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Prediction and Analysis of Near-road CO Concentrations due to Heterogeneous Traffic Using a Simplified-type Dispersion Model

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Abstract: The near-road traffic-related coverages of air pollutants have been recently identified as a major threat due to corroboration associating effusion from roadway traffic to adverse health effects. In this paper a basic microscale simulation model has been derived and analyzed to calculate short-term (hourly) near-road carbon monoxide (CO) concentrations from heterogeneous traffic usually observed on Indian roads. The sensitivity analysis and a case study is used to underline problems in estimating near-road CO pollutant effects. Procedure-based simulation models based on mathematically proficient simplified-type response surface methodology and minimum inputs variables combine the main factors of air pollution exposures: vehicle emissions and traffic flow, meteorology, and receptor point. We select the most significant parameters and then develop an assembly of multiplicative type-models that simulate the predicted CO values from "source" model CALINE4. The combined model is implemented to a case study in the Central Road Research Institute (CRRI), New Delhi area. It forecasts CO concentrations at the sampling station beside a roadway. We examine the spatial profiles of CO concentration estimations. The forecasted CO concentrations exhibited rational similitude with hourly measurements at 10 m receptor distance, like, the mean error, mean absolute error, NMSE, RMSE, FB and MG value between monitored CO concentrations and predicted CO concentrations from simplified model are found to be 0.466, 0.686, 0.384, 1.172, -0.06 and 0.937. This shows that modelled value reasonably matched the observed concentrations. The simplified-type model is proposed for epidemiological and risk analysis, exposure assessment, geographical information systems (GIS) and other uses.

Key words: Microscale simulation model, heterogeneous traffic, near-road air pollution, carbon monoxide, sensitivity analysis, CALINE4, multiplicative type models, epidemiological studies.

Background

The geographical information systems (GIS) and geocoded data have been used in numerous types of environmental assessments like environmental epidemiology and risk assessment. Most of the research have employed pollutant exposure near to roads or at some distance from roads or residences or public buildings. Even with ease of display and analysis in GIS, the estimated data were crude substitute of dispersions since it partly took into account the essence of emissions, orographic factors, meteorological effects and other parameters that affect dispersions of pollutants, fate, transport, and exposure. Also, a quantifiable estimation of emission impact were not found (Huang and Batterman, 2000). Only limited studies have employed dispersion models in prediction of vehicular emissions. Such models, which

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can calculate spatial and temporal concentrations, are helpful in estimations of exposure and assist in other types of analyses.

The estimation of air pollutant emissions from roads have been studied by Lipfert and Wyzga (2008) and HEI (2010). While the proximity and traffic intensity measures are easily derived within GIS context, a substantial limitation of these are the possibility for erroneous exposure estimation since in such measures the effects of meteorology, time-activity configurations of the study subjects e.g. time spent at distant from the locality is considered and vehicle emissions are not considered. Moreover, the small scale variations in pollutant concentrations is improperly considered in such measures (Huang and Batterman, 2000).

The effects of traffic-related air pollution near road have been predicted by simulation models in a range of implementations (English et al., 1999; Bellander et al., 2001; Lin and Lin, 2002; Jin and Fu, 2005; Cook et al., 2005; Cohen et al., 2005). These models use dispersion parameters (like average emission factors, wind speed, wind angle, mixing height and road geometry etc.) usually built on the Gaussian plume model equation. Such type of models require large amount of data of pollutant concentrations, roadway geometry, source of emission, atmospheric meteorology and land use patterns. CALINE4 is a famous Gaussian-form line source model (Benson, 1989). With suitable input data, these simulation models are employed to forecast short- and long-duration concentrations of air pollutant at required location points termed as "receptors," and several receptors are required to display temporal and spatial concentrations at local, city and regional scales. The site-related emission data that runs such type of models is not trifling in development. The traffic emissions rely on numerous parameters, like the speed, number, class and age of vehicles, all of which can change considerably with time of day. The limitations of dispersion type models include, amongst others, errors related to unmeasured variations in emissions, large amount of input data requirement, requirement of exact site-specific information, basic and probably idealistic model postulations, the relevance of estimation of background concentration and a necessity for model validation.

An alternative procedure-based modelling tool is computational fluid dynamic (CFD) based models (Hanna et. al., 2004). Such models use the Navier-Stokes equations and are used in estimation of short-duration dispersion of pollutants, especially in zones with high buildings and complex topography, and with still or low winds, a condition where some other model types do not perform efficiently. Even though, CFD based models also require large amount of data inputs and computations, and have other limitations just explained for dispersion type models. Another latest method for air pollution impact estimation, named "land use regression" (LUR) based models, takes land features, traffic and additional data as independent parameters and fit pollutant concentrations calculated at multiple locations using statistical models, which are then utilized to estimate air pollutant exposures at other locations (Ryan and LeMasters, 2007).

The main benefit of LUR based models is their potential to demonstrate minor deviations in city scenario without the requirement for complete (and exact) emission data. Though, these type of models are specific to one area and cannot be assuredly generalized to areas with dissimilar land uses, landscape, emission types, etc. Since the regression models use observed pollutant concentrations as the dependent variable, they require a range of monitoring points and past data. LUR based models have been employed to calculate only long-duration pollutant concentrations. This research work concentrated on traffic related air pollutants effects on surrounding environment which have been one of the main causes of adverse human health diseases like asthma, impaired lung disorder, increased cardiovascular failure and increased death rate etc. (Ryan and LeMasters, 2007; WHO, 2005; Hart et al., 2009). A comparatively simple, consistent and accessible models that can be simply connected to a GIS or employed in additional studies would assist scientists for reasonable forecasts of air pollutant concentrations.

