THE USE OF GPS AND HIGH RESOLUTION VEHICLE EMISSION MODELING TO ASSESS ENVIRONMENTAL BENEFITS OF DRIVER BEHAVIOUR CHANGE PROGRAMS

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ABSTRACT

Driver behaviour change programs have become a crucial component of broader sustainability goals. Assessment of such programs require (ideally) detailed information on day-to-day driving combined with more precise estimates of fuel consumption, vehicle emissions and potentially other outcomes of interest. The current paper reports on an analysis conducted on 106 Sydney drivers who were monitored for five weeks using a GPS device, exposed to a financial intervention designed to improve driving behaviour, and then monitored again for five weeks. Using new Australian software (P∆P), we assess the changes in vehicle emissions following the intervention. P∆P is specifically designed to predict second-by-second impacts on vehicle emissions and fuel consumption due to changes in operational conditions (driving behaviour, road grade, etc.). The analysis demonstrates how detailed simulation and high quality input data can provide a more accurate and precise indication of changes in emissions and environmental outcomes. The findings will be of interest to those involved in designing and monitoring driver behaviour change programs as well as those interested in more accurate assessments of on-road driving and emissions profiles.

1. INTRODUCTION

Driver behaviour change programs have become a crucial component of broader sustainability goals. While many types of interventions around behaviour change have been introduced, interest is growing around directly incentivising improved behaviour, by attaching a price not just to the kilometres driven but how those kilometres are driven (Litman, 2009). The rationale here, although primarily safety driven, is that there could also be simultaneous environmental benefits, further strengthening the merits of such programs. In turn this requires (ideally) more detailed information on day-to-day driving combined with more precise estimates of fuel consumption, vehicle emissions and potentially other outcomes of interest.

Against this backdrop, the current paper reports on a study of 106 Sydney drivers who were monitored for five weeks using an in-vehicle GPS device, exposed to a financial intervention designed to improve driving around safety outcomes, and then monitored again for five weeks. Previous work showed significant reductions in vehicle kilometres travelled (VKT) and speeding that resulted from the interventions (Greaves et al., 2013). However, the question of interest here is whether this translates to significant environmental benefits widening the rationale for the program.

The answer to this question requires a computationally-efficient method for computing the fuel consumption and emissions from the GPS trace data, which in this study comprised over 80 million second-by-second records. Using new Australian software (P∆P) in conjunction with the GPS data, we assess the changes in vehicle emissions following the intervention (Smit, 2013). P∆P is specifically designed to predict second-by-second impacts on vehicle emissions and fuel consumption due to changes in operational conditions (driving behaviour, road grade, etc.). Following details of the P∆P model development and testing, we explain how the GPS data were processed and emissions computed for the analysis. Preliminary results are provided, before drawing conclusions as to the wider applicability of the findings.

2. THE P∆P MODEL

Various emission modelling software packages are available around the world, each with their own level of complexity and appropriate range of application (Smit et al., 2010). Examples are 'average-speed' models (e.g. COPERT, MOBILE), where emission rates (g/veh.km) are a function of mean speed, 'traffic-situation' models (e.g. HBEFA), where emission rates (g/veh.km) correspond to particular traffic situations (e.g. 'stop-and-go-driving', 'free-flow') 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.

Previous investigations have shown vehicle emission models need to reflect local fleet composition, fuel quality, climate and driving characteristics to provide reliable vehicle emission predictions. Large errors, up to a factor of 20 (Smit and McBroom, 2009), were found when overseas models were directly applied to Australian conditions without calibration.

2.1 Vehicle classification and input

The P∆P model is a new high resolution modal vehicle emission model specifically developed for Australian conditions (Smit, 2013). The software uses engine power (P, kW) and the change in engine power (∆P, kW) to simulate fuel consumption and CO_2 and NO_x emissions for 73 vehicle classes. The vehicle classification is shown in Table 1. Note that 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.

Table 1: COPERT Australia Vehicle Classification.

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 PC; +ADR36 (SUV-L); +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	

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.

