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Evaluating Traffic-related Near-road CO Dispersions on an Urban Road During Summer Season: A Model Inter-comparison

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Abstract: Three air pollution models, namely the 'California Line Source' (CALINE4) model, the 'Unique Dispersion Model' (UDM) and the 'Simplified Type Dispersion Model' (STM) have been analyzed for assessing the air pollutant concentration at one of the most congested traffic road in the city of New Delhi. The latter two models have been developed using the most influential input parameters of CALINE4 namely traffic flow and wind-speed observed by both sensitivity analysis and regression analysis studies. The model performance have been estimated and compared statistically with the traffic emitted airborne carbon monoxide (CO), the prevalent meteorology and the temporal distribution of the monitored hourly average CO concentrations in summer time. The study has displayed that the UDM model would generate better predictions as compared to other models for different meteorological and traffic conditions. The complete study reveals that the similarity between the monitored and the modelled CO concentrations have been reasonably satisfactory for UDM and CALINE4 models. Further detailed assessment confirms that the UDM model performed superior in comparison to the CALINE4.

Key words: Air quality modelling, CO, vehicular pollution, model evaluation, urban air quality, urban road, model comparison, near-road pollutant dispersion.

Background

There is an increasing international agreement on raised health risks for near-road inhabitants. Atmospheric air pollution has become a subject of prime concern, mainly in metro cities and urban zones and expeditious industrial development along with emissions from transportation sector are considered as the major sources. The condition is notable and slowly becoming more demanding and it is likely to grow in near future with the increasing population (Andria et al., 2008; Banerjee, 2010). In India, little attention is focused on the harmful effect of transport emissions to the natural environment, even though according to some studies contribution of traffic emissions to the total air pollution of the environment is in the range of 40-80% for many developing countries (Goyal et al., 2006; Sivacoumar and Thanasekaran, 1999). For example in Delhi, India, approx. 3000 MT of contaminated air pollutants are discharged daily and traffic related emissions contribute to almost 70% of total emissions. Among the other metropolitan cities, the traffic-related air pollution adds approximately 40, 50 and 80% of total air pollution levels in Guangzhou, Mumbai and Beijing respectively, (Goyal et al., 2006).

Atmospheric dispersion models are employed to evaluate the road traffic-related emissions on surrounding air quality for many reasons, like setting up of ambient air quality standards, health hazard and decision support assessment. It is therefore important

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to be able to predict with judicious accuracy the air pollutant concentrations related with vehicle emissions. In this context, analytical models have been established to simulate the impact of atmospheric dispersion on air pollutant concentrations found on an emission rate from a road. For open terrains, Gaussian dispersion models are generally used (e.g., Levitin et al., 2005; Berger et al., 2010; Venkatram et al., 2009; Chen et al., 2009).

Air quality models yield a deterministic correlation between the spatial and temporal variance of traffic-related emissions and pollutants, meteorology, and road planning. Air quality and dispersion models help to setup epidemiological connections between health and pollution. Models, though, need detailed input data (e.g. spatial and temporal allocation factors, traffic activity, emission rates, and meteorology) to generate acceptable estimates. Comprehensive literatures are available in framework of dispersion models applications for the estimation of ground level concentration (Al-Azmi et al., 2009; Bhanarkar et al., 2005; Sivacoumar et al., 2001) and air pollutant source-apportionment (Bhanarkar et al., 2005; Jiming et al., 2001; Kimmel and Kaasik, 2003). However, in India, limited numbers of studies have been performed on urban scale dispersion modelling system with the aim of comparison of the model predictions to observed concentrations and quantification of the source contributions (Bhanarkar et al., 2005).

Here we present outputs of a model inter-comparison to measure the ability of three models in simulation of air pollutant concentrations near roadways: CALINE, a model built by the California Department of Transportation; a unique dispersion model (UDM), a model developed by multiple polynomial regression tests carried out using the traffic flow and the wind speed as predictor variables for equivalent CO emissions as response variable; a simplified type model (STM) developed on the sensitivity analysis outputs of most influential parameters namely traffic flow, wind speed and weighted emission factor.

Methodology

Methodology included the 'sampling' and 'modelling' of the hourly average CO concentrations on an urban roadway in the city of New Delhi. The sampling programme included nomination of an urban roadway, collection of data of CO pollutant concentrations for the month of June in summer season. It also incorporated traffic computation for weekdays/weekends, meteorological variables and other required details.

Emission factors for automobiles were collected from the ARAI (2008) and the CPCB (2000) datasets for the 'free flowing' situations. The nominated models, CALINE4, UDM, and STM were implemented on the traffic roadway to predict the hourly average CO concentrations for summer season (June 2014). The development method of two models (UDM and STM) is presented in next sections. The model results were checked against measured CO concentrations by using statistical indices to evaluate the prediction performances of models.