The first aim of this research work was to establish an efficient model for prediction of near-road short and long-duration CO concentrations that simulate observed data and are validated by dispersion type models. The simplified-form model was superior to other existing models in many ways, like prediction of concentrations from a large number of receptor points and time durations, ease of calculations, and relatively restricted data demands. All these make the usage of the model in risk analysis, epidemiology and exposure evaluation, especially if forecasts are required for a huge quantity of receptor points and/or road sections. Moreover, the basic simplified model could be easily incorporated into GIS and some other software. The next aim of this research was to find important variables, knowledge gaps and exposure outlines that could be identified in risk and exposure analysis applications for emissions near road.

This research paper is compartmented as follows: Firstly the formulation of simplified form of type model in prediction of pollutants due to dispersion is reviewed. This includes the response surface methodology for main parameters, which are arranged in a segmental fashion to enable corroboration and development. The key parameters are identified through sensitivity analyses and model's behaviour is demonstrated. The main variables are selected and the parameters for the simplified-form model are then derived. The connected model is described by means of a case study performed at CRRI, New Delhi, in which a comparison of predicted CO concentrations to monitored concentrations near a major freeway is done. These presentations show many important outcomes regarding the distribution, temporal and spatial variations of predicted concentrations. In the end the consequences for risk assessment and exposure analysis, and limits of the developed model are discussed.

Methodology

Dispersion Modelling

The simplified type model was formulated to portray a Gaussian plume dispersion model (CALINE4) generated by the Department of Transportation, California, to forecast 1- and 8-hr CO concentrations at pre-defined receptor locations near roads (Benson, 1989). The input parameters include traffic volume, average emission rates (weighted emission factor), roadway geometry and hourly meteorological data. Each highway section is separated within a chain of segments, as a "corresponding" fixed line origin which is perpendicular to the direction of wind and positioned at the middle point of segment, from which increasing concentrations are estimated and added to forecast the concentrations at predefined receptor points. A simplified-form dispersion model was developed using multiplicative variable equations which are easy to apply and elucidate, primarily demonstrating a response surface assessment for specific developments within the model.

The sensitivity analyses for each model inputs were performed in CALINE4 (Dhyani, 2017; Benson, 1989; Dhyani and Sharma, 2017). For the formulation of the simplified-form model, the sensitivity analyses of significant variables were performed, and each parameter was independently altered over a larger duration than performed earlier, though rest of the variables were fixed at minimal values. The receptor points were fixed perpendicularly from the centreline 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 analysis employed 1 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 1). The normal conditions presumed: ambient temperature = 35.5°C; mixing height = 480 m; background concentration (0.1-3.1 mg m^{-3}); mixing zone width = 36 m; wind speed = 1.8 m s^{-1}; vehicle flow = 9,213 vehicles hr^{-1}; atmospheric stability category (SC = B); road at grade level and an assumed large rate of emission to get adequate accuracy in model results. The following inputs were varied in the sensitivity analysis of the secondary data (Dhyani, 2017): weighted emission factors of 3.3, 3.4, 4, 4.1, 4.9 and 5.7 gm mile $^{-1}$, wind speeds of 0.5, 1, 1.5, 1.8, 2, 3, 4 and 5 m s^{-1}; wind angles from 0 to 180° in 10° rise, vehicle volumes from 5857 to 12,550 vehicles/ hr in additions of 836 and the road at grade level.

The estimated concentrations at each receptor point are graphically shown. The input variable of CALINE4 examined in previous sensitivity analyses like surface roughness, variation in wind direction, highway dimensions (with length, width and height), deposition velocity and other variants (Dhyani, 2017; Benson, 1989; Dhyani and Sharma, 2017). These could be significant in exceptional circumstances, but in general they illustrated minor effects.

Simplified-type Dispersion Model

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

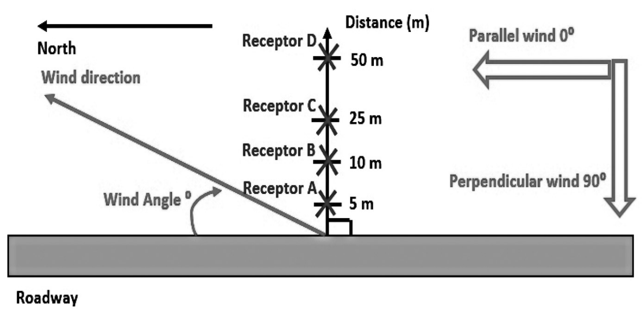

Figure 1: Description of wind and road coordinate system for any wind and road direction.

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%. This principle fits merely to the standard modelled settings, e.g., even landscape, and at grade road level. In general, the input variables that make small variances were neglected. 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}. For calm conditions, no computations were tried (the hour's pollution concentration was noted as unobtainable). 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:

$$C_{X(WEF)} = (q_1 \exp(-q_3 (x - q_2))) \quad (1)$$

$$C_{X(TF)} = (q_4 \exp(-q_6 (x - q_5))) \quad (2)$$

$$C_{X(WS)} = (q_7 \exp(-q_9 (x - q_8))) \quad (3)$$

$$C_{XT} = C_{x(WEF)} + C_{x(TF)} + C_{x(WS)} \quad (4)$$

$$C_{XT} = \{(q_1 \exp(-q_3 (x - q_2))) + (q_4 \exp(-q_6 (x - q_5))) + (q_7 \exp(-q_9 (x - q_8)))\} \quad (5)$$

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 1, 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°. The modelled concentrations from Eq. (5) using the evaluated parameters followed the observed concentration with a mean absolute percentage error (mape) of 69 whereas on comparison with CALINE4 predictions (mape) is found to be 170. A graphical presentation of the performance of the simplified-form model with respect to CALINE4 is displayed in Figure 2D.

