Line source emission modelling

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Abstract

Line source emission modelling is an important tool in control and management of vehicular exhaust emissions (VEEs) in urban environment. The US Environmental Protection Agency and many other research institutes have developed a number of line source models (LSMs) to describe temporal and spatial distribution of VEEs on roadways. Most of these models are either deterministic and/or statistical in nature.

This paper presents a review of LSMs used in carrying out dispersion studies of VEEs, based on deterministic, numerical, statistical and artificial neural network techniques. The limitations associated with deterministic and statistical approach are also discussed.

Keywords: Vehicular pollutant; Deterministic models; Numerical models; Statistical models; Multilayer perceptron; Model limitations

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1. Introduction

In recent years, in most of the countries, the air pollution from industrial and domestic sources has markedly decreased due to passage of various acts by different governments. However, there has been a substantial increase of air pollution caused by the vehicular exhaust emissions (VEEs) due to addition of more and more vehicles on roadways to meet increase in transportation demand (Sharma and Khare 2001a; Mayer, 1999). Line source emission modelling (LSEM) is an important tool in screening of VEEs and helps in control and management of urban air quality. The US Environmental Protection Agency (EPA) and many other research institutes have developed a number of line source models (LSMs) for estimating vehicular pollutant concentrations. All these models involve deterministic and/or stochastic approach which, at present, are most widely used. In the recent past, artificial neural network (ANN) and in particular, multilayer perceptron (MLP) has also been applied in modelling the line source dispersion phenomena. Sharma and Khare (2001a)
described various VEEs modelling studies in the domain of analytical modelling techniques—deterministic, numerical and statistical. The present review is aimed at readers with little or no understanding of LSM techniques. It is designed to act as a guide through the literature so that the readers may be able to appreciate these techniques. The review is divided into several sections, beginning with a brief introduction to the LSM approaches and followed by relevant LSM studies based on deterministic, numerical, statistical and ANN techniques. Some of the common practical problems and limitations associated with deterministic, numerical, statistical and ANN techniques have also been discussed.

2. Theoretical approaches of LSEM

The deterministic mathematical models (DMM) calculate the pollutant concentrations from emission inventory and meteorological variables according to the solutions of various equations that represent the relevant physical processes. In other words, differential equation is developed by relating the rate of change of pollutant concentration to average wind and turbulent diffusion which, in turn, is derived from the mass conservation principle. The common Gaussian LSM is based on the superposition principle, namely concentration at a receptor, which is the sum of concentrations from all the infinitesimal point sources making up a line source. This mechanism of diffusion from each point source is assumed to be independent of the presence of other point sources. The other assumption considered in DMM is the emission from a point source spreading in the atmosphere in the form of plume, whose concentration profile is generally Gaussian in both horizontal and vertical directions.

Considering the above assumption, the basic approach to develop deterministic LSM is the coordinate transformation between the wind coordinate system \((X_1, Y_1, Z_1)\) and line source coordinate system \((X, Y, Z)\). Let the length of the roadway be ‘L’, which makes an angle ‘\(\theta\)’ with the wind vector. The middle point of the line source can be assumed as the origin for both coordinate systems, which also have the same Z-axis. The line source is along Y-axis and the wind vector is in the \(X_1\) direction. In the line source coordinate system, all parameters, viz., \(X, Y, Z\) and \(L\) are known from the road geometry. A hypothetical line source is assumed to exist along \(Y_1\) that makes the wind direction perpendicular to it (Fig. 1). The concentration at the receptor is given by Csanday (1972):

\[
c = \frac{Q_L}{2\pi\sigma_Y\sigma_Z} \left[ \exp\left\{ \frac{(Z-H)^2}{\sigma_Z^2} \right\} + \frac{1}{2} \exp\left\{ -\frac{(Z+H)^2}{\sigma_Z^2} \right\} \right] \int_{-L/2}^{L/2} \exp\left\{ \frac{VY_1-Y_1X}{2\sigma_Y^2} \right\} dY_1. \tag{1}\n\]

where \(Q_L\) is the line source strength (unit/m³); \(\sigma_Y\) and \(\sigma_Z\) the horizontal and vertical dispersion coefficients, respectively, and are functions of distance \(X\) and stability class; \(XI\) the receptor distance from the line source; \(Z\) the receptor height above ground level (m); \(H\) the height of line source (m); \(u\) the mean ambient wind speed at source height (m/s); and \(L\) the length of the roadway (m).

Using the above relationship between wind and line source coordinate system, Luhar and Patil (1989) later developed a general finite line source model (GFLSM) as given below:

\[
c = \frac{Q_L}{2\sqrt{2\pi\sigma_Z\sigma_Y}} \left[ \exp\left\{ \frac{[Z-H_0]^2}{2\sigma_Z^2} \right\} + \frac{1}{2} \exp\left\{ -\frac{[Z+H_0]^2}{\sigma_Z^2} \right\} \right] \times \left\{ \frac{\text{erf}\left( \frac{VY_1-Y_1X+H_0}{\sqrt{2}\sigma_Y} \right)}{\text{erf}\left( \frac{VY_1-Y_1X-H_0}{\sqrt{2}\sigma_Y} \right)} \right\}, \tag{2}\n\]

where \(\theta\) is the angle between roadway and wind direction, \(u_0 = u \sin \theta\) \(UP_0\), \(U0\) is the wind speed correction due to traffic wake (Chock, 1978), \(H_0 = H + H_p\), \(H_p\) is the plume rise.

