Development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand – Why is it needed?

Robin Smit, James McBroom

INTRODUCTION

This paper is the first of a series of short papers that discusses the ongoing development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand, as 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?
- What are the data quality issues in model development?
- What is the best model structure for such a model and how does the model perform?
- Application and outlook on further development.

THE NEED FOR MODELS

Why do we need models to estimate traffic emissions? There are two main reasons for this.

- It is not feasible in terms of costs and effort to adequately measure traffic emissions in real-time in the field (discussed below).
- From a policy perspective, it is necessary to examine trends in traffic emissions, as well as to make projections into the future, where the latter, of course, cannot be measured.

Emissions from individual vehicles are a function of many, often interacting, variables such as vehicle design characteristics, the way a vehicle is being driven (driving behaviour), deterioration of engine and emission control components (ageing effects) and driving mode (cold, hot; running, idling, parked). Consideration of numerous individual vehicles, each of them having unique properties (e.g. personal driving style, power-to-mass ratio) and each of them interacting with other vehicles and road features, adds another layer of complexity. So, given the large number of on-road vehicles and the many factors that influence emissions from individual vehicles, vehicle emissions are highly variable in practice. This is illustrated in Figure 1, depicting measured NO_x emissions from four Australian cars over the same driving cycle.

Clearly, emissions behaviour for each vehicle is quite different, both in terms of the magnitude of the emissions and the time allocation of peaks. This is despite the fact that the vehicles were driven in a similar way and that measurements were made under controlled conditions (laboratory). Moreover, these data show the variation in emissions for a rather homogeneous group of vehicles (i.e. three-way catalyst petrol passenger cars of similar model years). Comparison with other vehicle classes (e.g. diesel cars, trucks, buses) will similarly show large differences in emission profiles (e.g. Brown *et al.* 1999). This means that in order to adequately capture mean emission levels for a mixture of vehicles in a traffic stream, a substantial number of vehicles need to be sampled. Add to that the variation in infrastructure features, traffic conditions, weather conditions, driving styles, etc. and it becomes clear that is not yet feasible in terms of costs and effort to adequately measure traffic emissions in real-time in the field. So models are needed to estimate emissions and dispersion.

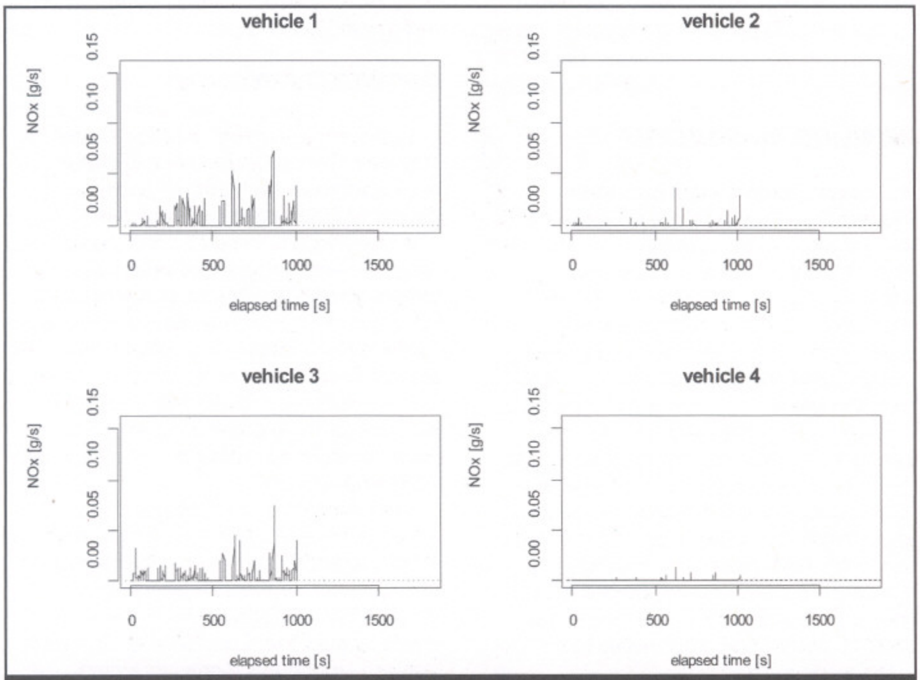


Figure 1 – Measured NO_x Exhaust Emissions (1 Hz) over CUEDC(P) Driving Cycle for Four Different Australian Petrol Cars (ADR 37/01, Model Years 1999-2001), Source: DEH 2005.

Models are often used in practice to quantify traffic impacts on the environment. This occurs at different scales, ranging from local road projects (e.g. hot spot analysis) to entire urban or regional transport networks and even national or global emission inventories. Importantly, each type of emission model has its own intended and appropriate scale of application. For instance, aggregate emission factor models are applied at national level, average speed models are applied at network level, whereas more detailed models are used for local impact assessment (Smit *et al.* 2009). Ideally, a model framework (Figure 2) should be used that is consistent and matches the quality and level of detail of available traffic data and takes into account specific requirements (e.g. accuracy) at each scale of interest (local, regional, national, international).

THE NEED FOR A HIGH RESOLUTION MODEL

This paper series specifically focusses on the development of a new high resolution traffic emissions model using new Australian test data. This effort is inspired by the belief that a number of ongoing developments will facilitate demand for, development of and application of more complex, detailed and comprehensive high resolution emission models. These would address increasingly complex research questions and study objectives ultimately leading to a finer spatial and temporal allocation of traffic emissions. The following developments have been identified to substantiate this belief:

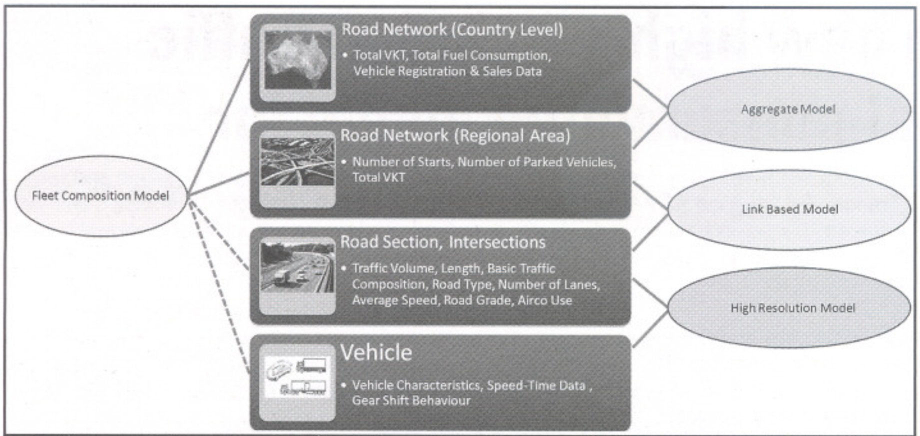


Figure 2 – Road Traffic Emissions and Fuel Consumption Framework

- Substantial improvements can be expected with respect to the **quality** and **availability** of input data. Ongoing developments in and application of intelligent sensor, communications and computing technology in vehicles and at the road side is now paving the way for wide scale collection of real-time field data on vehicle movement in time and space (e.g. Hoose *et al.*, 2008). This development is also seen in Australia (www.ausdsrc.com.au).
- A related point is the growing application of (high-tech) adaptive **traffic control measures** to improve traffic flow (to alleviate congestion), improve reliability and reduce accidents (e.g. Noland and Quddus 2006; Panis *et al.* 2006).
- Ongoing developments in the field of and application of high-resolution **on-board emission measurements** (e.g. North *et al.* 2005) will create opportunities for large on-road emission measurement databases (including many different vehicles) that can then be used for emission model development.
- There is increasing interest around the world in the effects of **local scale traffic measures** on traffic emissions, air pollution and fuel consumption. These kinds of measures will generate relatively small effects, so sensitive high-resolution models will be needed to accurately predict the correct direction and magnitude of the effects.

