Through-tunnel estimates of vehicle fleet emission factors

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HIGHLIGHTS

\begin{itemize}
  \item Drive-through approach is developed to determine tunnel emission factor.
  \item Sen Slope method is less biased than entrance-exit approach.
  \item Diesel fleet emission factor is obtained with bivariate regression.
\end{itemize}

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ABSTRACT

On-road measurements of traffic-related gas and particle pollutant concentrations in three tunnels in Hong Kong and high resolution pollutant concentration profiles obtained while driving through the tunnels were used to derive the individual pollutant gradients using parametric and non-parametric (Sen – Thiel) slopes and compared with the commonly used entrance-exit two points calculation. The fuel based emission factors of measured pollutants for individual tunnels at different times of day were derived from gradients using a new method based on fuel carbon balance principle. Combined with the tunnel traffic volume and composition, the average tunnel emission factors were analyzed by linear regression to derive the diesel fleet emission factors. Average nitrogen oxides (NO\textsubscript{x}) and black carbon (BC) emission factor for diesel fleets are 29.3 \pm 11.0 gNO\textsubscript{2} kg\textsuperscript{-1} and 1.28 \pm 0.76 g kg\textsuperscript{-1} of fuel, respectively. The results from the study were compared with the emission data from vehicle chasing approaches and the literature, showing reasonable agreement. Practical limitations and future direction for improvement of our method were also discussed. The method presented in this study provides a convenient drive-through approach for fast determination of tunnel and individual vehicle fleet emission factors. It can be used as an effective and fast approach to validate the emission inventory and to evaluate the effectiveness of policy intervention on the traffic emissions.

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1. Introduction

On-road vehicle emissions are an important contributor to air pollution in urban areas. In Hong Kong, vehicle emission was a major emission source of NO\textsubscript{x}, PM\textsubscript{2.5} and CO accounting for 23%, 21% and 59% of total emission in 2013, respectively (HKEPD, 2015).

Sound policy decision on control and management of vehicle emission depends on a reliable emission inventory and the emission characteristics of the vehicle fleets (Smit and Kingston, 2015). Vehicles emission factors (EFs) characterize the amount of pollutant emitted per mass of fuel consumed (fuel based), per distance driven (task based) or per energy used (task based). EFs change over time with for example vehicle deterioration due to accumulating mileage, implementation of more stringent emission standards, change of fuel specifications, and advance in emission control technologies (Carslaw and Rhys-Tyler, 2013; Dallmann et al., 2012). It is essential to have accurately estimated and up-to-
date emission factors of the on-road vehicle fleets, for developing successful air quality plans to minimize impact of road transport on public health and the environment, and monitor the effectiveness of such plans.

Different methods have been developed to measure the vehicle emission factors. Chassis dynamometer methods test vehicles under controlled conditions in laboratories using standard driving cycles. Results are of high repeatability and comparability at the expense of complexity and high cost (Traver et al., 2002). This limits the number of vehicles to be tested and may not reveal a statistical characterization of the overall vehicle fleet. Moreover, the standard testing cycle may fail to reproduce real-world driving conditions (Franco et al., 2013). Portable Emissions Measurement Systems (PEMS) provide another way to measure the task-based EFs. They have the advantage of setting the equipment on-board the vehicle under investigation, which allows real-world on-road measurements (Huang et al., 2013; Weiss et al., 2011). However, measurement for light-weight vehicles may be biased by the added weight from the system (Franco et al., 2013) and the turnover time is also long, hindering broad application. Emission measurement in real-world conditions, capable of collecting large number of vehicle emissions in a short time in both task-based and fuel-based contexts, include roadside measurements (Dallmann et al., 2012; Hansen and Rosen, 1990), remote sensing (Chan et al., 2004; Chan and Ning, 2005; Ning and Chan, 2007; Singer and Harley, 2000) and tunnel studies (Cheng et al., 2006; Dallmann et al., 2012). Remote sensing systems show their effectiveness in employing the infrared and ultraviolet absorption to measure gases pollutants, but there are limitation in the measurement of particulate matter emission (Moosmuller et al., 2003). Conventional tunnel studies measure pollutant concentrations at the tunnel’s entrance and exit, average emission factors of vehicles are estimated from the concentration difference of the tunnel ends (Pierson and Brachaczek, 1983; Pierson et al., 1996). Some other studies also investigated tunnel emissions at midpoint and outside as background (Kristensson et al., 2004; Nogueira et al., 2015). It is difficult to determine EFs of specific vehicle classes unless a bore is specifically dedicated to this component of the fleet (Geller et al., 2005; Jamriska et al., 2004). An advantage of tunnel studies over the remote sensing is the well-defined wind (Franco et al., 2013). On-road plume chasing approaches have been developed for the estimation of fuel-based EFs of individual vehicles (Shorter et al., 2005) and demonstrated its effectiveness in characterizing on-road emissions of various vehicle classes (Ning et al., 2012; Wang et al., 2012). On-road and roadside measurement setups have been shown to agree well (Ježek et al., 2015a).