Numerical LSMs also come under the deterministic modelling technique which are based on numerical approximation of partial differential equations.
representing atmospheric dispersion phenomena. First-order closure models, also called K-models, have their common roots in the atmospheric diffusion equation derived by using a K-theory approximation for the closure of the turbulent diffusion equation. These models are time dependent and are applied through computer software; eulerian grid, lagrangian trajectory, hybrid of eulerian-lagrangian and random walk particle trajectory approaches are the commonly used techniques. The detailed methodology of development of numerical LSMs is available elsewhere (Rezler, 1989).

In contrast to deterministic modelling, the statistical models calculate concentrations by statistical methods from meteorological and traffic parameters after an appropriate statistical relationship has been obtained empirically from measured concentrations. Regression, multiple regression and time-series technique are some key methods in statistical modelling. The time-series analysis techniques (Box-Jenkins (B-J) models) have been widely used to describe the dispersion of VEEs at trafficked intersection and at busy roads. Auto-regressive integrated moving averages (ARIMA), ARIMA with exogenous inputs (ARMAX) and transfer function noise (TFN) algorithm have been adopted in LSM studies (Sharma, 1998). The Box and Jenkins (1976, 1970) models are empirical models created from the historical data and it is important that the iterative model building process proposed by Box and Jenkins is always followed. Further, ARIMA models do not specifically distinguish the physical causes of dispersion phenomena (e.g. meteorological variables, emission rates of the sources, etc.) in their input. Such models represent the 'Black Box' approach. All possible uncertainties of the model are taken into account by a 'noise' variable with assigned statistical properties (Juda, 1986). The TFN model is a dynamic model describing the dependent variable as a response to the 'impulses' of the independent variables, with the latter playing the role of time-dependent forcing functions in an ordinary linear differential equation. The characteristics of the response are described by the impulse response functions. The technique is quite general and useful in handling multivariate time series. It specifically builds into the model dynamics of impulse and response that is capable of describing a wide range of physical phenomena (in linear regime). One important feature of TFN modelling is that, because of its ability to control statistically the past variations that are common in two time series, it is a very good way to avoid spurious correlations and true causality in time series (Milionis and Davis, 1994a).

ANN is a kind of statistical modelling technique offering several advantages over traditional phenomenological or semi-empirical models, since they require known input data set without any assumptions. ANNs are parallel computational models comprised of densely interconnected adaptive processing units. These networks are fine-grained parallel implementation of nonlinear static or dynamic systems. The important feature of these networks is their adaptive nature, where 'learning by example replaces programming' in solving problems. This feature makes such computational models very appealing in application domains where one has little or incomplete understanding of the problem to be solved but where training data are readily available. Using readily available inputs, the neural-network model automatically develops its own internal model and subsequently predicts the output. For LSEM, the MLP structure of the neural networks seems to be the most suitable for predicting VEEs (Moseholm et al., 1996). The multilayer perceptron consists of a system of layered interconnected 'neurons' or 'nodes', as illustrated in Fig. 2. The neural network model, shown in Fig. 2, represents a nonlinear mapping between an input vector and output vector (Gardner and Dorling, 1998). The 'nodes' are arranged to form an input layer, one or more 'hidden' layers, and an output layer with nodes in each layer connected to all nodes in neighbouring layers (Comrie, 1997). The input layer 'neurons' serve as buffer that distribute input signals to the next layer, which is a hidden layer. Each 'neuron' in the hidden layer sums its input signal, processes it with simple nonlinear transfer or 'activation function' (e.g., logistic and hyperbolic tangent) and distributes the result to the output layer. The 'neurons' in the output layer compute their output signal in a similar manner. The output signals from each neuron in an MLP propagate in forward direction; therefore MLP is also called as 'feed-forward' neural network (Haykin, 2001).

By selecting a suitable set of connecting weights and transfer functions, it has been shown that an MLP can approximate any smooth, measurable function between

\[ i = \left[ i_1, i_2, i_3 \right] = \text{input vector} \]
\[ o = \left[ o_1, o_2 \right] = \text{output vector} \]
\[ z = w o + b = \text{transfer function or activation function} \]

Fig. 2. A MLP with a hidden layer (Gardner and Dorling, 1998).
input and output vectors (Hornik et al., 1989; Gardner and Dorling, 1998). MLP has the ability to learn through training. A supervised back-propagation algorithm is commonly employed in the training of MLP (Haykin, 2001). Training requires a set of data, which consists of a series of input and associated output vectors. During training, the multilayer perceptron is repeatedly presented with training data and the weights in the network are adjusted until the desired input output mapping occurs. During training, the output from the multilayer perceptron is compared with the desired output. If the network output is not matched with desired output, an error signal is propagated back through the network. Training uses the magnitude of these error signals to adjust the weights and this process continues till the network output matches the desired output’ (Gardner and Dorling, 1998).

