Development of a New Traffic Emissions and Fuel Consumption Model with a High Resolution in Time and Space

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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 possibly 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 underpinned by various developments in the international arena, for instance with respect to input and emissions test data. Preliminary results are discussed showing that the new modelling approach appears to deliver good results in terms of model accuracy, reliability and robustness. It is believed that model performance can be further improved by exploring 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.

1. INTRODUCTION

Why do we use models to estimate traffic emissions? There are a number of reasons for this. Firstly, given the large number of on-road vehicles and the many factors that influence emissions from individual vehicles, it is not feasible to adequately measure traffic emissions in the field. Secondly, from a policy perspective, it is necessary to examine trends in traffic emissions, as well as to make projections into the future. As a consequence, models are often used 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 and average speed models are applied at network level; whereas 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 a number of beliefs:

1. Ongoing developments will facilitate demand for more 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 (this will be discussed in the next section).
2. A high resolution model provides a cost-effective approach to estimating emissions for traffic situations for which no measurement data are available.
3. There is a need 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.

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, 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).

2. RELEVANT INTERNATIONAL DEVELOPMENTS

There are various developments around the world that will likely lead to more common application of complex high resolution traffic emission models. Firstly, substantial improvements can be expected with respect to the quality and availability of input data. Ongoing applications of intelligent sensor, communications and computing technologies in vehicles and at the road side are 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 et al., 2006). Secondly, ongoing developments in 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. Thirdly, there is increasing interest around the world in the effects of local scale traffic measures on traffic emissions, air pollution and fuel consumption. These types 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.

3. DEVELOPMENT OF A HIGH RESOLUTION MODEL

The goal of this work is to develop a high resolution road traffic emission model for Australia and possibly New Zealand that is comprehensive[1], accurate, easy to use and understand, reliable and robust[2] and which 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).

[1] 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.

[2] 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).

3.1 EMISSION AND FUEL CONSUMPTION TEST DATA

Fortunately a large body of high-resolution Australian emissions test data is currently being generated for light-duty vehicles, and new and similar programs are anticipated for the coming years (e.g. DENISE). The recently completed NISE 2 study (Orbital, 2005; 2009) provide test data for about 400 petrol vehicles on a second-by-second basis for different driving cycles. This is a large database (more than 500 hours of test data) compared to international standards. In addition, there is a substantial amount of high resolution test data (about 270 hours) available from the diesel NEPM vehicle test programs involving 75 diesel vehicles (Anyon et al. 2000) and the Diesel Test & Repair Program involving 370 diesel vehicles (Zito and Iankov, 2008). All programs reflect vehicle operation in Australian road and traffic conditions. Together, these datasets represent approximately 95% of the Australian vehicle fleet in terms of main vehicle types (excluding motorcycles and LPG vehicles), allowing development of a model that can truly simulate traffic emissions[3].

It is noted that New Zealand's on-road fleet, however, is not equivalent to Australia's on-road fleet. A clear difference is for instance the substantial proportion of imported used vehicles in New Zealand (MOT, 2007). 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 (e.g. Ford Falcon's and new European and Japanese vehicles) can be used for the development of a New Zealand version of the high resolution model.

3.2 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 the 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 e.g. 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; that is, accuracy, robustness, reliability, comprehensiveness and optimal interfacing). Further research in this area is required. 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, p.20).

[3] 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 cause local and regional air quality impacts and greenhouse emissions. There are cases, of course, where individual vehicles are of concern, such identifying high-emitting vehicles in real-time in e.g. tunnels.

4. PRELIMINARY RESULTS

This section shows and discusses some initial results. It is noted that development is ongoing and that certain aspects of the model will change when time progresses and more vehicle test data is incorporated in order to achieve an optimum model.

4.1 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. 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*.

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

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

$E_{t,m}$' 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 ($\log TAD9_t^N$) 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, 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.

