A Brisbane tunnel study to assess the accuracy of Australian motor vehicle emission models and examine the main factors affecting prediction errors

R. Smit, P. Kingston, R., Tooker , D. Neale, S. Torr, R. Harper, E. O'Brien, D. Harvest, D. Wainwright

ABSTRACT

Statistical analysis has been applied to vehicle emissions data collected in a recent Brisbane tunnel study with the aim being to validate newly developed Australian vehicle emission models and examine which factors are the main contributors to prediction errors.

The results suggest that the COPERT Australia vehicle emission model is generally accurate at the fleet level, when compared with similar international studies, but under-estimates emissions by 2 to 36%, depending on the pollutant. These findings apply only to the specific measurement conditions in the tunnel (high speed, free-flow).

Regression analysis revealed that light and heavy diesel vehicles are consistently and strongly associated with prediction errors across all pollutants. Whereas fleet level prediction of PM emissions by COPERT is good, a substantial under-prediction of PM emissions from diesel trucks is suggested by the statistical analysis. For NOx, the analysis suggests that modern large petrol passenger vehicles (e.g. SUVs) play an important role in the under-estimation of emissions.

This indicates that further targeted emissions testing for these vehicles using e.g. PEMS would benefit vehicle emission modelling practice and air quality assessments in Australia. Other tunnel datasets in other cities, preferably of longer duration than a week, could be analysed in a similar fashion to see if these results are confirmed.

Keywords: Vehicle emissions, tunnel, validation, traffic impact

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 (particulates, ozone) in the U.S. account for about 210,000 premature deaths per year, with motor vehicles being the largest contributor, contributing to around 58,000 premature deaths per year.

Comprehensive measurement of transport emissions in urban networks is cost prohibitive due to the large number of vehicles that operate on our roads with substantially different emission profiles, large spatial and temporal variability in vehicle activity and many real-world factors that influence emission levels.

Modelling tools are therefore commonly used to estimate fuel consumption and emissions. Models are also required to make projections into the future. Vehicle emission prediction software is well-established in Europe and the US. However, these models do not adequately represent Australian conditions in terms of fleet mix, vehicle technology, fuel quality and climate. Large errors of up to a factor of 20 have been reported when overseas models are directly applied to Australian conditions without calibration (Smit and McBroom 2009). Therefore two software packages were recently developed for Australian conditions using comprehensive empirical data from major Australian laboratory emission testing programs. COPERT Australia[1] has been developed to estimate motor vehicle emissions at a regional and national level (UQ 2014), while a power based model (PΔP) was developed for more localised assessments (Smit 2014).

As models are simplifications of reality, their limitations and accuracy should be clearly established. This paper will present results from a recent tunnel emissions study that was conducted in Brisbane. Statistical analysis has been employed with the aim to address two research questions:

1. How accurate are the newly developed Australian vehicle emission models (model validation)?
2. What factors are the main contributors to the prediction errors?

TUNNEL STUDIES

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 and they 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 measurements, 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, which 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, for example, to commonly occurring urban driving conditions at lower speeds. Tunnels may also have significant uphill and downhill gradients, affecting emissions. The same applies to 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 and affects vehicle emissions.

Furthermore, assumptions relating to the unknown proportion of vehicles in cold-start mode and actual vehicle loads 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[2] to total concentrations. Nevertheless, tunnel studies provide a useful approach to (partially) validate vehicle emission models for specific traffic situations (high speed free-flow drive conditions).

TUNNEL MEASUREMENTS

Brisbane's Clem Jones Tunnel (CLEM7) has 4.8 km of twin 2-lane tunnels, with a cross sectional area of about 60 m^2, linking major Brisbane roads. Air monitoring equipment was installed in the north tunnel ventilation vent on 25 August 2014 (DSITI, 2015), as is shown in Figure 1.

Air monitoring data (five minute average) was collected by the Department of Science, Information Technology and Innovation (DSITI) in the vent for over a week for a number of key air pollutants (CO, NO, NO_2, NO_x, PM2.5, PM10, speciated VOCs and PAHs), as well as variables quantifying

Figure 1. Installing measurement equipment in the CLEM7 Northbound tunnel vent.

conditions in the tunnel vent (temperature, relative humidity, atmospheric pressure).