Site Characteristics

The present research was performed in Delhi, India. The corridor selected for the study was 2 km stretch of National Highway-2 (NH-2) passing through Delhi to Agra city (Figure 1). The selected corridor is at a geographical location of 28°37′39.99″ N 77°14′29.04″ E respectively at 216 metres above mean sea level (MSL). It receives both local and inter-city traffic, with nearly 0.2 million automobiles commuting every day. It was a dual roadway with three lanes on each road (total six lanes). The local LCVs and HCVs entry was regulated in the city from 0600 to 2100 PM.

Traffic Characteristics

Total traffic flow at the highway stretch was found to be 1,79,396 automobiles per day (1,93,332 passenger car unit or PCU). The cars (4Ws) contained 49.5% of total traffic with two wheelers (2Ws) as 29.6%, three wheelers (3Ws) 8.3%, HCV 6.1%, LCV 4.5% and buses 2.1%. The monitored diurnal pattern of traffic flow is presented in Figure 2. The morning (0900–1100 hrs) and evening traffic peak (1800–2000 hours) is clearly visible. Steady upsurge in heavy commercial vehicles (HCV) during nighttime (2100 hour onwards till 0600 hour) could be observed (Figure 2). It shows that a distinctive diurnal deviation in composition and number of the vehicular traffic is perceived at the highway corridor.

Meteorology

The research work was performed in the summer season of June 2014. The micro-meteorological variables such as wind direction, wind speed and relative humidity, were monitored in-situ. The data of hourly mixing height were gathered from the Indian Meteorological Department (IMD) (Attri et al., 2008). The major wind direction perceived was from southeast. The hourly P-G stability classes were evaluated using solar insolation wind speed and cloud cover (day and night time) (Turner, 1994).

Figure 1: Micro-meteorological measurement at selected stretch of NH-2 corridor, near CRRI gate. (*Source:* Dhyani (2017))

CALINE4 Sensitivity Analysis

The sensitivity analyses for each model inputs were performed in CALINE4 (Dhyani, 2017; Benson, 1989; Dhyani and Sharma, 2017). For the formulation of the sensitivity analyses, the significant variables were independently altered over a large duration, though rest of the variables were fixed at minimal values. The receptor points were fixed perpendicularly from the centre-line of road by distance x (m). Wind angle α is defined for a particular receptor point such that $\alpha = 0°$ designates the wind flowing parallel to the road; $\alpha = 90°$ or 270° is for winds flowing normally to the road; and $\alpha = 180°$ is also for winds parallel to the road. Most of the CALINE4 analyses employed one hour operation, a road segment of length 2 km (straight), uniform landscape, an assembly of receptors fixed perpendicular to road from the centre of link, downwind receptor length of 5, 10, 25 and 50 m and receptor height of 1.8 m respectively (Figure 2). The conclusion from results of sensitivity analysis have been briefed in Table 1. In Table 1, the input variables have been classified as most influential (100%), influential (50–75%), moderately influential (30–50%) and less influential (0 to 20%) on the basis of their effect on CO prediction capabilities in CALINE4 model. *It was observed that wind speed and weighted emission factor were most influential (100%) and traffic flow influential (50-75%) on output CO predictions.*

Dispersion Models

CALINE4

This is the latest version of the CALINE models series, established by the California Department of Transportation (Benson, 1989). CALINE4 is a model based on Gaussian equation, proficient of predicting CO concentrations (and other non-reactive gases), NO_2 (incorporates a sub-model for NO_2 production) and aerosols. The model splits the road into a series of elements, each signifying a part of it and the pollutant concentration at the receptor is estimated by adding the contribution from each up-wind element. Effectually, the model exemplifies the road as a chain of finite line sources, located normal to the wind direction and positioned at the element midpoint. Cumulative

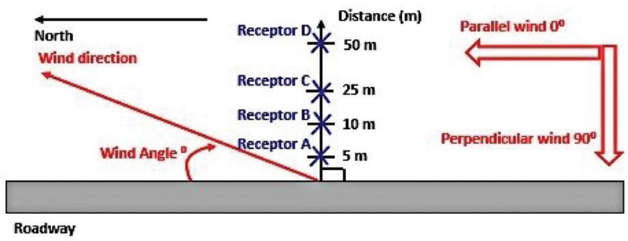

Figure 2: Description of wind and road coordinate system for any wind and road direction. (*Source:* Ahmad, S. et al., 2018)

downwind concentrations are predicted conferring to the cross-wind Gaussian formulation for a finite length line source,

$$C(x, y, 0: H) = \frac{Q}{\pi \sigma_Z u} \int_{y_1 - y}^{y_2 - y} \exp\left(\frac{-y^2}{2\sigma_y^2}\right) dy \qquad (1)$$

where u is wind speed; Q is linear source strength; σ_y and σ_z are horizontal and vertical Gaussian dispersion parameters; and y_1 and y_2 are endpoints of finite line source, y-coordinates ($y_1 < y_2$). For the calculation of σ_z, CALINE4 includes the thermal turbulence due to traffic, along with the atmospheric turbulence. The latter has negligible influence on near-road dispersion, and increases at larger distances from roadway (Benson, 1982, 1992). σ_y is directly estimated from the standard deviation of wind direction, and σ_θ is calculated using a methodology developed by Draxler (1976).

