Atmospheric Pollution Research 4 (2013) 336-345

Atmospheric Pollution Research

www.atmospolres.com

Development and performance of a new vehicle emissions and fuel consumption software (PΔP) with a high resolution in time and space

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ABSTRACT

This paper reports on the development and performance 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 modeled accounting for main vehicle type, fuel type and technology level. The model uses data from a large verified Australian emissions database containing around 2 500 modal emission tests (1 Hz) and about 12 500 individual bag measurements. The minimum input requirements for the model are speed–time data (1 Hz) and vehicle types. This kind of information is typically available from microscopic traffic simulation models, on–road measurements or expert judgment. The user of the model can also specify the road gradient, the vehicle loading and the use of air conditioning. Default values are provided for each of these where location–specific data are unavailable. The PΔP model aims for an optimum balance between model complexity and prediction accuracy. The performance results for the PΔP model results are good with, for instance, average R^2 values of 0.65 and 0.93 for NO_X and CO_2/fuel consumption, respectively. This performance compares well with that reported for other models with different complexity. The emission algorithms are shown to be robust with respect to prediction errors. Aggregation of the 1 Hz prediction results in time/space (e.g. 100 m road segments) and across vehicle classes (e.g. passenger car, SUV, articulated truck, etc.) further improves prediction performance.

Keywords: *Road transport, emission, fuel consumption, high resolution, road traffic*

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Article History:

Received: 17 March 2013

Revised: 07 June 2013

Accepted: 09 June 2013

doi: 10.5094/APR.2013.038

1. Introduction

Road transport is a major source of air pollution and greenhouse gas emissions around the world. Models are commonly used to estimate fuel consumption and air emissions for road transport. This is because measurements are often not feasible, from both a technical and cost perspective, due to the large number of vehicles that operate on our roads and the many factors that influence emission levels. Models are also required to make projections into the future.

Similar to transport models, a hierarchy of vehicle emission models can be distinguished based on the level of complexity and types of application (Smit et al., 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 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.

There are a number of developments that are expected to lead to an increased use of modal models. Firstly, there is an increasing focus on the reduction of population exposure to air pollution and (health) risk. 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. This type of assessment requires a fine spatial and temporal allocation of vehicle emissions in study areas, which can be achieved with modal models.

Secondly, there is increasing interest around the world in the effects of local traffic conditions on traffic emissions, fuel consumption and exposure to air pollution. For instance, application of adaptive traffic control measures is growing to improve traffic flow (to alleviate congestion), improve reliability and reduce accidents (Akcelik, 2006; Noland and Quddus, 2006). It is essential to know if these measures adversely affect or improve air pollution and greenhouse gas emissions. Sensitive models are therefore needed to accurately predict the correct direction and magnitude of these effects as this kind of measure typically generates relatively small but still significant impacts.

Thirdly, substantial improvements are expected with respect to the quantity, quality and level of detail (resolution) of traffic data, which are essential inputs to vehicle emission models. For instance, wide scale automated collection of real–time field data on vehicle movement in time and space (using e.g. GPS, video imaging technology) is now becoming a reality due to ongoing developments in, and application of, intelligent sensor, communications and computing technology in vehicles and at the road side (Hoose et al., 2008).

Finally, vehicle testing programs in which emissions are measured at a high resolution in time (typically 1–10 Hz) are increasingly common. This creates opportunities for the construction of large emission measurement databases (including many different vehicles) that can then be used for development of accurate modal models.

This paper reports on the development of a new modal model, the P∆P model, which is based on high resolution Australian test data. The objectives of this research are to develop a model that is comprehensive, accurate, reliable and robust, easy to use and which interfaces readily with appropriate traffic models and (emerging) traffic field data.

2. Modal Vehicle Emission Models

Modal models 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 can be included to simulate the effects of emission–control technology such as catalysts. These models require a substantial amount of detailed input data, which may not always be available to model users at traffic stream level, or too difficult or even impossible to obtain (e.g. gear shift behavior in traffic streams). In order to address this problem, part of the required input data may be simulated within the software. Gear shift behavior, for instance, is usually simulated to compute instantaneous engine load and engine speed. This, however, introduces unknown errors to the model predictions, which may offset accuracy gains from detailed modeling.

A particular issue is the number of test vehicles on which the model is based, and the extent to which the model represents the on–road vehicle fleet. With respect to the emission algorithms, it is clear that accurate emission models need to be based on measurements on a large number of vehicles in various driving conditions to adequately capture and reflect the large variability in emissions behavior of different vehicles (even among vehicles of the same brand and model). Given the time required to develop complex modal models, the number of vehicles and vehicle types included is typically limited.

This raises the question if model complexity can be reduced without compromising prediction accuracy. This would make a model easier and less costly to use. A few validation studies (Lacour et al., 2001; Smit et al., 2010) have shown that more complex emission models do not necessarily lead to more accurate predictions, which seems to support this notion.

Simplified 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 a power–based model (Sonntag and Gao, 2007). The P∆P model aims for an optimum balance between model complexity and prediction accuracy. With respect to the last criterion, it is noted that prediction errors depend on both accuracy of model input and accuracy of model algorithms. The quality of traffic input data (e.g. traffic volume, road length, speed–time profile) is a relevant issue with respect to prediction accuracy, and it has been found that accurate input data are at least as important as accurate emission algorithms (Smit, 2008).

3. P∆P Model Approach

Previous investigations have shown that vehicle emission models need to reflect local fleet composition and driving characteristics to provide adequate vehicle emission predictions. Large errors were found when overseas models were directly applied to Australian conditions without calibration (e.g. Smit and McBroom, 2009), 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, known as "COPERT Australia" (Smit and Ntziachristos, 2012).

