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Simulating fuel consumption and vehicle emissions in an Australian context

Robin Smit[1], Jordi Casas[2,3], Alex Torday[4]

[1] University of Queensland, Centre for Transport Strategy, Brisbane, QLD 4072, Australia

[2] TSS- Transport Simulation Systems SL, Barcelona, Spain

[3] Universitat de Vic, Vic, Spain

[4] TSS- Transport Simulation Systems PTY, Sydney, Australia

Email for correspondence: mr.robin.smit@gmail.com

Abstract

Road transport is a major source of air pollution and greenhouse gas emissions around the world. There is an increasing interest in accurate information on local vehicle emission levels for policy development and sustainable traffic management. Previous studies have shown that emission predictions for the Australian situation need to reflect both the Australian fleet and driving behaviour to avoid unreliable outcomes. This paper discusses a new Australian vehicle emission software (PΔP) and a case-study where traffic simulation software (Aimsun) is combined with PΔP to demonstrate how consistent results can be achieved for the Australian situation. The case-study is an Australian city modelled using the microscopic simulator to generate the required trajectory data of each individual vehicle for the emission model. The simulation results are used in a number of ways: to assess the impacts of urban driving behaviour on fuel consumption, to create maps showing where and when elevated emission levels occur and to compare results with another program (COPERT Australia). The paper will also discuss where further research is required.

1. Introduction

The environmental impacts of road traffic are commonly evaluated at different scales using both transport and emission models and, in the case of air pollution, dispersion and exposure models. The scale of application of such models ranges from a single point near a road to entire urban or regional road networks, and even national or global assessments. Due to the continued growth in vehicle use and associated deterioration in driving conditions (congestion), the prediction of traffic emissions has become increasingly relevant to air quality problems, climate change and mitigation policies. The development of reliable emission estimates is therefore needed to ensure that the use of this information results in sound policy decisions (Smit et al., 2008).

Importantly, there is increasing interest in accurate assessment of near-road air quality and the effects of local-scale traffic measures and technological developments (e.g. Noland and Quddus, 2006) on fuel consumption, emissions and air pollution.

One of the reasons is that air pollution shows a strong temporal and spatial component. For instance, substantially elevated concentration levels typically occur near intersections as compared with midblock sections, and even larger differences are found at locations only hundreds of meters away from major roads. This has been known for a long time. For instance, Claggett, Shrock and Noll (1981) reported that CO concentrations measured in the queue zone at an intersection were on average four times higher than at midblock.

Adequate spatial and temporal attribution of vehicle emissions is now of increased importance because of a new international (and Australian) focus on the reduction of population exposure to air pollution and (health) risk (NEPC, 2011). This new exposure reduction approach means that there will be a focus on improving air quality in places where the largest number of people is likely to be exposed, which is typically in areas with a high density of roads. As a consequence, it will be important to know exactly which parts of the population are exposed to relatively high air pollution levels (e.g. near busy roads), what the level of impact is, and when this occurs.

Another reason is the focus on reduction of greenhouse gas emissions and improvement of fuel efficiency in transport operations, which includes the assessment of possible trade-offs with air pollutant emissions. Various traffic management measures are available to improve traffic flow, safety and emissions including signal coordination, intelligent traffic light control, dynamic speed limits and ramp metering. However, as these types of traffic measure have a relatively small effects on fuel consumption and traffic emissions (in the order of 10-20%), sensitive and accurate models are needed to predict the extent of their environmental impacts.

2. Vehicle Emission Models

Similar to transport models, a hierarchy of vehicle emission models can be distinguished, each with their own level of complexity and range of application (Smit, Ntziachristos and Boulter, 2010). These include ‘average-speed’ models (e.g. COPERT, MOBILE), where emission rates (g/veh.km) are a function of mean travelling speed, ‘traffic-situation’ models (e.g. HBEFA, ARTEMIS), where emission rates (g/veh.km) correspond to particular traffic situations (e.g. ‘stop-and-go-driving’, ‘freeflow’) and ‘modal’ models (e.g. PHEM, CMEM, MOVES), where emission rates (g/s or g/ driving mode) correspond to specific engine or vehicle operating conditions. Whereas average speed and traffic situation models are designed to operate at national or city network level, modal models are designed for local area assessments.