The information generated by a high resolution model can be used in its own right (e.g. emission inventory, prediction of greenhouse gas emissions) or it can be fed into local air quality dispersion models to carry out, for example, "hot spot" analysis and impact assessment of traffic management measures. This would provide more accurate predictions than a screening model, which is important in cases where sensitivity is required. Examples include cases with poor air quality close to guideline values (e.g. at critical locations such as a new residential area near a busy highway) or in cases where policy measures are likely to cause relatively small impacts on emissions and fuel consumption (e.g. specific traffic management measures such as dynamic speed limits, traffic signal coordination, metering signals).

THE NEED FOR AN AUSTRALIAN/NEW ZEALAND MODEL

So why do we need a traffic emissions model that is specifically developed for Australia and New Zealand? Surely, these types of complex and detailed models are being or have been developed overseas, as was shown in Smit (2008). In addition, commonly used microscopic traffic simulation packages such as AIMSUN, VISSIM and PARAMICS already have incorporated traffic emission prediction capabilities (EC 2000). It would be easy and certainly cost-effective to just use these models directly instead of developing a new model here.

The problem is that there are no reasons to expect reliable output for Australian road and traffic conditions. Overseas emission algorithms are based on overseas vehicle emissions datasets, which do not (necessarily) reflect driving behaviour, vehicles, fuels, climate and fleet composition in Australia and New Zealand. For example, compared to Australia, Europe has a significantly higher percentage of diesel cars, i.e. up to almost 45% depending on the European country (EEA 2004) compared to 4% in Australia (ABS 2006). Similarly, Australia has a different composition of fuels and a different mixture of emission standards (CONCAWE 2006), as well as different climatic conditions. This, in turn, likely results in different calibration of engine management systems and/or a different configuration of emission reduction technologies[1]. Anecdotal evidence suggests that other important differences exist as well, such as a larger proportion light-duty vehicles with six and eight cylinder engines and a larger proportion of automatic gear boxes in Australia.

All of the above aspects are known to be relevant with respect to emissions. The issue of validity can, of course, be ignored but the risk is that poor emission predictions will cause poor infrastructure decisions and poor policy making decisions. The use of Australian driving behaviour and associated emissions data to either recalibrate overseas models and/or to develop a new prediction tool with improved acuracy is therefore the preferred option.

THE NEED FOR A NEW MODEL

So why do we need to develop a **new** high-resolution traffic emissions model for Australia and New Zealand? Australia already has a long history on the development of detailed high resolution models (e.g. Kent at al. 1982; Post *et al.* 1985). More current high resolution models are CSIRO's CVEM model (e.g. Leung and Williams 2000) and SIDRA TRIP (Akçelik and Besley 2003). There are a few reasons we believe support the development of a new model:

- In contrast to CVEM and SIDRA TRIP, which are deterministic models providing point estimates, a **statistial model** can be developed that will enable quantification of the level of uncertainty of model predictions (e.g. confidence intervals). This is important additional information for policy makers and model users.
- Although a new model can include variables that are also used in CVEM and SIDRA TRIP, it should incorporate new ones as well. This will further **enhance prediction accuracy.**
- The model will largely be based on a large body of **high-resolution Australian emissions** test data that is currently being generated for light-duty vehicles. The currently ongoing NISE 2 study (DEH 2005) will ultimately (early to mid 2009) provide test data for about 360 petrol vehicles on a second-by-second basis, which is a very large database (more than 200 hours of test data), even compared to international standards. In addition, there is a substantial amount of high resolution test data (about 50 hours) available from the diesel NEPM vehicle test programs, involving 80 diesel vehicles (Anyon *et al.* 2000). Both programs reflect vehicle operation in Australian road and traffic conditions and they have, to the knowledge of the authors, not been used by CVEM and SIDRA TRIP.
- The model will take into account the Australian (or local) **fleet composition at micro level**. In other words it will be calibrated to reflect the relative proportions of specific vehicle make and models.
- Explicit consideration of multidisciplinary aspects is often lacking in the development of traffic emissions models. A good understanding of other disciplines such as traffic modelling (generating input data) and dispersion modelling (using emission predictions) is essential to develop an optimised interfacing with other models and to prevent errors (e.g. incorrect interpretation of input data definitions).

The new model attempts to achieve an **optimum balance** between (desired) prediction accuracy and input data quality, as was discussed in Smit (2008, figure 3, p.20).

The goal of this new work is to develop a high resolution road traffic emission model for Australia and New Zealand that is comprehensive[2], accurate, easy to use and understand, reliable and robust[3] and which interfaces readily with appropriate traffic models and (emerging) traffic field data. The next short paper will discuss specific data quality issues that concern high resolution models.

REFERENCES

ABS, 2006, *Survey of Motor Vehicle Use,* Australian Bureau of Statistics, www.abs.gov.au.

Akçelik, R. & Besley, M., 2003, Operating cost, fuel consumption and emission models in aaSIDRA and aaMOTION. *Proceedings of the 25th Conference of Australian Institutes of Transport Research* (CAITR 2003), Adelaide, 3-5 December 2003, pp. 1-15.

Anyon, P., Brown, S., Pattison, D., Beville-Anderson, J., Walls, G., Mowle, M., 2000, *In-Service Emissions Performance - Phase 2 Vehicle Testing*, National Environment Protection Council Service Corporation, Canberra, Australia, ISBN 0 642 323 348.

Brown, S., Bryett, C., Mowle, M., 1999, *In-Service Emissions Performance - Drive Cycles*, Vol. 1, National Environment Protection Council Service Corporation, Australia, Canberra, ISBN 0 642 32323 2.

CONCAWE, 2006, *Motor Vehicle Emission Regulations and Fuel Specifications – Part 1, 2004/2005* Update, Brussels, Report 5/06, June.

DEH, 2005. *NISE 2 – Drive Cycle and Short Test Development – Final Report,* Department of the Environment and Heritage (DEH), Prepared by Orbital Australia Pty. Ltd., September, Canberra.

EC, 2000, SMARTEST, The European Commission, *Transport RTD Programme of the 4th Framework Programme*, Final Report, Contract No. RO-97-SC.1059, Leeds, UK.

EEA, 2004, *Size and Composition of the Vehicle Fleet*, European Environment Agency, Prepared by Giannouli, M. and Mellios, G., LAT, Thessaloniki, Greece.

Hoose, N., North, R., Polak, J.W., Cohen, J. & Richards, M., 2008, The use of mobile sensors and GRID computing managing the environmental impact of traffic. *Proceedings of the 7th European Congress on Intelligent Transport Systems and Services. Geneva.*

Kent, J.H., Post, K., Tomlin, J.A., 1982, Fuel consumption and emission modelling in traffic links, *Proceedings of SAE-A/ARRB 2nd Conference on Traffic Energy and Emissions*, 82140, 10.1-10.20, Melbourne, Australia.

Leung, D.Y.C., Williams, D.J., 2000, Modelling of motor vehicle fuel consumption and emissions using a power-based model. *Environmental Monitoring and Assessment,* **65**, 21-29.

Noland, R.B. and Quddus, M., 2006, Flow improvements and vehicle emissions: effects of trip generation and emission control technology. *Transportation Research-D*, **11**, 1-14.

North, R.J., Ochieng, W.Y., Quddus, M.A., Noland, R.B., Polak, J.W., 2005, Development of a vehicle emissions monitoring system. *Transport*, **158**, 167-177.

Panis, L., Broekx, S., Liu, R., 2006, Modelling instantaneous traffic emission and the influence of traffic speed limits. *Science of the Total Environment,* **371**, 270-285.

Post, K., Kent, J.H., Tomlin, J., Carruthers, N., 1985, Vehicle characterization and fuel consumption prediction using maps and power demand models. *International Journal of Vehicle Design*, **6 (1)**, 72-92.

Smit, R., 2008, Developments in road traffic emission and fuel consumption modelling: some recent experiences from Europe. *Clean Air and Environmental Quality,* **42 (3)**, 18-21.

Smit, R., Dia, H., Morawska, L., 2009, Road Traffic Emission and Fuel Consumption Modelling: Trends, New Developments and Future Challenges, in *Traffic Related Air Pollution,* Nova Publishers, USA, book in preparation.