Nitrogen oxides (NO, NO_2, NO_x) were measured using a light emission (chemiluminescent) analyser (Teledyne API200). Carbon monoxide (CO) was measured with an infrared absorption instrument utilising the gas filter correlation technique (Teledyne API300). Particle concentrations were measured with a Thermo Scientific 1405-DF TEOM Continuous Dichotomous Ambient Air Monitor to simultaneously measure PM2.5 and PM10 particles. VOCs and PAHs were sampled with canisters and analysed using gas chromatography-mass spectrometry (GC/MS).

The pollutant monitoring data was checked by pre- and post-test calibration, as daily calibration for zero and span values could not be carried out during the test period. Particulate matter monitoring data collected with the TEOM instrument were verified according to Australian Standard AS/NZS 3580.9.13:2013. Examination of five-minute data was performed to check the quality and validity of the raw concentration measurements, before hourly averaged values were computed. A switched-flow mode NO_x analyser can generate aliasing and time alignment errors in raw NO_2 measurements in environments with rapidly changing concentration levels (CSIRO 2011). The occurrence of these errors was verified and corrected (0.4% of the 5-minute data; DSITI 2015).

Tunnel emissions were computed by multiplying hourly measurements of time-aligned and background-corrected concentrations by tunnel air flow data (m^3/h). Ambient concentration data from nearby stations were used as an estimate of concentrations at the tunnel entrance point (DSITI 2015). Hourly vehicle travel in the tunnel is quantified with a variable called 'vehicle kilometres travelled' (VKT). Hourly VKT were computed by multiplying total traffic volume (veh/h) derived from classified traffic counts and tolling statistics with total distance (km) (DSITI 2015).

IN-TUNNEL FLEET MIX

The CLEM7 tunnel uses camera imaging technology to collect relevant vehicle information, including 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 individual vehicles were allocated to one of the 226 vehicle classes used in COPERT Australia. About 13% of LPN could not be matched with Queensland vehicle registration data, reflecting unidentified license plates and the portion of interstate and unregistered vehicles. So there is some residual uncertainty in the hourly in-tunnel fleet mix. The computed fleet mix is effectively based on a sample of the in-tunnel situation.

A comparison between the average Queensland fleet[3] (UQ 2014) and the in-tunnel fleet based on analysis of license plate numbers shows that there are significant differences. First, the proportion of diesel vehicles (both light-duty vehicles or LDVs and heavy-duty vehicles or HDVs) is substantially higher in the tunnel (30% versus 18% in the Queensland fleet), and the proportion of petrol and LPG vehicles is subsequently lower. Second, the tunnel has a lower proportion of small and large passenger cars, but a higher proportion of SUVs, as compared with the Queensland average fleet.

Finally, the vehicle fleet in the tunnel is substantially younger with better engine and emission control technology, as compared with the average 2010 Queensland fleet. This is partly explained with the difference in base year, but also expected to reflect a tendency for newer vehicles to use tolled tunnels. This is illustrated in Figure 2, which shows the diesel HDV 'technology class' distribution or ADR standard (Australian Design Rule).

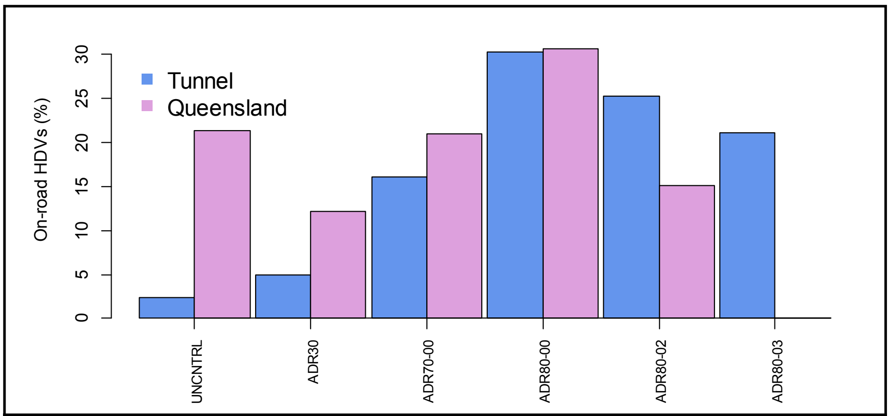


Figure 2. HDV fleet distribution over vehicle technology classes in the tunnel (base year 2014) and the average Queensland fleet (base year 2010), reflecting increasingly stringent emission standards from left to right, UNCNRTL = uncontrolled, ADR = Australian Design Rule.