Combined Dispersion Model

Wind speed was related to concentration by an inverse power law equation

$$C_{WS} = q_{10} \times (WS^{q11})\ C_{WS} = 0.5 \quad (6)$$

where C_{WS} = concentration (ppm) for wind speed WS (m s^{-1}), q_{10} and q_{11} = calculated variables, and $C_{WS=0.5}$ = concentration estimated at the standard wind speed of 0.5 m s^{-1}. Variables q_{10} and q_{11} were evaluated as 0.7647 and –0.9069, correspondingly, for the range of wind speeds (0.5-5 m s^{-1}) and (5-50 m) distances selected.

As stated, larger traffic flow escalated vertical dispersion, and its influence on concentration relies on downwind distance and wind angle. Many types of model and parameterization techniques were attempted, and tried to fit for winds that were both parallel and perpendicular to the roadway. The opted model was:

$$C_{TF} = q_{12} \times (TF^{q13})\ C_{TF} = 5857 \quad (7)$$

where C_{TF} = concentration at traffic flow TF (vehicles hr^{-1}) and X (m) downwind distance; $C_{TF=5857}$ = concentration estimated for 5857 vehicles hr^{-1}; and estimated parameters are q_{12} = 425132; q_{13} = –1.47554. Weighted emission factor also had an inverse relation to concentration. The relation developed was:

$$C_{WEF} = q_{14} \times (WEF^{q15})\ C_{WEF} = 3.3 \quad (8)$$

where C_{WEF} = concentration at weighted emission factor WEF (g mile^{-1}) and downwind distance X (m); $C_{WEF=3.3}$ = concentration predicted at weighted emission factor of 3.3 gm mile^{-1}; and estimated parameters are q_{14} = 2.5784 and q_{15} = –0.9485.

By multiplying Eqns. (5), (6), (7) and (8), a multiplicative model was fitted which included 15 variables and five input parameters (wind direction, average emission factor, wind speed, distance of receptor from road and traffic volume rate). Setting the multiplicative constituents together, the concentration $C_{X,WS,WEF,TF}$ (ppm) at X (m) distance, wind speed WS, weighted emission factor WEF and traffic flow TF was given by:

$$C_{X,WS,WEF,TF} = C_{Xt} \times C_{ws} \times C_{WEF} \times C_{TF} \quad (9)$$

$$C_{X,WS,WEF,TF} = \{(q_1 \exp(-q_3 (x - q_2))) + (q_4 \exp(-q_6 (x - q_5))) + (q \exp(-q_9 (x - q_8)))\}$$