All modal models simulate emissions at a high resolution in time and space, but they vary in level of complexity and demand for input data. The most complex modal emission models (e.g. Barth et al., 2000; Atjay et al., 2005) are deterministic and compute instantaneous emission rates (g/s) as a function of various engine variables (e.g. engine speed and load, injection timing, oil temperature, air-to-fuel ratio). Algorithms that simulate catalyst reduction efficiency can be included to simulate the effects of emission control technology. Gear shift behaviour is usually simulated to compute instantaneous engine load and engine speed using detailed input data (e.g. gear ratios, wheel size). Less complex modal models have been developed ranging from a relatively simple fundamental driving mode model (Midenet et al., 2004), an instantaneous speed/acceleration model (Rakha et al., 2004) to power-based models (Sonntag and Gao, 2007).

Previous investigations have shown vehicle emission models need to reflect local fleet composition and driving characteristics to provide reliable vehicle emission predictions. Large errors, up to a factor of 20 (Smit and McBroom, 2009b), were found when overseas models were directly applied to Australian conditions without calibration, because these models do not reflect Australian vehicles, fuels, climate, fleet composition and driving conditions. Indeed, this was the main reason for the development of a dedicated Australian version of the COPERT software (Smit and Ntziachristos, 2012). So a modal emission model employed in Australia needs to reflect the local fleet composition and driving characteristics in order to provide adequate vehicle emission predictions for the Australian situation.

3. P∆P Model

A new modal model for Australian conditions has been developed (Smit, 2013). The P∆P model uses engine power (P, kW) and the change in engine power (∆P, kW) as the main model variables to simulate vehicle fuel consumption and CO_2 and NO_x emissions. The model uses a similar vehicle classification as COPERT Australia, which was recently released and further discussed in section 4.3. A total of 73 vehicle classes are modelled accounting for main vehicle type, fuel type (petrol, diesel) and technology level (Australian Design Rules). The main vehicle types are defined as small passenger car (PC-S, engine capacity < 2 litres), medium passenger car (PC-M, 2-3 litres), large passenger car (PC-L, > 3 litres), compact and large SUVs (SUV, 4WDs), light-commercial vehicle (LCV, GVM ≤ 3.5 t), rigid medium commercial vehicle (MCV, GVM 3.5-12.0 t), rigid heavy commercial vehicle (HCV, GVM 12.0-25.0 t), articulated truck (AT, GVM > 25 t), light bus (GVM ≤ 8.5 t) and heavy bus (GVM > 8.5 t). ADRs refer to "Australian Design Rules", which are the emission standards adopted in Australia. ADRs have been aligned with EU standards from about 2003 (before 2003 US standards were used). The input to the model is speed-time data (1 Hz) and information on road grade, vehicle loading and use of air conditioning (on/off). This information is used to compute the required (change in) engine power for each second of driving. The vehicle emission algorithms were developed and tested in distinct steps:

- Create a verified empirical database for model development.
- Develop mathematical relationships between empirical emissions data and engine power.
- Develop the PΔP simulation tool for on-road driving conditions.
- Model performance assessment.

3.1 Verified Database

The model has used data from a verified Australian emissions database with about 2,500 modal emission tests (1 Hz) and about 12,500 individual bag measurements. Each modal test contains approximately 30 minutes of laboratory-grade second-by-second emissions and speed data based on real-world Australian driving cycles (CUEDC-P and CUEDC-D) that were developed from on-road driving pattern data in Australian cities (NEPC, 1999; DEH, 2005). In addition to these real-world cycles, test data from the DT80 test cycle has been used (NEPC, 1999). The DT80 test is an Australian in-service emissions test that is conducted to assess emissions performance of on-road diesel vehicles. The DT80 test simulates worst-case driving conditions (e.g. full open throttle acceleration, high cruise speeds) in order to capture worst-case emission levels. This is useful data as it ensures that emissions data are available over the full range of operating conditions, including extreme accelerations.

All modal emissions test data were subjected to a verification and correction protocol (Smit and Ntziachristos, 2012). This included time re-alignment, verification of emission traces (analyser drift, clipping) and computation and verification of test statistics (e.g. BSFC, mean thermal efficiency). For each vehicle class, one representative vehicle was selected for model development taking into consideration mean fuel consumption and emission levels as compared to the class average values.