MODEL PREDICTION ERRORS

Figure 3 shows hourly emission predictions and observations in goodness-of-fit plots for each pollutant. A dot point represents one hourly value. The grey dashed 45° lines indicate a perfect fit without bias. Any dot points on this line show model predictions that are equivalent to observations. If a point lies below the 45° line, the model under-predicts, and if is lies above the 45° line, the model over-predicts. A linear ordinary least-squares (OLS) regression model was fitted to these data:

$$P = \beta O + \varepsilon \qquad \textbf{Equation 1}$$

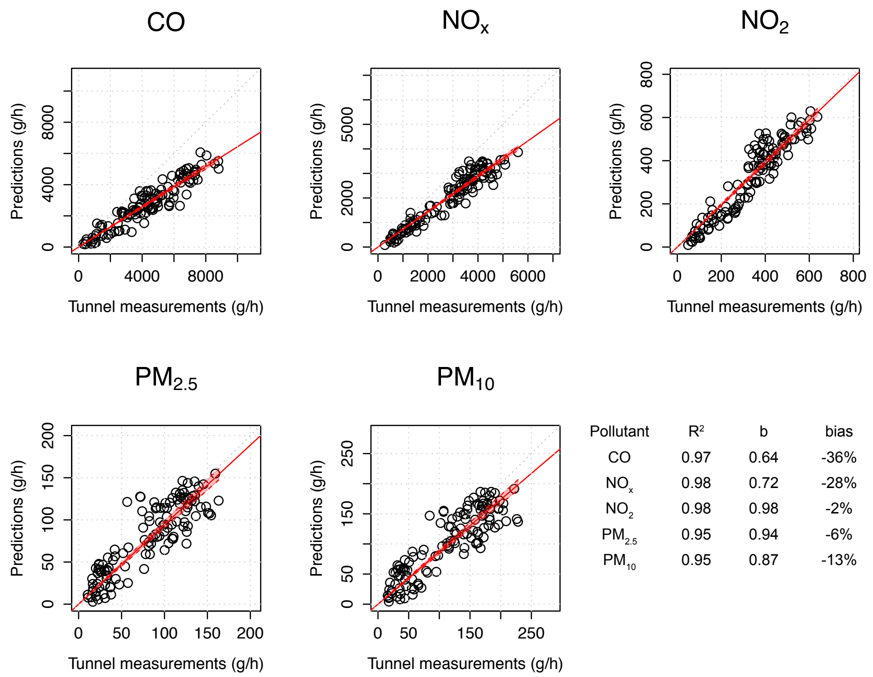
In this model, P represents the vector of hourly predictions, O the vector of hourly observations, β is the vector of regression coefficients (β_0, β_1) and ε is the vector of error terms. This model is useful as the slope (β_1) can be used to estimate the systematic error or bias in COPERT predictions in relation to the measured tunnel emissions. The coefficient of determination (R^2), estimated slope (b_1) and bias are included in Figure 3.

The regression model indicates that the prediction software generally under-estimates emissions by 2 to 36%, depending on the pollutant. These validation results appear to be relatively 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).

A plausible factor for this consistent underestimation may be (in part) an incomplete representation in the COPERT Australia emission factors of vehicles with high or even excessive emissions ('high emitters'). Vehicle ageing has a significant and unavoidable effect (increase) on vehicle emissions, and this is aggravated by poor maintenance and tampering. Although COPERT Australia simulates the effects of ageing with generic mileage correction algorithms, they are based on limited overseas data. In fact, recent research indicates that these correction algorithms underestimate ageing effects on emissions substantially and thus require further improvement (Borken-Kleefeld and Chen 2015). The lack of maintenance and repair programs in Australia is expected to make this modelling issue even more important.