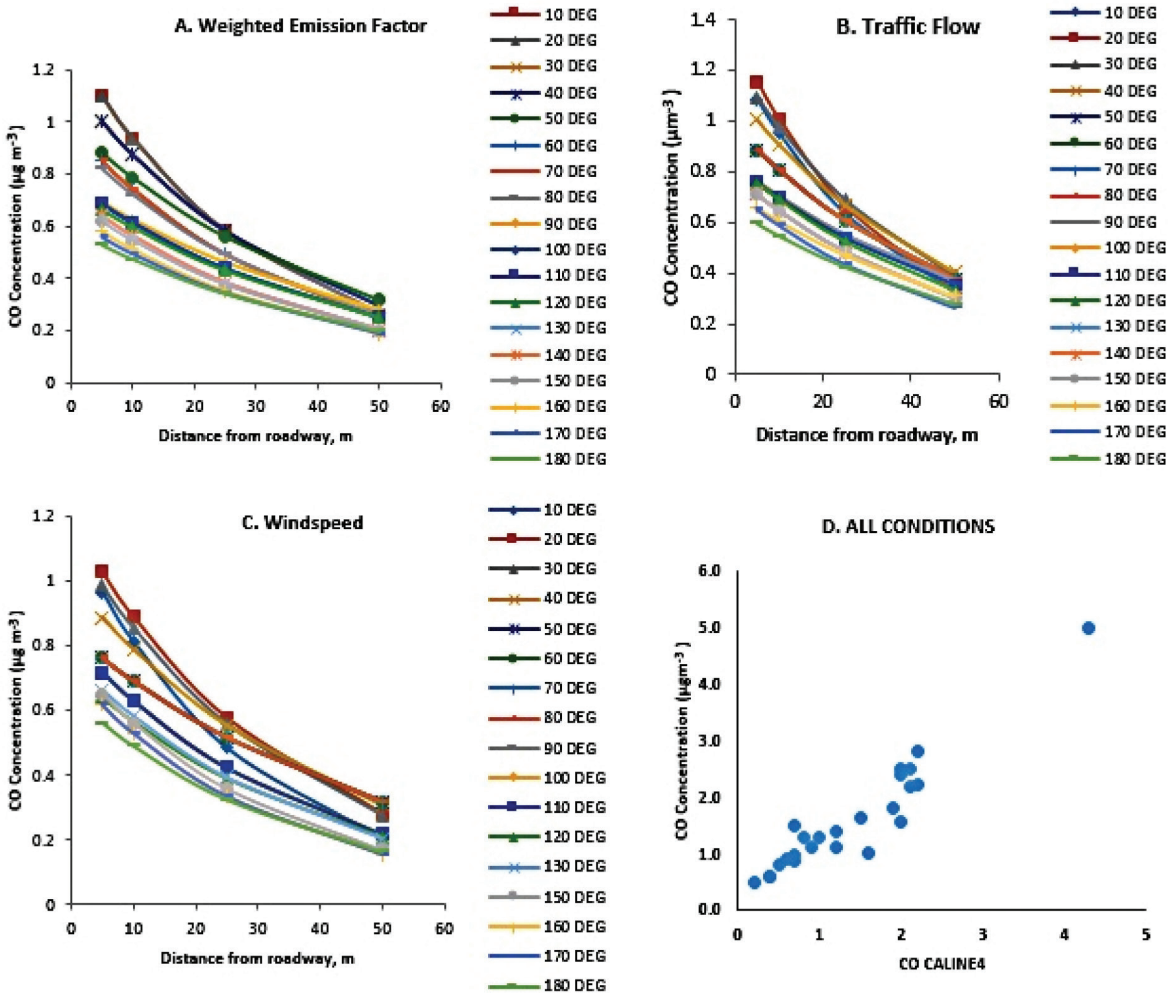

Figure 2: Comparison of CALINE4 model predictions (shown as solid lines) and simplified type dispersion model (shown as points) showing effects of A) wind speed; B) weighted emission factor; and C) traffic flow for four receptor distances (5, 10, 25 and 50 m) from the roadway. All plots use nominal conditions (wind speed = 1.8 ms-1, wef = 4 g mile-1; VPH = 9,210; wind angle = 70°). Panel D plots concentrations from the two models for all conditions.

$$\left\{ q_{10} \times q_{12} \times q_{14} \left(\left(\frac{(WS^{q11})C_{WS} = 0.5}{q_{12} \times q_{14}} \right) \times \left(\frac{(TF^{q13})CTF_{=5857}}{q_{10} \times q_{14}} \right) \times \left(\frac{(WEF^{q15})C_{WEF=3.3}}{q_{10} \times q_{12}} \right) \right) \right\} \quad (10)$$

The calculated variables are described in Table 1. Using these variables, Eq. (10) forecasts CO concentrations (in ppm). For any angle of wind, traffic flow from 5,857 to 12,550 vehicles hr^{-1}, receptor distances 5 to 50 m distance from the road and for at grade level roads.

Model Evaluation

Firstly the simplified-form model was tested by exploring inter-model accordance by using absolute relative error statistics, relative errors, correlations and scatter graphs. The simplified model potential was measured across the complete range of input variables. Subsequently, a partial assessment of the simplified-form model was performed by matching actual CO measurements to hourly average predictions for the year 2014 at the Mathura Road, New Delhi monitoring site, which is operated by the Central Road Research Institute, CRRI, New Delhi. The passageway selected for the investigation was 2 km segment of National Highway-2 (NH-2) going from Delhi to city of Agra (Figure 3). The selected road segment is at geographical location of 28°37′39.99″N 7714′29.04″°E correspondingly and at 216 metres over mean sea level (MSL). The particular stretch accommodates to both intra-city and inter-city vehicles. The neighbouring land usage is mainly housing, even though there are

Table 1: 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	0.0268	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. (5) 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}.

many industrial and commercial amenities within 5 km of the study area. The CO concentration, traffic flow, vehicle vintage and meteorological values were used from secondary data taken from Dhyani (2017). At CRRI it was observed by an air pollution measurement mobile vehicle, which was positioned at 5 m distance far from width of mixing zone using Infra-Red Gas Filter Correlation Detector (CPCB approved instrumentation) (CPCB Draft Report, 2016). Surface meteorological data are also recorded at this location. The total traffic flow recorded at the highway stretch was 1, 79, 396 vehicles day^{-1} (1, 93, 332 passenger car unit or PCU). The data of age (vintage) of vehicles (diesel and petrol) was gathered from fuel station reviews via a set form near to the study area. The age profile data collected from fuel stations review and traffic volume videos (e.g., percentage of 2W-4S vehicles and 2W-2S, percentage of CNG, LPG, diesel and petrol run vehicles in different vehicle classes) were used to evaluate the weighted emission factors (WEFs) which is selected as an input parameter in CALINE4 model.

The WEF is a function of automobile movement (traffic volume) and automobile emission factor (vehicle category, vintage, type, age profile, fuel type, etc.). For evaluation of WEF (g m^{-1}) (illustrating standards for vehicles of all types) emission factors for Indian vehicles were used (ARAI, 2008; CPCB, 2000). The study was performed using a 24-hour data