Recently, the use of high resolution monitors in a mobile platform has allowed the characterization of tunnel concentration profiles and the estimation of the average particle number emission factors (Perkins et al., 2013). In this study, we have used a mobile platform and a drive-through approach to acquire the pollutant concentration profiles in three tunnels in Hong Kong. Different traffic characteristics in the tunnels mean different individual tunnel emission factors. Linking these with traffic volume and composition, we further calculated the diesel fleet based emission factors and compared those with results in the literature and derived using the EMission FACTors model from California Air Resources Board that modified by vehicle activity data of Hong Kong (EMFAC-HK). The study provides a method to validate the emission inventory and to evaluate the effectiveness of policy intervention on the traffic emissions.

2. Methods

2.1. Tunnels

The measurement campaign took place from spring to summer 2014 in three Hong Kong tunnels: Aberdeen, Lion Rock, and Tai Lam, as shown on the map in Fig. 1. The traffic count ratio of medium- and heavy-duty vehicles (including double deck diesel buses and diesel goods vehicles above 5.5 tonnes) to total vehicles for Aberdeen, Lion Rock and Tai Lam Tunnels were 16%, 13% and 27%, respectively (HKTD, 2015). The tunnels selected in this study had different traffic compositions which contrasts the effect of individual vehicle classes on the tunnel emissions. The three tunnels are:

- The Aberdeen Tunnel consists of two bores each with two lanes. Both bores are 1.85-km long with slope 0.4–0.5% grade (the highest point is at the center of the tunnel). It connects Wong Chuk Hang Road and Canal Road Flyover in the Hong Kong Island. The vehicle speed limit is 70 km h\(^{-1}\) and the tunnel carries 6.5 \times 10^4 vehicles per day (ISD, 2014);
• The Lion Rock Tunnel is a twin-bored two-lane tunnel connecting Kowloon and New Territories. The old bore serves southbound traffic towards Kowloon, while the new bore, the Second Lion Rock Tunnel serves northbound traffic. The total traffic flow is $9.0 \times 10^4$ vehicles day$^{-1}$ (ISD, 2014). The Lion Rock Tunnel, which is 1.41-km long, has a negligible roadway grade of 0.25%. Its posted speed limit is 70 km h$^{-1}$.

• The Tai Lam Tunnel is a dual three-lane tunnel of 3.80-km long and is part of the Tsing Long Highway. The road gradient of both bores of the Tai Lam Tunnel is 1.15%, where southbound is an uphill road. It is a transport link between West Kowloon and the western New Territories and acts as a major access route to mainland China. The posted speed limit is 80 km h$^{-1}$. Its daily average traffic flow is $6.0 \times 10^4$ vehicles day$^{-1}$ (ISD, 2014).

The details of tunnel characteristics are shown in Table 1. In general, ventilation in the tunnels is provided by natural means and the traffic-induced piston effect. Mechanical ventilation systems are only activated occasionally during heavy traffic or in emergencies. Information on the activation periods of the mechanical ventilation systems in various tunnels was obtained from the tunnel management and Transport Department of Hong Kong. Only measurements made when the mechanical ventilation system was deactivated were included in the data analysis.

### 2.2. Measurements in tunnels

A mobile on-board platform with high time resolution air monitors was used to measure the on-road air pollutant concentrations while driving through the tunnels. The same platform has been used in our previous investigation on individual vehicle plumes, as on-road plume chasing and analysis system, OPCAS (Ning et al., 2012). In this study, the sampling set-up was reconfigured with the inlet installed one meter above the platform roof to limit the impact of individual vehicle plumes. Two separate sampling lines were used — one for gaseous pollutants (NOx and CO2) and one for particulate pollutants including PM$_{2.5}$, Black Carbon (BC), Ultrafine Particle (UFP) number, and Polycyclic Aromatic Hydrocarbon (PAH). Both line featured ¼-inch tubing – Teflon for gas analyzers and flexible conductive tubing for PM-related metrics. A TSI Q-Trak was used for CO measurement as well as probing the ambient temperature and relative humidity (RH). The details of the measuring devices are listed in Table S1. High time resolution (1–8 s) was essential for measuring the changes of gas and particle concentrations while driving through the tunnels. Additionally, a high resolution Global Positioning System (GPS, G-STAR IV) was used to record vehicle location data in order to establish the time taken to pass through the tunnel. A video camera was also synchronized with the same time stamp to ensure the accurate interpretation of the data stream for data quality assurance. A data acquisition system collected the real-time data from all the analyzers in the OPCAS platform using serial connections.

