A TUNNEL STUDY TO VALIDATE AUSTRALIAN MOTOR VEHICLE EMISSION SOFTWARE

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Abstract

Reliable motor vehicle emission predictions are needed and the magnitude of prediction errors needs to be understood to ensure sound policy decisions. This study reports on a comparison between measured in-tunnel fleet emissions (CO, NO_x, $PM_{2.5}$) and predictions made with COPERT Australia and PIARC. Measurements were taken from a 6.8 km tolled motorway tunnel that links several major roads in Brisbane, Australia.

COPERT Australia generally performs significantly better than PIARC and has the added benefit of being capable of estimating emissions for a large range of pollutants. PIARC showed very good agreement for one situation (LDV NO_x). The validation results are good, when compared to similar international research work. COPERT Australia emission factors for the Queensland fleet are conservative, and it is recommended that they are used for tunnel air quality assessments in the absence of tunnel emission measurements.

Keywords: vehicle, emission, tunnel, validation.

1. Introduction

Motor vehicles are a major source of air pollution and greenhouse gas emissions in urban areas around the world. The close proximity of motor vehicles to the general population makes this a particularly relevant source from an exposure and health perspective. This is illustrated by Caiazzo et al. (2013) who estimated that total combustion emissions in the U.S. account for about 210,000 premature deaths per year (particulates, ozone), with motor vehicles being the largest contributor, causing about 58,000 early deaths per year.

2. Model validation

There are several methods used to (partially) validate vehicle emission models, such as on-board emission measurements (PEMS), remote sensing, near-road air quality measurements and tunnel studies. Tunnel studies have been extensively used around the world to compare model predictions with observed values. In these studies, emission factors, expressed as grams of pollutant per vehicle kilometre (g/veh.km), are determined using the differences between the concentration levels at the tunnel entrance and exit, combined with tunnel features (e.g. road length), traffic flow and traffic conditions, as well as either measured tunnel air flow or a dilution factor based on a tracer gas (e.g. SF_6). Regression analysis is often used to develop mean emission factors (g/veh.km) by time of day for basic vehicle classes (e.g. LDV, HDV).

Tunnel validation studies have specific strengths and weaknesses. A strength is that emissions are derived from a large sample of the on-road fleet, thereby adequately capturing inter-vehicle variability in emissions, including ‘high emitters’.

Moreover, measurements are carried out under relatively controlled conditions. For instance, the air dilution conditions are better known in tunnels than in open road experiments, and the influence of meteorological parameters such as wind speed and wind direction is usually negligible.

Also, the spatial resolution aligns better with distance-based emission factors (g/km) commonly used in vehicle emission models, as compared with localised validation methods such as remote sensing and near-road air quality measurements.

However, there are also some challenges with tunnel studies. They rely on indirect measurements rather than direct exhaust measurements, and this can introduce errors. They also represent only a limited range of operating conditions (typically ‘smooth’, uncongested, high-speed driving). As a consequence, validation results cannot be directly translated to e.g. lower speed urban driving conditions. Tunnels may also have significant uphill and downhill gradients, affecting emissions. The so-called ‘piston effect’, which occurs with one-way traffic flow, and any forced ventilation in the direction of the traffic flow combine to produce an effective tail wind that reduces aerodynamic drag on the vehicles in the tunnel.

Furthermore, assumptions relating to the unknown proportion of vehicles in cold-start mode and actual vehicle loads, etc. are required to make a comparison with model predictions. For particulate matter, an additional problem originates from the contribution of both exhaust and non-exhaust sources to total concentrations (due to tyre and brake wear and particle re-suspension, possibly even direct dust emissions from e.g. gravel trucks).

Nevertheless, tunnel studies provide a useful approach to (partially) validate vehicle emission models for specific traffic situations (high speed free-flow drive conditions).

3. Tunnel measurements

Brisbane's Clem Jones Tunnel (CLEM7) is one of the largest infrastructure projects completed in Queensland. It has 6.8 km of tollway and 4.8 km of twin 2-lane tunnels (or tubes) linking major Brisbane roads, with a cross-sectional area of about 60 m^2.