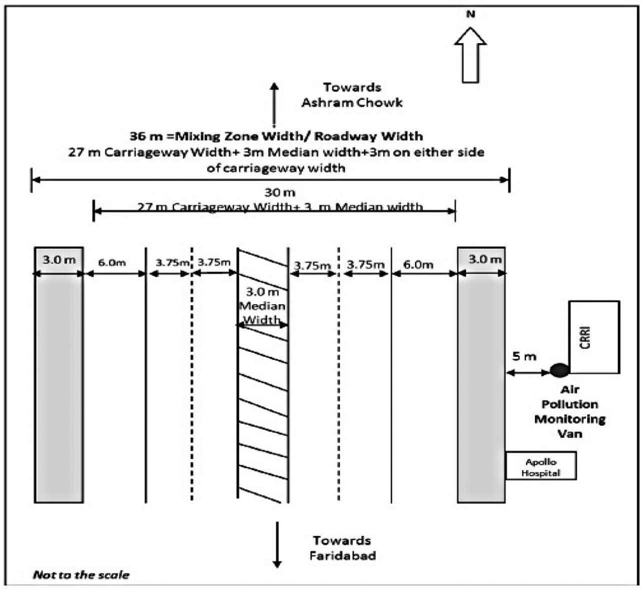

Figure 3: Experimental site. (*Source*: Dhyani (2017)

run under regular conditions and 1-hour averaged traffic and meteorological variables were used to forecast CO concentrations at pre-set receptors locations nearby the particular road stretch so that the forecasted concentrations of CO could be matched with recommended 1-hour CO NAAQ standard (i.e., 4 mg m^{-3}). We forecasted hourly CO concentrations by using the CALINE4 model and the simplified-form model, where the weighted emission factors, the monitored traffic flow and the CRRI meteorological data were input variables.

New Delhi Case Study

To generate a more intricate presentation, 5, 10, 25 and 50 m receptor locations on a straight stretch normal to national highway NH2, Mathura Road, in front of CRRI gate, New Delhi were modelled. The study was performed in summers in the month of June 2014. The simplified-form model was operated to evaluate CO concentrations at each receptor point for each hour in 2016. Hourly average percentage concentrations were studied and plotted, and nominated based on the highest and lowest average concentration within the modelled dominion.

Results

CALINE4 Sensitivity Analysis

Figure 4 portrays the sensitivity analysis outcomes, in which each parameter was altered from the normal conditions. Wind speed had a large influence, e.g., concentrations decreased by 80% as wind speed raised from 0.5 to 5 m s^{-1} (Figure 4C). Wind reduces the pollutant concentrations inversely, but the preliminary horizontal and vertical dispersion variables are also determined by wind speed, that marginally declines the dilution effect (Dhyani, 2017; Benson, 1989; Dhyani and Sharma, 2017). Greater traffic flow upsurges CALINE4 calculations due to its proportionality with emission rates. Although, the influence on pollutant concentrations is less than proportionate since larger flow rates also enhance dilution effect due to heat flows due to vehicle that elevate vertical dispersion. For winds flowing parallel to the road, the counter effect is higher, and moderated for crosswinds at positions out of the mixing zone width (Dhyani, 2017; Benson, 1989; Dhyani and Sharma, 2017). For the aim of the sensitivity analysis estimation, the rates of emission were kept as constant while the traffic flow were varied. For example, a 2-fold rise in traffic flow (5,856 to 12,550 vehicles hr^{-1}) and for winds flowing over the road normally (wind angle = 90°; the standard condition in the sensitivity analysis evaluation), the concentrations of the curbside were unchanged, but reduced by 56% at a distance of 25 m and 54% at 50 m (Figure 4).

For winds flowing parallel over the road (wind angle = 0°), the same variation reduced the concentrations by 44.4% at the curbside and by 20% at 5 to 50 m distance. Similarly for average/weighted emission factor (wef), for 72% rise in weighted emission factor (3.3 to 5.7 $gmile^{-1}$) and for winds flowing parallel over the road (i.e. wind angle = 0°), there was reduction in concentrations by 44.4% at the curbside and by 20% for 5 to 50 m distances. And for winds flowing over the road normally (i.e. wind angle = 90°; the standard condition in the sensitivity analysis), it reduced by 50% at 25 m distance and 16.66% at 50 m (See Figure 4A).

Validation of the Simplified-type Dispersion Model

A graphical presentation of the performance of the simplified-form model with respect to CALINE4 at 10 m distance from roadway is displayed in Figure 2D and at 5, 10, 25 and 50 m receptor distance in Figures 5A, 5B, 5C and 5D.

- The mean error between the simplified model and CALINE4 is 1.181, 1.36, 1.998 and 1.015 for 5, 10, 25 and 50 m receptor distance. It is small and signifies that predicted CO from simplified model is comparable to CALINE4 data. The error between CO from simplified model and monitored CO value is very small (0.466), indicating good performance of simplified model in CO prediction. (See Figure 5 and Table 2).