Each tunnel was measured over three separate days (a Sunday and two weekdays each). These days were split into a morning set of transits starting around 09:00 h, mid-day transits starting around 13:00 h and afternoon transits starting around 16:00 h. Rush hour periods were avoided after initial trial runs as congestion inside the tunnel led to the appearance of dominant plumes from individual vehicle in the drive-through tunnel measurements. Typically, three to seven trips were repeated in each one-hour sampling session for the route through each bore of the tunnels. While driving along the preset sampling route covering the studied tunnels, the on-road mobile platform was maintained at a distance of at least 10–15 m from any preceding vehicle, following the approach of Perkins et al. (2013). The speed of mobile platform was monitored closely through the speedometer to keep the mobile platform at quasi-constant speed. The on-board video recording was used to identify the events that might affect the measurements, and ensure reported data were not from an individual vehicle plume.

### 2.3. Traffic counting and categorization

Simultaneous with the drive-through tunnel measurements, traffic volume and composition of both bores were counted manually on an hourly basis from one end of each tunnel. The traffic conditions were also recorded with video cameras for post-analysis and off-site traffic counting in case of missing on-site data. Each of the 1-h periods was divided into four 15-min segments and the vehicle number was counted for alternate 15-min sessions, followed by averaging the counts in the sessions for hourly traffic volumes of each vehicle class (Rakowska et al., 2014). The classification of vehicle types followed the EMFAC-HK 16 Vehicle Classes System (private cars, motorcycles, taxis, light goods vehicles, medium and heavy goods vehicles, public and private light buses, franchised single and double decker buses and non-franchised buses, i.e. coaches) (HKEPD, 2014). The calculated traffic volume data were then re-grouped into major categories, including gasoline passenger cars (PC), light-, medium- and heavy-diesel goods vehicles (LDV, MGV and HGV), diesel single decker (SD) and double decker (DD) buses (termed franchised buses in Hong Kong) and Liquid Petroleum Gas (LPG) taxis and public light buses. The grouping intends to reflect the different fuels used, fleet-based functions for private and public transport or goods transport. The traffic volume and composition analysis follow the same classification hereafter in the study.

| Table 1 |
|---|
| Characteristics of the tunnels and the statistics of the sampling campaign. |
| Aberdeen | Lion Rock | Tai Lam |
| Length/km | 1.85 | 1.41 | 3.80 |
| Cross-section/m$^2$ | 110 | 83 (southbound) | 158 |
| 86 (northbound) | | | |
| Gradient/% | 0.4–0.5 | 0.25 | 1.15 |
| Uphill direction | From each end towards centre | northbound | southbound |
| Traffic flow/vehicles day$^{-1}$ | 65,000 | 90,000 | 60,000 |
| Traffic flow/vehicles day$^{-1}$ | Feb 27th, Mar 2nd 6th | Mar 10th 13th, Apr 13th |
| Sampling dates (2014) | Jul 10th 16th, Aug 3rd | Sun, 2*Thu |
| Sampling days | Sun, Wed, Thu | Sun, Mon, Thu |
| Sunday observational transits | 24 | 27 | 10(N),10(S) |
| Weekday observational transits | 56 | 70 | 24(N),18(S) |

Note: In the case of Tai Lam where there is a significant difference between flows in the bores the number of transits is split into those in a northwards direction (N) and those running southwards (S).
2.4. Emission factor calculation

Prior to the sampling campaign, the instruments underwent standard calibrations, described in details elsewhere (Rakowska et al., 2014). The on-road PM$_{2.5}$ concentration measured by Dust Trak II was presented without further correction, and the PM$_{2.5}$ concentration data was used only for cross comparison of different tunnels with similar aerosol characteristics, and not intended for comparison with gravimetric PM$_{2.5}$ mass concentration. For the black carbon measurements, on-road Aethalometer AE33 data were taken directly for analysis (Drinovec et al., 2015). UFP number concentrations higher than 100,000 particles cm$^{-3}$ were corrected for coincidence error following the approach by Westerdahl et al. (2005). The Ecochem PAS 2000 raw values were recorded with a range of 0–5000 ng m$^{-3}$.

A typical example of a pollutant concentration profile through a tunnel is given in Fig. 2, which shows measurements for the southbound bore of Tai Lam Tunnel during a Thursday afternoon measurement (16:07 h). The figure shows the increase in pollutant concentrations with distance into the tunnel. The distance assumed that the van with the OPCAS moved at a constant speed according to the protocol. A pollutant gradient was expected as the tunnels are usually not mechanically ventilated and the air is driven out by the piston effect. The rate of change in concentration along the bore (dC/dL) is described by the equation:

\[
dC/dL = Q_d/A \uparrow \text{Up}
\]  

(1)

where \( C \) is the pollutant concentration, \( L \) is the distance into the tunnel and the volume of air leaving the tunnel is a product of the bore area \( A \) and the piston velocity \( \uparrow \text{Up} \) and \( Q_d \) is the amount of emitted pollutant per second for each meter (i.e. the line source strength).