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 is based on the combination of fuel type (petrol, diesel), main vehicle type and ADR category. 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). A total of 73 vehicle classes are modeled. The main vehicle types are defined as small passenger car (PC–S, engine capacity <2 L), medium passenger car (PC–M, 2–3 L), large passenger car (PC–L, >3 L), 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 (BUS-L, GVM≤8.5 t) and heavy bus (BUS-H, GVM≤8.5 t). Eleven ADR categories are included ranging from uncontrolled to ADR79/02 (Euro 4) and ADR80/02 (Euro IV).

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 in three distinct steps:

- Creation of a verified empirical database for model development.
- Development of mathematical relationships between empirical emissions data and engine power.
- Development of the P∆P simulation tool for on–road driving conditions.

These steps are discussed in the following sections.

4. Empirical Data

A large number of vehicle emissions tests are available from various Australian test programs. These emissions data have been collated in a verified emissions database with about 2 500 modal emission tests (1 Hz) and about 12 500 individual bag measurements. The modal data files contain typically around 30 minutes of laboratory–grade second–by–second emissions and speed data based on real–world driving cycles that were developed from on–road driving pattern data in Australian cities. The real–world driving cycles were developed for four distinct traffic situations–congested (Con), residential (Res), arterial (Art) and freeway (Fwy)–and five main vehicle classes–light–duty vehicles (LDVs), medium commercial vehicles (MCVs), heavy commercial vehicles (HCVs), articulated trucks (ATs) and buses (BUSs)–to reflect the different speed–acceleration characteristics due to different power–to–mass ratios. The cycles are shown in Figure 1.

In addition to the real–world cycles, modal data from the DT80 test cycle have been used. The DT80 test is an Australian in–service emissions test that is conducted to assess emissions performance of on–road diesel vehicles. The 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 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 (analyzer drift, clipping) and computation and verification of test statistics (e.g. BSFC, mean thermal efficiency).

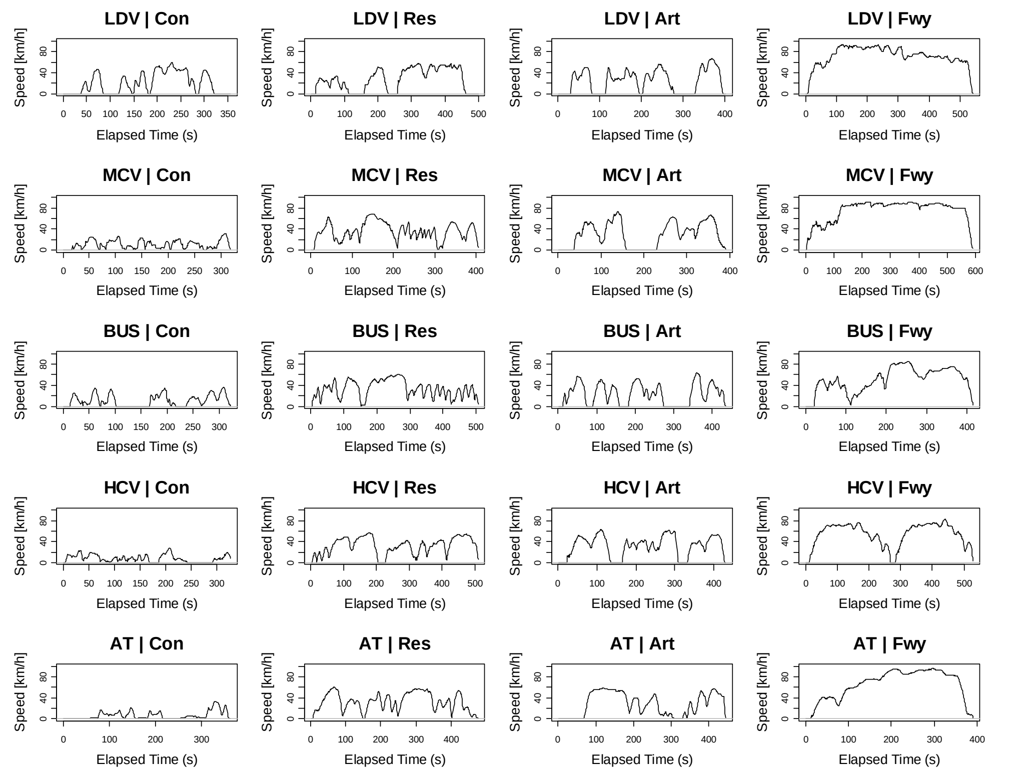

Figure 1. *Australian real–world driving cycles by traffic situation and main vehicle type.*

For each of the vehicle classes, one representative vehicle was selected for model development taking into consideration mean fuel consumption and emission levels as compared to the class average values. The empirical data files contained emissions and speed–time data for the real–world driving cycle and, when available, the DT80 driving cycle. These files were then split into two data files, one for model development ("Con", "Res", "Fwy", "DT80") and one for model validation ("Art").

5. Model Development

The first step was to develop a mathematical relationship between engine power and emission measurements during the tests. All measured second–by–second (1 Hz) speed–time data were smoothed and all speeds less than 0.5 km/h were set to zero. On–road speed measurements and recorded driving patterns are discrete in time and value due to measurement methods or numerical imprecision. Pre–processing of discrete speed–time data (smoothing) was 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. Smoothed speed–time profiles were created using a T4253H (running median and Hanning filter) smoothing algorithm (Velleman, 1980), which is recommended for driving cycle analysis and development (UNECE, 2008). The effect of smoothing on average driving cycle power is generally small with a maximum of a few percent. However, the effects can be substantial in specific parts of the test cycle where extreme peaks in power are removed. The smoothed profiles were used to compute and add time–series of acceleration, engine power and normalized engine power to the modal test files. Acceleration (a_t, m/s^2) is computed as:

$$a_t = \begin{cases} (v_2 - v_1) \div (t_2 - t_1) & t = 1 \\ (v_{t+1} - v_{t-1}) \div (t_{t+1} - t_{t-1}) & 2 \le t \le n-1 \\ (v_n - v_{n-1}) \div (t_n - t_{n-1}) & t = n \end{cases} \tag{1}$$