Unique Dispersion Model (UDM)

A CO dispersion model has been developed for calculating traffic-related near-road CO concentrations of the study area. Regression work is performed after analyzing traffic and meteorological parameters that influence the near-road CO concentrations, and the goodness of fit of the model is examined using statistical indices. Linear coefficient of determination (R^2) relating individual variables (like traffic flow, weighted emission factor, wind speed, wind angle and mixing height above mixing zone width) with the CO concentration has been performed to find out their influence on the near-road CO concentrations. The regression results shows that the traffic flow (TF) has the largest coefficient of determination ($R^2 = 0.2877$), wind speed (WS) has the second largest ($R^2 = 0.2605$) followed by weighted emission factor (WEF) which has a $R^2 = 0.2585$. Wind angle (WA) has the lowest R^2 value ($R^2 = 0.0775$). Also, test of significance has been performed on the traffic flow (TF), wind speed (WS), and weighted emission factor (WEF), to select the variable with highest significance in the modelling procedure. The variable is of significance if its P value is found to be less than 0.05.

Results demonstrate that the traffic flow (TF) variable is found to be of highest significance affecting road side CO concentration. Its P value is lower than 0.01217.

Table 1: Review of sensitivity analysis of CALINE4 model for different input variables (*Source*: Dhyani and Sharma, 2017)

Input variables	*Sensitivity of model*	*Remarks*
Wind speed (ms^{-1})	Inversely proportional(e.g. 40% upsurge in wind speed will end in 30-40% reduction in estimated concentration)	Most influential
Road to wind angle (PHI Degree)	Predicted concentrations varies from parallel (0°) to normal (90°) wind direction from roadway. More sensitive to approximately parallel wind enviroments (PHI = 5° – 30°)	Moderately influential
Stability class (P-G Class A-F)	Variation in stability class A to F (5 m to 10 m distance from mixing zone width) ended in ~15% upsurge in concentration. Model is more sensitive at distance far from mixing zone width. Approximately 50%-60% rise in predicted concentration from stability class A to F (at 50 m distance from mixing zone width)	Moderately influential
Mixing height (m)	Model sensitive at lower mixing height up to 50 m regardless of any stability class, after that any default figure could be utilized.	Less influential
Weighted emission factor (gm^{-1})	Exactly proportional (e.g. 10% rise in WEF will end in 10% rise in predicted concentration)	Most influential
Traffic volume (Vehicles $hour^{-1}$)	Proportional (e.g. 10% rise in TV will end in ~8% rise in predicted CO concentration)	Influential
Roadway width (m)	Nearly 15-20% drop in concentration with 30% rise in mixing zone width	Moderately influential
Surface roughness (cm)	Any default value could be used between Zo = 50 – 200 cm	Less influential

In the second place wind speed (WS) is found, having a *P* value of 0.01521, while weighted emission factor (WEF) is in the third place, with a *P* value of 0.01859 (Table 2).

Table 2: Coefficient of determination (R^2) and significant value (*P* value) for different traffic parameters

Parameter	R^2	*P Value*
Traffic flow (TF)	0.2877	0.01217
Wind speed (WS)	0.2605	0.01521
Weighted emission factor (WEF)	0.2585	0.0189
Wind angle (WA)	0.0775	0.487

Therefore, weighted emission factor (WEF) is left out and the traffic flow (TF) and wind speed (WS) variables are selected for the modelling procedure. Multiple polynomial regression tests were carried out using the traffic flow and the wind speed as predictor variables for equivalent CO emissions as response variable. The testing followed different mathematical arrangements of the explanatory variables (square, square root, power three inverses etc.). Regression work was performed in MATLAB R2013a surface fitting tool, wherein, the Bisquare option was employed. The predicted CO concentration model can be shown as follows (Figure 3):

$$\begin{aligned} CO = {} & 5.326 - (5.377\times WS) + (0.0007593\times TF) \\ & + (1.026\times WS^2) + (0.0002885\times WS\times TF) \\ & - (1.313\times10^{-7}\times TF^2) - (4.725\times10^{-5}\times WS^2\times TF) \\ & + (2.265\times10^{-10}\times WS\times TF^2) + (4.475\times10^{-12}\times TF^3) \end{aligned}$$

Here, CO stands for near-road CO concentration (mg/m^3) at 5 m distance perpendicular to the centre of road link, WS is wind speed and TF is the traffic flow (veh/hr). The model equation was operated for CO measurement of the study area where WS varies from 1.5 and 4.0 (m/s), and TF varies from 2000 and 13000 (veh/h).