3.2 Model Development

First, a mathematical relationship was developed between engine power and emission measurements during the tests. Engine power (kW) was computed for each second of driving using dynamometer load algorithms, which varied with the different test programs, in combination with additional algorithms to simulate internal vehicle losses due to drive train and tyre rolling resistances. The vehicle emission rate (e_t, g/s) was then fitted to the following equation:

$$e_t = \begin{cases} \alpha & v_t = 0 \\ \beta_0 + \beta_1 P_t + \beta_2 \Delta P_t + \beta_3 P_t^2 + \beta_4 \Delta P_t^2 + \beta_5 P_t \Delta P_t + \varepsilon \;\; where\ \varepsilon \sim AR(p) & v_t > 0 \end{cases} \qquad (1)$$

In this equation P_t represents engine power (kW) at time t. For idling conditions (speed = 0 km/h) a constant average value (g/s) is used. For non-stationary (moving vehicle) driving conditions a multivariate time-series regression model has been fitted using the generalised least-squares method, where β_0, …, β_5 represent the regression coefficients. An autoregressive model was used to account for autocorrelation effects on the residuals. Residual analysis (Neter et al., 1996) was used to verify that the assumptions of the regression analysis were not violated. The variable ΔP_t quantifies the change in power over the last three seconds of driving and is computed as:

$$\Delta P_t = P_t - P_{t-2} \tag{2}$$

ΔP_t aims to include "history effects" into the model. This is important because vehicle operating history 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).

3.3 Tool Development

It is important that total driving cycle emissions for the vehicles used in model development match those of the average values of similar vehicles in the empirical database. A calibration factor φ is therefore computed as the ratio of total cycle emissions (g) for the vehicles used in model development to average total cycle emissions of all tested vehicles of a particular vehicle class, in the same test conditions (drive cycle, etc.). Vehicle emission rates in the simulation tool (e_t^*, g/s) are then computed as:

$$e_t^* = \varphi\, e_t \tag{3}$$

Typical values for φ are 0.9-1.2 for fuel consumption and CO_2 emissions, and 0.6-1.7 for NO_x emissions.

For the simulation tool, an estimate of second-by-second on-road engine power demand is required, which reflects the impacts of vehicle loading, road grade and use of auxiliaries. The on-road engine power prediction model consists of a set of algorithms that quantify the resistive forces that are exerted on the vehicle while driving. A motor vehicle requires engine power to overcome all these resistive forces and to run its accessories (e.g. air conditioning). For the PΔP model, power algorithms have been adopted from Rexeis et al. (2005), which accounts for tyre rolling resistance, aerodynamic drag, inertial drag, gravitational resistance, drive train resistance and power required to run auxiliaries. The power components are predicted for each second of driving and require input on speed, acceleration, road grade, vehicle mass (including loading) and use of air conditioning. These algorithms also require vehicle specific information such as aerodynamic drag coefficient, frontal area and rolling resistance coefficients. This vehicle specific information was collected for all vehicles and hard coded into the software.

Finally, a few operational boundaries are applied to the emission simulation. Firstly, instantaneous P_t and ΔP_t values cannot exceed 110% of the minimum and maximum values encountered during the tests. Secondly, emission rates are capped at a maximum value, which is dependent on the vehicle test. If the ratio of the maximum engine power in the test to the rated engine power is less or equal to 50%, then the maximum rate is set to 1.50 times the maximum observed value. If the ratio is between 50-75%, or larger than 75%, then the maximum emission rate is set to 1.25 and 1.05 times the maximum observed value, respectively. The simulation will also check for the occurrence of unrealistically high engine power during the simulation. This could occur, for instance, when a LDV driving cycle is used for an articulated truck. In this case the truck cannot deliver the acceleration rates required to follow the speed-time input data and the rated power of the truck will be exceeded. The simulation will not report the results for these situations if rated engine power is exceeded more than 5% of the time.

3.4 Model Performance

Model validation and model verification (Smit, 2013) showed that the performance results for the PΔP modeling software results are good with average R^2 values of 0.65 and 0.93 for NO_x and CO_2/Fuel Consumption, respectively. This means that on average approximately 65% to 93% of the variation in instantaneous emissions can be explained with the models. These results compare well and are generally similar or better as compared with reported results from other models (e.g. Atjay et al., 2005; Silva et al., 2006). The validation showed that the PΔP emission algorithms are robust with respect to prediction errors (RMSE) and goodness-of-fit (R^2) and sometimes even exhibit improved performance as compared with the results from model verification.

There is, however, a systematic under-prediction (about 5%) for fuel consumption and CO_2 emissions in arterial conditions. The average bias for NO_x emissions is small at -1%, despite the large bias for some vehicle classes. This means that at fleet level large systematic prediction errors tend to cancel each other out. Prediction bias can be reduced by inclusion of the validation data in a second round of model fitting and aggregation of prediction results to fleet level to cancel out systematic errors. Another way to reduce prediction errors is to spatially aggregate the second-by-second emission predictions. This means that predictions are made for a specific length of road or road links, as is done in the case study.