The rate of change in pollutant concentrations can be related to the linear source strength. However, this requires that the tunnel is well mixed and needs an accurate value for the plug-flow velocity \( \uparrow \text{Up} \). These requirements were not easily met, so emission factors in this study were calculated following the carbon–balance method that has been widely used in remote sensing (Bishop et al., 2012; Ning and Chan, 2007; Zhang et al., 1995) and plume chasing studies (Ning et al., 2012; Wang et al., 2012), in which fuel based emission factors are typically determined by the ratio between the incremental pollutant and carbon dioxide concentrations inside the vehicle plume. In the current study, we deployed a novel drive-through approach to measure the pollutant profiles inside the tunnels to determine the average tunnel emission factor \( EF_{mp} \) (g kg$^{-1}$) for individual tunnel bores, calculated by using a formulation of fuel carbon balance method:

\[
EF_{mp} = w_\text{f}(dC_P/dL)/(dCO_2/dL)
\]  

(2)

in which, \( dC/dL \) is the slope of pollutant profile inside tunnel, \( C_P \) and \( CO_2 \) are the concentrations of pollutant \( p \) and \( CO_2 \) (in weight so that \( g \) is the need conversion from the mixing ratios), \( L \) the distance into the tunnel and \( w_\text{f} \) the carbon weight fraction of the fuel. Carbon weight fraction is 0.82 for LPG (EPA, 2015) and 0.87 for diesel (Dallmann et al., 2013) and motor gasoline (EPA, 2015). Although the carbon weight fraction of LPG is 5.7% different to that diesel and gasoline, LPG vehicles overall fuel consumption is an order of magnitude lower than the medium and heavy diesel vehicles. This allowed us to use 0.87 for \( w_\text{f} \) throughout the study. The emission factor calculation in Eq. (2) represents an average value in a tunnel, which includes all the vehicles passing through it. As medium- and heavy-diesel vehicles have significantly high fuel consumption, pollution emission within the tunnels is dominated by diesel, with characteristically large \( CO_2 \) emissions. Consequently, the portion of carbon in \( CO \) is typically less than 1% of the total fuel carbon as illustrated by the typical pollutant concentration profiles in Fig. 2. We thus simplify Eq. (2) by neglecting \( CO \) with an advantage of avoiding data loss due to the absence of \( CO \) values for some tunnel transits.

The tunnel emission factor for an individual pollutant \( p \) is the aggregation of the emission factors from the different vehicle classes \( k \) through the summation:

\[
EF_{mp} = \sum_{k=0}^{n} N_k F_k EF_{mp,k} / \sum_{k=0}^{n} N_k F_k
\]  

(3)

where \( EF_{mp,k} \) is the average tunnel emission factor from Eq. (2), the integer \( k \) represents the vehicle type category, \( N_k \) is the hourly flow of vehicle type \( k \), \( F_k \) is the fuel consumption (kg km$^{-1}$) of vehicle type \( k \) and \( EF_{mp,k} \) is the emission factor for pollutant \( p \) for vehicle type \( k \). As the hourly flows of vehicles have been observed and the fuel consumption for these types can be obtained it would be possible to determine the individual emission factors of the various vehicle types by multi-variate linear regression. However, this is dependent on the record showing a significant variation in the relative amount of fuel used (i.e. \( N_k F_k \)) in the tunnel in the set of observations. There are total of 54 valid traffic profiles that have been obtained from the tunnel drive-through measurements including each bore of the three tunnels, three days for each tunnel and three time periods for each day. Multiple linear regression typically requires about twenty rows of data for each variable, so at best it would be possible to extract the emission factors for three fleet types and in some cases only two, so we have reduced the

![Fig. 2. Typical pollutant concentration profiles measured from a driving through transit in the Tai Lam Tunnel in the afternoon on a weekday.](image)
vehicle fleet to a combined gasoline/LPG fleet (g) and a diesel fleet (d). This simplifies the problem, as we can plot the observed emission factor against the proportion of fuel used by the diesel fleet \((N_{d}F_{d}/(N_{d}F_{d} + N_{g}F_{g}))\) and here the intercepts at 0 and 1 represent the emission factors of the gasoline/LPG and diesel fleets. The fuel consumptions of the two fleets in Hong Kong were taken from the EMFAC-HK with the diesel fleet used 0.4218 kg C km\(^{-1}\) and gasoline/LPG vehicles at 0.0764 kg C km\(^{-1}\). These values are sensitive to both the fleet mix and the driving conditions, but the ratio formulated above to establish proportion is likely to be less sensitive to driving conditions than the absolute values.

3. Results and discussion

3.1. Tunnel profile

The traffic in the tunnels measured during this study showed distinct weekday and weekend pattern with overall lower traffic volume on Sundays compared with weekdays. However, the portion of LPG/Gasoline traffic increased on Sundays by 20–26%, and diesel traffic reduced due to less goods transport activities, much as expected. Different tunnels also showed variation of the traffic composition with Tai Lam Tunnel bearing a higher portion of diesel traffic than others on weekdays, while the other two tunnels feature more LPG and gasoline traffic. Detailed traffic count data is shown in Table S2. The contrast of the traffic composition among the tunnels serves to provide the necessary range of inputs for regression, as discussed in the following section.