2.2 Model development

The model uses 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. In addition to these real-world cycles, test data from the DT80 test cycle are used. 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 have been subjected to a verification and correction protocol. This includes 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 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 (et, g/s) is then fitted to the following equation:

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

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:

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

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:

$$e_t^* = \varphi\, e_t \quad (3)$$

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 account for tyre rolling resistance (vehicle loading), aerodynamic drag, inertial drag (accelerations, vehicle loading), gravitational resistance (road grade), 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.

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.

2.3 Model performance and application in previous studies

Model validation and model verification showed that the performance results for the P∆P 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, 2013). 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 P∆P 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 (Smit, 2013).

The P∆P has been combined with a microscopic simulation model (AIMSUN) to estimate emissions in Adelaide CBD in morning peak hours (Smit et al., 2013). The traffic software generated almost 10,000 second-by-second driving patterns for different vehicle types (cars, trucks, buses). P∆P 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. 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 1.

Figure 1: Predicted Total NO_x Link Emissions in the Adelaide CBD Network for Two Time Periods (07:00-08:00, left chart, and 08:00-09:00, right chart) (Source: Smit et al., 2013).

Boulter and Smit (2013) used P∆P to assess the emission impacts of variable speed limits (VSL). The results are visually summarised in Figure 2. 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.

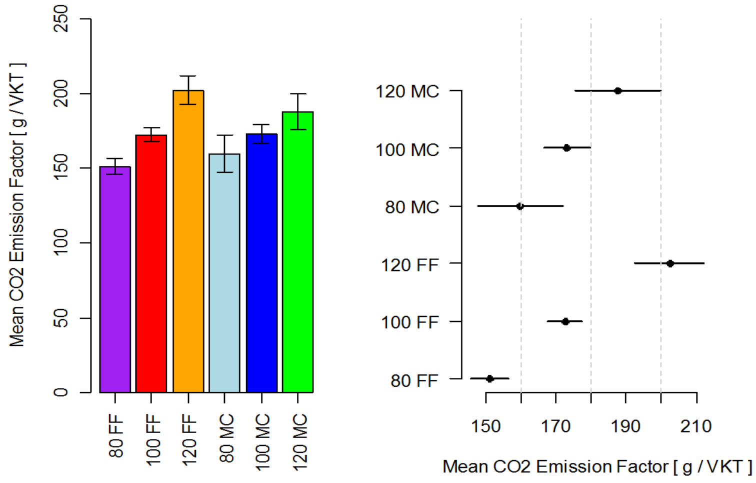

Figure 2: Mean CO_2 vehicle emission rates for different speed limits (80, 100, 120 km/h) and traffic conditions (FF = free flow, MC = more congested), including 95% confidence intervals. (Source: Boulter and Smit., 2013).

3. GPS DATA

GPS data from a broader study of driver behaviour was used as input into PΔP to examine the impact on vehicle emissions of a pay-as-you-drive financial intervention (see Greaves et al., 2011 for more details). The data comprised second-by-second GPS data collected from 106 drivers in Sydney, Australia over a five-week 'before' period and a five-week period following the introduction of the intervention. In addition to the GPS data, information on the drivers, trips and vehicles were collected. These data were used to identify the driver of each trip and the vehicle class used for the emissions modelling.

For the purposes of the analysis presented in this paper, only data for trips collected from the study participant were used. This ensured that comparisons between the before and after phases only included driving by the same person. Data from four drivers with incomplete vehicle information were also excluded leaving 102 drivers to be included in this analysis.

To prepare the data for input into PΔP, the latitude and longitude of each observation were used to identify the spatial characteristics of each location. Subsequent to this, missing observations were imputed up to a maximum of five observations representing five seconds of driving. The imputed observations were assumed to have the same spatial characteristics as the previous (known) observation. The speed was calculated using the formula shown in equation 4.

$$spd_i = spd_{kp} - round\left(\frac{spd_p - spd_{nkp}}{timelag_t - timelag_c + 1}\right) \tag{4}$$

Where:

spd_i is the imputed speed, spd_{kp} is the previous known speed, spd_p is the previous speed (known or imputed), spd_{nkp} is the next known speed, $timelag_t$ is the total missing time (in seconds) and $timelag_c$ is the time between the current observation and the previous known observation. An example is shown in Figure 3. Smoothing of the vehicle speeds for known and imputed observations was conducted as part of PΔP simulation using a T4253H filter (running median and Hanning filter). Information necessary for the emissions modelling was also added, including if the GPS data were associated with the before or after period and the appropriate vehicle class. Generic assumptions were also made here for gradient, loading and the use of air conditioning.

