Development of a new high-resolution traffic emissions and fuel consumption model

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Abstract

This paper 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). A high-resolution model is needed to adequately address increasingly complex policy questions. The development of such a model is facilitated by various developments in the international arena, for instance with respect to input and emissions test data. Some preliminary results are discussed, which show that the new modelling approach appears to produce satisfactory results in terms of model accuracy, reliability and robustness. It is believed that model performance can be further improved by exploring various options such as other statistical methods, modelling of individual vehicles instead of composite vehicles, use of (different combinations of) other prediction variables (e.g. other power functions, longer history effects), different response variables (other transformations, fuel-based indices), and so forth. It is also important to explore 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.

Refereed Paper

This paper has been critically reviewed by at least two recognised experts in the field.

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INTRODUCTION

Why do we use models to estimate traffic emissions? There are a number of reasons for this. First, given the large number of on-road vehicles and the many factors that influence emissions from individual vehicles, it is not feasible (yet) to adequately measure traffic emissions in the field[1]. So models are needed to do this. Second, from a policy perspective, it is necessary to examine the trends in traffic emissions, as well as to make projections into the future, where the latter cannot be measured. As a consequence, 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 a national level, average speed models are applied at a network level, and more detailed models are used for local impact assessment (Smit et al. 2009).

This paper reports on the development of a new high-resolution traffic emissions model using Australian test data. This effort is inspired by the belief that a number of ongoing developments will facilitate demand for, and development and application of, more complex, detailed and comprehensive high-resolution emission models, to address increasingly complex research questions and study objectives, ultimately leading to a finer spatial and temporal allocation of traffic emissions. It is noted that this model is part of a modelling framework that contains other models for more aggregate scales (e.g. fleet composition model, average speed model, national model).

RELEVANT INTERNATIONAL DEVELOPMENTS

There are various developments around the world that will likely lead to a more common application of complex high-resolution traffic emission models. First, substantial improvements can be expected in 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). 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, Broekx and Liu 2006). Second, ongoing developments in the field 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. Third, 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 (Smit 2008), so sensitive high-resolution models will be needed to accurately predict the correct direction and magnitude of the effects.

DEVELOPMENT OF A HIGH-RESOLUTION MODEL

The goal of this work is to develop a set of high-resolution road traffic emission algorithms that aligns with the following criteria: it is comprehensive[2], accurate, practical, easy to use and understand, reliable and robust[3], and interfaces readily with appropriate traffic models and (emerging) traffic field data. In addition, it should be able to quantify the level of uncertainty of model predictions (e.g. confidence intervals). A high-resolution model provides a cost-effective approach to estimating emissions for traffic situations for which no measurement data are available.

Emission and fuel consumption test data

We are in the fortunate position now that a large body of high-resolution Australian emissions test

[1] Emissions from individual vehicles are a function of many, often interacting, variables such as vehicle design characteristics, the way the 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.

[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).

data is currently being generated for light-duty vehicles, and new and similar programs are expected for the coming years. The NISE 2 study (Orbital 2005, 2009) provides test data for about 400 petrol vehicles on a second-by-second basis. This is a very large database (more than 200 hours of test data), even by 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. *Figure 1* shows the driving cycles (speed–time profiles) used in the NEPM vehicle test programs for different types of diesel vehicles and road / flow conditions.

Together, these datasets represent approximately 95% of the Australian vehicle fleet, in terms of main vehicle types (excluded are motorcycles and LPG vehicles), allowing development of a model that can truly simulate traffic emissions[4]. It is noted that New Zealand's on-road fleet is not equivalent to Australia's on-road fleet. A clear difference, for instance, is the substantial proportion of imported used vehicles in New Zealand. Therefore, modal test data on a sample of New Zealand's in-use vehicles should ideally be used to the extent these data are available. In addition, the New Zealand on-road fleet can be examined to determine which parts of the Australian database can be used for the development of a New Zealand version of the model.

Model considerations

A number of considerations are made before the new high-resolution traffic emission model is developed. First, assessment of environmental impacts is really a multidisciplinary exercise that involves traffic modelling, emission modelling and possibly dispersion / exposure modelling. However, 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).