AUTHORS

Robin Smit
Pacific Air & Environment,
59 Melbourne Street,
South Brisbane, QLD 4101, Australia
corresponding author,
robin.smit@pae.net.au,
Tel: 61 (0)7 3004 6400

James McBroom
Griffith School of Environment,
Griffith University,
Nathan QLD 4111, Australia.

1 e.g. size, location of catalysts, mix of catalyst material.
2 For instance, it should include many pollutants and fuel consumption to provide insight in possible trade-offs between these components. It should also include all major vehicle technology classes that drive on our roads.
3 This means that model predictions should be realistic and non-extreme in all simulated conditions, which includes extrapolation or not entirely realistic input data from traffic models (e.g. simulated driving patterns).

Climate Change @ Work

The practicalities of climate change impacts on the workplace will discussed at a workshop organised by the Workplace Research Centre at the University of Sydney entitled Climate Change @ Work: Creating the Sustainable Workplace. Scheduled for April 3, 2009 at the Hilton Hotel in Sydney, the workshop will explore aspects of jobs, human resource management, workplace relations, and skill needs in terms of business sustainability to minimize the impacts of global warming. Details about the workshop can be obtained from www.wrc.org.au.

Schwartz, J., Litonjua, A., Suh, H., Verrier, M., Zanobetti, A., Syring, M., Nearing, B., Verrier, R., Stone, P., MacCallum, G., Speizer, F.E., Gold, D.R., 2006, Traffic related pollution and heart rate variability in a panel of elderly subjects. *Thorax*, **60**, 455-61.

Seaton, A., MacNee, W., Donaldson, K., Godden, D., 1995, Particulate air pollution and acute health effects. *Lancet*, **345**, 176-8.

Seaton, A., Soutar, C.A., Crawford, V., Elton, R., McNerlan, S., Cherrie, J., Watt, M., Agius, R., Stout, R., 1999, Particulate air pollution and the blood. *Thorax*, **54**, 1027-32.

Simpson, R., Denison, L., Petroeschevsky, A, Thalib, L., Williams, G., 2000, Effects of ambient particle pollution on daily mortality in Melbourne, 1991-6. *Journal of Exposure Analysis & Environmental Epidemiology,* **10**, 488-96.

Simpson, R., Williams, G., Petroeschevsky, A., Best, T., Morgan, G., Denison, L., Hinwood, L., Neville, G., Neller, A., 2005a, The short-term effects of air pollution on daily mortality in four Australian cities. *Australian and New Zealand Journal of Public Health,* **29**, 205-12.

Simpson, R., Williams, G., Petroeschevsky, A., Best, T., Morgan, G., Denison, L., Hinwood, A., Neville, G., 2005b, The short-term effects of air pollution on hospital admissions in four Australian cities *Australian and New Zealand Journal of Public Health*, **29**,213-21.

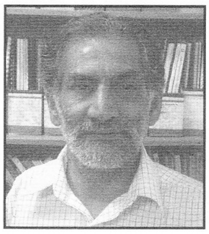
Sram, R.J., Binkova, B., Dejmek, J., Bobak, M., 2005, Ambient air pollution and pregnancy outcomes: a review of the literature. *Environmental Health Perspectives,* **113**, 375-82.

Tsuji, H., Larson, M.G., Venditti, F.J., Manders, E.S., Evans, J.C., Felman, C.L., Levy, D., 1996, Impact of reduced heart rate variability on risk for cardiac events. The Framingham Heart Study. *Circulation*, **94**, 2850-8.

WHO Europe, 2003, *Health aspects of air pollution with particulate matter, ozone and nitrogen dioxide: report on a WHO working group.* Rep. 92, WHO, Bonn, Germany.

Wittmaack, K., 2007, In search of the most relevant parameter for quantifying lung inflammatory response to nanoparticle exposure: particle number, surface area, or what? *Environmental Health Perspectives,* **115**, 187-94.

AUTHORS



Bin Jalaludin
MBBS(Syd) MPH(Syd) PhD(Syd) MRCP(UK) FAFPHM
Director, Centre for Research, Evidence Management and Surveillance
Sydney South West Area Health Service, Sydney; and
Conjoint Professor, School of Public Health and Community Medicine
University of New South Wales, Sydney.

Address for correspondence:
Professor Bin Jalaludin
Centre for Research, Evidence Management and Surveillance
Sydney South West Area Health Service
Locked Bag 7017
Liverpool NSW 1871
AUSTRALIA

T: (02) 9828-6000
F: (02) 9828-6012
E: b.jalaludin@unsw.edu.au

Correction

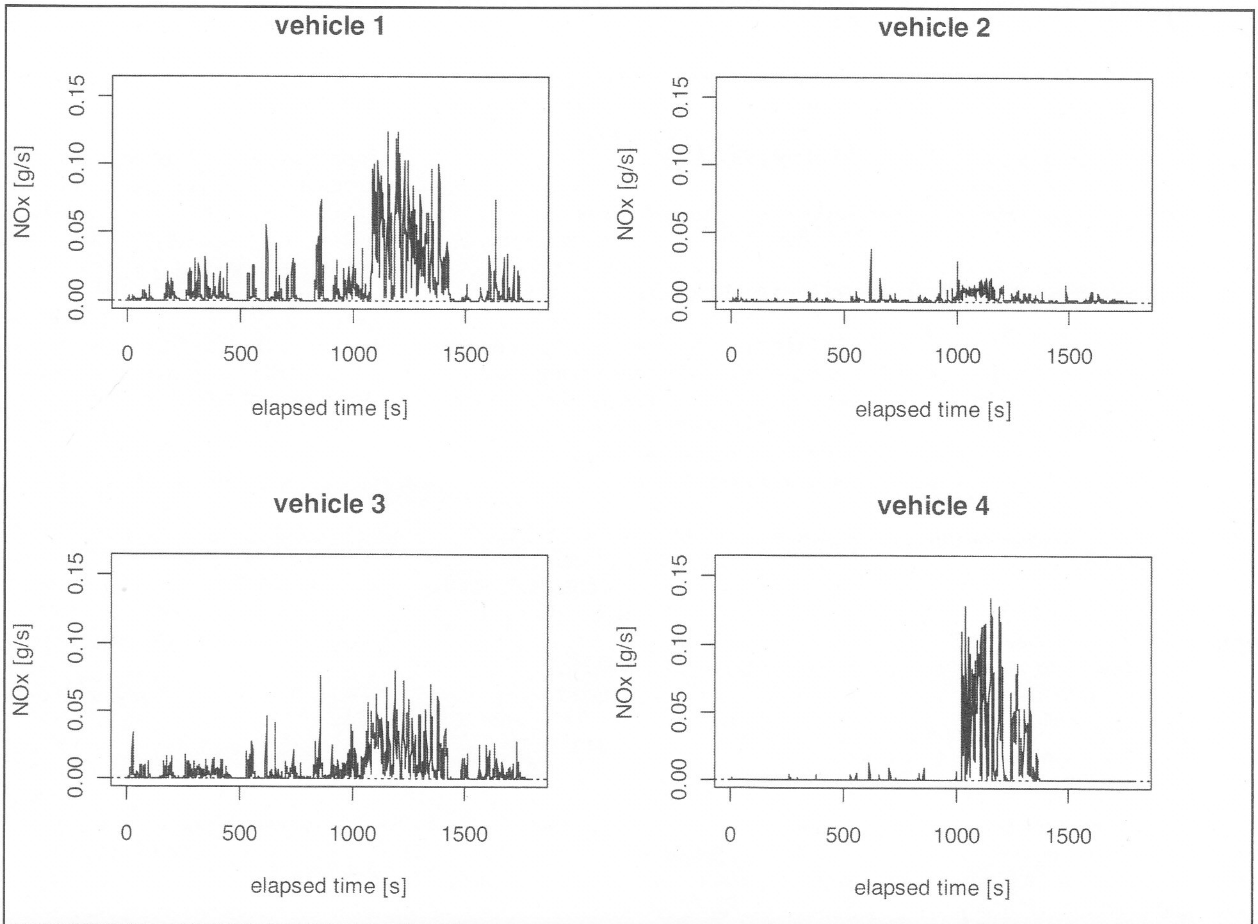


Figure 1 on page 14 of the February 2009 issue was incomplete (Smit and McBroom traffic modelling article). The correct figure is reproduced above.

