TRANSPORT EMISSIONS SIMULATION

PΔP: A SIMULATION TOOL FOR VEHICLE EMISSIONS AND FUEL CONSUMPTION SOFTWARE WITH A HIGH RESOLUTION IN TIME AND SPACE.

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Road transport is a major source of air pollution and greenhouse gas emissions around the world. Comprehensive measurement of transport emissions in urban networks is not feasible due to the large number of vehicles that operate on our roads, large spatial and temporal variability and the many factors that influence emission levels. Modelling tools are therefore commonly used to estimate fuel consumption and air emissions. Models are also required to make projections into the future. Vehicle emission prediction software is well-developed in Europe and the US. However, they do not adequately reflect Australian conditions in terms of fleet mix, vehicle technology, fuel quality and climate.

This article provides an overview of a new Australian vehicle emission software and its applications. The software predicts second-by-second fuel consumption, air pollution and greenhouse gas emissions with a high resolution in time and space. It uses engine power and the change in engine power as the main model variables and includes all relevant vehicle classes. It links well with output from microscopic transport models.

A free "light" version of the software is available on request.

EMISSIONS SIMULATION

A hierarchy of vehicle emission models exists reflecting different levels of complexity and different types of application. 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 factors (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 factors (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 the national or city network level, modal models are designed for local assessments.

more localised assessments. This short paper will focus on PΔP and its applications.

Tool Design.
The PΔP model uses engine power (P, kW) and the change in engine power (ΔP, kW) to simulate fuel consumption and CO_2 and NO_x emissions for 73 vehicle classes (Smit, 2013a). The vehicle classification

The model was developed using empirical data from a verified Australian emissions database with about 2,500 second-by-second emission tests (1 Hz) and about 12,500 individual aggregated '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 (Composite Urban Emissions Drive Cycle for Petrol or Diesel vehicles; CUEDC-P and CUEDC-D) that were developed from on-road driving pattern data in Australian cities. In addition to these real-world cycles, test data from the DT80 test cycle are used. The DT80 test is the Australian Transport Council's in-service emis-

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Vehicle emission prediction software is well-developed in Europe and the US. However, they do not adequately reflect Australian conditions in terms of fleet mix, vehicle technology, fuel quality and climate. Large errors of up to a factor of 20 (Smit and McBroom, 2009), have been reported when overseas models are directly applied to Australian conditions without calibration. Therefore two software packages were recently developed for Australian conditions using comprehensive empirical data from major Australian emission testing programs. COPERT Australia has been designed to estimate motor vehicle emissions at regional and national level (Ntziachristos et al., 2013), whereas a power based model (PΔP) was developed for

Main Category	Sub Category	Fuel Type	Emission Control Standard
Passenger Car	Small (< 2.0 L); Medium (2.0 - 3.0 L); Large (≥ 3.0 L)	Petrol; Diesel	Uncontrolled; ADR27;ADR37/00-01; ADR79/00-05
SUV	Compact (≤ 4.0 l); Large (> 4.0 l)	Petrol; Diesel	Similar to "Passenger Car" but also including ADR36 (SUV-L) and ADR30 (SUV-Diesel)
Light Commercial Vehicle	GVM ≤ 3.5 t	Petrol; Diesel	Uncontrolled; ADR36 (P); ADR30 (D); ADR37/00-01; ADR79/00-05
Heavy Duty Truck	Medium; Heavy; Articulated	Diesel	Uncontrolled; ADR30; ADR70; ADR80/00; ADR80/02-05
Bus	Light Bus (≤ 8.5 t); Heavy Bus (> 8.5 t)	Diesel	

Table 1. Vehicle Classification.

is shown in Table 1. ADR emission standard is used as a proxy for 'emission control technology level'. ADRs refer to "Australian Design Rules", which are the emission standards adopted in Australia.

