

APPLICATION OF A NEW HIGH RESOLUTION TRAFFIC EMISSIONS TOOL: IMPACT OF CONGESTION ON NO_x AND CO₂ EMISSIONS

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ABSTRACT

This paper discusses the development and application of a new high resolution traffic emissions and fuel consumption model. The model is needed to adequately address increasingly complex policy and research questions. Over recent years, a large body of test data has become available in Australia, which amounts to hundreds of hours of second-by-second emissions and driving behaviour data for relevant vehicle classes. The data were measured using real-world driving cycles that were developed from Australian on-road driving data. This large amount of data inspired the development of a new hybrid model with a number of innovative aspects. The model uses (new) model variables that reflect vehicle and driving aspects known to influence vehicle emissions (e.g. speed fluctuation, delta power, power oscillation) and employs a statistical approach to find the best empirical relationships. The algorithms are designed to combine an engineering and a statistical approach. This paper will discuss that the information generated by the model can be used in various ways, for instance to develop an emission inventory, to analyse the impacts of particular traffic management measures (e.g. dynamic speed limits, traffic signal coordination, metering signals). In this paper we will demonstrate this by examining the effects of congestion on emissions and fuel consumption.

INTRODUCTION

Road traffic is an important global source of air pollution and greenhouse gas emissions and its significance is increasing. It is therefore not surprising that reduction of transport emissions (both air pollutants and greenhouse gases) is now high on political agendas around the world. A number of developments around the world are expected to lead to common application of traffic emission models that operate a high spatial and temporal resolution:

- An increasing interest 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, so sensitive models will be needed to accurately predict the correct direction and magnitude of the effects.
- Substantial improvements can be expected with respect to the availability and quality of model input data. Wide scale collection of real-time field data on vehicle movement in time and space is facilitated by increasing application of intelligent sensor, communications and computing technologies in vehicles and at the road side (e.g. Hoose et al., 2008) and by the growing application of adaptive traffic control measures to improve traffic flow, improve reliability and reduce accidents (e.g. Noland and Quddus, 2006; Panis et al., 2006).
- Developments in high-resolution on-board emission measurements (e.g. North et al., 2005) will create opportunities for large on-road emission measurement databases that can then also be used for emission model development.

A substantial number of complex and detailed overseas emission models already exist and are used extensively. In addition, commonly used microscopic traffic simulation packages such as AIMSUN, VISSIM and PARAMICS have already incorporated traffic emission prediction capabilities. It has been shown, however, that direct application of these overseas models in Australia and New Zealand leads to large errors that cannot be ignored (Smit and McBroom, 2009a; 2009b).

The problem is that overseas emission algorithms are based on overseas vehicle emissions datasets, which do not reflect local driving behaviour, emission and fuel legislation (i.e. vehicle technology and fuel specification), climate and fleet composition. 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 about 4% in Australia (ABS 2006). Differences in fuel and emission standards will result in different calibration of engine management systems and/or a different configuration of emission reduction technologies, with subsequent effects on real-world emissions behaviour. The Australian car fleet is also characterised by a large proportion of large engines (e.g. V6, V8) and a preponderance of automatic transmissions and 4WDs. For instance, the majority (about 75%) of the Australian car fleet has an engine capacity of more than 2 litres. This contrasts with the UK and Dutch car fleets where these vehicles only make up about 10% of the fleet because smaller engines are dominant (Smit, Rose and Symmons, 2010).

All of the above aspects are known to be relevant with respect to emissions and fuel consumption. 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 accuracy is therefore required.

This paper discusses the development of a new resolution road traffic emission model that:

- is based on local empirical emissions data
- is comprehensive, accurate, robust, transparent and easy to use and understand
- interfaces readily with appropriate traffic models and (emerging) traffic field data
- is able to quantify the level of uncertainty of model predictions (e.g. confidence intervals).

MODEL STRUCTURE

This model is a hybrid that uses (theoretical) and newly developed variables known to influence vehicle emissions in combination with a statistical (“black box”) approach to find the best empirical relationships. This model is designed to combine the “best of both worlds” in order to achieve the best possible outcomes. Traffic emission rates are simulated using multivariate regression functions for individual vehicles in the traffic stream (Smit and McBroom, 2009c-f):

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

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

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

$$\varepsilon \sim AR(1, 2, 3, \dots) \quad (3)$$

$E_{t,m}'$ represents the square-root transformed predicted emission rate and $\beta_0, \dots, \beta_{10}$ 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 1 (next page).

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).

Table 1: Model Variables

Variable	Formulae	Units
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	$\Delta P_{3_t} = P_t - P_{t-2}$	kW
delta power over last nine seconds at time = t	$\Delta P_{9_t} = P_t - P_{t-8}$	kW
oscillation power over last nine seconds at time = t	$oP_{9_t} = P_t - P_{t-1} + \dots + P_{t-7} - P_{t-8} $	kW
logarithm of distance-normalised total absolute difference in speed (TAD) over last nine seconds at time = t	$\log TAD_{9_t}^N = \log \left(1 + \frac{1000 (v_t - v_{t-1} + \dots + v_{t-7} - v_{t-8})}{\sum_t^{t-8} x_t} \right)$	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).

