to week-days only. The classified traffic volume data was extracted from the video by playing the videos on wide screen display. The heterogeneous traffic volume was converted to homogeneous volume by multiplying each 5 min count data with Passenger Car Unit (PCU) pertaining to a vehicle type. The PCU value of vehicle types suggested by Indo-HCM (2017) is used for conversion of volume. The average number of vehicles stopping at the intersection during the red time length is also extracted from the video. The red time length, cycle time length and COC are observed in the field. To measure Carbon Monoxide (CO) at the signalized intersections, a portable CO measurement device (Carbon Monoxide meter) was used which measures the CO concentration in the air at regular interval. The device is comprise of a high accuracy sensor (stabilized electro-chemical Gas-specific), and provide fast response and stable readings under the wide range as 0-1,000 part per million (ppm). A picture of CO meter used in this study for measuring CO concentrations is shown in Figure 3.

Analysis of Field Data

The approach traffic volume data collected at different intersections was extracted at 5 min interval and composition of traffic was determined. The observed traffic composition of five different vehicle types from the different intersections is shown in Figure 4.



Figure 3. Carbon Monoxide meter (CE)

The variation of COC with respect to RT, CT, AVT, and AVCR combined for all intersections was analyzed separately. It is found that the COC values were significantly increased with increase with RT,

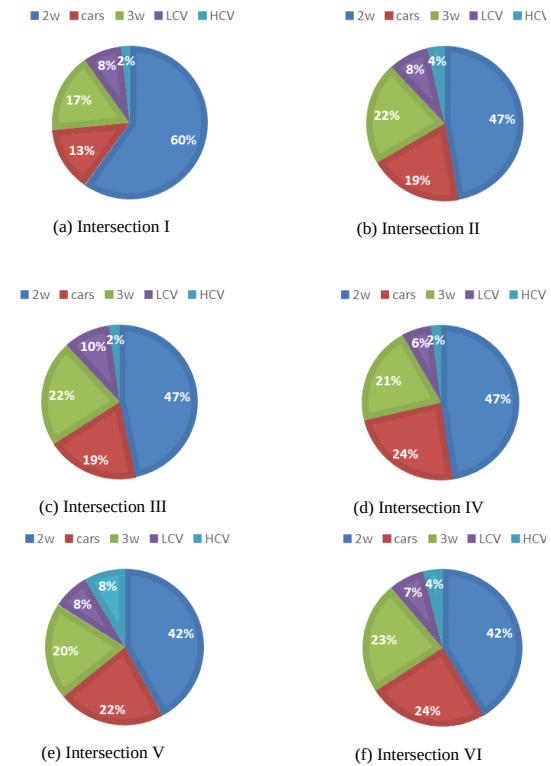


Figure 4. Observed traffic compositions at various intersections

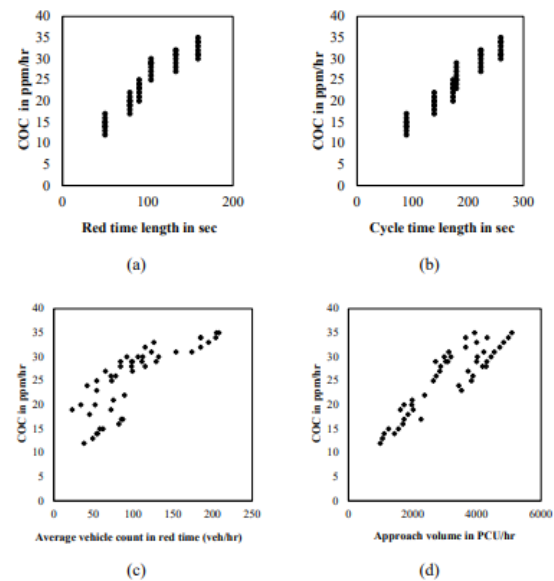


Figure 5. Variation of COC with (a) RT (b) CT (c) AVCR (d) ATV

CT, AVCR, and ATV. The variation of COC with RT and CT combined for different intersections is presented in Figures 5.

The variation of COC with respect to the variables RT, CT, AVCR, and ATV indicates that the COC value is increasing with the increase in them. The acceleration and deceleration of the vehicles stopping and moving at the intersection are causing much release of COC. Figure 5 indicates that the variation in COC at intersections is not only because of the number of vehicles but also the time the vehicles are stopped at the intersection.

