

Development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand – data quality considerations

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ABSTRACT

A large body of Australian laboratory test data is or will be available for the development of a new high resolution traffic emissions prediction tool. Consideration of data quality is an essential step in the development of this empirical model. Several potential issues are discussed in this paper. Although the majority of issues can be dealt with either before, during or after model development, not all issues can be addressed due to a lack of information or empirical data. This is not a problem specific for Australia: international research is ongoing to address these issues. As part of an ongoing process of model improvement, the relevance of gaps in knowledge need to be further explored and eventually addressed.

INTRODUCTION

This paper is the second of a series of short papers that will be published in 2009, which discuss the ongoing development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand. This high resolution model is part of a modelling framework that contains other models for more aggregate scales (e.g. fleet composition model, average speed model). Each short paper will address a separate issue with respect to this development:

- Why is an Australian/New Zealand high-resolution model needed (Smit and McBroom, 2009a)?
- What are the data quality issues in model development (this paper)?
- What is the best model structure for such a model and how does the model perform?
- Application and outlook on further development.

EMPIRICAL BASE OF TRAFFIC EMISSION MODELS

Traffic emission models are developed from emission measurements. Although there are different measurement methods available, collection of emissions and fuel consumption data from on-road vehicles is commonly conducted in **laboratories using chassis or engine dynamometers**. A review of emission models (Smit *et al.* 2009) revealed that the majority of current traffic emission

models are based on laboratory emission testing studies, which is not surprising as this is the prominent approach to measuring vehicle emissions.

The obvious advantage is that measurements take place under controlled conditions, which allows for investigation of specific variables such as ambient temperature and driving behaviour on exhaust emissions. In addition, specific types of emissions such as evaporative and start emissions can be specifically measured and investigated. A disadvantage of laboratory testing is the limitation on the number of vehicles or engines that can be tested due to time and budget constraints. Given the large inter-vehicle variability in emissions (refer to our previous paper), empirical data for a large number of (representative) vehicles is required to provide accurate estimates of mean traffic emissions. For instance, it has been shown that emission tests of at least 600 Euro 2 petrol cars are required to obtain a mean emission factor that is accurate within 10% (Smit *et al.* 2005).

Laboratory vehicle exhaust emission testing may be conducted using tedlar sample bags (denoted as “bag measurement”) that are analysed after completion of the driving cycle (which simulates typically a few minutes up to an hour of driving), or may be conducted using continuous measurement at a high time resolution (typically 1-10 Hz). As it is the method prescribed by emission legislation around the world, bag sampling has traditionally been the dominant approach. However, continuous measurements have become increasingly common around the world. The high resolution model cannot be developed from aggregate bag data and requires continuous test data. There are a number of other issues with laboratory testing – and with continuous measurements in particular – which will progressively be discussed in this paper.

In addition to dynamometer testing, emissions and driving pattern data can be collected while driving on the road. An advantage of this approach is that emissions are measured in the real world, which means that factors that may not be reflected in laboratory test data but which are known to be relevant, are reflected in the test data (e.g. road grade effects, air conditioning use, personal driving style including gear shift behaviour). Up to recently, **on-board systems** suffered from practical problems

(e.g. costs, size and weight of equipment) and quality issues (e.g. high detection limits, unrealistic spikes) (Elst *et al.* 2004). This, however, is changing rapidly now with the development of improved and new systems (North *et al.* 2005) and increased use of on-board test data in emission models (ISSRC, 2008). On-board testing of a large number of vehicles can still be restricted by labour time and costs (North *et al.* 2005).

Other methods such as **remote sensing, tunnel studies** and **on-road or near-road modelling** are commonly used for emission model validation purposes and have contributed significantly to an increased understanding of model accuracy and real world emission behaviour of vehicles (e.g. high emitters). Direct use of these data in the development of high resolution emission models is not possible for various reasons. Firstly, these type of measurement typically reflect specific vehicle operating conditions and/or traffic conditions. Secondly, the data do not have sufficient resolution in time and space.