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.

MODEL PERFORMANCE

A large body of high-resolution and high quality Australian emissions test data has recently been generated for light-duty petrol vehicles, and new and similar programs are anticipated for diesel vehicles ("DENISE") for the coming years. 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. We have fitted the multivariate regression functions to these second-by-second empirical emissions data for NO_x and CO₂ for 8 'typical' Australian petrol cars:

1. Ford Falcon (passenger car, model year 1991, ADR37-00)
2. Toyota Camry (passenger car, model year 2000, ADR37-01)
3. Holden Commodore (passenger car, model year 2004, ADR79-00)
4. Ford Falcon (passenger car, model year 2006, ADR79-01)
5. Toyota Landcruiser (SUV, model year 1994, ADR36)
6. Nissan Murano (SUV, model year 2006, ADR79-01)
7. Toyota Hilux (light-commercial vehicle, model year 2003, ADR36)
8. Holden Rodeo (light-commercial vehicle, model year 2006, ADR79-01)

Second-by-second emissions test data were obtained from chassis dynamometer tests using speed–time profiles that reflect real-world operation. A least-squares multiple autoregressive approach was used to estimate the regression coefficient values. Residual analysis 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 involved back-transformation.

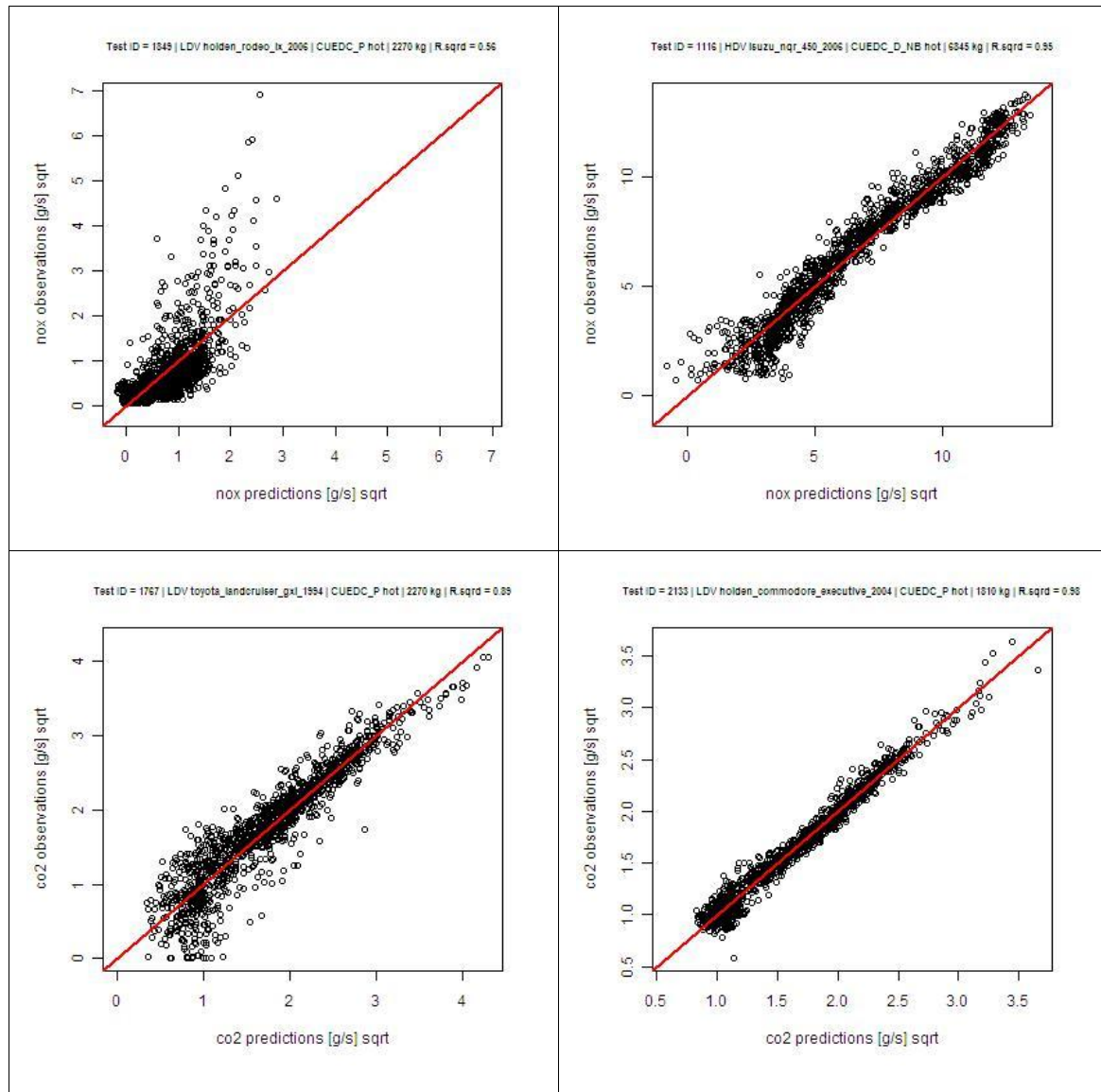


Figure 1: Best-Case and Worst-Case Goodness-of-Fit Plots

The model generally predicts NO_x and CO₂ emission rates (g s^{-1}) quite well with a coefficient of determination (R^2) ranging between 0.56-0.95 for NO_x and 0.89-0.98 for CO₂. This means that 56% to 98% of the variation in instantaneous emissions can be explained with the algorithms. Figure 1 shows four goodness-of-fit plots with the best and worst models for each pollutant.

Figure 2 shows the worst and best time-series plots of predicted and observed emissions. It includes a chart showing the speed-time profile used during emissions testing (bottom chart). Figure 2 shows that NO_x predictions are less accurate for the 2006 Holden Rodeo in specific circumstances, where a substantial number of large peaks cannot be explained by the model. In contrast, Figure 3 shows that the CO₂ predictions for the 2004 Holden Commodore are nearly perfect and they follow the observations well. 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).