FACTORS DRIVING PREDICTION ERRORS

Vehicle classes will have different impacts on prediction errors, varying with the pollutant that is considered. For instance, it is possible that errors in CO emission predictions are mainly caused by inaccuracies in petrol car emission factors, whereas CO emission factors for diesel vehicles are, in fact, quite accurate. This type of information is highly relevant for further improvement of prediction software because it facilitates more cost-effective and focussed vehicle emission measurement programs that



Pollutant	R^2	b	bias
CO	0.97	0.64	-36%
NO_x	0.98	0.72	-28%
NO_2	0.98	0.98	-2%
$PM_{2.5}$	0.95	0.94	-6%
PM_{10}	0.95	0.87	-13%

Figure 3. Hourly COPERT Australia predictions versus measured tunnel emissions by pollutant including validation statistics table (grey dotted line = 45° line, red line = linear regression line, red shading = 95% confidence intervals)

target specific vehicle classes, which show substantial discrepancies between observed and predicted emission factors.

An attempt was therefore made to use two different statistical methods to determine the vehicle classes that are largely responsible for prediction errors using the hourly tunnel data and the known fleet mix for each hour.

Hours with reduced average speeds less than 75 km/h (*e.g.* due to tunnel maintenance) were removed to ensure homogeneous and comparable traffic conditions. Hourly data with less than one vehicle going through the tunnel per minute were also 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 particles (PM).

Method 1 – Composite LDV and HDV emission factors

The first method examines two basic vehicle classes, *i.e.* LDVs (cars, light-commercial vehicles, motorcycles) and HDVs (trucks, buses). A composite emission factor (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 linear regression model is fitted (Smit and Kingston 2015a; 2015b):

$$e = \varphi + \beta PHDV + \varepsilon \qquad \textbf{Equation 2}$$

In this model, e is a vector of hourly composite emission factors (g/VKT), φ is a constant high-emitter offset value (g/VKT), β is a vector of regression coefficients (intercept β_0 and slope β_1), P_{HDV} is the vector of hourly HDV percentages, and ε is the vector of independent and normally distributed random error terms. This model is useful as it can be used to estimate the mean emission factors (including 95% confidence intervals) for LDVs and HDVs by setting P_{HDV} to zero and 100%, respectively. To illustrate this, Figure 4 shows the results for NO_2.

The regression model based on tunnel measurements predicts a composite LDV NO_2 emission factor of 72 mg/km (±9%). COPERT Australia predicts an average LDV NO_2 emission factor of 89 mg/km for the Queensland fleet, which reflects the vehicle distribution differences discussed earlier, and a substantially lower value of 63 mg/km for the actual fleet mix in the tunnel. This value is 13% lower than the value measured in the tunnel and this difference is statistically significant ($p < 0.05$).

The tunnel measurements produce a composite HDV NO_2 emission factor of 428 mg/km (±18%). COPERT Australia predicts an average HDV NO_2 emission factor of 777 mg/km for the Queensland fleet, but a substantially lower value of 436 mg/km for the actual fleet mix in the CLEM7 tunnel, which is similar to the measured value (2% error). These results indicate that prediction errors for NO_2 are small overall, and largest for LDVs.

Figure 5 shows the results for PM10.

The regression model based on tunnel measurements predicts a composite LDV PM10 emission factor of 21 mg/km (±14%). COPERT Australia predicts an average LDV PM10 emission factor of 37 mg/km for the Queensland fleet, and a substantially lower value of 20 mg/km for the actual fleet mixes in the tunnel. This value is 4% lower than the value measured in the tunnel, but this difference is not statistically significant ($p > 0.05$).

The tunnel measurements produce a composite HDV PM10 emission factor of 210

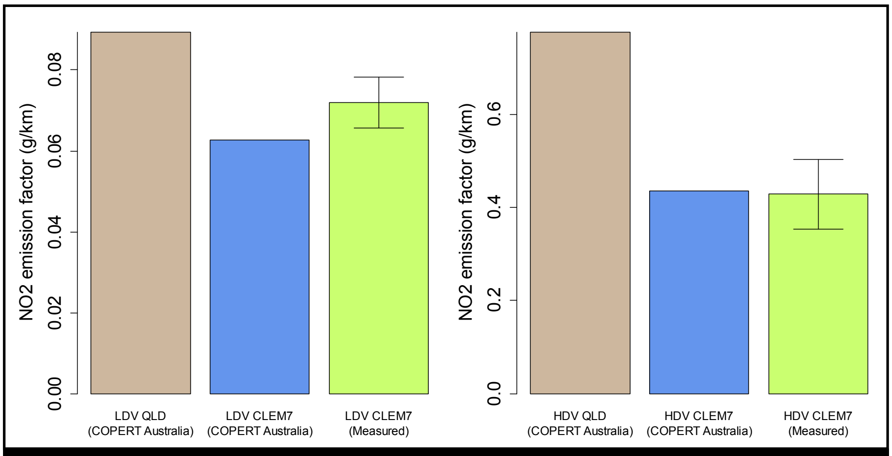


Figure 4. Composite NO_2 emission factors for LDVs and HDVs including 95% confidence intervals and comparison with COPERT Australia.