where v_t represents instantaneous (smoothed) vehicle speed (m/s) at time t, which varies from the cycle start time t=1 to the cycle end time t=n. In order to compute engine power, dynamometer power (P_t^*, kW) was computed for each modal test using the dynamometer load algorithms, which varied with the different test programs. For instance, one of the test programs used the dynamometer algorithms for petrol LDVs as specified in ADR79/01 (Euro 2):

$$P_t^* = \left(\alpha + \beta \, v_t^2 + M \, a_t \right) v_t \tag{2}$$

where α and β represent power absorption coefficients [N and N/(km/h)^2, respectively] and M is the vehicle test mass (kg). Typical values for passenger cars, SUVs and LCVs are 7.10, 10.53, 11.44 N for α, 0.04810, 0.07241, 0.07865 N/(km/h)^2 for β and 1 360, 1 810 and 2 150 kg for test mass, respectively. Other test programs used proprietary dynamometer loading algorithms where P_t^* is a function of v_t, a_t, M, as well as aerodynamic drag coefficient and frontal area. Engine power (P_t, kW) was computed for each second of driving using these study–specific dynamometer algorithms in combination with additional algorithms to simulate internal vehicle losses due to drive train and tire rolling resistances that are not accounted for in the dynamometer algorithms (Rexeis et al., 2005). The vehicle emission rate (e_t, g/s) was then fitted to the following equation:

$$e_t = \begin{cases} \alpha & v_t = 0 \\ \beta_0 + \beta_1 P_t + \beta_2 \Delta P_t + \beta_3 P_t^2 + \beta_4 \Delta P_t^2 + \beta_5 P_t \Delta P_t + \varepsilon & v_t > 0 \end{cases} \quad (3)$$

For idling conditions (v_t=0 km/h) a constant average value (g/s) is used. For non–stationary (moving vehicle) driving conditions a multivariate regression function has been fitted using the ordinary least–squares method, where β_0, ..., β_5 represent the regression coefficients. 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:

$$\Delta P_t = P_t - P_{t-2} \quad (4)$$

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, for instance due to the use of a timer to delay command enrichment or oxygen storage in the catalytic converter (e.g. Barth et al., 2000), but also due to inertia effects that span over several seconds of driving. Table 1 shows an example of model and vehicle parameters that are used in the emissions simulation. Note that some parameters in Table 1 will be discussed later in this paper.

6. Model Performance

This section discusses both model verification and model validation. Model verification assesses how well a model predicts the data on which it is based, whereas model validation assesses how well a model predicts with respect to independent data. The empirical data were split to enable both assessments.

6.1. Model verification

The P∆P model generally predicts fuel consumption rates and CO_2 emission rates (g/s) quite well with a coefficient of determination (R^2) ranging between 0.80–0.98, and an average value of 0.93. This means that approximately 80% to 98% of the variation in instantaneous emissions can be explained with the algorithms. For NO_X the results are more variable with R^2 values varying from 0.17–0.90, and an average value of 0.65. Figure 2 shows four goodness–of–fit plots with the best and worst models with respect to R^2 for each pollutant, where each dot points represents one second of data of the test cycles.

Root–Mean–Square–Error (RMSE) is a frequently used measure of the differences between predictions and observations. It aggregates the second–by–second errors into a single measure of predictive power. Normalized RMSE is used to make RMSE scale–independent and it is computed by dividing RMSE by the range of observed values. Normalized NRMSE varies from 2–12% for fuel consumption predictions and 3–21% for NO_X emissions predictions.

It is instructive to show time–series plots of predicted and observed emissions and the speed–time profile used during emissions testing. Figure 3 shows an example for an ADR79/01 (Euro 4) diesel passenger car. The black line represents the observations and the red dot points predictions. The model for this vehicle class predicts fuel rates (and hence CO_2 emissions) well with an R^2 of 0.94 and a root–mean–squared error (RMSE) of 0.26 g/s. This is also the case for the emission peaks, which are important to assess local effects of changes in driving behavior (e.g. due to changes in signal settings at an intersection). Note that the extreme DT80 test is included (t=1 417–1 668 seconds), showing the highest fuel rates in the combined test.

Table 1. *Model and vehicle parameters for an ADR80/00 (Euro III) heavy diesel bus (BUS–H–Diesel)*

Parameter	Value	Unit
Vehicle Parameters		
Make	Volvo	
Model	B12B	
Type	Bus	
A – Frontal area	6.5	m^2
Cd – Aerodynamic drag coefficient	0.62	
R_0–R_5 – Rolling resistance coefficients	0.000000–0.00715	
Tare mass	14 500	kg
GVM	23 500	kg
Rated engine power	313	kW
Engine capacity	12.0	L
α	0.94	g/s
Model Parameters		
β_0	2.14	g/s
β_1	0.04045	g/s kW
β_2	0.00077	g/s kW
β_3	0.00006	$g/s/kW^2$
β_4	0.00002	$g/s/kW^2$
β_5	0.00006	$g/s/kW^2$
φ	1.001	
$E_{max.obs}$	18.41	g/s
ϕ	1.05	