Second, 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 for the new model, such as a relatively

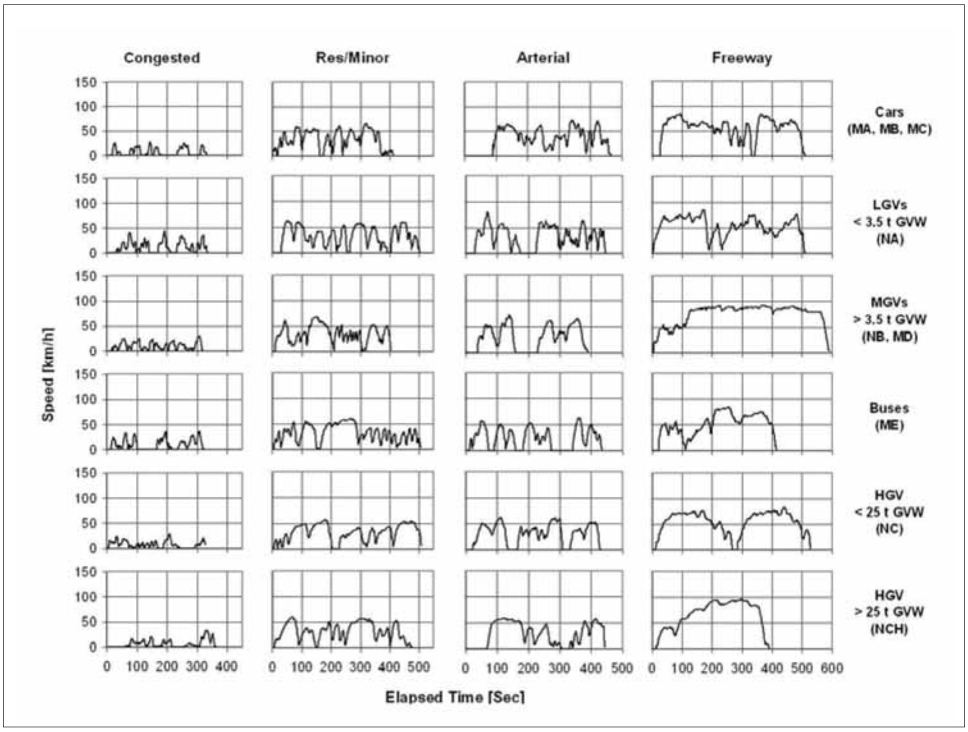


Figure 1
Driving cycles used in the diesel NEPM test program

[4] From a policy perspective we are generally not interested in individual vehicles but in traffic streams, where the collection of various vehicles on a road or in road networks impacts on local and regional air quality and greenhouse emissions. There are cases, of course, where individual vehicles are of concern, such identifying high-emitting vehicles in real-time, e.g. tunnels.

simple 'fundamental driving mode model', which predicts emissions for a limited number of discrete driving modes (idle, accelerating, decelerating, cruising) to very complex models that use many vehicle parameters and compute instantaneous emissions (g/s) as a function of, for example, engine speed, gear shift behaviour, catalyst behaviour and engine power.

However, no information exists that can be used to determine the best model structure in terms of the criteria outlined at the beginning of this section (accurate, robust, reliable, comprehensive, understandable, useable, optimal interfacing), and this is something that needs to be investigated. With respect to the last criterion, 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).

As will be discussed later, the basic input data that are required to make emission predictions are speed–time data for each basic vehicle class (e.g. passenger car, SUV, rigid truck, etc.). The emission algorithms could be used as a stand-alone model if speed–time data were collected from other sources (e.g. driving cycles, as discussed in Smit and McBroom 2009a) or in the field using, for instance, on-board GPS equipment (e.g. by employing a floating car technique) or roadside video sensor and image processing technology. However, given the common use of traffic models, a good way is to incorporate the emission algorithms into existing traffic models that generate the required input data (e.g. microscopic simulation models). As an alternative approach, the required input data could be extracted from the traffic models and used for subsequent emission modelling.

It has been shown that directly applying overseas traffic emission models or overseas traffic models with emissions-prediction capabilities to Australian conditions can lead to large errors in the emission predictions (Smit and McBroom 2009b; 2009c). So, use of Australian emission algorithms is essential to prevent poor infrastructure decisions and poor policy-making decisions.