The pollutant concentration profiles displayed a generally positive trend with increasing distance into the tunnel as shown in Fig. 2, consistent with the expectations that the tunnels were not mechanically ventilated at the time of monitoring. However, this also conceals some underlying messages. The slope is not always positive as would be expected from Eq. (1). The cross sectional area of the tunnel is constant and the piston velocity is unlikely to vary, so it seems the occasional variations in the concentration gradient arise from local changes in the linear source strength caused by interference of passing-by vehicle plumes from adjacent lanes inside the tunnel, suggesting the tunnel is often poorly mixed over its cross section. In addition, the variation in response time of the instruments producing different pollutant concentration profiles means that local peaks may not match exactly. The CO seems to lag behind in responding to the change of concentration after entering the tunnel due to the slow response of electrochemical sensor. The PAH analyzer has the slowest response with 8 s time resolution, so the peaks are not as distinct as that of CO\(_2\). However, such minor variations do not affect the average slope of pollutant concentration inside the tunnel.

Eq. (1) implies a relationship between the pollutant concentration gradient and linear source strength, which is a function of traffic flow and composition. Support for this can be seen in the supplementary material (Fig. S1) which illustrates a general correlation between the CO\(_2\) gradient and vehicle flow. The relationship between vehicle flow and gradient is far from perfect, but this is understandable when the variation of traffic mix is considered. As an example, the measurements made in the Lion Rock Tunnel with the highest vehicle flow (almost 3300 per hour) are from Sunday and at these times more than 80% of the traffic flow derives from passenger automobiles, taxis and motorcycles, a considerably larger fraction than for other days. There is also important a distinct difference between the two bays of the Tai Lam Tunnel, with the south bory tending to have a higher CO\(_2\) concentration gradient perhaps the result of vehicles driving uphill within the tunnel.

3.2. Tunnel emission factors

The ratio \((\text{d}C_{x}/\text{d}L)/(\text{d}C_{\text{CO}_2}/\text{d}L)\) is taken as the slope between the measured pollutant and the CO\(_2\) concentrations as shown in Fig. 3. The figure shows the concentrations of six pollutants measured during a transit of the Tai Lam Tunnel. The data derives from the transit shown in Fig. 2. Plots from each tunnel transit were also visually inspected to ensure they displayed a coherent set of data. The slope was determined by least square regression, and checked against a Sen–Thiel slope, which is less sensitive to spurious spikes in the instrumental observations. The regression slope was usually rejected if the two methods did not agree and show almost perfect overlap. Where they disagreed, the differences were large and sometimes had slopes with different signs. The data plotted in Fig. 3 suggests a fairly consistent slope, implying there were relatively constant emission factors during the transit through the tunnel. However, there are a number of places where it deviates. As was noted earlier in the discussion of Fig. 2, there was a plateau-like feature with regard to the pollutant gradient for PM\(_{2.5}\), BC and PAH when platform passes 1.5–2.7 km into the north bore of the Tai Lam Tunnel. By contrast the CO shows a dip in concentrations in Fig. 3(a), giving a hint that a diesel vehicle, which would typically have with comparatively low CO emissions, was responsible. This vehicle was presumably the origin of the local pulses of pollutants which appear again in Fig. 3(c) and (d) and possibly Fig. 3(e) as a deviation from the best fit line, starting after the CO\(_2\) concentration reaches around 550 ppm, although it is less clear for PAH.
suggests that the pollutant pulse in this part of the tunnel resulted from a vehicle with enhanced emission factors for PM$_{2.5}$, BC and PAH and a lower CO emission factor. While it is clear that there are deviations from a straight line (regression coefficients were typically greater than 0.9 as in Table S3), the gradient determined here is an estimate of the average emission factor for the entire tunnel.

As discussed earlier, changes in the composition of the vehicle fleet lead to changes in the pollution gradients in the tunnels (i.e. as in Fig. S1). Similarly these changes would likely lead to changes in the emission factors for the tunnels. As noted before, the traffic composition changes with a higher proportion of automobiles typical of Sundays. This is evident in the bar charts of Fig. 4(a) and (b) that display the CO and NO$_x$ (expressed as NO$_2$) emission factors in the tunnels. Carbon monoxide emission factors are generally higher on Sundays, which might reflect the higher emission of this pollutant from gasoline engines relative to diesel. The emission factors for NO$_x$ seem to be typically higher on the weekdays.

