The Hong Kong Polytechnic University

Department of Civil and Structural Engineering

Developing a Tunnel Based Model for Monitoring Vehicle Emissions

by

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of Master of Philosophy

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CERTIFICATE OF ORIGINALITY

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Mak Kai Long

ABSTRACT

Tunnel emission models are one of the most useful tools in measuring and quantifying vehicular emissions. A speed modified simple mass balance model has been developed for the purposes of monitoring the change of pollutant emissions.

This research intends to develop a new effective emission monitoring model on existing tunnel monitoring data. The result will be useful for the government to assess the effectiveness of her air pollution abatement programmes. The methodology involves collecting speed profiles, pollutant concentration profiles, analyzing the data statistically, and developing a speed modified simple mass balance model.

Instantaneous vehicular exhaust concentration data was collected by using an instrumented car travelling through tunnel. The traffic flow-speed curve for tunnel was developed successfully. A strong correlation between vehicle speed and pollutant concentration was obtained in the field work. The impact of speed was then introduced to modify the simple mass balance model to estimate pollutant emission factors based on this tunnel

study. In the validation test, the speed modify simple mass balance model was compared with the emission factor obtained by remote sensing technique. By statistical analysis, there was no significant difference between the speed modified emission factor and remote sensing estimation.

Compared to the popular pollutant emission factor models, it appear that the refined speed modify mass balance model is robust in developing tunnel based emission factor model.

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1 Introduction

1.1 *Background of research*

Vehicular emission is one of the major sources of urban air pollution. Much effort has been exerted by environmental protection administrations to curb vehicle emissions. According to the Hong Kong Environmental Department (HKEPD) annual report (2006), motor vehicles, especially diesel vehicles, are the main contributors of high concentrations of respirable suspended particulates (RSPs) and nitrogen oxides (NOx) at street level in Hong Kong. In order to tackle this problem, in the year 2000, the government committed HK$1.4 billion to many programmes that targeted the reduction of RSPs and NOx emissions from motor vehicles. These programmes included lowering the sulphur content in diesel to 0.005% wt and introducing ultra low sulphur diesel in 2000. At year 2001, the government tightened motor vehicle fuel requirements, introduced Euro III emission standards for newly registered vehicles in step with the European Union, and required newly registered taxis to be fuelled by LPG or petrol. At the end of 2001, over 13,000 (70%) of the diesel taxis had been replaced by LPG models. In 2002, the government commenced grants to help install particulate removal devices in heavy pre-Euro diesel. In 2003, the government introduced the mandatory requirement that pre-Euro diesel vehicles, not more than four tonnes, be retrofitted with emission reduction devices. A pertinent regular monitoring programme is essential to evaluate the effectiveness of these on-road vehicle emission programmes.

The most common method to monitor vehicle emissions is to observe the emission factors in road tunnels. According to Singer and Harley (1996), emission factor is defined as the amount of air pollutant species emitted per unit mass of fuel burned. More generally, the emission factor is expressed as task-based in g/km, or per work done of the engine in g/kWh. Emission is influenced by many factors, such as the type of engine (gasoline or diesel), after-treatment device, driving cycle, and composition of vehicle fleet and fuel composition. Because of the stability of a road tunnel environment, observation of daily or annual vehicular emission can be performed in road tunnels. There are existing data collected by road tunnel management companies in Hong Kong. These data can be used for the analysis of vehicle emission factors so as to save huge amounts of expense on data collection. A new effective emission monitoring model will be developed based on these existing data. The result will be useful for government to assess the effectiveness of its air pollution abatement programmes.

1.2 *Objective of study*

To supplement the government's roadside air quality monitoring stations, this project proposes to develop a mathematical model using the instantaneous data collected from tolled tunnels in Hong Kong. The existing tunnel operators have to collect data including factors such as air pollutants and traffic flow, by law. In this thesis, various tunnel based models adopted for vehicle emission factor estimation were reviewed. All these models are based on the well-known mass-balance theory. This research project tries to develop a speed modification to the model to improve estimation.

The main objective of this project is to use the routine monitoring data collected by the tunnel operators to develop a pollutant estimation model. The following are the specific objectives:

a) To review the theories and applications of the current mass balance road tunnel emission models which estimate vehicle emission factors;

b) To identify suitable data collection methods to collect instantaneous vehicle speed data which has imminent impact on vehicle exhaust;

c) To conduct site surveys to collect traffic flow and emission data at a selected road tunnel;

d) To identify the relationships between the pollutant concentrations and traffic characteristics;

e) To develop a pollutant concentration profile along the selected tunnel in order to fully utilize the routine tunnel air monitoring data;

f) To identify the effects of tunnel ventilation on the air pollutant concentration; and

g) To develop a tunnel based model to monitor vehicle emissions.

1.3 *Outline of thesis*

This thesis describes the development of a speed-modified, simple mass balance model (SMBM) based on the monitoring data obtained by tunnel management companies in Hong Kong. In Chapter 2, a detailed description of existing tunnel emission models is presented. Application of the tunnel emission models and their limitations will be discussed. In Chapter 3, a detailed description of existing tunnel data is presented. Details of the development of a pollutant concentration model by traffic flow are also provided in this chapter. A review of the methodologies of data collection in tunnels is presented in Chapter 4. In this chapter, the advantages and limitations of each method of collecting pollutant concentration data, vehicle speed data and the equipment used are reviewed. Chapter 5 focuses on our tunnel data sampling methodologies. Field data collection is necessary to develop a pollutant concentration model, a speed profile and a pollutant concentration profile for the tunnels. Details of the development of a speed-modified SMBM are also provided in this chapter. Comparisons of our SMBM and other models are presented in Chapter 6. This is followed, by a summary of the present work and several suggestions for future research in Chapter 7.

2 Existing Tunnel Emission Models

Air quality models are used to predict concentrations of one or more species in space and time with sets of dependent variables. Modelling provides the ability to assess the current and future air quality in order to make policy decisions. An effective air quality management system must be able to provide accurate information about the current and likely future trends, so that necessary assessments regarding the extent and appropriate air pollution control management strategies can be made precisely.

The air quality models can be classified as point, area or line source models. Line source models are used to simulate the dispersion of vehicular pollutants near highways or roads where vehicles continuously emit pollutants. At present, most of the widely used highway dispersion models are Gaussian based. These models, such as the Caline 4, require various input parameters pertaining to meteorology, traffic, and road geometry land-use patterns. Various input parameters used in these models are not always accurately known, consequently the models have to be used carefully to prevent unreliable predictions. Inaccuracy may occur due to the usage of improper emission factors for different categories of vehicles, or due to the operation of the vehicles. Another factor of inaccuracy in these models pertains to the absence of on-site meteorological data. The use of on-site meteorological data about wind speed, direction, atmospheric stability conditions and mixing height is recommended. To obtain a full picture of the pollutant emission model, different types of pollutant emission models will be reviewed in this chapter.

2.1 *Linear regression*

Many vehicle emission factor models based on emission measurements have been used widely. The features are being updated continuously in order to estimate the emissions contribution to air pollution more precisely. (Jost et al., 1994; Joumard et al., 1995a; Zachariadis and Samaras, 1997). Linear regression analysis was applied to model CO concentrations in many studies. For example, Drozdowicz et al. (2001) suggested modelling the CO concentration with six parameters by linear regression. They employed the plot with observed value versus calculated values to show that 75% of the trials fell within an absolute error of less than 30%. However, residual analysis was not mentioned in the paper.

Funasaka (1998) suggested examining the relationship between the concentration of CO and the traffic volume by using linear regression analysis. He modeled CO concentration with the traffic volume hourly using two classes of vehicles, gasoline and diesel vehicles, as independent variables. Weekly data from the Osaka tunnel was used for modelling at that time. However, he did not give much detail about the residual analysis. His model showed that gasoline vehicles have a 15% larger coefficient than diesel vehicles.

Chan and Rudy (1990) suggested that the vehicle emission and the ventilation rate are the major factors to determine the pollutant concentration in vehicle tunnels. Chan et al. (1996) suggested modelling CO concentration by linear model. The model assumes that CO emissions are inversely proportional to vehicle speeds.

Equation 1: $$C = \sum a_i * n_i + \sum \frac{b_i}{n_i} + \frac{1}{v} \sum c_i * n_i + A$$

where

C	=	CO concentration (ppm)
n_i	=	The traffic volume of the vehicle class
v	=	The vehicle speed (km/h)
a_i, b_i, c_i	=	Constant coefficient
A	=	The statistical constant

According to El-Fadel and Hashisho (2001), the assumption of Equation 1 is not always true and it cannot be applied to other tunnels unless extensive measurements and model calibrations are conducted. They suggested a modified version of a simple mass balance model for pollutant concentration (Equation 2).

Equation 2: $$C = \frac{L \ * e_p}{S_p * U_{out} * A}$$

where

C	=	Pollutant concentration (ppm)
L	=	Tunnel length (m)
e_p	=	Pollutant produced per vehicle depending on velocity (m^3/min)
S_p	=	Car spacing (m)
U_{out}	=	Air speed at tunnel exit (m/min)
A	=	Tunnel cross-sectional area (m^2)

However the car spacing variable is difficult to determine. In addition, the model assumes that there is no chemical reaction between the emitted species.

2.2 *Time series model*

Another modelling method was suggested by Box and Jenkins. Box and Jenkins (1976) advocated a methodology for time series based on finite-parameter models with second order properties. This approach was named after the statisticians George Box and Gwilym Jenkins. For a Box-Jenkins time series model, the observations must be discrete and the intervals of time must be equally spaced in between. The ARIMA process of order (p, d, q) is defined as in Equation 3.

Equation 3: $Z_t = \phi_1 Z_{t-1} + ... + \phi_p Z_{t-p} + \alpha_t - \theta_1 \alpha_{t-1} - ... \theta_p \alpha_{t-p}$

where $Z_t = \nabla^d Y_t$ and d is the order of differencing. It is also called the backward difference operator. In particular, d is usually 0, 1, or at most 2.

For example, for d = 1, $Z_t = \nabla^d Y_t = Y_t - Y_{t-1}$

The error term is also assumed to follow a white noise process in this time series analysis model. That means the error term is independent, zero mean and of constant variance. In order to decide which model is suitable, the auto-correlation function (ACF) and the partial auto-correlation function (PACF) are useful.

In general, linear regression analysis is used if there is limited data available. For handling more data, time series analysis has been suggested in some studies. Goyal et al. (2005) suggested modelling the pollutant concentration using a combination of ARIMA and regression models. According to Chatfield (1989), when observations are taken on two or more variables, it may be possible to use the variation in one time series to explain the variation in another series. Furthermore, most of the probability theories of time series deal with stationary time series, and for this reason time series analyses often require converting non-stationary series into stationary ones. In our study, it is necessary to remove the trend effect of vehicle types from the data set and then model the variation in the residuals by means of a stationary process. However, few researchers have used the ARIMA model for modelling residuals from linear regressions.

2.3 *Piston effect model*

The piston effect of vehicles refers to a moving vehicle, which induces airflow by pushing and shearing the surrounding air. Chen et al. (2002) suggested a way to model the piston effect of vehicles as expressed in Equation 4 and Equation 5.

Equation 4: $$r = \sum \frac{N_i \times \tau \times A_i \times h_i}{A_f} \quad \text{or} \quad {z_s}^+ = \frac{r u_*}{v}$$

Equation 5: $$u^+ = \frac{1}{\kappa} \ln\left(\frac{z}{z_s^+}\right) + 8.5$$

where

R	=	Average roughness height (cm)
Ni	=	Average traffic flow rate
τ	=	Average travel time
A_i	=	Base area of vehicle (m^2)
h_i	=	Height of vehicle (m)
A_f	=	Base area of tunnel (m^2)
${z_s}^+$	=	Dimensionless roughness parameter
u_*	=	Friction velocity (m/sec)
v	=	Average traffic speed (m/sec)
κ	=	von Karman constant (0.41)
z	=	Vertical coordinate (m)

In the equations, the roughness contributed by the vehicle depends on the vehicle size relative to the tunnel dimension and traffic flow rate. Chen's study showed that incorporating the piston effect into an SMBM would improve its reliability in estimating emission factors. However, some parameters in the piston effect model (such as the friction velocity) are difficult to obtain. Furthermore, the piston effect model was designed for estimating the emission factor of an entire vehicle stream over a short period of time. An average traffic speed is applied to the model instead of individual vehicle speeds. For modelling emissions of individual types of vehicles, an alternative modelling method or modification is needed.

2.4 *Gaussian dispersion model*

Motor vehicles emit pollutants which are transported and dispersed locally, regionally and globally. The transport and dispersion of vehicular pollutants are due mainly to the motion of air and the diffusion process. The dispersion model is affected by many factors including the pollutant level of the vehicles, the prevailing meteorological condition and the topographical condition. In Hong Kong, due to the large number of tall buildings on both sides of the streets, pollutants cannot be dispersed easily due to the "canyon effect". The Gaussian model estimates the time-averaged pollutant concentration profiles at any distance in the crosswind direction, horizontal and vertical. The governing equation contains four different factors:

$$\chi(x,y,z;H) = \left[Q/(2\pi u\sigma_y\sigma_z)\right]\exp\left[-y^2/(2\sigma_y{}^2)\right]*\left\{\exp\left[-(H-z)^2/(2\sigma_z{}^2)\right]+\exp\left[-(H+z)^2/(2\sigma_z{}^2)\right]\right\}$$

where

χ	=	Air pollutant concentration in mass per volume
Q	=	Pollutant emission rate in mass per time
u	=	Wind speed at the point of release
σ_y	=	The standard deviation of the concentration distribution in the crosswind direction at the downwind distance x
σ_z	=	The standard deviation of the concentration distribution in the vertical direction at the downwind distance x
H	=	The effective height of the centreline of the pollutant plume

In the model, wind speed at the point of release and the standard deviation of the concentration distribution in the crosswind direction at the downwind distance are included. As it is difficult to obtain wind speed data at each point, it is not possible to use the Gaussian model in tunnel studies.

2.5 *Simple mass balance model (SMBM)*

In tunnel studies, an SMBM is widely used in determining emission factors of vehicles. Conservation of mass acts as the basic principle in developing the model. The method of measuring mobile source emissions in tunnels has been described in detail by Pierson et al. (1983, 1990) and Gertler et al. (1997, 1999). A SMBM across a multi-channel tunnel is expressed as in Equation 6.

Equation 6: $$M = \sum_i (C_{out} V_{out})_i - \sum_j (C_{in} V_{in})_j$$

where
C_{out} = Concentration pollutant leaving the exit (g/m^3)
C_{in} = Concentration pollutant entering the entrance (g/m^3)
V_{out} = Volume of air exiting the exit during time t, m^3
V_{in} = Volume of air entering the entrance during time t, m^3

Several assumptions have been made for Equation 6. Since the airflow in a tunnel is highly turbulent, it is assumed that there is a uniform mixing and distribution of pollutants caused by air and vehicle movement throughout the tunnel. The cross sectional pollutants concentration is uniformly distributed in the entire tunnel. Measured pollutants are assumed to be long-lived without deposition, decomposition and reaction between exhausted species in the short measuring period. In addition, the air velocity and pollutants emission rate are assumed to be constant throughout the tunnel. The mass of a specific pollutant passing through the tunnel is assumed to be the same. Given the total traffic count N and the known length L of the tunnel, the average emission factor in g/vehicle.m is given by Equation 7.

Equation 7: $$EF = \frac{M}{N * L}$$

where
N = Total traffic count during time t
L = Tunnel length (m)
M = The result from equation 6

In the case of one entrance and one exit channel (i=j=1), the emission factor is expressed as in Equation 8.

Equation 8: $$EF = \frac{(C_{out}U_{out} - C_{in}U_{in})At}{NL}$$

where

C_{out}	=	Concentration pollutant leaving the exit (g/m^3)
C_{in}	=	Concentration pollutant entering the entrance (g/m^3)
U_{out}	=	Volume of air exiting the exit during time t, m^3
U_{in}	=	Volume of air entering the entrance during time t, m^3
N	=	Total traffic count during time t
L	=	Tunnel length (m)
A	=	Tunnel cross-sectional area (m^2)
t	=	Sampling time (min)

Pierson et al. (1996) used this SMBM in his study at the Fort McHenry and Tuscarora Mountain Tunnel. They found that computer modelling (MOBILE 4.1 and MOBILE 5) had a tendency to over-predict the result. In addition, they first applied remote sensing measurements to obtain the pollutant emission. They made a comparison between the tunnel bag measurements and the average of the concurrent remote sensing CO/CO_2 ratios. The results showed that there is no significant difference between remote sensing and bag sampling at the 80% significance level.

Modifications to an SMBM

Chang et al. (1981) conducted a tunnel study at the Tuscarora Mountain Tunnel in 1977. They suggested an approximation for estimating the airflow speed. The approximation held that the volume of air injected from the inlet ducts per minute and per unit length of the tunnel was uniform and independent in distance. The inlet rate was set equal to α A where α is in min^{-1}. The total volume of air injected per minute at the inlet was αLA in $m^3 min^{-1}$. The volume of air entering the entrance portal per minute was $\mu_0 A$ where μ_0 is the speed of the airflow in the tunnel at X=0. The total volume of air leaving the exit was the sum of the contributions of the air entering through the entrance. The air speed at exit was related to the entrance as expressed in Equation 9.

Equation 9: $W_{out} = W_{in} + \alpha L$

where

W_{out}	=	Air speed at tunnel exit (m/min)
W_{in}	=	Air speed at tunnel entrance (m/min)
α	=	Ventilation rate (min^{-1})
L	=	Tunnel length (m)

Sjodin et al. (1998) applied Equation 9 to calculate the emission factors for Carbon monoxide (CO) and Nitrogen oxide (NOx) in the Tingstad tunnel study. They suggested that the air speed at exit was equal to the sum of the air speed at the entrance and the product of ventilation rate and tunnel length as shown in Equation 9 above with α as the ventilation rate. It was reported that the emission factor is increased by a factor up to 10 during congestion compared to smooth driving conditions.

Besides that theoretical approach, Rogak et al. (1998) conducted a field experiment in the Cassiar Tunnel in Vancouver and developed an air-speed-dependent speed ratio. The Cassiar Tunnel in Vancouver is a twin-bore highway tunnel, and the north-bound tunnel was selected for this study. It is 730-m long, 14-m wide, and 7-m high. Axial fans were suspended from the tunnel roof. A steady experiment and a transient experiment were performed to estimate the airflow in the tunnel. In the steady experiment, inert gas (SF_6) was released approximately 5 m past the tunnel entrance and 1 m above ground. In the transient experiment, SF_6 was released by a vehicle as it traveled through the tunnel. By performing the steady and transient tracer experiments, an air-speed-dependent correction factor (F) was developed. It was suggested that the speed ratio is inversely proportional to the air velocity inside the tunnel as expressed later in Equation 10. However, it is not reliable when the air speed is lower than 2 m/sec, which occurred in early morning hours. They further proposed a correction factor with a simple function. The gaseous pollutant emission factor can be obtained by applying Equation 10 and Equation 11.

Equation 10: $$F = \frac{8}{1.65V} + 0.25$$

where
V = Wind speed (m/s)

And the modified emission factor model was expressed in Equation 11.

Equation 11: $$EF = \frac{(AF)(C_{out} - C_{in})F}{NL}$$

where

C_{out}	=	Concentration pollutant leaving the exit (g/m^3)
C_{in}	=	Concentration pollutant entering the entrance (g/m^3)
AF	=	Airflow in the tunnel (m^3/sec)
N	=	Total traffic count during time t
L	=	Tunnel length (m)

In case of negligible difference between the entrance and exit air speed, Equation 8 was modified by Gorse (1984), and the emission factor is expressed in Equation 12.

Equation 12: $$EF = \frac{(C_{out} - C_{in})AUt}{NL}$$

where

C_{out}	=	Concentration pollutant leaving the exit (g/m^3)
C_{in}	=	Concentration pollutant entering the entrance (g/m^3)
A	=	Tunnel cross-sectional area (m^2)
t	=	Sampling time (min)
N	=	Total traffic count during time t
L	=	Tunnel length (m)
U	=	Mean air flow velocity (m/min)

Rogak et al. (1998) applied Equation 12 in the Cassiar tunnel study and obtained emission factors of CO, CO_2 and NOx. They applied regression analysis to develop the emission factors for different vehicle classes. By comparing the results to the predictions of MOBILE 5A, it was proved that an SMBM is very reliable and sensitive.

The mass balance model employed in the tunnel method estimates the aggregate emission factor of the entire vehicle fleet passing through the tunnel. To estimate the emission factor for individual vehicle classes, we have to use statistical methods. EL-Fadel and Hashisho (2001) suggested the aggregate emission factor should express as Equation 13.

Equation 13: $$EF_{veh} = \sum_i \frac{n_i}{n_t} EF_i$$

where

EF_i	=	Emission factor for i^{th} vehicle class (g/km)
n_i	=	Traffic volume of i^{th} vehicle class in a certain sampling period
n_t	=	The total traffic volume in the sampling period

EL-Fadel and Hashisho (2001) suggested using multiple linear regression methods to determine the vehicular emission factors of certain vehicle categories. They applied this to a model in which the emission factor is fitted as a function of the proportions of light-duty and heavy-duty vehicles. In their study, passenger cars and delivery vans are classified as light-duty vehicles, whereas buses and trucks are classified as heavy-duty vehicles. The composite vehicular emission factor is assumed to be linearly combined with emission factors of different vehicle classes. The composite emission factor is expressed as Equation 14.

Equation 14: $$EF_{veh} = \frac{n_{LDV}}{n_{LDV} + n_{HDV}} EF_{LDV} + \frac{n_{HDV}}{n_{LDV} + n_{HDV}} EF_{HDV} + \varepsilon$$

where

EF_{LDV}	=	Emission factor of light-duty vehicle classes (g/km)
EF_{HDV}	=	Emission factor of heavy-duty vehicle classes (g/km)
n_{LDV}	=	Traffic volume of light-duty vehicles in specific sampling periods
n_{HDV}	=	Traffic volume of high-duty vehicles in specific sampling periods
ε		The random error for average emission factor

2.6 *Quasi-Steady-State Mass Balance (QSSMB) Model*

A more advanced mass balance model, the Quasi-Steady-State Mass Balance Model (QSSMB), was developed to account for the one-dimensional spatial variation of pollutants concentration. In this model, pollutant deposition and effect of tunnel ventilation are considered. As in a simple balance model, the ventilation of tunnel and vehicular emission rate is assumed to be constant. It is assumed that no chemical reaction occurs among the emitted tailpipe gases during sampling. The conservation of mass equation (Chang et al., 1981; Chang and Ruby, 1990; EL-Fadel and Hashisho, 2000; EL-Fadel and Hashisho, 2001) is expressed as Equation 15.

Equation 15: $U(x)\frac{dC(x)}{dx} = q - kC(x) - \alpha_{out}C(x) + \alpha_{in}C_d$

where

q	=	Source strength (g/m^3.s)
C(x)	=	The pollutant concentration at distance x down stream (g/m^3)
C_d	=	The pollutant concentration in the air entering through ventilation systems (g/m^3)
α_{in}	=	The inflow rate from ventilation systems (s^{-1})
α_{out}	=	The outflow rate from ventilation systems (s^{-1})
k	=	The pollutant deposition rate or deposition coefficient (s^{-1})

Having solved the differential equation, the general solution is shown as Equation 16.

Equation16:

$$EF_{veh} = \frac{A\left\{(k+\alpha_{in})C(x) - \alpha_{in}C_d + \left[\alpha_{in}C_d - (k+\alpha_{in})C_{in}\right]\left(\frac{U(x)}{U_{in}}\right)^{-\left(\frac{k+\alpha_{in}}{\alpha_{in}-\alpha_{out}}\right)}\right\}}{n_t\left(1-\left(\frac{U(x)}{U_{in}}\right)^{-\left(\frac{k+\alpha_{in}}{\alpha_{in}-\alpha_{out}}\right)}\right)}$$

where

A	=	Tunnel cross-section area (m^2)
n_t	=	Number of traffic count during sampling time t

The air velocity is uniform in the entire tunnel, Ex. $U(x)=U_{in}=U$. In the case of natural ventilation or longitudinal ventilation, the rate of ventilation at the inlet and outlet duct is zero (i.e. $\alpha_{in} = \alpha_{out} = 0$). The governing equation and the equation for natural ventilation with and without deposition are shown in Table 1.

Table 1 List of the SMBM and QSSMBM formulae for different tunnel ventilations

Model	Boundary conditions	Governing equations
Balance Transverse	$U_{in}=U_{out}=U$, $\alpha_{in}=\alpha_{out}=\alpha$	$EF_{veh}=\dfrac{A\left\{(k+\alpha_{in})C_{out}-\alpha C_d+\left[\alpha C_d-(k+\alpha)C_{in}\right]e^{-(\frac{k+\alpha}{U})L}\right\}}{n_t(1-e^{-(\frac{k+\alpha}{U})L})}$
Longitudinal with disposition	$U_{in}=U_{out}=U$, $\alpha_{in}=\alpha_{out}=0$, $k\neq 0$	$EF_{veh}=\dfrac{kA(C_{out}-C_{in}e^{-kL/U})}{n_t(1-e^{-kL/U})}$
Longitudinal without deposition	$U_{in}=U_{out}=U$, $\alpha_{in}=\alpha_{out}=0$, $k=0$	$EF_{veh}=\dfrac{AU(C_{out}-C_{in})}{n_tL}$

3 Tunnel Data Availability and Appreciation

3.1 *Data availability*

In order to apply an SMBM, it is necessary to have the tunnel geometrical, traffic flow, and air pollutant concentration data. The road tunnel operators in Hong Kong are required to monitor the traffic flow and gaseous air pollutant concentration. However, not all the operators were willing to provide their full set of data. Their data sets were not sufficient to be fed into the SMBM. Although much effort was spent, we could only obtain bits and pieces of data from some of the tunnel operators. The more comprehensive sets of data were obtained from the Lion Rock Tunnel (LRT) operators and the Aberdeen Tunnel (ABT) operators.

Lion Rock Tunnel data

The data sets obtained by the Lion Rock Tunnel operators include the hourly carbon monoxide and nitrogen oxide concentrations, hourly traffic volume by vehicle classes, and ventilation rate data, for the period January 2001 to January 2006. The CO and NO_2 concentration data were obtained by API Model 300 and Opsis Model AR-501 respectively. The tunnel operators broke-down the traffic flow into three classes, by toll fee. Class one is defined as private cars, taxis and motorcycles. Class two includes single deck buses, light buses & goods vehicles of 5.5 tons & less. Class three is defined as double deck buses & goods vehicles above 5.5 tons. The Lion Rock Tunnel in Hong Kong was opened to traffic in November 1967, as a 1430 m twin-bored toll tunnel. It connects Sha Tin in the New Territories and Kowloon Tong. It has two lanes in each direction, with the toll booths located at the Sha Tin exit. The daily tunnel traffic volume was about 92 000 vehicles in 2006. Hourly CO and NO_2 observations were available for analysis. The fixed locations of pollutant concentration data collection points are shown in Figure 1. All the monitoring points were located at 2.1m above ground. Either the North or South tube of the LRT is closed for maintenance every weekday, excluding public holidays, from 1:30 am to 6:00 am. To obtain a more accurate result, the tunnel data from 00:00 to 06:00 have been deleted in order not to complicate our analysis. The annual average traffic volume and pollutant concentration are listed in Table 2.