A phased approach

The development of the model will be conducted using a phased approach. The first phase will be a 'proof of concept' stage in which a limited number of model structures will be tested for a particular vehicle class. This is basically a pilot project in which a preliminary set of potential models with the full functionality of the anticipated final models will be developed and tested. Importantly, this development phase will be conducted in consultation with various stakeholders, to obtain a clear view of market interest, model requirements and expectations of model performance. The second phase will then involve further model optimisation (e.g. in terms of accuracy) by exploring new options, further model development (e.g. for all vehicle classes), preparation of a user guide with clear guidance on how and when to use the model, and release of the final model with an agreed-upon functionality and performance.

Some preliminary results

This section shows and discusses some preliminary results of the development of a new high-resolution model for an 'average modern petrol car', using preliminary test data from the NISE 2 study. The measured emissions behaviour of this average modern car has been constructed by averaging 1 Hz emissions test data for 10 randomly selected ADR37/01 petrol cars, thereby creating a composite vehicle emissions trace in time (vehicle A). For validation purposes, the same process was repeated using emissions test data for 8 different cars of the same technology class, thereby creating a composite validation vehicle emissions trace (vehicle B). It is noted that ADR37/01 is only one of several 'vehicle technology' classes that need to be considered in a model. Some vehicle details are presented in *Table 1*.

Using the emission trace for vehicle A, two statistical models were developed, which predict high-resolution emission rates (E_t, g/s) for NO_x (which is notoriously difficult to model) and fuel consumption. The model structure is a multivariate regression function (*Equations 1* and 2).

$$E_t' = \beta_0 + \beta_1 v_t + \beta_2 a_t + \beta_3 v_t a_t + \beta_4 P_t + \beta_5 P_t^2 + \beta_6 P_t v_t + \beta_7 \Delta P3_t + \beta_8 \Delta P9_t + \beta_9 oP9_t + \beta_{10} \log \mathrm{TAD9}_t^N + \varepsilon \quad (1)$$

$$\varepsilon \sim \mathrm{AR}(1, 2, 3, \ldots) \quad (2)$$

E_t' represents the square-root transformed predicted emission rate and $\beta_0 \ldots \beta_{10}$ 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 2*. The variables include traditional variables such as instantaneous speed, acceleration and power, as well as newly developed variables that quantify the change in power ($\Delta P3_t$, $\Delta P9_t$) and oscillation in either speed ($\log\mathrm{TAD9}_{tN}$) or power ($oP9_t$) over a pre-defined period of time

Table 1
Vehicle details

Composite vehicle	Make	Model	Year of manufacture	Engine capacity (L)	Number of cylinders
A	FORD	FALCON AU	1999	4.0	6
A	FORD	MAGNA	2000	3.5	6
A	FORD	FALCON AU	2000	4.0	6
A	FORD	323 PROTÉGÉ	2001	1.6	4
A	FORD	TARAGO	2000	2.4	4
A	FORD	ACCENT	2001	1.5	4
A	FORD	ASTRA	2001	1.8	4
A	FORD	FALCON UTE	1999	4.0	6
A	LANDROVER	FREELANDER	2000	1.8	4
A	HONDA	CRV	2000	2.0	4
B	NISSAN	X-TRAIL	2002	2.5	4
B	HOLDEN	UTE	2002	5.7	8
B	FORD	COROLLA	2001	1.8	4
B	FORD	MAGNA	1998	3.0	6
B	FORD	COMMODORE VT	2000	3.8	6
B	FORD	TARAGO	1998	2.4	4
B	FORD	LASER	2001	1.6	4
B	NISSAN	PULSAR	2001	1.8	4

Table 2
Model variables

Variable	Formula	Unit
Instantaneous speed at time = t *	v_1	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 nine 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*	$\log \mathrm{TAD9}_t^N = \log\left(1 + \frac{1000\left(\lvert v_t - v_{t-1}\rvert + \ldots + \lvert v_{t-7} - v_{t-8}\rvert\right)}{\sum_t^{t-8} x_t}\right)$	m s^{-1} km^{-1}

Source: Smit and McBroom (2009d)

* This variable is directly obtained from speed–time data

** This variable can be either measured directly during dynamometer emissions testing or can be estimated using established algorithms (e.g. Bosch Automotive Handbook) 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, e.g. 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.