Air monitoring equipment was installed in the north tunnel ventilation stack on 25 August 2014. Air monitoring data (5 minute average) was collected by DSITI in the north tunnel ventilation stack for over a week for a number of key air pollutants (CO, NO, NO_2, NO_x, $PM_{2.5}$, PM_{10}, speciated VOCs and PAHs), as well as variables quantifying conditions in the tunnel vent (temperature, relative humidity, atmospheric pressure).

The pollutant monitoring data was checked by pre- and post-test calibration, because daily calibration for zero and span values could not be carried out during the test period. Examination of five minute data was performed to check the quality and validity of the raw concentration measurements, before hourly averaged values were computed.

Fleet-averaged (composite) emission factors (g/km) were computed using hourly measurements of time-aligned and background-corrected concentrations, tunnel air flow and estimation of hourly travel in the tunnel, which is quantified with a variable called 'vehicle kilometres travelled' (VKT). Hourly VKT was computed by multiplication of total traffic volume (veh/h) derived from classified traffic counts and tolling statistics by total distance (km).

The CLEM7 tunnel uses camera imaging technology to collect relevant vehicle information, which includes date and time stamped license plate numbers (LPNs). The LPN data were cross-referenced with vehicle registration information from the Queensland Department of Transport and Main Roads (DTMR), and each vehicle was assigned a corresponding COPERT Australia vehicle class. About 13% of LPN could not be matched with Queensland vehicle registration data, reflecting unidentified LPNs and interstate and unregistered vehicles. As a consequence, the distribution of vehicles over the 226 COPERT vehicle classes was effectively based on a fleet sample covering 87% of vehicles going through the tunnel during the measurement period. So there is some residual uncertainty in the in-tunnel fleet mix, but the analysis should provide a reasonable estimate of the vehicle break down for each hour.

4. A specific issue: high emitters

It has long been known that fleet emissions are dominated by a small percentage of high emitters, and that the impact of high emitters is increasing. For instance Zhang et al. (1995) found that about 10% of the vehicles in Melbourne were responsible for half or more of the total CO and HC exhaust emissions, and similar findings have been reported around the world. Emission factor data from recent remote sensing studies (Park et al., 2011) show that the skewness of emission distributions for CO, HC and NO_x has increased over the last decade due to high emitting vehicles, whereas fleet-average emissions have decreased considerably.

Bishop et al. (2012) reported that 1% of on-road vehicles in the USA contributed about 10% to total vehicle emissions in the late 1980s, and that this contribution of 1% of on-road vehicles now has increased to about 30%. These researchers noted that finding, repairing, and/or scrapping only the highest-emitting 2% of the fleet would eliminate half of the exhaust hydrocarbon emissions.

Similar findings have been reported for the Australian fleet. NIWA (2008) performed remote sensing measurements in Brisbane, Perth and Sydney on about 53,000 vehicles and the results show that 10% of the most polluting vehicles are responsible for approximately 70%, 60% and 50% of total CO, HC and NO emissions, respectively.

So total fleet emissions are becoming increasingly sensitive to a small number of high emitting vehicles. In line with international studies, the CLEM7 measurements exhibit quite scattered emissions data, as will be shown later. This is at least in part due to hourly variations in the fleet mix (fuel type, engine and emission control technology, etc.).

It also suggests that the distributions of emissions from vehicles in the tunnel are highly skewed. This skewness arises when the majority of the vehicles have low emissions, but some vehicles exhibit (very) high emission levels and have a disproportionate impact on total vehicle emissions. These vehicles are commonly referred to as 'high emitters'. Studies have shown that vehicle emissions of these vehicles can be e.g. 50 times higher, respectively, than a properly functioning catalyst car (e.g. Sjödin et al., 1997), and improper maintenance (and tampering) has been indicated as the principal reason for the skewness of vehicle emission distributions.

This vehicle emissions behaviour reflects two main trends 1) the penetration of cleaner vehicles into the fleet over time due to increasingly strict emission standards and improved control technologies, and 2) the presence of vehicles that are badly tuned or have been tampered with, have engine issues and/or have malfunctioning or partly functioning emission control systems (catalysts, lambda sensors, faulty fuel caps, fuel injector malfunction, worn turbochargers, clogged air filters etc.).