4. Application – A Case Study

The minimum input requirements for the emission simulation are speed-time data (1 Hz) and a selection for which vehicle types the simulation should be run. This kind of information is available from various sources including microscopic traffic simulation models, expert judgment or on-road measurements. Additional input on road grade, vehicle loading and air-conditioning use are optional, but can be set to default values in the absence of information.

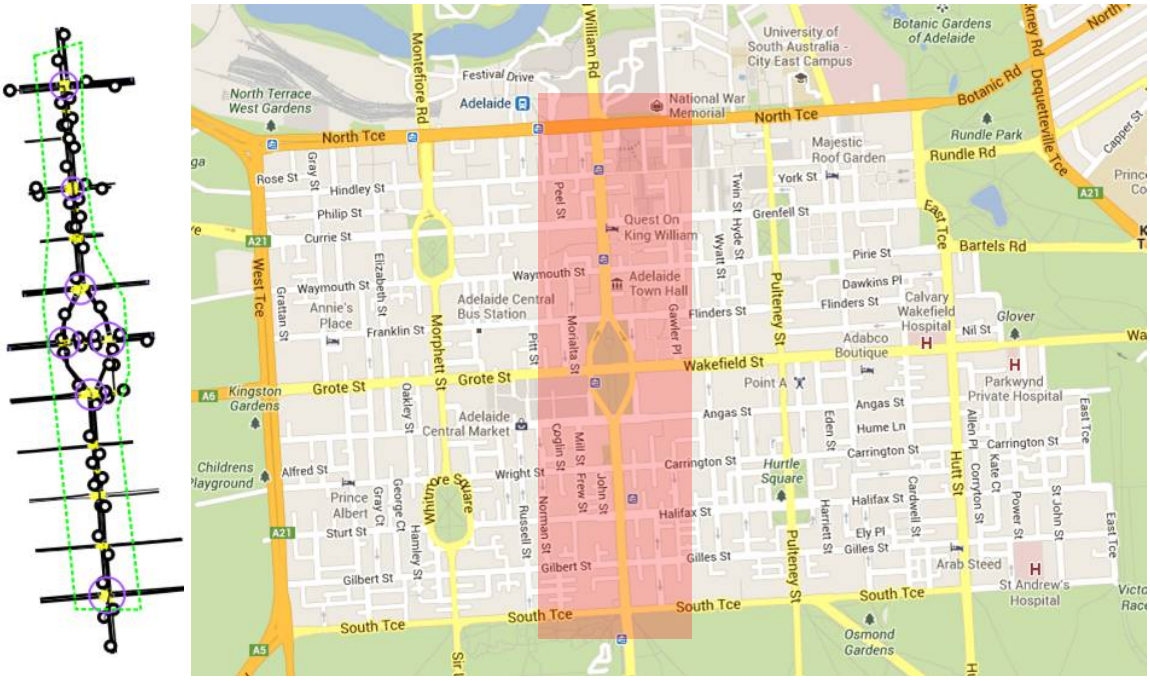
For the purpose of testing the emissions calculation using a microscopic simulation model, a sub-area of the Adelaide 2011 base case CBD model has been used. This model has been developed by University of South Australia for the Department of Planning, Transport and Infrastructure (DPTI) using the Aimsun (Aimsun, 2012) simulation package. The study area is shown in Figure 1 and it embraces the King Williams street crossing the CBD from north to south and from south to north. In term of vehicle types, it includes cars, trucks and PT buses.

The case study network consists of 95 road links and the simulation is conducted for two time periods (7:00-8:00 AM, 8:00-9:00 AM) and involves a total of 2149 vehicles (84% LDVs, 16% HDVs) driving through the network. A total of 9402 driving patterns were generated by Aimsun, which add up to almost 3500 minutes or 60 hours of high resolution speed time data. Each driving pattern has allocated a unique ID which is a combination of link ID, vehicle ID and simulation period ID. The driving patterns were combined with the PΔP emission algorithms to estimate a number a statistics for each driving pattern:

- total fuel consumption in grams
- total NO_x emission in grams
- total distance in meters
- average speed in km/h

More than 400,000 emission values were computed after combination of the simulated LDV and HDV driving patterns with the corresponding 48 LDV or 25 HDV PΔP vehicle classes.

