

## Technical Note

### USE OF MICROSCOPIC SIMULATION MODELS TO PREDICT TRAFFIC EMISSIONS

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#### Abstract

Microscopic traffic simulation models (MSMs) such as AIMSUN, VISSIM and PARAMICS have internal traffic emission prediction capabilities.

We have conducted a preliminary investigation and compared updated AIMSUN emission algorithms with measured emissions data on Australian light-duty petrol vehicles, which revealed large discrepancies.

A large underestimation of emissions has been found, up to more than two orders of magnitude for individual microtrips and, on average, an underestimation of a factor of about 20 (NO<sub>x</sub>), 1.5 (HC), 4 (CO<sub>2</sub>, freeway) and an overestimation of a factor of about 1.3 (CO<sub>2</sub>, non-freeway). These differences were statistically significant at the 95% level for the majority of cases.

We recommend further examination of these discrepancies including other MSMs and all relevant vehicle classes (e.g. diesel trucks) and recalibration of emission algorithms in MSMs using local test data that reflects Australian vehicle emissions and driving behaviour.

#### INTRODUCTION

Microscopic traffic simulation models (MSMs) such as AIMSUN, VISSIM and PARAMICS have internal traffic emission prediction capabilities. There is, however, no reason to expect reliable emissions and fuel consumption output for Australian road and/or vehicle conditions.

Emission algorithms in MSMs are based on overseas vehicle emissions datasets, which do not reflect Australian vehicles, fuels, climate and fleet composition. For example Australia has:

- a larger proportion of six and eight cylinder engines;
- a significantly lower percentage of diesel cars;
- a different composition of fuels;
- different emission standards;
- vehicles with different calibration of engine management systems;
- vehicles with different configuration of emission reduction technologies (e.g. size, location of catalysts, catalyst material);
- different climatic conditions; and
- other emissions behaviour aspects.

This raises concern about the validity of direct use of overseas emissions and fuel consumption algorithms in Australian traffic modelling. To illustrate the importance of this issue we have examined and verified – to a limited extent only – updated emission algorithms (Panis et al. 2006) for the AIMSUN simulation model by means of an example.

**METHODOLOGY**

We have used recent Australian emissions test data (Orbital 2005) on 58 Australian light-duty petrol vehicles (model years 1986-2002) for this purpose. The vehicles represent a cross section of typical vehicles on Australian metropolitan roads. These emissions data were collected in a vehicle emissions testing laboratory (Orbital, Perth) on a second-by-second basis by driving these vehicle over a half-hour real-world driving cycle (speed-time profile) called ‘CUEDC-P’ (composite urban emission drive cycles for petrol vehicles), which was developed from Australian driving pattern data collected in the field.

The CUEDC-P includes arterial, residential, freeway and congested driving conditions. The driving cycle and the range (min-max) of speed values at each point in time is shown in the polygon chart at *Figure 1*.

The mean absolute error (MAS) in instantaneous speed for each vehicle (except two) was verified to be less than ± 2.0 km/h (as specified in ADR79/00), with an average MAS of 1.13 km/h. This indicates that the selected 58 vehicles have all been driven in a similar fashion, as shown in *Figure 1*. This means that emissions test data can be aggregated for comparison to AIMSUN emissions algorithms.

As a next step, the CUEDC-P cycle was broken up into thirteen stop-go-stop segments, i.e. so-called ‘microtrips’. The segmented cycle is shown in *Figure 2*.