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

Robin Smit and James McBroom

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 adressed.

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 published[1] – 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 A/NZ 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 <u>before</u> 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

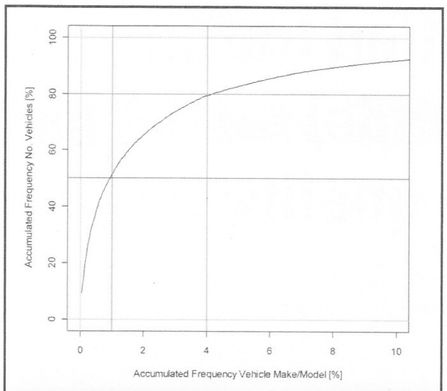


Figure 1. Distribution of Number of Registered Passenger Cars in Queensland over Vehicle Make and Model Combinations (Data Source: ABS, 2007).

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 useage (annual mileage), emission control systems, and in some cases, specific considerations[2]. 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 orginal 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 implictly (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.* duel-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 less[3], *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 clipped[4] 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 indentified 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 emprical 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 adressed as part of an ongoing process of model improvement.

REFERENCES

ABS 2007, *Motor Vehicle Census*. Australian Bureau of Statistics, 31 March 2007, Report 9309.0.

Atjay, D.E., Weilenmann, M., 2004, Static and dynamic instantaneous emission modelling. *International Journal of Environment and Pollution,* **22**, 3, 226-239.

Atjay, D.E., Weilenmann, M., Soltic, P., 2005, Towards accurate instantaneous emission models. *Atmospheric Environment,* **39**, 2443-2449.

Barth, M., An, F., Younglove, T., Scora, R., Levine, C., Ross, M., Wenzel, T., 2000, *Development of a Comprehensive Modal Emissions Model,* National Corporate Highway Research Project. Transportation Research Board. April.

CONCAWE 1999, *Fuel Quality, Vehicle Technology and Their Interactions.* by McArragher *et al.*, CONCAWE Automotive Emissions Management, Brussels, March.

CSIRO 2008, *Modelling of the Future of Transport Fuels in Australia.* by Graham, P., Reedman, L., Poldy, F., CSIRO Report IR 1046, June.

DEH 2005, *NISE 2 – Drive Cycle and Short Test Development – Final Report.* Department of the Environment and Heritage (DEH), Prepared by Orbital Australia Pty. Ltd., September.

Elst, D.A.M.M., Smokers, R.T.M., De Koning, J.W., 2004, *Evaluation of the Capabilities of On-Board Emission Measurement System for the Purpose of Generating Real-Life Emission Factors.* TNO Report 04.OR.VM.039.1/DE.

Hawley, J.G., Bannister, C.D., Brace, C.J., Cox, A., Ketcher, D., Stark, R., 2004, Vehicle modal emissions measurement – techniques and issues. *Journal of Automobile Engineering,* **218**, 1-15.

ISSRC 2008, *International Vehicle Emissions Model.* http://www.issrc.org/ive/.

NEPC 2000, *In-Service Emissions Performance - Phase 2 Vehicle Testing.* by Anyon, P., Brown, S., Pattison, D., Beville-Anderson, J., Walls, G. & Mowle, M., National Environment Protection Council Service Corporation, Australia, ISBN 0 642 323 348.

NIWA 2008. *Assessing Vehicle Air Pollution Emissions,* National Institute of Water & Atmospheric Research (NIWA), Christchurch, New Zealand, by Bluett, J., Dey, K., Fisher, G., Report CHC 2008-001, July.

North, R.J., Ochieng, W.Y., Quddus, M.A., Noland, R.B., Polak, J.W., 2005, Development of a vehicle emissions monitoring system. *Transportation Research* D, 167-177.

NRC 2000, *Modeling Mobile-Source Emissions.* National Research Council, National Academy Press, Washington D.C., www.nap.edu/openbook/.

Smit, R., Smokers, R. & Schoen, E., 2005, VERSIT+ LD: Development of a new emission factor model for passenger cars linking real-world emissions to driving cycle characteristics. *Proceedings of the 14th Symposium Transport and Air Pollution,* Graz, Austria, ISBN 3 902465 16 6, 177-186.

Smit, R., Dia, H., Morawska, L., 2009, Road Traffic Emission and Fuel Consumption Modelling: Trends, New Developments and Future Challenges. in "Traffic Related Air Pollution and Internal Combustion Engines", Nova Publishers, U.S.A., *book in preparation* (https://www.novapublishers.com/catalog/product_info.php?products_id=9546).

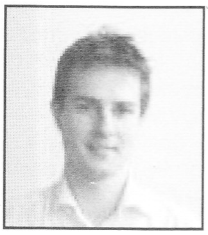
Smit, R., McBroom, J., 2009a, Development of a New High Resolution Traffic Emissions and Fuel Consumption Model for Australia and New Zealand – Why is it needed? *Air Quality and Climate Change,* **43**, 1, 14-16.

Watson, H.C., 1995, Effects of a wide range of drive cycles on the emissions from vehicles of three levels of technology. *SAE Technical Paper Series,* 950221, 119-132.

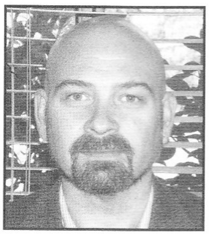
Zhang, K., Frey, C., 2008, Evaluation of response time of a portable system for in-use vehicle tailpipe emissions measurement. *Environmental Science and Technology,* **42**, 221–227.

Zhang, Y., Stedman, D.H., Bishop, G.A., Guenther, P.L., Beaton, S.P., 1995, Worldwide on-road vehicle exhaust emissions study by remote sensing. *Environmental Science and Technology,* **29**, 2286-2294.

AUTHORS



Robin Smit
Pacific Air & Environment,
59 Melbourne Street, South Brisbane, QLD 4101, Australia
corresponding author,
robin.smit@pae.net.au,
Tel: 61 (0)7 3004 6400



James McBroom
Griffith School of Environment,
Griffith University,
Nathan QLD 4111, Australia.

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.

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.

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

Robin Smit and James McBroom

ABSTRACT

This paper discusses the ongoing development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand. The model structure and some preliminary results are discribed showing that the new modelling approach appears to deliver satisfactory results in terms of accuracy, reliability and robustness. It is believed that model performance can be further improved by exploring various other options. It is also important to examine the performance of other model structures (*e.g.* simpler or more complex models) and further examine the interactions between availability and quality of input data, level of model detail and overall prediction accuracy.

INTRODUCTION

This paper is the third 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 (Smit and McBroom 2009b)?
- What is the best model structure for such a model and how does the model perform (this paper)?
- Application and outlook on further development.

MODEL CONSIDERATIONS

The development of the new high resolution traffic emission should take into account a number of considerations. Firstly, road traffic impact assessment is really a multidisciplinary exercise but explicit consideration of multidisciplinary aspects is often lacking in the development of traffic emissions models – so a thorough understanding of other disciplines such as traffic modelling (generating input data) and dispersion modelling (using emission predictions) is essential to optimise interface with other models and to prevent errors (*e.g.* incorrect interpretation of input data definitions). Secondly, a review of international traffic emission models showed that numerous models exist or are being developed with varying levels of detail (Smit *et al.* 2009); therefore, various "model structures" are possible ranging from a relatively simple "fundamental driving mode model", which predicts emissions for a limited number of discrete driving modes (idle, acceleration, deceleration, cruise), to very complex models that use many vehicle parameters to compute instantaneous emissions (g s^{-1}) as a function of, for example, engine speed, gear shift behaviour, catalyst behaviour and engine power.

