COPERT Australia: Developing Improved Average Speed Vehicle Emission Algorithms for the Australian Fleet

Robin Smit [1], *Leonidas Ntziachristos*[2]

[1] Department of Science, Information Technology, Innovation and the Arts, Air Quality Sciences, Inventory, Modelling and Assessment Unit, Brisbane, Australia, robin.smit@qld.gov.au

[2] Laboratory of Applied Thermodynamics, Aristotle University, PO Box 458, GR 54124, Thessaloniki, Greece.

Abstract
This paper discusses the methods and data used for the development of average speed emission algorithms for a dedicated COPERT model for Australia. These algorithms are based on a verified modal emissions database for 766 Australian vehicles, and it uses a vehicle manoeuvre based approach to create 100 m driving segments as input for statistical modelling. Comparison of COPERT 4 with COPERT Australia 1 shows that differences in predictions with the hot running average speed algorithms are not systematic and vary from large to insignificant, depending on the pollutant and vehicle class. As a consequence, the direction and magnitude of the difference in predicted network emission between the two models will be a function of 1) location and base year (i.e. local fleet composition), as well as 2) traffic activity and performance (traffic volumes, congestion levels, etc.). These results confirm the need for an Australian model. The COPERT Australia 1 model will account for the differences in Australian fleet characteristics, fuel composition, driving behaviour and local conditions, as compared with Europe.

Introduction

Average speed vehicle emission models are commonly used around the world to estimate emissions from road traffic at a national or regional level. In countries such as Australia it is convenient to use well-known models such as COPERT, MOBILE, and MOVES.

However, preliminary investigations showed that an average speed model used in Australia needs to reflect local fleet composition and driving characteristics in order to provide adequate vehicle emission predictions for the Australian situation. For instance, a vehicle emission model based on Australian measurements predicted total urban network emission levels of CO, THC and NO_x for an Australian city of up to a factor of 2 higher as compared with COPERT III predictions (Smit, 2006). Similarly, mean NO_x prediction errors as compared with observed values for freeway conditions were a factor of 1.6 to 2.0 higher for COPERT 4 and MOBILE 6, respectively, when compared to an Australian average speed model (Smit and McBroom, 2009a).

Another study (Smit and McBroom, 2009b) compared the default (European) emission algorithms in a commonly used microscopic traffic simulation package to measured modal emission rates for 60 typical Australian petrol vehicles. Observed average emission rates (g/km) for 15 stop-go-stop segments were compared with predicted values based on the European algorithms (Panis et al. 2006). A large underestimation of emissions was found, up to more than two orders of magnitude for individual microtrips. On average an underestimation of a factor of about 20 (NO_x), 1.5 (HC), 4.0 (CO_2, freeway) and an overestimation of a factor of about 1.3 (CO_2, non-freeway) was reported. These investigations clearly suggested that direct use of overseas vehicle emission models in Australia can lead to substantially biased results.

The main reasons for these differences is thought to lie in the fact that overseas models are based on overseas vehicle emissions datasets, which do not reflect Australian vehicles, fuels, climate, fleet composition and driving conditions. The Australian fleet varies substantially from European fleets, despite the fact that Euro standards have been adopted in Australia since about 2003 (before 2003 US standards were used).

One of the main differences with European fleets is the low penetration of diesel light-duty vehicles in the Australian fleet, i.e. 6% in the Australian fleet (ABS, 2007) compared with approximately 33% in the European countries (ANFAC, 2010). The Australian light-duty fleet is mainly fuelled with petrol and the heavy-duty fleet with diesel, although there is some limited use of E10, LPG and CNG. Other important differences relate to vehicle technology. For instance, the Australian passenger car fleet has a large proportion of large passenger cars and (4WD) SUVs. The majority (about 75%) of the Australian car fleet has an engine capacity of more than 2 litres. This contrasts with e.g. the UK and Dutch car fleets where these vehicles only make up about 10% of the fleet because smaller engines are dominant (Smit et al., 2010a). Another difference in the Australian car fleet is the large share of cars with automatic transmissions – about 70% (Smit et al., 2010a), which is substantially higher compared to what is known in European countries.