The input to the model is speed-time data (1 Hz) and information on road grade, wind speed, 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.

sions test that is conducted to assess emissions performance of on-road diesel vehicles[1]. 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 have

been subjected to a verification and correction protocol (Smit, 2013b). This includes time re-alignment, verification of emission traces (analyser drift, clipping) and computation and verification of test statistics (e.g. Brake Specific Fuel Consumption (BSFC) and mean thermal efficiency). For each vehicle class, one representative vehicle is selected for model development.

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

$$e_t = \begin{cases} \alpha & v_t = 0 \\ \beta_0 + \beta_1 P_t + \beta_2 \Delta P_t + \beta_3 P_t^2 \\ + \beta_4 \Delta P_t^2 + \beta_5 P_t \Delta P_t + \varepsilon & v_t > 0 \\ \text{where } \varepsilon \sim ARMA(p, q) \end{cases}$$

$$\text{(eq. 1)}$$

P_t represents engine power (kW) at time t and is a function of operational variables (vehicle speed, acceleration) and vehicle characteristics (vehicle mass). For idling conditions (speed = 0 km/h) a constant average value (g/s) is used. For non-stationary driving conditions (moving vehicle) 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 is used to account for autocorrelation effects on the residuals. The variable ΔP_t quantifies the change in power over the last three seconds of driving and is computed as:

$$\Delta P_t = P_t - P_{t-2} \qquad \text{(eq. 2)}$$

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.

Total driving cycle emissions for the vehicles selected for model development must match average values of similar vehicles in the empirical database. A calibration factor φ is therefore incorporated in the software. It is computed as the emission ratio of the vehicle used in model development to the average value for all tested vehicles of the same vehicle class. Vehicle emission rates in the simulation tool (e_t^*, g/s) are then computed as:

$$e_t^* = \varphi \, e_t \qquad \text{(eq. 3)}$$

On-Road Power Algorithms

$$P_{rolres} = (\tau_0 + \tau_1 v_t + \tau_4 v_t^4) \, g \, M \, v_t$$

$$P_{air} = 0.5 \, \rho \, C_d \, A \, \Delta v_t^3$$

$$P_{inert} = (M_{veh} \Lambda + M_{load}) \, v_t \, a_t$$

$$P_{grade} = g \, M \, v_t \, G$$

$$P_{transm} = fac \, P^* \, (\eta - 1) \qquad \text{for } P^* < 0$$

$$P_{transm} = fac \, P^* \, ((^1/\eta) - 1) \qquad \text{for } P^* \geq 0$$

$$P_{aux} = \omega \, \kappa \, P_{rated}$$

Input variables:

v_t	=	Vehicle speed (m/s)
v_a	=	Air speed (m/s)
Δv_t	=	v_t - v_a (m/s)
G	=	Road gradient (%)
ω	=	Auxiliaries on/off factor (value is 1 or 0)
M_{load}	=	Mass of the payload and/or passengers and luggage (kg)

Internal/derived variables:

a_t	=	Acceleration (m/s²)
g	=	Gravitational constant (9.81 m/s²)
η	=	Transmission efficiency (-)
ρ	=	Air density (kg/m³)
Λ	=	Rotating mass factor (function of vehicle speed) (-)

Vehicle parameters:

A	=	Frontal area (m²)
C_d	=	Aerodynamic drag coefficient (-)
fac	=	Technology correction factor (-)
M	=	Vehicle mass including Load (kg)
M_{veh}	=	Tare mass (kg)
P^*	=	Total power to overcome the driving resistances without transmission losses (W)
P_{rated}	=	Rated engine power (W)
$\tau_{0,1,4}$	=	Rolling resistance Coefficients (function of vehicle loading)
κ	=	Ratio of rated engine power to power demand for auxiliaries (airco, compressor) (-)

Table 2. On-Road Power Algorithms in PΔP.