The model is basically a hybrid model in which 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 and to be able to predict confidence levels, thereby combining the 'best of both worlds'.

Figure 2 shows some preliminary results of this approach. It can be seen that the model generally predicts NO_x emission rates quite well, with a correlation of determination (R^2) of 0.81, meaning that 81% of the variation in emissions can be explained by the model. Emission peaks, which are important to assess local effects of changes in driving behaviour (e.g. due to changes in signal settings at an intersection), are generally allocated to the correct points in time. Some overshoot occurs when the composite vehicle goes into freeway driving (about 500 seconds). When the entire driving cycle is integrated, the model overpredicts total NO_x emissions by 4%. Appendix A shows relevant statistics of the model-fitting procedure.

Figure 3 presents the results for the composite validation vehicle. The model still predicts NO_x emission rates well, with a correlation of determination (R^2) of 0.78, indicating that the model is robust. Emission peaks are still generally allocated to the correct points in time; however, substantial overprediction occurs when the validation vehicle changes to freeway driving. As a consequence, the model overpredicts total NO_x emissions for the entire cycle by 50%.

Examination of the reasons behind this anomaly (overshooting) in the model predictions reveals that some large Australian cars activate a so-called lean-burn fuel injection strategy during freeway driving conditions (Orbital 2005), which reduces fuel consumption but increases NO_x emissions. Other cars in the dataset do not exhibit this behaviour. Three of the ten cars that underlie the emission trace for vehicle A use this lean-burn strategy, whereas only one such car is used in vehicle B emission trace. This results in individual vehicles having significantly different emissions in these driving conditions, and vehicle A will reflect the increase in

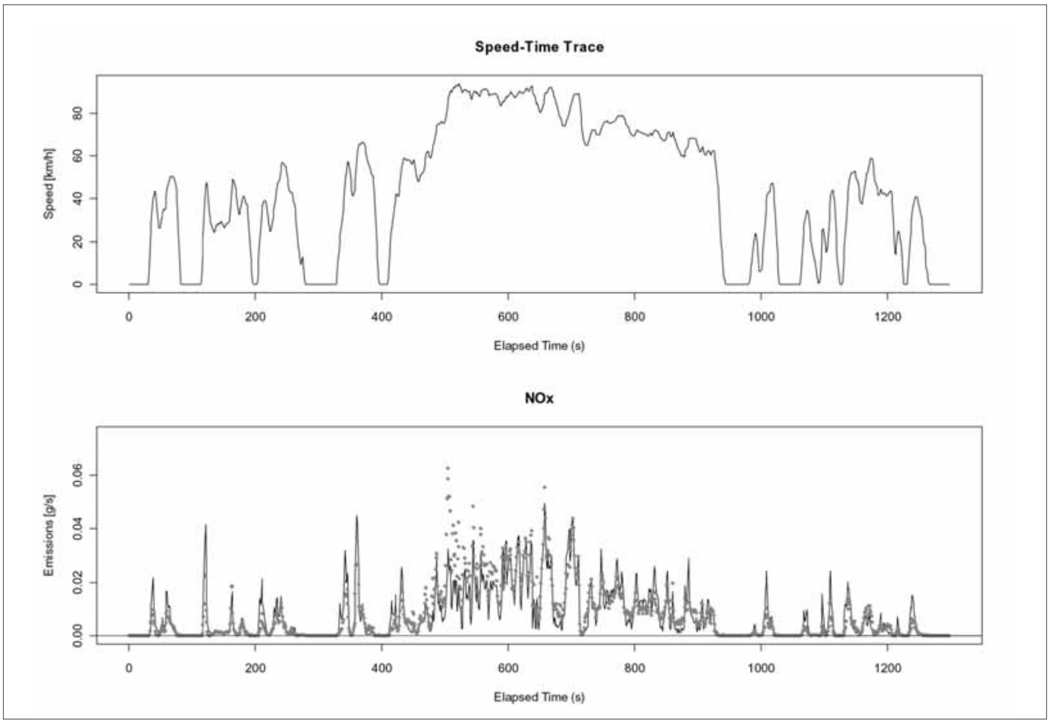


Figure 2
Vehicle A model verification. Top chart: driving cycle; bottom chart: measured (line) and predicted (dots) high-resolution NO_x emission rates (1 Hz)