AVAILABLE AUSTRALIAN EMPIRICAL DATA

The previous paper concluded that the new high resolution model should be based on Australian test data. Over the last decade or so, a large body of laboratory emission data on Australian vehicles has been published¹ – or is in the process of being completed. Although new empirical data should be included in future updates to improve prediction accuracy, the currently available empirical data are sufficient to develop an ANZ high resolution model. These data involve highly time-resolved second-by-second emissions tests of hundreds of vehicles for the majority of (relevant) model years, fuels and vehicle types. Nevertheless, there are a number of potential issues with the quality of these data that need to be considered before a model is developed. These issues are discussed in the remainder of this brief paper.

VEHICLE SAMPLE

There are a large number of vehicle make and models in the on-road fleet. For instance, there were more than 2000 possible combinations of light-duty vehicle models and makes registered in Queensland in 2007 (Figure 1). In addition, the distribution of vehicles is highly skewed, as is

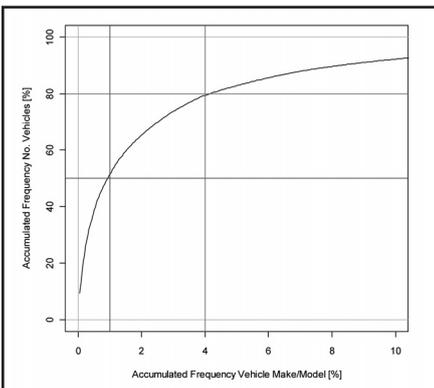


Figure 1. Distribution of Number of Registered Passenger Cars in Queensland over Vehicle Make and Model Combinations (Data Source: ABS, 2007).

shown in Figure 1. For instance, almost 10% of all registered passenger cars are Holden Commodores, followed by Ford Falcons (9%) and Toyota Corollas (about 5%). In fact, about 1% and 4% of the possible model/make combinations make up 50% and 80% of the registered on-road vehicles, respectively.

Australian testing programs commonly attempt (but not always) to test a vehicle sample that is representative of the on-road fleet in a particular State or area (e.g. DEH, 2005). A vehicle sample matrix is then designed using e.g. data on vehicle registration, vehicle usage (annual mileage), emission control systems, and in some cases, specific considerations². In reality, however, it is often not possible to obtain all the vehicles that were identified in the initial vehicle sample matrix for testing. For instance, the test facility may not be set up to test all vehicle types (e.g. 4WD or AWD vehicles) or vehicles may not be available or unsuitable (e.g. mechanical problems) for testing (e.g. NEPC 2000), which leads to modifications of the original vehicle matrix.

The above points imply that direct use of the available empirical emissions data – without further consideration of microlevel fleet characteristics – can lead to substantially biased models. This issue can be addressed by implicitly (before development of emission algorithms) or explicitly (after development of emission algorithms) weighing of emission predictions for individual vehicles according to their share in total VKT.

A more difficult point to address is that high emitters, i.e. vehicles that exhibit (very) high emission levels, may not be adequately reflected in the test data. A world-wide study concluded that for all fleets the total exhaust emissions are dominated by a small percentage of high-emitters. For instance, the data showed that about 10% of the vehicles in Melbourne are responsible for half or more of the total CO and HC exhaust emissions (Zhang *et al.* 1995). Australian laboratory test data generally do show highly skewed emissions distributions (e.g. DEH 2005), which suggests that high emitting vehicles are – at least to some extent – included in the test data. However, concerns

of potential recruitment bias have been voiced overseas, where it was reported that owners of high-emitting vehicles tend not to register their vehicles and are reluctant to submit their vehicles for testing (NRC, 2000). So, verification of adequate inclusion of high emitters in Australian test data is required and should be based on independent data sources such as remote-sensing (e.g. NIWA 2008). It is noted though that these independent data need to be carefully examined to ensure proper comparison is made. For instance, remote sensing data collects a sample of specific air pollutants (e.g. NO instead of NO_x) at a specific location reflecting certain predominant vehicle operating conditions (e.g. acceleration under grade) and may use different methods from standard laboratory testing (e.g. for PM). In the meantime, the available Australian data used for model development should be based on 'as-received' vehicle conditions (i.e. no repairs conducted).