Figure 1: Case Study Area: Adelaide CBD



The simulation also verified the occurrence of unrealistically high engine power demands. This could occur, for instance, when a light truck driving pattern is used for an articulated truck. In this case the truck cannot deliver the acceleration rates required to follow the speed-time input data and the rated power of the truck will be exceeded. The simulation flags the results in cases where the rated engine power is exceeded more than 5% of the time, i.e. where a simulated driving pattern is identified as 'unachievable' for a particular vehicle type. Overall, 2% of the LDV driving patterns and 11% of the HDV driving patterns were flagged. These flagged predictions were omitted from the computation of total link emissions.

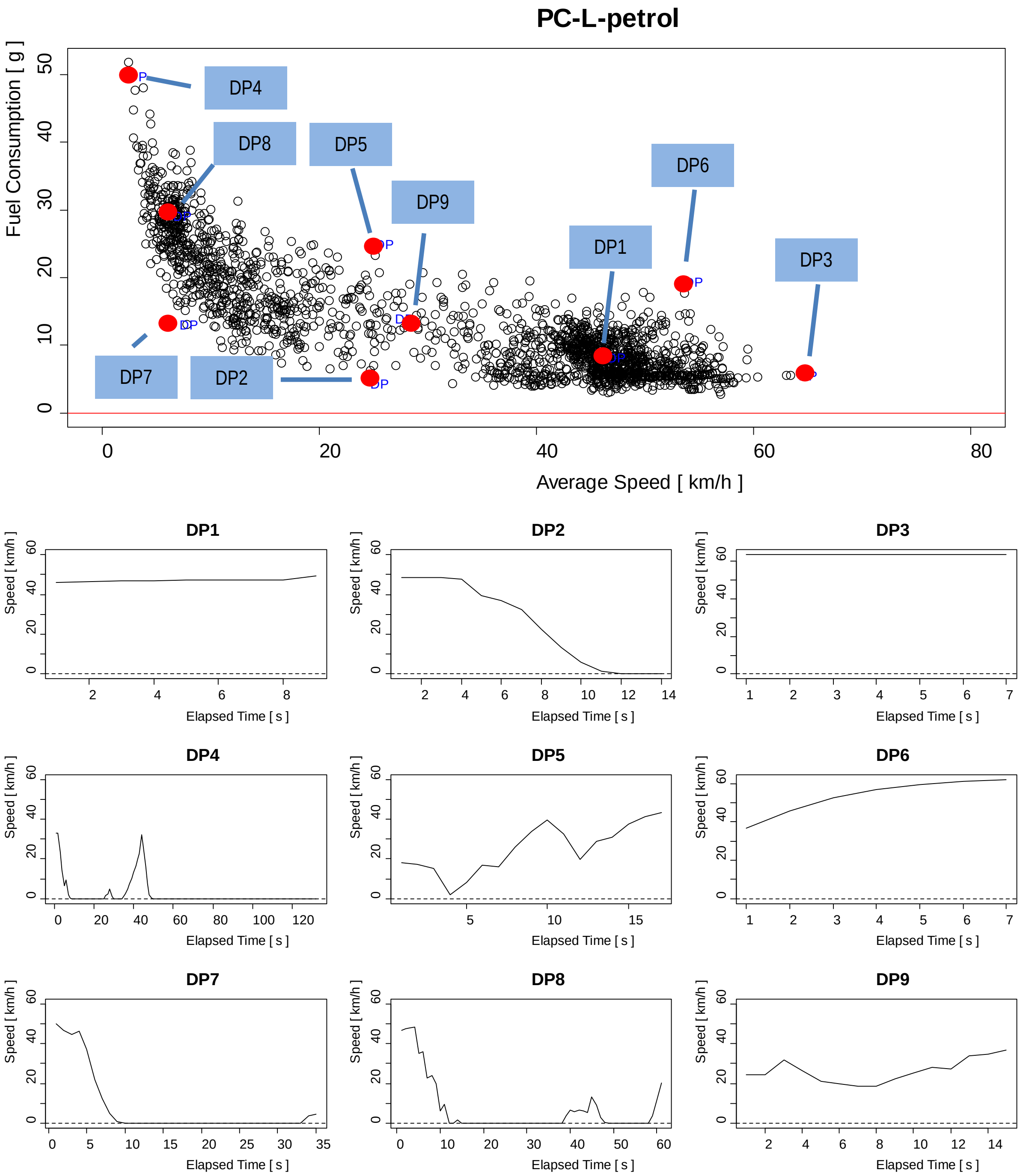
As will be discussed in section 5 further integration of PΔP and Aimsun will resolve this issue by e.g. speed data smoothing and linkage of the 73 PΔP vehicle classes with more detailed Aimsun classes. To ensure that total link emissions reflect contributions from all vehicles in the case-study, omitted values were replaced with the average emission prediction (grams per vehicle) for the link.