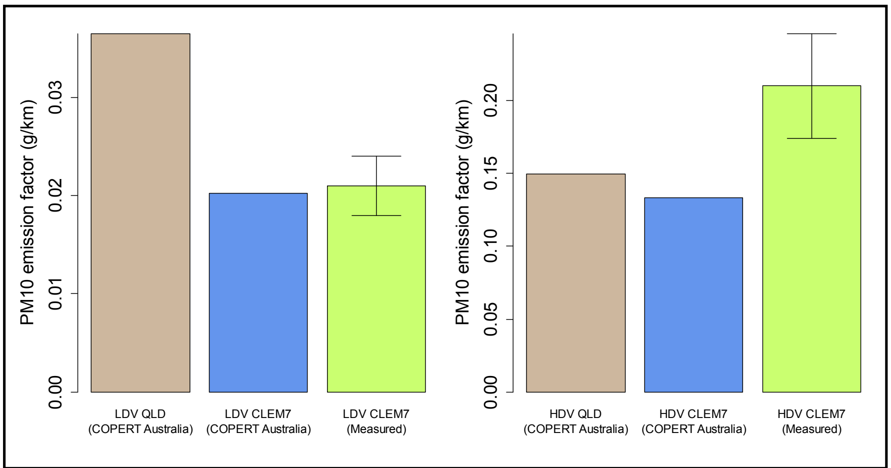


Figure 5. Composite PM10 emission factors for LDVs and HDVs including 95% confidence intervals and comparison with COPERT Australia.

mg/km (±17%). COPERT Australia predicts an average HDV PM10 emission factor of 150 mg/km for the Queensland fleet, and a lower value of 130 mg/km for the actual fleet mixes in the tunnel, which is 37% lower than the measured value. The difference is statistically significant ($p < 0.05$). These results indicate that overall prediction errors for PM10 are small, but significant for HDVs (under-estimation).

Smit and Kingston (2015b) presented similar results for CO, NO_x and PM2.5, which are summarised here:

- Prediction errors for CO are significant overall, and likely caused by under-estimation of composite emission factors for LDVs. However, prediction errors are significantly reduced when the impacts of road gradient and cold starts are included in the composite emission factors.
- Prediction errors for NO_x are significant overall, and caused by under-estimation of composite emission factors for both HDVs and LDVs, but for LDVs in particular.
- Prediction errors for PM2.5 are not significant overall, and the composite emission factors for neither LDVs nor HDVs differ significantly from measured values.

Method 2 – Multiple regression analysis of prediction errors

The second method uses a more detailed vehicle classification and includes other variables. To assess the nature, magnitude and significance of the effect of different vehicle classes and other variables on the observed emission prediction errors, a multiple regression model is defined:

$$E = \beta X + \varepsilon \qquad \textbf{Equation 3}$$

In this model, E represents the vector of predictions errors, which is computed as P/O, β is the vector of regression coefficients, X is a matrix of predictor variable observations and ε is the vector of independent and normally distributed random error terms. Vector columns in X include:

- the percentage of a particular vehicle class in the fleet for each hour of measurement:
  - o (petrol) motorcycles (MCY)
  - o light-duty petrol vehicles (LDP)
  - o light-duty diesel vehicles (LDD)
  - o heavy-duty diesel vehicles (HDD)
  - o diesel buses (BUS)
  - o gaseous fuel vehicles (LPG)
- the ratio of the background concentration to measured tunnel vent concentration (B, -)
- three meteorological variables:
  - o ambient temperature (T, °C)
  - o relative humidity (H, %)
  - o atmospheric pressure (P, atm.)

Automated stepwise variable selection was used to select the set of model variables that best correspond with hourly prediction errors for each pollutant (Venables and Ripley 2002). The Akaike Information Criteria (AIC) was used to automatically select the best model. AIC is a commonly used statistic that measures the relative goodness-of-fit of different models, which is then used to rank the models against each other. 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).