General Considerations for COPERT Australia

Given the differences in fleet characteristics and local conditions, the need for a dedicated Australian vehicle emission model became clear. For its intended purposes (network modelling), the average speed approach was considered to be a satisfactory compromise between model accuracy and the availability of input data (see also Smit et al., 2010b). Also, two conditions had to be met to develop a model that could deliver reliable emission information: 1) availability of a substantial empirical emissions data base for Australian vehicles on which to base emission factor development, and 2) emissions data based on a real-world driving cycle that truly reflects Australian driving behaviour. It is well known that 'typical' driving conditions can substantially differ between and also within cities (e.g. Niemeier, 2002). It is therefore important to use emissions data that are based on representative driving conditions for the region that the model will be applied to.

A large amount of vehicle emissions test data have been made available from various Australian test programmes that were conducted over time. These emissions data have been collated in a verified emissions database with about 2,500 modal emission tests and about 12,500 individual bag measurements. The modal data files typically contain 30 minutes of laboratory-grade second-by-second emissions data over real-world Australian driving cycles that were developed from on-road driving pattern data in Australian cities. The database consists of one cycle for petrol light-duty vehicles (CUEDC-P, Figure 1) and six (vehicle class dependent) cycles for diesel vehicles (CUEDC-Ds, Figure 2)[1]. The CUEDC-P and CUEDC-Ds have instantaneous speeds between zero and about 100 km/h.

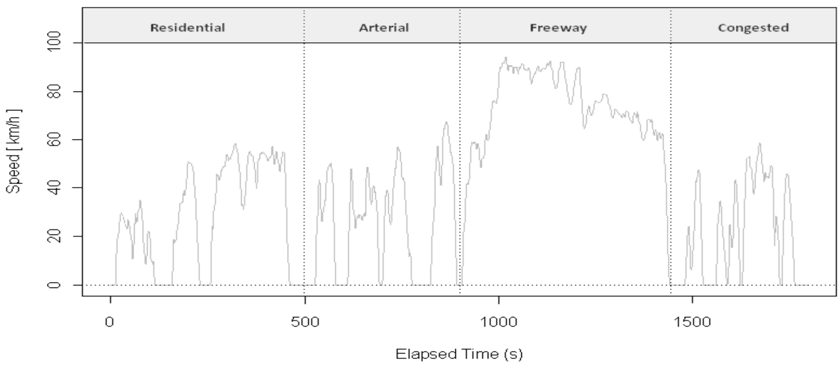

Figure 1: Australian CUEDC-P Driving Cycle.

[1] CUEDC stands for 'Composite Urban Emission Drive Cycles' and '-P' or '-D' denotes petrol or diesel.