The PΔP software is effectively used as a post processor to Aimsun to generate emissions and fuel consumption data that are specific for the Australian fleet. This information can be used in various ways to examine specific research questions. A few examples are discussed in the following sections.

4.1 The Impact of Urban Driving Behaviour on Fuel Consumption

Figure 2 shows an extract of the emissions database. It visualises the predicted fuel consumption in total grams per driving pattern for large petrol passenger cars and for all links with a length between 75 and 125 m (n = 1960).
There is a visible trend between average speed and total fuel consumption (i.e. lower average speed, higher fuel consumption and vice versa), but also a significant amount of scatter at a particular average speed.

Figure 2: Fuel consumption versus average speed for large petrol passenger cars (Top Chart) and driving behaviour for specific points (Bottom Charts)



Analysis of the driving patterns at particular points of average speed and fuel consumption reveals that situations with the highest predicted fuel consumption are associated with either driving behaviour that involves (strong) accelerations (DP5, DP6) at speeds above around 20 km/h or traffic conditions that impose significant queuing and idling (DP4, DP8) at speeds below around 20 km/h.

In fact, driving with a lot of idling is predicted to cause the highest levels of fuel consumption for this vehicle class, and therefore the highest levels of greenhouse gas emissions (CO_2). This is an interesting finding as idling emissions expressed as grams per second are typically low as compared with situations that require substantial engine power such as acceleration manoeuvres and high speed driving conditions. This effect is caused by the duration idling can take place as is shown in DP4 where is takes the vehicle 132 seconds to cover a distance of 87 m. This is in contrast with DP6 where it takes the vehicle just 7 seconds to drive a distance of 104 m. Figure 2 also shows that (approximately) constant speed and deceleration manoeuvres are associated with lower fuel consumption values.

4.2 Emission Maps

The computed emission for each vehicle class and driving pattern was allocated to their respective link and time period and aggregated to produce total link emissions. It is noted that VKT based weighting factors for base year 2010 were used for each vehicle class to ensure that total link emissions reflect the on-road fleet composition. For instance, 4% and 11% of total VKT is driven by small ADR79/00 and ADR79/01 petrol passenger cars, respectively. Figure 3 visualizes the results of this aggregation with emission and fuel consumption maps. These maps can be used to identify air pollution or greenhouse gas hot spots in the network, and to track how emissions at specific locations change over time.

Figure 3: Predicted Total NO_x Link Emissions in the Network for Two Time Periods (07:00-08:00, left chart, and 08:00-09:00, right chart)

This spatial and temporal emissions information can be fed into air quality models to assess the impacts of local traffic conditions on air pollutant concentration levels. Importantly, a further division of road links into smaller segments is possible and would allow for even better spatial allocation of emissions.

4.3 Comparison with Other Models

A new dedicated Australian vehicle emissions software ('COPERT Australia') was released in February 2013 (http://www.emisia.com/copertaustralia/General.html). COPERT is a European model and it stands for COmputer Programme to calculate Emissions from Road Transport. COPERT 4 is used world-wide to calculate air pollutant and greenhouse gas emissions from road transport, e.g. for submission of national road transport inventories to satisfy the requirements of the Convention on Long Range Trans-boundary Air Pollution (CLRTAP) and the UN Framework Convention on Climate Change (UNFCCC). Different calculation methods are included for (engine) exhaust emissions and non-exhaust emissions (Ntziachristos et al., 2009). Exhaust emissions are simulated separately for hot and cold conditions and two types of non-exhaust emissions are simulated (particulate matter from the wear of tyres and brakes and evaporative hydrocarbon emissions).
COPERT's hot running emission module can be classified as an 'average speed model'. Average speed emission algorithms are commonly used around the world to estimate emissions from road traffic at a national or regional level. In essence, these models combine emission factors (grams/veh.km) with traffic activity data (VKT) using a detailed breakdown by vehicle class. The emission factors are a function of traffic performance ('average travel speed'), as well as several other factors such as fuel quality, ambient temperature, ageing, etc. Average speed models are well suited to be interfaced with, or use output from macroscopic transport models.
A fundamental change with respect to COPERT 4 is explicit consideration of the required spatial resolution of the average speed algorithms in COPERT Australia. It was considered that macroscopic transport models are the most likely source of input data for emission predictions. A driving distance of 100 m was therefore selected as an appropriate scale for emission factor development. A procedure was developed to derive hot running emission algorithms at this spatial resolution using second-by-second emissions test data (Smit and Ntziachristos, 2012).