The next step is to include algorithms that predict second-by-second on-road engine power demand for each vehicle. A motor vehicle requires engine power to overcome all resistive forces while driving and to run its accessories (e.g. air conditioning). On-road power algorithms in PΔP are adopted from Rexeis et al. (2005) with some modifications, and account for tyre rolling resistance (P_{rolres}), aerodynamic drag (P_{air}), inertial drag (P_{inert}), gravitational resistance (P_{grade}), drive train resistance (P_{transm}) and power required to run auxiliaries (P_{aux}), as is shown in Table 2.

The power components are predicted for each second of driving and require input on speed, acceleration, road grade, wind speed, 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.

The simulation will check for the occurrence of unrealistically high engine power during the simulation. This could occur, for instance, when a light-duty vehicle 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.

Model validation and model verification 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 (Smit, 2013a). 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 (R²) and sometimes even exhibit improved performance as compared with the results from model verification.

Application.
As a minimum, PΔP requires 1 Hz speed-time data and a selection of the appropriate vehicle class. This information can be obtained from various sources:

• Microscopic transport models
• On-road GPS measurements
• Drive Cycles

PΔP + Transport Models.
PΔP has been combined with a microscopic simulation model (Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks or AIMSUN) to estimate emissions in Adelaide CBD in morning peak hours (Smit, Casas and Torday, 2013). The traffic software generated almost 10,000 second-by-second driving patterns for different vehicle types (cars, trucks, buses). PΔP then estimated fuel consumption and emissions for each driving pattern. The highest predicted fuel consumption and emissions were associated with driving behaviour that involves (strong) accelerations and traffic conditions that impose significant queuing and idling. Driving at (approximately) constant speed and deceleration manoeuvres are associated with lower fuel consumption and emissions. This is illustrated in Figure 1.

The emission predictions were then used to identify air pollution or greenhouse gas 'hot spots' in the network, and to track how emissions at specific locations change over time. An example is shown in Figure 2.
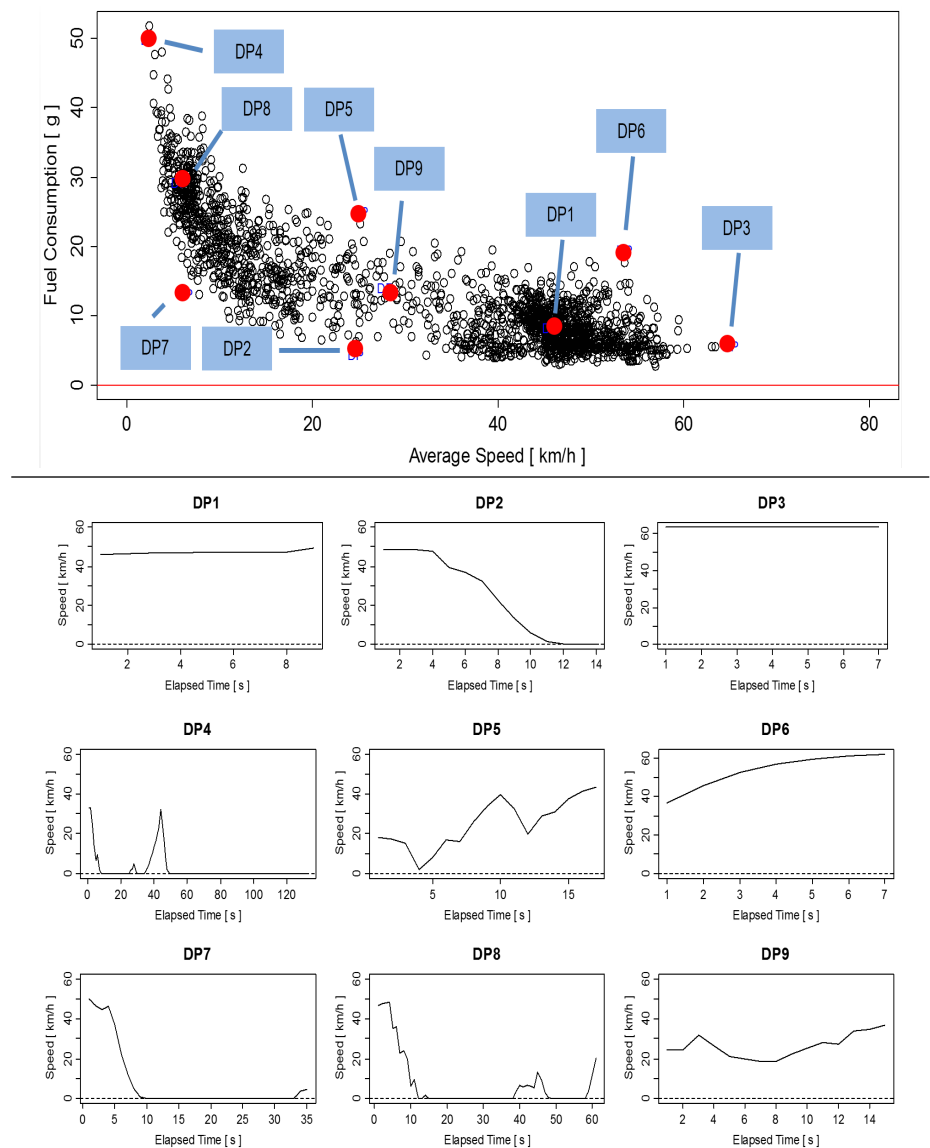
PΔP + GPS data.
PΔP has been combined with a large database of on-road driving data to assess the emission impacts of an intervention program where 102 Sydney drivers were monitored for five weeks using a GPS device (Smit, Greaves and Allison, 2014). The