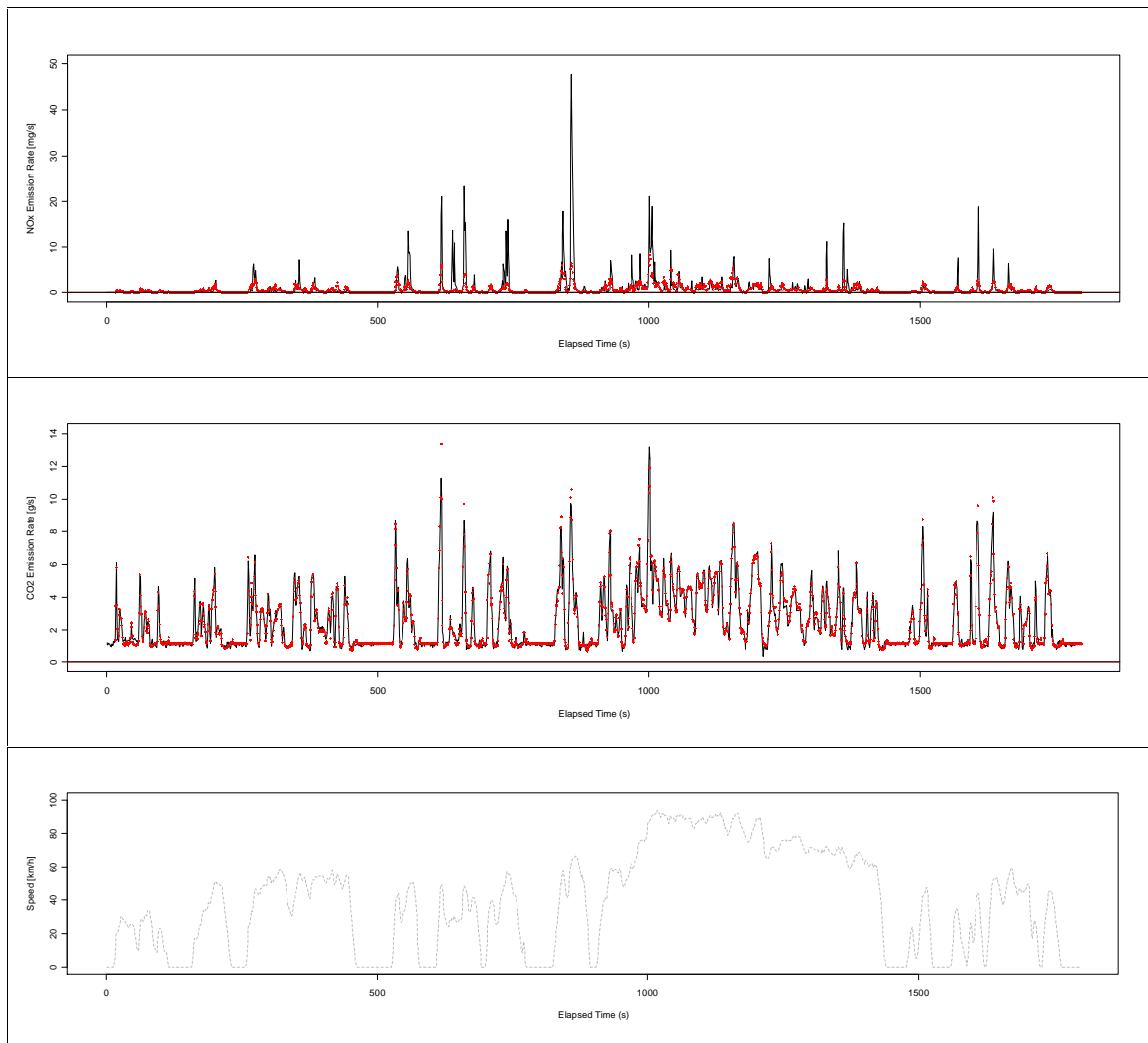


Figure 2: Measured (Line) and Predicted (Dots) High Resolution Emission Rates (1 Hz), Top Chart: Worst-Case Time-series Plot (2006 Holden Rodeo) for NO_x, Middle Chart: Best-Case Time-series Plot (2004 Holden Commodore) for CO₂, Bottom Chart: Driving Cycle

However, individual vehicle emissions are not of particular interest in terms of model application. Individual vehicle emission algorithms are useful from a modelling perspective, as they ensure that the large inter-vehicle variability in real-world emissions is adequately reflected in the model predictions for traffic streams (i.e. optimise overall model performance). However, the sum of emissions from all individual vehicles in a traffic stream is needed to assess the effects of road traffic on (local) air quality and greenhouse gas emissions.

Figure 3 therefore shows total ‘traffic stream’ emissions (g s^{-1}) for all eight vehicles combined. It is clear from these charts that total emissions are simulated well by the regression models, with R^2 values of 0.95 (NO_x) and 0.98 (CO₂). The total emissions profile is replicated well even though there is a difference in model performance for the individual vehicles. Total cumulative emissions (g) have an error of -4% for NO_x and -1% for CO₂, which means that the predicted sum of instantaneous predictions over the selected speed-time profile is 4% and 1% lower than the observed value.