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 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	$\log TAD9_t^N = \log\left(1 + \frac{1000\,(\lvert v_t - v_{t-1}\rvert + \ldots + \lvert v_{t-7} - v_{t-8}\rvert)}{\sum_{t}^{t-8} x_t}\right)$	m s^{-1} km^{-1}

* 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)

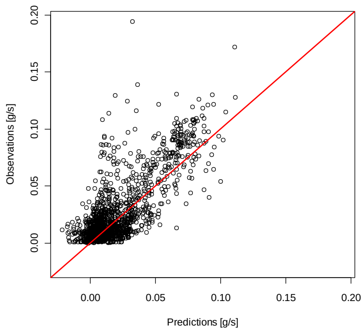
4.2 INITIAL MODEL RESULTS

We have used NO_x and CO_2 emissions testing data for 5 representative models and makes in the Australian petrol car fleet for initial testing of the model concept:

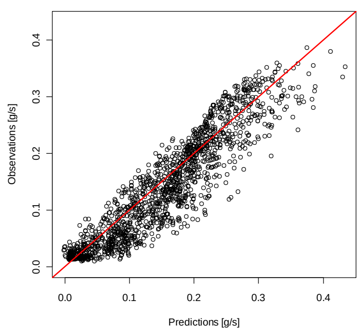
- Mitsubishi Magna (1986 – ADR 37)
- Ford Falcon (1988 – ADR 37/00)
- Toyota Camry (1995 – ADR 37/00)
- Toyota Corolla (2001 – ADR 37/01)
- Holden Commodore (2000 – ADR 37/01)

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.

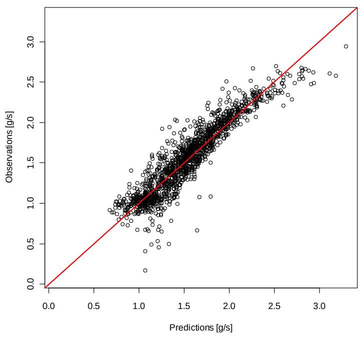
The model generally predicts NO_x and CO_2 emission rates (g s^{-1}) quite well with a coefficient of determination (R^2) ranging between 0.62-0.85 for NO_x and 0.88-0.94 for CO_2. This means that 62% to 94% of the variation in instantaneous emissions can be explained with the models. Figure 1 shows four goodness-of-fit plots with the best and worst models for each pollutant.



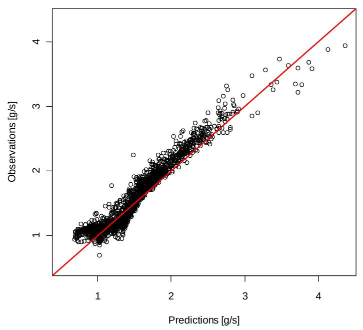
NO_x, Toyota Corolla, 2001 (R^2 = 0.62)



NO_x, Ford Falcon, 1988 (R^2 = 0.88)



CO_2, Mitsubishi Magna, 1986 (R^2 = 0.88)



CO_2,, Holden Commodore, 2000 (R^2 = 0.94)

Figure 1 – Goodness-of-Fit Plot

Figure 2 and 3 show time-series plots of predicted and observed emissions (lower chart) and include a chart showing the speed-time profile used during emissions testing (upper chart). It can be seen that the NO_x predictions follow the observations quite well in figure 2. This is also the case for the 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). Figure 3 shows that predictions are not as good for the Toyota Corolla, where a substantial number of large peaks cannot be explained by the model. This problem has also been found by other researchers around the world. De Haan and Keller (2000), for instance, found it impossible to construct a modal emission model that could accurately simulate the irregular emissions behaviour of modern cars.