MODEL STRUCTURE

This current model is basically a hybrid model where model variables that reflect (theoretical) aspects known to influence vehicle emissions are combined with a statistical ("black box") approach to find the best empirical relationships. This model is designed to combine the "best of both worlds" to achieve the best possible outcomes, and will include confidence intervals around the predictions. It is noted that development is ongoing and that certain aspects of the model will change when time progresses and more vehicle test data are incorporated in order to achieve an optimum model. Traffic emission rates are simulated using multivariate regression functions for individual vehicles in the traffic stream:

$$E_{t,m} = [E'_{t,m}]^2 \qquad (1)$$

where $E_{t,m}$ represents the back-transformed predicted emission rate (g s^{-1}) for pollutant m.

$$E'_{t,m} = \beta_0 + \beta_1 v_t + \beta_2 a_t + \beta_3 v_t a_t + \beta_4 P_t + \beta_5 P_t^2 + \beta_6 P_t v_t + \beta_7 \Delta P3_t + \beta_8 \Delta P9_t + \beta_9 oP9_t + \beta_{10} \log TAD9_t^N + \varepsilon \qquad (2)$$

$$\varepsilon \sim AR(1, 2, 3, \ldots) \qquad (3)$$

Table 1 – Model Variables

Variable	Formulae	Unit
Instantaneous speed at time = t *	v_t	m s^{-1}
Acceleration at time = t	$a_t = \frac{dv}{dt} \approx (v_t - v_{t-1})$	m s^{-2}
Instantaneous power at the wheels at time = t **	P_t	kW
Delta power over last three seconds at time = t	$\Delta P3_t = P_t - P_{t-2}$	kW
Delta power over last three seconds at time = t	$\Delta P9_t = P_t - P_{t-8}$	kW
Oscillation power over last nine seconds at time = t	$oP9_t = \lvert P_t - P_{t-1}\rvert + \ldots + \lvert P_{t-7} - P_{t-8}\rvert$	kW
Logarithm of distance-normalised total absolute difference in speed (TAD) over last nine seconds at time = t	$\log TAD9_t^N = \log\left(1 + \frac{1000\left(\lvert v_t - v_{t-1}\rvert + \ldots + \lvert v_{t-7} - v_{t-8}\rvert\right)}{\sum_t^{t-8} x_t}\right)$	m s^{-1} km^{-1}

$E_{t,m}'$ represents the square-root transformed predicted emission rate and β_0, ..., β_{10} represent the regression coefficients. This transformation was used to improve model fit and to prevent prediction of negative emission rates. The model variables are derived from speed-time data and an overview is presented in Table 1. They include traditional variables such as instantaneous speed, acceleration and power, but also newly developed variables that quantify the change in power ($\Delta P3_t$, $\Delta P9_t$) and oscillation in either speed ($logTAD9_t^N$) or power ($oP9_t$) over a pre-defined period of time prior to the point in time for which the prediction is made. These variables aim to quantify and include "history effects" into the model. This is important because vehicle operating history (i.e. the last several seconds of vehicle operation) can play a significant role in an instantaneous emissions value, for example, due to the use of a timer to delay command enrichment or oxygen storage in the catalytic converter (*e.g.* Barth *et al.* 2000). As we are dealing with time series-data, the statistical model also needs to account for autocorrelation effects. Autocorrelation is a term used to describe the relationship of data with itself, which occurs frequently when data is measured through time (time-series). To account for autocorrelation effects, we have developed first, second or third order autoregressive (AR 1, 2, 3) statistical models.

Initial Model Results

We have used NO_x and CO_2 emissions testing data for five representative models and makes in the Australian petrol car fleet for initial testing of the model concept:

- Mitsubishi Magna (1986 – ADR 37)
- Ford Falcon (1988 – ADR 37/00)
- Toyota Camry (1995 – ADR 37/00)
- Toyota Corolla (2001 – ADR 37/01)
- Holden Commodore (2000 – ADR 37/01)

Second-by-second emissions test data were obtained from chassis dynamometer tests using speed–time profiles that reflect real-world operations from the preliminary NISE 2 study (Orbital 2005). A least-squares multiple autoregressive approach was used to estimate the regression coefficient values. Residual analysis (Neter *et al.* 1996) was then used to verify that the assumptions of the regression analysis were not violated (i.e. normality of error terms, constant error variance and presence and effect of outlying observations). The last step of the modelling process involves back-transformation.

The model generally predicts NO_x and CO_2 emission rates (g s^{-1}) for each vehicle quite well with a coefficient of determination (R^2) ranging between 0.62-0.85 for NO_x and 0.88-0.94 for CO_2. This means that 62% to 94% of the variation in instantaneous emissions can be explained with the models. The sum of emissions from all vehicles in a traffic stream is needed to assess the effects of road traffic on (local) air quality and greenhouse gas emissions. Figure 1 and 2 therefore show total traffic stream emissions (g s^{-1}) for all five vehicles combined. It is clear from these charts that total emissions are simulated well by the regression models. The total emissions profile is replicated well even though there is a difference in model performance for the individual vehicles. In Figure 1, predicted instantaneous NO_x emissions (g s^{-1}) for the traffic stream have a mean absolute error of 31% (Barth et al. 2000). Total cumulative emissions (g) have an error of +15%, which means that the predicted sum of instantaneous predictions over the selected speed-time profile is 15% higher than the observed value.

In Figure 2, predicted instantaneous CO_2 emissions (g s^{-1}) for the traffic stream have a mean absolute error of 8%. Total cumulative emissions (g) have an error of +2%, which means that the predicted sum of instantaneous predictions over the selected speed-time profile is 2% higher than the observed value.

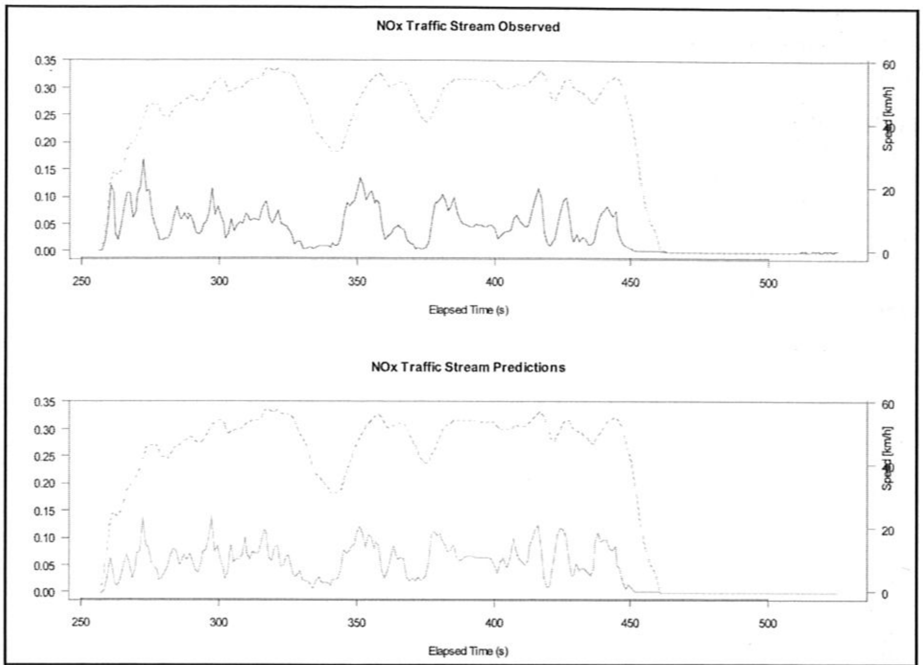


Figure 1 – Time-series Plots for All five Vehicles Combined (1 Hz), Top Chart: Observed Total NO_x Emissions, Bottom Chart: Predicted Total NO_x Emissions (1 Hz), Arterial Speed-Time Profile in both Charts (light-Grey Dotted Line)