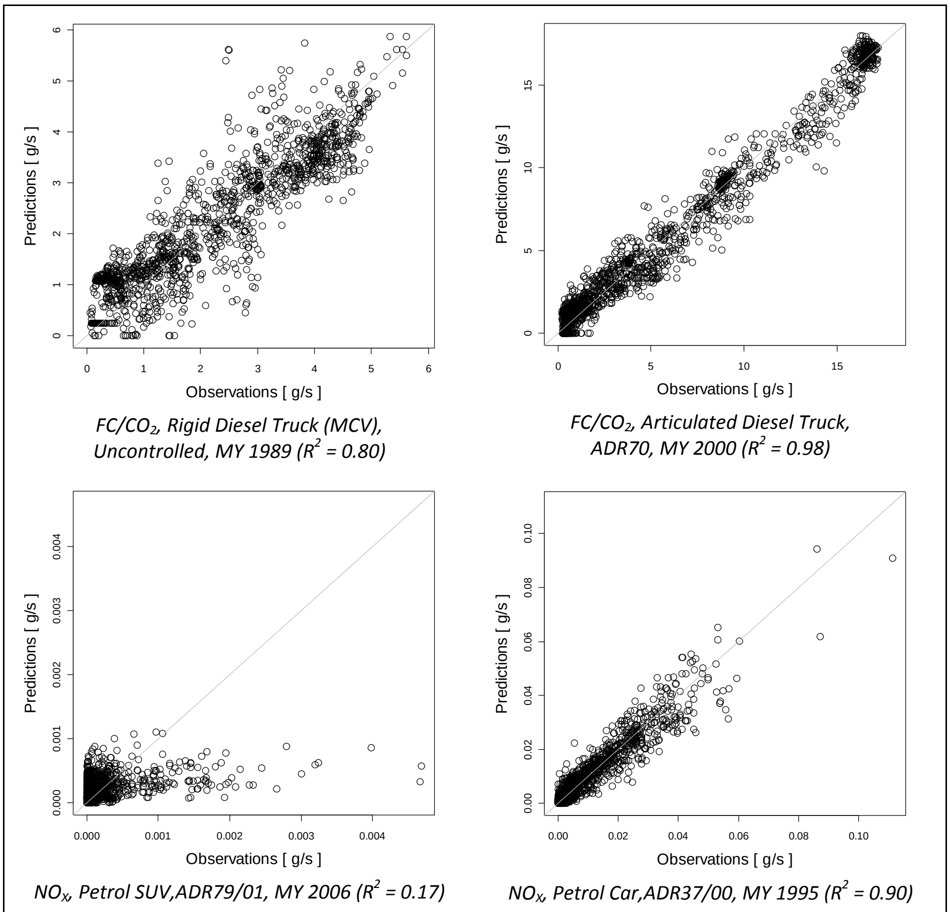

Figure 2. *Goodness–of–fit plots (R^2) for a selection of vehicles.*

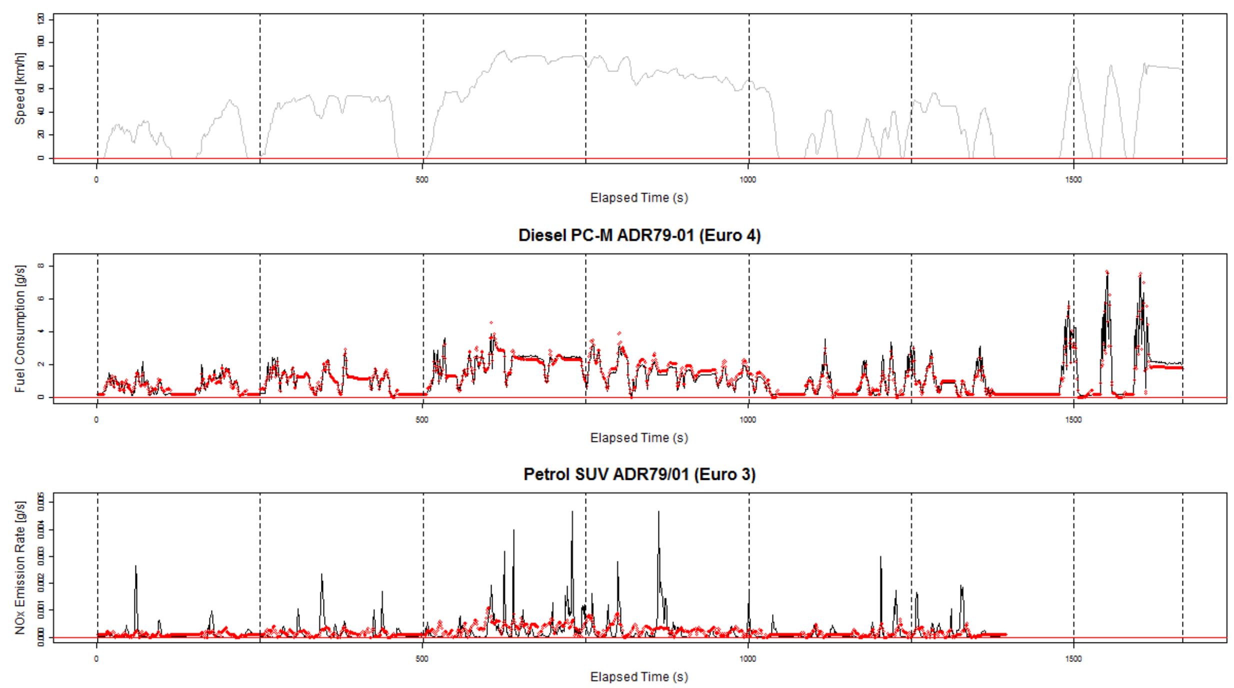

Figure 3. *Top chart: speed –time profile, middle chart: fuel consumption time–series plots for diesel passenger car (PC–M), MY 2007, ADR79–01 (Euro 4), bottom chart: NO_X time–series plots for petrol SUV, MY 2006, ADR79–01 (Euro 3), second–by–second predictions (red dots) and observations (black line).*

Figure 3 also shows the ADR79/01 (Euro 3) petrol SUV again, the worst performing model for NO_X. The model for this vehicle class predicts NO_X emissions poorly with an R^2 of 0.17 and a root–mean–squared error (RMSE) of 0.004 g/s. It is interesting to note that the model is unable to reproduce the emission peaks, which means that they are not related to power and the change in power. Given the low emission rates for this vehicle, it is likely that the peaks are caused by small deviations in the air–to–fuel ratio, which affect catalyst efficiency, but which will not be reflected in the P and ΔP values. This effect becomes more important and more pronounced when modern vehicles with low NO_X emissions are compared with older technology vehicles with higher base NO_X emission levels. This is clear from Figure 2 where a 1995 petrol car with an average emission rate of 9.41 mg/s shows a substantially better model fit then a 2006 petrol SUV with an average emission rate of 0.17 mg/s. This result exposes a limitation in power based modeling at a high resolution for some modern petrol vehicles. This problem has also been reported by other researchers around the world, as will be discussed in Section 7. De Haan and Keller (2000), for instance, reported difficulties with constructing a modal emission model that could accurately simulate the irregular emissions behavior of (at the time) modern cars.