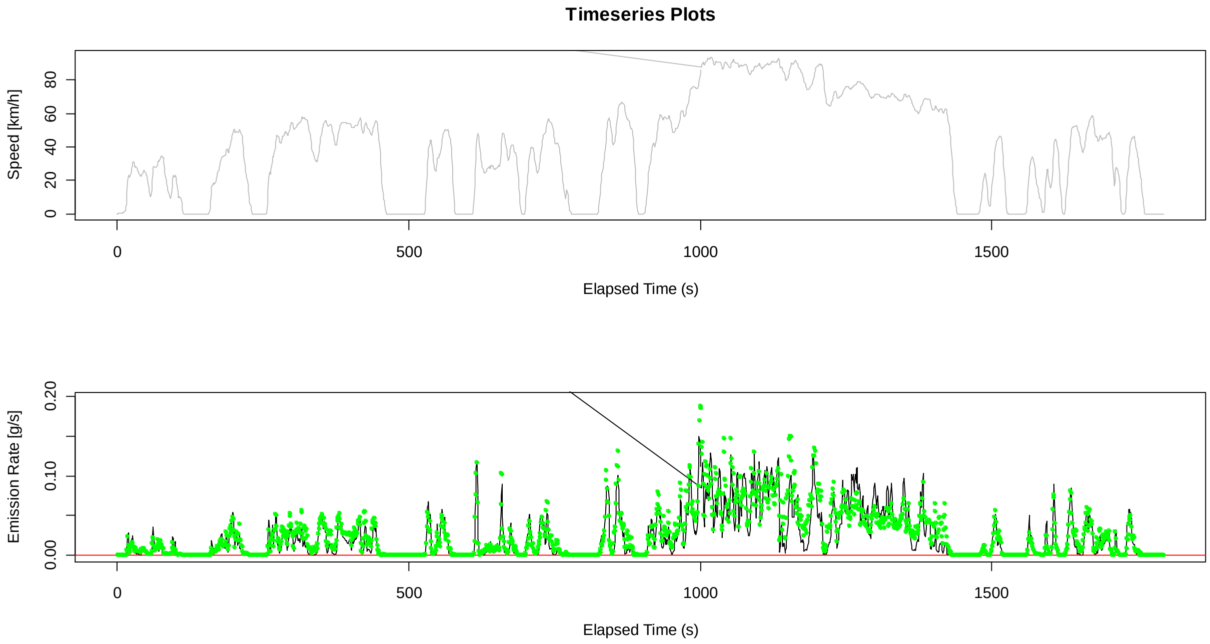


Figure 2 – Time-series Plots for a 1988 Ford Falcon, Top Chart: Driving Cycle, Bottom Chart: Measured (Black Line) and Predicted (Green Dots) High Resolution NO_x Emission Rates (1 Hz)