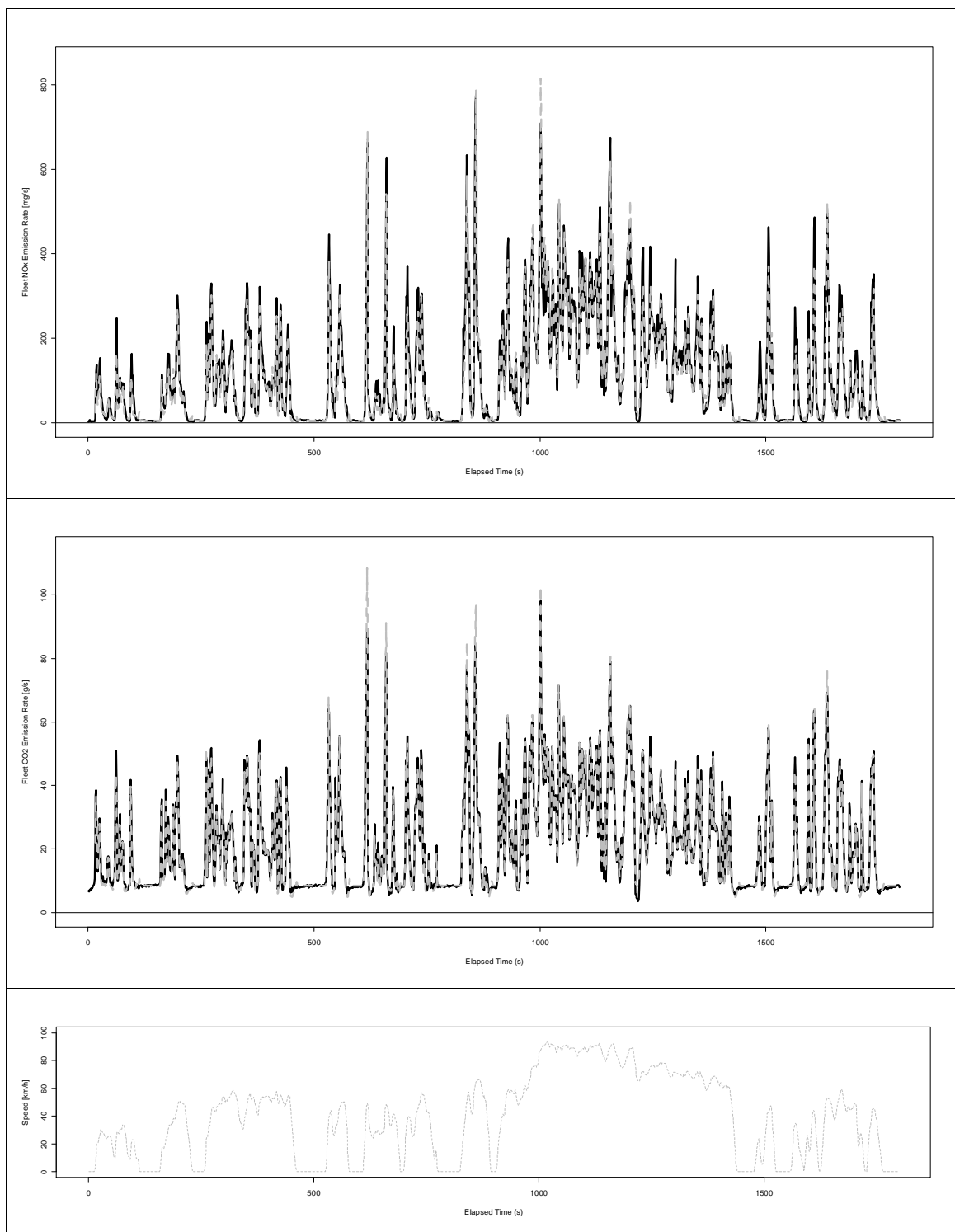


Figure 3: Time-series Plot - All Vehicles Combined ("Fleet"), Observations (Black Line) and Predictions (Grey Dotted Line) for NO_x and CO₂, Bottom Chart presents the Driving Cycle

MODEL APPLICATION: IMPACTS OF CONGESTION

The high resolution model can be used in various ways and for different purposes. The strength 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 others like average speed models cannot be appropriately used. On the other hand, the high resolution model is relatively input data intensive as it 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:

- representative driving cycles may be used to quantify “typical” driving behaviour for a particular traffic situation; or
- (microscopic) traffic simulation models can generate these data for each vehicle in the traffic stream.

Some examples of model applications have been published elsewhere and they include assessment of the impact on emissions and fuel consumption of:

- freeway speed limit reduction from 100 to 80 km/h with radar control (Smit and McBroom, 2009g); and
- a national ecodriving program (Smit, Rose and Symmons, 2010).

In this paper we will examine the impacts of congestion on emissions. We will use a set of driving cycles that reflect typical driving conditions in situations with increasing levels of congestion on either urban roads or freeways. These cycles were developed in Europe from a database of recorded real-world driving patterns and associated traffic data (e.g. traffic volume, density) for urban (Boulter et al., 2005) and freeway driving (TNO, 2001). For freeway conditions, six traffic situations are defined in terms of average speed category (i.e. range of mean spot speeds) and traffic volume. For urban conditions, six traffic situations are defined in terms of speed range category and traffic density. Figure 4 and 5 present these driving cycles and it includes the definition of the traffic situations in the titles.