REAL WORLD DRIVING BEHAVIOUR

It has been demonstrated that (aggregate) emission factors based on the standard driving cycles such as the Eurotest and FTP cycles (used in the Australian Design Rules or ADRs) substantially underestimate emissions in "real-world" driving (e.g. Watson 1995). These cycles are also characterised by relatively low speed and acceleration levels, which limits the range of vehicle operating conditions. Thus, sole use emissions data that is based on standard cycles may lead to biased and imprecise emission models due to a substantial amount of extrapolation beyond measured operating conditions. Fortunately, the available Australian test data is based on real-world driving cycles such as the CUEDC-D and CUEDC-P. These cycles have been derived from measurement of driving behaviour in Australian cities. To prevent model bias these data will be used in the development of the new high resolution model.

There are however, a few remaining issues. Although the CUEDCs are representative of urban driving, they do not reflect the entire mode of operation for freeway driving. The CUEDC-P has instantaneous speeds up to 94 km/h, whereas freeway driving may occur at higher speeds. To some extent this issue can be addressed through extrapolation of test results using e.g. a power-based model, but it appears necessary to verify these predictions with overseas data in the absence of Australian data. Another issue is that there are a number of real-world factors that affect emissions, but which are not reflected in laboratory test data. Examples are road grade effects, air conditioning use and variation in driving style (including gear shift behaviour). To some extent these omissions can be addressed in model development. For instance, a power based model can simulate the effects of road grade, vehicle loading, etc. on power demand and hence emissions. Similarly, correction algorithms may be introduced for air conditioning use.

Real-world variation in driving styles are not easily addressed due to a general lack of data on the distribution of driving styles in the real-world.

TEST FUELS

The composition and quality of fuel has a significant impact on emissions (e.g. CONCAWE 1999). Commercial fuels change in time and obvious examples are the phasing out of lead from petrol and the ongoing reduction of sulfur content in diesel fuels. Emission predictions need to be corrected for these changes. Fortunately, test fuels in Australian emissions testing programs have typically been based on commercial fuels. However, a detailed breakdown on fuel composition is often not provided, so back-to-back comparison of current commercial fuels to test fuels (and subsequent correction) is not always possible, except for a few basic parameters such as sulfur content and cetane index in some cases. A related point is the ongoing diversification of transport fuels in on-road vehicles (CSIRO 2008). This includes increased use of alternative fuels (E10, CNG, biodiesel, etc.), but also specific fuel combinations (e.g. dual-fuelled LPG-diesel trucks). As these fuels will all have specific emission profiles, they ideally should be treated as separate vehicle classes, using empirical emissions test data in their model development. In the absence of Australian empirical data, emissions can be developed using overseas empirical data (if available) or estimated using correction factors derived from the international literature.

TIME ALIGNMENT

High resolution models around the world typically correlate emissions and vehicle or engine state on a second by second basis (Barth *et al.* 2000; Atjay *et al.* 2005). For the development of a high resolution traffic emissions prediction tool, data quality requirements are more demanding than for more aggregate prediction tools (e.g. for urban emission inventories). Emissions are highly variable where a few seconds of driving may be dominated by short-duration (few seconds) or long-duration (minutes) high emissions events (e.g. due to gear changing, high acceleration, high speeds) or could reflect the typically low emission levels of modern vehicles. A journey through the road network, on the other hand, will include and average out these different emission levels. Thus it becomes important to use highly time-resolved emissions and vehicle operation measurement data that correctly quantify the **frequency, magnitude and location** of emission peaks in time. This is a particularly tricky issue.

Transport of emissions in the car exhaust and measurement systems (sample lines, analysers) affects test results in two ways, 1) it causes a delay and 2) it results in smoothed emission peaks (i.e. smaller peaks spread over a longer time period) due to turbulence and mixing.