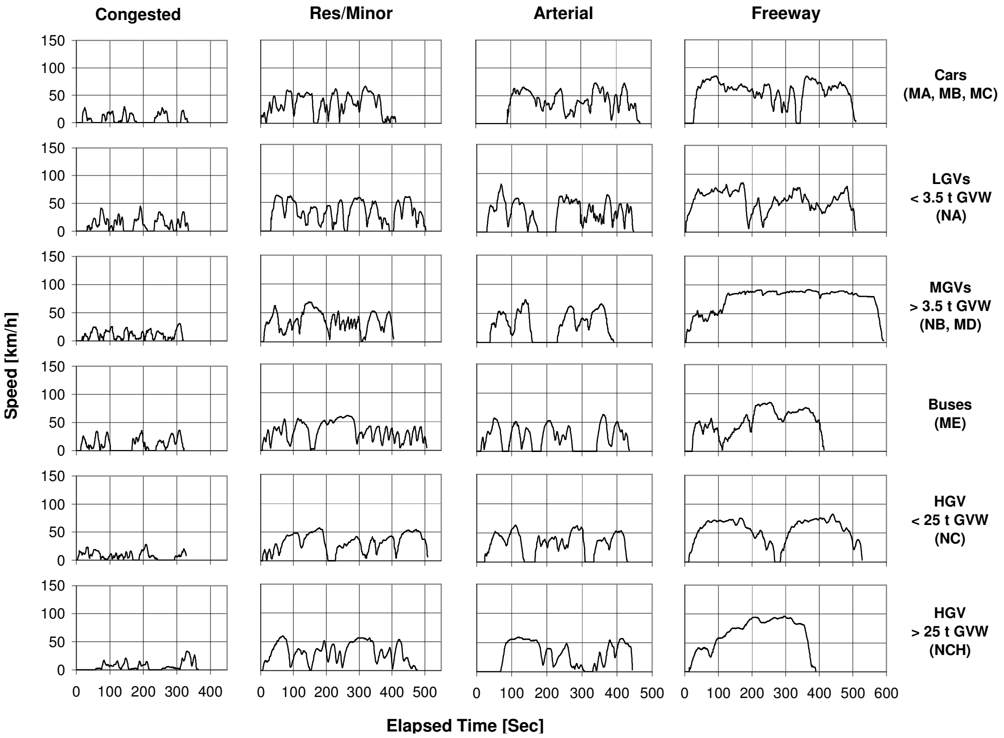

Figure 2: Australian CUEDC-D Driving Cycles (Source: Smit, 2006).

It was considered that use of the COPERT 4 vehicle classification would ensure consistency and a smooth incorporation of Australian emission factors into the COPERT software. However, an alternative vehicle classification scheme is used in COPERT Australia to adequately reflect the Australian fleet characteristics and the structure of the Australian empirical database. The classification is based on the combination main vehicle type[2], fuel type and ADR category. ADRs refer to “Australian Design Rules”, which are the emission standards adopted in Australia.

Developing Hot Running Emission Algorithms for COPERT Australia

One fundamental change with respect to COPERT 4 was the explicit consideration of the required spatial resolution of the average speed algorithms in COPERT Australia. It was considered that macroscopic transport models[3] are the most likely source of input data for emission predictions. A driving distance of 100 m was therefore selected as an appropriate scale for emission factor development. A procedure was developed to derive hot running emission algorithms at this spatial resolution using modal test data.

First, all modal test data were subjected to a verification and correction protocol. This included: 1) filtering of 1 Hz speed-time data with a T4253H smoothing algorithm (Velleman, 1980); 2) (constant) time re-alignment by maximizing the Pearson correlation between fuel rates and instantaneous positive drive power; 3) verification of emission traces (analyzer drift, clipping) and; 4) computation of verification statistics (e.g. BSFC – Brake Specific Fuel Consumption, mean thermal efficiency, mean measured and computed cycle power[4]). A verified modal dataset for 766 Australian vehicles was prepared for subsequent regression modelling.

[2] These are: small passenger car (PC-S, engine capacity < 2 l), medium passenger car (PC-M, 2-3 l), large passenger car (PC-L, > 3 l), compact SUV (SUV-C, 4WD, ≤ 4 l), large SUV (SUV-L, 4WD, ≤ 6 l), light-commercial vehicle (LCV, GVM ≤ 3.5 t), medium commercial vehicle (MCV, GVM 3.5-12.0 t), heavy commercial vehicle (HCV, GVM 12.0-25.0 t), articulated truck (AT, GVM > 25 t), light bus (GVM ≤ 8.5 t) and heavy bus (GVM > 8.5 t).

[3] Macroscopic models consider the performance and behaviour of traffic streams in road networks, whereas microscopic models consider the motion of individual vehicles.

[4] Measured power refers to measured absorbed power by the dynamometer and computed power refers to computed power based on (proprietary) dynamometer algorithms, which typically require input regarding vehicle parameters (e.g. test mass, power absorption coefficients) and the drive cycle (speed-time data). Comparison of the two is used to test whether there were any failures in the application of the dynamometer loading during the test.