program exposed drivers to a financial intervention to improve driving around safety outcomes. Assessment of the emissions impacts required a computationally-efficient tool that can readily use millions of second-by-second records as input. PΔP was fit-for-purpose after necessary GPS data preparation, which mainly involves imputation of missing records and smoothing of speed-time data.

Analysis of the emission results for 102 drivers before and after the intervention demonstrates that changes

in total travel (Vehicle Kilometers Travelled, VKT) and changes in driving behaviour both affect emission impacts. The preliminary results indicate that VKT is the main factor driving the change in CO_2 emissions in this type of intervention, whereas driving behaviour changes also affect emissions. Figure 3 show that the overall emission change is a function of a large number of individual driving patterns in the before and after intervention phase, each with their own unique sequence of idling, acceleration and speeds. However, changes in mean CO_2 emission rates (g/km)

TOP: Figure 1a. Fuel consumption versus average speed for large petrol passenger cars (100m drive segments).
BOTTOM: Figure 1b. 9 Driving Patterns (DPs) for specific points
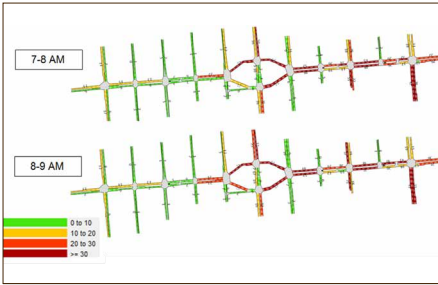Source: Smit, Casas and Torday, 2013

Figure 2: Predicted Total NO_x Link Emissions in the Adelaide CBD Network for Two Time Periods.
Left: 07:00-08:00
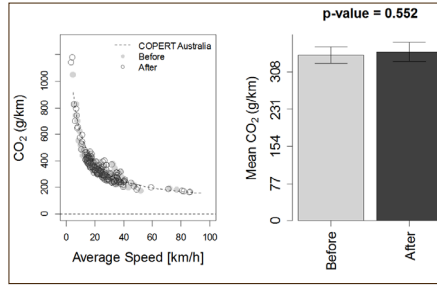Right: 08:00-09:00
Source: Smit, Casas and Torday, 2013