With respect to the first point, transport delay is typically accounted for by shifting the raw data back a constant number of seconds. However, time delay may be dynamic and a function of exhaust flow rate, which in turn is a function of driving conditions (e.g. idle, acceleration). The difference compared to a constant delay can be up to several seconds. There appears to be some controversy on this issue. According to Hawley *et al.* (2004), sample line transport and analyser response (T90-T0.5) delay times are fixed and independent of vehicle and engine conditions. However, Atjay *et al.* (2005) mention that the transport of exhaust gas from the tailpipe to the CVS mixing point is a function of exhaust flow rate, which varies between 0.3 and 16 seconds for a specific vehicle. It seems reasonable to assume that these different findings are due to measurement set up, where the point where dilution starts (e.g. at exhaust or at CVS mixing point) is of particular interest. So, depending on the laboratory configuration, dynamic time alignment may be needed to account for delay and to correlate emissions to the correct driving conditions. Otherwise, use of a constant time delay value for all driving conditions may introduce errors with respect to time allocation of emissions. With respect to the second point, raw emissions data are not corrected for smoothing effects.

It is important to note that transport delay and mixing inside the vehicle exhaust system is not relevant for our specific goal – *i.e.* to accurately model what comes out of the exhaust as a function of driving behaviour (modelled as vehicle speed in time) - as these processes occur inside the vehicle and do not lead to exposure. We are interested to know what is released into the atmosphere, so the delay and mixing (including formation/destruction) of emissions in the engine and catalyst system is a real-world effect between operation and emissions of a vehicle. Nevertheless, a remaining concern is the delay and smoothing from the tailpipe to the analysers. It is important to know exactly where dilution starts, e.g. if air is diluted at the tailpipe then there would be no issue with constant delay correction.

Improvement of time alignment and correction for smoothing effects (underestimation of peaks) may be achieved via a postprocessing procedure (e.g. filtering). The aim of this procedure is to deconvolute the data and reconstruct the true signal from the measurements. Complex modelling has recently been proposed to (partly) correct for time delays and/or smoothing effects (Atjay and Weilenmann, 2004; Atjay *et al.* 2005; Zhang and Frey, 2008). Although these correction methods appear to generally improve both magnitude and timing of peaks, overshoots and undershoots can also be observed and extensive validation results do not appear to be available. This means that care is needed in using these methods. Essentially, any post-processing method should be validated to make sure that potential gains in accuracy are not outdone due to incorrect postprocessing methods.

QUALITY OF MEASUREMENT EQUIPMENT

Ideally, a measurement system should respond instantaneously and completely to changes in driving conditions and associated exhaust emission rates. In reality, each type of measurement equipment has certain finite response times, depending on the pollutant. When exhaust emission rates change more quickly than the response time, the measurements may not respond quickly or completely enough, leading to biased results. Generally, faster response gas analysers have a better match with respect to timing and the magnitude of peaks than equipment with longer response times (Zhang and Frey, 2008).

Simply because data are recorded or presented every second (*i.e.* sampling frequency) does not mean that these measurements have adequate resolution to predict changes in emission levels for each second. For instance, to have second-by-second resolution, the sampling frequency of any analyser should be 0.5 seconds or less³, *i.e.* > 2 Hz. So unless sampling frequency is higher than 2 Hz, input data for model development may need to be converted in averaged values for more than 1 second. An essential data quality verification step is to compare aggregated (cumulative) modal results to bag results for each vehicle. The difference between the two should be small, in the order of a few percent. Large differences could indicate that peak emissions have been clipped⁴ or are a result of other artefacts such as drop out and the effects of humidity on NO_x, leading to underestimated emissions. It is expected that these errors are rare as test data are normally checked during the testing programs.

Another point of consideration is the quality of the dynamometer. Dynamometer system configuration (e.g. hydraulic or electrical power absorption unit) and specifications (e.g. base inertia, response time, power absorption capability, motoring capabilities, permissible axle loading) can vary and affect how well on-road driving conditions are replicated. So in order to optimise the accuracy of the emission model, it is important to use test data from laboratories that use high-quality transient

dynamometers and high quality analytical equipment and are regularly calibrated. In addition, the extent to which vehicle specific parameters are taken into account are important, e.g. are dynamometer settings based on coast-down test results, are they based on more general setting as specified by legislation (ADRs) or based on empirical formulae.