The subsequent panels of Fig. 4(c–h) show the emission factors as a function of the percentage of the tunnel traffic as diesel medium and heavy goods vehicles and large buses. Each data point represents the average daily emission factors for Aberdeen, Lion Rock Tunnel and each bore of Tai Lam Tunnel. Error bar represents the standard deviation of the emission factors determined from the multiple transits through the tunnels. The plots lend some support to the picture that was developed in Fig. 4(a) and (b) that an increasing proportion of gasoline vehicles from weekday to Sunday increased the CO emission factor, while NO$_x$ emission factor follows the trend in the diesel vehicle fraction. Fig. 4(c) and (d) make the decrease in CO and in increase NO$_x$ emission factors with the proportion of diesel vehicles more explicit. By contrast the proportion of lighter vehicles (automobiles, motorcycles and LPG taxis) has a positive trend with emission factors for CO in the tunnels. There is also some evidence of an increase in the particulate emission factors of PM$_{2.5}$, BC and PAH as the diesel vehicle fraction increases as shown in Fig. 4(e), (f) and (g). There is little that can be drawn from the trend in UFP shown in Fig. 4(h), but this data often appeared to be much noisier than the other particulate measurements, possibly because the instrument became saturated when particle concentrations rose above $10^4$ particles cm$^{-3}$ so the correction may not effectively capture the concentration of actual peak that often occurs at the end of tunnel. As a consequence, the regression as shown in Fig. 4(h) tends to underestimate the slope of UFP concentration profile and its emission factor.

3.3. Individual vehicle fleet emission factors

Fig. 5 shows the relation between the average tunnel emission factor and the portion of the diesel fuel used by the tunnel fleet. As mentioned earlier, bivariate regression is used to derive the gasoline/LPG and diesel fleet emission factors. Two sets of results were presented here to check the data consistency. One set of emission factors was estimated from the slope as described in Eq. (2) using least squared regression (displayed as black squares), while a second set of emission factors was calculated by manually estimating the difference between concentrations measured entering and exiting the tunnel (displayed as open diamonds). The fitting method is likely to be less biased by observer choice of pollutant concentrations at either end of the tunnel. However, the fitting method tended to reject more tunnel profiles as giving unreliable estimates of slope (usually rejected when the slope from least squared regression and the Sen slope differed, typically they agree within 5% and disagreements could be very large or where there

![Fig. 4.](image1)

![Fig. 5.](image2)
were large peaks or troughs or missing data). The manual method thus utilized more of the tunnel profiles, and had the potential to yield better estimates because more data were used to obtain the average emission factor. Nevertheless the two sets of emission factors often agree reasonably well (see Table 2), showing the robustness of the slope method for emission factor calculation. The two intercepts of the fit with the ordinate axis at 0 and 1 proportion of diesel fuel represent the emission factors of the gasoline/LPG and diesel fleets in the tunnels, respectively.

Table 2 lists the individual pollutant emission factors by the two different methods with the relative standard error as standard error over the mean value. There is a reasonable agreement between the values established from linear regression of concentrations in the tunnel and the entrance-exit difference method. Nevertheless, the errors are not small for some cases and additionally some of the emission factors are consistently close to zero, or even negative, but with no statistically significant difference with zero value at 95% confidence level. This is the case for PM$_{2.5}$, BC and UFP from the gasoline/LPG fleets, which implies a degree of uncertainty of the tunnel gradient approach for derivation of fleet emission factors, especially where they make small contributions to the overall emissions. Require changes to the data collection during tunnel transits to improve the method is discussed further in the conclusion. The relative standard errors show a clear pattern in which CO for gasoline/LPG fleet, NOx, PM$_{2.5}$, BC and PAHs for diesel fleet are below 0.3 while others are substantially higher, suggesting the robusness of the method for these pollutant that are also consistently major emissions from the two fleets. UFP estimates are not robust and show high relative standard errors, which we attribute to the underestimation of the concentration peak due to the instrument limit as discussed earlier.

Table 3 shows a comparison of the fleet emission factor from this study and other studies both locally and in other cities (Dallmann et al., 2012; Lau et al., 2015; Park et al., 2011; Wang et al., 2012). Only diesel fleet BC and NOx data are presented since gasoline/LPG emissions factors are close to the method uncertainty while data for other pollutants are not abundant in the literature. The results are within the range of reported values for the diesel vehicles, showing the generally higher emissions in Chinese cities of Hong Kong, Beijing and Chongqing, and lower emissions in California and Europe. Of particular interest is the comparison with the recent plume chasing measurement of diesel franchised buses in 2013-14 in Hong Kong (Lau et al., 2015), which showed a higher NOx but lower BC emissions from the franchised buses than HDGV, due to the mandatory retrofitting of Diesel Particulate Filter (DPF) on franchised buses seems to have effectively reduced PM emissions. The mixed tunnel diesel fleets of both light and heavy duty diesel vehicles from this study showed reasonably good consistency with the chasing method.