Figure 1 Location of receptors

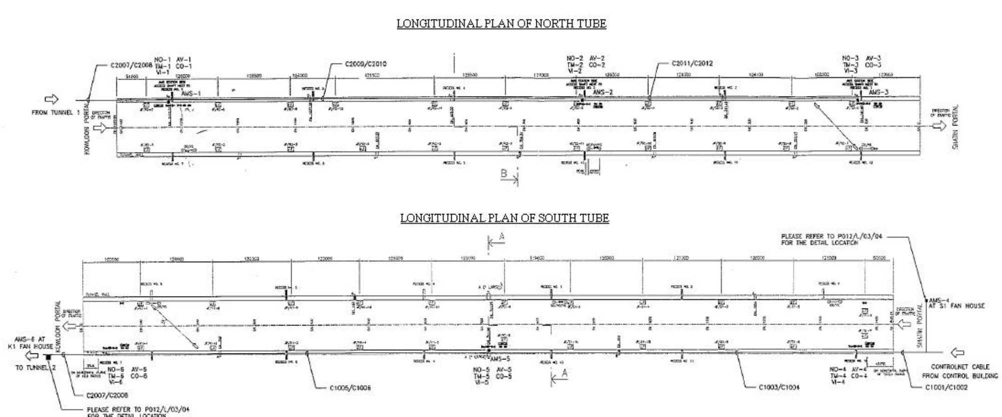


Table 2 The annual average traffic volume and pollutant concentration (Lion Rock Tunnel)

North Tube (vehicle/hr)						
Year	Class one	Class two	Class three	Total	CO (ppm)	NO_2 (ppm)
2001	1421	325	411	2158	6.94	0.17
2002	1389	320	433	2142	6.52	0.17
2003	1360	321	433	2114	5.96	0.18
2004	1284	316	412	2013	3.30	0.22
2005	1347	343	407	2098	4.70	0.16
2006	1394	360	404	2160	4.56	0.21
South Tube (vehicle/hr)						
2001	1441	312	403	2158	6.21	0.18
2002	1416	310	424	2151	4.95	0.17
2003	1361	306	424	2092	5.80	0.16
2004	1279	304	410	1993	3.45	0.19
2005	1323	322	400	2045	3.08	0.15
2006	1338	333	391	2063	3.34	0.17

The average traffic volume remained constant from 2001 to 2006 in both tubes. Furthermore, the proportion of vehicle class also remained unchanged. However, the CO concentration recorded a significant drop. It showed that the average CO concentration in the North tube was 6.94 ppm in 2001, and 4.56

ppm in 2006. This represents a 34% drop. The result is similar to the results of the South tube, where the percentage difference is around 45%.

The average NO_2 concentration varied from 0.16 ppm to 0.22 ppm, and 0.15 ppm to 0.19 ppm for the North and South tube respectively. When compared to the previous year, both the North and South tubes recorded a sharp decrease in average NO_2 concentration in 2005, the percentage differences were 27% and 21% for the North and South tube respectively. Other than the sudden drop in 2005, the NO_2 concentration was quite stable during those years.

Aberdeen Tunnel data

Another available data set was obtained from the Aberdeen Tunnel Management Company for the period January 2003 – October 2006. The hourly emission data in terms of NO_2, CO, and vehicular traffic flow data of the South tube for the first week of every quarter were made available. Similar to the Lion Rock Tunnel, the tunnel operators broke-down the traffic flow into three classes, by toll fee. Class one is defined as private cars, taxis and motorcycles. Class two includes single deck buses, light buses & goods vehicles of 5.5 tons & less. Class three is defined as double deck buses & goods vehicles above 5.5 tons. The Aberdeen Tunnel is a two-tube tunnel linking Happy Valley and Wong Chuk Hang near Aberdeen on Hong Kong Island, Hong Kong. It shortens the travel time between the North and the

South of Hong Kong Island. It connects the Wong Chuk Hang Road in the south to the Canal Road Flyover in the north. The tunnel is 1.9 kilometres long and was used by 57,400 vehicles daily in 1999.

For the Aberdeen Tunnel, the operation hours of each tube and the vehicle classification breakdown are the same as for the LRT. The annual average traffic volume and pollutant concentration are listed in Table 3.

Table 3 The annual average traffic volume and pollutant concentration (Aberdeen Tunnel)

South Tube						
Year	Class one	Class two	Class three	Total	CO (ppm)	NO_2 (ppm)
2003	753	222	199	1175	3.65	0.16
2004	763	236	198	1198	2.93	0.17
2005	803	238	194	1236	2.58	0.14
2006	849	241	191	1282	3.17	0.14

The average traffic volume had an increasing trend from 2003 to 2006 in the South tube, and the proportion of vehicle classes remained unchanged. The CO concentration recorded a drop from 2003 to 2005. However, a significant increase was noted in 2006. It showed that the average CO concentration in the South tube was 2.58 ppm in 2005 and 3.17 ppm in 2006, which represents a 22% increase. The average NO_2 concentration varied from 0.14 ppm to 0.17

ppm. It was 0.16 ppm in 2003 and 0.14 in 2006, which represents a 12.5% drop.

3.2 *Relationships between the pollutant concentrations and traffic volume*

One of the objectives of this study is to model vehicle exhaust emissions in tunnels. Based on the collected data, Funasaka et al. (1998) suggested that regression analysis is one of the most flexible and widely used techniques in statistics modelling to quantify the emission of each type of vehicle. Routine monitoring data of traffic flow and CO emission at the Lion Rock Tunnel of Hong Kong were used for investigation. A typical regression model attempts to explain variation in a dependent variable (Y_i), by mapping the relationship of Y to a specified set of independent variables as a linear function. Using least squares estimation techniques, we arrive at a prediction equation that allows us to estimate conditional means on the dependent variables. The basic regression model can be expressed as Equation 17.

Equation 17: $\hat{Y}_i = \alpha + bX_i$

where a is the intercept, b is the coefficient of the independent variable.

Wittink (1988) suggested using the least squares method for computing intercept and coefficients. The least squares method involves a way of choosing a and b so that the sum of the squared deviations is minimized.

Equation 18: $$\sum\left(Y_i - \hat{Y}_i\right)^2$$

where $\hat{Y}_i$ is the predicted value of Y_i

This means choosing the straight line that minimizes the sum of the squared vertical distances between the line and the dots in the scatter plot.

With sample data for Y and X, coefficients can be obtained. With these estimates, fitted values for Y using the sample data can also be obtained. The closer of these fitted values to the actual values for Y in the sample, the better the model fits. In addition, the difference between actual values (Y_i) in the sample and fitted values ($\hat{Y}_i$) is called a residual.

A relative measure of the goodness of fit is obtained by taking the ratio of the explained variation over the total variation.

Equation 19: $$R^2 = \frac{Explained \quad \text{var}iation \quad in \quad Y}{Total \quad \text{var}iation \quad in \quad Y}$$

R^2 is often referred to as the coefficient of determination. In a simple linear regression model, the largest possible value for R^2 is equal to 1, and the smallest is 0. These indicate a perfect fit and complete lack of fit respectively. It indicates that the model accounts for approximately how many percentage points of the variation can be explained in the model.

For linear regression modelling, Weisberg (1985) and Ostle et al. (1988) suggested there are some assumptions about the error term.

Assumption 1: The error term has an expected value of zero for each observation. The specific value for this error may vary from one observation to another, but on the average it should be independently and normally distributed with zero mean and constant variance.

Assumption 2: The residuals should follow the normal distribution. Sen (1990) suggested a normality plot should be used for testing normality. If the plot were an approximately straight line, the residuals would be taken to follow a normal distribution.

Assumption 3: The last assumption is that the error term for each observation should equal an unknown constant. Residual plot is always used for testing constant variance. If the plot shows no pattern, the residuals should be randomly plotted on the graph.

Test for coefficient significance

If the assumption holds, a hypothesis test can be used for testing whether the coefficient is significant to zero or not. In addition, the critical region is obtained by the t-distribution with n-2 degrees of freedom. For a large amount of sampling data with a 95% significance level, the critical region will follow the Z distribution and be equal to 1.96.

H_0: the specific coefficient is equal to 0

H_1: the specific coefficient is not equal to 0

$$Test \quad statistic = \frac{b}{S_b}$$

where b is the coefficient of the model, S_b is the estimated standard error of b.

Linear regression method

To test the sensitivity of the results using the simple linear regression model, the set of CO concentration data from January 2001 to December 2005 of the Lion Rock Tunnel (LRT) is used in this section. The general relationship between concentration "C" and variables that affect it can be expressed as Equation 20.

Equation 20:

$$C = B_1 + B_2 \text{ Class1 vehicles} + B_3 \text{ Class2 vehicles} + B_4 \text{ Class3 vehicles} + \delta$$

where B_1 is the intercept, B_2, B_3, B_4 are the coefficients to be determined by the regression model and δ is the error term.

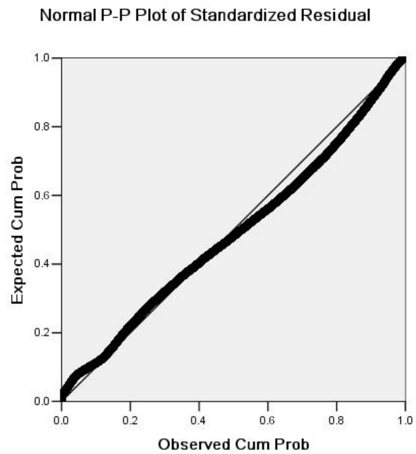
SPSS, a statistical software, was used for modelling. During the model development process, the parameter coefficients were calculated and a t-test was carried out to measure the significance of each parameter. If the coefficient is significant, the t-value should be larger than 1.96. The variables are finally included in the function, as well as the values of the corresponding coefficients and t-test values are shown in Table 4.

Table 4 Numerical result of linear regression model

Variable	Coefficient	t-value	Significance t
(a) North tube			
Constant	3.084	84.352	0.000
n.Class 1	0.002	65.377	0.000
n.Class 2	0.001	4.348	0.000
n.Class 3	0.001	20.231	0.000
(b) South tube			
Constant	1.330	73.772	0.000
s. Class 1	0.001	11.899	0.000
s. Class 2	0.001	0.118	0.000
s. Class 3	0.002	19.218	0.000

All parameters are significant and included in the model. In addition, the R-squares are 0.108 and 0.092 respectively for the North and South tubes. Because the R-square represents only about 10% of the information presented in the model, it is obvious that the data is not represented well by regression. In order to test the suitability of a particular statistical model, residual analysis is essential. For the best performance of a regression model, residuals should follow normal distribution, zero mean and constant variance. A normal probability plot was used for testing the normality, and a residual plot was used for testing the constant variance as shown in Figure 2 and Figure 3.

Figure 2 (a) PP-plot of the residual and (b) a residual plot of the North tube



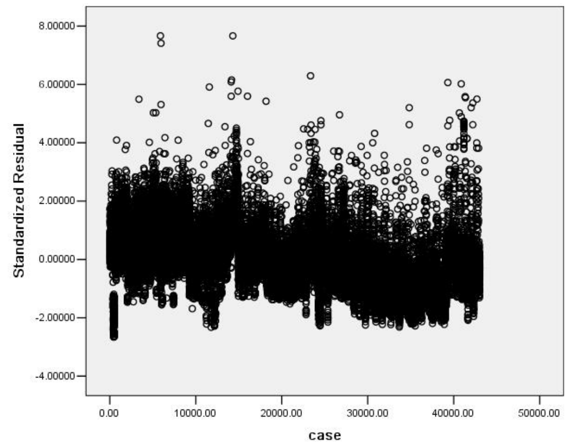
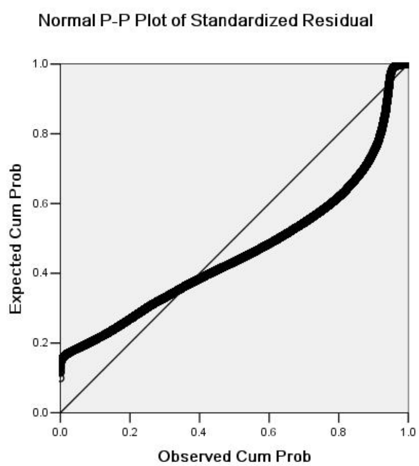
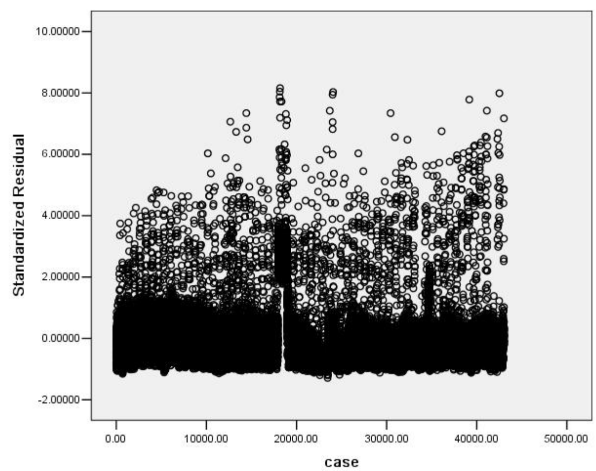


Figure 3 (a) PP-plot of the residual and (b) a residual plot of the South tube





PP plots are also called normal probability plots; they can be used to test normality. For the North tube, the normal probability plot (Figure 2a) shows that most of the points lie on a straight line, therefore we can claim that the residuals are following the normal distribution. However, the residual plot shows that most of the points lie on the positive side, which leads to a non-zero variance. Because the residuals show a pattern, they represent some of the information that is not represented in the model.

The normal probability plot of the South tube (Figure 3a) showed that the residuals of the South tube did not follow normal distribution. As most of the residuals are located on the negative side on the plot, the underlying assumptions confirm that the linear model is not suitable for analysing the data.

As the residuals do not obey the assumptions of liner regression, the estimates of the standard errors may suffer severe distortions and possibly lead to incorrect conclusions. Williams (1996) suggested three ways to solve the problem:

1. Reference the residuals to the normal probability plot, all the points that do not follow on the straight line can be deleted and considered as outliers. This can ensure that the residuals are following normal distribution. However, as some of the data are being deleted, it leads to loss of information and a lack of representation.

2. Reconstruct the model using transformation. In general, transformation with an exponential function or a logarithm function is preferred. However, this is not always successful.

3. Reconstruct the model with different parameters.

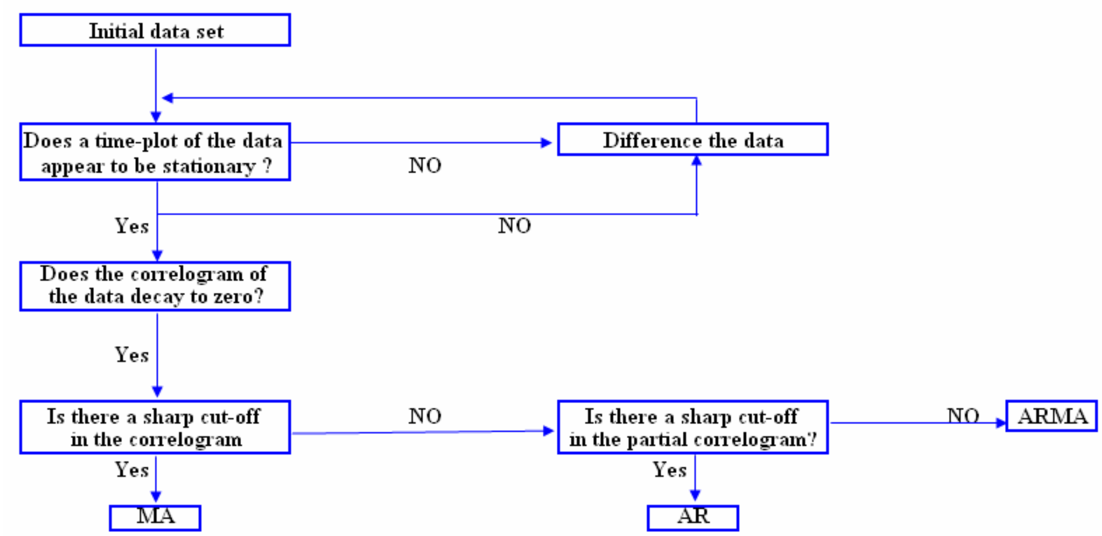
As mentioned previously, a wrongly estimated error term may lead to an incorrect conclusion, so further action should be undertaken. As the tunnel data are ordered in time and are not exchangeable, a time series modelling is applied to the residuals.

Time series analysis has been suggested for handling a large volume of data. Goyal et al. (2005) suggested modelling pollutant concentration by using a combination of ARIMA and regression models. To identify which model should be used, Diggle (1990) suggested that on the one hand, if there is a sharp cut-off in the auto-correlation function, a moving average model should be fitted. On the other hand, if there is a sharp cut-off in the partial auto-correlation, an appropriate auto-regression model should be fitted. The behaviours of auto-regression and moving average models are shown in Table 5 and the complete identification process is summarized in Figure 4.

Table 5 Behaviour of the auto-correlation and partial correlation

Process	Auto-correlation	Partial correlation
AR(p)	Exponential decay	Zero after lag p
MA (q)	Cuts off after lag q	Exponential decay

Figure 4 Flowchart illustrating the identification process



A combination of linear regression and time series models

In this model, the residual of the regression is modeled by a time series model. As the data are ordered in time and are not exchangeable, Box et al. (1994) suggested that a time series model should be considered. Schlink et al. (2001) also suggested if the observed data are auto-correlated, time-series models should be used.

As mentioned in the previous chapter, a wrongly estimated error term may lead to an inaccurate conclusion, and further action should be undertaken. As the tunnel data are ordered in time and are not exchangeable, time series models can be used to model the residuals.

Based on the ARIMA, the model was modified as follows:

$C = B_1 + B_2$ Class1 vehicles + B_3 Class2 vehicles + B_4 Class3 vehicles + δ_t

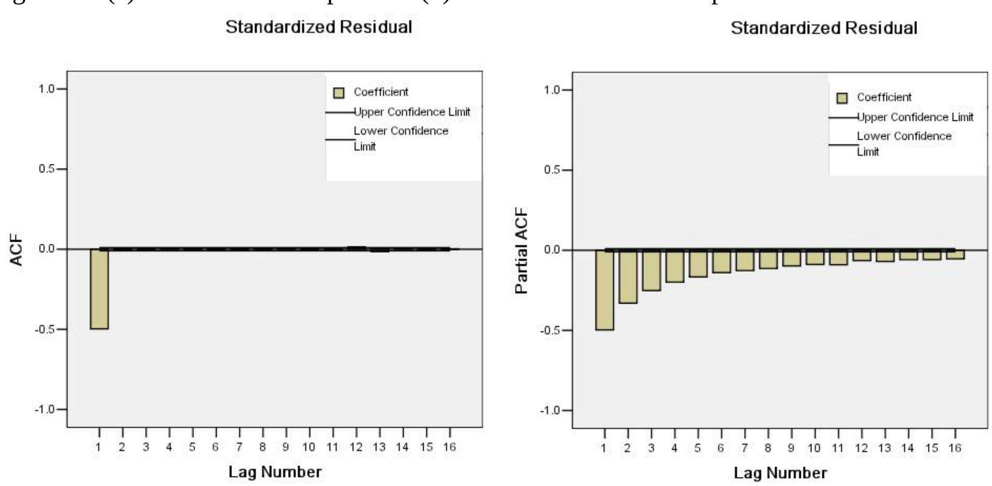
$$\delta_t = \phi_1\delta_{t-1} + \ldots + \phi_p\delta_{t-p} + \alpha_t - \theta_1\alpha_{t-1} - \ldots - \theta_p\alpha_{t-p}$$

where δ_t is the error term of the linear regression

North tube:

In order to decide which model is more suitable, useful tools are the auto-correlation function (ACF) and the partial auto-correlation function (PACF). The ACF and PACF, after one difference, are shown in Figure 5.

Figure 5 (a) Auto-correlation plot and (b) Partial auto-correlation plot



Box and Jenkins (1994) suggested that the MA model should be fitted, if the partial auto-correlation plot (PACF) shows a sine wave pattern and there is a clear cut-off on the auto-correlation function (ACF). In the case above, the ACF displayed had a clear cut-off at lag 1 in the PACF die off. Therefore, it was reasonable to conclude that the error term may follow a ARIMA(0,1,1) model. The statistical software SPSS has been used for this modelling. A time series analysis was applied to the residuals modelling. The modified model was shown as follows:

$$\text{CO.north} = 2.53 + 0.003\ \text{n.Class1} + 0.001\ \text{n.Class2} + 0.002\ \text{n.Class3} + \delta_t$$

$$\delta_t = \alpha_t - 0.995\alpha_{t-1}$$

Time series analysis assumes that the error term should follow the white noise process, as previously mentioned. In order to check the error assumption, diagnostic plots ACF and PACF, are used for residual analysis. They are shown in Figure 6.

Figure 6 Residual plot of the North Tube (a) Autocorrelation plot and (b) Partial autocorrelation plot

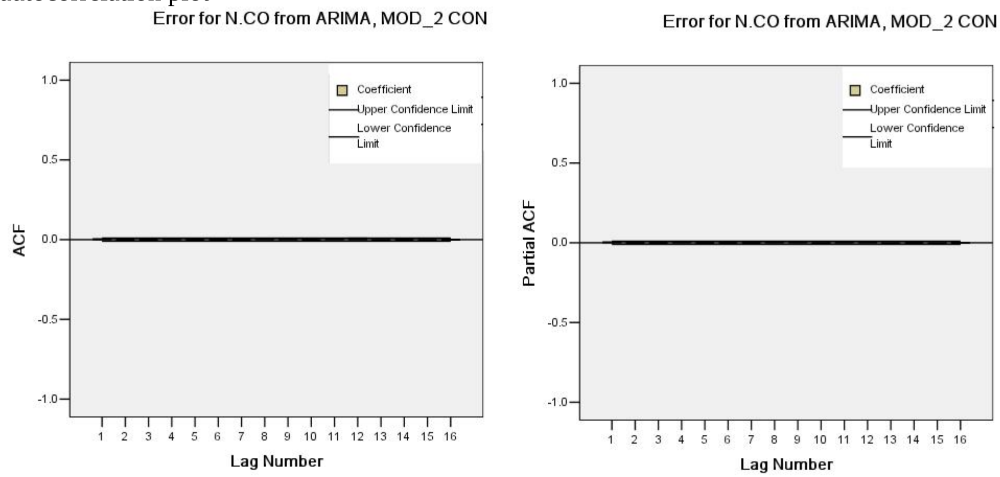


Table 6 Correlation matrix of the North Tube time series model

Correlation Matrix

		Non-Seasonal Lags	Regression Coefficients			
		MA1	N.C1	N.C2	N.C3	Constant
Non-Seasonal Lags	MA1	1.000	0[a]	0[a]	0[a]	0[a]
Regression Coefficients	N.C1	0[a]	1.000	-.071	-.047	-.006
	N.C2	0[a]	-.071	1.000	-.830	-.001
	N.C3	0[a]	-.047	-.830	1.000	.000
Constant		0[a]	-.006	-.001	.000	1.000

Melard's algorithm was used for estimation.

a. The ARMA parameter estimate and the regression parameter estimate are asymptotically uncorrelated.

In Figure 6, the autocorrelation and partial autocorrelation functions for the residuals showed that they are all small values, especially when they were compared to the plots for the raw data. As most of the lags lie below the standard line, the residuals can be claimed as zero mean and constant variance. Another way to test for constant variance is by studying the correlation matrix (Table 6). As all the coefficients in the correlation matrix are very small, there are no significant relationships between variables. This confirms the result from the diagnostic plot.

For the South Tube:

Using a similar approach as previously done with the North Tube, with reference to ACF and PACF, the error term may follow an ARIMA(0,0,5) model. By using a time series to model the residuals, the modified model is as follows:

CO.south = 0.958 + 0.001 s.Class1 + 0.001 s.Class2 + 0.002 s.Class3 + δ_t

$$\delta_t = \alpha_t + 0.792\alpha_{t-1} + 0.883\alpha_{t-2} + 0.281\alpha_{t-3} 0.199\alpha_{t-4} + 0.001\alpha_{t-5}$$

Figure 7   Diagnostics plot of CO South Tube

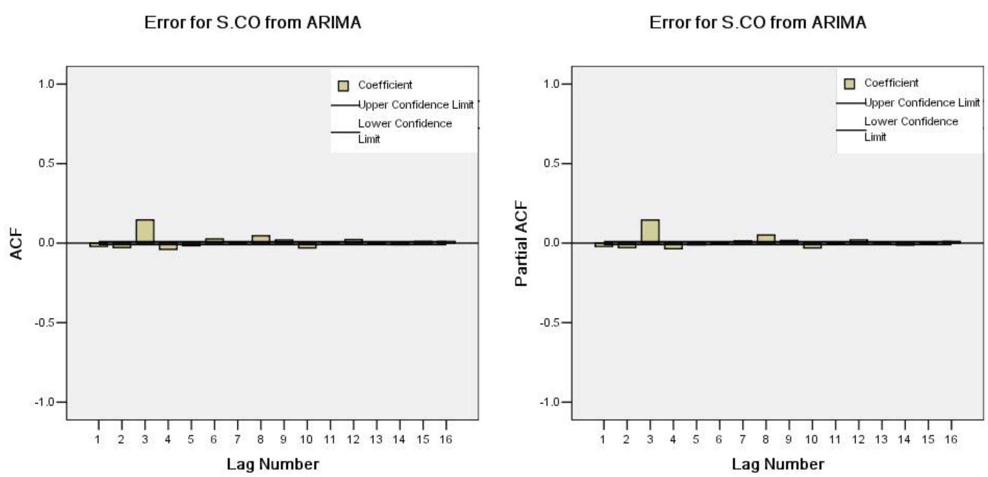


Table 7 Correlation matrix of the South Tube time series model

Correlation Matrix

		Non-Seasonal Lags					Regression Coefficients			
		MA1	MA2	MA3	MA4	MA5	S.C1	S.C2	S.C3	Constant
Non-Seasonal Lags	MA1	1.000	.674	.619	.224	.180	0[a]	0[a]	0[a]	0[a]
	MA2	.674	1.000	.737	.588	.145	0[a]	0[a]	0[a]	0[a]
	MA3	.619	.737	1.000	.720	.537	0[a]	0[a]	0[a]	0[a]
	MA4	.224	.588	.720	1.000	.569	0[a]	0[a]	0[a]	0[a]
	MA5	.180	.145	.537	.569	1.000	0[a]	0[a]	0[a]	0[a]
Regression Coefficients	S.C1	0[a]	0[a]	0[a]	0[a]	0[a]	1.000	.240	-.611	.000
	S.C2	0[a]	0[a]	0[a]	0[a]	0[a]	.240	1.000	-.758	.000
	S.C3	0[a]	0[a]	0[a]	0[a]	0[a]	-.611	-.758	1.000	.000
Constant		0[a]	0[a]	0[a]	0[a]	0[a]	.000	.000	.000	1.000

Melard's algorithm was used for estimation.

a. The ARMA parameter estimate and the regression parameter estimate are asymptotically uncorrelated.