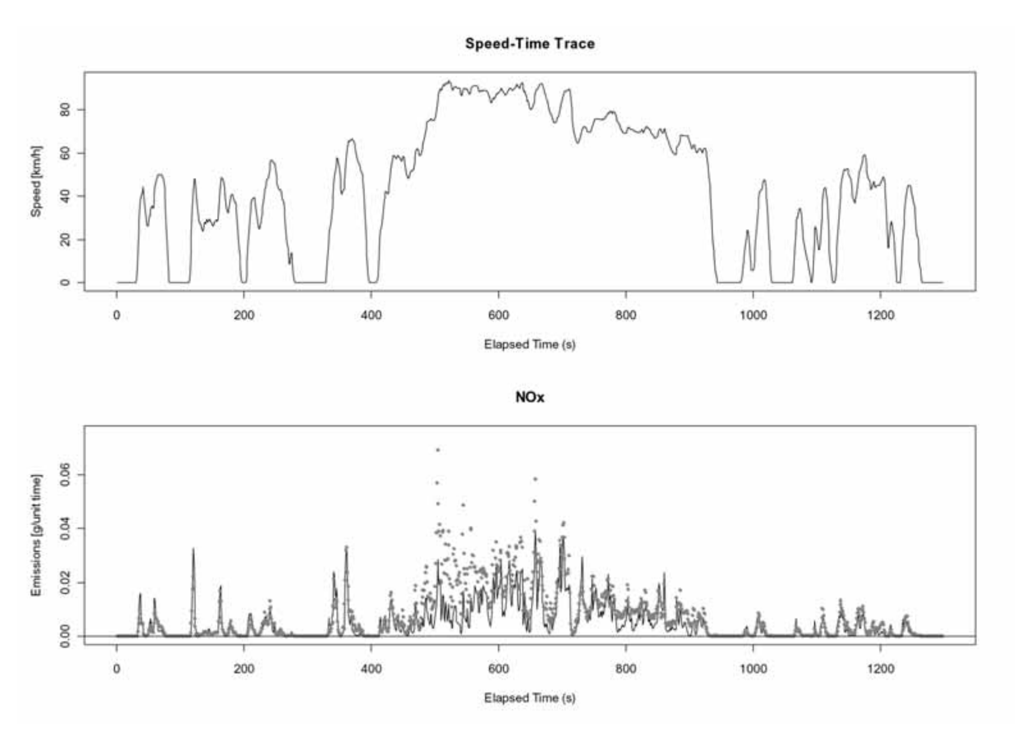


Figure 3
Vehicle B model validation. Top chart: driving cycle; bottom chart: measured (line) and predicted (dots) high-resolution NO_x emission rates (1 Hz)

NO_x more than vehicle B. This finding underlines the need for large datasets, to enable quantification of 'typical' average emissions behaviour, and suggests modelling of individual vehicles will significantly improve model performance. This has been confirmed in recent work (Smit and McBroom 2009e).

Figure 4 shows the results for fuel consumption. As expected, the model performs better for fuel consumption than for NO_x emissions, with a correlation of determination (R^2) of 0.94 and an integrated underprediction of total cycle emissions of 1%. Model performance for the validation vehicle (not shown) is similar with R^2 of 0.95, and an underprediction of total cycle emissions of 4%. Appendix A shows relevant statistics of the model fitting procedure.