One particular problem concerns the accurate measurement of exhaust particulate matter, where particle size and number distributions are dynamic and continually changing due to agglomeration and deposition. PM measurements are a function of measurement setup (heated sampling lines etc.) and choice of analysers. For instance, LLSPs have a fast response time – which is needed for the high resolution model – but the accuracy of derived mass-based emission rates must be treated with caution. Other analysers such as TEOMs have a better correlation with filter-based methods, but are not as fast. Again comparing cumulative mass-based emissions with filter based values is an important quality assurance step. There is the additional problem to what extent laboratory measurements correspond to real-world PM emissions. When particulates are emitted from the exhaust into the atmosphere the final size distribution and particle number concentration in the atmosphere depend on many factors such as chemical exhaust particulate composition, ambient air PM concentration, relative humidity and ambient temperature. There is, however, no easy way to address this issue.

CONCLUSIONS

Consideration of data quality is an essential step in the development of any empirical model. If this step is not adequately thought through, the final model will be subject to the GIGO principle. We have identified a large body of Australian laboratory test data as the best data source for the development of a high resolution traffic emissions prediction tool. A number of general issues have been discussed (see Table 1) – and, where possible, ways to address them.

Although the majority of issues can be dealt with either before, during or after

Table 1. Data quality issues for traffic models

Representativeness of the vehicle sample	- weighting factors to account for on-road fleet - further analysis of high emitter vehicle inclusion
Real-world driving behaviour	- use real world cycles - simulation of road grade, loading, etc. - correction for aircon use
Test fuels	- new vehicle classes - correction for specific fuel parameters
Post-processing method (only if can be validated)	- dynamic time alignment - de-smoothing of peaks
Quality of measurement equipment	- determine appropriate averaging times - compare aggregated modal to bag results - exclude test data based on low quality test facilities - further research into particulate matter

model development, not all issues can be addressed due to a lack of information or empirical data, most notably high emitters, real-world gear shift behaviour and dynamic time lag correction. However, this is not a problem specific for Australia. Indeed, international research is ongoing to address these issues. This will not prevent the development of a high quality model, but the gaps in knowledge need to be clearly acknowledged, their relevance further explored and eventually addressed as part of an ongoing process of model improvement.

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Footnotes

- 1 Examples of relevant data sets are the diesel NEPM work (e.g. NEPC, 2001) and the NISE 2 petrol study (e.g. DEH, 2005).
- 2 e.g. suitability of a vehicle to operate on a particular fuel such as ethanol (DEWHA, 2008).
- 3 This follows from the "Nyquist-Shannon sampling theorem", which states that in a sampled signal no information above half of the sampling frequency is available.
- 4 Emissions are greater than the range of the emissions analyser, resulting in the maximum analyser value and not the actual maximum.
- 5 Hydrocarbons condense in the sampling system and are no longer part of the gaseous mixture which is flowing to the detectors.
- 6 Garbage in garbage out.

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Predicting increasing drought from coral cores

According to an article in the April 2009 issue of *Australasian Science* by Nerilie Abram, the southern part of Australia will be subject to increasing drought in the near-future. The El Niño circulation pattern originating from the Pacific, and the equivalent from the Indian Ocean called the Indian Ocean Dipole (IOD), are tending to compliment each other, reducing the strength and frequency of rainfall. Evidence for this pattern has been found in the climate history obtained from drilling cores in massive corals, growing in the tropical oceans off northern Australia. These cores provide detailed records of changes in rainfall and temperature back to the mid-19th century. They show that recent global warming has changed the ocean and atmospheric circulation patterns in the Indian Ocean area, creating stronger and more frequent variations in the IOD, resulting in major declines in winter rainfall over southern Australia.