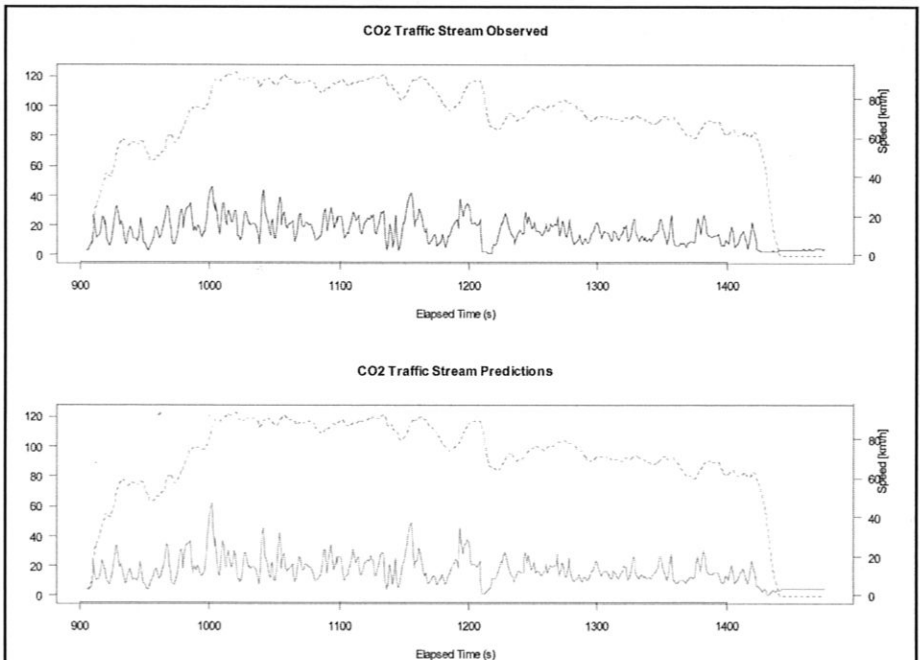


Figure 2 – Time-series Plots for All five Vehicles Combined (1 Hz), Top Chart: Observed Total CO_2 Emissions, Bottom Chart: Predicted Total CO_2 Emissions (1 Hz), Freeway Speed-Time Profile in both Charts (light-Grey Dotted Line)

CONCLUSIONS AND OUTLOOK

Some preliminary results were discussed in this paper showing that the new modelling approach appears to deliver satisfactory results in terms of model accuracy, reliability and robustness. There are, however, various other options that we still want to explore to further improve on model performance such as optimum lag correction and further model verification and validation (*e.g.* splitting database, data for different driving cycles). It is also important to explore the performance of other model structures (*e.g.* simpler or more complex models) and further examine the trade-off between level of model detail and overall prediction accuracy.

REFERENCES

Barth, M., An, F., Younglove, T., Scora, R., Levine, C., Ross, M., Wenzel, T., 2000, *Development of a Comprehensive Modal Emissions Model,* National Corporate Highway Research Project. Transportation Research Board, Washington D.C.

Neter, J., Kutner, M.H., Nachtsheim, C.J., Wasserman, W., 1996, *Applied Linear Statistical Models,* 4th Edition, McGraw-Hill, Chicago, IL.

Orbital, 2005, NISE 2 – Contract 2 *Drive Cycle and Short Test Development,* Department of the Environment and Heritage, September.

Smit, R., Dia, H., Morawska, L., 2009, Road Traffic Emission and Fuel Consumption Modelling: Trends, New Developments and Future Challenges, in *Traffic Related Air Pollution,* Nova Publishers, USA, book in preparation.

Smit, R., McBroom, J., 2009a, Development of a New High Resolution Traffic Emissions and Fuel Consumption Model for Australia and New Zealand – Why is it needed? *Air Quality and Climate Change,* **43**(1), 14-16.

Smit, R., McBroom, J., 2009b, Development of a New High Resolution Traffic Emissions and Fuel Consumption Model for Australia and New Zealand – Data Quality Considerations, *Air Quality and Climate Change,* **43**(2), 13-16.

AUTHORS

Robin Smit
PAEHolmes,
59 Melbourne Street,
South Brisbane,
QLD 4101
Corresponding author,
robin.smit@paeholmes.com,
Phone: 07 3004 6400

James McBroom
Griffith School of Environment,
Griffith University,
Nathan
QLD 4111.

New Members for January to June, 2009

The following new members have recently joined the Society. We hope that their membership is both rewarding to them and their organisations and that they become personally involved in the activities of their respective Branches.

INDIVIDUAL MEMBERS

Name	Company	State
Giovanni Agosti	Envirolab Services Pty Ltd	NSW
Michael Arch	Concordia Pacific	NSW
Holly Marlin		NSW
Janelle Pickup	Department of Environment & Climate Change NSW	NSW
Sandra Taylor	Envirolab Services Pty Ltd	NSW
Heather Tilley		NSW
John Wassermann	Wilkinson Murray Pty Ltd	NSW
Dr Perry Davy	GNS Science	NZ
Theda Hall	Golden Bay Cement	NZ
Dr Andreas Markwitz	GNS Science	NZ
Jayne Metcalfe	Emission Impossible Ltd	NZ
Dr Bill Trompetter	GNS Science	NZ
Dr Wendy Barron	CSIRO	QLD
Adjunct Professor Damian Lockie	Faculty of Law, Bond University	QLD
Christy McConaghy		QLD
Len Turczynowicz	Golder Associates Pty Ltd	SA
Dr Colin Allison	CSIRO	VIC
Dr Valerio Bisignanesi	EPA Victoria	VIC
Dr Robert Edis		VIC
Urs Meier (student)	Connell Wagner	VIC
Matthew Meere	Nyrstar	TAS
Alexis Davie	ALCOA – Kwinana Refinery	WA
Dr Annemarie J. B. M. De Vos	The University of WA	WA
Dr Anthony Horton		WA
Peter Mountford		WA

ORGANISATION MEMBERS

Company	Member Representatives	State
Geodatalink	Ella Castillo Shannon Benz	QLD
X Strata Mount Isa Mine	Ed Turley	QLD

Organisation Membership is open to any company, government department or organisation that is closely associated with the Objects of the Society. An Organisation Member may:

1. Nominate up to two representative members, who will each have all membership rights.
2. Nominate up to two additional people to receive copies of the "Air Quality and Climate Change" journal.
3. Seek the member rate for CASANZ conferences, seminars, courses, etc. for up to any two people from the organisation.
4. Be listed in the "Air Quality and Climate Change" journal as an Organisation Member.

Development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand – Model application

R. Smit and J. McBroom

ABSTRACT

This paper concludes a series of brief papers in which we have presented and discussed the development of a new high resolution model for Australia and New Zealand. We show in this paper that the information generated by a high resolution model can be used in various ways. It can be used in its own right (*e.g.* emission inventory) or it can be fed into local air quality dispersion models to carry out, for example, "hot spot" analysis and impact assessment of traffic management measures. This would provide more accurate predictions than a screening model, and would be important in cases where sensitivity is required. Examples include cases where predicted air quality is close to guideline values (e.g. at critical locations such as a new residential area near a busy highway) or cases where policy measures are likely to cause relatively small impacts on emissions and fuel consumption (*e.g.* specific traffic management measures such as dynamic speed limits, traffic signal coordination, metering signals).

INTRODUCTION

This paper is the last of a series of four short papers that have been published in 2009 and 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 paper discussed different aspects: the first paper explored the need for such a model (Smit and McBroom 2009a), the second paper discussed the various data quality considerations (Smit and McBroom 2009b) and the third paper presented the model structure (Smit and McBroom 2009c). This final paper will showcase the value of the model by showing a few possible applications.

APPLICATION OF TRAFFIC EMISSION MODELS IN PRACTICE

There are various purposes for which traffic emission and fuel consumption information is required for road networks. Three main modelling objectives can be distinguished:

1. impact assessment (*e.g.* verify compliance with air quality standards);
2. development of emission inventories (*e.g.* source priorisation, identification of high-priority areas); and
3. design and evaluation of transport policies and/or traffic measures (trend analysis, scenario testing).

Emission predictions may be conducted at the local, regional, national or even global scale. For instance, predictions may be required as input for local (*e.g.* hot spot analysis) or regional air quality modelling (*e.g.* photochemical smog modelling). Or they may be needed to assess the impacts of new road projects or the implementation of (new) traffic management measures such as lower speed limits, traffic signal coordination and metering signals on freeway on-ramps.