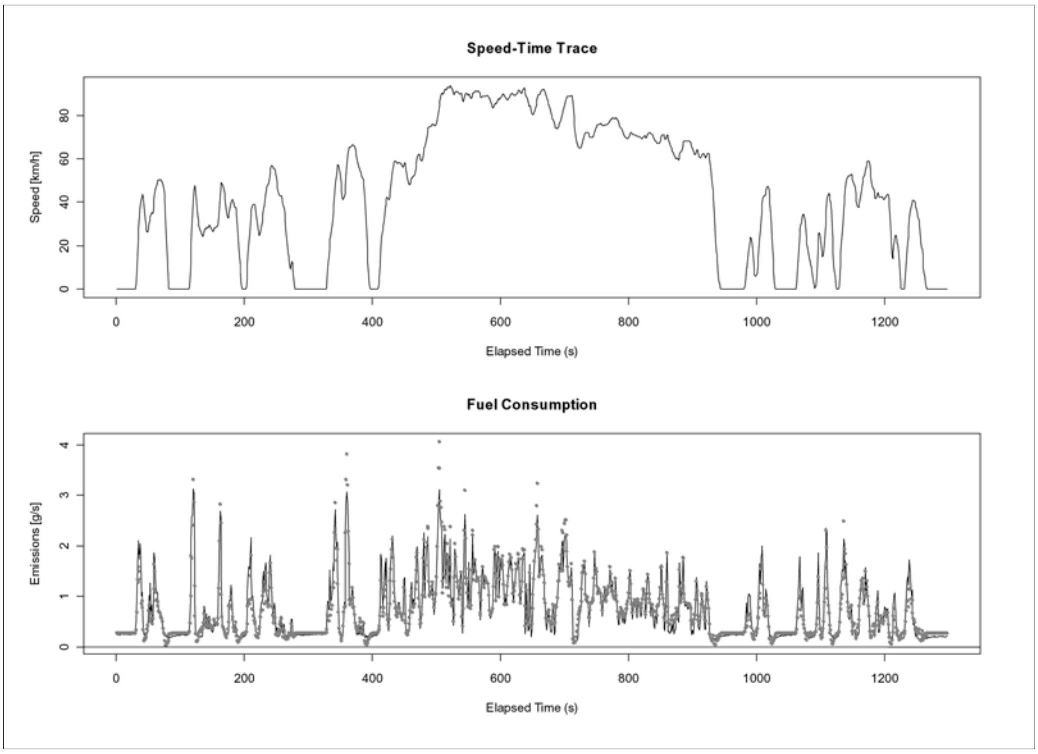
COMPARISON OF OVERSEAS AND AUSTRALIAN MODELS

The initial results of the Australian model are good when compared with performance of international models. For instance, Silva et al. (2006) compared three high-resolution emission models to on-board test data and concluded that R^2 values for CO, HC and NO_x were 'typically less than 0.40', whereas fuel consumption was slightly less than 0.75. These three models were developed in the USA and Europe and have a more complex structure (and hence larger input data requirements) than the empirical model presented in this paper. Another very detailed and complex European model[5] (Atjay and Weilenmann 2004) that was developed separately for two Euro 2 petrol cars showed better results, with R^2 values for NO_x of 0.94 and 0.99 respectively (CO, CO_2 and HC were similarly high, with R^2 values greater than 0.94). So, it is possible to develop very accurate models for specific vehicles. However, this comes at a cost (money, effort, etc.) in terms of model development, model application (input data requirements) and possibly also with respect to overall prediction accuracy for traffic streams, as will be discussed later. In terms of Australian models, another statistical model (artificial neural network model) currently under development (Dia and Boongrapue 2008) showed similar performance in terms of accuracy as the first version of our model, with R^2 values of 0.79 for NO_x and 0.97 for fuel consumption.

There is generally not a lot of information on other criteria such as robustness. There are some reports that complex emission models revealed unrealistic or peculiar prediction behaviour in certain traffic conditions (Rakha, Ahn and Trani 2004; Smit 2006),

[5] This model has a complex structure in which instantaneous emissions (g/s) are computed as a function of engine speed, gear shift behaviour, catalyst behaviour, brake mean effective pressure and change in manifold pressure.

Figure 4 Vehicle A model verification. Top chart: driving cycle; bottom chart: measured (line) and predicted (dots) high-resolution fuel consumption rates (1 Hz)



which indicates the need for further emissions testing, fine tuning and testing of these complex emission models, to ensure robust and valid model predictions in all situations.