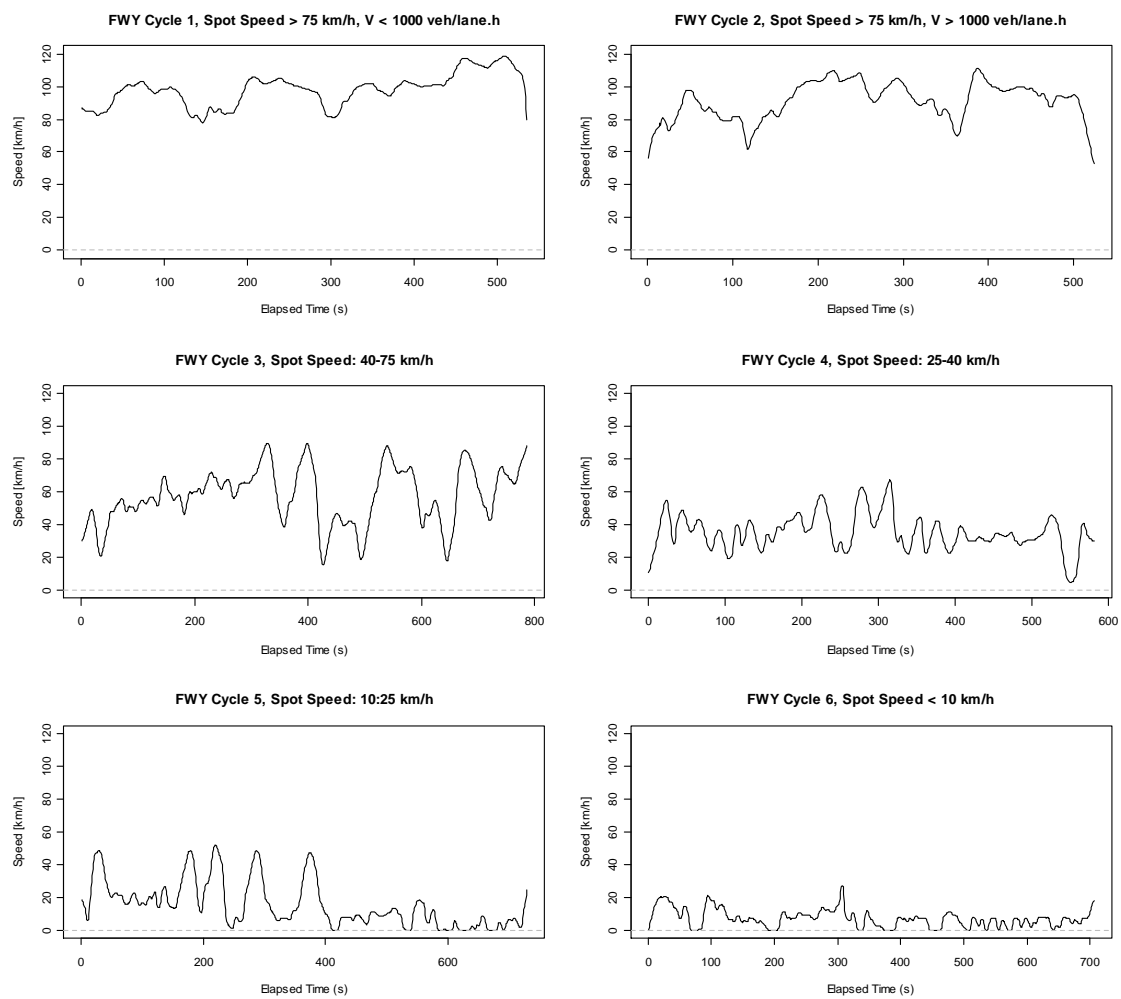


Figure 4: Congestion-Specific Driving Cycles for Freeway Driving (Speed Limit = 100 km/h)

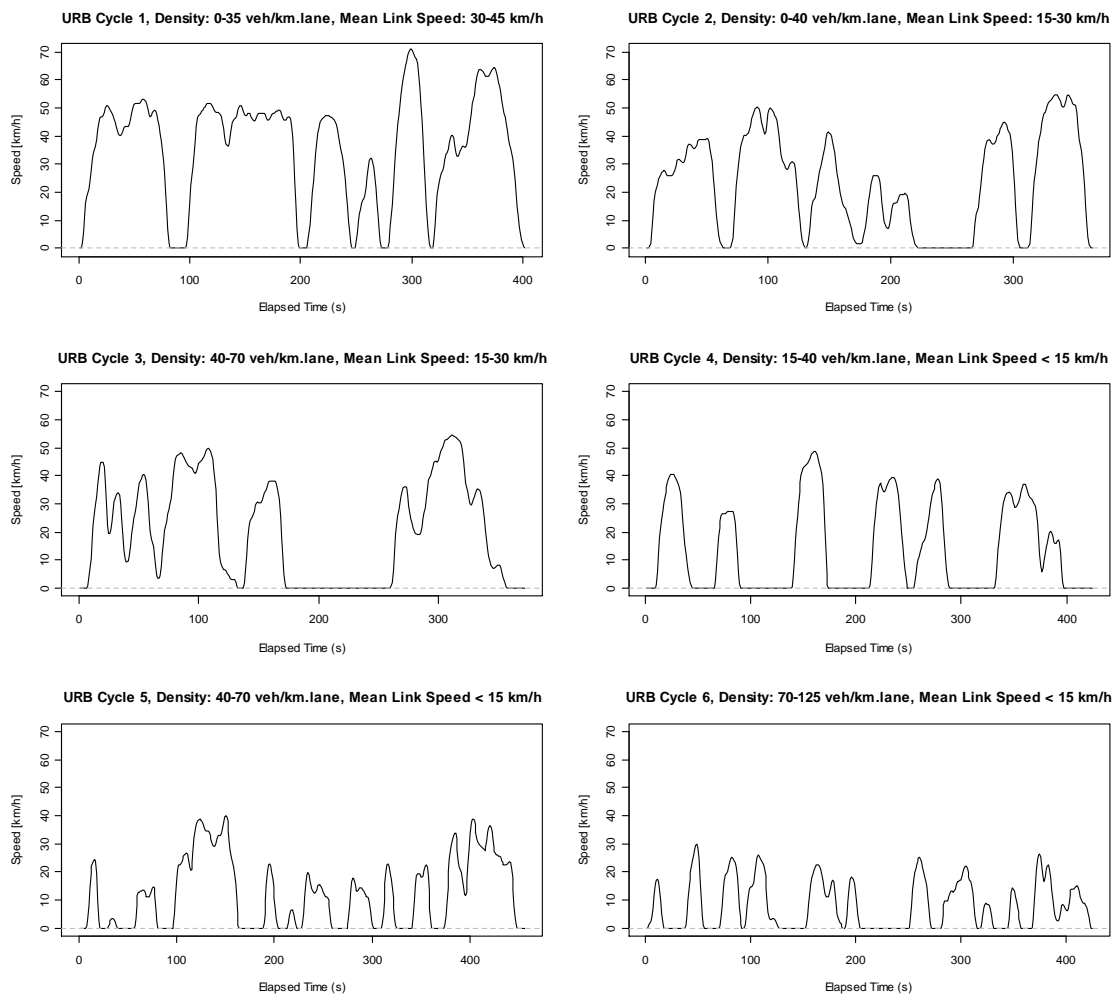


Figure 5: Congestion-Specific Driving Cycles for Urban Driving

The driving cycles were used as input to the emission algorithms to:

- estimate second-by-second emission levels in grams per second, and subsequently
- sum the second-by-second cycle emissions (grams) and divide by total cycle distance (km) to estimate (normalised) mean emission rates in grams per km, or rather grams per vehicle kilometer travelled (VKT).