Simplifies Type Model (STM)

A simplified form of dispersion model based on rational parameters was developed which predicted analogous outputs as from CALINE4, directed by outcomes of sensitivity analysis. A multiplicative and segmental model framework based on simplified models for individual key input variable was used, therefore permitting simple upgrades. We tried to make a parity within replicating CALINE4's result exactly, by using easily obtainable data, and making computations quick and easy, and we kept those input variables that affected calculated concentrations larger than 10-15%. It was assumed that stability category and mixing height had negligible influence in most conditions and therefore not included.

Similar to previous Gaussian type dispersion models, low/quiet winds were not exactly modelled. We fixed the lowest wind speed at 0.5 m s^{-1}. The rest of the variables were modelled using multiplicative type models. A range of model assemblies for the models were assessed, comprising power law, exponential, and polynomial regression based models, amongst others, and variable coefficients were assessed by non-linear Newton gradient search techniques and maximum likelihood estimates. After checking a range of terms, an exponential model was found to be closely related to the concentration outlines observed for 5 to 50 m distances at every wind angle. For a particular traffic flow, vehicle mix, wind speed, wind angle, weighted emission factor and SC, pollutant concentrations can be calculated by:

$$C_{x(WEF)} = (q_1 \exp(-q_3(x - q_2))) \tag{2}$$

$$C_{x(TF)} = (q_4 \exp(-q_6(x - q_5))) \tag{3}$$

$$C_{x(WS)} = (q_7 \exp(-q_9(x - q_8))) \tag{4}$$

$$C_{xT} = C_{x(WEF)} + C_{x(TF)} + C_{x(WS)} \tag{5}$$

$$= \{(q_1 \exp(-q_3(x - q_2))) + (q_4 \exp(-q_6 (x - q_5))) + (q_7 \exp(-q_9(x - q_8)))\} \tag{6}$$

where C_{XT} = calculated concentration (ppm) at X (m) distance; q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8 and q_9 = fitted coefficients. Parameters q_1 to q_9, displayed in Table 3, were evaluated for 18 wind subdivisions (i.e. 10° to 180°). The wind angle is equally proportional, e.g., a wind angle of 10° is equal to 350°. A graphical presentation of the performance of the simplified-form model with respect to CALINE4 is displayed in Figure 3.

Model Evaluation

The quantitative assessment of performance of three models addresses whether the relevant trends in the validation variables with changes in experimental parameters are reproduced. To perform quantitative assessment of the model performance, a set of statistical performance measures (SPM) are defined. According to Duijm and Carissimo (2002), SPM should provide (i) a measure of bias in model predictions, i.e. the tendency of a model to systematically over- or under-predict relevant variables, and (ii) a measure of the spread in predictions, i.e. the degree of scatter around a mean value.

Table 3: Estimated variables determined by wind angle for simplified-form CO model (values in ppm)

Wind Angle (°)		*Parameter* q_1	q_2	q_3	q_4	q_5	q_6	q_7	q_8	q_9
10	350	1.2417	1.2036	0.0318	1.2049	1.2030	0.268	1.1017	1.1994	0.0345
20	340	1.2417	1.2036	0.0318	1.2826	1.2067	0.0277	1.1510	1.2015	0.0289
30	330	1.1090	1.2027	0.0272	1.1944	1.2048	0.0231	1.0993	1.2015	0.0283
40	320	1.1090	1.2027	0.0272	1.0864	1.2006	0.0203	0.9717	1.1970	0.0235
50	310	0.9622	1.1963	0.0226	0.9506	1.1970	0.0191	0.8209	1.2144	0.0195
60	300	0.9451	1.2515	0.0274	0.9506	1.1970	0.0191	0.8209	1.2144	0.0195
70	290	0.9451	1.2515	0.0274	0.9506	1.1970	0.0191	0.8209	1.2144	0.0195
80	280	0.9030	1.2269	0.0256	0.9506	1.1970	0.0191	0.8209	1.2144	0.0195
90	270	0.7450	1.1540	0.0204	0.8116	1.1779	0.0162	0.7943	1.2016	0.0263
100	260	0.7461	1.1855	0.0222	0.8085	1.2811	0.0171	0.7943	1.2016	0.0263
110	250	0.7461	1.1855	0.0222	0.8085	1.2811	0.0171	0.7943	1.2016	0.0263
120	240	0.7165	1.3894	0.0215	0.8084	1.2178	0.0184	0.7090	1.1185	0.0250
130	230	0.7047	1.2132	0.0256	0.7646	1.1777	0.0191	0.7290	1.3133	0.0262
140	220	0.7047	1.2132	0.0256	0.7646	1.1777	0.0191	1.1463	1.1861	0.1293
150	210	0.6791	1.1689	0.0249	0.7646	1.1777	0.0191	0.7288	1.2137	0.0298
160	200	0.6418	1.1717	0.0252	0.7014	1.1480	0.0166	0.6943	1.1436	0.0306
170	190	0.6158	1.1205	0.0245	0.6890	1.9957	0.0198	0.6943	1.1436	0.0306
180	180	0.5734	1.0871	0.0216	0.6342	1.1955	0.0169	0.6234	1.1328	0.0272