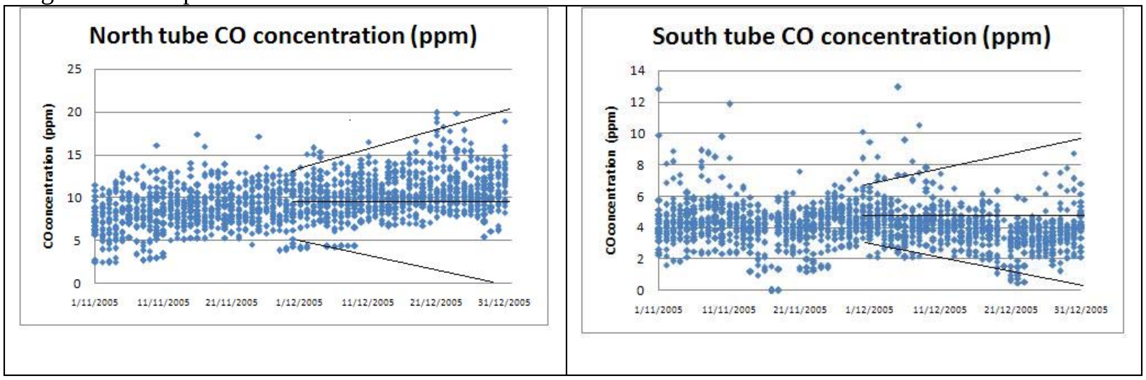
From the ACF and PACF plots, the model can be considered as a good fit model. Again, as all the coefficients in the correlation matrix (Table 7) are very small, this confirms the independence of variables.

Model validation

After a model is finalized, forecasting is important and relatively straightforward using SPSS. Data from January 2003 to December 2005 were used for modelling and the model was used to predict the concentration of January 2006. The prediction mean and 95% confidence interval of the North and South Tubes are plotted in Figure 8.

In both cases, most of the measured values fall well within the 95% confidence intervals envelope, showing that the models are accurate.

Figure 8 The prediction mean and 95% confidence interval of the North and South Tubes



Summary

In appreciating the available tunnel data, two statistical models have been used to explore the correlations among parameters. A linear regression model involves fewer parameters and is easier for calculation, but a mixed model adopts the time series approach and gives a better performance. Comparing the linear regression model and the time series model, the parameter estimates differ significantly. The difference is owing to the modelling of the error term. For a linear regression model, the error term should be independent, normally distributed with zero mean and constant variance. However, the errors (residuals) using this model do not always exhibit these characteristics such as in the situation above. As the tunnel pollutant emissions data are collected depending on time, time series analysis is therefore applied for modelling the error term. In most of the cases, times series modelling provides a good fit model. Although the time series model is more complex, it gives a much more accurate result. However, due to the fact a time series model is a mean based estimation, it can only provide a general picture of the trend.

Data are claimed as time series data if and only if they are ordered in time, continuous and cannot be exchanged. In the case of the Aberdeen Tunnel, the data set was only available for every first week in each quarter. Modelling regression residuals by a time series analysis is not applicable. Furthermore, for making a prediction, a time series is not very useful. As shown in Figure 8, the range of the 95% confidence interval of prediction is very large; it is mainly due to the fact that a standard deviation of time series increases sharply when prediction iteration increases. Therefore, another method was needed to study a non-continuous data set and monitor the pollutant emissions in the tunnel.

Linear regression is a statistical methodology that is used to relate variables. It is perfectly suitable for predict a dependent variable by one or more independent variables. However, the reliability of the model depends to the sample size of the model. The prediction of the model is reliable if and only if the samples are coming from the same group as prediction criteria. For different prediction interval or criteria, another sampling and modelling process are suggested.

Besides modelling by regression analysis, a simple mass balance method (SMBM) is another common way to model pollutant concentration with traffic volume. As mentioned in the previous chapter, the major parameters of an SMBM are the change of pollutant concentration from entry to exit and the wind speed, but not the driving patterns. The driving patterns are the speed and driving modes of vehicles, which affect the emission of motor vehicles. (Jensen 1995; Ericsson, 2000; Brundell-Freij and Ericsson, 2001; Hung et al., 2002) Therefore, the measurement of driving patterns is widely used to predict the vehicle emission. We suggested improving the prediction of SMBM by including the driving pattern. Furthermore, the tunnel data collected by the tunnel operators were very useful in estimating vehicle emission factors and related simulation models, but the data were collected at 2.1m above ground. Due to the point of the data collection being far from the breathing zone, a method of converting the tunnel data to breathing zone data was needed. Therefore, on-site measurement was needed. The survey was undertaken in the LRT to obtain the driving pattern and pollutant concentration.

4 Field Data Collection Method

4.1 *Gaseous pollutant concentration data collection and measurement methods*

There are two possible ways to collect continuous air quality data in a tunnel. First, by placing a reasonably large number of air quality measuring points along the tunnel so that the data collected can be assumed to be continuous along the tunnel. This can be done either by air bags or on-site equipment such as remote sensing and air quality analysers. Another possible method used to collect continuous air quality data in a tunnel is the car floating technique, whereby air quality data are collected continuously using an instrument car.

Fixed-measuring methods

Air-Bag sampling

In the Chung-Cheng Tunnel study, Hsu et al. (2001) applied a method of sampling gaseous pollutants by using an integrated bag technique for pollutant sampling. In order to obtain an accurate result, each sample should sample at the same pump rate. The concentration of pollutants was analysed by a fixed gas analyser in a laboratory. However, gaseous pollutants may react with each other inside an air bag. This leads to uncertainties on the reliability of the results.

Air quality analysers

Air quality analysers are the most common way to obtain gaseous pollutant concentration data in a tunnel (Robert et al., 1984; Gertler et al., 1997; Gillies et al., 2001; Sternbeck et al., 2002). Fixed gas analysers for data collection are usually set up, in the breathing zone, at the entry and exit of a tunnel. Due to the expensive cost of equipment, only a few point measurements are used to obtain data. In addition, this sampling method suffers from being a discrete database.

Remote sensing

A remote sensing technique involves the use of a remote sensor placed near the road level to measure, by absorption, the individual vehicle exhaust plume. Emissions are expressed as a concentration ratio of pollutants to CO_2, which can also be normalized to fuel consumption based on the stoichiometry of the combustion process. This technique allows the screening of a large number of vehicles under real operating conditions. The remote sensing technique had been applied by Bishop et al. (1996) in the Tuscarora Mountain and Fort McHenry Tunnels. Due to the small sample size and technical problems, the result of the measurements was inconclusive in both studies.

Car floating technique

Another possible method used to collect continuous air quality data in a tunnel is the car floating technique. The air quality data are collected continuously by an instrumented car. As the air quality in road tunnels depends on the traffic speed, the traffic speed is recorded by using the 'car chasing' technique. The instrumented car is equipped with a speed meter and driven to mimic the speed of the front vehicle. Therefore, the instrumented car is kept a few car distances from the front car. Kittelson et al. (2000) reckoned that the car chasing technique can help to simulate a more realistic traffic condition and pollutant concentration.

4.2 *Speed data collection and measurement methods*

It is obvious that vehicle speed is one of the main factors reflecting one's driving behaviour. Therefore, vehicle speed should be taken into account for tunnel studies. This would also be crucial criteria for developing an effective emission model. Although the significance of vehicle speed has not been shown in previous or existing emission measuring models, collecting the speed data and creating the speed profile is useful for further analysis. The following introduces a cost effective way to collect such data.

Instrumented vehicles provide a way to gather information about vehicle operation and traffic conditions in the real world environment. To capture the real world vehicle speed and other relevant parameters, the car chasing method is the most direct method. It is a very common technique used in developing driving cycles. Lin and Niemeier (2002) and Austin et al. (1993; 1995) adopted the car chasing method to collect speed data from light duty vehicles using the refined chase car protocol. The speed profile was recorded by chasing vehicles.

Jensen (1995) also used a car chase technique where a measuring car followed selected vehicles. Velocity was recorded every second. Thirteen streets and roads were observed. Six streets in a middle-sized town of 50 000 inhabitants were chosen to represent different traffic flows. Two motorways, two express roads and three highways in the main road network were chosen to represent steady and unsteady traffic flows. (Esteves-Booth et al., 2001)

4.3 *Measuring Equipment*

Brundell-Freij and Ericsson (2001) measured driving patterns that were influenced by external environmental factors. In this study, five different-sized passenger cars were installed with data-logging systems and Global Positioning System (GPS) receivers. The measurement cars were driven by 29 randomly chosen families. Each family borrowed a car of the same size and performance as their ordinary ones and drove the measurement car for two weeks in the city of Vasteras, Sweden. By using GPS to collect vehicle speed data, it could also be used to learn the positions and the street types travelled. However, GPS reception is suspended inside tunnels, so a vehicle's tunnel speed cannot be captured.

A microwave speed sensor is an alternative way for capturing vehicle speed that was developed from the Doppler principle. The relative movement between the sensor and the test surface are detected by a planar antenna. It projects two radar beams at 45 degree angles; when striking the test surface, the radar beams reflect back to the sensor antenna. The resulting double frequency is directly proportional to the speed.

Hung and Lee (2003) compared the limitation and suitability of three, vehicle speed measuring devices: the infrared tachometer, GPS receiver and microwave speed sensor. They found that the GPS faced signal obstruction caused by tall buildings or the high density of advertisement light boxes. It was not suitable to use in tunnels due to the obstruction of the satellite. As microwave receptors are not affected by tunnel environment, a microwave speed sensor is more suitable than a GPS for inside tunnel measurement.

4.4 *Summary*

Under limited resources, the car chasing technique is usually applied. Researchers can collect both the pollutant concentration and speed data for analysis of the emission behaviour. The car chasing technique allows for the collection of driving patterns of many target vehicles using only one set of instruments.

In conclusion, both remote sensing and car chasing techniques have their advantages and disadvantages as discussed above. They can develop a reasonable, representative driving and pollutant concentration profile. To obtain an exact pollutant concentration unaffected by a background air pollutant, a remote sensing method is more suitable. However, it is very expensive to install and maintain. The car chasing technique is more suitable for collecting vehicle speed data under limited resources. The cheaper car chasing technique allows more frequent updates of the driving behaviour and pollutant profile. However, this methodology requires a surveyor and a trained driver during the data collection period.

5 Developing Hong Kong Tunnel Based Model

5.1 *Survey planning*

After reviewing several sampling methods, car floating and chasing techniques were used in this study. A private car equipped with a portable gas analyser and speed detectors was used to collect a set of continuous CO, NO_2 and speed data.

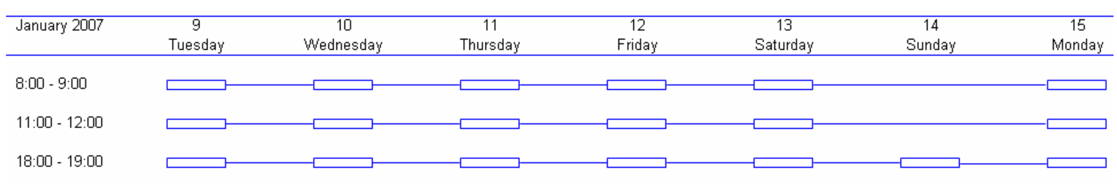
Vehicle speed related data

Pollutant emissions depend very much on vehicle operating modes, i.e. idling, cruising, acceleration and deceleration. (Hung et al., 2002) A car chasing technique was used in this project. A driver was required to follow a target car's motion including accelerating, decelerating, cruising and idling. This method has the least influence on a target driver's behavior, and allows for a more realistic traffic pattern. As crossing lanes is not allowed in road tunnels, there is less chance of losing the target car. If however, the target car gets away from the chasing vehicle (e.g., it illegally changes to another lane), the chasing car should follow a motion similar to the front car.

Field data collection schedule

Peak and off-peak hours are important factors for driving patterns. They were classified as traffic condition factors by Ericsson (2000). They define congested traffic conditions. Peak hours are the hours with the maximum traffic flow in a day. In Hong Kong, according to the Transport Department, the morning peak period is from 07:00 a.m. to 10:00 a.m. and the evening peak period is from 04:00 p.m. to 07:00 p.m. (HKTD, 2006a). The measurement time in this project was confined to an hour in the morning peak period, from 08:00 a.m. to 09:00 a.m.; a late morning off-peak hour from 11:00 a.m. to noon, and an evening peak hour from 06:00 p.m. to 07:00 p.m. Field measurements were carried out in the LRT in Hong Kong between January 9 and 15, 2007, according to the sampling schedule (Figure 9).

Figure 9 Sampling schedule



Instrumented vehicle

A Nissan Pathfinder (3300 c.c.) was used as the instrumented chase vehicle in this research. It was installed with the following equipment: 1) a microwave speed sensor and a data acquisition instrument, 2) a 12V DC to 240V AC inverter as the power supply for the microwave speed sensor, infra-red tachometer and lap-top computer, 3) a portable CO gas analyser (Interscan Corporation, Series 4000), and 4) a NO_2 gas analyser (Interscan Corporation, Series 4000).

Gas analyser (Interscan Corporation, Series 4000)

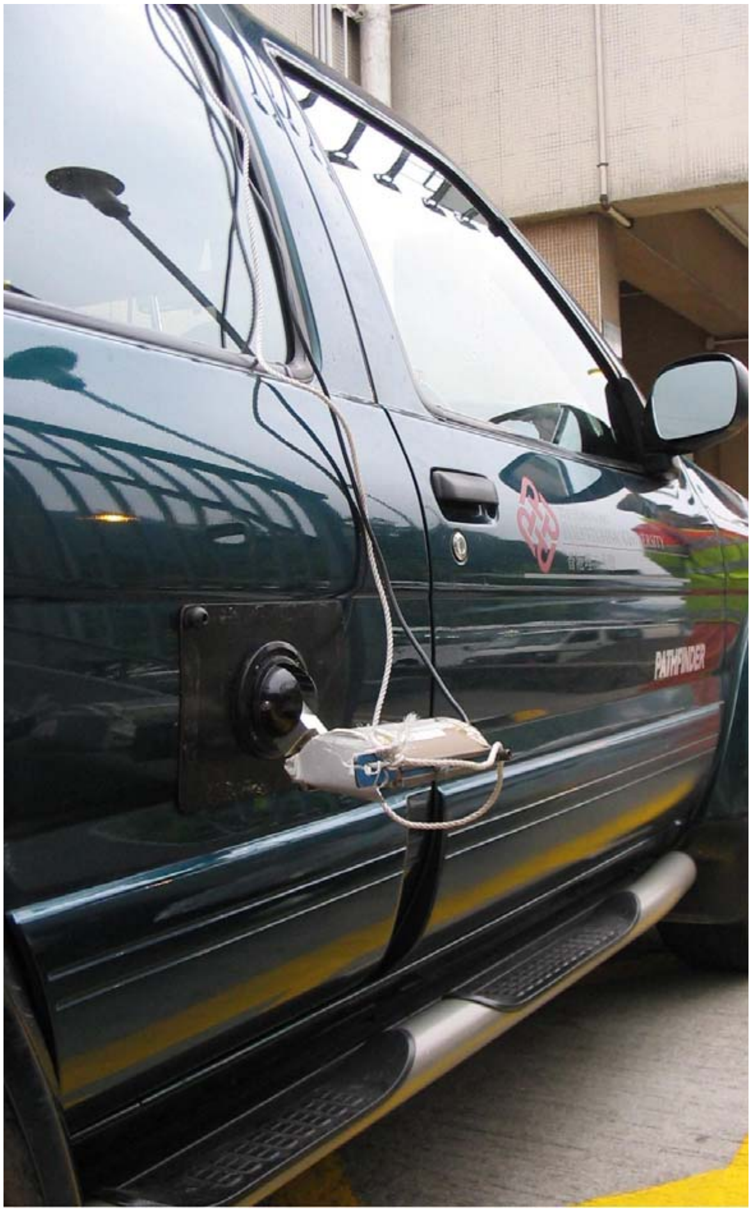
An instrumented car was used to collect the pollutant data in the tunnel. A portable CO and NO_2 gas analyser (Interscan Corporation, Series 4000) was used to measure CO concentration. The detection range of the CO monitor is between 0 to 19.99 ppm, and 0 to 999 ppb for the NO_2 gas analyser. Before the field work sampling, the instruments were calibrated by introducing a known gas concentration and adjusting the span control to its proper level. The air outside the car was sampled through a tube that stretched outside of the car through a window.

Microwave speed sensor (Darwin Microwave Speed Sensor)

Car chasing experiments were performed directly behind moving vehicles to obtain speed data. Kittelson et al. (2000) suggested that a car chasing technique could help to simulate more realistic traffic conditions and pollutant concentrations. We employed a Darwin microwave speed sensor to record the instantaneous speed data while driving through the tunnel.

The microwave speed sensor detects the relative movement between itself and the ground surface by emitting microwave beams obliquely to the ground surface using the antenna (Richardson et al., 1982). Inside the antenna, a microwave oscillator radiates two symmetrical radar beams at an angle of 45°. Upon striking the ground surface, a small part of the microwave is scattered back into the sensor antenna within the intended detection area and inherently suppresses any signals from outside this detection area using spreading-spectrum coding. The Doppler signal is obtained by comparing the transmitted and received microwave signals. This Doppler signal frequency is proportional to the vehicle speed and the cosine of the microwave radiation angle with respect to the horizontal ground plane (Heide et al., 1999). The two-beam planar system automatically compensates for the systematic measuring errors that occur due to the mounting of the equipment and the pitch angle variation, as well as to the influence of changing ground conditions (Heide et al., 1996; Tsuha et al., 1982).

Figure 10 Actual installation of the microwave speed sensor



In our survey, the microwave antenna was fixed at the side of the instrumented vehicle. The data acquisition system, power supply system and a lap-top computer were placed into the glove compartment and monitored by the surveyor. The actual installation and specification of the microwave speed sensor is shown in Figure 10.

5.2 *Results of sampling data*

5.2.1 Traffic volume

The speed of the vehicles measured in each survey trip is shown in Table 8. The average speed inside the tunnel varied from 43 km/h to 58 km/h. The average traffic volume within the sampling hour varied from 1994 veh/h to 3160 veh/h. On weekdays, the average traffic volume in the afternoon period was relatively low in both tubes. For the North Tube, there was no significant difference in traffic volume between weekday and weekend sampling periods, except during the morning period when volume dropped by 20% at the weekends. In the South Tube, the traffic volume through the tunnel was very stable during the weekends. It stayed at a level of about 2300 veh/h. The average traffic volume reached the highest on weekday mornings and evenings, at a level of about 3000 veh/h.

Table 8 The average vehicle speed and traffic volume

North Tube (To Shatin)						
	Weekday			Weekend		
	08:00 - 09:00	11:00 - 12:00	18:00 - 19:00	08:00 - 09:00	11:00 - 12:00	18:00 - 19:00
Sampling hour	5	5	5	1	1	2
Average vehicle speed (km/h)	52.38	45.01	57.83	56.12	55.96	54.44
Average traffic volume (vehicles/h)	2553.2	2153.42	2746.2	1994	2089	2606
South Tube (To Kowloon)						
Average vehicle speed (km/h)	43.18	53.02	53.09	46.81	51.39	54.53
Average traffic volume (vehicles/h)	2964.0	2458.0	3023.4	2244	2354	2378

5.2.2 Driving patterns in road tunnels

Average Speed

Carbon monoxide, hydrocarbon, nitrogen oxides and particulate matters are the major pollutants of vehicular emission. Tunnel base modelling is used to estimate these pollutants, because traffic flow and speed are assumed to be constant in road tunnels.

The average speed in the South Tube was 43.2 km/hr during the weekday morning peak hour; it was 10 km/hr lower than the other two periods. In the North Tube direction, there was an obvious lowest speed during the weekday evening peak hour. It was 45 km/hr, but it was 52.4 km/hr and 53.8 km/hr in the morning peak hour and the afternoon off-peak hour respectively. The lower average speed was the result of the high traffic intensity. The lowest average speed appeared in different periods in the two directions; this is because the road function of the tunnel is to connect the urban area, Kowloon, to the residential area, Sha Tin. In the morning, people traveled mainly in the south direction to go to work or school and the higher traffic intensity resulted in a lower average vehicle speed. On weekends, the average speed was 46.8 km/hr in the morning peak hour, in the South Tube direction. It was the only period that recorded an average speed under 50 km/hr among all periods in both directions. It indicates that the traffic flow was smoother in all periods other than the morning peak hour in the South Tube.

Speed Flow Relationship

In order to present the relationship between vehicle speed and traffic volume, a speed flow relationship is studied. In the speed-flow relationship analysis, the traffic flow (in vehicles per hour per tunnel direction) is plotted in Figure 11 and Figure 12.

Figure 11 Speed-flow relation of LRT (North Tube)

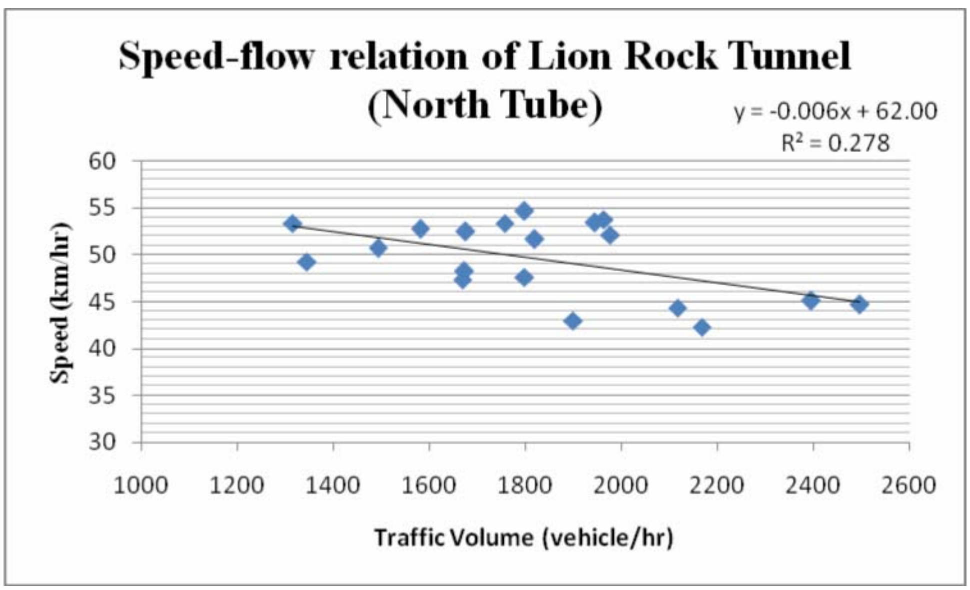
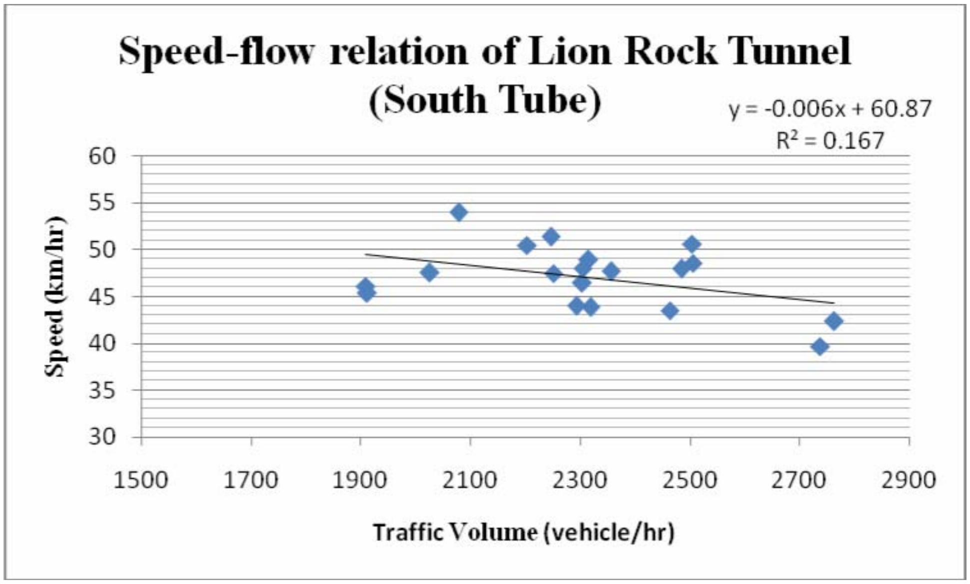


Figure 12 Speed-flow relation of LRT (South Tube)



In Figure 11 and Figure 12, the speed-flow relations were plotted, and the linear regression was also plotted in each graph. Since the raw data followed a downward trend, the linear regression adequately illustrated the relationship. Both graphs had best fitted lines with negative slopes. The negative slope indicated that when the traffic volume increases, the speed of moving vehicles decreases which leads to a longer exploure time inside the tunnel. (Zhou and Hall, 1999)

5.2.3 Pollutant concentration

The CO and NO_2 concentration inside the tunnel was measured continuously in each survey. The average CO and NO_2 concentrations from the field work were used to compare with the data obtained by the tunnel management companies. The mean and range of hourly CO and NO_2 concentrations of tunnel data and field data are plotted in Figure 13 and Figure 14 respectively.