We will show in this paper that the high resolution model can be used in different ways to answer particular questions. The advantage of the model is that it is designed to be sensitive to changes in driving behaviour, which makes it appropriate to use in cases where other models cannot be used. The disadvantage is that it is relatively data intensive because it specifically requires speed-time data. Speed-time data can be obtained from different sources. The most reliable way is to record speed–time profiles in the field using, for instance, on-board GPS equipment (*e.g.* by employing a floating car technique) or road-side video sensor and image processing technology. In the absence of field data for a specific local situation, there are two main options, as will be shown later in this paper:

1. readily available and representative driving cycles may be used to quantify "typical" driving behaviour for a particular traffic situation; or
2. (microscopic) traffic simulation models can generate these data for each vehicle in the traffic stream.

EXAMPLE 1 – IMPACT ASSESSMENT OF SPECIFIC TRAFFIC MEASURES

We noted previously that a high resolution model is needed to address increasingly complex research questions and study objectives. One example is an assessment of the impacts of a lower speed limit on a freeway from the common 100 km h^{-1} to an 80 km h^{-1} speed limit with strict radar control. Speed-time data were sampled in both traffic situations in Europe, which were then compressed into two driving cycles (Elst and Winkel 2004) as shown in Figure 1.

The driving cycles were used as input to the emission algorithms for five Australian vehicles that were presented in Smit and McBroom (2009c) to:

1. estimate second-by-second emission levels in grams per second, and subsequently

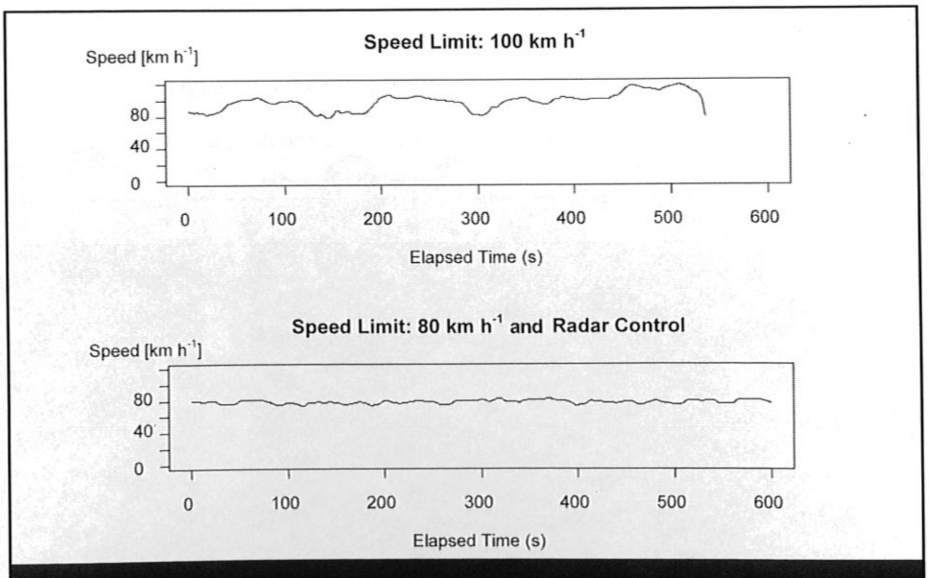


Figure 1 – Driving cycles for two freeway situations

Table 1— Impact of speed limit reduction on vehicle emission rates (g km^{-1})

Vehicle	CO_2			NO_x		
	100 km h^{-1} Speed Limit [g (veh.km)$^{-1}$]	80 km h^{-1} Speed Limit [g (veh.km)$^{-1}$]	Difference [%]	100 km h^{-1} Speed Limit [g (veh.km)$^{-1}$]	80 km h^{-1} Speed Limit [g (veh.km)$^{-1}$]	Difference [%]
Vehicle 1	250	230	-8%	3.4	2.6	-24%
Vehicle 2	138	126	-8%	0.4	0.1	-76%
Vehicle 3	152	146	-4%	0.9	1.0	+6%
Vehicle 4	173	149	-14%	1.2	0.6	-50%
Vehicle 5	159	162	+2%	1.3	1.3	+2%
Traffic Stream (total)	**872**	**814**	**-7%**	**7.2**	**5.6**	**-23%**

2. sum the second-by-second cycle emissions and divide by total distance to estimate mean emission rates in grams per km.

The results are presented in Table 1. It can be seen that the reduction of the speed limit is predicted to result in a net reduction in NO_x and CO_2 emissions of 23% and 7%, respectively, at traffic stream level. Interestingly, the reductions are not consistent for all individual vehicles. Some vehicles may experience an increase in emission rates, whereas others show an opposite reaction. The magnitude of the effect can also be quite different, varying from only a few percent change to a difference of about 75%. These differences in emission behaviour are expected and due to vehicle specific differences in *e.g.* engine management systems.

EXAMPLE 2 – DEVELOPMENT OF AN URBAN EMISSION INVENTORY

There is a need in Australia and New Zealand for a consistent and harmonised modelling framework with appropriate modelling tools for each scale that takes into account input data availability at different levels. This framework can be developed from the bottom-up using a high resolution model. A high resolution model provides a cost-effective approach to estimating emissions for traffic situations for which no measurement data are available, as was shown in the previous section.

A similar approach is taken to showcase the development of a traffic situation model. This type of model provides composite emission factors (g (veh.km)$^{-1}$) for various vehicle classes for well-defined discrete traffic situations. Smit *et al.* (2008) developed such a model for 18 different traffic situations for two road types, i.e. 10 different freeway traffic conditions, which were defined in terms of "speed limit" (80, 100, 120 km h^{-1}), "speed category" (< 10, 10-25, 25-40, 40-75, >75 km h^{-1}) and "volume-to-capacity ratio category" (≤ 0.5, > 0.5) and eight different urban (arterial) traffic conditions, which were defined in terms of "speed category" (< 15, 15-30, 30-45, 45-60, > 60 km h^{-1}) and "traffic density category" (< 40, 40-70, >70 passenger car equivalents (lane.km)$^{-1}$). Driving behaviour in each traffic situation is quantified with representative driving cycles like the ones presented in Figure 1. The driving cycles for the urban speed range (0-60 km h^{-1}) were input into the high resolution model in a similar fashion as in the previous section. Individual vehicle results were then averaged to arrive at composite emission factors (g (veh.km)$^{-1}$). The final results for NO_x are plotted by mean speed in Figure 2, where each data point represents a particular traffic situation on either an urban road (arterials) or a freeway.

It can be seen that the mean emission factors generally exhibit an increasing trend with increasing mean speed for both freeways and arterials, but that emission factors can be higher or lower (about ±25%) for different traffic situations with similar average speeds. The composite emission factors (g (veh.km)$^{-1}$) now have to be multiplied with traffic volume (veh h^{-1}) and road length (km) data to estimate total emissions (g h^{-1}) for a section of road. Aggregating the results for all of the roads in the network then results in the required emission inventory. The emission inventory, in turn, can then be used, for instance, as input for regional (photochemical) air quality modelling, source prioritisation or identification of high-priority emission areas. The information needed to determine the actual traffic situation for a particular section of road (i.e. road type, speed limit, mean speed, V/C ratio, traffic density) can be readily sourced from commonly available transport models, along with traffic volume and road length information (Smit *et al.* 2008).