On the basis of eq. (4) in paper, the supplementary variables are q_{10} = –0.7647; q_{11} = –0.9069; q_{12} = 425132; q_{13} = –1.47554; q_{14} = 2.5784 and q_{15} = –0.9485. Applicable to the rate of emission of 1 g km^{-1} hr^{-1}. (*Source:* Ahmad et al., 2018)

Seventeen basic statistical calculations were used for assessing the efficacy of the models. The absolute bias (AB) underlines the series of concentration as the mean bias. The mean absolute error (MAE) is the average of the absolute biases. The absolute error is the absolute of the difference between the observed value and predicted value. MAE displays an expected amount of error from the average of predicted concentration. The long standing performance of a correlation in evaluating a value is delivered by mean bias error (MBE), which makes the assessment of the actual deviance between the observed and estimated value of each value. The ideal figure of MBE is zero. A positive figure gives the average extent of over-estimation in the estimated figure and vice versa. The mean squared error (MSE) is a quantification of how near a predicted value is to the observed values. The lower the mean squared error, the nearer the fit is to the observations.

The fractional bias (FB), which is a well-proportioned dimensionless number, aggregates the result from data groups having substantially different levels of concentrations (Cox and Tikvart, 1990). It indicates a good relation between the means of the modelled and measured concentrations. It alters between −2, i.e. maximum over prediction and +2, i.e. maximum under prediction. An FB value = 0 shows perfect accordance between monitored and predicted values. The normalized mean square error (NMSE) estimates the correlation between number values of monitored and predicted concentrations, on a point-by-point basis (‘microstatistics’). It has a span of $0 < \text{NMSE} < \infty$, where 0 shows perfect arrangement between monitored and predicted values. The root mean square error (RMSE) offers the quality of model in relations of its deviation and neutrality. The standard deviation (SD), of which the nearer values for monitored and modelled, shows toward the model performance. When a set of data covers different groups of data with P_i/O_i or O_i/P_i equal to 10, 100 or more, the geometric mean bias (MG) is suitable because over-predictions and under-predictions have equal weight (Hanna et al., 1993).

An “ideal” model would give *MG*=1, but *MG*=1 does not represent that predictions match with measurements. An MG greater than 1 implies that the model overestimates and an MG less than 1 that the model underestimates. The geometric mean variance (VG)