It is noted that there are some differences for trucks and cars, where e.g. truck NO_x emissions are substantially higher than cars but more normally distributed. For instance, Jiménez et al. (2000) performed remote sensing measurements and concluded that the ratio of maximum to minimum NO_x emissions is 7 for trucks and 750 for cars, reflecting both the impacts of improved vehicle engine and emission technology and high emitters.

Interestingly, under-representation of emissions from high emitters in the US MOBILE emission factor model was considered to be one of the chief reasons for MOBILE under-predicting real-world fleet emissions (NRC, 2000).

So it is important to include these valid outliers in the determination of composite emission factors from the in-tunnel measurements. However, this can pose specific issues in the model fitting process that need to be addressed, as will be discussed in the next section.

5. Method

A composite emission factor (e, g/VKT) is computed when total tunnel emissions (g/h) are divided by total travel (VKT/h) for each hour of measurement. These normalised hourly emissions can then be plotted against the percentage of heavy-duty vehicles (P_{HDV}) and a simple linear regression model can be fitted:

$$e = \alpha + \beta P_{HDV} + \varepsilon \quad (1)$$

In this model, a and b are fitted regression coefficients (intercept and slope, respectively) and ε is the error term. This model is useful as it can be used to estimate the mean emission factors (including 95% confidence intervals) for light-duty vehicles (LDV) and heavy-duty vehicles (HDV) by setting P_{HDV} to zero and 100%, respectively.

As a first step, hours with reduced average speeds less than 75 km/h (due to e.g. maintenance) were removed to ensure homogeneous and comparable traffic conditions. In addition, data points with less than 1 vehicle per minute were removed. This is important because hourly data with a small number of vehicles can be significantly influenced by errors in urban background concentrations, in particular for pollutants with relatively high background levels such as PM.

It has been assumed that the occurrence of high emitters in a particular hour will significantly affect the average emission factor (g/km) and will show up as outliers in the emissions data.

So a two-step approach was employed in the regression analysis. First a robust weighted linear modelling (RWLM) approach was used to identify outliers in the hourly emissions data for each pollutant. This regression is weighted with the total VKT for each hour and thus accounts for the higher accuracy of data points with more vehicles.

Any hourly emission values that exceed the median value plus three times the standard deviation are tagged as outliers. These values are shown with red '+' symbols in Figure 1, which shows an example for CO.

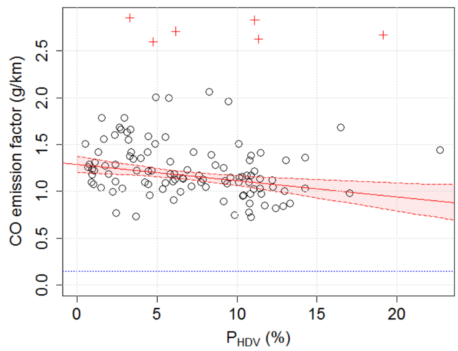

Figure 1. Measured CO fleet-averaged emission factors, fitted model including 95% prediction interval and outliers (red +).

RWLM is not sensitive to outliers, which is useful for the outlier detection method discussed before, but at the same time does not properly reflect high hourly emissions in the model.

So, as the second step, a weighted ordinary least squares (OLS) linear regression was performed on the hourly emissions data without outliers to compute the regression coefficients and their standard errors. This regression is again weighted with total VKT for each hour. The final regression model is defined as:

$$e = \varphi + \alpha + \beta P_{HDV} + \varepsilon \quad (2a)$$

$$\varphi = \overline{e_h} \times P_h \quad (2b)$$

The 'high emitter' emission offset φ is computed as the mean of the hourly emission values that were tagged as outliers (e_h) multiplied with the proportion of outliers in the data. It is thus assumed that 1) high emitters form a low portion of the fleet and occur randomly in time (see below), 2) they significantly impact on normalised emissions (g/km) when they are in the tunnel, and 3) they are not significantly affected by the proportion of HDVs.