### 3.4. Comparison of tunnel and EMFAC-HK emission factors

The measured tunnel emission factors are compared with the aggregated emission factor derived from the EMFAC-HK model that has often been used in Hong Kong to estimate the emissions from the local vehicle classes as shown in Fig. 6. The EMFAC-HK model data are from the input of vehicle speed of 70 km h$^{-1}$ at environmental temperature of 25 °C and relative humidity of 50%. As each set of tunnel transits was associated with vehicle counts for the various classes, it is possible to use the EMFAC-HK vehicle emission to reconstruct the aggregated average emission factors of the fleet present in the tunnel. These calculations give results with the unit g km$^{-1}$, which can be converted to fuel mass emission factors knowing the fuel consumption and proportional contribution of individual vehicle classes. However, this was not always explicit in the data we used, but as the CO$_2$ emission factors are also available in EMFAC-HK, these were used as a convenient way to determine the fuel based emission in the unit g kg$^{-1}$. The results are listed in Table S4, along with the fuel consumption for the various vehicle classes (Dallmann et al., 2013).

The bar charts in Fig. 6 present the individual class emission contribution to the total emission from EMFAC-HK reconstruction. The gasoline private cars make the dominant contribution to the CO (i.e. $\text{EF}_m$) in the tunnels with other vehicle classes being more evenly spread. It is especially noticeable that motorcycles (MC) make a noticeable contribution due to the large emission factor (~112 g kg$^{-1}$ as shown in Table S4), even though their numbers are small in the tunnels. It is also possible to see that medium and heavy goods vehicles make little contribution to Aberdeen Tunnel on Sundays, when the flow of these commercial vehicles is light. The NOx emission factors (i.e. $\text{EF}_{m\text{NOx}}$) are dominated by the larger vehicles, the goods vehicles and the buses. However, taxis can make a contribution in Aberdeen Tunnel as they are a significant part of the vehicle flow especially on Sunday. Not surprisingly the PM$_{2.5}$ emission factors (i.e. $\text{EF}_{m\text{PM}_{2.5}}$) as with the NOx are largely derived from the goods vehicles, but the buses make little contribution to the PM$_{2.5}$ emission due to the mandatory DPF retrofitting that has effectively reduced PM emission from local bus fleets. This is consistent with our recent findings from on-road plume chasing study (Lau et al., 2015).

The individual vehicle class emissions from EMFAC-HK can then be used to reconstruct the tunnel emission factor ($\text{EF}_m$) using the summation expressed in Eq. (3) with tunnel traffic composition. The inserts to Fig. 6 compare the reconstructed and the observed emission factors derived from the slope method. The PM$_{2.5}$ emission factors from this study were photometric and not adjusted with a gravimetric correction, so the data is presented for reference only. In general, there is an agreement between the trend between the two methods for estimating the tunnel emission factors, but those estimated from EMFAC-HK are much lower (i.e. typically two to three times lower) than the observations made during the tunnel.

### Table 2

| Pollutant | Gasoline/LPG fleet | Diesel fleet |
|-----------|--------------------|-------------|
|           | Sen slope | Entrance-exit | LSR regression | Entrance-exit | LSR regression |
| CO        | 28.9 ± 4.9 (0.17) | 31.0 ± 3.9 (0.13) | 9.6 ± 8.5 (0.89) | 10.6 ± 6.8 (0.64) |
| NOx       | 3.4 ± 3.2 (0.94) | 4.7 ± 2.7 (0.57) | 29.3 ± 5.6 (0.19) | 31.8 ± 3.0 (0.10) |
| PM$_{2.5}$| −0.13 ± 0.10 (0.77) | −0.09 ± 0.09 (1.00) | 0.72 ± 0.17 (0.24) | 0.72 ± 0.16 (0.22) |
| BC        | −0.04 ± 0.23 (5.75) | −0.08 ± 0.21 (2.63) | 1.28 ± 0.39 (0.30) | 1.46 ± 0.36 (0.25) |
| PAH       | 0.0013 ± 0.0001 (0.08) | 0.0009 ± 0.0009 (1.00) | 0.0060 ± 0.0017 (0.28) | 0.0065 ± 0.0016 (0.25) |
| UFP       | −0.094 ± 0.89 (9.47) | −0.69 ± 0.82 (1.19) | 2.36 ± 1.53 (0.65) | 2.56 ± 1.41 (0.55) |

Note: The numbers in the brackets are the relative standard error defined as standard error divided by the mean.

transits for CO and NOx emissions. There are a number of probable reasons for this, for example, the difference in the model assumption and on-road driving conditions of vehicles such as tunnel gradient, vehicle loading and cold-start mode; the representativeness of the vehicle base emission data as model input for fleet emission factor calculation; and the representation of inter-vehicle variability in emissions including ‘high emitters’ etc. Nevertheless, the underestimation of the EMFAC-HK NOx emissions compared with on-road fleet emissions observed from this study is consistent with the previous studies that often show a similar discrepancy (Lau et al., 2011).

Closer examination of the data reveals that not only are the estimates made by EMFAC generally lower than measured in on-road studies, though additionally they show a smaller degree of variation. Similar work in Hong Kong examining the plumes of individual vehicles the size of the fleet emissions observed from this study is consistent with the highly variable nature of the emissions from individual vehicles the size of the fleets sampled during tunnel transits would also be highly variable.