There are however two aspects that will reduce prediction errors. Firstly, emissions from individual vehicle classes are not of particular interest in terms of model application. The amount of travel (expressed as vehicle kilometers travelled or VKT) for each vehicle class changes with time, as new vehicles enter the fleet and old vehicles are progressively removed from the fleet. So the VKT–weighted sum of emissions from all vehicles classes is needed to assess the effects of road traffic on (local) air quality and greenhouse gas emissions. As a consequence, overall model performance tends towards an average of the performance of individual vehicle classes.

Secondly, spatial/temporal aggregation of predictions will reduce prediction errors. This is illustrated in Figure 4 for one vehicle class for four different spatial resolutions, i.e. 100 m segments, 500 m segments, 1 000 m segments and the cycles "Con", "Res" and "Fwy". It is clear that model performance improves and prediction errors are reduced with decreasing spatial resolution, although the smallest error is observed for 1 000 m segments.

Finally, with respect to model bias, the emissions profile over the entire driving cycle (combination of "Con", "Res", "Fwy" and "DT80") is replicated well even though there is a difference in model performance for the individual vehicle classes. For fuel consumption and CO_2 emissions, total driving cycle emissions (g) are within ±1% of observed values, whereas for NO_X these are within ±3%.

6.2. Model validation

The emission algorithms were used to predict fuel consumption and emissions for the validation dataset, i.e. the "Arterial" driving cycle, which was not used in model development. A comparison between the model validation and model verification results with respect to model performance is shown in Figure 5.

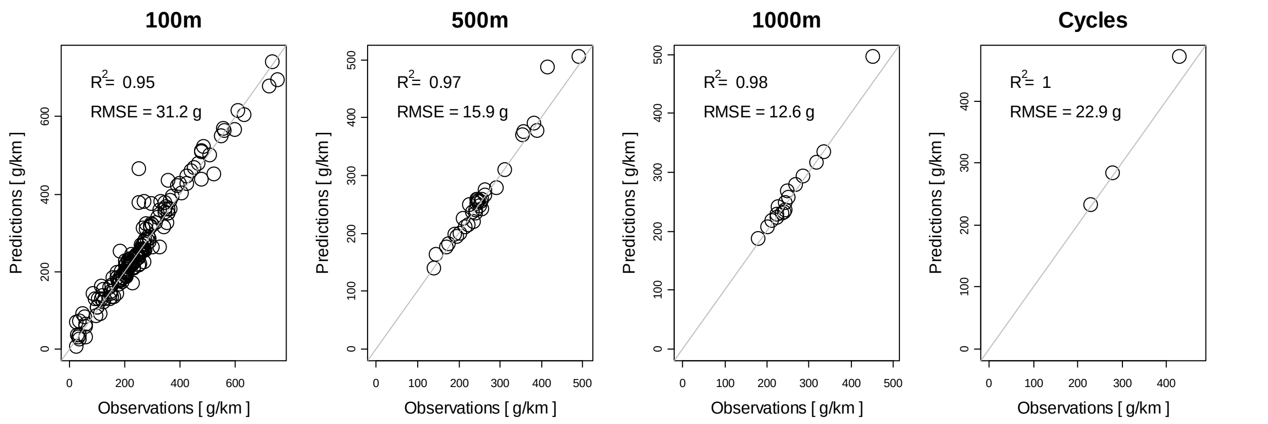

Figure 4. *Example of the effect of spatial aggregation on model performance (fuel consumption).*

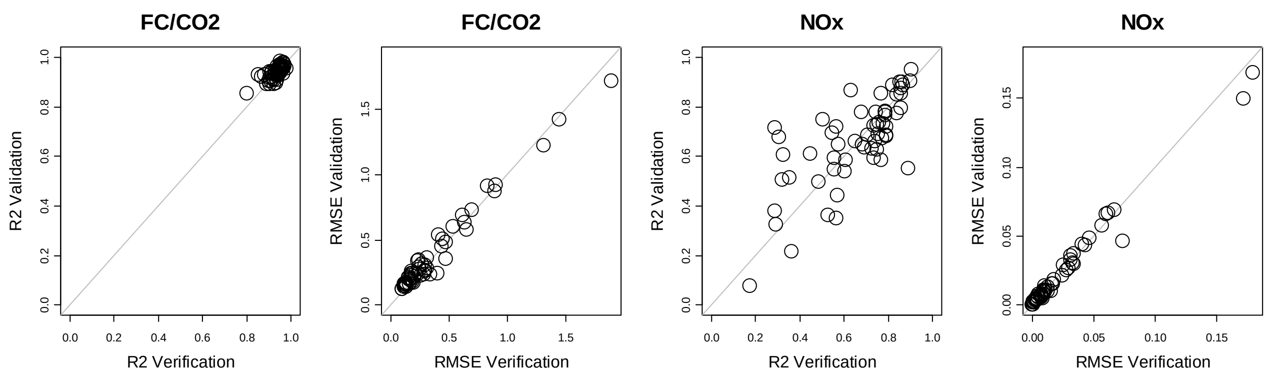

Figure 5. *Comparison of model performance for verification and validation data (each dot point represents a vehicle class).*

With respect to prediction errors (RMSE) the validation and verification show quite similar results for both fuel consumption/CO_2 and NO_X. This demonstrates that the emission algorithms are robust with respect to prediction performance. The same applies for R^2 for fuel consumption and CO_2, but the results are more variable for NO_X.