For the CLEM7 data the number of hours with outliers (significant 'high emitter impacts') was 5% for CO and 2% for NO_x, NO_2 and $PM_{2.5}$. This percentage is in line with overseas reports. For instance, Choo et al. (2007) analysed 837,829 I/M test results in California and found that approximately 4.6% of all vehicles are labelled as 'gross polluters'.

Residual analysis (Hair et al., 1998) was performed to verify that the assumptions of regression analysis were not violated (e.g. homoscedasticity and normality of error terms).

6. Results

Validation results are shown here for three pollutants, i.e. CO, NO_x and $PM_{2.5}$.

6.1. CO emission factor validation

Figure 2 shows the results for CO.

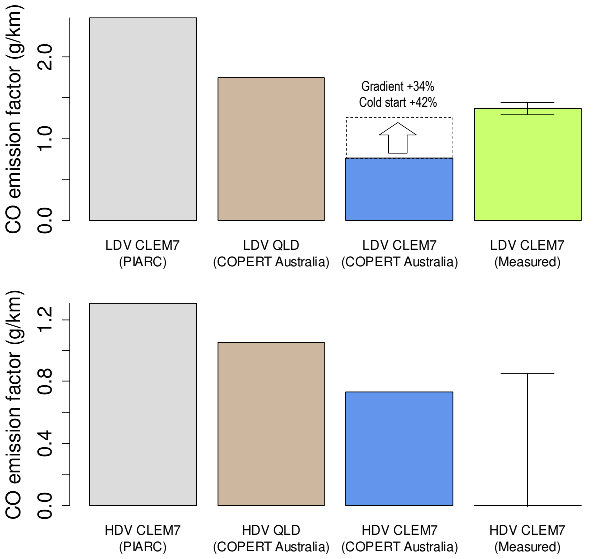

Figure 2. Fleet-averaged CO emission factors for LDVs and HDVs including 95% confidence intervals and comparison with COPERT Australia/PIARC.

Composite hot running emission factors computed with COPERT Australia are shown for both the average Queensland fleet ('QLD') and for the tunnel fleet mix ('CLEM7'). The computed PIARC CO emission factor is based on the actual fleet mix in the tunnel and includes the impacts of road gradient. PIARC does not estimate the impacts of piston flow on emissions.

The regression model predicts a composite LDV CO emission factor of 1.4 g/km (±6%). The PIARC CO emission factor for LDVs is 81% higher than the value measured in the tunnel, and this difference is statistically significant ($p < 0.05$).

COPERT Australia predicts an average LDV emission factor of 1.8 g/km for the Queensland fleet, but a substantially lower value of 0.8 g/km for the actual fleet mix in the CLEM7 tunnel. This shows the large impact of variation in local fleet mix on vehicle CO emissions.

The LDV COPERT Australia emission factor for CO at high speed driving conditions is 44% lower than the value measured in the tunnel. This difference is statistically significant ($p < 0.05$).

A possible reason for the underestimation of CO emissions in COPERT could be additional emissions due to cold starts and road gradient. These are not reflected in the COPERT Australia (hot running) emission estimates for the CLEM7 tunnel, but both have a substantial impact on CO emission levels. The PIARC method for the CLEM7 tunnel suggests an increase in the CO LDV emission factor of 34% due to road gradient effects. Similarly, Cold starts contribute, on average, 42% to total CO emissions for the Queensland fleet (UQ, 2014). These factors reduce the prediction error substantially, as shown in Figure 2, but it is likely that other factors such as high emitting vehicles in the on-road fleet also play a role.

Setting P_{HDV} to 100%, a negative composite HDV emission factor of –0.1 g/km is estimated for CO with the tunnel model, with a 95% confidence interval of -1.0 to +0.8 g/km. This large uncertainty in the predicted values is expected, given the low percentage of HDVs in the on-road fleet causing large extrapolation effects. The COPERT Australia CO emission factor for HDVs is 0.7 g/km and falls inside the 95% confidence interval, and the difference is therefore not statistically significant ($p < 0.05$)[1].