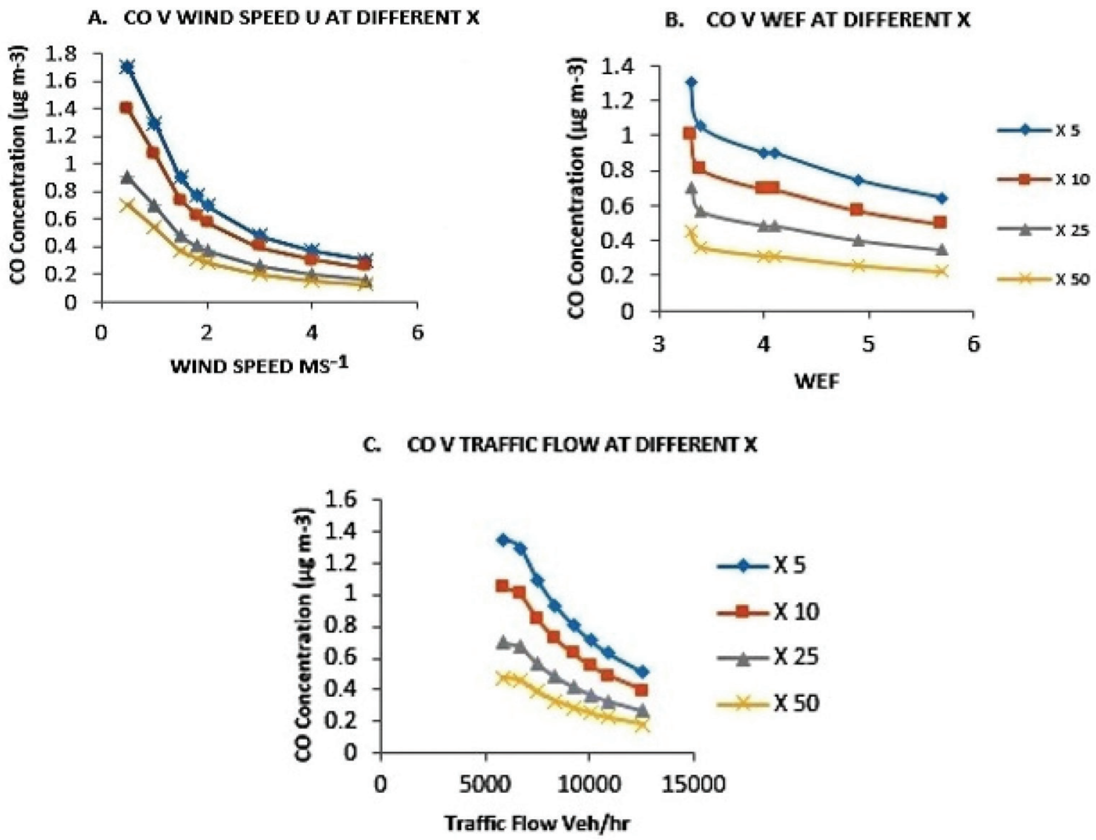

Figure 4: Predicted CO concentrations showing sensitivity to: A) Weighted Emission Factor; B) Traffic Flow; C) Wind speed. All Plots use nominal conditions (wind speed = 1.8 ms^{-1}, wef = 4 g mile^{-1}; VPH = 9,210; wind angle = 70°).

Table 2: Statistical parameters indicating performance of simplified-type dispersion model with respect to CALINE4 model performance in CO prediction at receptor distance of 5, 10, 25 and 50 m

Statistical parameters	*CO simplified model vs CO CALINE4 at receptor distance of*		*CO simplified model vs monitored CO at receptor distance of*	*CO simplified model vs CO CALINE4 at receptor distance of*	
	5 m	*10 m*	*10 m*	*25 m*	*50 m*
Mean error	1.181	1.360	0.466	1.998	1.015
Mean absolute error (MAE)	1.267	1.487	0.686	2.222	1.388
Avg CO monitored – Avg CO predicted	-0.342	-0.114	-0.114	0.448	1.035
Percentage relative error in average concentration (%)	18.661	6.258	-5.889	32.388	-56.432
Global mean bias (GB)	0.696	0.565	0.114	0.310	-0.131
Fractional bias (FB)	0.170	0.060	-0.06	-0.278	-0.786
Average square error	3.668	6.090	1.373	19.316	6.773
Normalized mean square error (NMSE)	0.919	1.704	0.384	7.605	4.623
Root mean square error (RMSE)	1.915	2.467	1.172	4.395	2.602
Geometric mean bias (MG)	0.814	0.948	0.937	1.502	1.740
Index of agreement (*R*)	0.876	0.761	0.939	0.596	0.936