Second, an automated procedure was created to extract driving pattern segments and their associated modal emissions data from the verified database for each vehicle to create a segmented emissions database. The process is graphically demonstrated in Figure 3 using a random driving cycle as an example, and described in the following steps.

1) Spatial resolution is set to 100 m.

2) Evaluation of each speed point and assignment of driving mode "tags" to each second of data using the following scheme for $2 \le t \le n-1$:

$$tag = \begin{cases} v_{t-1} = 0 \,\&\, v_t = 0 \,\&\, v_{t+1} = 0 & \text{"}idle\text{"} \\ v_{t-1} = 0 \,\&\, v_t > 0 \,\&\, v_{t+1} = 0 & \text{"}idle\text{"} \\ v_{t-1} = 0 \,\&\, v_t = 0 \,\&\, v_{t+1} > 0 & \text{"}move\ (start)\text{"} \\ v_{t-1} = 0 \,\&\, v_t > 0 \,\&\, v_{t+1} > 0 & \text{"}move\text{"} \\ v_{t-1} > 0 \,\&\, v_t > 0 \,\&\, v_{t+1} > 0 & \text{"}move\text{"} \\ v_{t-1} > 0 \,\&\, v_t > 0 \,\&\, v_{t+1} = 0 & \text{"}move\text{"} \\ v_{t-1} > 0 \,\&\, v_t = 0 \,\&\, v_{t+1} > 0 & \text{"}move\text{"} \\ v_{t-1} > 0 \,\&\, v_t = 0 \,\&\, v_{t+1} = 0 & \text{"}move\ (end)\text{"} \end{cases}$$

3) The idle periods are extracted (indicated in top chart in Figure 3) and segment distance (i.e. 0 m), segment time (s) and total emissions (g) are stored for later use. The remaining "non-idle" or "move" speed-emissions data are used in the next steps. These data typically consist of so-called 'micro-trips', or 'stop-go-stop' driving patterns. Figure 3 shows five micro-trips in the top chart, denoted with A, B, C, D and E.