3. Line source deterministic models

Historically, as far as modelling of VEE is concerned, the work of Sutton (1932) may be regarded as the first of its kind. One of the early studies on deterministic vehicular pollution modelling was reported in Waller et al. (1965). The analytical method for estimating the pollution levels from motor vehicles in the vicinity of highways of common geometric configuration was developed by Chen and March (1971). The preliminary computational examples indicated that this method was capable of representing, in a realistic manner, all the physical variations accounted in the derivation. Dilley and Yen (1971) derived an analytical solution to a two-dimensional transport and diffusion equation that described the downwind pollutant concentration from an infinite crosswind line source. Both large scale and mesoscale winds were included in their model. Further, the analysis showed that mesoscale winds are not significant in reducing pollutant concentration. Peters and Klinzing (1971) described two separate equations for ground level as well as elevated line source and analysed the effects of diffusion coefficient in line source dispersion. Using the diffusion equation, Lamb and Neiburger (1971) came out with a model for computing pollutant concentrations resulting from both point and line sources. Later, this model was tested with respect to its diffusion characteristics by computing the hourly CO concentrations on a particular day at 760 locations in the Los Angeles basin. The model results showed reasonably good agreement with observed values. Csanyday (1972) developed a hypothetical model for a finite line source and it was applicable only when the wind was perpendicular to the roadway. Calder (1973) studied the effect of oblique wind on line source pollution dispersion near roadways. He showed that the concentration at roadside receptor increases marginally as wind direction becomes parallel to the highway. Dabberdt et al. (1973) presented a practical multipurpose urban diffusion model (APRAC-1A) for predicting inert vehicular pollutant concentration. The model requires routinely available meteorological and traffic parameters for prediction of concentration isopleths, sequential hourly values and frequency distributions. A model for the diffusion of pollutants from a line source in an urban atmosphere was also developed by Sharma and Myrup (1975). This study revealed that wind shear (variation of wind with height) was responsible for turbulent diffusion in lower atmosphere. Based on the finite length approximation, Stukel et al. (1975) formulated a line source dispersion model for estimating particulate/gaseous pollutant concentration in urban roadways. In another study, Nicholson (1975) presented a scalar budget box diffusion model for prediction of CO concentration in street canyons. Fay and King (1975) formulated a Gaussian model, considering vehicle-induced effects on dispersion of pollutants. This model assumed that near the road, vehicle wake-induced turbulence dominated over atmospheric turbulence. Therefore, dispersion of pollutants was assumed to be independent of atmospheric parameters except wind speed and dependent upon the drag characteristics of passing vehicles.