One issue with this approach is that a subset of the predictor variables, *i.e.* the proportions of a particular vehicle class, is correlated among themselves. If a particular vehicle class increases, others necessarily have to decrease as the sum of all proportions adds up to 100%. Serious multicollinearity among the predictor variables can result in instability and uncertainty in the estimated regression coefficients.

A formal and widely used method of detecting the presence of multicollinearity is computation of variance inflation factors (VIFs). These factors quantify how much of the variation in a particular predictor variable can be explained by the other regressor variables. VIFs were calculated for selected model variables to check for multicollinearity issues[4]. The modelling results are shown below in Table 1. It shows overall model significance and performance (R^2), as well as VIFs. The statistically significant model variables are also presented, including model regression coefficients and p-values.

Although the models are all statistically significant ($p < 0.05$), they explain a small to modest proportion of the variability in the data (14–31%). Various factors potentially contribute to the scatter in the tunnel emission measurements and variation in prediction errors that are not accounted for in the model:

- Uncertainty in measured background concentrations.
- Uncertainty in estimated hourly VKT.
- Uncertainty in the vehicle classification with about 13% unidentified license plates.
- Uncertainty in assumptions about cold-start proportions and vehicle loads.
- Smoothing of emissions and dynamic time delay in the tunnel.

Nevertheless the method presented here is useful in identifying which vehicle classes associate strongly with prediction errors. It is clear that light and heavy diesel vehicles feature prominently in the table, which indicates that further emissions testing for these vehicles would benefit vehicle emission modelling practice in Australia.

The impact of a particular model variable is quantified using the multiple regression algorithms presented in Table 1. This is done in three steps for each pollutant individually:

- Step 1) Compute the mean prediction

error and identify the hour in the design matrix that is closest to this value. This particular hour is defined as the 'base case' and it quantifies a particular combination of 'typical' tunnel conditions in terms of proportions of each vehicle class, meteorological conditions and background concentrations.[5] The regression model is then used to compute the prediction error E_{base} for the selected hour

- Step 2) An alternative case is defined where the maximum value for a particular model variable is used.[6] The regression model is then used to compute the prediction error E_{alt}, including the 95% confidence interval.
- Step 3) The impact is considered differently for vehicle class variables and the other variables:
  - For vehicle class variables, the level of over-prediction or under-prediction in COPERT Australia is of interest. Since $E_{alt} = P_{alt}/O_{alt}$, the effect of a particular vehicle class set at 100% on the fleet-averaged emission factor can be assessed as over-estimation ($e_{alt} > 1$) or under-estimation ($0 < e_{alt} < 1$).
  - For the meteorological and background concentration variables, the *sensitivity* of the prediction errors to variation in these variables is of interest. These variables are not explicitly modelled in COPERT Australia, and are therefore assessed differently. The sensitivity (%) for a particular variable range is calculated as $100 \times (E_{alt} - E_{base}) / E_{base}$.

Table 2 shows the results of this analysis.

The following conclusions are drawn from the statistical analysis:

- **CO:** COPERT under-predicts tunnel emissions by about 36%. The multiple regression analysis is inconclusive and no particular vehicle class could be identified that specifically causes the under-estimation of the composite CO emission factor in COPERT. In fact, LDDs are identified to significantly over-estimate CO emissions, which suggest that other factors must explain the discrepancies between predicted and observed variables. As discussed before, the combined effects of road grade, cold starts and high emitters are likely candidates for this systematic under-estimation in CO emissions, and it is suggested that correction factors are developed and included in future tunnel emission estimates. The observations are sensitive to small variations in

Pollutant	Model performance			Significant factors		
	p-value	R^2	VIF	variable	b	p-value
CO	< 0.001	0.30	< 1.3	Intercept	10.586	0.010
				LDD	0.022	< 0.001
				P	-9.720	0.014
				T	-0.030	0.021
NO_x	< 0.001	0.31	< 3.3	Intercept	8.093	0.007
				LDD	0.025	< 0.001
				H	0.005	< 0.001
				P	-8.533	0.005
				LDP	0.005	0.041
NO_2	< 0.001	0.22	< 1.0	Intercept	0.280	0.015
				LDD	0.027	< 0.001
				BUS	0.106	0.032
$PM_{2.5}$	< 0.000	0.31	< 1.6	Intercept	33.294	0.001
				LDD	0.062	< 0.001
				HDD	-0.041	< 0.001
				T	-0.192	< 0.001
				P	28.719	0.003
PM_{10}	< 0.001	0.14	< 1.1	Intercept	0.936	< 0.001
				B	0.889	0.004
					-0.018	0.016

Table 1: Multiple regression models for prediction errors: performance and parameters.