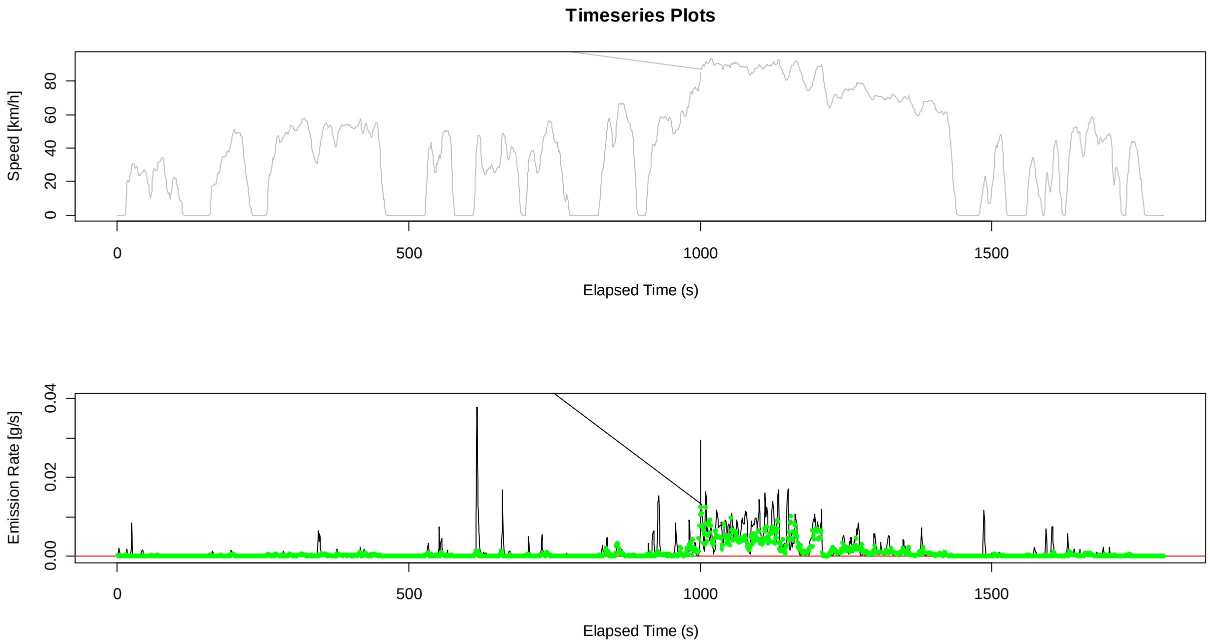


Figure 3 – Time-series Plots for a 2001 Toyota Corolla, Top Chart: Driving Cycle, Bottom Chart: Measured (Black Line) and Predicted (Green Dots) High Resolution NO_x Emission Rates (1 Hz)

It is important to note, however, that individual vehicle emissions are not of particular interest in terms of model application. 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. Individual vehicle models are useful from a modelling perspective to adequately reflect the large inter-vehicle variability in emissions predictions for traffic streams and to optimise overall model performance.

Figure 4 and 5 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 4, predicted instantaneous CO_2 emissions (g s^{-1}) for the traffic stream have a mean absolute error of 9%[4]. Total cumulative emissions (g) have an error of -5%, which means that the predicted sum of instantaneous predictions over the selected speed-time profile is 5% lower than the observed value.

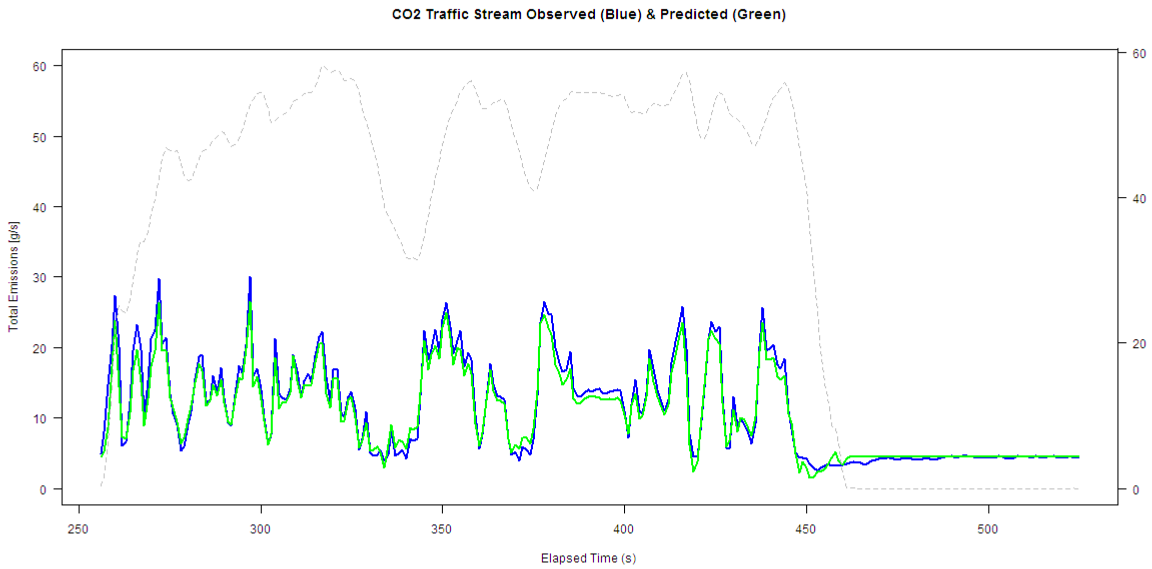


Figure 4 – Time-series Plots for All 5 Vehicles Combined (1 Hz), Observed Total CO_2 Emissions (Blue), Predicted Total CO_2 Emissions (Green), Arterial Speed-Time Profile (Light-Grey Dotted Line)

In figure 5, predicted instantaneous NO_xemissions (g s^{-1}) for the traffic stream have a mean absolute error of 27%. 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.

[4] This error is computed as mean(absolute(predictions – observations))/mean(observations).