EXAMPLE 3 – INTERFACING WITH TRAFFIC MODELS

The objective of a particular study determines the size of the study area, and thus size of the modelled road network, that needs to be considered. This, in turn, determines the extent of the available input data. For instance, (macroscopic) strategic transport models such as EMME2 and TRANSTEP typically simulate traffic flows in large urban networks and provide relevant information for each road link such as traffic volume for a few basic vehicle classes, average speed and road length (Smit 2006). These models provide sufficient information to develop a

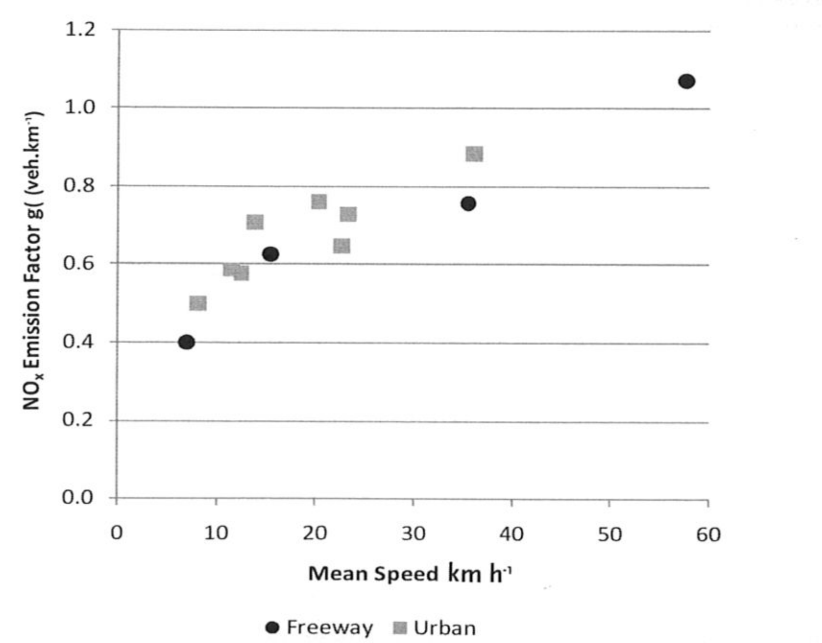


Figure 2 – Mean NO_x emission factors for petrol passenger cars

regional emission inventory, as was shown in the previous section.

More complex (microscopic) traffic simulation models such as AIMSUN, VISSIM and PARAMICS are also commonly used in practise. These models provide very detailed information as they simulate how individual vehicles move through a road network. They can, in principle, output speed-time and location data for each individual vehicle. However, this is typically not a standard output of these models, additional coding is required to extract this type of information, which can be cumbersome. So it makes sense to consider integrating traffic emission algorithms with the traffic simulation software. This would ensure ease of use and correct use of the emission algorithms (quality control). There are of course, a number of issues that require further examination such as the quality of the generated driving patterns, which can sometimes be unrealistic, such as excessive accelerations (Smit *et al.* 2007), that will affect the accuracy of the emission predictions.

A final note is that the majority of available traffic simulation models already have internal emission prediction capabilities. We have compared updated AIMSUN emission algorithms (Panis *et al.*, 2006) with measured emissions data on Australian ligh-duty petrol vehicles to test the validity of using these emission algorithms in Australia (Orbital 2005). This work revealed large discrepancies. Figure 3 shows, as an example, measured and predicted NO_x emissions at a second-by-second resolution.

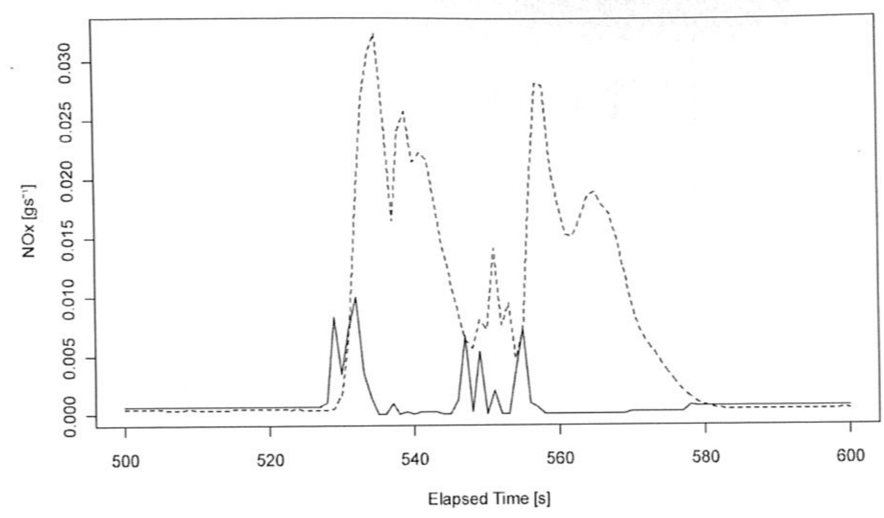


Figure 3 – Comparison of instantaneous AIMSUN NO_x predictions (solid line) to measured Australian emissions (dashed line) for light-duty petrol vehicles

This clearly demonstrates that AIMSUN predictions are substantially biased (underestimation), but also that the presence, magnitude and the locations of emission peaks occur at different times. Use of these AIMSUN algorithms would thus allocate emissions peaks to the wrong network location and time. This shows the importance of using an Australian emission algorithm (like our high resolution model), or at least recalibration of existing emission algorithms, in order to prevent poor emission predictions with consequently poor infrastructure and policy making decisions.

CONCLUSIONS AND OUTLOOK

This paper concludes a series of brief papers in which we have presented and discussed the development of a new high resolution model for Australia and New Zealand. The model is not operational yet as it is currently in a "proof of concept" phase. For instance, more work is required to include more emissions test data and validate the emission algorithms with independent data sources. We have shown in this paper that the information generated by a high resolution model can be used in various ways. It can be used in its own right (*e.g.* emission inventory, prediction of greenhouse gas emissions) or it can be fed into local air quality dispersion models to carry out, for example, "hot spot" analysis and impact assessment of traffic management measures. This would provide more accurate predictions than a screening model, and would be important in cases where sensitivity is required. For instance, in cases where predicted air quality is close to guideline values (*e.g.* at critical locations such as a new residential area near a busy highway) or in cases where policy measures are likely to cause relatively small impacts on emissions and fuel consumption (*e.g.* specific traffic management measures such as dynamic speed limits, traffic signal coordination, metering signals).

REFERENCES

Elst, D.A.M.M., Winkel, R.G., 2004. *Ritcycli, Deelrapport: Verzamelen en Opnemen van Praktijkritdata in Stedelijke Omgeving en t.b.v. Evaluatie van Rotterdam Overschie (in Dutch, Title"Driving Cycles: Collection of Driving Patterns in an Urban Area for Evaluation of Rotterdam Overschie"),* TNO report 04.0R.VM.015.1/DE, 11 May.

Orbital, 2005. *NISE 2 Contract 2 Drive Cycle and Short Test Development,* Department of the Environment and Heritage, Canberra, September.

Panis, L.I., Broekx, S., Liu, R., 2006, Modelling instantaneous traffic emission and the influence of traffic speed limits. *Science of the Total Environment,* **371**, 270-285.

Smit, R., 2006. *An Examination of Congestion in Road Traffic Emission Models and Their Application to Urban Road Networks,* Ph.D. Dissertation, Griffith University, Brisbane, Australia. March.

Smit, R., Smokers, R., Rabé, E., 2007, A new modelling approach for road traffic emissions: VERSIT+. *Transportation Research Part D,* **12**, 414-422.

Smit, R., Poelman, M., Schrijver, J., 2008, Improved road traffic emission inventories by adding mean speed distributions. *Atmospheric Environment,* **42**, 916-926.

Smit, R., Dia, H., Morawska, L., 2009, Road Traffic Emission and Fuel Consumption Modelling: Trends, New Developments and Future Challenges, in *Traffic Related Air Pollution and Internal Combustion Engines,* Demidov, S. and Bonnet, J. (Eds.), Nova Publishers, U.S.A., https://www.novapublishers.com/catalog/product_info.php?products_id=9546

Smit, R., McBroom, J., 2009a, Development of a New High Resolution Traffic Emissions and Fuel Consumption Model for Australia and New Zealand – Why is it needed? *Air Quality and Climate Change,* **43**(1), 14-16.

Smit, R., McBroom, J., 2009b, Development of a New High Resolution Traffic Emissions and Fuel Consumption Model for Australia and New Zealand – Data Quality Considerations. *Air Quality and Climate Change,* **43**(2), 13-16.

Smit, R., McBroom, J., 2009c, Development of a New High Resolution Traffic Emissions and Fuel Consumption Model for Australia and New Zealand – Model Structure. *Air Quality and Climate Change,* **43**(3), 15-18.

AUTHORS

Robin Smit
PAEHolmes,
59 Melbourne Street,
South Brisbane,
QLD 4101
Corresponding author,
robin.smit@paeholmes.com,
Phone: 07 3004 6400

James McBroom
Griffith School of Environment,
Griffith University,
Nathan
QLD 4111.