Figure 13 The mean and range of hourly CO concentration of tunnel data and field data

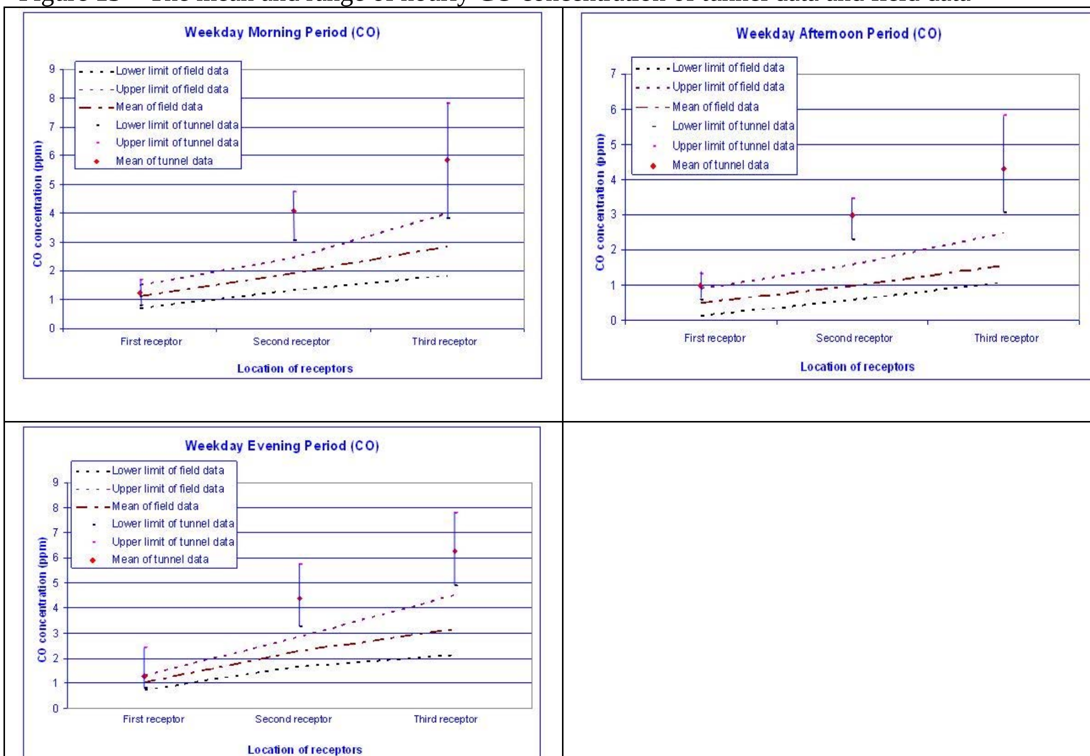
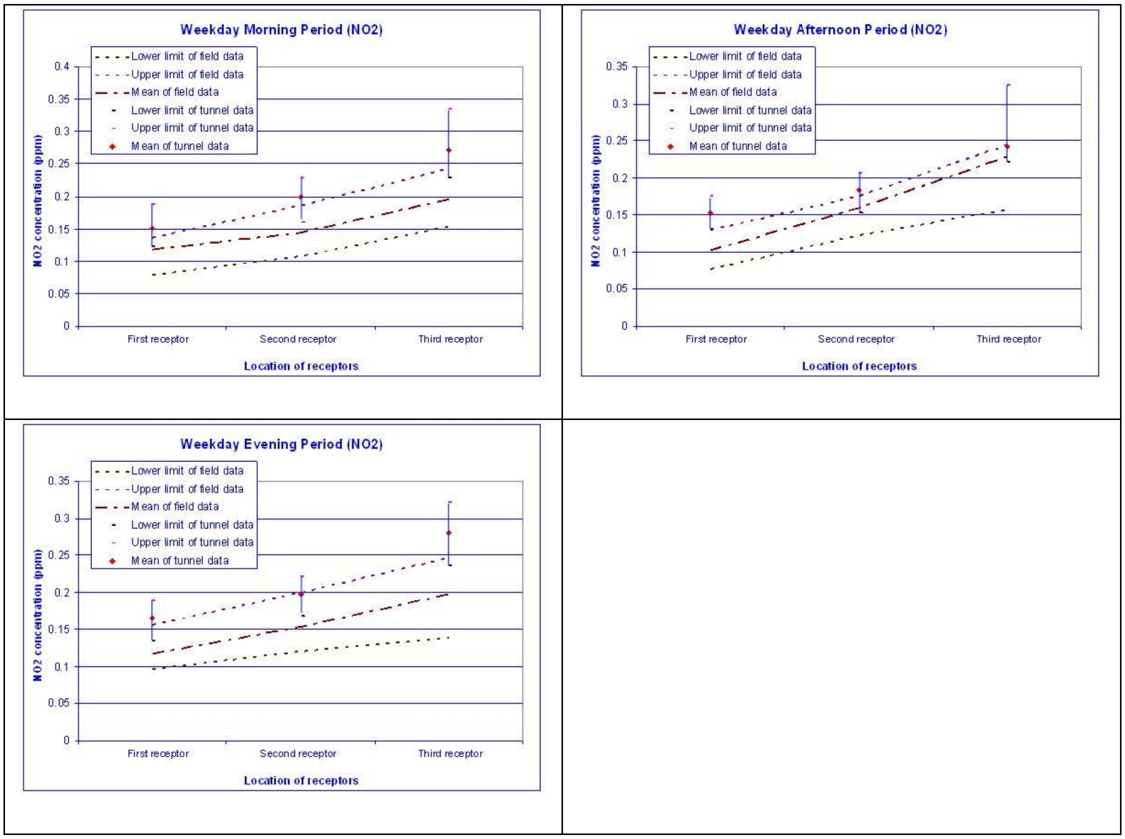


Figure 14 The mean and range of hourly NO_2 concentration of tunnel data and field data

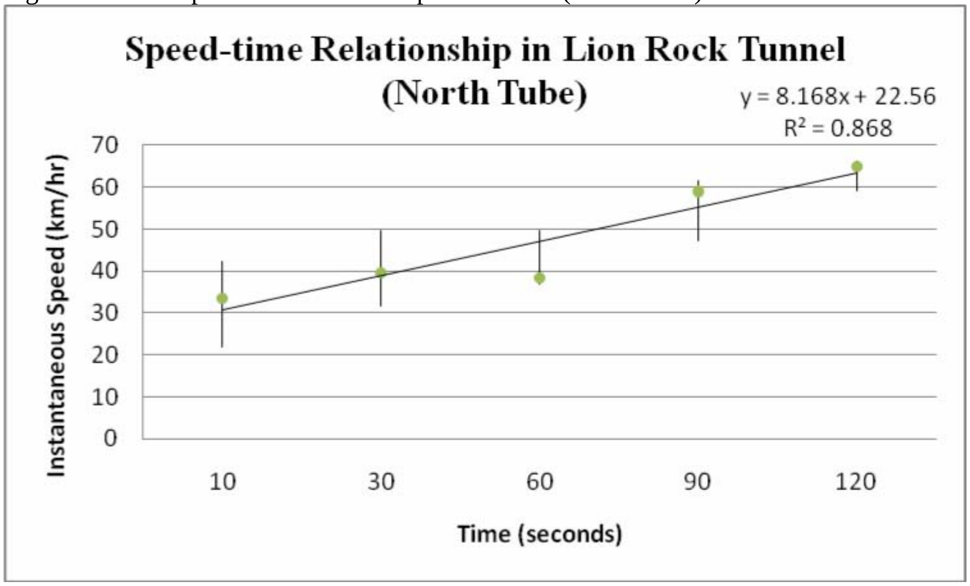


The average CO concentration obtained from our field work varied from 0.14 ppm to 4.73 ppm, and the hourly average CO concentration obtained by the tunnel operators varied from 0.61 ppm to 7.82 ppm. The average NO_2 concentration obtained from our field work varied from 0.122 ppm to 0.335 ppm and the hourly average NO_2 concentration obtained by the tunnel operators varied from 0.076 ppm to 0.246 ppm. It appears that the tunnel air quality monitoring data always gave us higher pollutant concentrations. Both sets of data show a similar increasing trend from the entrance to the exit. This is because vehicles push the air forward in tunnels, and create air flows towards the exit. This phenomenon is similar to the finding of Rogak et al. (1998) who also found that the CO concentration at the exit of a tunnel is always higher than at the entrance. Furthermore, the concentrations in both the tunnel air monitoring data and our field data showed a linear relationship. This agrees with the discoveries of Chang and Rudy (1990) who also found a linear relationship between the pollutant and the distance through the tunnel.

5.3 *Development of the tunnel speed profile*

In order to illustrate driving behaviour, one of the most useful methods is the speed time profile. It provides the simplest visual presentation of a driving pattern. Some critical driving characteristics can be identified readily from the speed time profile, such as maximum speed, and the proportion of idles and stops per kilometer. In this section, the speed time relationship is studied; the maximum, mean and minimum instantaneous speeds are plotted at every 30 seconds in Figure 15 and Figure 16.

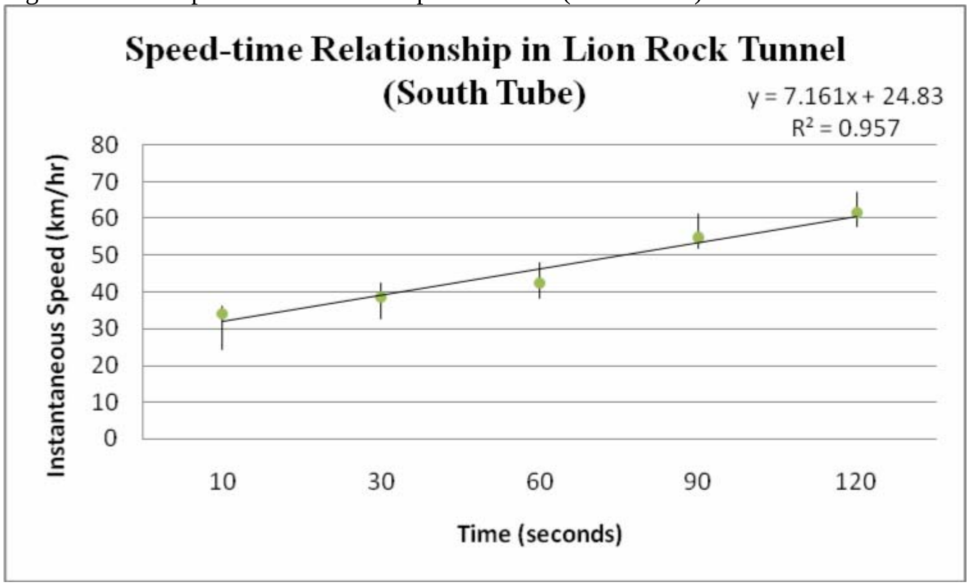
Figure 15 The speed-time relationship of the LRT (North Tube)



In Figure 15, the entering speed of the LRT (North Tube) was about 22 km/hr to 42 km/hr. The speed kept constant in the middle of the tunnel. As the cars exited the tunnel, the speeds kept on increasing towards the end. The exit speeds ranged from 59km/hr to 66 km/hr.

In Figure 16, the entering speed of the LRT (South Tube) was about 25 km/hr to 37 km/hr. Similar to the North Tube, the speed kept constant in the middle of the tunnel. Near the end of the tunnel, the speeds kept increasing towards the end. The exit speeds ranged from 58km/hr to 68 km/hr. The trend line added to the figures shows that a linear and increasing relationship might also exist in the speed-time relationship for both tubes.

Figure 16 The speed-time relationship of the LRT (South Tube)



5.4 *Development of the pollutant concentration profile*

There are ample studies to estimate vehicle emission factors in order to quantify and monitor changes of vehicle emission, which is a major source of air pollutants. Ingalls et al. (1989) first reported tunnel-base emission factors in the Van Nuys Tunnel experiments. A field study was conducted to record pollutant concentrations. El-Fadel and Hashisho (2000) suggested a long-term periodic tunnel monitoring programme to assess the progress of abatement measures in meeting on-road emission targets. It is clear that ad hoc field measurements at tunnels can only yield data over a relatively short period of time. The data obtained is insufficient to produce a model with a significant confidence level (Shendell and Naeher, 2002). However, tunnel operators are required to monitor air quality in road tunnels at fixed monitoring points. This amount of data is very useful in estimating vehicle emission factors and related simulation models.

We have adopted a very simple approach to converting the tunnel data to breathing zone data. We collected a set of continuous data at the breathing zone and tried to explore its relationship with the corresponding set of discrete data at fixed points in a selected tunnel which was obtained by a tunnel management company. To implement this simple approach, we had to select an appropriate method to conduct the co-relation analysis.

Therefore, regression analysis was employed in this case. Regression analysis is one of the most flexible and widely used techniques of statistics modelling methods (Funasaka et al, 1998). A typical regression model attempts to explain variation in a dependent variable (Y_i), by mapping the relationship of Y to a specified set of independent variables as a linear function. Using least squares estimation techniques; we arrived at a prediction equation that allows us to estimate conditional means on the dependent variable.

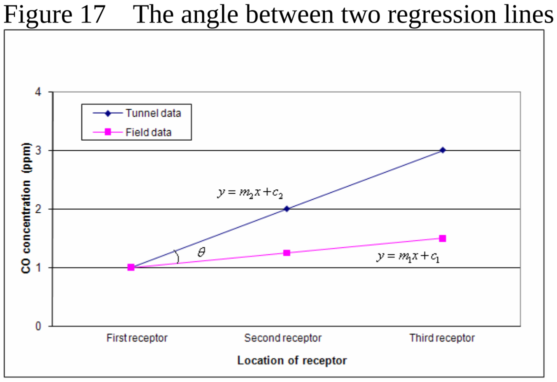
In order to obtain a concentration profile inside a tunnel, gaseous pollutant concentration should be modelled by the location of receptors. Using

Williams' (1996) model, the variation between sampling points was omitted by discrete point measurement.

Profile development

Hsu et al. (2001) indicated that there is a linear relationship in pollutant concentration from inlet to outlet; a similar approach was undertaken for this tunnel data and field data. A linear regression model was used for determining the CO concentration by the location of receptors. For each study sample, two regression lines were formed. The angle between two regression lines can be calculated by Equation 21.

Figure 17 The angle between two regression lines



Equation 21: $\tan\theta = \frac{m_1 - m_2}{1 + m_1 m_2}$

Where $\theta =$ the angle between two regression lines, $m_1, m_2 =$ the slopes of tunnel regression and field regression respectively. The angle between two regression lines in different sampling periods is listed in Table 9.

Table 9 The angle between two regression lines in different sampling periods

	Morning period		Afternoon period		Evening period	
North Tube	Angle between (Degree)	Traffic flow (veh/hr)	Angle between (Degree)	Traffic flow (veh/hr)	Angle between (Degree)	Traffic flow (veh/hr)
9/1/2007	18.4	2566	30.0	2092	20.9	2705
10/1/2007	19.1	2513	29.6	2111	22.0	2757
11/1/2007	24.4	2679	33.7	2310	18.3	2778
12/1/2007	20.7	2548	33.7	2143	24.9	2774
15/1/2007	26.5	2460	27.9	2111	17.3	2717
Mean	21.8	2553.2	30.9	2153.4	20.7	2746.2
SD	3.5	81.1	2.6	89.4	3.0	33.4
South Tube	Angle between (Degree)	Traffic flow (veh/hr)	Angle between (Degree)	Traffic flow (veh/hr)	Angle between (Degree)	Traffic flow (veh/hr)
9/1/2007	23.3	3042	28.0	2451	25.5	2983
10/1/2007	24.0	2889	27.0	2448	23.0	2908
11/1/2007	24.7	2930	29.9	2242	20.5	2971
12/1/2007	23.2	3015	34.9	2591	23.6	3264
15/1/2007	22.1	2944	27.9	2558	19.3	2991
Mean	23.5	2964.0	29.5	2458.0	22.4	3023.4
SD	1.0	63.0	3.2	136.5	2.5	138.4

The average angle between two regression lines for the morning period and evening period were 22.6 degrees and 21.6 degrees respectively. In the afternoon period, the average angle between the two regression lines was 30.2 degrees. The standard error of all three study periods did not exceed 2.8 degrees. For further analysis, a cluster analysis was performed. This analysis is in the next section.

Cluster analysis

Chan et al. (1996) suggest ventilation rate is one of the major factors that affect pollutant concentrations. According to the tunnel management company, ventilation rate depends on the traffic volume. Eight units of fresh air supply fans and two units of exhaust air fans are operated at high speed within the tunnel at peak hours. Each unit of the supply / exhaust air fan has a volume flow rate of $47.2m^3/s$ and $80m^3/s$ respectively, in high speed.

Pierson et al. (1990) found that the pollutant concentration is highly related to traffic volume in tunnel studies; they suggested that this relationship leads to another significant relationship between the angle (θ) and the traffic volume. Chaney (1978) suggested that the concentration of pollutants is the highest at low speed. He concluded that a remote receptor might show better results by exposing longer in time. In that case, the remote receptor could obtain a higher pollutant concentration, by providing a smaller angle between two regression lines. The hypothesis is that the angle between two regression lines may be strongly influenced by the number of vehicles per hour. In order to test the hypothesis, cluster analysis is used. Krzanowski (2000) suggests that a cluster analysis be used for grouping similar kinds of objects into respective categories and for discovering the structures of the data.

The angles (θ) were first allocated into two groups by traffic volume. Traffic volume greater than 2500 veh/h was classified as group one; all other volumes were in group two. Statistical software SPSS was used for separating the data into two main cluster groups by a mean cluster analysis method. The result is shown in Table 10.

Table 10 The result of cluster analysis

	Group 1 (> 2500 veh/h)	Group 2 (< 2500 veh/h)
Separated by traffic flow	21	9
Separated by cluster method	19	11

The result shows only two out of thirty clusters were not following the assumption; the final cluster centres for group one and group two are 21.86 and 29.90 respectively. As over 93.3% of the data was allocated into the same group as a hypothesis, there should be a high correlation between the angles (θ) and the traffic volume.

Validation

A cluster centre from each group was used to predict the angle between two regressions. A fixed ratio for each group can simply be calculated by the tangent of the angle. The fixed ratios for group one and group two are 0.401 and 0.575 respectively. Tunnel data on the 13th of January, 2007 was used for testing the effectiveness, the slope and traffic volume. The data is listed in Table 11.

Table 11 The slope and traffic volume of tunnel data

		Slope of tunnel data	Traffic volume
Morning period	North Tube	0.9726	1994
	South Tube	1.8192	2768
Afternoon period	North Tube	1.2714	2089
	South Tube	2.6494	2683
Evening period	North Tube	2.4388	2845
	South Tube	2.4124	2807

The slope of the estimated regression line was calculated by Equation 21, and the first point of tunnel data was used with point-slope form for finding the liner equation of the estimated field trend. Figure 18 depicts the simulation result of field measurements.

Figure 18 a) Comparison between simulation and field data

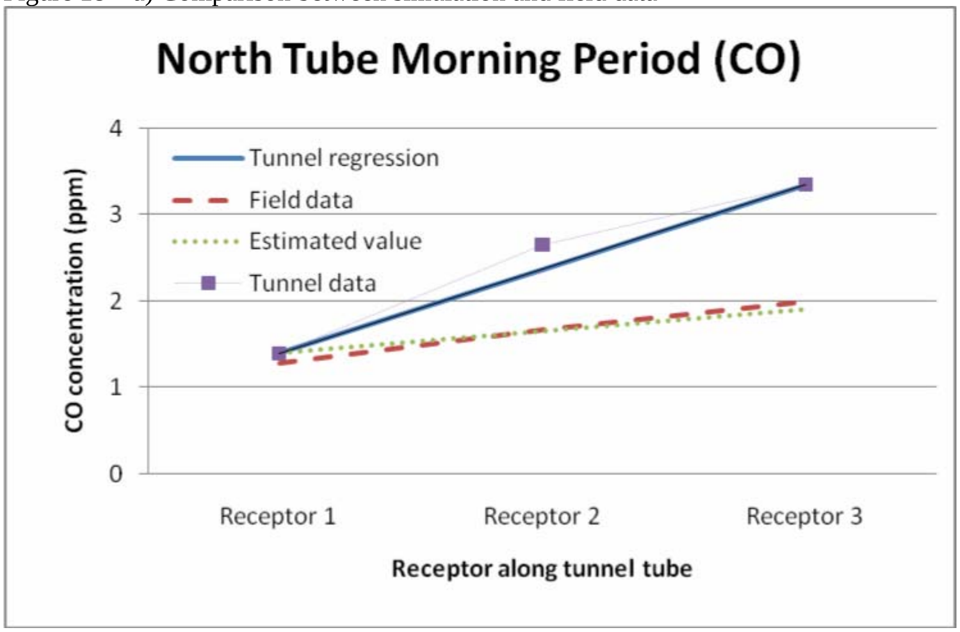


Figure 18 b) Comparison between simulation and field data

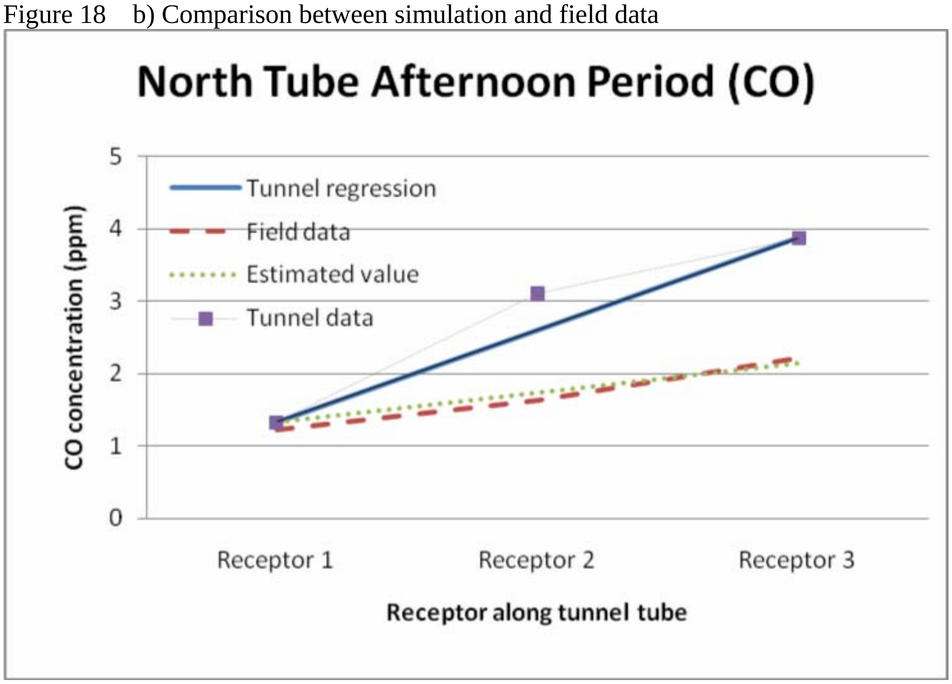


Figure 18 c) Comparison between simulation and field data

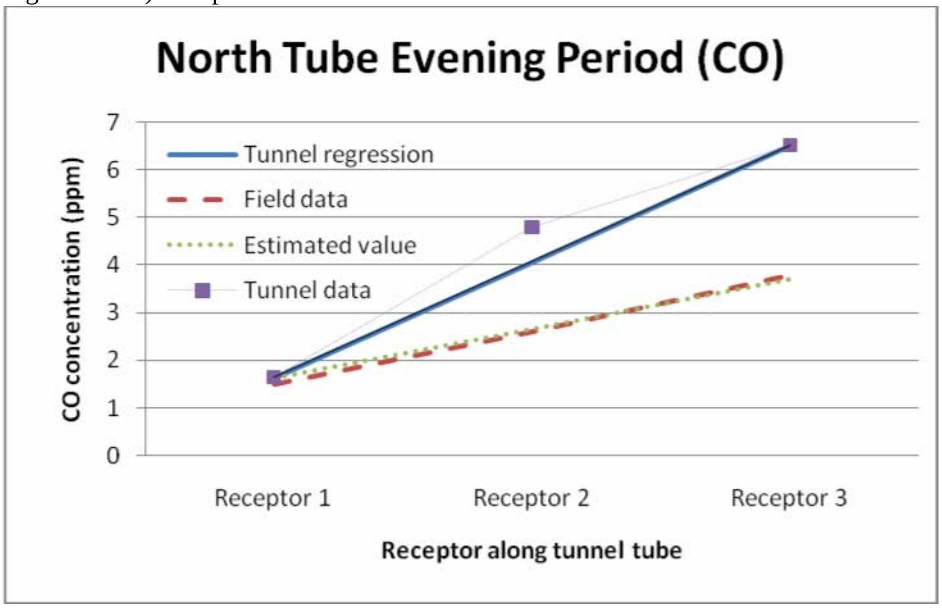


Figure 18 d) Comparison between simulation and field data

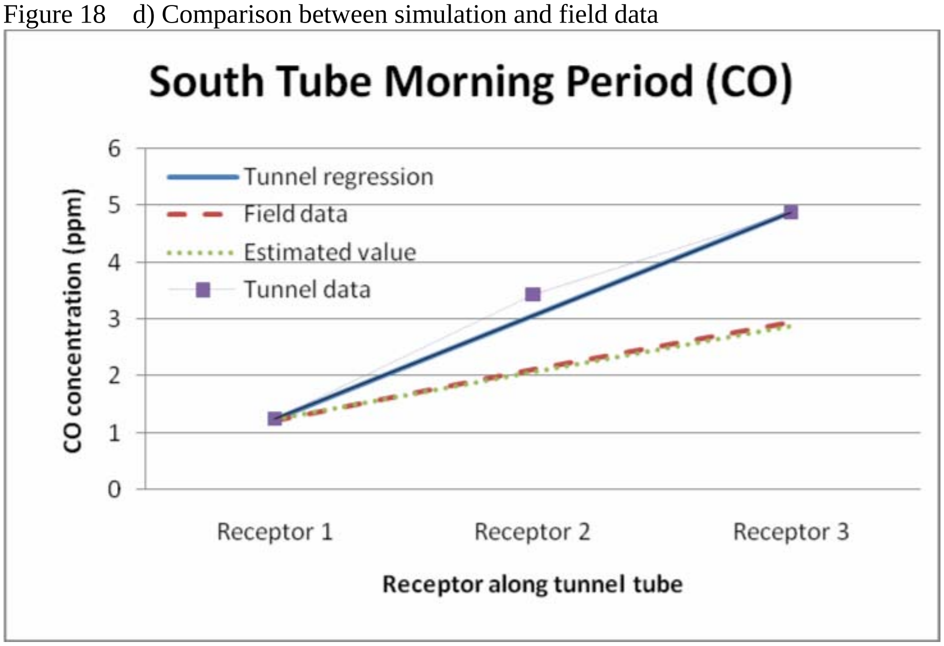


Figure 18 e) Comparison between simulation and field data

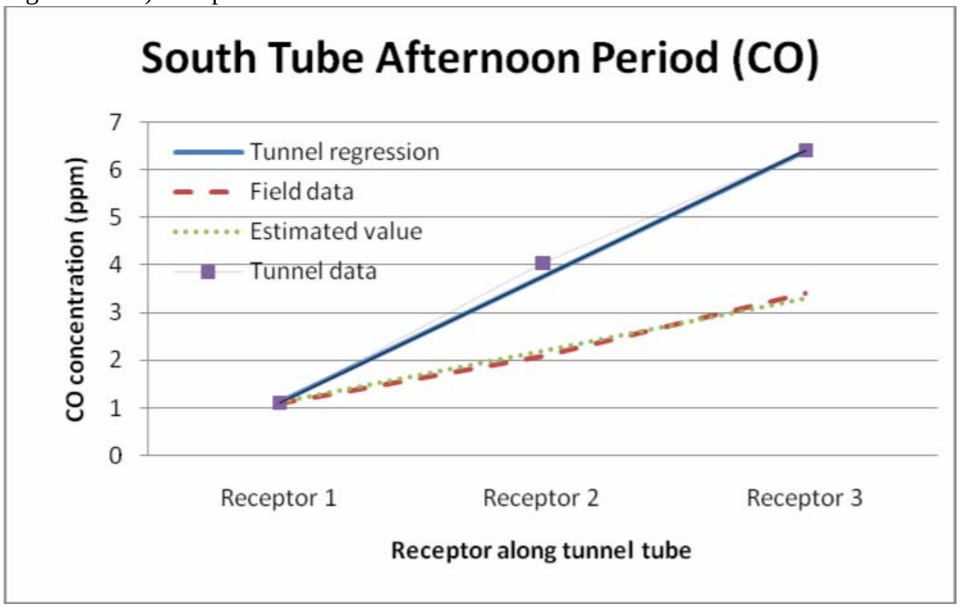
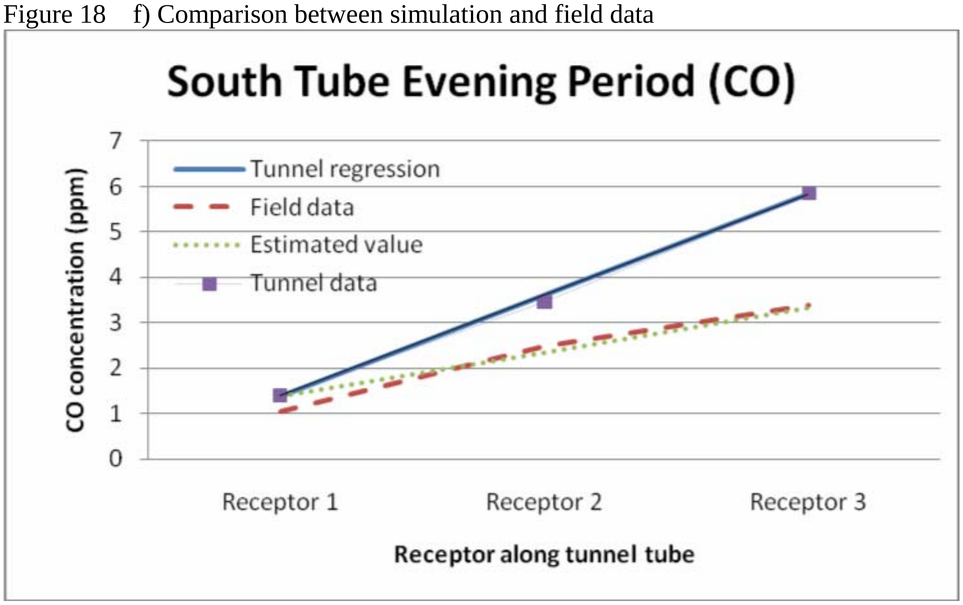


Figure 18 f) Comparison between simulation and field data



Six cases were used for testing the effectiveness of the method. The plots showed that the simulation is very close to the field measurement with no more than a 9% difference. In all six cases, the simulation underestimated the last point. The underestimations ranged from 1.35% to 5.83%.