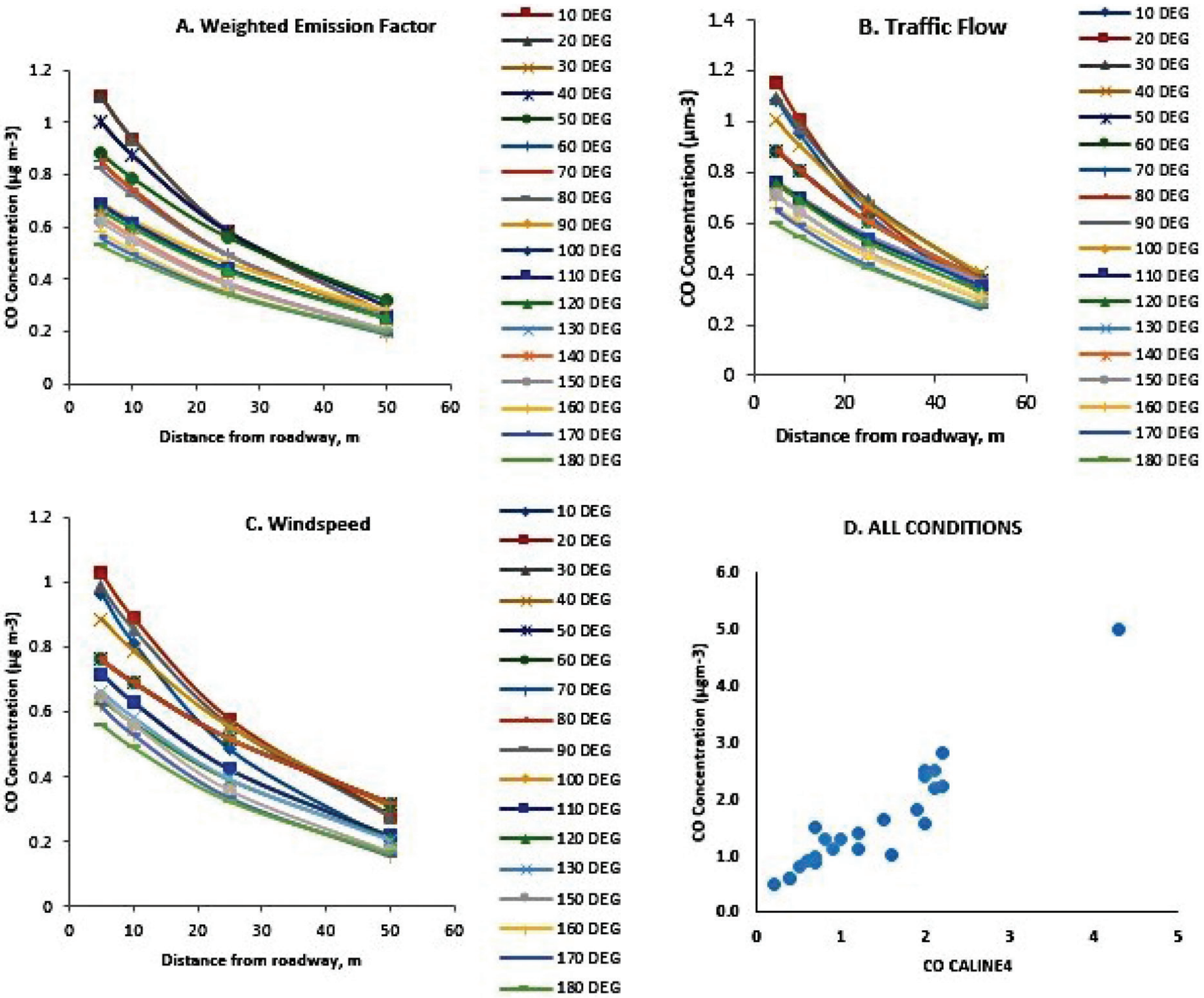

Figure 3: Inter-comparison of predictions of CALINE4 model (shown as solid lines) and simplified type dispersion model (shown as points) showing impacts of: (A) wind speed; (B) weighted emission factor; and (C) traffic flow for four receptor distances (5, 10, 25 and 50 m) from the roadway. All graphs use normal settings (wind speed = 1.8 ms^{-1}, wef = 4 g mile^{-1}; VPH = 9,210; wind angle = 70°). Panel D represents CO concentrations from the two models for all conditions. (*Source*: Ahmad, S. et al., 2018)

represent the scatter in the model predictions around a mean value. Here, "excellent" model performance in terms of the validation target P_{max} from an experimental campaign is characterized by the measured variable being reproduced with a $0.77 < MG < 1.3$ (i.e. a mean bias within a factor of 1.3), and a $VG < 1.6$ ("factor two scatter"). Furthermore, the measured variable should be reproduced with an FAC2 of 75%, and key trends in the prediction of the measured variable should be consistent with the experiments. For "acceptable" model performance, the measured P_{max} should be reproduced within $0.5 < MG < 2$ (i.e. a mean bias within a factor of two), $VG < 3.3$ ("factor three scatter") and FAC2 of 50%. The index of agreement (d) underlines the extent to which the monitored variate is precisely evaluated by the forecasted variate. The d value is not an estimation of association or correlation in a strict way but rather an evaluation of the level to which the model forecasts are error free. It scales between 0 and 1 with a calculated value of 1 representing perfect agreement between the monitored and modelled, while, 0 representing a complete disagreement (Willmott, 1982).

The fractional variance (FS) calculates the correlation between the deviation of the forecasted values and the deviation of the monitored values. Its span is $-2 < FS < 2$, where (–2) means largest under-prediction of the variance, and (+2) means largest over-prediction. A value of $FS = 0$ signifies perfect agreement. The FAC2 factor is defined as the fragment of readings in which the ratio P_i/O_i is found within the limits of $0.5 \le (P_i/O_i) < 2$.

Table 4: Performance measures of three models in CO estimation

	CALINE4	*UDM*	*STM*	*Monitored*
SD	0.86	0.68	0.28	0.82
AB	–0.42	0.001	–0.06	
ME	–0.22	0.07	–0.2	
MAE	0.33	0.24	0.85	
MSE	0.52	0.18	0.79	
MBE	–0.46	0.00	0.25	
GMB	–0.24	0.00	0.08	
REAC	–22.9	0.06	3033	
FB	–0.26	0.00	0.03	
NMSE	0.2	0.06	0.24	
RMSE	0.72	0.42	0.89	
MG	0.96	0.96	0.89	
VG	1.25	1.08	1.2	
D	0.82	0.91	0.95	
FS	0.06	–0.17	–0.87	
FAC2	0.72	1.0	0.63	
FAC5	1	1	0.95	
R	0.74	0.84	–0.15	

It specifies the degree of the model predictions. It has a span of 0 < FAC2 < 1, where FAC 2 = 1 signifies that all readings are in the limits of $0.5 \leq (P_i/O_i) < 2$, and FAC2 = 0 signifies that none of the readings are in that limit. Pearson's correlation coefficient (*R*) is a quantification of how well variations in forecasted concentrations follow variations in monitored concentrations. In actual, it is an estimation of a straight-line correlation, when forecasted concentrations are plotted vs. monitored concentrations. It has a span of $-1 < R < 1$, where ±1 signifies an ideal correlation, and 0 signifies no correlation. It does not estimate correlation in real numerical values between monitored and forecasted data.