The computed PIARC CO emission factor for HDVs is about 80% higher than the COPERT Australia value, and significantly different ($p < 0.05$) from the tunnel value.

6.2. NO_x emission factor validation

Figure 3 shows the results for NO_x. The regression model based on tunnel measurements predicts a composite LDV NO_x emission factor of 0.5 g/km (±7%). The computed PIARC NOx emission factor for LDVs is similar (3% lower) and this difference is not statistically significant ($p > 0.05$).

COPERT Australia predicts an average LDV NOx emission factor of 0.7 g/km for the Queensland fleet, but a substantially lower value of 0.3 g/km for

[1] Cold start effects on the CO HDV emissions are expected to be insignificant. The PIARC method for the CLEM7 tunnel suggests an increase in the CO HDV emission factor of 6% due to road gradient effects.

the actual fleet mix in the tunnel. These values have been corrected for the impacts of road gradient and piston air flow in the tunnel using the PΔP software (see Smit and Kingston, 2015 for a detailed description).

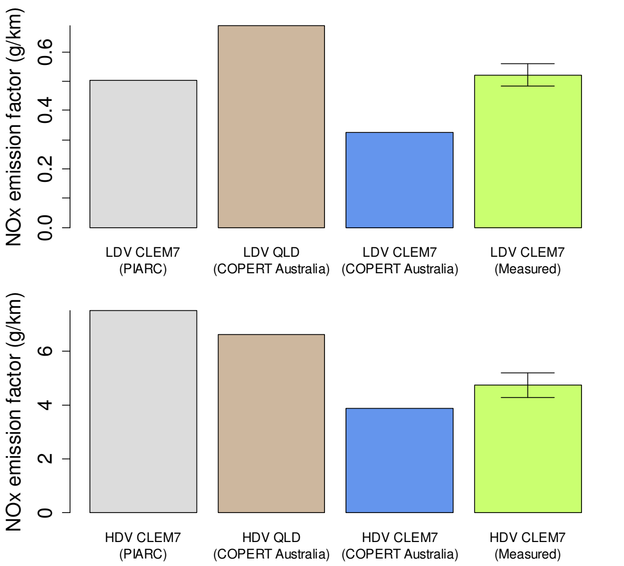

Figure 3. Fleet-averaged NO_x emission factors for LDVs and HDVs including 95% confidence intervals and comparison with COPERT Australia/PIARC.

The corrected LDV COPERT Australia NO_x emission factor is 38% lower than the value measured in the tunnel and this difference is statistically significant ($p < 0.05$). This may reflect to some extent cold start and humidity effects, and a higher-than-expected proportion of (diesel) vehicles with maintenance issues. The last point is of interest as there is a lack of high quality empirical vehicle emissions test data for Australian light-duty diesel vehicles in particular. This is in contrast to light-duty petrol vehicles for which extensive emission test programs have been carried out in Australia. As a consequence, European emission algorithms for diesel cars were directly used in COPERT Australia, and it is the only vehicle type that does not reflect Australian vehicle emission measurements.

The tunnel measurements produce a composite HDV NO_x emission factor of 5.2 g/km (±10%). The computed PIARC NO_x emission factor for HDVs is almost 60% higher and this difference is statistically significant ($p < 0.05$).

COPERT Australia predicts an average HDV NO_x emission factor of 6.6 g/km for the Queensland fleet, but a substantially lower value of 3.9 g/km for the actual fleet mix in the CLEM7 tunnel. These values have been corrected for the impacts of road gradient and piston air flow in the tunnel using the PΔP software. The corrected HDV COPERT Australia NO_x emission factor is 18% lower than the value measured in the tunnel, and the difference is statistically significant ($p < 0.05$). This may reflect heavy-duty diesel vehicles with e.g. maintenance issues and elevated NO_x emissions that are not yet fully reflected in the software.

6.3. $PM_{2.5}$ emission factor validation

Figure 4 shows the results for $PM_{2.5}$. The tunnel measurements produce a composite LDV $PM_{2.5}$ emission factor of 15 mg/km (±14%). PIARC does not provide $PM_{2.5}$ emission factors. COPERT Australia predicts an average LDV emission factor of 31 mg/km for the Queensland fleet, but a substantially lower value of 15 mg/km for the actual fleet mix in the CLEM7 tunnel, which is similar to the value measured in the tunnel.