Prediction of CO

This section of the study deals with prediction of CO values using two different methods. MLR and ANN models are developed to predict the CO values in the study area. ATV, RT, CT, and AVCR are considered as inputs and CO values are taken as output variables in both the models.

Multiple Linear Regression (MLR) Modeling

The field data observed at various intersections is used to develop a model for estimation of CO. The correlation and regression analysis was performed to examine the factor influencing CO values using field observed data. The variable for the analysis were identified as RT, CT, ATV, and AVCR of the intersection. The significance level (α) adopted for the correlation analysis is 0.05. A significant correlation has been observed between COC and all selected variables. The result of correlation analysis is given in the Table 2.

Multiple linear Regression (MLR) analysis was performed to develop a model for estimating COC. The MLR model developed in the study obtained an R^2 value of 0.75. All independent variables found to be significant on COC are provided with necessary details as result of MLR analysis in Table 3. The regression outputs are presented in Table 3.

The MLR model developed in the present study determine presence of COC in the air along the roadway at signalized intersections. The model proposed to determine COC has been shown in Equation 1.

$$Y = 8.67 + 0.81 * RT + 0.54 * CT + 0.74 * AVCR + 0.89 * ATV \quad (1)$$

Y = Carbon Monoxide concentration (COC) at the intersection in ppm/h.

RT = red time length in sec.

CT = cycle time length in sec.

AVCR = Average vehicle count stopping during the red time at the intersection in vehicles/h.

ATV = Approach volume of the intersection in PCU/h.

Model Validation

The MLR model developed in the present study has been validated based on the field data collected at 2 different intersections. These intersections have similar characteristics in terms of traffic and roadway conditions. The data observed at intersections III and VI are used as inputs to determine predicted COC values for the validation. The COC values as determined by using model were compared with the field observed values on a 45 degree angle line as show in Figure 6. As a result, it has been observed that there is no significant difference between the observed and predicted COC values as it following the 45 degree angle line. The successful model validation is also confirmed by RMSE (Root Mean Square Error) value estimated as 0.06, a P-value of 0.99 and an MAPE value of 0.17% between two sets of data.

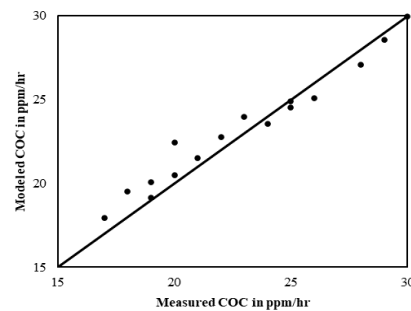


Figure 6. Validation of COC using field data

Table 2. Correlation matrix of selected variables

	CO	RT	CT	AVCR	ATV
CO	1				
RT	0.88	1			
CT	0.89	0.79	1		
AVCR	0.72	0.69	0.67	1	
ATV	0.93	0.86	0.84	0.63	1

CO= Carbon Monoxide in ppm/h.

RT = red time length in sec.

CT= cycle time length in sec.

AVCR= Average vehicle count stopping during the red time at the intersection in vehicles/h.

ATV = Approach volume of the intersection in PCU/h.

Table 3. Regression outputs

Variable	Co-efficient	t-value	P value
Intercept	8.67	5.45	8.95E-06
RT	0.81	4.37	0.000162
CT	0.54	4.54	0.000104
AVCR	0.74	3.84	0.000669
ATV	0.89	3.13	0.0041

Artificial Neural Networks (ANN) Modeling

ANN method is used to predict CO concentrations. Multi-layered feed-forward ANN is used in the present study for analysis. The study availed MATLAB for ANN modeling. ANN comprises three layers namely the input layer, hidden layer for calculating input weights and output layers. In this study, CO values are given as output layer and proportional share of vehicles and average traffic speed are given as input layers. ANN utilizes 70% of the data for training, 15% for testing and 15% for validation. The number of hidden layers and neurons are decided based on the trial and method iterations. The network structure with less error between the measured and ANN modeled values is chosen to be the optimal structure. In this study, the network structure for predicting the CO values is optimized at 2 hidden layers and 10 neurons. The output of ANN modeling is presented in Figure 7(a). The output is plotted in four different sections for observed and modeled values. The first section considers the training data (70% of given data), second section represents validation data (15% of given data), third sections show testing data (15% of the given data), and fourth section shows the plot between all the observed and modeled values. The trend of measured and ANN modeled CO values is presented in Figure 7(b).