Summary

The slope relation profiles showed a good fit with the fieldwork results. They provided reliable estimates of the continuous breathing zone pollutant concentration profiles. The hypothesis that the angle between two regression lines may be strongly influenced by the number of vehicles per hour was supported by the experimental data.

Although the assessment methodology for CO and NO_2 throughout this study had certain technical and analytical limitations, it was sensitive to an appropriate level in a context where resources were limited and no previously model existed. Improvements to this method may allow for its application in other tunnels. No doubt, this method can help with converting the collection of air-quality monitoring data from a profile that has discrete data points at a few fixed-monitoring points in a tunnel to a continuous breathing zone pollutant profile. The full use of continuous monitoring data can help to estimate vehicle emission factors and their subsequent changes, and reduce sampling costs.

5.5 *Methodology in estimating local emission factors*

In our study, the car floating and chasing techniques were used. A private car equipped with a portable gas analyser and speed detectors was used to collect a set of continuous CO, NO_2 and speed data. Concentrations of gas pollutants were measured and recorded by portable gas analysers.

As mentioned above, an SMBM has assumed measured pollutants without deposition, decomposition and reaction between exhaust species over a short measuring period. In reference to Bidewell et al. (1972) and McMahon et al. (1979), the deposition velocities of CO are equal to zero and approximately 1.9 cm/s for NO_2. Since CO and NO_2 are very stable in tunnel measurement, they were selected for this study.

5.5.1 Effect of vehicle speed

Many studies have shown a strong correlation between gaseous emission rates and vehicle speed. Sigsby et al. (1987) undertook a test of 46 vehicles' driving cycles; it was found that NOx increased steeply with decreases in speed. Kean et al. (2003) studied the emissions from on-road vehicles, and they suggest that vehicle speed is an important parameter for capturing emissions. Pierson et al (1990) performed a tunnel study in the Van Nuys Tunnel; they aimed to study the difference between high speed and low speed emission rates. They found that the CO emission rate had a 48% reduction when the speed increased from

9 km/h to 26 km/h. In contrast, the NOx emission rate recorded a 26% increase when speed increased from 9 km/h to 26 km/h. The result was confirmed by Singh and Huber (2001) by using the microscale emission factor model (MicroFacCO). They recorded a similar result with a 42% increase in CO emission rate when speed increased from 20 km/h to 60 km/h. Joumard et al. (2003) developed driving cycles for light duty goods vehicles, and found that the emission rate of CO decreased when speed increased. There was a 52% reduction on the CO emission rate when vehicle speed increased from 20 km/h to 100 km/h. Furthermore, they recorded a 22% decrease on the NOx emission rate when vehicle speed changed from 20 km/h to 60 km/h. However, a 14% increase in the NOx emission rate was recorded when speed changed from 60 km/h to 100km/h. Both numerical results showed that there was a strong correlation between vehicle speed and pollutant emission.

In the analyses of the tunnel experiments, the measured vehicle speed was used as an input to models such as EMFAC and MOBILE. However, Rogak et al. (1998) found that “effective vehicle speed” could not be used to simulate the tunnel conditions as an input to MOBILE because the driving cycles in MOBILE changed as the average speed changed.

Vehicle speed has not been taken into account in the SMBM. In order to improve the numerical model of calculating emission factors, Chan et al. (1996)

proposed a simple model to predict the CO concentration in one of the busiest vehicle tunnels of Hong Kong. The study was based on the finding of Chang and Rudy (1990), which stated that the vehicle emission and the vehicle speed were the major factors to determine pollutant concentrations in vehicular tunnels. Chan et al. model assumed that the ventilation rate was fixed at a specific time; this was a common operation practice in most of Hong Kong's vehicular tunnels. The proposed model postulated the CO concentration as a function of different vehicle class, the traffic volume of different vehicle classes, vehicle speed, some constant coefficients corresponding to the vehicle classes and a statistical constant. The morning and afternoon survey data were used to determine the constant coefficients and statistical constants by a linear regression method.

Equation 22: $$C_{CO} = \sum a_i n_i + \sum \frac{b_i}{n_i} + \frac{1}{U_{veh}} \sum c_i n_i + B$$

The second term ($\sum \frac{b_i}{n_i}$) describes the impact of the piston effect on CO concentration. The increase in traffic volume leads to the increase of piston effect and hence the reduction in CO concentration. The third term ($\frac{1}{U_{veh}} \sum c_i n_i$) indicates a reduction in CO emission with increasing vehicle speed. From the examination results, Chan reckoned that the model was satisfactory in predicting the CO pollution in the Cross Harbour Tunnel.

Chan et al. (2004) further suggested modelling pollutant emission factors in terms of a polynomial of vehicle speed. The effect of driving behaviour on the average emission factors of CO, HC and NO for petrol vehicles as a function of instantaneous speed profiles in Hong Kong were studied. The equation of emission factor (g/vehicle.km) for a petrol vehicle in the year 2001 is shown as in Equation 23.

Equation 23: $$EF_{CO} = -0.5476 + 0.0201V + \frac{126.416}{V^{1.5}} - \frac{36.9838(\ln V)}{V^2} - \frac{111.4223}{V^2}$$

Where V represents the vehicle speed in km/h, and EF_{CO} represents the emission factor of CO (g/vehicle.km).

5.5.2 Development of a speed modified SMBM

In the previous section, the importance of adding the vehicle speed and piston effect in the emission factor estimation model was shown. In order to obtain a better estimation for SMBM, we suggest adding the vehicle speed variable to the model. The correlation between the difference of pollutant concentration and $\frac{S_{out}}{S_{in}}$ is studied. It is found that the value of correlation for CO is 0.722 and 0.659 for NO. Furthermore, a linear trend is simply shown by an x-y plot.

Figure 19 x-y plot between speed ratio and ΔCO

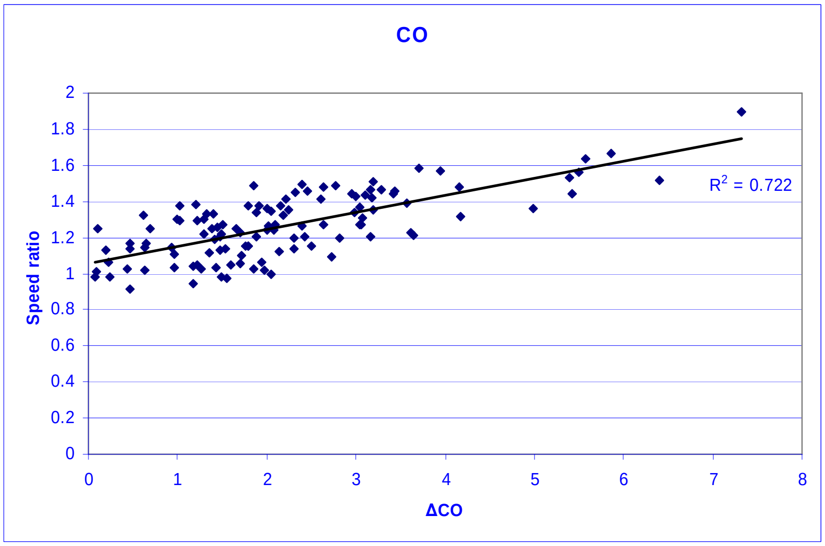
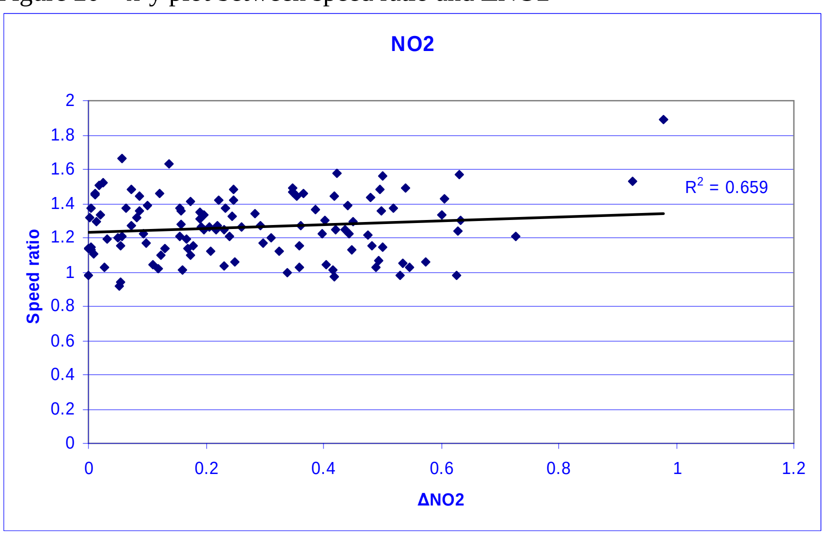
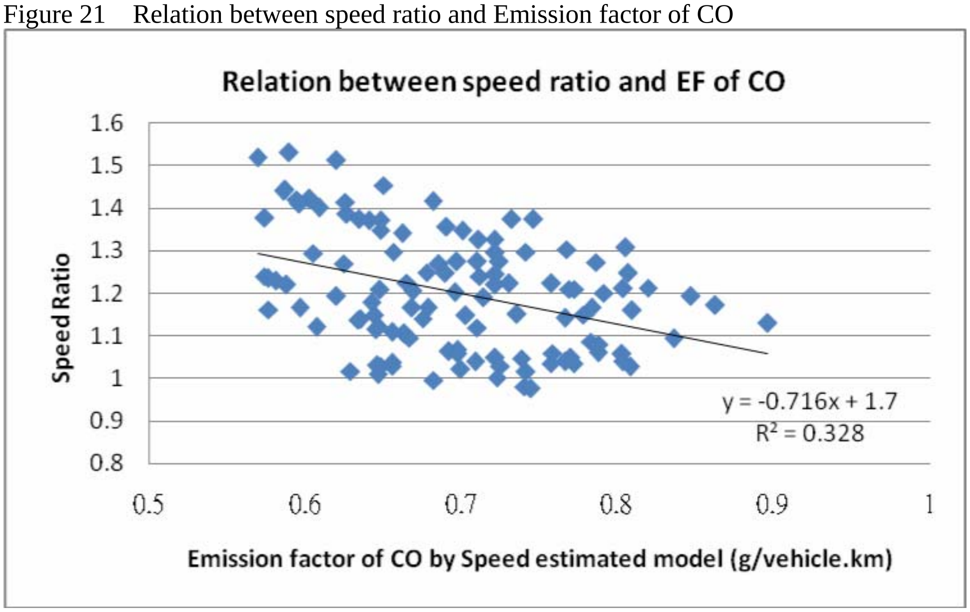


Figure 20 x-y plot between speed ratio and ΔNO2



The LRT file sampling data were then applied to Equation 23, and the emission factor of CO was calculated. The relationship between the speed ratio and the emission factor of CO that was obtained by Equation 23 is shown in Figure 21. The results showed that although the R-square is only 0.328; a linear trend was obviously obtained.

Figure 21 Relation between speed ratio and Emission factor of CO



As there is a strong correlation between the speed ratio and pollutant concentration, we suggested modifying the SMBM by multiplying the speed ratio. After the modification, the speed modified SMBM is expressed as in Equation 24.

Equation 24: $$EF = \frac{(C_{out} - C_{in})UAt}{NL} * \frac{S_{out}}{S_{in}}$$

where

C_{out}	=	Concentration pollutant leaving the exit, g/m^3
C_{in}	=	Concentration pollutant entering the entrance, g/m^3
U	=	Mean air flow velocity, m/min
A	=	Tunnel cross-sectional area, m^2
t	=	Sampling time, min
N	=	Total traffic count during time t
L	=	Tunnel length, m
S_{out}	=	Vehicle speed when exiting tunnel, km/h
S_{in}	=	Vehicle speed when entering tunnel, km/h

5.6 *SMBM Results*

As described above, the traffic emission factor can be estimated by SMBM according to the measurements of traffic flow. In order to obtain a better estimation, it is reasonable to include the traffic speed in the calculations. The sampling result was applied to Equation 24 for estimating CO and NO_2 emission factors. Numerical results are shown in Table 12.

Table 12 Emission factor of the LRT study by SMBM

	SMBM (CO) (g/vehicle.km)	Speed Modified SMBM (CO) (g/vehicle.km)	SMBM (NO_2) (g/vehicle.km)	Speed Modified SMBM (NO_2) (g/vehicle.km)
North Tube	0.6805	0.9958	0.0897	0.1105
South Tube	0.6175	0.8717	0.0767	0.0923

It is revealed in Table 12 that the estimation of the speed modified SMBM always has a higher value on prediction than the original one. The numerical results showed that the emission factor of CO in the North Tube was 0.6805 g/vehicle.km for the original SMBM and 0.9958 g/vehicle.km for the modified SMBM, representing a 47% difference. The result was similar in the South Tube, where the percentage difference is 43%.

In order to find out if there is any significant improvement for the speed modified SMBM, the sampling result was applied to Equation 4 and 5 for modelling the piston effect and estimating the emission factor. By reference to Transport planning and design manual (TPDM), the base and height of different types of vehicles are shown in Table 13. With these input, the estimated emission factors by the piston effect model are shown in Table 14.

Table 13 Input parameters for the piston effect model

	Vehicle base area (m^2)	Vehicle height (m)
Private cars	14.49	2
Taxi	14.49	2
Invalid Carriage	14.49	2
Light Bus	15.87	3
Bus		
Single Deck	30.00	3.5
Double Deck	30.00	4.6
Articulated	37.50	3.5
Light Goods Vehicle	25.00	3.5
Medium Goods Vehicle	27.50	4.6
Heavy Goods Vehicle		
Rigid	27.50	4.6
Articulated	40.00	4.6
Special Purpose Vehicle	30.00	4.6
Trailer	33.75	4.6
Pedestrian Controlled Vehicle	6.88	-

Table 14 Emission factor of the LRT for the piston effect model

	With piston effect (CO) (g/vehicle.km)	With piston effect (NO_2) (g/vehicle.km)
North Tube	1.5048	0.1802
South Tube	1.3682	0.1558

The results show that the estimation with piston effect has a higher prediction than the original SMBM and modified SMBM. The estimated emission factor of CO in the North Tube was 1.5048 g/vehicle.km with Chen's model and 0.9958 g/vehicle.km with the modified SMBM, representing a 33% difference. This result is similar to the observation in the South Tube, where the percentage difference was 34%. A chi-square test was applied for testing significant difference between the speed modified SMBM and the piston effect model. The hypothesis of the chi-square test is as follows:

H_0: The new SMBM = Piston effect model

H_1: The new SMBM $\neq$ Piston effect model

$$\chi^2 = \sum \frac{(Xp - Xn)^2}{Xn}$$

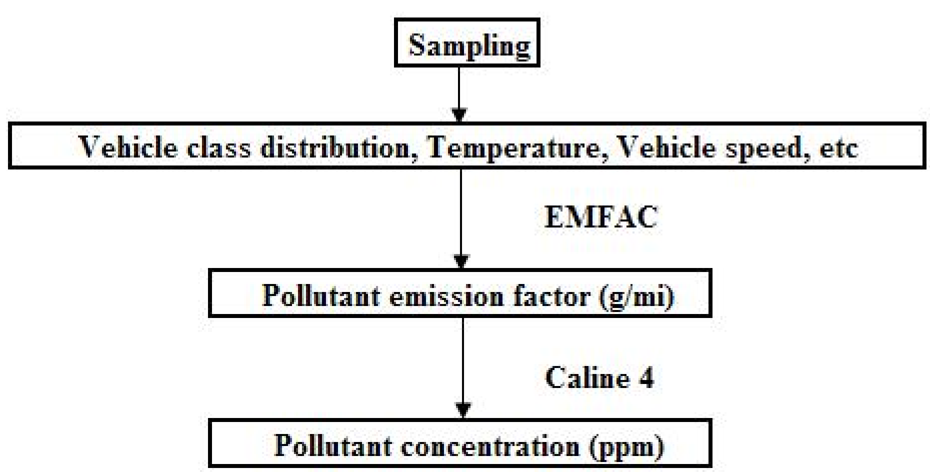
where Xp is the estimated value of the new SMBM, Xn is the estimated value of the piston effect model.

In our case, 116 samples were compared, by referring to a chi-square table with 95% significant level, the test statistics equaled 124, and led us to the result that we could not reject H_0 for both CO and NO_2. The chi-square test showed that there is no significant difference between the speed modified SMBM and a piston effect model with 95% significant level.

5.7 *Comparison of the SMBM model with other models*

Besides numerical models, computer modelling programmes, such as the Caline 4 and EMFAC are also commonly used. For estimating the pollutant emission concentration, Caline 4 and EMFAC need to be used together. Benson (1989) and Coe et al. (1998) suggested that emission factors applied to Caline 4 should be generated by the EMFAC model.

Figure 22 Flowchart illustrating the estimation process



Regardless of where a receptor is, the emission rate of the pollutant acts as the most important factor affecting CO emission concentration. The final output from Caline 4 is directly proportional to the emission factors entered into the programme.

EMFAC

The California Air Resource Board has released EMFAC 2002 as its latest version of the California mobile source emission inventory model. EMFAC is the most commonly used emissions modelling tool for the quantification of pollutants from on-road sources. It is a FORTRAN computer model which is capable of estimating emission inventories from the years 1970 to 2040. The EMFAC 2002 database is mainly based on a Californian vehicle emission inventory. EMFAC calculates the emission rates of HC, CO, NOx, PM, lead, SO_2, and CO_2 for each vehicle class within each year. Individual estimations can be obtained as a function of ambient temperature, relative humidity, altitude and speed.

The emission factors calculated by EMFAC 2002 depends on the input parameters (e.g., vehicle speed, ambient temperature, relative humidity, etc.). Since the parameters make significant impacts on the EMFAC results, a systematic study has been conducted to compare the relative impact of each individual parameter on the emission result.

The results of numerical modelling are compared with computer modelling. In our study, EMFAC HK was used for estimating the emission factors. EMFAC HK is operated in the same manner as the EMFAC 2002. The modelling methodology follows the California Air Resources Board's EMFAC model but with modifications due to local factors and the substantial reduction of the 'smoky vehicle' problem in recent years. In addition, EMFAC HK has taken into consideration vehicle emission standards for newly-registered vehicles and Euro I franchised buses, the introduction of ultra-low sulphur diesel, and the LPG vehicle programme for taxis and light buses. Based on the traffic volume, ambient temperature and relative humidity, which were obtained at the beginning of each sampling trip, EMFAC HK was then used for determining the hourly emission factors. The proportion of vehicle classes changes from time to time, therefore the program constant on the exhaust tech fractions screen needed to be edited for every simulation. The results of EMFAC HK show that the average of the overall emission factor for CO was 2.08 g/vehicle.km and 0.34 g/vehicle.km for NO_2.

The emission factors of CO and NO_2 plotted together with the 95% confident interval are shown in Figure 23 and Figure 24. Furthermore, a statistical t-test was preformed on the CO emission estimation. The result was that there is no significant difference with the mean between the new SMBM and the Piston effect model estimation.

Figure 23 Emission factor of CO and 95% CI

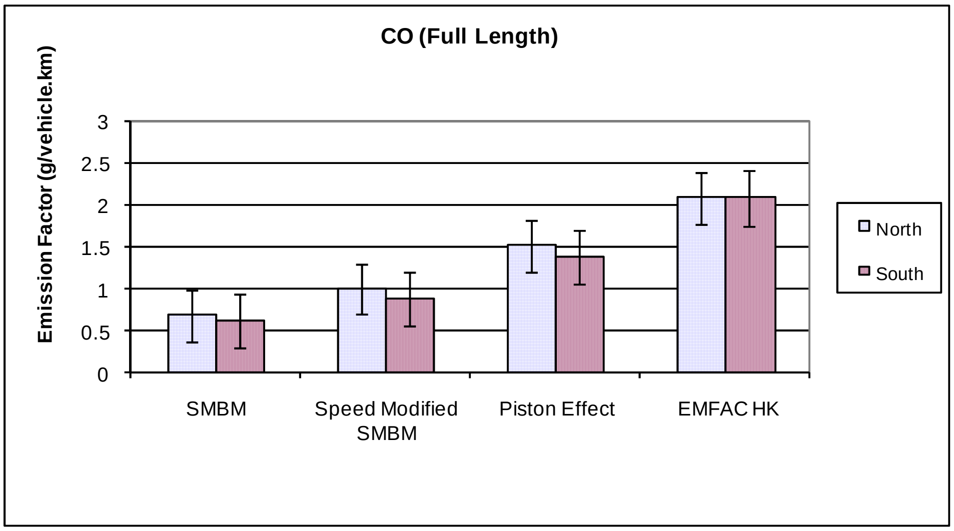
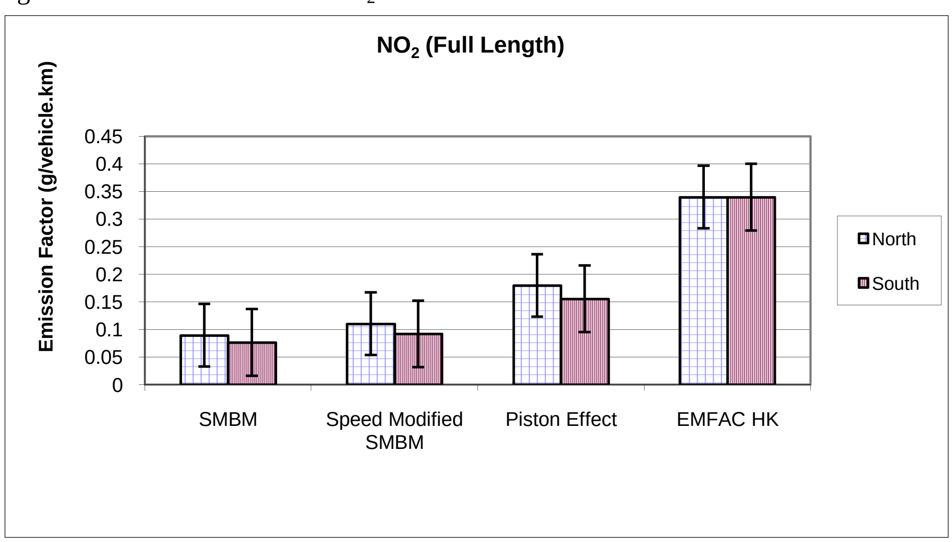


Figure 24 Emission factor of NO_2 and 95% CI



Furthermore we separated the data into two groups, tunnel entrance half-length and tunnel exit half-length, respectively. The separated data were fed to the SMBM, speed modified SMBM, and piston effect model (Figure 25 - Figure 28). The results show that the pattern is very similar to the full tunnel length estimation, but slightly different in the percentage difference. In the tunnel entry half-length, the estimated emission factor of CO with the speed modified SMBM estimation is 0.732 g/vehicle.km for the North Tube. This result is approximately 99% less than the result from the piston effect model. The result is similar in the South Tube, where the percentage difference is 102%. This is mainly due to the fact that vehicle speed in the entrance half of the tunnel was relatively slow and thus the emission factors estimated by the speed modified SMBM are relatively small.