The results of the last step are presented in Figure 6 and 7. Increasing numbers on the x-axis correspond with an increasing level of congestion.

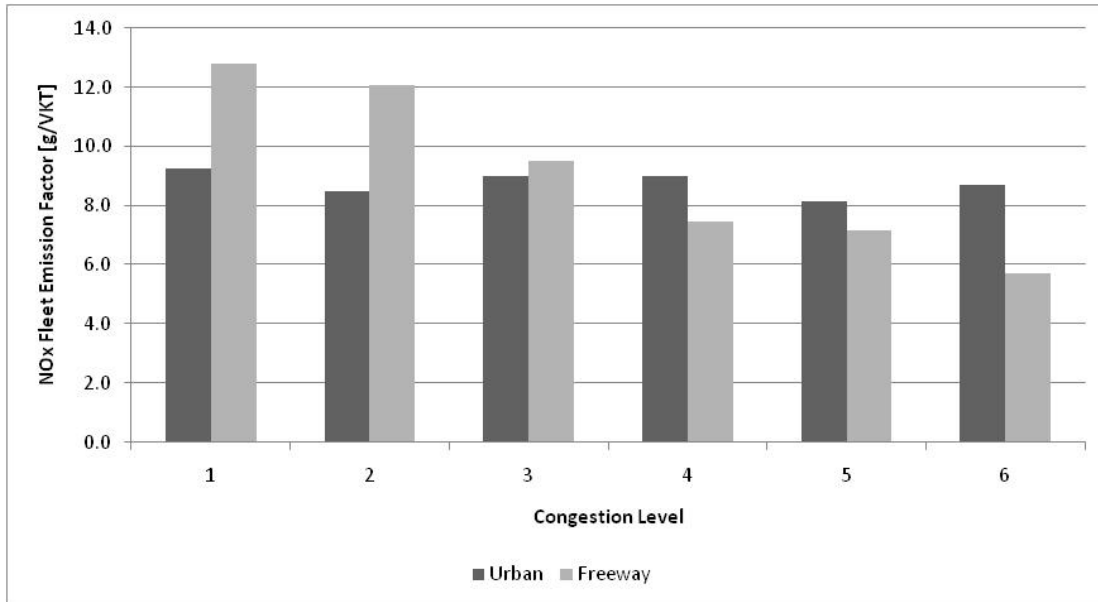


Figure 6: Computed Effects of Congestion on NO_x Emissions (8 Vehicles)

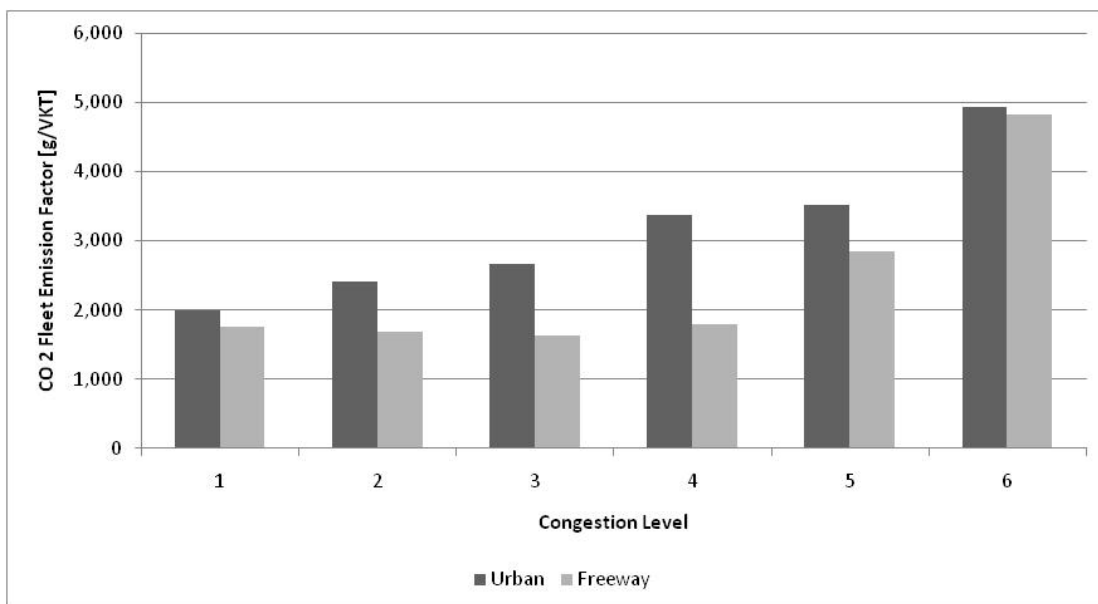


Figure 7: Computed Effects of Congestion on CO₂ Emissions (8 Vehicles)