The General Motor (GM) corporation experimental data reported by Cadle et al. (1976) were the earliest field experimental data used for understanding traffic influences on adjacent roadways. These data were taken over a simulated test track of four lane free way of 5 km long at the GM proving grounds in Milford, Michigan, USA. Chock (1977a) conducted a number of experiments to evaluate the influence of traffic on dispersion of pollutants near urban roadways. He observed the variations in upwind dispersion due to crossroad wind, which occurred within a few meters of the road. The US EPA developed a number of air pollution models for highway which included CALINE (Beaton et al., 1972), EGAMA (Egan et al., 1973), and HIWAY (Zimmerman and Thompson, 1975). The popular HIWAY model was based on the Gaussian equation with the assumption of a series of finite line sources. CALINE model is also a Gaussian-based LSM, but it has got separate equations for calculating pollutant concentration under crosswind and parallel wind conditions. Chock (1977b) and Noll et al. (1978), evaluated these models and found that the EPA-HIWAY model overestimates pollutant concentrations adjacent to the highway. This model avoids the cumbersome integration necessary for the conventional Gaussian model that makes point source assumption; instead it uses an infinite line source approach and specifies one dispersion parameter as a function of wind road orientation from the source. Later, a series of improved versions of CALINE model, viz. CALINE-2,
CALINE-3 and CALINE-4 were developed by Ward et al. (1977) and Benson (1979, 1989). Middleton et al. (1979) developed a dispersion model for estimating the concentration of inert gaseous pollutants from the curved circular and straight sections of a complex road interchange. For small wind angles, pollutant concentration predicted from a finite road length well matched with the concentration estimates obtained from an infinite LSM. For complex roadway geometry, Colwill et al. (1979) conducted experiments to observe the change in pollutant concentration over a short distance at a site downwind of an isolated motorway and within a road complex. DeTar (1979) came out with a model which estimated the concentration of pollutants from line sources. This model was applicable at various receptor heights, distances, wind speed and direction. Eskridge et al. (1979) presented a finite-difference highway model, which was based on the surface layer similarity theory and vehicle wake theory to determine the atmospheric dispersion along a roadway. The model simulation results were compared with the GM experiment data and showed that they are closer to the observation than the other Gaussian-formulated EPA highway model (HIWAY). In another study, Green et al. (1979) found that the actual ground level concentrations might decrease with decreasing wind speed particularly when it dropped below some critical value. Data from an ongoing model validation program for dispersion of pollutants from roadways in Texas showed that pollutant concentrations did not increase as rapidly with decreasing wind speed as predicted by most models which were based on Gaussian formulation. Rao et al. (1979) studied the impact of traffic-induced turbulence on the near roadway dispersion of air pollutants. The study concluded that there is a noticeable augmentation of turbulent kinetic energy due to wake-generated moving traffic. Later, Rao et al. (1980) evaluated four Gaussian models, namely, GM (Chock, 1978), HIWAY (Zimmerman and Thompson, 1975), AIRPOL-4 (Carpenter and Clemena, 1975), CALINE-2 (Ward et al., 1977) and three numerical models—DANARD (Danard, 1972), MROAD-2 (Krisch and Mason, 1975) and ROADS (Pitter, 1976). Their comparative results showed that GM model simulations were more precise than any other model. Peterson (1980) presented an updated version of HIWAY model, i.e. HIWAY-2, released by EPA in May 1980. The difference between the original and improved version was that the latter model gave more realistic concentration estimates as it used an updated dispersion algorithm. Rao and Keenan (1980) modified the Pasquill-Grifford dispersion curves built in the EPA-HIWAY model and found that the modified HIWAY model (HIWAY-3) had better simulation of the physics of the near-roadway dispersion compared to the original HIWAY model. Further, an empirical aerodynamic drag factor was also developed to handle pollutant dispersion under low wind conditions. HIWAY-4 is another version of HIWAY model developed by incorporating modified dispersion curves and an aerodynamic drag factor to the original HIWAY model. Chang (1980) reviewed various urban air quality simulation models. These models were based on either Gaussian principles or the conservation of mass principle with the gradient-transport approximation. The EPA rollback model (EPARM) and a generalized rollback model (GRM) were evaluated by Chang et al. (1980a). Both models showed similar predictions when identical inputs were used for estimation. Data from GM dispersion experiments were utilized by Sedefian and Rao (1981) to assess the characteristics of traffic-generated turbulence and its effects on the dispersion process near roadways. They found that the dispersion next to the highway was dominated by the traffic and its influence decreases considerably at further downwind distances and at higher elevations. However, at low wind speeds and perpendicular cases, the traffic contribution to the total diffusivity was still about 50% at a downwind distance of 30 m. The use of analytical models for estimating the vehicular pollution dispersion on Indian urban roadways having heterogeneous traffic was reported by Munshi and Patil (1981). The authors applied the atmospheric turbulent diffusion laboratory (ATDL) model to estimate the pollutant concentration for Bombay city, which is one of the most populated and trafficked cities in India. Hickman and Colwill (1982) described a simple and effective method of estimating pollutant concentrations around highways, which used the Gaussian dispersion theory with empirical modifications so that it accurately represented the roadside situation. This model was calibrated and validated with the measured CO concentration at three different locations in UK. Using Texas and GM data, Rodden et al. (1982) evaluated 5-line source dispersion models namely CALINE-3, CALINE-2, AIRPOL-4, HIWAY and TRAPS-IIM (Bullian et al., 1980). All the four models showed poor performance when compared with observed data. The time resolution and vertical spacing that were necessary to resolve vehicle wake turbulence and the role of pseudo-turbulence in modelling pollutant diffusion near the roadway was discussed by Eskridge and Rao (1983). The study revealed that velocity variances measured in GM experiment data were dominated by the wake-passing effect (time variation in the wind velocity as a vehicles wake passes the observation point) and were inadequate to resolve the wake-turbulence effect. The Texas Instrumentation model (TEXIN) for predicing air quality near road-way intersection was developed by Nelli et al. (1983). The TEXIN model predictions were also compared with three intersection models—Inter section Midblock Model, program MICRO and Indirect Source Guidelines. Their comparative results showed that the TEXIN
model predictions were better than other three models. Using the Gaussian equation, Segal (1983) presented a Graphical Input Microcomputer model (GIMM) for predicting CO concentration from various types of line sources. This model appeared to be suitable for screening purposes as it required less computational time. Hickman and Waterfield (1984) developed a computer code for predicting air pollutant concentrations for roadway traffic. The code provided a wide range of information required for air quality assessment, such as, concentration of pollutants corresponding to traffic flows, weather conditions and exposure periods. Cohn and Gaddipati (1984) developed an interactive graphics method for highway air pollution analysis. This approach was developed to resolve problems associated with the use of coordinates in CALINE-3 and HIWAY-2 models. A digital computer model simulation of traffic flow has been developed by Beiruti and Al-Omishy (1985). Later, this model was used to predict NOx and HC concentrations at three busy traffic roads in Baghdad, Iraq. It showed a good agreement with the measured concentrations. Cooper (1987) reviewed various models used for estimating the impact of indirect sources on CO and air quality. A methodology for predicting the 8-h concentration by using 1-h CO concentrations was also discussed. Hlavinka et al. (1987) presented an improved