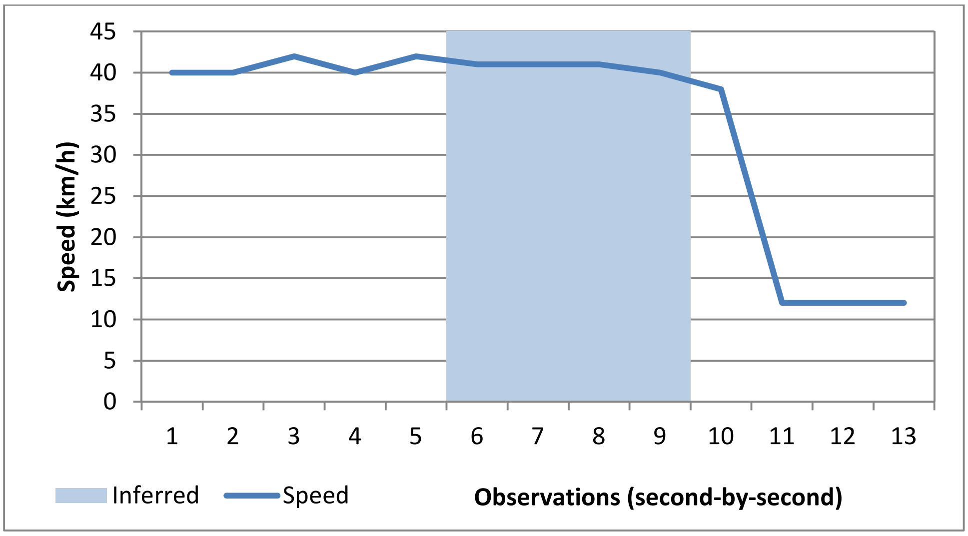

Figure 3: Example of inferred speeds

The dataset used for import consisted of a total of 22,026,941 observations representing 208,140 km and 6,119 hours of driving. Finally PΔP requires driving patterns to be longer than 100m, and any patterns less than this distance are excluded. It is noted that there are a number of reasons for the 100 m restriction in the software:

- the model needs speed-time data for the three seconds before t = t to compute the change in engine power, so drive segments need to be long enough to reduce the impact of "boundary effects" (i.e. assumption delta P equals zero for t = 1,2,3)
- improve prediction accuracy through spatial aggregation
- prevent infinite emission factors (g/km) for "idling only" input

3. RESULTS

The intervention comprised charging drivers for each kilometre driven with multipliers for speeding and night time driving. Table 2 shows the overall results. To provide an indication as to the impact of the PAYD intervention on vehicle emissions, drivers were divided into four categories based on their change in speeding (denoted as an increase or Spd+ or a decrease or Spd- in Table 2) and VKT (denoted as an increase or VKT+ or a decrease or VKT- in Table 2) between the before and after phases. Average figures were calculated for the drivers in each of these groups and are shown in Table 2.