Figure 25 Emission factor of CO in the entrance half-length

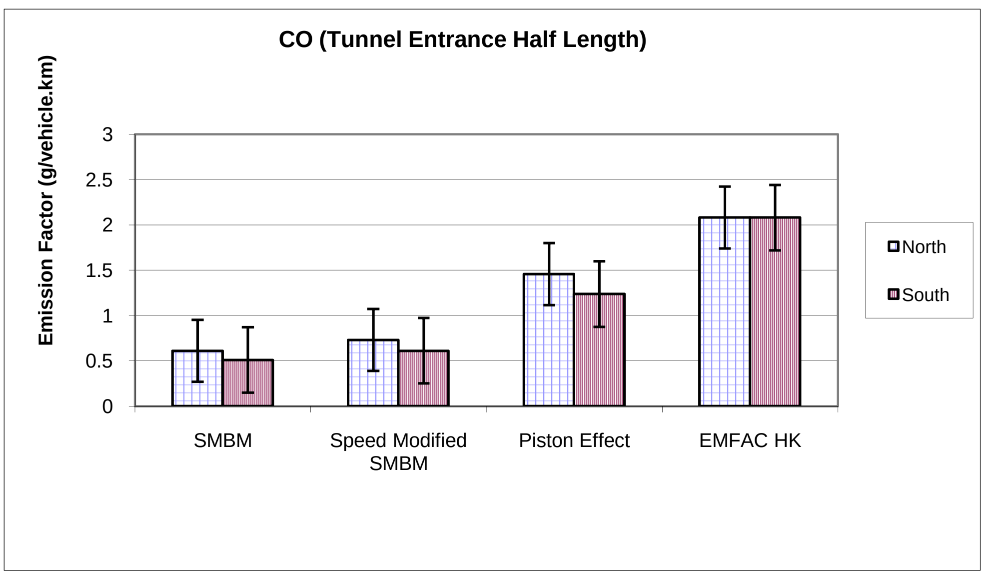


Figure 26 Emission factor of CO in the exit half-length

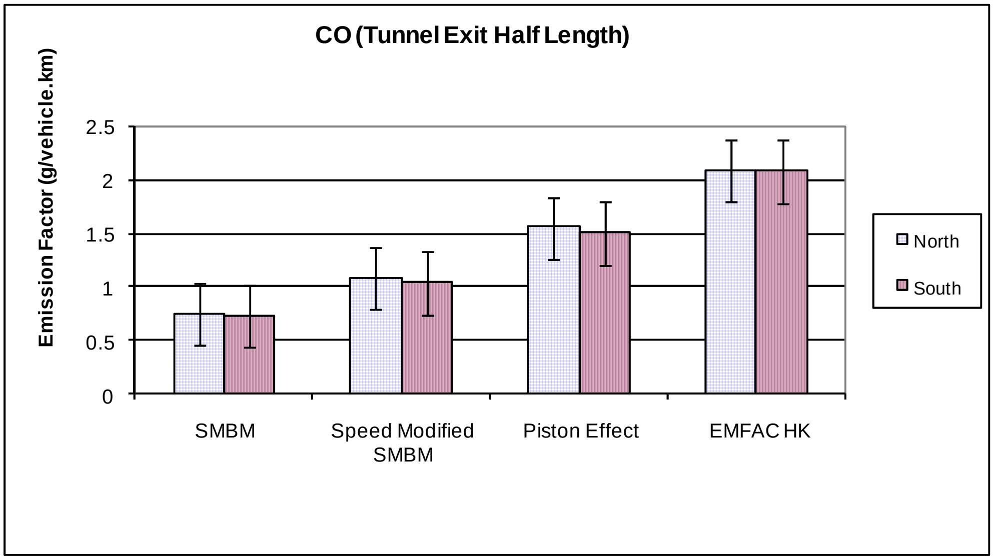


Figure 27 Emission factor of NO_2 in the entrance half-length

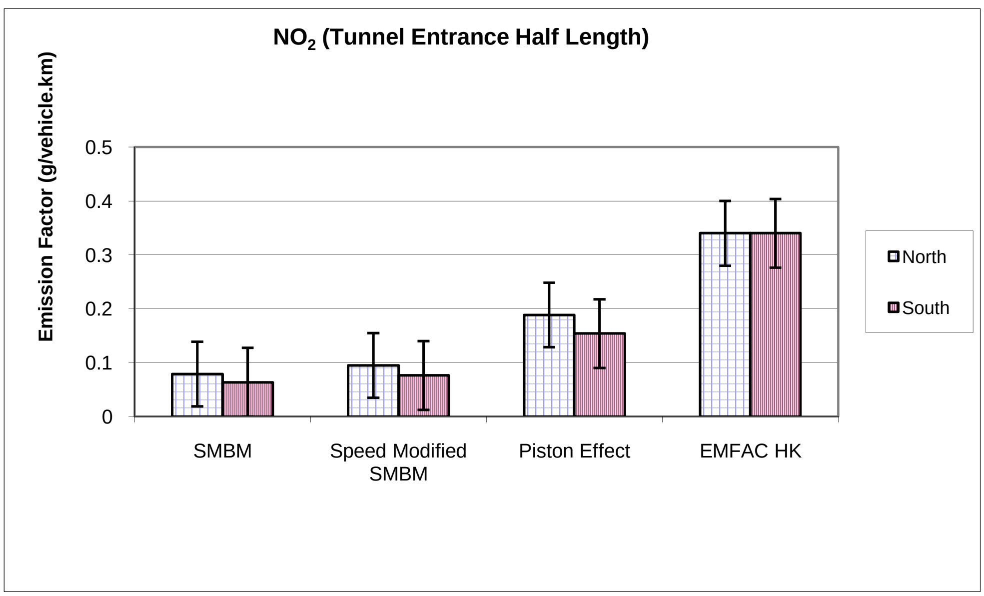
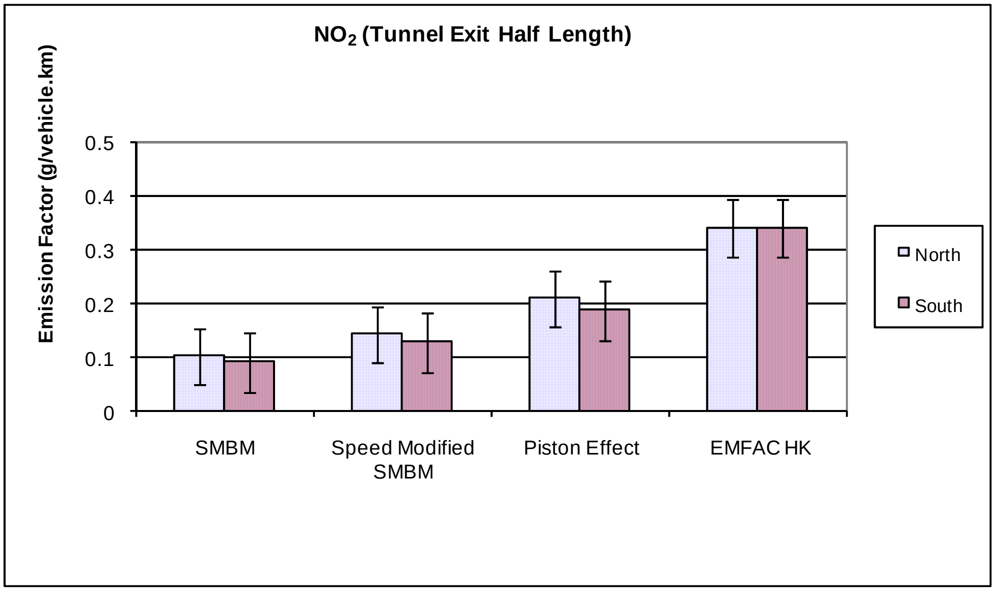


Figure 28 Emission factor of NO_2 in the exit half-length



Although the pattern of the exit half-length is very similar to the entrance half-length, the percentage differences between the models have been narrowed. The results show that the speed modified SMBM estimation is 1.073 g/vehicle.km for the North Tube. This is approximately 44% less than the one obtained in the piston effect model. The corresponding difference in the South Tube is 45%. A statistical t-test shows that there is no significant difference between the models on the exit half-length data set. One of the major reasons for the reduction in the percentage differences may be due to the changes in driving pattern. Different from the entrance first half, the vehicles tended to accelerate when they exited the tunnel. This led to a higher speed ratio, and thus a higher estimated emission factor. In brief, the speed modified SMBM is more sensitive to the variation of speed than the piston effect model.

6 Model Application in Monitoring Vehicle Emissions

We conducted a study to explore and validate the relationship between vehicle exhaust emissions and driving speeds in Hong Kong, in the fall of 2006. In previous chapters, a new SMBM was developed. In order to find out the significant value, the speed modified SMBM will be applied to our data, and the data provided by the tunnel management companies, in this chapter.

6.1 *Results of the study*

Speed modification was introduced to the speed modified SMBM in the last chapter, and the results show that it is more sensitive with the variation of speed than the other two models. In this chapter, the new SMBM is applied using the last six years of tunnel data. However, as the speeds of vehicles that entered and exited the tunnel were not available, estimations of those values were needed. Linear regression was applied with a speed-ratio ($\frac{S_{out}}{S_{in}}$), which was obtained by a car chasing measurement, and the hourly traffic volume. By using SPSS, the R-square of the equation is 0.812 and the model is listed below as Equation 25.

Equation 25: $$\frac{S_{out}}{S_{in}} = 1.161 + 0.0000521 * hourly \quad traffic \quad volume$$

Lion Rock Tunnel study

The speed ratio, which was needed for estimating the speed modified SMBM, calculated by Equation 25, and the numerical results are shown in Table15. Figure 29 depicts the changes of CO and NO_2 emission factors by years.

Table 15 Numerical emission factor results of the speed modified SMBM for the LRT

CO	North Tube (g/vehicle.km)			South Tube (g/vehicle.km)		
Year	Class one	Class two	Class three	Class one	Class two	Class three
2001	1.239	0.667	1.100	0.667	1.100	0.850
2002	1.049	0.667	0.950	0.667	0.950	0.550
2003	1.049	0.648	0.650	0.648	0.650	0.750
2004	0.668	0.573	0.400	0.573	0.400	0.550
2005	0.764	0.573	0.400	0.573	0.400	0.500
2006	0.861	0.478	0.600	0.478	0.600	0.450
NO_2	North Tube (g/vehicle.km)			South Tube (g/vehicle.km)		
2001	0.124	0.700	0.440	0.076	0.220	0.670
2002	0.095	0.900	0.300	0.057	0.800	0.370
2003	0.095	0.750	0.350	0.065	0.700	0.500
2004	0.124	0.450	0.480	0.153	0.450	0.550
2005	0.086	0.550	0.200	0.153	0.500	0.400
2006	0.143	0.200	0.230	0.172	0.285	0.275

The CO emission factor which was obtained by the speed modified SMBM recorded a significant reduction from 2001 to 2006, in both tubes. Furthermore, the proportion dropped in the North Tube class one, class two and class three vehicles to 30%, 28%, and 45%, respectively. In the South Tube, similar behaviour was recorded as 28%, 45% and 47%, for class one, class two and class three vehicles, respectively. When compared with the 30% drop of CO concentration, which was recorded by the tunnel management company, the emission factor estimations give a full picture of the emission reduction. It shows that the class three vehicles had the best improvement in pollutant emission. This improvement mainly relates to the installment of the particulate removal devices in the heavy pre-Euro diesel vehicles.

The NO_2 concentration decreased by 27% and 21%, for the North and South Tubes, between 2001 and 2006. However, estimating the emission factor model shows that not all classes of vehicles reported a drop in pollutant concentration emissions. For class one vehicles, Figure 29 shows that there was a 15% and 126% increase in the NO_2 emission factor. For class two vehicles, a 71% reduction was recorded in the North Tube. However, due to a relatively low value of emission factors obtained in 2001 from the South Tube, a 30% increase was recorded for the period between 2001 and 2006. For class three vehicles, both tubes recorded a significant decrease: 47% and 59% for the North and South Tubes, respectively.

Figure 29 a) The change of the CO and NO_2 emission factors, by year

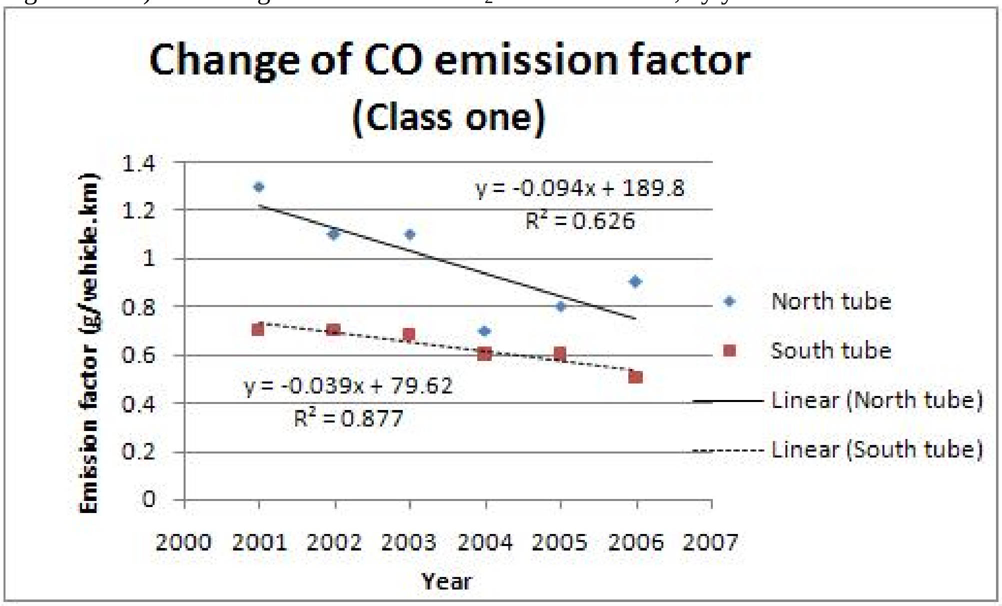


Figure 29 b) The change of the CO and NO_2 emission factors, by year

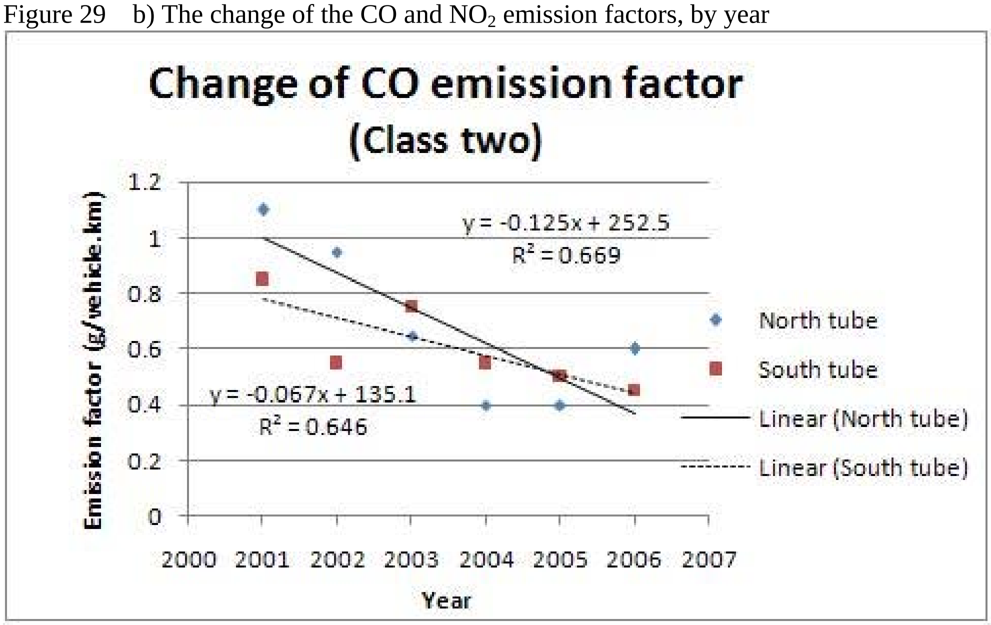


Figure 29 c) The change of the CO and NO_2 emission factors, by year

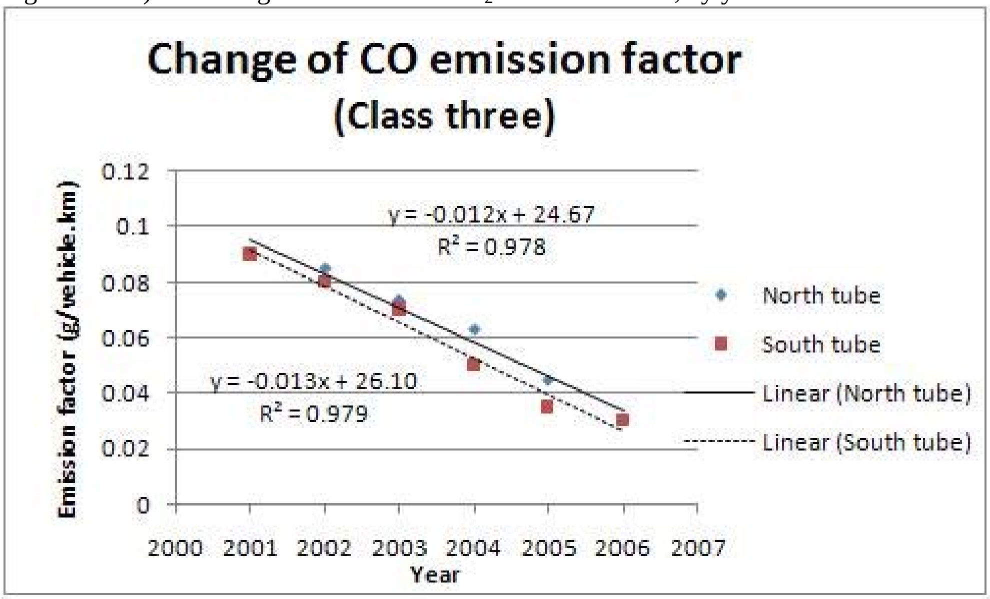


Figure 29 d) The change of the CO and NO_2 emission factors, by year

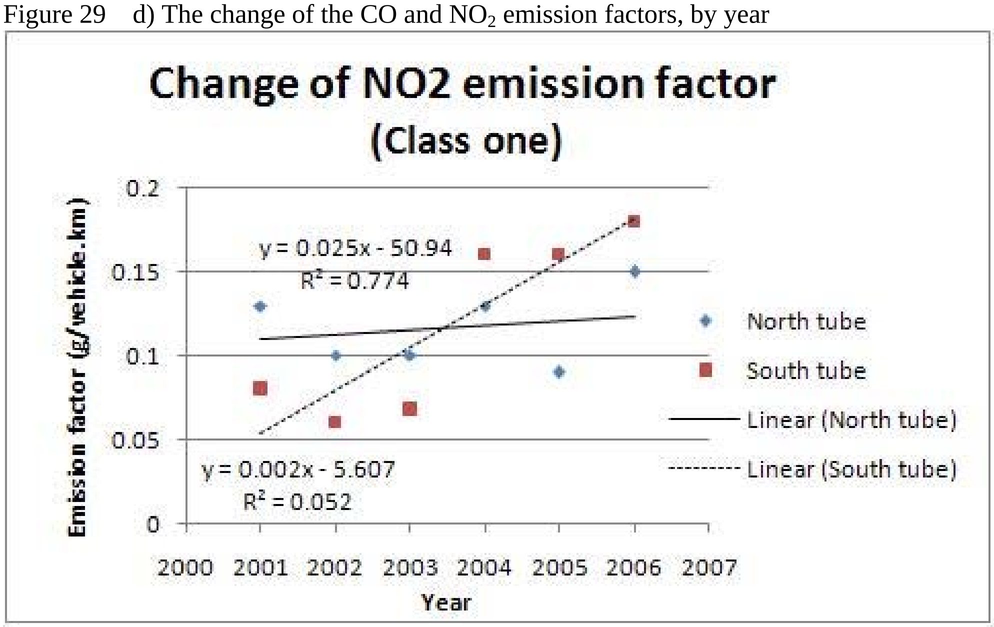


Figure 29 e) The change of the CO and NO_2 emission factors, by year

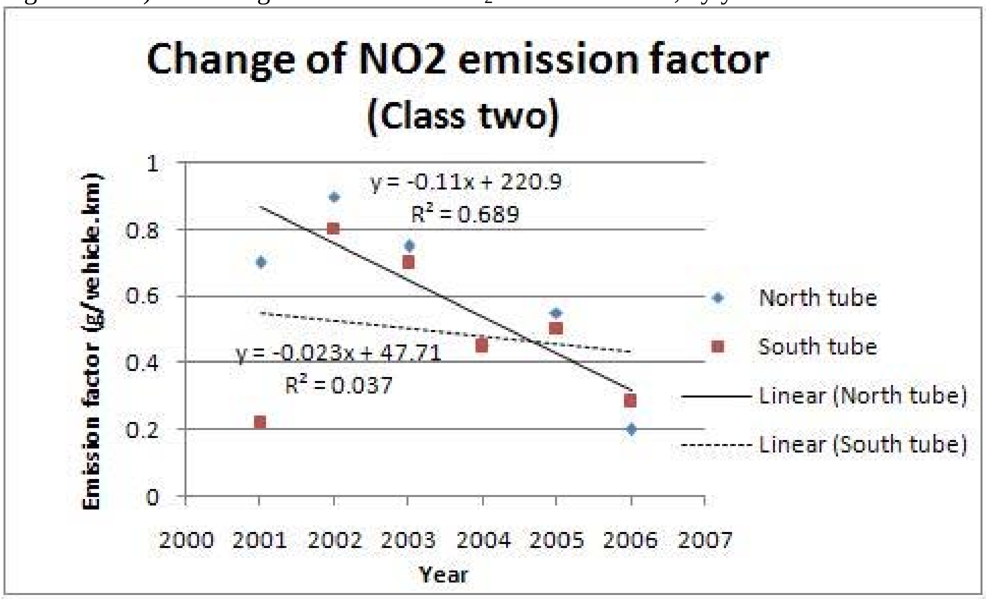
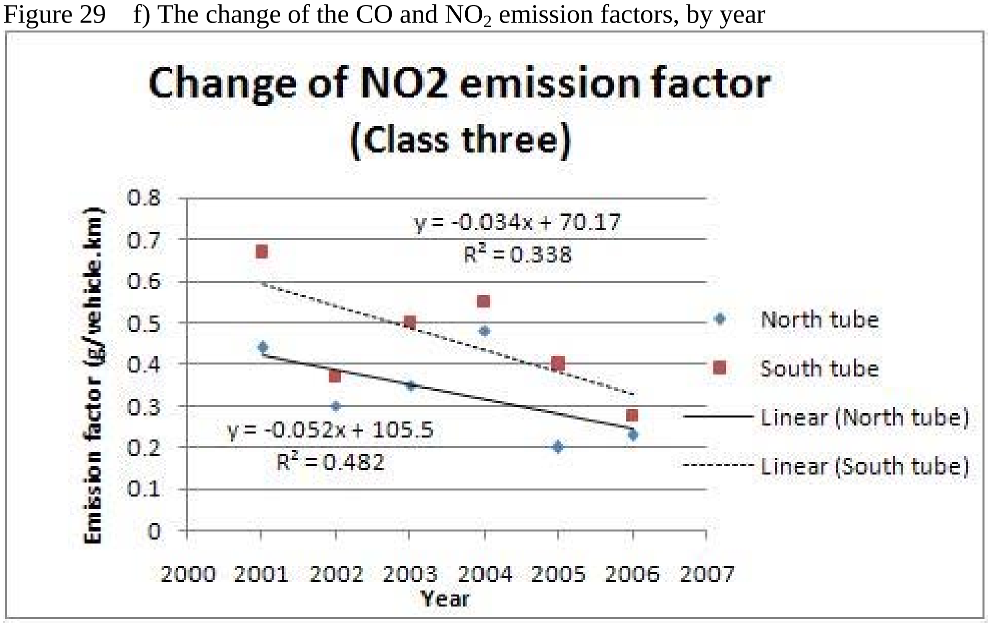


Figure 29 f) The change of the CO and NO_2 emission factors, by year



Aberdeen Tunnel Study

In the Aberdeen Tunnel, the pollutant concentration data together with the traffic volume were available in the first week of every quarter from January 2003 to October 2006. In order to show the applicability of the speed modified SMBM, the data obtained by the Aberdeen Tunnel Management Company was applied to estimate the emission factors. This time no on-road measurement was undertaken in the Aberdeen Tunnel before applying the speed modified SMBM; we used Equation 25 to obtain the speed-modified ratio and the numerical results are shown in Table 16.

Table 16 Numerical emission factor results of the speed modified SMBM for the Aberdeen Tunnel

CO	South Tube (g/vehicle.km)		
Year	Class one	Class two	Class three
2003	0.421	0.114	0.077
2004	0.385	0.103	0.056
2005	0.218	0.095	0.048
2006	0.215	0.073	0.038
NO_2	South Tube (g/vehicle.km)		
2003	0.054	0.079	0.144
2004	0.113	0.075	0.186
2005	0.116	0.036	0.139
2006	0.124	0.015	0.108

The CO emission factor obtained by the speed modified SMBM records a significant reduction from 2003 to 2006, in the Aberdeen Tunnel study. The proportions dropped in class one, class two and class three vehicles were 49%, 36%, and 50%, respectively. When compared with the 22% increase of CO concentration that was recorded by the tunnel management company, the emission factor estimations give a full picture of the emission reduction. Similar to the results of the LRT, it shows that the class three vehicles have the best improvement in pollutant emission.

According to tunnel management company data, the NO_2 concentration decreased by 12.5%, between 2003 and 2006. However, the emission factor model showed that not all classes of vehicles had reported a drop in pollutant concentration emissions. Similar to the LRT study, class one vehicles showed that there was a 129% increase in the NO_2 emission factor. For class two vehicles and class three vehicles, 81% and 25% reductions were recorded, respectively. The comparison between the LRT and Aberdeen Tunnel was studied, and the plots are shown in Figure 30.