Figure 4: Comparison of CO_2 and NO_x emission factors, COPERT Australia (Line) and Aimsun – PΔP (Black Dot Points, Yellow Points are mean values for 5 km/h speed bins)

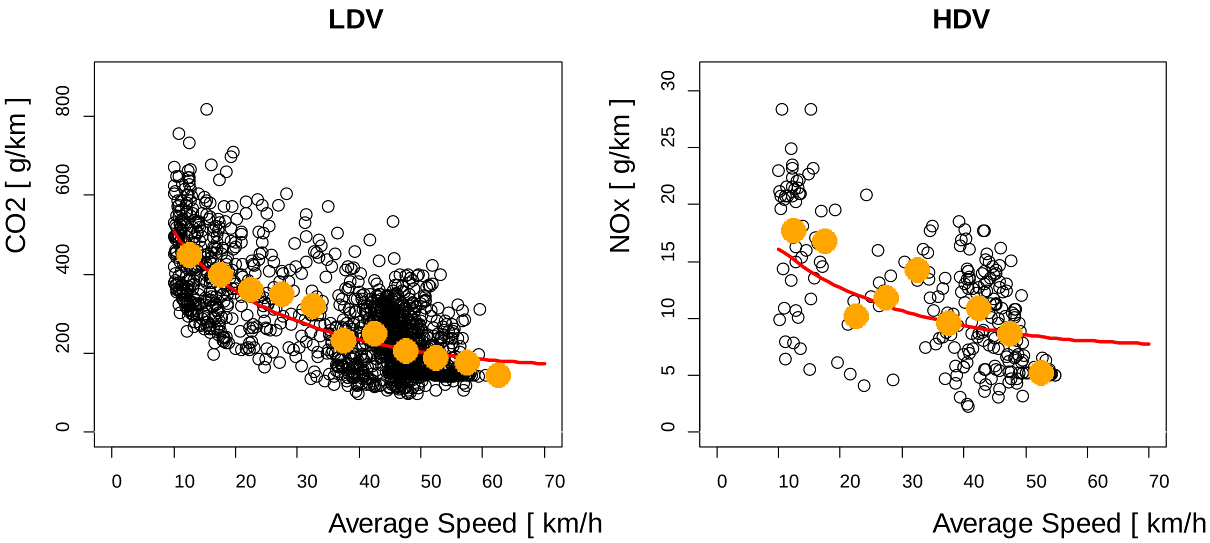


Figure 4 compares the PΔP emission predictions, expressed as grams per km, for individual driving patterns generated with Aimsun (black dot points) for all links with a length between 75 and 125 m with hot running emission predictions made with COPERT Australia (red line) for LDVs (CO_2) and HDVs (NO_x). The yellow dot points represent the average values of the PΔP predictions as computed for 5/km/h speed bins.
Figure 4 shows that the PΔP model in combination with output from Aimsun is able to resolve and explain the variation in vehicle emissions at a particular average speed, and also that the model compares quite well in terms of average or 'typical' emissions behaviour with the predictions made with COPERT Australia.

5. Discussion and conclusions

This paper reported on the development and application of a new simulation tool for road vehicles. The PΔP model predicts second-by-second fuel consumption, air pollution (NO_x) and greenhouse gas emissions (CO_2) with a high resolution in time and space. It uses engine power and the change in engine power as the main model variables to simulate vehicle fuel consumption and emissions for all relevant vehicle classes including cars, SUVs, light-commercial vehicles, rigid trucks and articulated trucks. A total of 73 vehicle classes are modelled accounting for main vehicle type, fuel type and technology level.

The minimum input requirements for the model are speed-time data (1 Hz) and vehicle types. This kind of information is available from microscopic traffic simulation models, and Aimsun output data have been used as input to the emission modelling process to demonstrate the use as a post-processing emissions tool for impact assessments. The emissions information is resolved in time and space and can be used in a variety of ways, and some of them were shown in this paper, for instance:

- hot spot analysis
- examination of driving conditions that lead to higher emission levels
- impact assessments
- scenario modelling
- input to air quality models

During this study it became clear that there are a number of steps that will further improve and streamline the interfacing between the traffic and emission algorithms.