### Table 3
Comparison of emission factors (mean ± 95% confidence interval) from this study with literature.

| Data source          | Vehicle type                        | Emission factor | Remark                                      |
|----------------------|-------------------------------------|-----------------|---------------------------------------------|
|                      |                                     | CO (g/kg)       | NOx (gNO2/kg)                              |
| This study           | Combined diesel fleet               | 29.3 ± 11.0     | 1.28 ± 0.76                                 |
|                      | Gasoline/LPG fleet                  | 28.9 ± 9.6      | Sen slope method derived fleet emission factor. |
| Lau et al. (2015)    | Franchised bus                      | 39.7 ± 3.9⁴     | 1.0 ± 0.2                                  |
|                      | Heavy duty goods vehicle            | 32.3 ± 1.6⁴     | Plume chasing approach on 625 goods vehicles and 136 buses from Hong Kong in 2013–2014. |
| Jezek et al. (2015b) | Petrol car                          | 6.34 (3.77–10.6)| 0.28 (0.15–0.46)                           |
|                      | Goods vehicles                      | 27.71 (17.89–38.24)| 0.47 (0.24–0.72)                           |
|                      | LGV (3.5–12 t)                      | 23.16 (17.89–27.46)| 0.64 (0.37–0.96)                           |
|                      | Buses                               | 55.88 (29.09–55.9)| 0.4 (0.24–0.65)                            |
| Dallmann et al. (2012)| Heavy-duty diesel truck            | 28 ± 1.5        | Fleet average of 667 (BC) and 557 (NOx) vehicles by roadside measurement at Caldecott tunnel in 2010. |
| Dallmann et al. (2013)| Light duty gasoline vehicle        | 14.3 ± 0.7      | Roadside measurement at Caldecott tunnel in 2010. |
| Wang et al. (2012)   | Heavy duty diesel vehicle           | 50.5            | Plume chasing of 192 HDDVs in Beijing, China on level gradient road in 2010. |
|                      | Heavy duty diesel vehicle           | 42.1            | Plume chasing of 124 HDDVs in Chongqing, China on level gradient road in 2010. |
| Park et al. (2011)   | Light duty gasoline vehicle         | 54.3 (mean)     | Plume chasing of 143 LDGV and 93 HDDT from Los Angeles in 2007 at cruise (>30 miles per hour) mode. |
|                      |                                     | 7.2 (median)    |                                             |
|                      | Heavy duty diesel truck             | 30.1            |                                             |

⁴ NOx in gNO2/kg.

b Median (1st and 3rd quartiles).

4. Conclusions

The present study used a drive-through approach to acquire the high resolution pollutants concentration profile inside the tunnels. The slope of the pollutant concentration gradient is likely to be less biased than the pollutant concentration measurements made as the monitoring platform enters or exits the tunnel. Methods that use the pollution gradient throughout the tunnel use more data so are likely to be a better approach to calculating the aggregate tunnel emission factors. Integrating the hourly traffic volume and composition allowed diesel and gasoline/LPG fleet emission factors to be derived through bivariate regression and showed agreement with the data from literature and local measurements. While this work has shown the potential of concentration gradients through the tunnel to estimate the on-road fleet emission factors during tunnel transits, a number of improvements would help derive more reliable estimates in future studies. Firstly, in order to have a more robust multiple regression that could estimate the EfM of more vehicle classes, the number of transits through the tunnels would need to increase to avoid the statistical issues with the small sample size especially for the larger less common vehicles or low-emission fleets. This might best proceed through trying to determine the composition of the tunnel and its fuel consumption within the plug that was used to derive the concentration profile, because this is an important source of error in determining the emission factors within the tunnel. Secondly, future work will explore the nature of the statistical problem (both in terms of vehicle numbers and variation between individual vehicle emission factors), with the intent to get an idea of the appropriate number of the transits to achieve statistically reliable outcomes. The highly heterogeneous distribution of on-road vehicle emissions from the same vehicle class could increase the uncertainty of the measurements given the short transit time through the tunnel. Monte Carlo simulations may be applied to estimate the uncertainty of the emission measurements. Lastly, the inter-tunnel variation of the road gradient and traffic speed may affect the accuracy of the multiple regressions because of the assumption that the class specific emissions are the same across different tunnels. Further work may also target specific tunnels with long time series of measurement including variation of the traffic composition to minimize the uncertainty.
Fig. 6. (a) Estimates of the tunnel emission factor for CO from EMFAC (EFm) for various elements of the vehicle fleet in the Aberdeen Tunnel (AB), Lion Rock Tunnel (LR) and the north (TLN) and south bore (TLS) of the Tai Lam Tunnel on Sundays and weekdays. The insert compares the sum of the EMFAC derived emission factors (EFm) with the measured emission factor in the tunnel, EFm. (b) Plots as in (a) for NOx. (c) Plots as in (a) for PM2.5.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.atmosenv.2015.10.086.

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