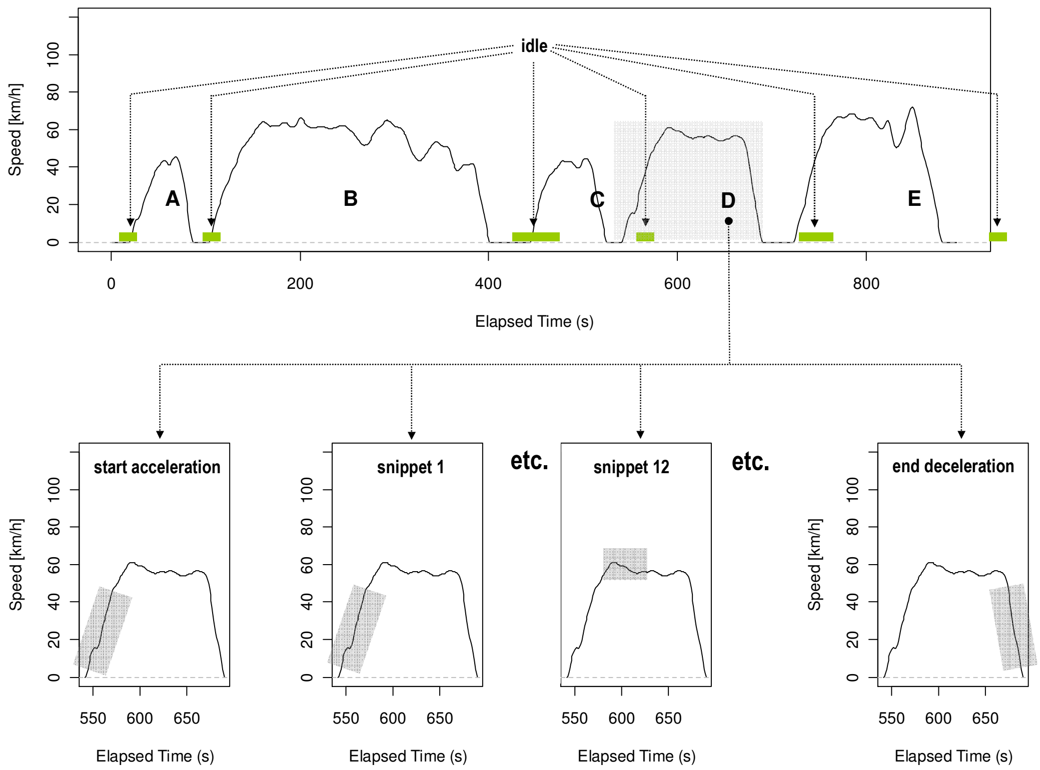

Figure 3: Schematic of Segmented Database Creation.

4) Three types of driving segments are then extracted from the "move" speed-emissions data:

a) Driving segments that start with an acceleration are determined for each micro-trip through computation of the cumulative distance from the start point of the micro-trip and determination of the point in time where the absolute difference between the cumulative distance and the spatial resolution (set to 100 m) is at a minimum.

b) Driving segments that end with a deceleration are determined for each micro-trip through back-computation of the cumulative distance from the end point of the micro-trip and determination of the point in time where the absolute difference between cumulative distance and the spatial resolution is at a minimum.

c) 'Snippets' are determined in a similar fashion as for start acceleration segments, but through repetition of this procedure with different starting points in each micro-trip: i.e. looping through subsequent seconds in the micro-trip.

The segment distance (m), segment time (s) and total emissions (g) for each 'start acceleration' segment, 'end deceleration' segment and 'snippet' are stored for later use. As an example, the three types of segments for micro-trip D are shown in the bottom chart in Figure 3 with a grey shading area. It is noted that segments are only stored as long as the segment distance is larger than 98 m and the proportion of missing values is less than 2.5%.

5) Finally, the idle segments are combined with either the 'start acceleration' or the 'end deceleration' segments to create a segmented database that contain only three types of driving segments:

1. Idle-acceleration vehicle manoeuvre;
2. Deceleration-idle vehicle manoeuvre; and
3. Snippets (i.e. moving vehicle without idling periods and at different start speeds).

In addition to segment distance and time information, emission rates (g/km), fuel rates (g/km), and average speed (km/h) are also computed for each segment. Following the approach used for COPERT 4 (Samaras and Geivanidis, 2005), average emission and fuel values were computed for defined speed intervals (bins) to avoid overweighting of specific speed intervals with a high number of data points. So, a final segmented database is created which includes the average emission values (g/km) for 100 m driving sections, classified in 64 average speed bins ranging from 0 to 145 km/h (2 km/h speed bins). The average emission levels per bin are then computed by taking the arithmetic mean of all segment emission values that fall into the particular speed bin. The procedure is shown in Figure 4 for one particular vehicle. The grey data points represent the individual emission values for the various segments and the black data points represent the bin averaged values. The bin boundaries are also shown with dashed vertical lines.

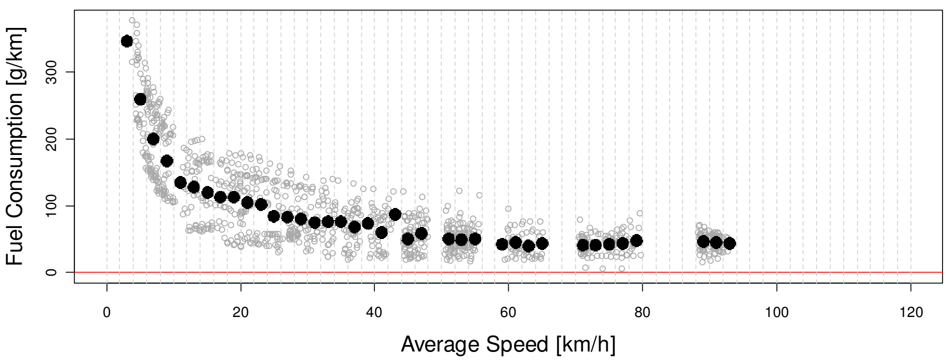

Figure 4: Computation of Binned Mean Emission Factors.