Figure 3. Emissions from a large petrol passenger car ADR37-01.
Left: CO_2 emission factors for all GPS driving patterns for one driver as function of average speed.
Right: The mean emission factors in the before and after phases including 95% confidence interval and p-value.
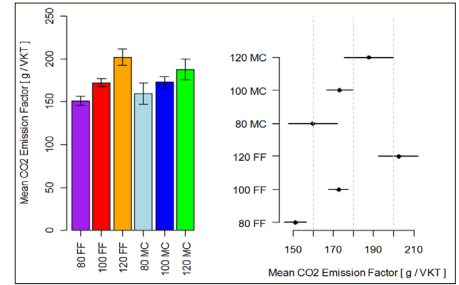Source: Smit, Greaves and Allison, 2014

Figure 4: Mean CO_2 vehicle emission rates for different speed limits (80, 100, 120 km/h) and traffic conditions.
FF = free flow
MC = more congested (including 95% confidence intervals).
Source: Boulter and Smit, 2013

were not statistically significant in this case ($p > 0.05$).

While it has become increasingly easy to collect disaggregated driving behaviour information, it is still complex to quantify emissions. It was concluded that the PΔP tool greatly simplifies this computation process, while still maintaining a sufficient level of disaggregation in the results to identify the key components affecting emissions.

PΔP + drive cycles.
Boulter and Smit (2013) used PΔP to assess the emission impacts of Variable Speed Limits (VSL). Established drive cycles for specific traffic situations were used to estimate the impacts of VSL for the

Australian on-road fleet. The results are visually summarised in Figure 4. The study suggests that reduced speed limits can result in significant CO_2 emission benefits for light-duty vehicles under free-flow motorway conditions, but that the results are less pronounced for more congested situations (traffic volume over 1000 vehicles per lane per hour).

Finally, PΔP has been used in combination with COPERT Australia to assess the impacts of tunnel emissions on local air quality (Smit, 2014). Whereas positive road grade in tunnels significantly increases fuel

consumption and emissions, air flow in the direction of traffic significantly reduces the aerodynamic drag and therefore reduce fuel consumption and emissions. PΔP was therefore used to compute correction factors for the combined effect of in-tunnel road grade, air flow (piston effect) and driving conditions.

Figure 5 shows the input and the second-by-second modelling results for a 4.7 km tunnel. The in-tunnel high speed driving conditions were replicated using a specific drive cycle that was developed from overseas on-road measurements on an uncongested highway with an 80 km/h speed limit. The simulation showed that the piston effect reduced emissions by 15-35%, road grade increased emissions by about 20-35%, depending on the vehicle class and pollutant. Overall, fleet emissions in the tunnel were reduced by 0-10%.
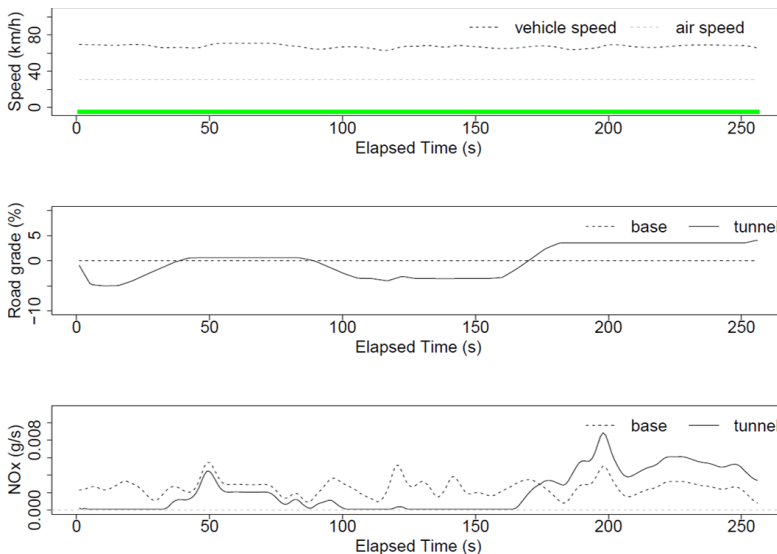

Figure 5: Simulation of the impacts of road grade, air flow and driving behaviour in a tunnel, "Base" represents the situation without road grade or air flow.
Source: Smit, 2014

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