Interestingly, the more stringent model validation step exhibits improved model performance in several cases. Figure 6 shows this effect for one vehicle class, i.e. Large ADR79/01 (Euro 3) Petrol Passenger Car, where the R^2 values are 0.31 and 0.59 for verification and validation, respectively, and the RMSE values are similar (0.010 g/s for both).

Figure 7 shows the results with respect to model prediction bias. As compared with the verification step, there is a significant increase in systematic prediction errors, with typical values of ±5% for fuel consumption and CO_2 emissions and of ±50% for NO_X emissions. It is, however, clear that large bias only occurs for vehicle classes with relatively low emission levels. On arterial roads there appears to be a tendency for under–prediction of fuel consumption and CO_2 emissions, with an average value of approximately –5%. The average bias for NO_X emissions is small at –1%, despite the large bias for some vehicle classes. This means that at the fleet level large systematic prediction errors tend to cancel each other out.

7. Development of the Simulation Tool

The emission algorithms discussed in Section 5 predict second–by–second fuel consumption and emissions. However, a few more steps are required to create the PΔP simulation tool:

- Calibration to average vehicle class emissions.
- Simulation algorithms for on–road engine power.
- Setting model prediction boundaries (100 m minimum distance, cap maximum prediction/extrapolation).

7.1. Calibration to vehicle class averaged emissions

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 introduced and 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:

$$e_t^* = \varphi\, e_t \tag{5}$$

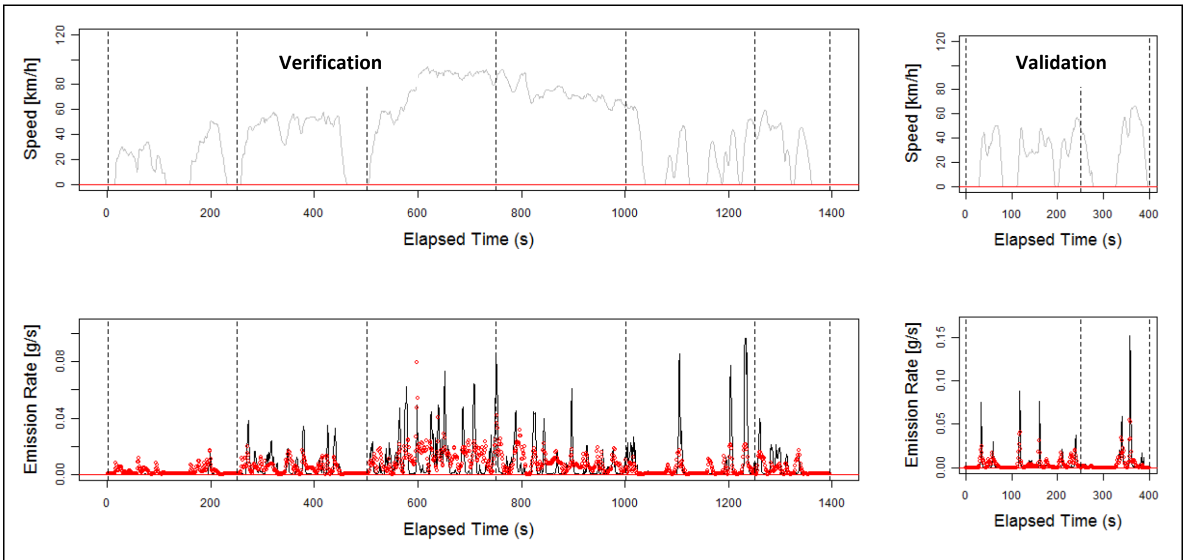

Figure 6. *NO_X time–series plots for large petrol car, MY 2006, ADR79–01 (Euro 3), top chart: speed –time profile, bottom chart: second–by–second predictions (red dots) and observations (black line).*

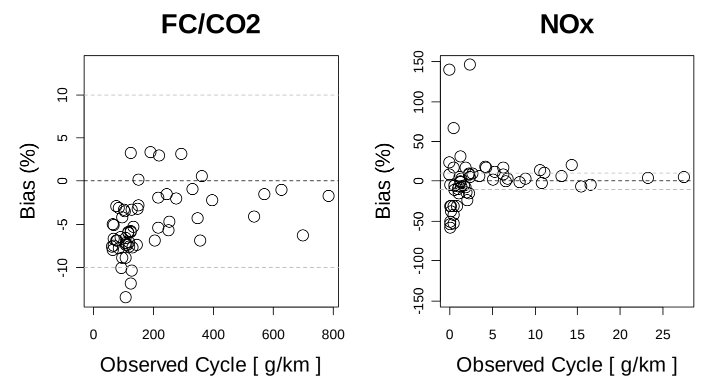

Figure 7. *Bias in the validation step as a function of observed cycle emissions (each point represents a vehicle class).*

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.

7.2. On–road power algorithms

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). The total second–by–second engine power (P_t, kW) that is required to propel a vehicle along a road, can be broken down into six power components:

$$P_t = P_{rolres,t} + P_{air,t} + P_{inert,t} + P_{grade,t} + P_{transm,t} + P_{aux,t} \tag{6}$$

where P_{rolres} is the power required to overcome tire rolling resistance (kW), P_{air} is the power required to overcome aerodynamic resistance (kW), P_{inert} is power required to overcome inertial resistance (kW), P_{grade} is the power required to overcome gravitational resistance (kW), P_{transm} is power required to overcome drive train resistance (kW) and P_{aux} is the power required to run auxiliaries (kW). 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 used in this research project and hard coded into the software.