- The sheer number of computational steps makes the process somewhat time consuming, which is fine when there is time available for number crunching. However, there also appears to be a need for more time efficient methods. There are several options that will improve computational efficiency that are yet to be explored.
    - In this study, for each individual driving pattern emissions were modelled for either all 48 or all 25 vehicle classes depending whether the simulated driving pattern related to an LDV or an HDV.
    - The interfacing between Aimsun and the PΔP algorithms can be improved and run times reduced by allocating one PΔP vehicle class (out of 73) to each simulated vehicle. This could be done through random selection taking into account the fleet composition.
    - Another option is to take a sample of simulated vehicles for each road link to reduce model run times.
- In this study the Aimsun driving patterns were directly used in the emissions algorithms without any pre-processing. Pre-processing of discrete speed-time data (smoothing) is normally required to account for noise in the speed-time data and to prevent significant errors in the calculation of the computed time-series of acceleration and engine power, in particular at higher speeds where unsmoothed speeds can lead to large differences in predicted engine power. In fact, all driving

cycles used for emissions testing were smoothed using a T4253H (running median and Hanning filter) smoothing algorithm before the data were used in the development of the P∆P model. The effect of smoothing on average driving cycle power was found to be generally small with a maximum of a few percent. However, the effects could be substantial in specific parts of the test cycle where extreme peaks in power are removed (Smit, 2013). It is anticipated that smoothing algorithms will be incorporated as a pre-processor for traffic simulation data, and this may further reduce the number of discarded driving patterns, which was discussed at the beginning of section 4.

The P∆P model can be used to develop more aggregated spin-off emission models that interface with more aggregated meso-scopic transport models, which will allow for quicker assessments for larger networks.

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References

Aimsun, 2012. Aimsun User's Manual. TSS- Transport Simulation Systems.

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 2000.

Claggett, M., Shrock, J., Noll, K.E., 1981. Carbon monoxide near an urban intersection, Atmospheric Environment, 15, 9, 1633-1642.

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

Midenet, S., Boillot, F., Pierrelée, J.C., 2004. Signalized intersection with real-time adaptive control: on-field assessment of CO2 and pollutant emission reduction. Transpn. Res.-D, 9, 29-47.

NEPC, 1999. In-Service Emissions Performance - Drive Cycles, National Environment Protection Council Service Corporation.

NEPC, 2011, National Environment Protection (Ambient Air Quality) Measure Review, May 2011, National Environment Protection Council Service Corporation (NEPC).

Neter, J., Kutner, M.H., Nachtsheim, C.J., Wasserman, W., 1996. Applied Linear Statistical Models, 4th Edition, McGraw-Hill, Chigago, IL, ISBN 0 256 11736 5.

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

Rakha, H., Ahn, K., Trani, A., 2004. Development of VT-Micro model for estimating hot stabilized light-duty vehicle and truck emissions. Transpn. Res.-D. 9, 49-74.

Rexeis, M., Hausberger, S., Riemersma, I., Tartakovsky, L., Zvirin, Y., Van Poppel, M., Cornelis, E., 2005. ARTEMIS - Assessment and Reliability of Transport Emission Models and Inventory Systems, WP400 - Heavy Duty Vehicle Emissions, DGTREN Contract 1999-RD.10429.

Silva, C.M., Farias, T.L., Frey, H.C., Rouphail, N.M., 2006. Evaluation of numerical models for simulation of real-world hot stabilized fuel consumption and emissions of gasoline light-duty vehicles, Transpn. Res.-D, 11, 377-385.

Smit, R., Ntziachristos, L., 2012. COPERT Australia: Developing Improved Average Speed Vehicle Emission Algorithms for the Australian Fleet, 19th International Transport and Air Pollution Conference, Thessaloniki, Greece, 26-27 November 2012.

Smit, R., Ntziachristos, L., Boulter, P., 2010. Validation of road vehicle and traffic emission models - A review and meta-analysis, Atmospheric Environment, 44, 2943-2953.

Smit, R., Poelman, M., Schrijver, J. 2008. Improved road traffic emission inventories by adding mean speed distributions, Atmospheric Environment, 42 (5), 916-926.

Smit, 2013. Development and Performance of a New Vehicle Emissions and Fuel Consumption Software (PΔP) with a High Resolution in Time and Space, Atmospheric Pollution Research, Accepted for Publication.

Sonntag, D., Gao, H.O., 2007. The MOVES from MOBILE: preliminary comparison of EPA's current and future emissions models, Transportation Research Board Annual Meeting, 2007, 1-17.