Pollutant	Sensitivity and Effect
CO	The **diesel light-duty** emission factor is over-estimated with a factor of 1.8 or more (LDD range 19-100%).
	The prediction error increases with 1-18% when pressure increases from 0.999 to 1.005 atm.
	The prediction error increases with 0-24% when temperature increases from 24 to 26 °C.
NO_x	The **diesel light-duty** emission factor is over-estimated with a factor of 1.7 or more (LDD range 21-100%).
	The prediction error is reduced with 4-16% when humidity increases from 49 to 64%.
	The prediction error increases with 2-13% when pressure increases from 0.999 to 1.005 atm.
	The **petrol light-duty** emission factor is under-estimated with a factor of 2.2 or more (LDP range 67-100%).
NO_2	The **petrol light-duty** emission factor is over-estimated with a factor of 2.2 or more. (LDD range 13-100%).
	The **diesel bus** emission factor is over-estimated with 21% up to a factor of 20 (BUS range 0-100%).
$PM_{2.5}$	The **petrol light-duty** emission factor is over-estimated with a factor of 4.2 or more (LDD range 22-100%).
	The **diesel heavy-duty** emission factor is substantially under-estimated, but extent cannot be accurately quantified (HDD range 2-100%).
	The prediction error increases with 2-38% when temperature increases from 25 to 26 °C.
	No consistent effect. The prediction error is either decreased up to 7% or increased up to 28% when pressure increases from 1.002-1.005 atm.
PM_{10}	The prediction error is increased with 20-62% when B increases from 0.06 to 0.50.
	The **diesel heavy-duty** emission factor is under-estimated with a factor 2 or more (HDD range 5-100%).

Table 2: Impacts of different model variables on prediction errors.

ambient temperature and pressure in the tunnel, explaining part of the scatter in the measurements.

- **NO_x**: COPERT under-predicts tunnel emissions with about 28%. It is noted that these NO_x emissions are corrected for the combined effect of road gradient and piston air flow using the PΔP software[7] (Smit and Kingston 2015a). The regression analysis suggests that light-duty petrol vehicles play a significant role in the under-prediction of NO_x emissions. Before a detailed analysis of the in-tunnel fleet mix, previous work (Smit and Kingston 2015a) used the average Queensland fleet mix, and found that COPERT emission factors for LDVs and HDVs *over-estimated* tunnel NO_x emissions by 23% and 13%, respectively. The under-estimation of 28% reported in this paper is based on COPERT predictions using the actual in-tunnel fleet mix. Since the tunnel has a larger proportion of newer vehicles and SUVs, as was discussed before, the results indicate that NO_x emissions from new petrol cars and SUVs in particular, are under-estimated and would require further investigation. Tunnel observations are sensitive to small variations in humidity and pressure in the tunnel, explaining part of the scatter in the measurements.
- **NO_2**: COPERT predictions are similar to measured tunnel emissions (error of only -2%). The regression analysis suggests that NO_2 emissions from LDDs and buses are significantly over-estimated, which indicates that under-prediction of NO_2 emissions for other vehicle classes or other factors (cold start, road gradient, high emitters) compensates for this.
- **PM2.5:** COPERT predictions are quite similar to measured tunnel emissions (error of only -6%). The regression analysis suggests that emissions from HDDs are substantially under-estimated, whereas emissions for LDDs are significantly over-estimated. This is an interesting result as it suggests that errors in emission factors offset each other. Tunnel observations are sensitive to small variations in temperature in the tunnel, explaining part of the scatter in the measurements.
- **PM10**: COPERT under-predicts tunnel emissions with about 13%. The regression analysis suggests that emissions from HDDs are substantially under-estimated, which is consistent with the results found in method 1 for this pollutant and for PM2.5. Tunnel observations are sensitive to the ratio of the background concentration to the concentrations in the tunnel vent, indicating that errors in background concentrations significantly affect measured emission factors.