Figure 30 a) Comparison between the Aberdeen Tunnel and the LRT

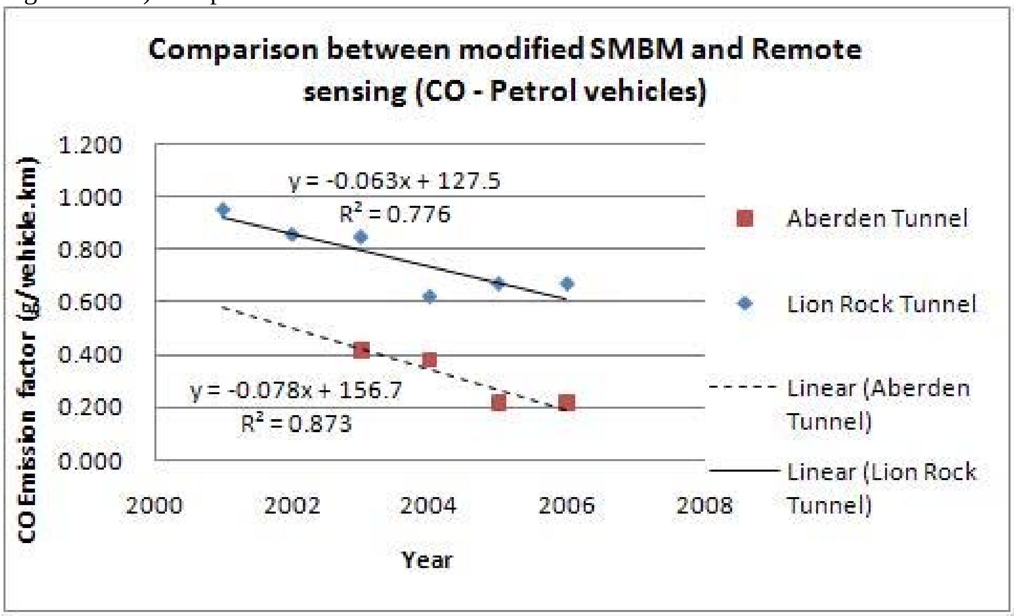


Figure 30 b) Comparison between the Aberdeen Tunnel and the LRT

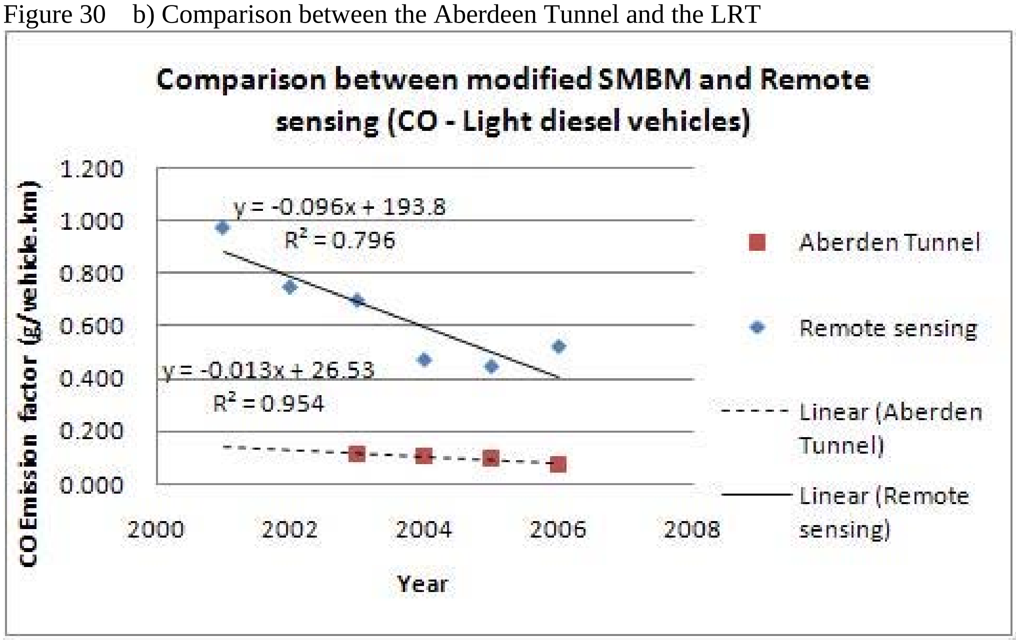


Figure 30 c) Comparison between the Aberdeen Tunnel and the LRT

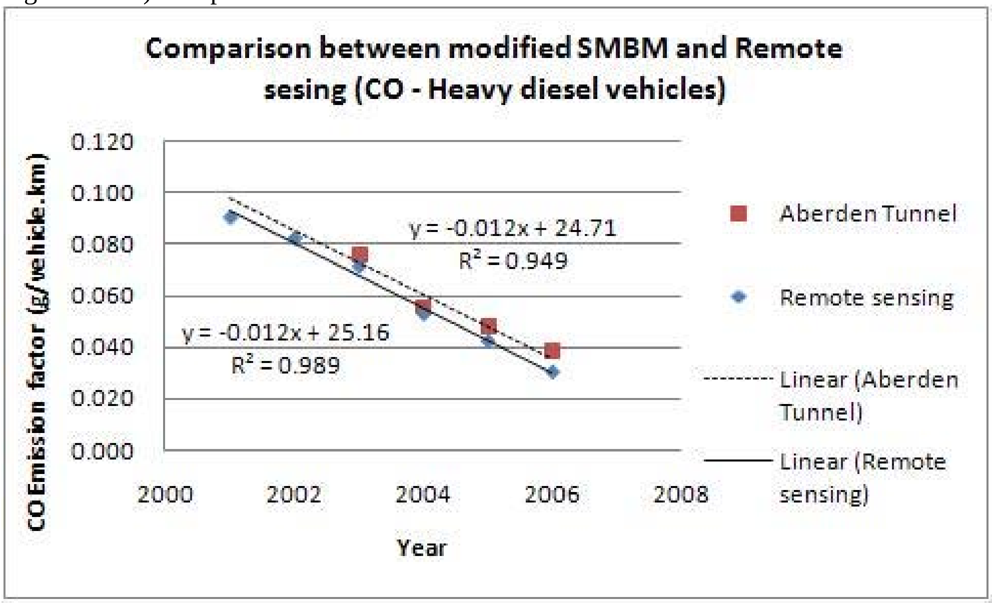


Figure 30 d) Comparison between the Aberdeen Tunnel and the LRT

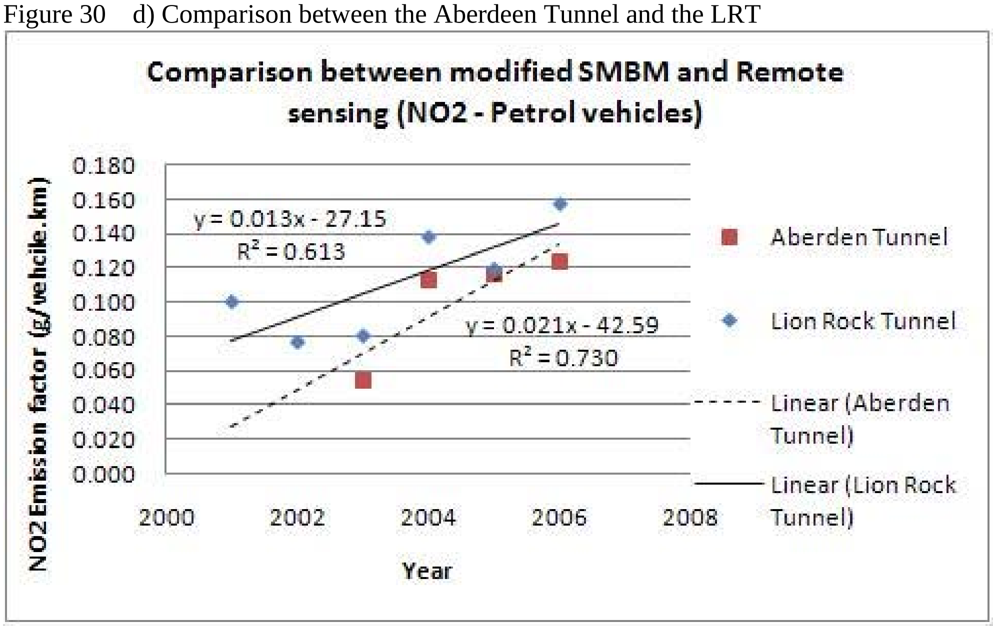


Figure 30 e) Comparison between the Aberdeen Tunnel and the LRT

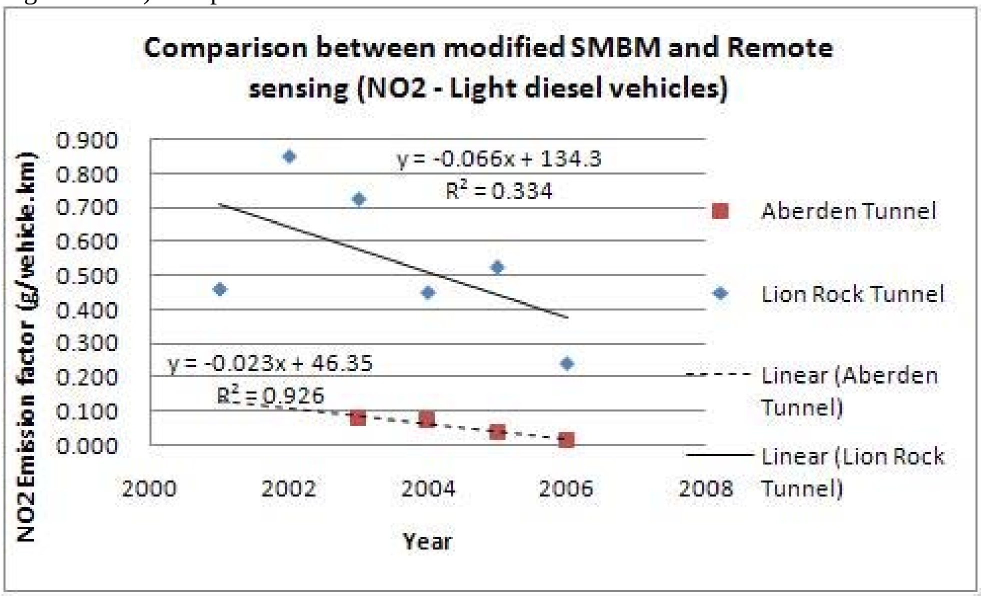


Figure 30 f) Comparison between the Aberdeen Tunnel and the LRT

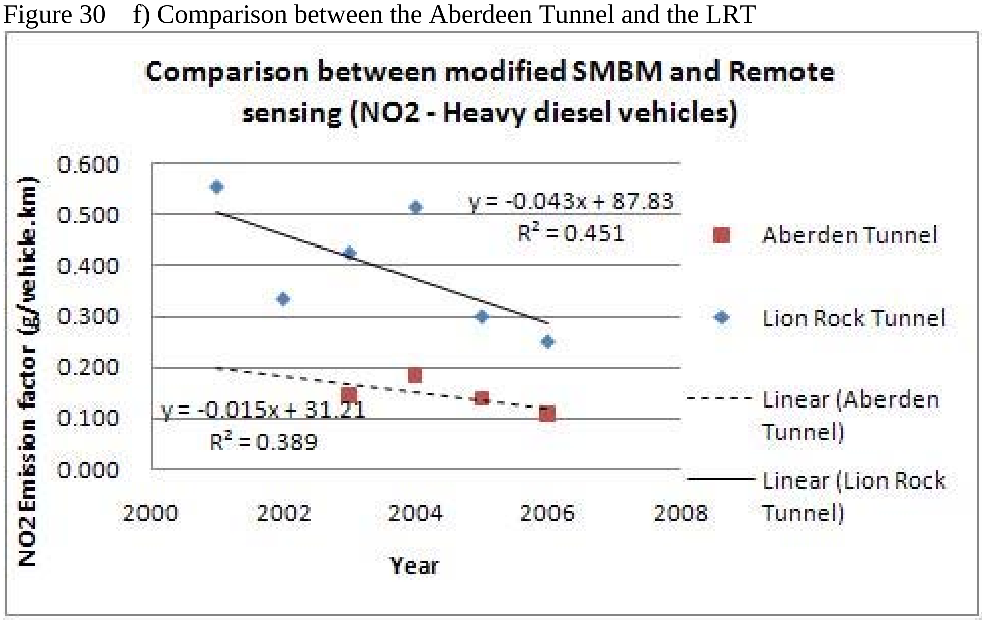


Figure 30 revealed that similar trends were recorded in both the LRT and Aberdeen Tunnel studies. Similar to the LRT, most of the vehicle classes record a decreasing trend except the NO_2 emission factor in petrol vehicles in the speed modified SMBM. Furthermore, in studying the slope of regression between the Lion Rock and Aberdeen Tunnels, it was found that the coefficient of slope is very similar.

6.2 *Comparison between the modified SMBM and remote sensing emission model*

Remote sensing is a powerful tool for measuring pollutant emissions as it allows a large number of vehicles to be examined. The emission data from the remote sensing sampling are expressed as concentration ratios of pollutants to CO_2. For calculating an emission factor, the fuel consumption depends on what model was usually used. In this section, the data obtained by The Hong Kong Polytechnic University (HKPOLYU) using a remote sensing sampling method were used to compare with the speed modified SMBM. A statistical test was used to test if there were any significant differences between the tunnel base speed modified SMBM and the fuel consumption model remote sensing method.

6.2.1 Methodology of estimating vehicle emission factors of remote sensing data

An on-road vehicle exhaust emissions survey using remote sensing technology offers a quick and effective method of monitoring emissions from in-use petrol vehicles under normal driving operation. The application of a remote sensing vehicle exhaust emissions testing system has been used in many countries. Chan et al. (2004, 2005) used the on-road remote sensing technology for measuring nine sites in Hong Kong during late 2001. Based on those emission data and using our testing system, the emission factors of CO, HC and NO_2 from our study were calculated under real-world vehicle driving conditions in respect to the instantaneous vehicle speed and acceleration/deceleration profiles.

The conversion equations in fuel-based emission factors, E_i (Holmen and Niemeier, 1998; Singer and Harley, 2000; Pokharel et al., 2002; Chan et al., 2004, 2005; Schifter et al., 2003, 2005), can be expressed as in Equation 26.

Equation 26: The fuel consumption dependence model

Petrol:	Diesel:
$E_{CO} = 1200 * \frac{\frac{CO}{CO_2}}{1 + \frac{CO}{CO_2} + \frac{3}{0.493} * \frac{HC}{CO_2}}$	$E_{CO} = 28 * \frac{\frac{CO}{CO_2}}{1 + \frac{CO}{CO_2} + \frac{3}{0.493} * \frac{HC}{CO_2}} * \frac{D_{fuel}}{M_{fuel}}$
$E_{NO} = 1293 * \frac{\frac{NO}{CO_2}}{1 + \frac{CO}{CO_2} + \frac{3}{0.493} * \frac{HC}{CO_2}}$	$E_{NO} = 30 * \frac{\frac{NO}{CO_2}}{1 + \frac{CO}{CO_2} + \frac{3}{0.493} * \frac{HC}{CO_2}} * \frac{D_{fuel}}{M_{fuel}}$

where

D_{fuel} = Fuel density (kg/l)
M_{fuel} = Molar Mass of fuel (kg/mol)

For diesel fuel, the molar mass of fuel is 0.01385 kg/mol, and the fuel density is 0.85kg/l (API, 2001).

Chan et al. suggested that fuel consumption depends on instantaneous vehicle speed in urban traffic conditions. Tong et al. (2000) studied the fuel consumption of on-road diesel vehicles in Hong Kong, and a curve-fitted formula for the fuel consumption of diesel vehicles in respect to instantaneous vehicle speed was developed. The relationship between instantaneous vehicle speed and fuel consumption is shown as the following:

$$G_j = 319.95 * V^{-1.1131}$$

For petrol vehicles, Jost et al. (1994) state that the relationship between petrol vehicles' fuel consumption in respect to vehicle speed can be shown as follows:

$$G_j = 85.04 * V^{-0.674}$$

The individual emission factor, EFi (g/km), can be calculated in terms of the following equation:

$$EF_i(g/km) = \frac{E_i G_j}{100}$$

A summary of the literature data for estimating Hong Kong emission factors is shown in Table 17.

Table 17 Emission factors of pollutant emissions of previous Hong Kong studies

	CO Emission factor (g/vehicle.km)	NO Emission factor (g/vehicle.km)
Diesel vehicles (Chan and Ning, 2005)		
Vehicle speed = 10 km/hr	1.40	1.36
Vehicle speed = 30 km/hr	0.43	0.44
Vehicle speed = 50 km/hr	0.25	0.28
Petrol vehicles (Chan et al., 2004)		
Vehicle speed = 10 km/hr	4.76	0.15
Vehicle speed = 30 km/hr	2.58	0.06
Vehicle speed = 50 km/hr	2.30	0.05

In Chan’s study, 9057 diesel vehicles’ emission data and 10781 petrol vehicles’ emission data were measured in nine sites in Hong Kong. The comparison between the average emission factors of petrol and diesel vehicles showed that the petrol vehicles emitted CO pollutant 3.4, 6.0 and 9.2 times higher than the measured diesel vehicles for the vehicle speeds of 10 km/h, 30 km/h and 50 km/h, respectively. However, diesel vehicles emitted NO pollutants 9.1, 7.3 and 5.6 times higher than petrol vehicles for vehicle speeds of 10 km/h, 30 km/h and 50 km/h, respectively.

6.2.2 Data application of remote sensing data

Lion Rock Tunnel

Regarding the fuel balance model for calculating pollutant emission factors, the same methodology was applied to the remote sensing data obtained by HKPOLYU. A similar remote sensing sampling method was obtained at the entrance of the LRT by HKPOLYU in the years 2001, 2003, 2004 and 2006, respectively. A typical on-road, remote-sensing, vehicle exhaust emissions testing system was setup at the entrance of the LRT site in Hong Kong as shown in Figure 31 and Figure 32. The concentrations of HC, CO, CO_2 and NO_2 were measured by a remote-sensing, vehicle exhaust emissions testing system (ESP AccuScan RSD 3000). The total sample sizes for all four years' samplings are listed in Table 18.

Figure 31 Sampling location of remote sensing in the LRT

Lion Rock Tunnel (Tunnel Entrance towards Kowloon)

Gradient = 3.1°

Figure 32 Actual setting of remote sensing in the the LRT

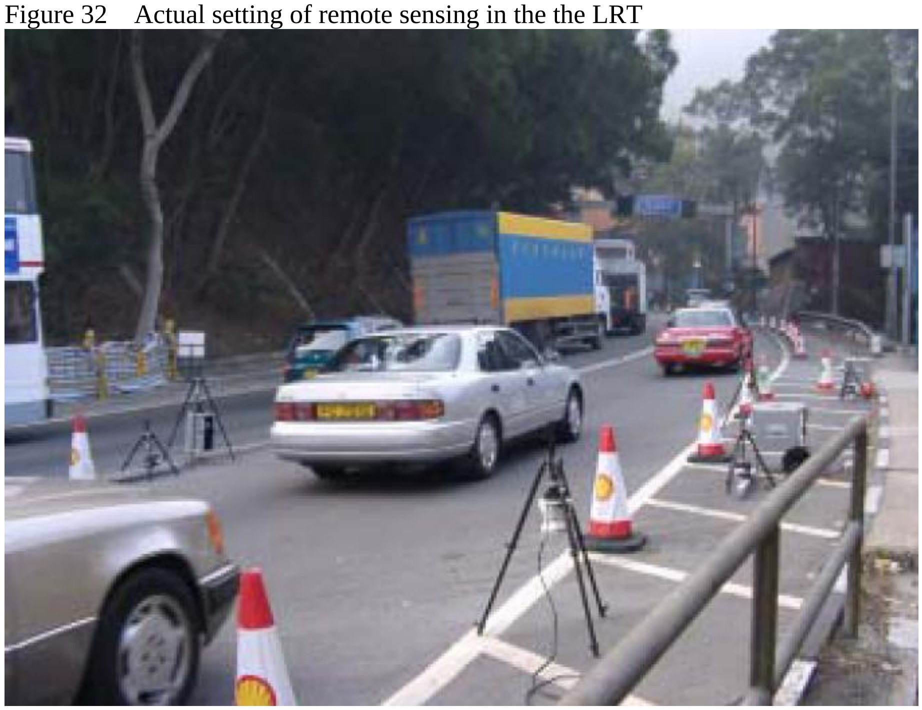


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Table 18 Sample size of remote sensing data in the LRT

	2001	2003	2004	2006
Petrol vehicles	3646	6270	7953	4008
Light Diesel vehicles	1559	975	2004	1419
Heavy Diesel vehicles	66	165	138	35

6.2.3 Results and discussion

Data Manipulation

As presented in chapter 3, the traffic volume data of the LRT and Aberdeen Tunnel was recorded and divided into three classes. Taxis mainly use LPG as fuel and private cars use petrol. To compare the modified SMBM and remote sensing emission factor model, the traffic volume of LPG vehicles was filtered out before calculating the emission factors of petrol vehicles. The data filtering method is described below. In the annual traffic census (TD, HKSAR, 2001; 2003; 2004; 2006), taxi use in both tunnels was directly deleted from the hourly traffic volume of class one vehicles. The results were rounded down if the traffic volume was not an integer after calculation.

Results of the remote sensing emission model in the LRT

Emission factors for petrol vehicles, light diesel vehicles and heavy diesels obtained by Equation 26 appear in Table 19. This reveals that when using the conversion equations in mass emission concentrations the standard deviation is very large. Emission factors recorded a significant drop from 2001 to 2006. The emission factor of CO recorded around a 30%, 88% and 90% drop for petrol vehicles, light diesels and heavy diesels, respectively. Similar behaviour was recorded in the NO_2 emission factor; the drop is around 43%, 74% and 80% for petrol vehicles, light diesels and heavy diesels, respectively.

For comparison, the emission factors of the remote sensing model for CO and NO_2 were plotted together with a 95% confident interval; it is shown in Figure 33 and Figure 34. Figure 33 shows that there is no significant difference between the fuels based emission study by remote sensing and SMBM, in all vehicle classes.

Table 19 Results of fuel based emission factors in the LRT

	Average emission factor (g.vehicle/km)			Standard deviation		
CO (g/vehicle.km)	Petrol	Light Diesel	Heavy Diesel	Petrol	Light Diesel	Heavy Diesel
2001	0.3673	0.2491	0.1257	1.4972	0.6495	0.1742
2002						
2003	0.2130	0.1167	0.0681	0.2704	0.4462	0.6100
2004	0.1598	0.0634	0.0507	0.9630	1.2227	0.2963
2005						
2006	0.2550	0.0286	0.0122	0.1649	0.1640	0.2899
NO (g/vehicle.km)						
2001	0.0812	0.3100	0.3764	0.6377	0.2635	0.1580
2002						
2003	0.0409	0.0500	0.0769	0.1690	0.3596	0.5683
2004	0.0387	0.1116	0.1569	0.7187	0.3532	0.0409
2005						
2006	0.0462	0.0784	0.0736	0.1541	0.1969	0.1554

Figure 33 a) A comparison between tunnel data and remote sensing data (CO)

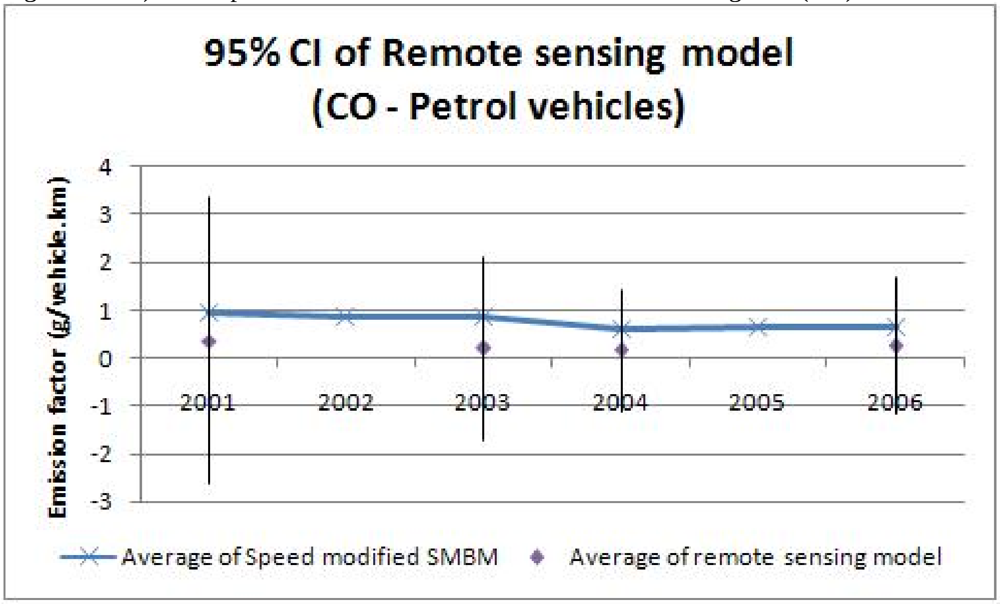


Figure 33 b) A comparison between tunnel data and remote sensing data (CO)

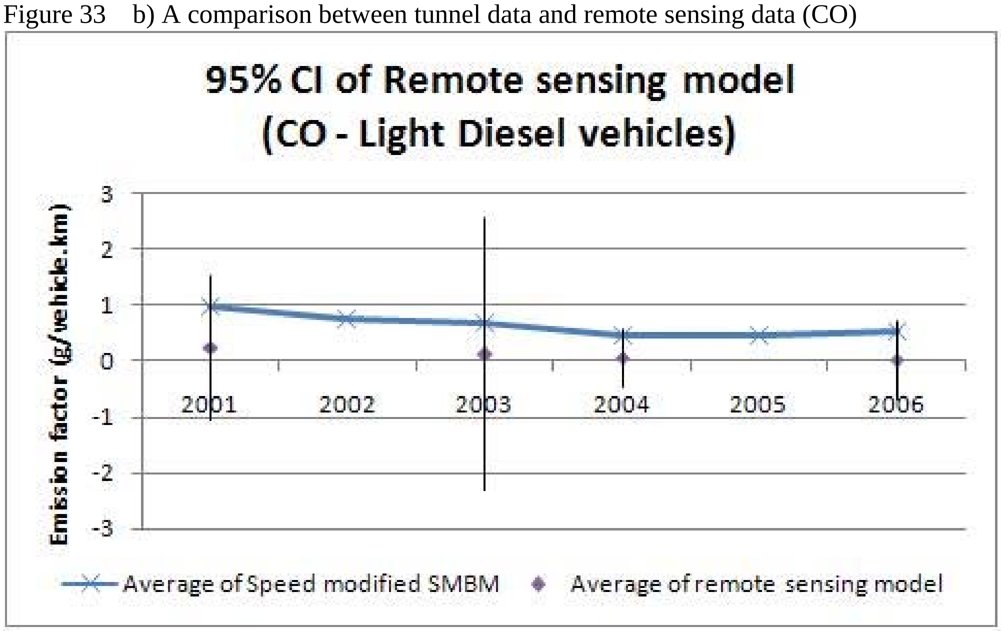
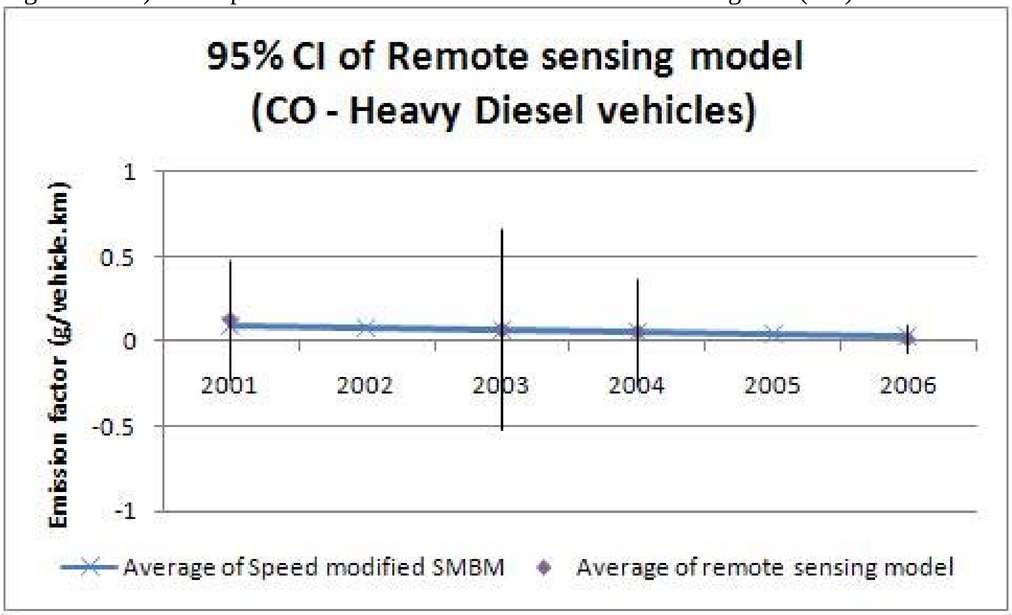


Figure 33 c) A comparison between tunnel data and remote sensing data (CO)



The case was very similar to the NO_2 emission factor application. Figure 34 reveals that there is no significant difference between the fuels based emission study and SMBM for petrol and heavy diesel vehicles. In the class of light diesel vehicles, there was a significant difference obtained at 95% significant level in the year 2003.