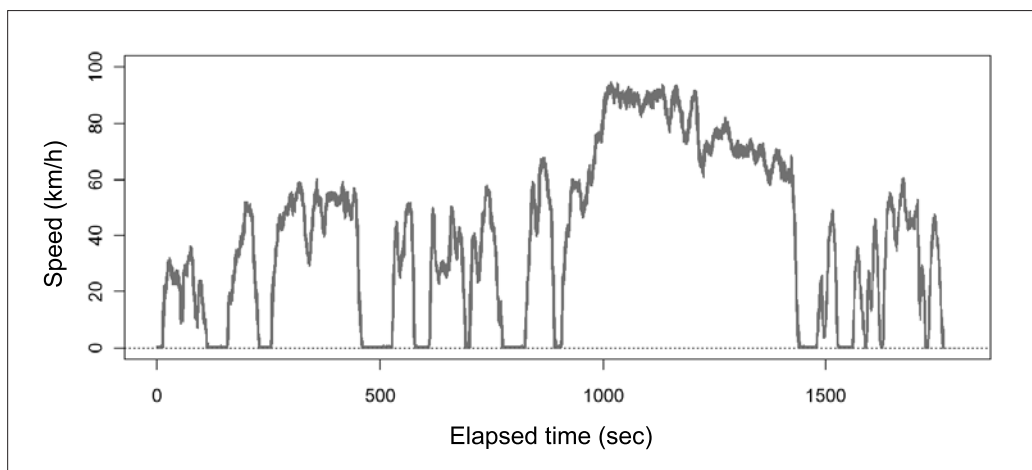
For each microtrip, cycle variables were computed such as average speed, distance driven, proportion idle time and speed noise. An overview of computed values, including road/flow type (residential, arterial, freeway, congested), is presented in *Table 1*.

Subsequently, second-by-second emissions test data for the 60 Australian petrol cars was used to compute average measured total emissions (g) of NO<sub>x</sub>, HC and CO<sub>2</sub> for each microtrip, including their 95% confidence interval. The speed time data for each microtrip (*Figure 2*) was then used as input to the AIMSUN emission functions for ‘petrol cars’ (Panis et al., 2006, Table 2, p. 276).

**RESULTS**

*Figures 3 to 5* each show the results for the three emission components and each figure includes two charts:

*Figure 1*  
Speed range for 58 light-duty petrol vehicles on the composite urban emission drive cycles for petrol vehicles (CUEDC-P)



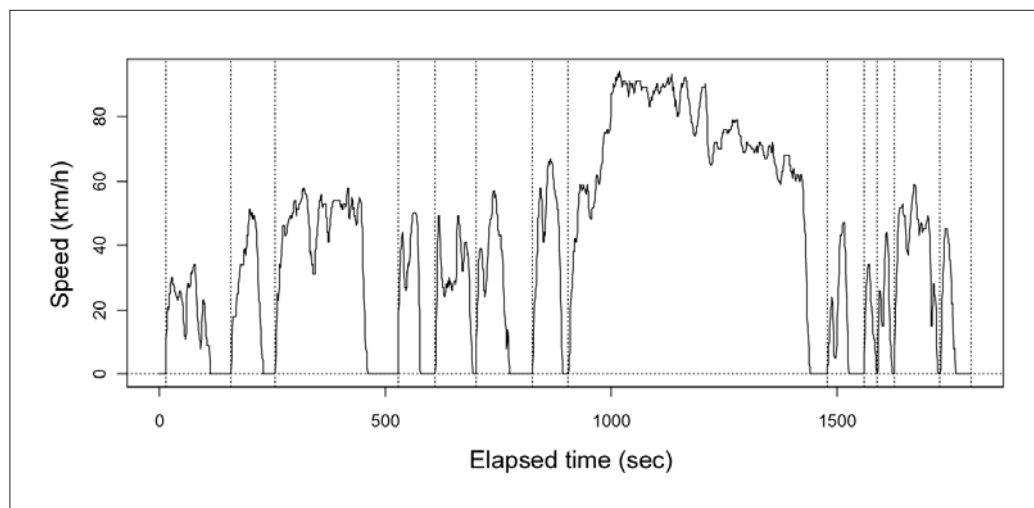


Figure 2  
Segmentation of  
CUEDC-P

**Table 1**  
**Computed Cycle Variables for Microtrips**

Microtrip (type*)	Time	Travel time [sec]	Distance [m]	Average speed [km/h]	Prop. idle time [%]	Speed noise [km/h]
1 (Res)	14 : 158	145	592	15	32%	7
2 (Res)	159 : 256	98	630	23	28%	14
3 (Res)	257 : 527	271	2617	35	25%	11
4 (Art)	528 : 610	83	502	22	40%	12
5 (Art)	611 : 699	89	723	29	9%	10
6 (Art)	700 : 824	125	717	21	40%	15
7 (Art)	825 : 904	80	851	38	16%	18
8 (Fwy)	905 : 1477	573	10783	68	7%	17
9 (Con)	1478 : 1558	81	306	14	42%	15
10 (Con)	1559 : 1588	30	150	18	7%	11
11 (Con)	1589 : 1625	37	211	21	14%	13
12 (Con)	1626 : 1727	102	1095	39	5%	14
13 (Con)	1728 : 1796	69	265	14	52%	14