DISCUSSION AND CONCLUSIONS

Statistical analysis has been applied to vehicle emissions data collected in a recent Brisbane tunnel study with the aim to address two research questions 1) How accurate are the newly developed Australian vehicle emission models (model validation)?, and 2) Which factors are the main contributors to the prediction errors?

The results suggest that the COPERT Australia is generally accurate at fleet level, when compared with similar international studies. COPERT underestimates emissions by 2% to 36%, depending on the pollutant.

These findings apply only to the specific measurement conditions in the tunnel, *i.e.* a free-flow speed of about 70–80 km/h, the particular tunnel road gradient profile and ventilation conditions (piston effect) and the specific young fleet mix. As a consequence, these results cannot be used to make generic statements about accuracy of the software. Instead, other studies are required to quantify prediction accuracy in other urban conditions, using for instance remote sensing or near-road air quality measurements.

Regression analysis was conducted to determine which vehicle classes and other factors have the largest impacts on the prediction errors. This type of information is highly relevant because it facilitates more cost-effective and focussed vehicle emission measurement programs targeting specific vehicle classes that 'drive' prediction errors.

It is clear that light and heavy diesel vehicles are identified consistently to associate strongly with prediction errors across all pollutants. Whereas fleet level prediction of PM emissions by COPERT is good, a substantial under-prediction of PM emissions from diesel trucks is suggested by the statistical analysis. For NO_x, the analysis suggests that modern large petrol passenger vehicles (*e.g.* SUVs) play an important role in the underestimation of emissions.

This indicates that further targeted emissions testing for these vehicles using *e.g.* PEMS would benefit vehicle emission modelling practice and air quality assessments in Australia. Other tunnel datasets in other cities, preferably of longer duration than a week, could be analysed in a similar fashion to see if these results are confirmed.

The statistical analysis also showed that small natural variations in meteorological parameters such as temperature, pressure and humidity have a statistically significant effect on observed emissions and therefore prediction errors.

Various factors contribute to the significant scatter in the tunnel emission measurements and variation in prediction errors that are not accounted for in the model. These include uncertainty in measured background concentrations, assumptions regarding cold starts, vehicle loads, etc., estimated hourly VKT, vehicle classification (13% unidentified license plates) and smoothing of emissions and dynamic time delay in the tunnel.

There are a number of factors that complicate the comparison of COPERT PM2.5 and PM10 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.

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FOOTNOTES

[1] **CO**mputer **P**rogramme to calculate **E**missions from **R**oad **T**ransport **Australia**

[2] Due to tyre and brake wear and particle re-suspension, possibly even direct dust emissions from *e.g.* gravel trucks.

[3] Based on an analysis of vehicle registration data for base year 2010.

[4] Large values of VIF indicate possible multicollinearity associated with a particular model variable. In general, values larger than 5 indicate a possible multicollinearity problem, while values larger than ten indicates that multicollinearity is almost certainly a problem.

[5] For instance, for CO the average prediction error is –36% and hour 78 has the same prediction error and the following conditions MCY = 0.8%, LDP = 78.1%, LDD = 18.7%, HDD = 1.1%, BUS = 0%, B = 0.05, T = 24°C, H = 44% and P = 0.999 atm.

[6] For instance, when the LDD variable is considered, LDD is set to 100%, all other vehicle classes are set to zero, and B, T, H and P remain the same.

[7] The PΔP software simulates NO_x and CO_2 emissions at a high resolution (1 Hz) and accounts for the effects of speed, acceleration, road gradient, vehicle loading, air-conditioning and wind speed on emissions.

AUTHORS

Dr. Robin Smit
Science Leader
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102
E-mail: robin.smit@qld.gov.au
Phone: 07 3170 5473

Phil Kingston
Senior Technical Officer
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

Rhiannon Tooker
Environmental Officer
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

Dr. Don Neale
Science Leader
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

Steve Torr
Principal Environmental Officer
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

Russell Harper
Senior Technical Officer
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

Esther O'Brien
Senior Technical Officer
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

Daniel Harvest
Technical Officer
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102

David Wainwright
Director
Department of Science, Information Technology and Innovation
Ecosciences Precinct, 41 Boggo Rd, Dutton Park, QLD 4102