The CO values determined using the ANN model was compared with values observed on the field on a 45-degree angle line as shown in Figure 7(b). As a result, it was observed that there was no significant difference between the observed and ANN predicted CO values when following the 45-degree angle line. ANN model obtained an R^2 value of 0.964. The successful model validation is also confirmed by RMSE (Root Mean Square Error) values estimated as 0.003 (which is less than 20%) between the modeled and observed CO values. The model obtained a P-value of 1.10 (which is greater than 0.05) and Mean Absolute Percentage Error (MAPE) value of 0.09%.

Conclusions

In many urban cities of developing countries like India, traffic emissions are the major sources for deteriorating air quality. Carbon Monoxide is one of the predominant pollutants emitted from the vehicles which have adverse effects on health of the people. Present paper demonstrates models for estimation of CO concentration present in the air at signalized intersections. The field data collected at various locations was used to examine the factors affecting CO concentration. The CO values are found to be increased with increase in traffic

volume. The correlation analysis indicated that all the variables RT, CT, AVCR, and ATV are showing significant impact on CO emission at intersections. The approach traffic volume (ATV) has highest correlation of 0.93 with CO values. The study proposed a MLR equation for estimating CO concentrations if all the factors are present at the intersections. ANN model was developed to predict the CO values explaining the non-linearity between the variables. The models include factors such as RT, CT, AVCR, and ATV as influencing variables for estimating COC. The validation of CO models was performed with field data observed at other intersections. The models validation illustrates that the estimated COC are constantly following the observed COC under the same sets of traffic and roadway conditions. The RMSE and MAPE estimates confirm that there is no significant difference between estimated and observed COC values. The results of the study also depicted that ANN model has better fitted the data than MLR model. The analysis and process of training in ANN modeling is better because the given data is

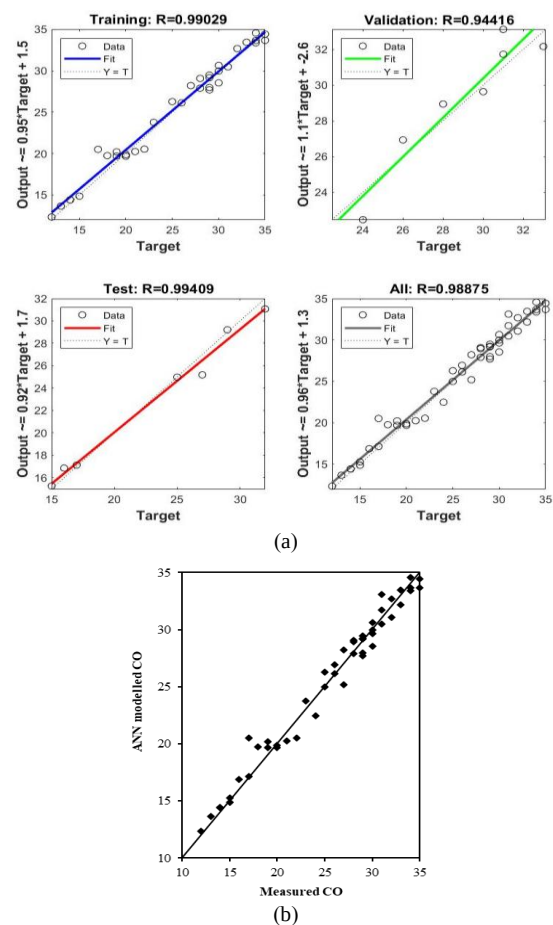


Figure 7. (a) Output of ANN modeling and (b) Measured v/s ANN modeled values

converted into different layers and the relation between them is checked number of times. Therefore, the reliability of the ANN model increases when compared to MLR model. The present study is an attempt to bring attention in regard to COC and its impact in future due growth in traffic volume and congestion at the signalized intersections. The study was performed with the field data observed in two cities with similar size and region. The scope of the study may be extended to include the pollutants other than CO releasing from the vehicles. Further studies may also include the seasonal and temporal variations in CO values. The study may also be extended by including different vehicle parameters such as emission rate, age and size of the vehicle. Present study recommends the transportation agencies to seek necessarily measures to control the numbers of new registered vehicles and discourage the uses of aged vehicles in the cities. The Pollution Control Board (PCB) authorities should regulate the increase of CO levels to minimize the adverse effects of CO in future years.

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