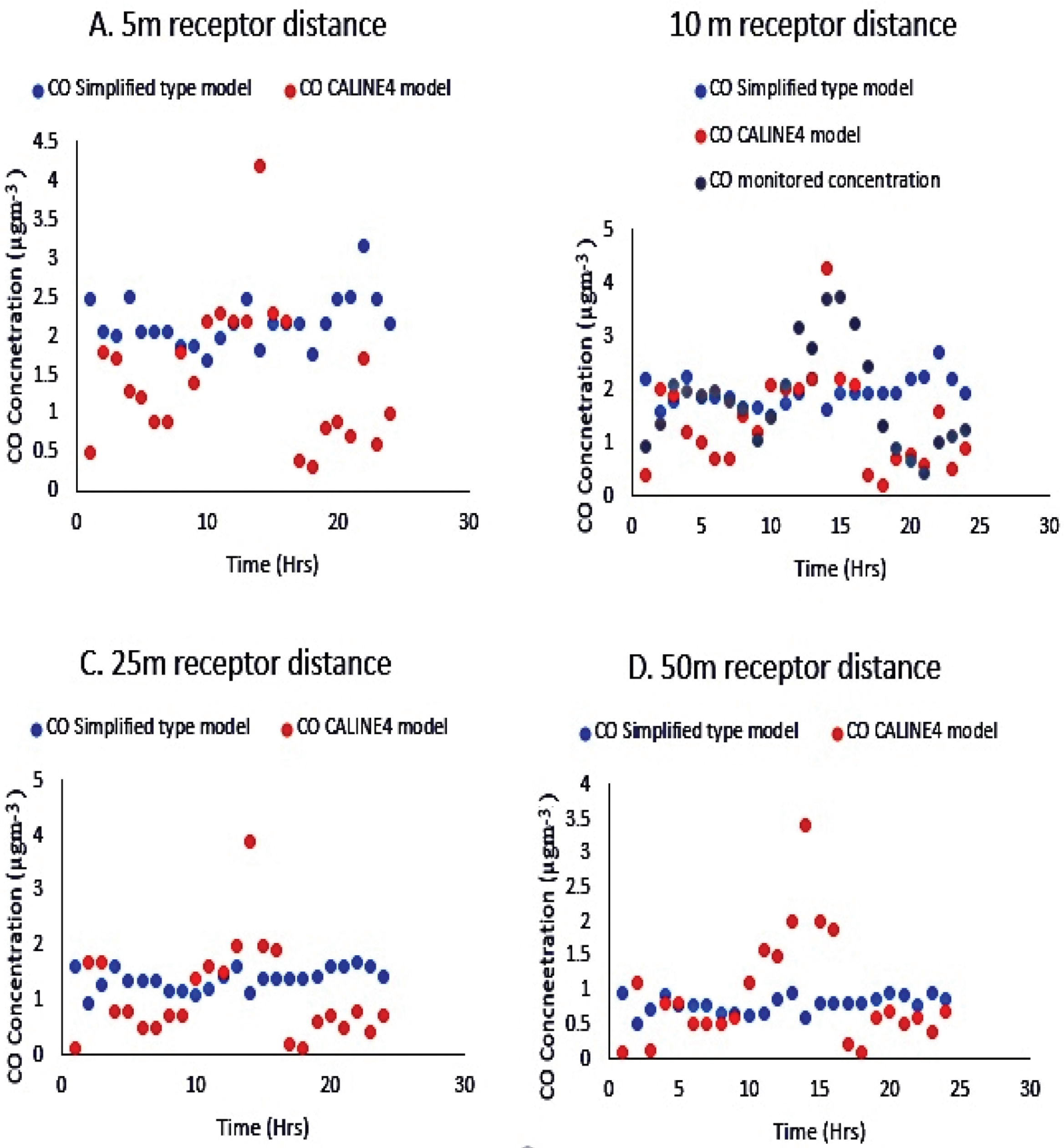

Figure 5: Predicted CO concentration versus time for simplified-type dispersion model and CALINE4 at receptor distance of : A) 5 m from roadway; B) 10 m from roadway, C) 25 m from roadway; and D) 50 m from roadway.

- Difference between average modelled CO concentrations from simplified model and CALINE4 is relatively small (–0.342, –0.114, 0.448 and 1.034 µg m^{-3}, for receptor distance of 5, 10, 25 and 50 m respectively), representing a relative error in the average concentration not more than 18.661%, 6.258%, 32.388% and –56.432%. The difference is the best for 10 m receptor distance from roadway with percentage relative error in average concentration only 6.528%. For difference in CO from simplified model and monitored CO at 10 m receptor distance it is –0.114 with percentage error of only –5.889%, representing good performance of simplified model till 10 m receptor distance.
- The FB value for the simplified model wrt CALINE4 is relatively small (–0.17, 0.06, –0.278 and –0.786 for receptor distances of 5, 10, 25 and 50 m respectively). The FB value is acceptable till receptor distance of 25 m with value at 10 m exceptionally good (–0.06) indicating the accuracy of estimation of CO wrt CALINE4 values. The

FB value for simplified model wrt monitored data at 10 m receptor distance is –0.06 indicating good performance of simplified model. The value of FB indicates a small overall overestimation of CO concentrations. The model performance is considered acceptable if $-0.7 < FB < 0.7$ (Dubey et al., 2013).

- The MG of the simplified model wrt CALINE4 data is 0.814, 0.948, 1.502 and 1.74 for receptor distance of 5, 10, 25 and 50 m. This means that MG follows the ideal value of 1.0 with only by 0.186, 0.052, –0.502 and –0.74 indicating very small biases till receptor distance of 10 m. For distance more than 10 m biases are large. The MG value of simplified model wrt monitored CO at receptor distance of 10 m is 0.937, which is also close to ideal value indicating accurate performance of simplified model in CO prediction till 10 m receptor distance.
- The model produces less comparable data wrt CALINE4 data except for receptor distance 5 m as RMSE is large (1.915, 2.467, 4.395 and 2.602 for receptor distances 5, 10, 25 and 50 m). However RMSE value between predicted CO from simplified model and monitored CO at 10 m receptor distance is small (1.172) indicating satisfactory performance in CO prediction.
- The normalized mean square error (NMSE) which represents the overall deviations between modelled CO concentrations from simplified model and CALINE4 CO values equals 0.919, 1.704, 7.605 and 4.623 for receptor distance of 5, 10, 25 and 50 m. It indicates that the simplified-type dispersion model does not accurately describes the CO concentrations in time and space wrt CALINE4 CO values for all receptor distances because the performance of the model is considered acceptable if NMSE ≤ 0.5 (Dubey et al., 2013; Raducan and Stefanescu, 2012). However the NMSE value for CO concentrations from simplified model and actual CO concentrations at 10 m receptor distance is 0.384, i.e. less than 0.5. This shows that simplified model accurately predicted CO concentrations till receptor distance of 10 m.
- The index of agreement (R) of the simplified model wrt CALINE4 data is 0.876, 0.761, 0.596 and 0.936 at receptor distance of 5, 10, 25 and 50 m. For relation wrt monitored data the R value is 0.939. All the values are close to ideal value of 1, thus showing the relevance of predicted CO from model.