An important point of discussion is how accurate an emission model can and should be in practice. There is always a trade-off between model accuracy and input accuracy. Availability of detailed input data decreases with road network size. If an emission model requires more detailed input data than are available, simplifying assumptions need to be made, which leads to reduced accuracy. For instance, some emission models (Atjay, Weilenmann and Soltic 2005; Zalinger, Ahn and Hausberger 2005) require gear shift behaviour as input; but, in reality, data on gear shift behaviour in traffic streams are not available. This means that assumptions need to be made internally in order to run the model, introducing unknown errors to model predictions. There may well be a cost-effective optimum level of modelling detail ('model structure') for a certain application when considering several aspects such as study objective (e.g. screening study, hot spot analysis) and quality of input data (e.g. simulated driving patterns from traffic simulation models). Further research is needed to generate more insight in this subject.

CONCLUSIONS AND OUTLOOK

This paper discussed 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). A high-resolution model is needed to adequately address increasingly complex policy questions. Development of this model is further facilitated by various developments in the international arena, for instance with respect to increasingly detailed input and emissions test data.

Some preliminary results were discussed, showing that the new modelling approach appears to deliver satisfactory results in terms of model accuracy, reliability and robustness. It is believed (and currently being tested) that model performance can be further improved by exploring various options such as other statistical methods, modelling of individual vehicles instead of composite vehicles, use of (different combinations of) other prediction variables (e.g. other power functions, longer history effects), different response variables (other transformations, fuel-based indices) and so forth. 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.

However, it is essential now to engage in discussions with various stakeholders (policy makers, transport planners, traffic engineers, scientists, etc.) to get a clear idea of what potential model users expect from such a high-resolution model in terms of its functionality, easy of use (e.g. input data demands) and expected accuracy. A one-day workshop appears a good way in which to do this and anyone who is interested in participating is invited to contact the first author.

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APPENDIX A

NO_x

Coefficients:	Value	Std. error	*t*-value	*p*-value
(Intercept)	0.009139258	0.004042073	2.261032	0.0239
spd	0.000486595	0.000141544	3.437766	0.0006
accel	–0.008044506	0.001875502	-4.289255	0.0000
I(spd * accel)	-0.001314364	0.000357178	-3.679860	0.0002
P_one	0.004910467	0.000838193	5.858395	0.0000
I(P_one^2)	0.000026194	0.000002781	9.419631	0.0000
I(P_one * spd)	0.000016427	0.000003123	5.259574	0.0000
dP_three	0.000595443	0.000061831	9.630158	0.0000
dP_nine	-0.000120998	0.000059100	-2.047339	0.0408
oP_nine	-0.000102741	0.000060363	-1.702050	0.0890
lnTAD_nine_n	0.000000029	0.000000292	0.098458	0.9216
Residual standard error:	0.02049731			

Fuel consumption

Coefficients:	Value	Std. error	*t*-value	*p*-value
(Intercept)	0.5235273	0.012727683	41.13296	0.0000
spd	0.0048213	0.000656773	7.34090	0.0000
accel	0.0580085	0.010960844	5.29234	0.0000
I(spd * accel)	0.0067534	0.001689426	3.99746	0.0001
P_one	0.0038029	0.004185020	0.90869	0.3637
I(P_one^2)	0.0002657	0.000016409	16.19396	0.0000
I(P_one * spd)	0.0000420	0.000018282	2.29958	0.0216
dP_three	0.0006897	0.000348667	1.97821	0.0481
dP_nine	0.0005082	0.000341485	1.48815	0.1370
oP_nine	-0.0003552	0.000319064	-1.11340	0.2657
lnTAD_nine_n	0.0000013	0.000001741	0.73040	0.4653
Residual standard error:	0.08276447	_	_	_

Robin Smit

Robin Smit has 15 years' experience in air pollution and greenhouse gas emissions in both Europe and Australia.

He has specialised in the modelling of road traffic emissions and fuel consumption at various scales (local, regional, national) and holds a M.Sc. (Wageningen University, The Netherlands) and Ph.D. degree (Griffith University, Brisbane, Australia).

James McBroom

James McBroom is a lecturer in statistics at Griffith University in Brisbane. He is experienced in computationally intensive statistics, generalized and linear mixed effects models, spatio-temporal modelling, numerical analysis and operations research, stochastic processes, repeated measures and longitudinal data models, Bayesian statistics and MCMC and statistical applications in the Social Sciences.

He has worked as a consultant to numerous research organisations such as Menzies, School of Health Research and the Oxford Project to Investigate Memory and Ageing (OPTIMA).

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