\* Res = Residential, Art = Arterial, Fwy = Freeway, Con = Congested

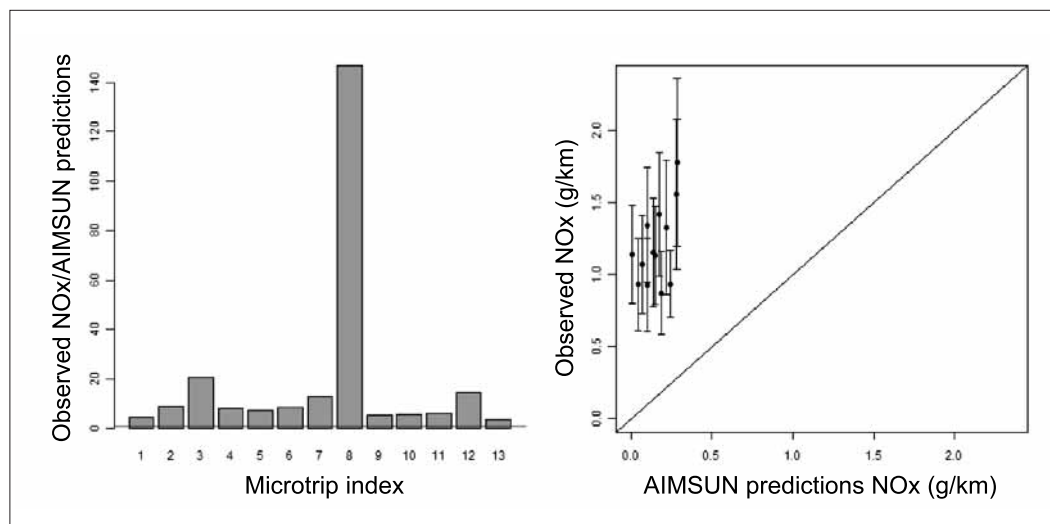


Figure 3  
Comparison of  
AIMSUN NO<sub>x</sub>  
predictions to  
measured  
Australian  
emissions  
(petrol cars)

Figure 4  
Comparison of  
AIMSUN HC  
predictions to  
measured  
Australian  
emissions  
(petrol cars)

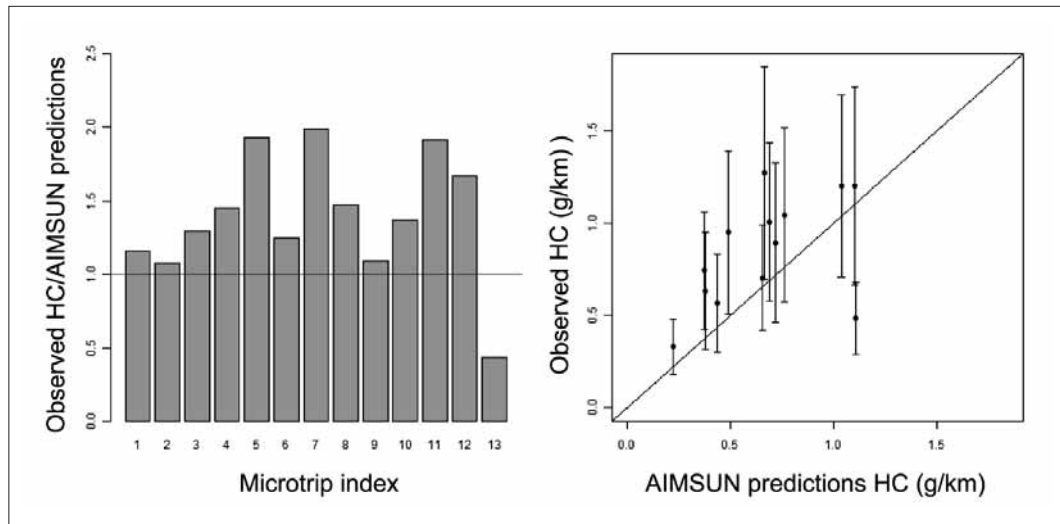
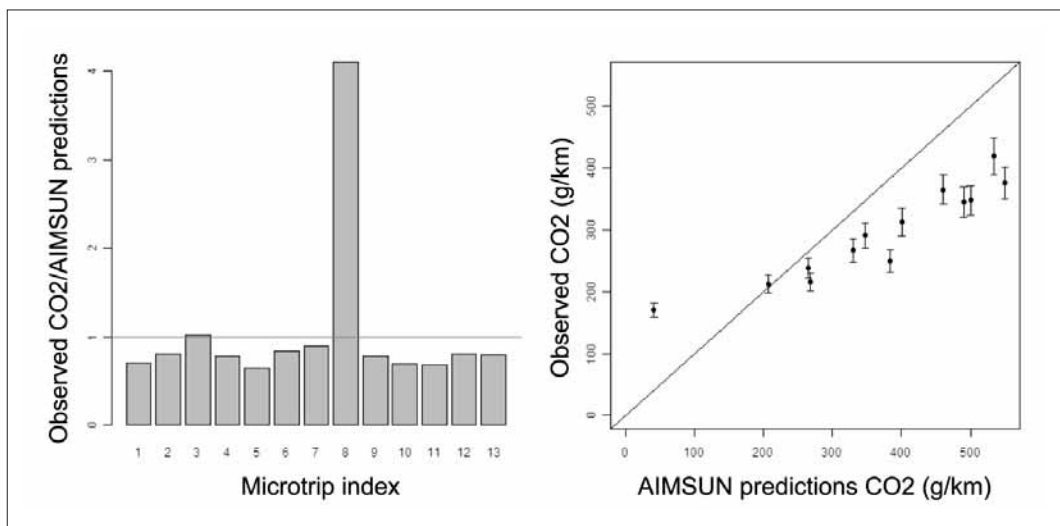