The simulation provides some interesting results. For NO_x emissions, increasing levels of congestion (moving from left to right in Figure 6) result in a consistent and substantial reduction in emissions by about 60%. For urban driving, on the other hand, no consistent trend can be observed and NO_x emissions appear relatively stable over the six congestion categories. The reason for this effect has to do with the different engine management systems used in individual vehicles. It is known for instance that a number of popular large Australian cars activate a lean-

burn fuel injection strategy during freeway driving conditions, which reduces fuel consumption but increases NO_x emissions (Smit and McBroom, 2009h).

For CO₂ emissions, the results are similar for both urban and freeway driving. CO₂ emissions increase substantially and consistently with the level of congestion with a factor of about 2.5 (150%) for urban driving and 2.7 (175%) for freeway driving. There is, however, a difference in the rate of change in emission levels with congestion. Whereas emissions increase almost linearly with congestion for freeway driving, emissions are relatively stable for congestion levels 1-4 in urban driving conditions, but then rapidly increase.

CONCLUSIONS

In this paper we have presented a new Australian traffic emissions model that operates at a high resolution (1 Hz) and is sensitive to changes in driving behaviour. The paper has shown that the new modelling approach appears to deliver satisfactory results in terms of model accuracy, reliability and robustness. As a demonstration of one of several possible applications, the model has been used in this paper to examine the impacts of congestion on emission levels of 8 typical Australian vehicles in urban and freeway driving conditions.

REFERENCES

- ABS, 2006. Survey of Motor vehicle Use, Australian Bureau of Statistics, www.abs.gov.au.
- 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, 2000.
- Boulter, P.G., Barlow, T., McCrae, I.S., Latham, S., Elst, D., Van der Burgwal, E., 2005. Road Traffic Characteristics, Driving Patterns and Emission Factors for Congested Situations, EU Work Package 5, OSCAR, Deliverable 5.2.
- EEA, 2004. Size and Composition of the Vehicle Fleet, European Environment Agency, Prepared by Giannouli, M. and Mellios, G., LAT.
- 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.
- Noland, R.B. & Quddus, M., 2006. Flow improvements and vehicle emissions: effects of trip generation and emission control technology. *Transpn. Res.-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.
- Orbital, 2005. NISE 2 Contract 2 Drive Cycle and Short Test Development, Department of the Environment and Heritage, September 2005.
- Orbital, 2009. Second National In-Service Emissions Study (NISE2) Light Duty Petrol Vehicle Emissions Testing, by Roads and Traffic Authority of NSW, RTA.07.2828.0309, March 2009.
- 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.
- Smit, R., McBroom, J., 2009a. Use of microscopic simulation models to predict traffic emissions -Technical Note, *Road and Transport Research*, 18 (2), 49-54.
- Smit, R., McBroom, J., 2009b. Use of overseas emission models to predict traffic emissions in urban areas - Technical Note, *Road and Transport Research*, 18 (3), 52-60.

Smit, R., McBroom, J., 2009c. Development of a new traffic emissions and fuel consumption model with a high resolution in time and space, 32nd Australasian Transport Research Forum (ATRF 2009), 29 Sep - 1 Oct 2009, Auckland, New Zealand.

Smit, R., McBroom, J., 2009d. 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), February 2009, 14-16.

Smit, R., McBroom, J., 2009e. 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), May 2009, 13-16.

Smit, R., McBroom, J., 2009f. 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), August 2009, 16-18.

Smit, R., McBroom, J., 2009g. Development of a new high resolution traffic emissions and fuel consumption model for Australia and New Zealand – model application, *Air Quality and Climate Change*, 43 (4), November 2009, 14-16.

Smit, R., McBroom, J., 2009h. Development of a new high resolution traffic emissions and fuel consumption model, *Road and Transport Research*, 18 (4), 3-13.

Smit, R., Rose, G., Symmons, M., 2010. Assessing the impacts of ecodriving on fuel consumption and emissions for the Australian situation, 33rd Australasian Transport Research Forum (ATRF 2010), 29 Sep - 1 Oct 2009, Canberra, Australia (In Preparation)

TNO. 2001. Emissions and Congestion – Estimation of Emissions on Road Sections and the Dutch Motorway Network, by Gense, N.L.J., Wilink, I.R., Van de Burgwal, H.C., TNO Report 01.OR.VM.044.1/NG.

AUTHOR BIOGRAPHIES

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