Discussion

The mean error, mean absolute error, NMSE (<0.5), RMSE, FB (acceptable value: between –0.7 and 0.7) and MG (ideal value 1) between predicted CO from simplified model and CALINE4 data at 10 m receptor distance is found to be –0.36, 1.36, 1.487, 1.704, 2.467, 0.06 and 0.948 respectively. The results are not much comparable to CALINE4 data. However on comparison of modelled CO from observed CO at 10 m receptor distance the values are satisfactory (–0.271, 0.466, 0.686, 0.384, 1.172, –0.06 and 0.937). This indicates that combined model satisfactorily describes CO concentrations till receptor distances of 10 m and its performance deteriorates after 10 m.

The “reasonable” or “moderate” results of the model at CRRI can be elucidated by a number of causes. First, even though there was hourly traffic counts, the WEF was estimated using (Dhyani, 2017; ARAI, 2008; CPCB, 2000) average emission factors, but, these are average pollutants data (g km^{-1}) (which are independent of speed). Even though the emission factors provided by ARAI are inclusive and includes large class of Indian vehicles but these are not frequently updated. Thus, this leads to a substantial uncertainty in emission factors. Second, there are a number of limitations in the Gaussian plume models, and they do not integrate the latest advances in theory of turbulence. Thus, for example, hourly estimations are seldom considered “zero” level of concentrations that resembled to some of the more enhanced CO observations at CRRI.

This assessment is not a complete corroboration of the model. Rather, it describes the form of representation that can be predictable in conditions where information are restricted to a specific site. For carbon monoxide (CO), we expect that long-duration concentrations can be estimated satisfactorily, which offers a level of confidence in simplified dispersion models. A more uncertainty is expected in short-term predictions.

In this paper, we selected a prominent dispersion model, CALINE4, within a simplified-type model which is comparatively easy and practical to use. In some way, our inspiration was to implement the current model in estimation of traffic emitted pollutant impacts in the perspective of an environmental epidemiological examination. The methodology also appears to be implementable for risk assessment, GIS, hot-spot analyses and traffic engineering and urban planning domains. The model takes moderate number of input parameters to rapidly evaluate predictions of near-by concentrations of air pollutant which are analogous to "source" model concentrations. Such type of procedure-based simulation models facilitate the addition and arrangement of the main parameters of air pollution impacts near to road: vehicle emissions, receptor sites and meteorology. A research was employed to validate the model's presentation and the characteristic of close road impacts, and they reveal many significant outcomes that perhaps are not well perceived by impact valuation experts. The maximum concentrations are almost certainly to happen near downwind side of main roads and intersections in duration of higher emissions (e.g., weekday rush hour) and adverse meteorology (e.g., low wind speeds). Concentration profiles are sharp, and receptors must be placed within distance of 30 to 50 m to reduce errors. We doubt that the found results can be applied to various additional receptor points, and they have significant inferences for epidemiological and further researches. Coupling vehicle emissions, traffic flows and dispersion models helps in estimation of pollutant concentrations at particular sites and durations of attention, letting estimation of specific emission.

The simplified-form model has some drawbacks. Firstly, this is a basic model which accommodates all the precincts of the fundamental dispersion models. For instance, the results for complex landscape or low winds is not likely to be exact. Furthermore, for calm winds no calculations are performed, a constraint usual in Gaussian plume models. Significant errors and impact miscalculation is produced due to this prohibition, especially if calm conditions are recurrent, particularly in times of peak hour. Secondly, even if the simplified-form model estimates match satisfactorily to CALINE4 predictions, this however does not characterize a corroboration of the model. Nor the assessment of calculations to observations at CRRI a complete appraisal, far lesser confirmation of the model. Studies using much wider, varied, and descriptive data are required for determination of model corroboration. Thirdly, the simplified-type model is devised for basic road dimensions, specially, straight road sections. Curved type roads cannot be exhibited, even though this is not likely to be significant for longer roads. Fourthly, alike any model, exact data of input variables are required to generate precise estimates. Finally, although the simplified-form model produces a broad series of results and is empirical, we do not have strong corroboration showing if its estimations are superior to much simpler measurements, e.g., short-term wind measurements or observations based on proximity.

Conclusions

After an extensive sensitivity analysis of the "source" model, CALINE4, to recognize major inputs and parameters, an effective simplified-form model was established which replicates near road vehicle dispersions. The use of the developed model in actual conditions exhibited overall accordance with observed CO concentrations and the correlation of measurements per hour with predictions was merely reasonable. This has significant effects for sampling drives meant for portraying near roads pollutant levels; for instance, the errors in assessing long-duration concentrations from short-duration monitoring can be big, particularly for receptors on upwind side. It also advocates that monitoring during several seasons is desirable than to cover the monitoring duration in a season, and that the changeability is reliant on receptor site. LUR models along with exposure assessments can be upgraded by considering for such differences. The simplified-form model expedites numerous studies. We expect uses stemming impact estimation in epidemiological surveys investigating the link amid traffic air pollutants and health issues, in addition to the assessments of hazards of health. Since it is mathematically proficient, the simplified-type model could be employed in Monte Carlo studies, a technique to handle ambiguities within input variables. The model can also aid in assessment of monitoring schemes proposed to evaluate means and additional statistics, e.g., estimating the suitable figures of sampling locations or durations.

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