Figure 5  
Comparison of  
AIMSUN CO<sub>2</sub>  
predictions to  
measured  
Australian  
emissions  
(petrol cars)



- (left) a barplot with ratios of observed emission levels to AIMSUN predictions for each microtrip; and
- (right) a scatterplot showing both AIMSUN predictions and observations (measured), including 95% confidence intervals.

The barplot includes a horizontal line which represents a ratio of one, which means predictions are equal to the observations. The scatterplot shows a 45° line, which represents a ‘perfect fit’, i.e. any points on this line mean that predictions are equal to the observations, which is where we would ideally like to be. If a confidence interval crosses the 45° line, this means that the difference between prediction and observation is not statistically significant at the 95% level.

Figure 3 shows that measured NO<sub>x</sub> emission levels are substantially higher than AIMSUN predictions, on average a factor of 20 higher, with in one case (microtrip 8, freeway driving) a difference of more

than two orders of magnitude. This is a dramatic result and it shows that AIMSUN predictions for NO<sub>x</sub> are substantially biased towards underestimation of traffic emissions, particularly in freeway traffic conditions. Figure 3 also shows that the results are statistically significant at the 95% confidence level.

For hydrocarbons (HC), the results are better compared to NO<sub>x</sub>, as is shown in Figure 4. Measured HC emission levels are on average a factor of 1.4 higher, but with a maximum difference of a factor of 2.3 (microtrip 13, congested conditions). The results are statistically significant at the 95% confidence level for 30% of the microtrips (i.e. 5, 7, 11, 13), where the error is approximately a factor of ±2.

For CO<sub>2</sub>, measured emission levels are on average a factor of 1.3 lower for non-freeway driving, and a factor of 4.1 higher for freeway driving conditions. All of the results, except one (microtrip 3), are statistically significant at the 95% confidence level.

Figure 6 shows, as an example, measured and predicted  $\text{NO}_x$  emissions at a second-by-second resolution. It clearly demonstrates that AIMSUN predictions are substantially biased (underestimation), as was seen before, but also that the presence, magnitude and the locations of emission peaks occur at different times. This is of particular concern to the use of microscopic simulation models which simulate driving behaviour in time (e.g. second-by-second). Use of AIMSUN algorithms would thus allocate peaks in emissions to the wrong network location and time.