version of TEXIN model, i.e., TEXIN-2. This model used the critical movement analysis (CMA) procedure for estimating traffic flow parameters, MOBILE-3 to determine free flowing traffic cruise emissions and CALINE-3 to model the pollutant distribution downwind of an intersection. Kunler et al. (1988) discussed the applicability of various air quality models for describing the dispersion of car exhaust emissions. The impact of VEEs, namely, CO and NOx on forest cover has also been discussed. Hoydysh et al. (1987) used four distinct approaches, i.e., solution of the Navier-Stokes equations, two-dimensional semi-empirical models, zero-dimensional semi-empirical models and empirical adaptation of Gaussian line source dispersion to model air flow and mass dispersion in street canyons. The results indicated that none of the approaches gave accurate distribution of pollutant concentrations in street canyons. In another study, a chemical mass balance (CMB) model was formulated by Khalil and Rasmussen (1988) which was applied for CO apportionment among residential wood burning sources and automobile sources in Olympia, Washington. Gronskii (1988) studied the influence of car speed on dispersion of exhaust emissions. He also pointed out that vertical diffusion of exhaust gas tends to be larger from high speed driving cars than low speed driving cars. His experimental results, when compared with HIWAY-2 predictions, showed that HIWAY-2 under-predicted the pollutant concentrations. Sculey (1989) reviewed four representative approaches namely IIM, MICRO-2, TEXIN-2 and CALINE-4. The study suggested an alternative emission analysis procedure, which could be used in standard LSMs to estimate air quality conditions at the intersection. Luhar and Patil (1989) presented a GFLSM, based on the Gaussian diffusion equation, pertaining to heterogeneous traffic conditions, at two traffic junctions in Bombay city. The GFLSM predictions were later compared with GM, CALINE-3 and HIWAY-2 model predictions, which showed that GFLSM performed with reasonable accuracy for Indian traffic conditions. Using historical meteorological and vehicular data, Cooper (1989) derived meteorological persistence factor (MPF) and vehicular persistence factor (VPF) for Florida city. Further, a worst case ‘total persistence factor’ was also derived which, is equal to the product of the mean annual second-highest MPF and the mean VPF defined (TPF). Kono and Ito (1990a) developed a microscale dispersion model—the OMG volume source model. Later, the OMG volume source, JEA model, Tokyo model and EPA-HIWAY-2 model results were compared with the measured SF6 concentration and it was found that OMG volume source model predictions were superior to the other two models (Kono and Ito, 1990b). Singh et al. (1990) developed an analytical dispersion model (IITCO) for computing CO concentration for heterogeneous traffic. The performance of the IITCO model was compared with the pollution episodic model (PEM) and intersection mid-block model (IMM). The results showed better performance of IITCO model when compared with PEM and IMM. In another study, the IITCO model was applied to Kuwait traffic. The results were compared with the US operational model, namely the IMM (Zanaidi et al., 1991). Among the simulations obtained from both the models, the performance of IMM was found to be better than IITCO. Miles et al. (1991) developed a hybrid approach for assessing air quality implications of urban planning. This hybrid approach was a combination of both deterministic and statistical models. It was a function of vehicular traffic and basic meteorology. Using the theory of large eddy simulation, Nieuwstadt (1992a) studied the dispersion characteristics of a passive line source pollutant in the convective atmospheric boundary layer. Further, he also studied the dynamics of line source by considering it into two parts—part-I (governed by the internal buoyancy) and part-II (governed by the ambient turbulence). For the latter part, he developed a simple integral plume rise model (Nieuwstadt, 1992b). Benson (1992) studied recent versions of CALINE models, namely, CALINE-3 and CALINE-4. He evaluated the predictive capability of CALINE-4 and found its performance to be better than CALINE-3. In another study, Alexopoulos et al. (1993) came out with a model for spatial and temporal evaluation of traffic emissions in metropolitan areas. The model was found to be useful where raw traffic
data, network and number of trip data were difficult to generate. Qin and Kot (1993) carried out dispersion studies in low wind conditions for three streets in Guangzhou city. Using the observed data, a simple operational model was proposed to simulate the dispersion of vehicular emissions in street canyons. Burden et al. (1994) used CALINE-4 and DMRB models for predicting NO\textsubscript{2} concentrations at roadway intersections, in Bristol, UK. The two models provided satisfactory predictions for flexible traffic volume. Akeredoiu et al. (1994) used the CALINE-4 model for forecasting CO at a roadway intersection. Chan et al. (1995) tested the applicability of four simple dispersion models, namely, APRAC, GZE, CALINE-4 and PWILG. These models were evaluated by comparing the predicted CO and NO\textsubscript{x} concentrations with measured values at street canyons in Guangzhou city. The models were found to be accurate in predicting maximum ground level concentrations. Derwent et al. (1995) used 1-year air quality data collected at one of the urban roadside locations in central London to evaluate Gaussian and box models. The predicted results were later used for a comprehensive validation of the published emission inventory estimates of London city. Further, a relationship between hourly mean NO\textsubscript{2} and NO\textsubscript{x} concentrations was also developed for local air quality management. Esplin (1995) presented approximate explicit solutions to the general line source problem that could be used down to angles of 151 between the line source and the wind vector, for angles below 151, he presented a point source approximation solution. Clifford et al. (1995) studied the mechanisms involved in the dispersion of pollutants around slow moving vehicles. The spatial distribution of tracer gas along and across the vehicles showed that a significant level of pollution was received by a commuter in a slow moving vehicle from the automobile immediately in front. Using traffic counts and fleet composition, Yu et al. (1996) developed a mathematical model for predicting trends in CO emissions. The model results were later used for examination of long-term trends in human exposure to CO. Chock and Winkler (1997) compared the impact on air quality predictions using a fixed layer-depth and a varying layer-depth structure in the urban airshed model (UAM). The analysis showed that the fixed layer-depth approach yielded substantially higher concentrations of CO, NO and VOC in the lower layer of atmosphere in isolated areas in early morning than the varying layer depth approach. Khare and Sharma (1999) presented a deterministic model for Delhi traffic conditions (heterogeneous in nature), i.e. Delhi Finite Line Source model (DFLSM). This model showed better prediction accuracy for CO compared to GFLSM (Luhar and Patil, 1989). Karim and Matsui (1998) and Karim et al. (1998) developed a computer model consisting of wind distributions, emission dispersion and modified Gaussian equation to identify street canyon and vehicle wake effects on transport of air pollution from urban road microenvironments. The computer model simulated and analysed the wind flow and their components in the street canyon considering a two-dimensional street canyon flow pattern. Vehicles wake turbulence was also estimated in microenvironments. Subsequently, the turbulent parameters were integrated in Gaussian equations to estimate CO and NO\textsubscript{x} concentrations. Later, Karim (1999) developed a traffic pollution inventory and modelled dispersion of vehicular pollutants in an urban environment. Buckland and Middleton (1999) presented nomograms for screening of vehicular pollution in congested street canyons. Sivacoumar and Thanasekaran (2001) evaluated four Gaussian dispersion models, namely, GM, CALINE-3, PAL-2 and ISCST-2 for Indian traffic conditions. The study revealed that GM model proved to be the best among four models, followed by CALINE-3, ISCST-2, and PAL-2. A detailed review on analytical modelling techniques, including deterministic and statistical modelling approach in the area of VEEs can be found in Sharma and Khare (2001a). Further, model performance evaluation and comparative assessment were also discussed in this review.