The regression model predicts a composite HDV $PM_{2.5}$ emission factor of 137 mg/km (±19%). The COPERT Australia $PM_{2.5}$ emission factor for HDVs is 118 mg/km and 14% lower than the measured value. It falls within the 95% confidence interval, so this difference is not statistically significant ($p < 0.05$).

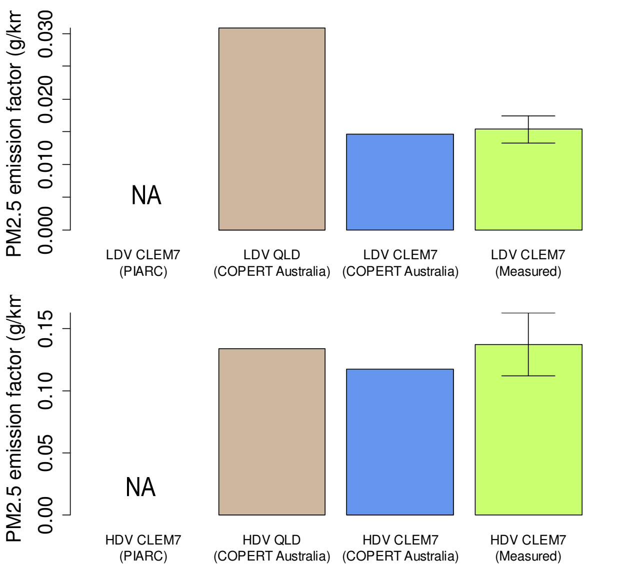

Figure 4. Fleet-averaged $PM_{2.5}$ emission factors for LDVs and HDVs including 95% confidence intervals and comparison with COPERT Australia.

There are a number of factors that complicate the comparison of COPERT $PM_{2.5}$ emission factors with results derived from the tunnel study. Firstly, background concentration levels are relatively high for PM and errors in background concentration data can significantly impact on results. There are also significant differences between the empirical base for the COPERT software and the tunnel results. Whereas laboratory emission measurements are conducted under strictly defined and controlled conditions, the tunnel PM samples measure particles that have aged (typically 8 minutes after emission from exhaust pipe) and have undergone several processes such as nucleation, coalescence and condensation that may significantly affect PM mass concentrations. Finally, tunnels are uncontrolled with respect to impacts of non-exhaust particulate matter emissions, and could be significantly influenced by e.g. trucks carrying dusty loads. Estimates of non-exhaust emissions are included in COPERT, but are uncertain. Given these considerations, the validation results for PM show a remarkably good performance of COPERT Australia.

7. Discussion and conclusions

The following conclusions are derived from the validation work for driving at about 70 km/h in tunnel conditions (road grade, piston effect):

- PIARC emission factors generally show the largest prediction errors, except for one very good agreement for LDV NO_x.
- Composite emission factors in COPERT Australia are not significantly different ($p < 0.05$) from those measured in the tunnel in 3 out of 6 cases.
- COPERT Australia emission factors for NO_x (HDV only), and $PM_{2.5}$ (all vehicles) have prediction errors within ±25%.
- COPERT Australia LDV emission factors for CO and NO_x are larger, and these emissions are substantially underestimated by about 40%.

The validation results appear to be good. For instance, a review of 50 international vehicle emission model validation studies showed that reported model prediction errors are generally within a factor of 2 for NO_x and within a factor of 3 for CO and PM, although differences as high as a factor of 5 have been reported (Smit et al., 2010) .

COPERT Australia generally performs significantly better than PIARC and has the added benefit of being capable of estimating emissions for a large range of pollutants, whereas PIARC provides estimates for CO and NO_x only. COPERT Australia emission factors based on the average Queensland fleet generally provide conservative emission factors for tunnel conditions so it is recommended that these values are used for tunnel air quality assessments when tunnel emission measurements are not available.

Acknowledgments

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