Figure 34 a) A comparison between tunnel data and remote sensing data (NO)

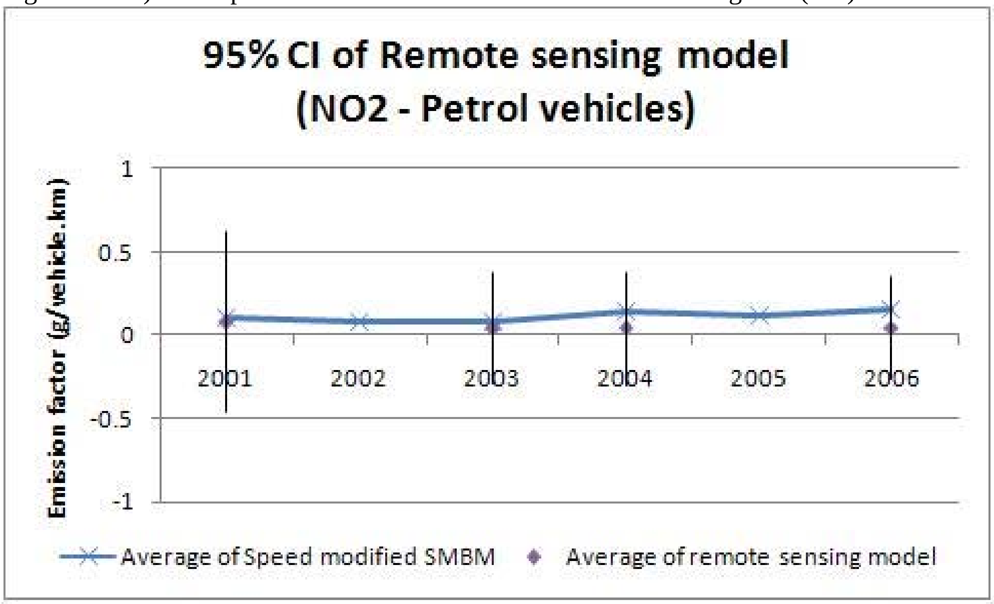


Figure 34 b) A comparison between tunnel data and remote sensing data (NO)

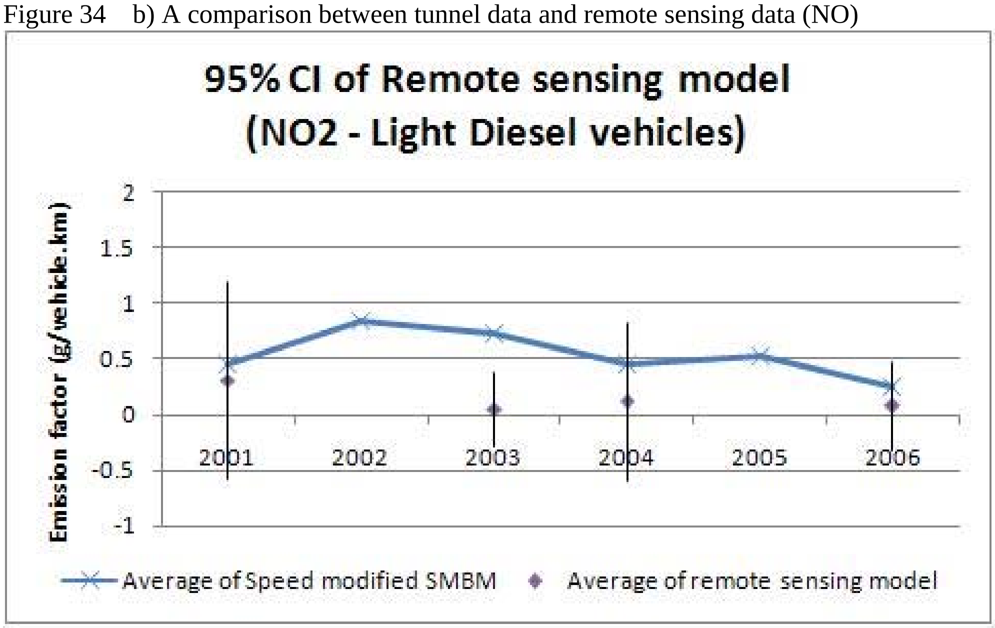
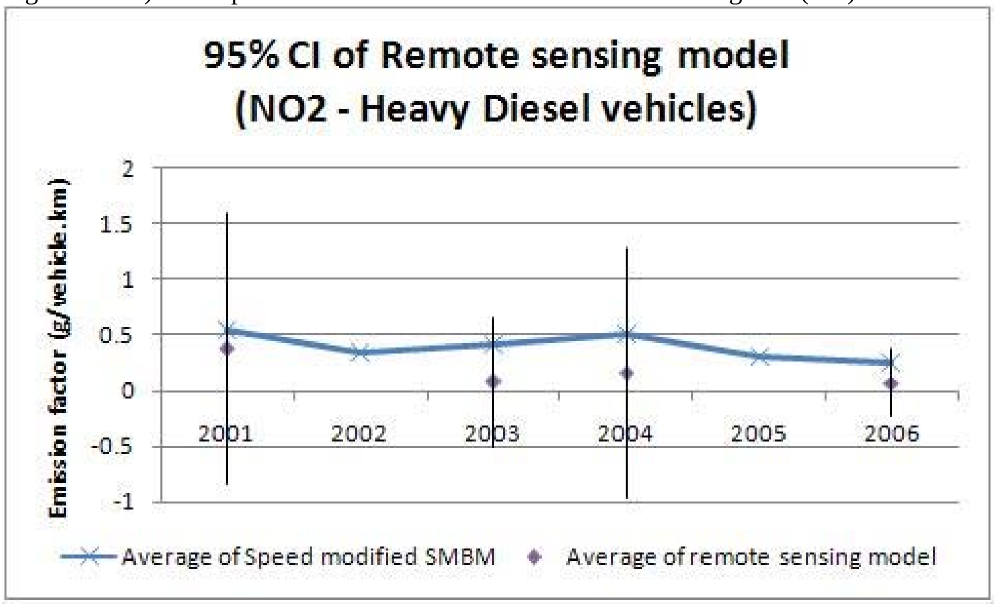


Figure 34 c) A comparison between tunnel data and remote sensing data (NO)



In order to study the trend of the pollutant emission factors, the annual result of both the speed modified SMBM and the remote sensing emission factor model were plotted. See Figure 35.

Figure 35 a) A comparison between the modified SMBM and remote sensing in the LRT

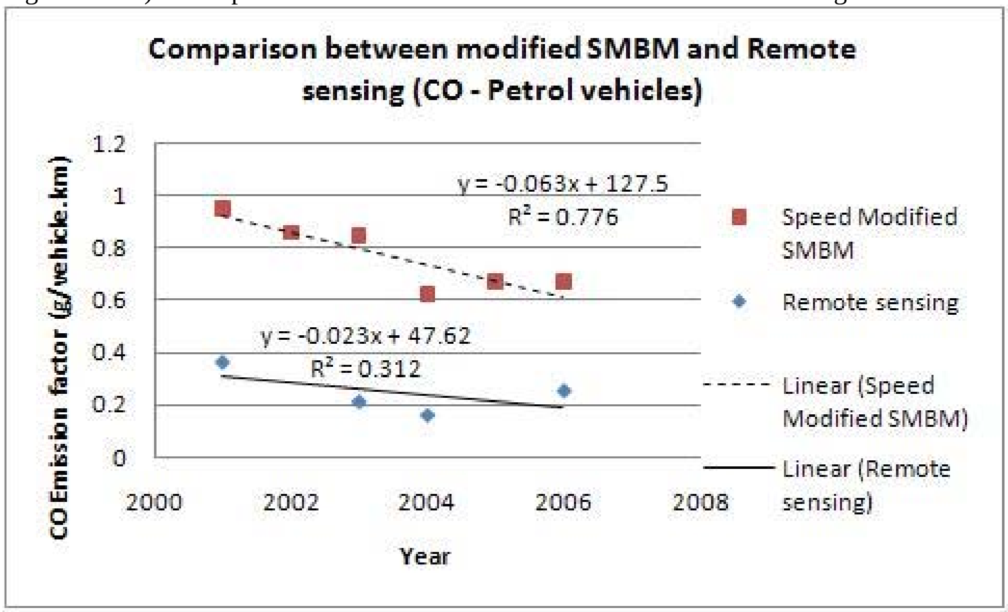


Figure 35 b) A comparison between the modified SMBM and remote sensing in the LRT

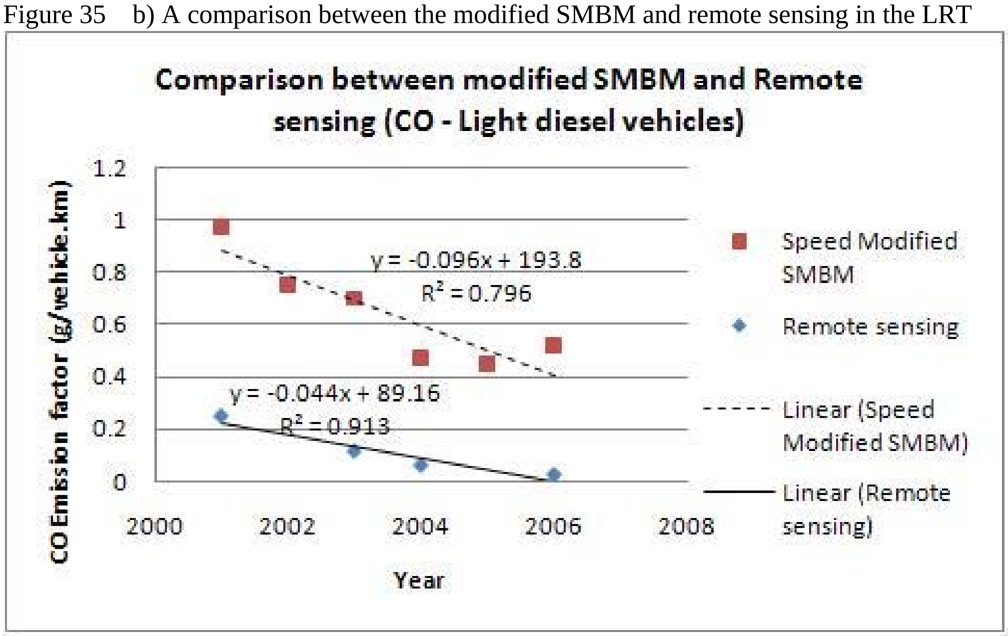


Figure 35 c) A comparison between the modified SMBM and remote sensing in the LRT

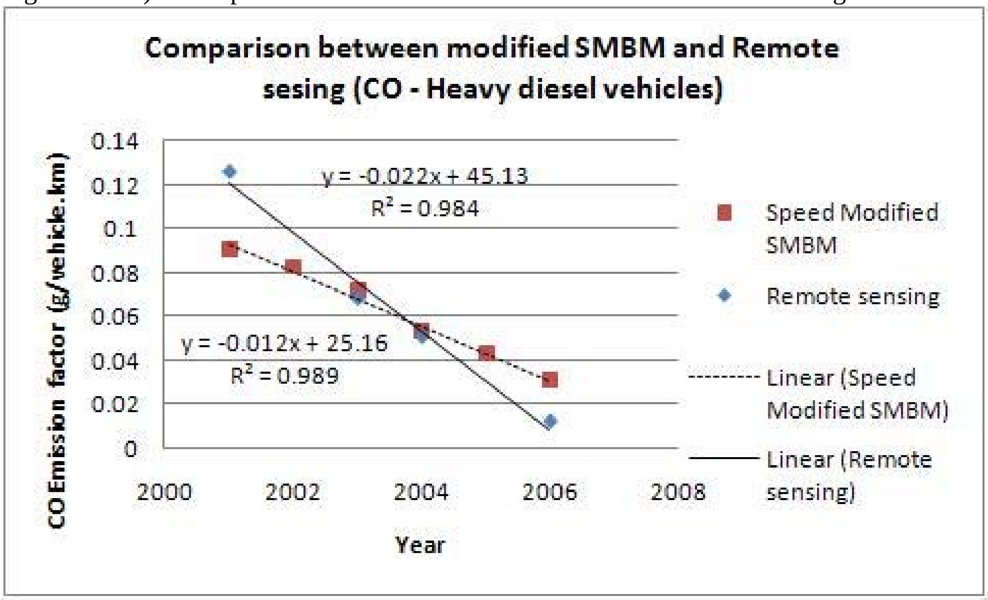


Figure 35 d) A comparison between the modified SMBM and remote sensing in the LRT

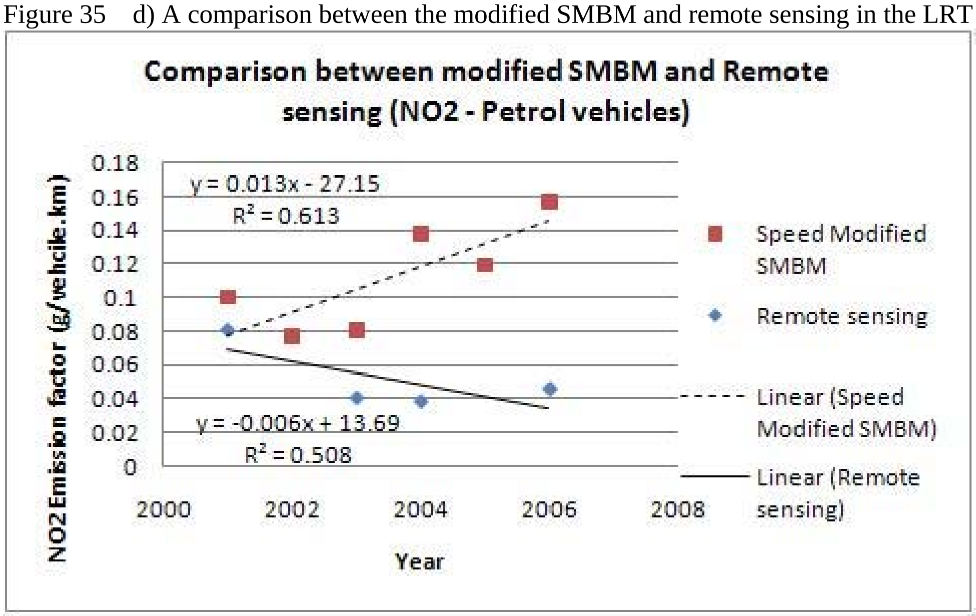


Figure 35 e) A comparison between the modified SMBM and remote sensing in the LRT

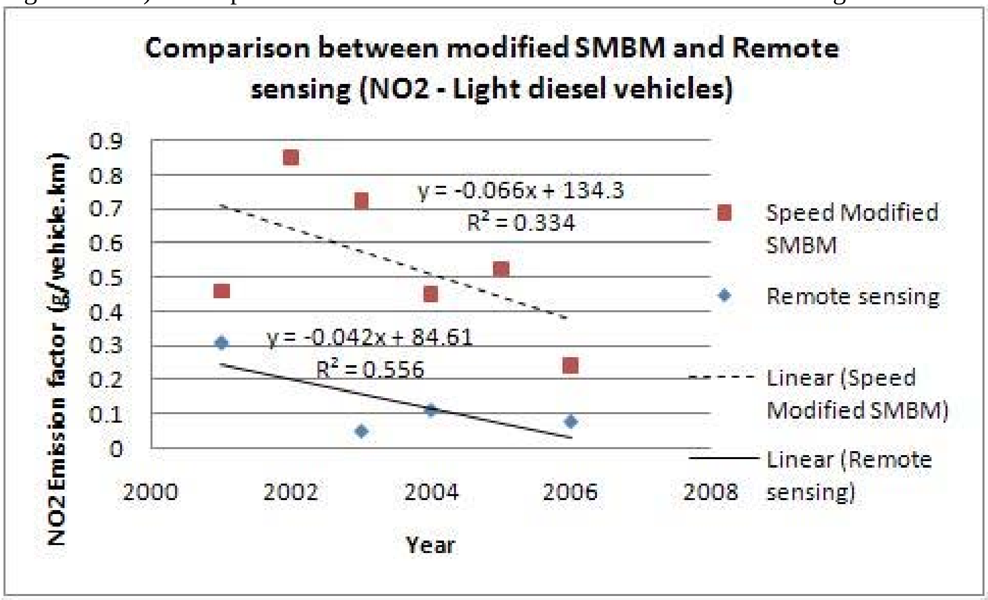
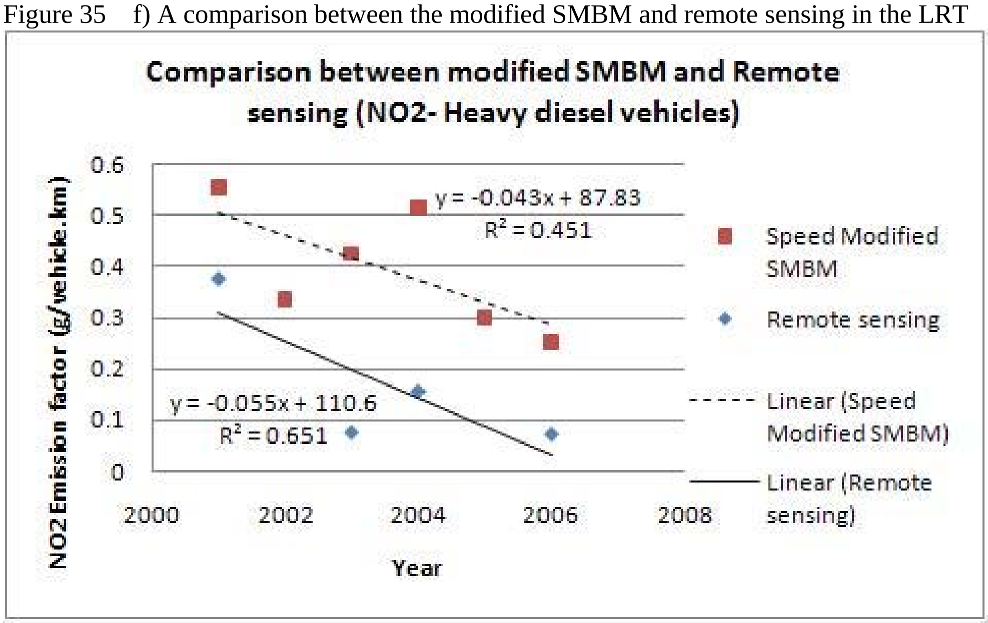


Figure 35 f) A comparison between the modified SMBM and remote sensing in the LRT



The plots revealed that there was a decreasing trend in pollutant emission factors except in the NO_2 emission factor in petrol vehicles in the speed modified SMBM. Otherwise, the decreasing trend of the speed modified SMBM and remote sensing were very similar. This great reduction in the pollutant emission factors was mainly due to the new Hong Kong Government policy. In 2002, the government commenced grants to help heavy pre-Euro diesel vehicles to install particulate removal devices, and it tightened emission standards for newly registered vehicles to Euro III. Furthermore, legislation was introduced in 2006, to tighten emission standards for newly registered vehicles to Euro IV standards.

7 Conclusions and Suggestions for Further Research

7.1 *Conclusions*

A comprehensive literature review showed the necessity for tunnel studies, in order to obtain a cheap and effective way to monitor vehicle pollutant emissions. Researchers came up with many studies on modelling pollutant emission factors, which were only suitable for specific conditions. With the development of transportation networks and vehicle models, traffic conditions and vehicular air pollutions are always changing. As a result, a pertinent regular monitoring programme is essential to monitoring the change in vehicle pollution. A cost effective tunnel emission model, using regular monitoring data obtained from the tunnel management companies is required for these purposes.

This study provides information to fill the gap by using the pollutant concentration and traffic volume obtained by the tunnel management companies for estimating the emission factors. Suitable modelling methods to apply the monitoring data were researched in this study. In our study, we tested the applicability of using simple linear regression in the routine monitoring data for modelling. The routine monitoring data of traffic flow and CO emission at the LRT, Hong Kong, were used for investigation. Regression models were developed through the analysis of the time variations as well as the ARIMA of CO concentrations and vehicular traffic. This model was developed successfully in almost all cases; the results showed most of the measured values fall well within the 95% predictive confidence intervals envelope. Based on the statistical analysis, it can be concluded that the combination of regression and time series models is a reasonable tool for modelling pollutant concentration. However, due to the large standard deviation of time series modelling, the model is not suitable for prediction.

For data collection, data obtained by the tunnel management companies are considered the easiest and cheapest way to record the vehicle traffic volume and pollutant concentration. However, due to the fact that receptors were far from the breathing zone, a correction was needed before the tunnel data could be used for analysis. For data collection in tunnels, there are various methodologies for collecting pollutant concentration data. The most commonly used method for obtaining continuous pollutant concentration through a tunnel is the car chasing method. Other methods, such as the remote sensing and fixed monitoring methods can only provide a discrete pollutant concentration database. As a result, the car chasing technique was used for collecting vehicle characterization and pollutant concentration data in the site surveys.

On-road measurement of vehicle pollutant emissions of CO and NO_2 was performed at the LRT, Hong Kong, in January 2007. Traffic flow, vehicle speed and the type of vehicle were measured at the same time. Instantaneous vehicular exhaust concentration data were collected by using an instrumented car travelling through the tunnel. This set of data was compared to the monitoring data obtained at fixed points in the tunnel in the same time period. Regression analysis was conducted on these two sets of data. Results show that the two sets of data were strongly correlated based on the relative slopes of their pollutant concentration profiles. The correlation was also found to be clustered by traffic volume.

In our study, we developed a successful traffic flow-speed curve for tunnels. The traffic speed can be found with the known traffic flow. Both the North and South Tubes record a downward trend in traffic speed when traffic flow increases. The negative slopes indicate that when traffic flow increases, the speed of vehicles decreases and leads to a longer exposure time inside the tunnel. Furthermore, a speed-time curve for tunnels was developed. By using regression analysis, the R-squares were 0.868 and 0.957 for the North and South Tubes, respectively. Based on the statistical analysis, it can be concluded that the vehicle speed inside the tunnel was reasonable and could be represented in a linear relationship with time.

As a result of the LRT fieldwork, a strong correlation between vehicle speed and pollutant concentration could be made. The impact of speed was then introduced to modify the SMBM to estimate pollutant emission factors based on this tunnel study. It was proposed to employ the speed ratio (i.e., the speed at the tunnel entrance over the speed at the tunnel exit) to modify the estimations of CO and NO_2 to obtain gram-per-kilometer emission factors for vehicles. Our estimated emission factors were compared to those factors estimated using the Hong Kong versions of the EMFAC, the SMBM, and the piston effect model. Results showed that the modified SMBM is relatively simple and can yield estimates with no significant difference at 95% significant levels to the piston effect models. The speed modified SMBM was then applied to the Aberdeen Tunnel for estimating the emission factors of pollutants. By directly applying the speed-volume relation equation and pollutant concentration correction that was obtained in the LRT, to the Aberdeen Tunnel data, the emission factors for CO and NO_2 were found. The results show a trend similar to the LRT study.

HKPOLYU obtained remote sensing data in the LRT. By referencing to the fuel balance model for calculating pollutant emission, the remote sensing based emission factors were compared to our speed modified SMBM in the LRT. A statistical t-test determined there was no significant difference between the fuel balance model and speed modified SMBM at the 95% significance level.

7.2 *Suggestions for further research*

In our study, a pollutant concentration profile was developed for the LRT only. Indeed, it is necessary to conduct further tests in order to determine a representative pollutant concentration profile. Furthermore, pollutant concentration profiles suffer from random errors. According to Clifford (1996), around 75% of the total amount of pollution received from a car in front, may be affected by the type of vehicles in the front, thereby affecting the experiment result. For this reason, it is hard to state any firm conclusion about the fixed angle between tunnel measurement and field measurement. In our case, a cluster centre was used for estimation. In the validation examples, we suggested that the estimate error did not exceed 10 percent. Besides the measuring error in sampling, a cluster centre could point out that the modelling method suffered from a limitation. When the point-slope form was being calculated, the first point from the tunnel data was used to find the estimated field regression line. If the first point of tunnel data was far away from the field data, the estimated field regression line might not be accurate. For this reason, it is recommended that a pilot study be considered. This experiment should consider as and indicates a need for further studies. The methodology employed for this experiment has shown that there should be some relationship in the angle between tunnel data and field data.

The research presented in this thesis suggests a speed modified SMBM for developing a representative pollutant emission estimating model with a focus on the cost efficiency. However, the tunnel selection will introduce a bias to the representativeness of the Hong Kong traffic environment. Furthermore, the tunnel selection leads to a traffic volume database problem. As the LRT only divided the vehicle categories into three classes, the traffic volume of LPG vehicles (mainly taxis and public min-vans) could not be known. As a result, we suggested applying the statistics of the annual average daily traffic (AADT) to define the number of petrol vehicles. As the AADT data were only obtained by samples and not by actual numbers, they may lead to calculating errors when petrol vehicle emission factors are being computed for comparison. To obtain a more representative emission factor of petrol vehicles, a tunnel with known taxi and mini-van traffic volume should be used and analysed. This would help to obtain a more representative emission modelling.

With limited resources, we used only three sampling periods for estimating the pollutant collection profile and the speed profile. To achieve a more realistic result, traffic conditions for each hour should be sampled. At the same time, it was meaningful to construct two profiles for individual hours. As a result, the traffic condition could be applied for estimation in the corresponding operating hours.

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