4. Line source numerical models

Danard (1972) developed a two-dimensional Eulerian model named as DANARD. It solved the mass conservation equation based on numerical methods outlined by Dufort and Frankel (1953). Using the boundary conditions imposed in DANARD, Ragland and Pierce (1975) derived the continuity equation for parallel and non-parallel diffusivity classes by an efficient matrix inversion technique. The model predicted concentrations for oblique and perpendicular cases by ignoring lateral diffusion. For parallel cases, the model solved the equation in three dimensions including lateral diffusion. Krish and Mason (1975) developed the MROAD-2 model, which was also a Eulerian two-dimensional grid model. It numerically solved the mass conservation equation. The size of the grid can be specified by the user and model allowed the existence of several line sources (all assumed to be perpendicular to the plane of the road), including elevated roadways. Pitter (1976) described ROADS model, which was a two-dimensional conservation model. The model determined the steady-state concentrations of pollutants by numerically solving the equations using the Lax-Wendroff finite difference scheme. Chock (1978) formulated a numerical model to solve advection diffusion equation for a line source. In this model traffic effects were considered as additive components of the eddy diffusivity tensor (K\textsubscript{ij}) over that of atmospheric effects in...
the following form:

\[ K_y = K_{y1}^I + K_{y2}^I, \]  

(3)

where \( K_{y1}^I \) is the ambient/atmospheric eddy diffusivity tensor and \( K_{y2}^I \) is traffic-induced component of eddy diffusivity tensor. Later, this model was validated for GM experiment data and was reported to be valid within \( \pm 10\% \) accuracy limits. Eskridge et al. (1979) presented a finite difference highway model. The model used surface layer similarity theory and vehicle wake theory of Eskridge and Hunt (1979) to determine the atmospheric structure along the roadway. The model results were compared with HIWAY model and found closure to the observed GM experimental data. Eskridge and Thompson (1982) developed the ROADWAY model. It was a finite difference model, which predicted pollutant concentration near a roadway. It assumed a surface layer describable by surface layer similarity theory with the superposition of the effects of vehicle wakes. This model could also predict velocity and turbulence along the road. ROADCHEM model (Eskridge and Thompson, 1982) was a version of ROADWAY which incorporated the chemical reactions involving \( NO, NO_2 \) and \( O_3 \) as well as advection and dispersion phenomena. In this version, surface layer similarity theory was used to produce vertical angle turbulence profiles. Maddukuri (1982) presented a numerical model for the estimation of vehicular exhaust (CO) dispersion. The model was based upon the semi-empirical equation of turbulent diffusion equation. Eskridge and Rao (1986) modified the ROADWAY model by using experimentally determined eddy diffusion coefficients. The revised version of ROADWAY was completely independent of the GM sulphate experiment data, whereas the initial version used the GM data to determine the diffusion coefficients needed in the wake theory. Later version of ROADWAY model predictions were closer to GM data than the initial version. Thompson and Eskridge (1987) experimentally studied the influence of vortex pair in turbulent diffusion behind vehicles. These experimental results were incorporated into ROADWAY model for improving its predicting efficiency. The model physics was based primarily on the vehicle speed, turbulence and diffusion of tracer. The calculation of air pollution from road traffic (CAR) model developed by the Dutch National Institute of Environmental Health (RIVM, 1991) and Dutch Institute of Applied Scientific Research (Van den Hout et al., 1989) was evaluated for a Dutch city by Eerens et al. (1993). The calibration of the model was done by using data from the Dutch National Air Quality Monitoring Network (Elskamp, 1989; Heida et al., 1989) and wind tunnel experiments (Van den Hout et al., 1989). The CAR model satisfactorily estimated the air pollutant concentrations in urban streets and was comparable with Dutch air quality standards.

5. Line source stochastic models

McGuire and Noll (1971) studied the relationship between maximum concentration and average time for \( CO, NO_x \) and \( NO_2 \) pollutants collected at 17 monitoring stations in California city. From the past studies on air pollution modelling, there existed substantial evidence that the series of pollution concentration and meteorological data were highly auto-correlated irrespective of time (Merz et al., 1972). McCollister and Wilson (1975) used the B-J type models for short-term forecast of oxidant and \( CO \) in Los Angeles basin. The model was one-dimensional and showed poor predictions for extreme events. Tiao et al. (1975) studied the effects of intervention caused by a new highway on the oxidant time series in the Los Angeles basin. A univariate analysis of the weekly averages of the daily maxima of oxidant, \( CO, NO_x, \) and total HC was done by Chock et al. (1975) for Riverside, CA. The relationships between the weekly averages of the daily maxima of the oxidant and the weekly averages of meteorological parameters were also investigated. Based on least-square technique, Aron and Aron (1978) presented a stochastic model for forecasting daily maximum \( CO \) concentrations at Los Angles basin. The analysis showed that \( CO \) concentration of the preceding days, pressure differences between nearby station, surface temperature, day of the week, length of daylight, solar radiation and inversion height were the most significant variables in model development. Hirtzel and Quon (1979) used auto-correlation function to model hourly and average eight-hourly \( CO \) concentrations measured at the continuous air monitoring program station in Chicago. In another study, Ledolter and Tiao (1979) presented a statistical model that predicted \( CO \) concentration on both sides of the freeway in Los Angles. Regression analysis technique was used by Chang et al. (1980b) to determine the relative impact of mobile and stationary sources on high \( NO_2 \) concentrations. The analysis showed that hourly \( NO_2 \) concentrations observed in Los Angles basin arise largely from vehicle emissions and support the assumptions used in generalised roll-back model (Chang et al., 1980a). Lincoln and Rubin (1980) applied multiple regression analysis to correlate
CO with daily average haze coefficient and total suspended particulate (TSP) in Downtown urban area of Los Angeles. Zamurs and Piracci (1982) developed a multiple linear regression model to predict CO concentration at selected intersections. Using a statistical theory, a simple formula for calculating dispersion from a continuous finite line source was presented by Mikkelsen et al. (1982). Jakeman et al. (1991) used a hybrid (deterministic and stochastic) model to predict seasonal extremes of 1-h average CO concentration. Bardeschi et al. (1991) noted the importance of time series of concentration emission and meteorological conditions during the hours prior to the high CO concentrations. In the recent past, a number of studies have been carried out using multivariate time series analysis in which various B-J modelling techniques have been applied for homogeneous traffic conditions (Hsu, 1992; Hernandez et al., 1992; Manteiga et al., 1993; Trier and Firinguetti, 1994; Milionis and Davis, 1994a, b). Liu et al. (1994) used Monte Carlo simulation method to predict personal exposure levels to CO in Taipei. The skewness and kurtosis methods were used by Zhang et al. (1994) to investigate the statistical distribution of CO and hydrocarbon (HC) emissions on a road in Denver, US. Glen et al., (1996) developed an empirical model of monthly CO for long-term trend assessment. Comrie and Diem (1999) examined the relationships between meteorology, traffic patterns and CO concentration at seasonal, weekly and diurnal time scales in Phoenix, AZ. Sharma et al. (1999) applied extreme value theory to know the expected number of violations of the National Ambient Air Quality Standards (NAAQS) to hourly and eight-hourly average CO concentrations for an air quality control region comprising of an urban road intersection followed by the development of an intervention analysis model (IAM) for the same AQCR (Sharma and Khare, 1999). Further, the authors (Sharma and Khare, 2000) used B-J modelling techniques to provide short-term and real-time forecast of the ambient air pollution levels due to vehicular sources at an urban intersection. In another study, Sharma and Khare (2001b), developed models for Delhi traffic conditions which were stochastic in nature and performed with reasonable prediction accuracy for CO concentration in heterogeneous traffic conditions.