7.3. Operational boundaries

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 (E_{max}=$E_{max.obs} \times \phi$). 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 (ϕ=1.50) times the maximum observed value $E_{max.obs}$. 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. It is noted that ϕ values are set arbitrarily, but are expected to be reasonable.

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.

8. Example of Simulation Output

Figure 8 shows an example of simulation input and output for three input driving cycles ("Congested", "Arterial", and "Freeway"). It is noted that the result are aggregated to fourteen main vehicle types using base year dependent travel-based weighting factors for the various ADR categories. The emission factors (g/veh km) can then be combined with data on traffic volume and road length to compute total emissions for each main vehicle type in these three traffic conditions.

9. Discussion

This paper discussed the development and performance of a new high resolution emission simulation model based on Australian test data. The approach has a few innovative aspects such as the use of delta power in model predictions, calibration to and connection with a larger emissions database, explicit consideration of an appropriate spatial and temporal scale and a comprehensive coverage of on–road vehicle classes. The objectives of the research project were to develop a model that is comprehensive, accurate, reliable and robust, easy to use and which interfaces readily with appropriate traffic models and (emerging) traffic field data.

9.1. Comprehensiveness

Vehicle emission models can be "incomplete" because they predict emissions for specific vehicle categories only (e.g. passenger cars) or because they are outdated (e.g. based on test data that do not reflect the latest developments in vehicle technology), effectively restricting predictions to a specific part of the on–road fleet. The PΔP Model is comprehensive because it includes all relevant vehicle classes and it is based on a large empirical database that includes recent technology vehicles. The current model includes ADR categories up to ADR79/02 (Euro 4) and ADR80/02 (Euro IV). Newer and future standards can be readily incorporated by using technology specific scaling factors (Ntziachristos and Samaras, 2001) and development of additional algorithms once new emissions data become available.

9.2. Accuracy

The performance results for the PΔP model results are generally good compared to other 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 PΔP model.

Ajtay et al. (2005) used brake mean effective pressure and engine speed and showed that this led to more accurate models as compared with a simplified speed–acceleration model, although this depended on the vehicle technology. For instance, for a Euro 2 diesel car both the complex and simplified models produced excellent results for NO_X with R^2 values of 0.99 and 1.00, respectively. In contrast, for Euro 3 petrol cars, the results were not good for both methods with R^2 values of 0.19 and 0.25, respectively. This result is similar to the observed performance for the Euro 3 petrol cars in this study (R^2 values of 0.17–0.56).

9.3. Scope of application

The PΔP model is designed for use in research studies or projects where detailed information is available regarding vehicle driving behavior and potentially other factors such as road grade and vehicle loading, and where a high spatial and temporal resolution in emissions and fuel consumption is required. It is expected that the software can be used in most cases, but there may be a few instances where use of the model is not suitable. One consideration is that the PΔP software does not explicitly simulate engine load and engine speed. As a consequence, gear shift behavior is implicitly included because predictions reflect the gear shift behavior during the emissions tests. However, this level of detail is not useful in the majority of applications due to a lack of input data (e.g. information on actual in–traffic gear shift behavior is scarcely – if ever – available). Nevertheless there are situations where the effects of gear shift behavior are of particular interest,