Results and Discussion

The mean diurnal deviations in the monitored and predicted CO concentrations are presented in Figure 4. It shows that CALINE4 and UDM tend to under-predict in morning and afternoon hours whereas reasonable predictions in evening hours and slight over-prediction at night hours. The under-prediction of CALINE4 is due to high "unstable" stability conditions almost perpendicular winds to road and lower values of emission factors. While reasonable predictions in evening hours is due to "stable" stability class, larger traffic flows and parallel wind directions. At night over-predictions is due to highly "stable" stability conditions, large values of emission factors and low wind speeds. Figure 5 shows scatter plots of predicted versus observed values for the three models for the test. As seen in Figure 5(a), the under-prediction is also observed in CALINE4 during morning and afternoon as scatter lies outside factor of two lines. All predictions of UDM lie within factor of two (Figure 5(b)). For greater concentrations monitored during this test day, all the three models reasonably predict the observations, as scatter lies within factor of two, while for lower scatter is large for CALINE4 and outside FAC2 lines. In case of STM, slight over-prediction and under-prediction is observed at lowest and highest concentration range (Figure 5(c)). This could be due to inaccuracy in data collection of traffic and meteorological parameters.

The mean diurnal variations in the measured and modelled CO concentrations for three models are shown in Table 4. The results showed that for summer season, UDM is found to be superior in CO predictions in comparison to CALINE4 and STM. The UDM had the lowest value of 0.0 for AB, MBE and FB and 0.06 for NMSE while highest value of FAC2 (1.0) and 0.84 for R in comparison to CALINE4 and STM. The UDM was found to be idealistic in CO predictions with observed data. However slight overestimations was found by STM with FB and MBE value of +0.03 and +0.25 and underestimations by CALINE4 with MBE and FB value of –0.46 and –0.26 respectively.

The UDM and STM had almost zero absolute bias (0.001 and –0.06) although significantly low value was observed in CALINE4 (–0.42). The mean absolute error and mean square error were lowest for UDM (0.24) followed by CALINE4 and STM (0.33 and 0.85), indicating superior performance of UDM. The mean bias error of UDM was zero indicating ideal performance in zero deviation of predicted value from actual. However little overestimation was found by STM (0.25) and under prediction from CALINE4 (–0.46). An FB value of zero (0.0) and (+0.03) was found in UDM and STM representing perfect agreement between predicted and observed values while slight under-prediction was observed by CALINE4 (–0.26). The NMSE value of 0.06 was observed for UDM indicating perfect correlation between predicted and observed concentrations while 0.2 and 0.24 is for CALINE4 and STM. Similarly lowest RMSE value was found in UDM (0.42) followed by CALINE4 (0.72) and STM (0.89), showing superior quality of UDM wrt CALINE4 and STM.

The MG value of 0.96 was calculated for UDM and CALINE4 with very little deviation from ideal value of 1; however lower value of 0.89 was found by STM. All three models performed excellently since both MG and VG values lie in the range of $0.77 < MG < 1.3$ (i.e. a mean bias within a factor of 1.3), and a $VG < 1.6$ ("factor two scatter") with UDM at the topmost performance having lowest VG among the three. The index of agreement representing the accuracy of predictions against the observed ones was very high in UDM and STM (0.91 and 0.95) wrt CALINE4 performance of 0.82. A perfect agreement between variance of predicted and observed concentrations was found for CALINE4 and UDM with FS value of 0.06 and –0.17 which is very close to ideal value of 0.0 with UDM depicting very little under-prediction. For STM slight under-prediction is observed with FS value of –0.87. The entire predicted datasets obtained by UDM models was found to be within a factor of two of their equivalent hourly measurements. An FAC2 value of 1 in UDM indicates perfect extent of predictions wrt observed values. For CALINE4 and STM, FAC2 was 0.72 and 0.63. Thus UDM had best performance and STM the least. The Pearson's correlation coefficient (*R*) was also highest for UDM with 0.84 value followed by 0.74 for CALINE4 and –0.15 for STM. Finally, the statistical outcomes attained from the UDM model are significantly superior to those acquired with the CALINE4 and STM model.