The binned data for all vehicles were then combined into a final (bin averaged) empirical Australian database with about 30,000 mean emission factors for CO, NO_x, CO_2 and fuel consumption, 18,000 mean emission factors for THC and 14,000 mean emission factors for PM. The final emissions database contains the following information for (on average) 100 m driving segments: 1) relevant vehicle information (vehicle class, fuel type, model year, mileage), 2) distance (m) and drive time (s), 3) emission factors (g/km), and 4) average speed. An automated procedure was set up to obtain the best model fit to the following equations:

$$e_1 = \delta + \tau\,\phi \qquad \text{Equation 1}$$

$$e_2 = \delta + \tau\, exp\left(\phi + 0.5\,\sigma^2\right) \qquad \text{Equation 2}$$

Where e_1 represents the emission factor (g/km) based on untransformed emissions data and e_2 represents the emission factor (g/km) based on log-transformed emissions data. The log-transformed and untransformed models were both used to find the best statistical model to describe the empirical data, as will be discussed below. δ is a constant 'bag offset value' (g/km) and is computed as the difference between bag and aggregated modal measurements (δ correction is typically within $\pm$15%). It accounts for the fact that bag measurements are likely to be more accurate. τ represents a 'particulate filter' calibration factor for particulate matter, which is used to correct PM average speed algorithms that are based on laser light scattering photometry data (diesel vehicles only). The "$0.5\sigma^2$" term is a correction for back-transformation of log-transformed data to compute the arithmetic mean instead of the geometric mean. ϕ represents the following model structure (or parts of it), which is also used in COPERT 4 (Samaras and Geivanidis, 2005):

$$\phi = \left(a + c\bar{v} + d\bar{v}^2\right) / \left(1 + b\bar{v}\right) + e/\bar{v} \qquad \text{Equation 3}$$

Where a, b, c, d and e are model parameters and average segment speed is represented by $\bar{v}$ (km/h). For each vehicle category and for each pollutant, parameters were fitted to the segmented emissions data for several variations to equation 3 using non-linear least-squares regression. For final model selection, first the best model fit for either e_1 or e_2 was determined using the Akaike Information Criterion. Then the best of two for each of 378 combinations of vehicle category and pollutant was selected using residual analysis and comparison of performance statistics such as root-mean-squared-error, adjusted R^2 and Kolmogorov-Smirnov (KS) test p-value.

Comparison of 'COPERT Australia 1' and 'COPERT 4'

The hot running COPERT Australia 1 algorithms were compared with the corresponding COPERT 4 algorithms. The results were highly variable. In some cases, the two models show quite similar predictions, whereas in other cases the results are quite different. Some examples are shown in Figure 5. An effort was made to find the best matching COPERT 4 algorithm for each COPERT Australia class. The corresponding vehicle classes are shown in the grey boxes in Figure 5. These grey boxes also include the mean differences computed for the speed range of 10 to 90 km/h, which vary from -46% to +113%. It is noted that these differences can be significantly larger for specific average speeds.