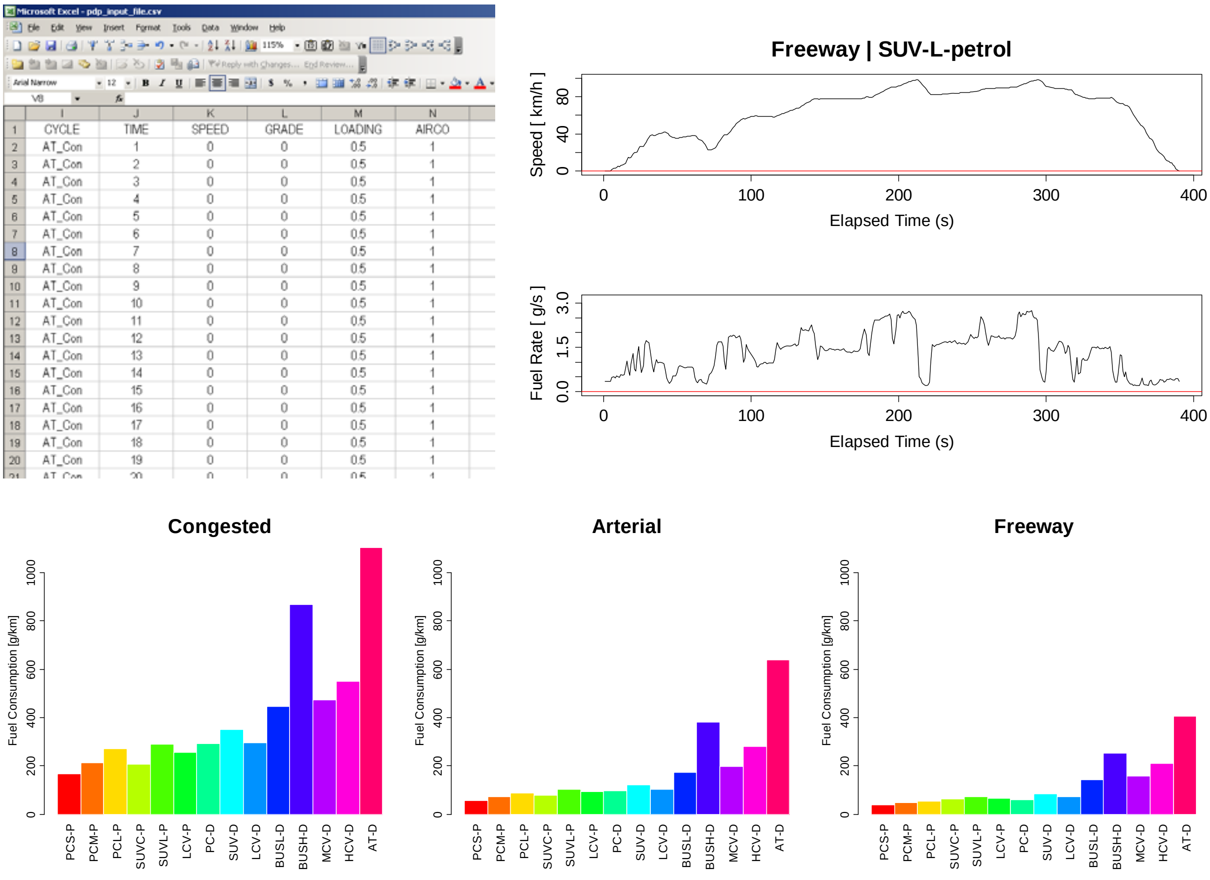

Figure 8. *Example of PΔP model simulation output (top left: part of input file, top right: time–series of speed and model predictions, bottom: graphical summary output).*

e.g. to examine the impacts of specific drive training programs (e.g. eco-driving) on emissions and fuel consumption. In these cases, the PΔP software is of limited use and will only predict the effects of changes in speeds, and not changes in gear shift behavior. More detailed models such as PHEM (Zalinger et al., 2008) and CMEM (Barth et al., 2000) should be employed in these cases.

9.4. Reliability and robustness

The validation showed that the PΔP emission algorithms are robust with respect to prediction errors (RMSE/NRMSE) and goodness–of–fit (R^2) as they show similar results to the verification step, and sometimes even exhibit improved performance. There is, however, an increase in prediction bias, which can be reduced by inclusion of the validation data in a second round of model fitting to address the systematic under–prediction (about 5%) for fuel consumption and CO_2 emissions in arterial conditions, and aggregation of prediction results to fleet level to cancel out systematic errors for NO_X. Another way to reduce prediction errors is to apply a spatial aggregation to the second–by–second emission predictions. This means that predictions are made for a specific length of road. A minimum length of 100 m will be used in the model simulations.

9.5. Ease of use and interfacing with traffic data

The minimum input requirements for the emission simulation are speed–time data (1 Hz), driving cycle or driving pattern name of ID and a selection for which vehicle types the simulation should be run. This kind of information should be available from microscopic traffic simulation models (e.g. AIMSUN, VISSIM, PARAMICS), expert judgment (e.g. modification of driving cycles) or on–road measurements using e.g. GPS. Additional input on road grade, vehicle loading and air–conditioning use are optional but can be set to default values (road grade=zero, vehicle loading=50% and air–conditioning use=off) in the absence of information.

Detailed spatial and temporal attribution of vehicle emissions is of increased importance because of an increasing focus on the reduction of population exposure to air pollution and (health) risk. In addition, detailed simulation of the impacts of changes in driving behavior on emissions through a variety of potential traffic management measures is required to address the desire to reduce greenhouse gas emissions and improve fuel efficiency. Integration of PΔP emission algorithms with e.g. microscopic traffic simulation models will generate time and space resolved traffic emissions information, which can be fed into air quality models that simulate dispersion and chemical conversion processes to predict air pollution concentration levels, exposure and health risks in urban areas. This type of analysis can be used to accurately identify air pollution "hot spots" or even greenhouse gas emission hot spots and assess the impacts of specific measures in urban areas. This way the PΔP software will support decision making in urban environments through scenario modeling, enhanced land use planning, policy development and improved traffic management.

9.6. Representativeness and use in other countries than Australia

The PΔP emission algorithms are representative for Australian conditions as they reflect the Australian fleet, driving conditions and driving behavior, as well as other relevant aspects such as

Australian fuel quality and fuel composition. Although the model is based on Australian data, it can in principle be used to generate first order estimates of emissions and fuel consumption in other countries. However, it is recommended that some calibration is conducted to better reflect local conditions. As a minimum, ADR/Euro emission standard equivalency tables and information on the local fleet composition are required to link the seventy three P∆P vehicle classes to the corresponding vehicle classes in the country of interest. If more accurate predictions are required, aggregated local emissions data (e.g. total cycle emissions in grams per km) can be used to calibrate the model using the variable φ (Section 7.1). A country specific version of the P∆P software can even be developed if more detailed local modal emissions data are available.

10. Further Work

The model will be extended to include other air pollutant emissions such as particulate matter (PM), hydrocarbons (THC) and carbon monoxide (CO) and new and future vehicle technologies. Research will be conducted to further improve model performance. Firstly, modal emissions data from more test vehicles will be incorporated into the model in time. Secondly, the impact of other ∆P definitions and other statistical approaches (e.g. time–series models) will be examined. Application of the software in practical applications will be useful to see how the model performs and how it compares to other models.

Acknowledgment

The Australian Government and the SA Department of Transport Energy and Infrastructure are acknowledged for commissioning vehicle emission test programs that have collectively provided the (unverified) empirical emissions data used in this research. These include the following test programs: the First and Second National In–Service Vehicle Emissions studies (NISE1 and NISE2), the Diesel Vehicle Emissions National Environment Protection Measure Preparatory Work (DNEPM) and the South Australian Test and Repair Program (SATR).

Appendix

Abbreviations

ADR: Australian design rule
AT: Articulated trucks
BSFC: Brake specific fuel consumption
GVM: Gross vehicle mass
HCV: Heavy commercial vehicle (GVM 12.0–25.0 tonne, rigid truck)
HDV: Heavy–duty vehicle (rigid truck, articulated truck or bus)
LCV: Light–commercial vehicle (GVM≤3.5 tonne)
LDV: Light–duty vehicle (passenger car, SUV or LCV)
MCV: Medium commercial vehicle (GVM 3.5–12.0 tonne, rigid truck)
P: Engine power
∆P: Change in engine power
PC: Passenger car
SUV: Sport utility vehicle
VKT: Vehicle kilometers travelled

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