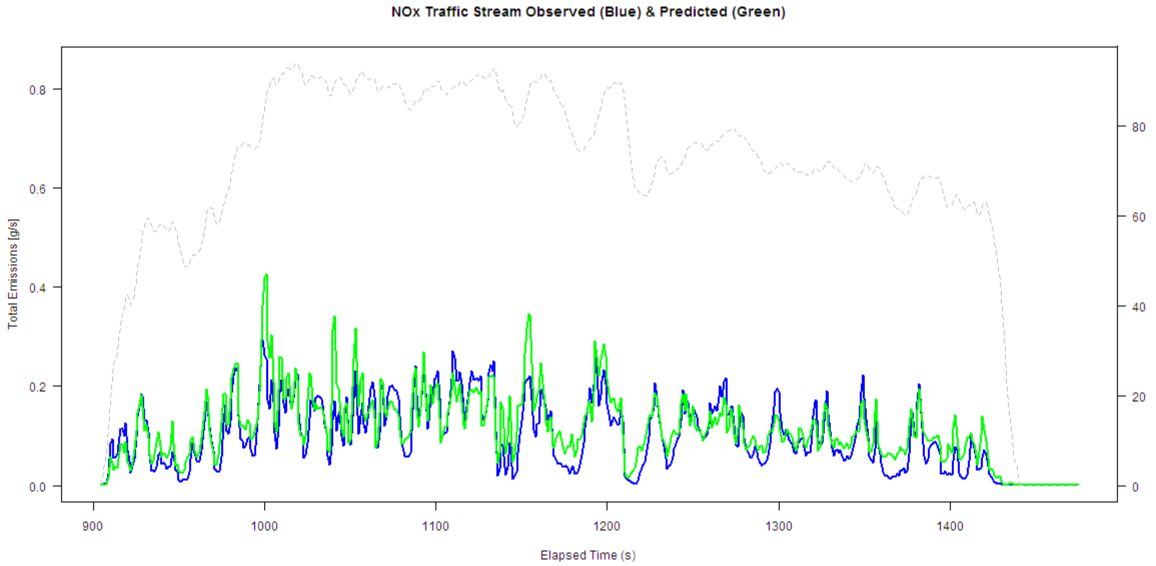


Figure 5 – Time-series Plots for All 5 Vehicles Combined (1 Hz), Observed Total NO_x Emissions (Blue), Predicted Total NO_x Emissions (Green), Freeway Speed-Time Profile (Light-Grey Dotted Line)

One final remark is made with respect to fleet composition. The distribution of registered vehicles over all possible combinations of models and makes is highly skewed. For instance, data from ABS (2007) showed that 11% of all registered passenger vehicles are Holden Commodores, followed by Ford Falcons (8%), Toyota Corollas and Toyota Camrys (both 5%) and Mitsubishi Magnas (3%). This means that simply taking available empirical test data, without consideration of micro-level fleet characteristics, and to then average the results can potentially lead to a substantially biased prediction tool. We have carried out some initial investigation of this issue for the driving patterns in Figure 4 and 5 and found that weighting the observed emission rates according to micro-level fleet composition (as compared to unweighted emission rates) leads to errors of ± 30% in instantaneous emission rates, which indicates this issue is a relevant one.

5. COMPARISON TO OVERSEAS AND AUSTRALIAN MODELS

These initial results are good compared to 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 larger 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

[5] This model has a complex structure where instantaneous emissions (g s^{-1}) are computed as a function of engine speed, gear shift behaviour, catalyst behaviour, brake mean effective pressure and change in manifold pressure.

terms of model development, model application (input data requirements) and possibly also with respect to overall prediction accuracy for traffic streams. 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.

6. CONCLUSIONS AND OUTLOOK

This paper discussed the ongoing development of a new high resolution traffic emissions and fuel consumption model for Australia and possibly 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 underpinned by various developments in the international arena, for instance with respect to input and emissions test data.

Preliminary results were discussed in this paper suggesting that the new modelling approach delivers good results in terms of model accuracy, reliability and robustness. There are other options that we still want to explore to further improve on model performance (Smit & McBroom, 2009a; 2009b). 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.

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