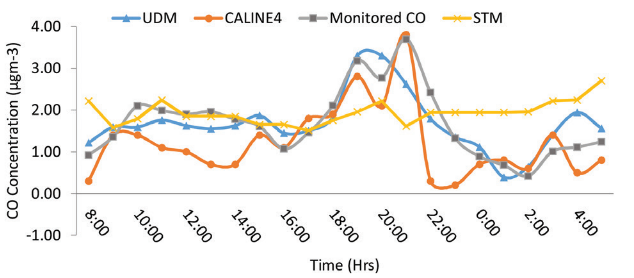

Figure 4: Comparison of modelled and monitored CO concentrations by CALINE4, UDM and STM.

Conclusions

The study illustrated the prediction performance assessments and comparison of three automobile exhaust dispersion models (CALINE4, UDM and STM) at one of the most congested urban roadway (NH2) in the city of New Delhi, the capital city of India. The overall assessment analysis exhibited that UDM exceeded CALINE4 and STM in CO estimations.

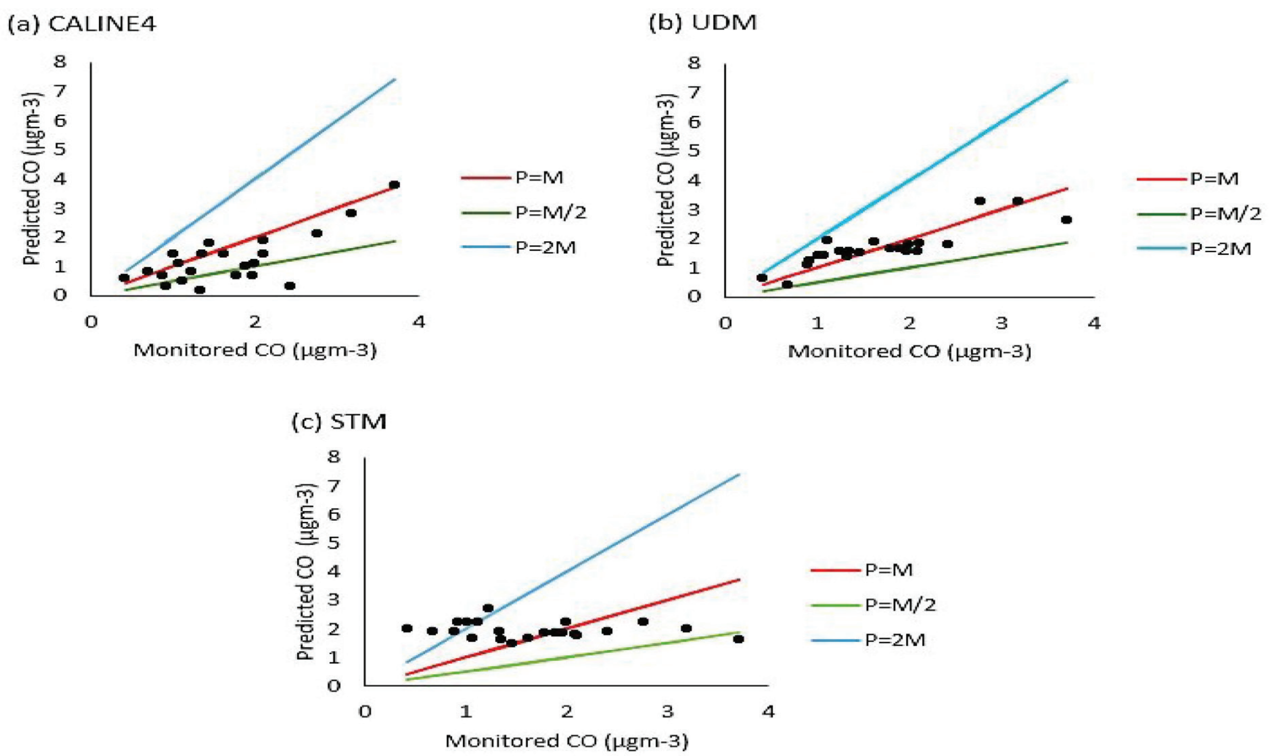

Figure 5: Scatter plots of predicted versus monitored CO (in µgm^{-3}) for CRRI, NH2 road, New Delhi. (a) CALINE4, (b) UDM and (c) STM.

The accordance between the monitored and modelled CO concentrations were fairly good for UDM and CALINE4 models. All the models exhibited an ability to predict the major part of downwind concentrations in a factor of two of the monitored values.

The UDM had the lowest value of AB, MBE, FB and NMSE while highest value of FAC2 and *R* in comparison to CALINE4 and STM. The UDM was found to be idealistic in CO predictions with observed data. However slight overestimations was found by STM with positive FB and MBE value and underestimations by CALINE4 with negative MBE and FB values.

The superior performance by UDM is due to it being a multiple polynomial regression equation based on traffic flow and wind speed data which are the most influential parameters in CO prediction observed both from previous studies of sensitivity analysis of CALINE4 model and statistical analysis. For improvement in prediction performance of STM, the data of sensitivity analysis taken from secondary source needs to be further assessed.

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