6. ANN-based LSMs

Literature on application of ANN in line source modelling is found to be very scanty (Nagendra and Khare, 1999). Moseholm et al. (1996) studied the usefulness of neural network in understanding the relationships between traffic parameters and CO concentrations measured near an intersection, which was sheltered from wind by multi-storied buildings. In another work, Dorzdowicz et al. (1997) developed a line source neural network model for estimating hourly mean concentrations of CO in the urban area of Rosario city. Eleven inputs, e.g. vehicular flux-vehicles/h (cars, taxis, median vehicles, trucks and buses), wind speed and direction, solar radiation, humidity, pressure, rain intensity and temperature were used for development of the ANN-based model. This model was later validated for each type of network (i.e., considering different number variable sets), and using approximately a set of 100 patterns. Using hourly NO$_X$ and NO$_2$ and meteorological data of Central London, Gardner and Dorling (1999) developed MLP neural network models. The predicted results showed better performance when compared with previously developed regression models (Shi and Harrison, 1997) for the same location.

7. Limitations of LSMs

Deterministic LSEM approach is the most logical and traditional approach for the prediction of air pollution concentrations, yet it is not free from limitations. The prediction capability of deterministic models depends on the condition fulfilling the simplifying assumptions, which are made in the model formulation. For instance, when unit time interval is short (i.e., p1 day) and 'steady state' assumptions required for the application of Gaussian type models are not met, deterministic models do not give satisfactory results (Fingi and Tebaldi, 1982). The Gaussian dispersion equation has a singularity at zero wind speeds. Therefore, all Gaussian-based models perform poorly when wind speeds are 0 m/s.

In general, Gaussian-based model predictions are reasonably accurate for long-term average concentrations and for the frequency distribution up to 90 percentiles (Kretzschmar et al., 1976). However, the predictions become inaccurate when the frequency distribution is 98 percentiles (Nieuwstadt, 1980). Further, deterministic models are not suitable for extreme value predictions (North et al., 1984). However, they are most suitable for long-term planning decisions (Benarie, 1980; Juda, 1986; Zanneti, 1990). Table 1 summarises the limitations of selected line source models.