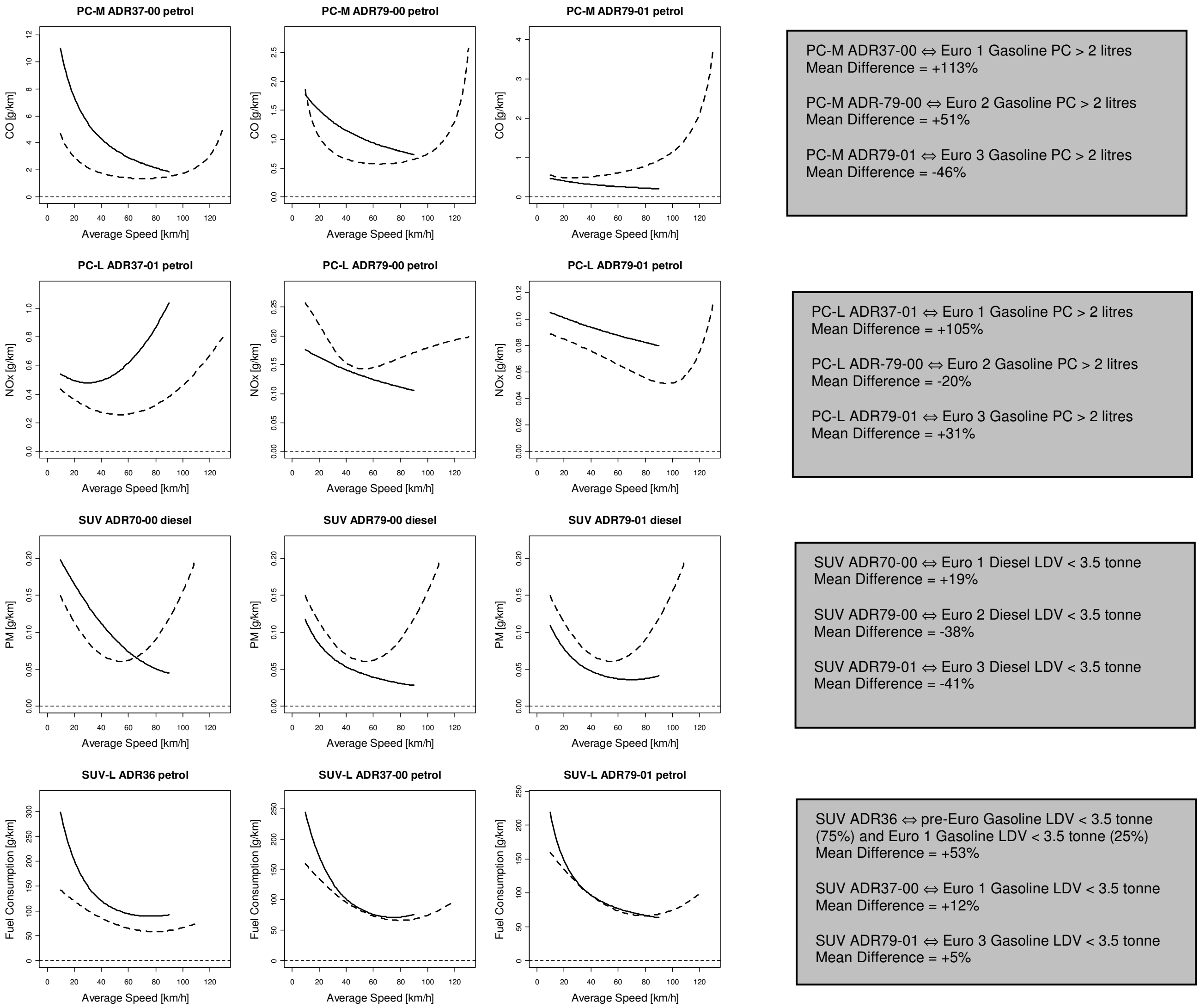

Figure 5: Comparison between COPERT Australia 1 (Solid Line) and COPERT 4 (Dashed Line) Hot Running Emission Factors for a Selection of LD Vehicle Classes and Pollutants, Grey Boxes on the Right Contain Information on the Corresponding Vehicles Classes in Both Models and the Average Difference (Range 10-90 km/h).

It is clear that the differences are not systematic and vary from large to insignificant, depending on the pollutant and vehicle class. This means that it is difficult to predict the direction and magnitude of the difference in network emission predictions between COPERT 4 and COPERT Australia 1 because this will be a function of 1) location and base year (i.e. local fleet composition), as well as 2) traffic activity and performance (traffic volumes, congestion levels, etc.).

These results confirm the need for an Australian model. The COPERT Australia 1 model will account for the differences in Australian fleet characteristics, fuel composition, driving behaviour and local conditions, as compared with Europe. It is anticipated that the differences at network level will be discussed for different case-studies in the future.

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