## DISCUSSION

This preliminary examination shows that differences between overseas emission functions used in current microscopic simulation models can indeed lead to substantial errors when predictions are compared to Australian emissions test data. However, the results are quite different for the different pollutants/greenhouse gases and/or driving conditions. It can be seen that the differences are quite large:

- $\text{NO}_x$ : Observations are on average almost a factor of twenty higher than AIMSUN predictions. For certain driving conditions (freeway driving), measured values can be even up to a factor of about 150 higher. These differences are statistically significant at the 95% level.
- HC: Observations are on average almost a factor of 1.5 higher than AIMSUN predictions. For certain driving conditions, measured values can be up to a factor of about 2 higher or lower than the predictions. These differences are

statistically significant at the 95% level for 30% of the cases.

- $\text{CO}_2$ : Observations are on average a factor of 1.3 lower and a factor of 4.1 higher than AIMSUN predictions for non-freeway and freeway driving, respectively. These differences are statistically significant at the 95% level for almost all the cases.

It is emphasised that the results presented in this letter reflect a preliminary analysis using a small sample (58) of light-duty petrol vehicles (cars, 4WDs, light commercial vehicles). In order to obtain a complete overview of potential errors in emission predictions from AIMSUN (i.e. at traffic stream level), other Australian vehicle classes<sup>1</sup> (and other MSMs) will need to be compared in a similar fashion and included in the analysis.

In our opinion, there are now 2 main options to move forward:

OPTION 1, 'Do nothing': Use AIMSUN and similar models 'as is' to predict traffic emissions and fuel consumption in Australia. We have shown that there is a large risk that poor emission forecasting is produced which, when left unchecked, in turn will cause poor infrastructure decisions and poor policy making decisions.

OPTION 2, 'Recalibration': Further examination of discrepancies including all vehicle classes and recalibration of emission algorithms using local test data that reflects Australian vehicle emissions and driving behaviour.

We strongly recommend Option 2.

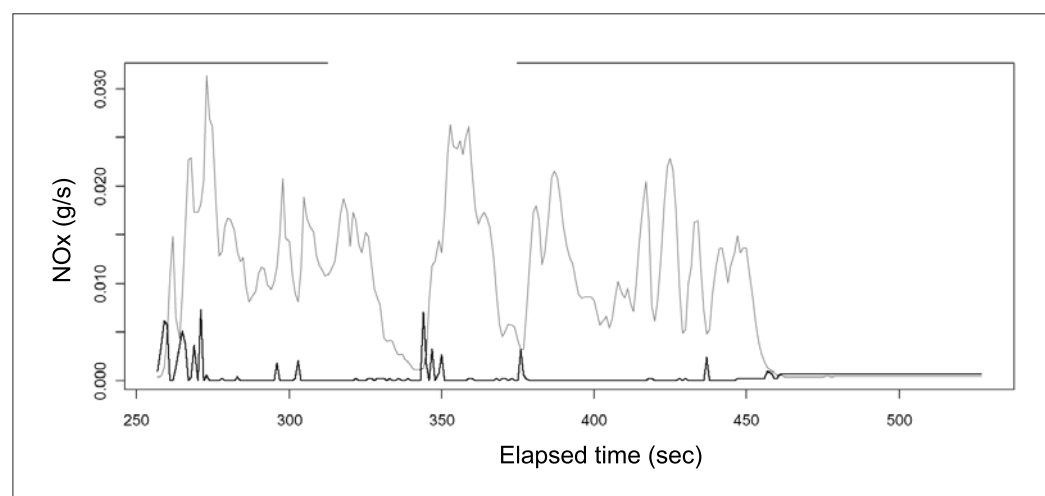


Figure 6  
Comparison of instantaneous AIMSUN  $\text{NO}_x$  predictions (black line) to measured Australian emissions (light grey line) for light-duty petrol vehicles

<sup>1</sup> Vehicle classes are defined in main vehicle type (car, light commercial vehicle, articulated truck, bus, etc.), fuel type (diesel, LPG, etc.), model years, etc.

## REFERENCES

ORBITAL (2005). *NISE 2 – Contract 2: Drive Cycle and Short Test Development*, Orbital Australia, for Department of the Environment and Heritage, Canberra, September 2005, viewed 1 June 2009 at [www.environment.gov.au/atmosphere/fuelquality/emissions/pubs/nise2final-report.pdf](http://www.environment.gov.au/atmosphere/fuelquality/emissions/pubs/nise2final-report.pdf).

PANIS, LI, BROEKX, S, and LIU, R (2006). Modelling instantaneous traffic emission and the influence of traffic speed limits, *Science of the Total Environment*, 371, pp. 270-285.

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