Numerical models have common limitations arising from employing the K-theory for the closure of diffusion equation. The K-theory diffusion equation is valid only if the size of the ‘plume’ or ‘puff’ of pollutants is greater than the size of the dominant turbulent eddies. The K-model assumption is also not valid for the convective boundary layer under strong instability. The other limitations of numerical models are large computational costs in terms of time and storage of data. It also requires large amounts of input data. The solutions
<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Model</th>
<th>Pollutant type</th>
<th>Receptor location and traffic type</th>
<th>Applicability</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>California line source model (Beaton et al., 1972)</td>
<td>CO, NOx, SPM</td>
<td>Roadside</td>
<td></td>
<td>Tendency to predict high pollutant concentration for parallel wind case</td>
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<td></td>
<td></td>
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<td></td>
<td>Homogeneous</td>
<td>No treatment of plume rise due to hot exhaust of vehicles</td>
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<tr>
<td>2.</td>
<td>HIWAY-1 (Zimmerman and Thompson, 1975)</td>
<td>CO</td>
<td>Roadside</td>
<td></td>
<td>Predicts poorly for low winds</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Homogeneous</td>
<td>Overestimates pollutant concentration for stable atmospheric condition and parallel wind case No treatment of plume rise due to hot exhaust of vehicles</td>
</tr>
<tr>
<td>3.</td>
<td>CALINE-2(Weidetal., 1977)</td>
<td>CO, NOx, SPM</td>
<td>Roadside</td>
<td></td>
<td>Predicts poorly for unstable and neutral stability conditions</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Homogeneous</td>
<td>Over-predicts the pollutant concentration for parallel wind cases and under-predicts for oblique wind conditions</td>
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<tr>
<td>4.</td>
<td>GM model (Chock, 1978)</td>
<td>CO</td>
<td>Roadside</td>
<td></td>
<td>Tendency to over-predict the concentration under parallel wind conditions</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Homogeneous</td>
<td>Predicts poorly for low winds</td>
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<tr>
<td>5.</td>
<td>CALINE-3 (Benson, 1979)</td>
<td>CO, NOx, SPM</td>
<td>Roadside</td>
<td></td>
<td>Tendency to predict high for parallel wind condition</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Homogeneous</td>
<td>No proper treatment for mechanical and thermal turbulence created by vehicle exhaust</td>
</tr>
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<td>6.</td>
<td>HIWAY-2 (Peterson, 1980)</td>
<td>CO</td>
<td>Roadside</td>
<td></td>
<td>Inadequate dispersion parameters</td>
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<td></td>
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<td></td>
<td>Homogeneous</td>
<td>No treatment of plume rise due to hot exhaust of vehicles</td>
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<tr>
<td>7.</td>
<td>HIWAY-3 (Rao et al., 1980)</td>
<td>CO</td>
<td>Roadside</td>
<td></td>
<td>Predicts poorly for low winds</td>
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<td></td>
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<td></td>
<td>Homogeneous</td>
<td>Tendency to predict high for parallel wind condition</td>
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<td></td>
<td>No treatment of plume rise due to hot exhaust of vehicles</td>
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<tr>
<td>8.</td>
<td>HIWAY-4 (Rao et al., 1980)</td>
<td>CO</td>
<td>Roadside</td>
<td></td>
<td>Tendency to predict high for parallel wind condition</td>
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<tr>
<td></td>
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<td></td>
<td>Homogeneous</td>
<td>No treatment of plume rise due to hot exhaust of vehicles</td>
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<tr>
<td>9.</td>
<td>CALINE-4 (Benson, 1989)</td>
<td>CO, NOx, Aerosol</td>
<td>Roadside</td>
<td></td>
<td>Tendency to predict high for parallel wind condition</td>
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<td>Homogeneous</td>
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Table 1 (continued)

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<thead>
<tr>
<th>Sl. No.</th>
<th>Model</th>
<th>Pollutant type</th>
<th>Receptor location and traffic type</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>10.</td>
<td>ISCST-2 (EPA, 1992)</td>
<td>CO, NO₂, SPM</td>
<td>Roadside</td>
<td>Tendency to predict high for parallel wind condition</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Homogeneous</td>
<td>No treatment for turbulence caused by heated exhaust</td>
</tr>
<tr>
<td>11.</td>
<td>GFLSM (Luhar and Patil, 1989)</td>
<td>CO, SPM</td>
<td>Roadside</td>
<td>Predicts poorly for low winds</td>
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<td></td>
<td></td>
<td>Heterogeneous</td>
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<tr>
<td>12.</td>
<td>DFLSM (Khare and Sharma, 1999)</td>
<td>CO</td>
<td>Roadside</td>
<td>Predicts poorly for low winds</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>Heterogeneous</td>
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</tbody>
</table>

obtained from numerical model are approximate one. Past studies revealed that the performance of numerical models namely DANARD (Danard, 1972), MROAD-2 (Krisch and Mason, 1975), ROADS (Pitter, 1976), ROADWAY (Eskridge et al., 1979) was not better than the Gaussian-based deterministic LSMs (Rao et al., 1978, 1980, 1986).

Limitations of statistical models include the requirements of long historical data sets and lack of physical interpretation. Another limitation of statistical model is that they cannot provide information about how pollutant levels would respond to emission controls, though statistical distribution modelling has been reported to be used in developing simple roll-back formulae for determining a desirable level of source emission control to meet with the objectives of air quality management (Georgopoulos and Seinfeld, 1982). The statistical models are therefore site specific.

The main reasons often cited for not using the MLP, in vehicular exhaust modelling is that they are difficult to implement. The other problem faced when training MLP is deciding upon the network architecture (i.e., number of hidden layers, number of nodes in hidden layers and their interconnection, Bozmar et al., 1993). At present, no procedure has been established for selecting a proper network architecture. Apart from these, no thumb rules exist in selection of data set for training, testing and validation of neural network based model.

8. Conclusion

The LSEM has been shown to be useful tool for prediction of urban air quality. Analytical modelling approaches including deterministic and statistical techniques, are commonly used for LSEM. Choosing the most suitable approach, depends on the complexity of the problem being addressed and the degree to which the problem is understood. Deterministic LSEM approach seems to be the most logical and traditional approach for modelling air pollution concentrations. The prediction capability of deterministic models depends on the condition fulfilling the simplifying assumptions, which are made in the model formulation. The Gaussian model is generally accepted for prediction of long-term average concentrations. Numerical models are most desirable solution, if adequate data, computational resources and other theoretical understanding of dispersion phenomena are available. Statistical models are site specific and do underperform when modelled with highly nonlinear data. In recent years, ANN approach, particularly MLPs are particularly apparent in applications where a full theoretical (deterministic and statistical) models cannot be constructed, and especially when dealing with complex conditions (Gardner and Dorling, 1998). The existing modelling studies relevant to temporal and spatial dispersion of VEEs reveals that most of the LSEM studies are made on homogeneous traffic conditions (Sharma and Khare, 2000,2001b). For heterogeneous traffic conditions, very few studies were carried out. The commonly used LSMs (Table 1) for air quality assessment performs poorly on parallel wind cases (Sivacoumar and Thanasekaran, 2001). A limited number of studies were reported on time series and ANN approaches in modelling of VEEs (Sharma, 1998; Nagendra and Khare, 2002).

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