Table 2: Change in emissions between before and after phases

Driver Category	No.	Average change (% change)					
		Distance (km)	Average Speed (km/h)	CO_2 Emissions (kg)	CO_2 Emissions (g/km)	NO_x Emissions (grams)	NO_x Emissions (g/km)
Spd+, VKT+	*12*	137.4 (+21%)	1.74 (+6%)	30.6 (+19%)	-5.23 (-2%)	71.83 (+22%)	0.00 (0%)
Spd-, VKT+	*40*	206.1 (+27%)	-0.06 (0%)	42.7 (+26%)	-1.85 (-1%)	110.73 (+33%)	0.02 (+4%)
Spd+, VKT-	*10*	-528.6 (-51%)	0.01 (0%)	-136.4 (-53%)	- 9.90 (-4%)	-338.33 (-62%)	-0.12 (-22%)
Spd-, VKT-	*40*	-296.0 (-26%)	-3.47 (-11%)	-56.9 (-23%)	8.64 (+4%)	-147.67 (-39%)	-0.06 (-19%)
Overall	102	-70.9 (-8%)	-1.26 (-4%)	-15.3 (-7%)	0.56 (0%)	-39.21 (-11%)	-0.01 (-3%)

Overall, the intervention resulted in significant reductions in VKT and average speed and while it is not reported here, speeding (see Greaves et al. 2013). In terms of emissions, the reductions in VKT had a substantial impact on reducing emissions of both CO_2 and NO_x as expected. However, what is less clear, is the impacts of changes in average speed on emissions, with very marginal changes for NO_x and increases in CO_2 per kilometre with reductions in average speed. One possible reason for this is that because the relationship between emissions and speed is non-linear, taking a U-shaped curve, it is conceivable that a side-effect of the intervention (which was focused on safety and not emissions) is that drivers moved to a less efficient point on the emissions curve.

The aggregate results, while providing an overall indication necessitates the need for a more in-depth analysis. For this purpose, four drivers were selected for more detailed analysis, based on different responses to the intervention in terms of changes in VKT and speeding behaviour. These drivers should not be considered representative of the sample but instead illustrate the potential benefits of a more disaggregate analysis. The results are shown in Table 3.

Table 3: Change in driving behaviour and emissions between before and after phases

Driver ID	VKT			Average speed (km/h)			Emissions CO2 (grams)			Emissions NOx (grams)		
	Before	After	Difference	Before	After	Difference	Before	After	Difference	Before	After	Difference
A	1,464	891	-39%	37	36	-4%	232,573	147,670	-37%	42	30	-29%
B	1,056	464	-56%	36	24	-32%	181,984	90,721	-50%	45	10	-78%
C	934	1,101	18%	28	31	11%	178,668	194,436	9%	32	31	-1%
D	724	966	33%	26	29	13%	212,160	262,348	24%	641	831	30%

It is interesting to explore how changes in total travel and changes in actual driving behaviour interact, and which one of those factors has the largest impacts. Figure 4 shows how emissions change with a change in VKT in the before and after phase. Data points that are close to the 45º line indicate that VKT is the main variable affecting the change in emissions. The change in driving conditions becomes more important, the further away a data point is from the 45º line. Figure 4 shows that VKT is generally the main factor influencing emission levels.

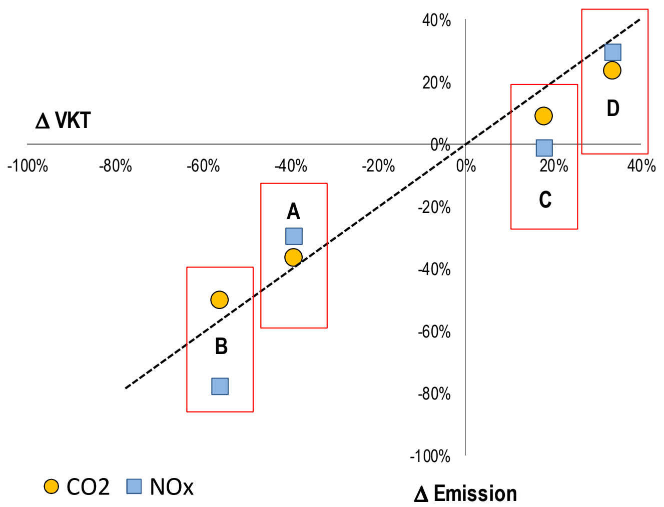

Figure 4: The change in total VKT versus the change in total emissions in the before and after phases for 4 individual drivers denoted as A, B, C, D.

An interesting finding is that the change in observed driving behaviour generally has a mitigating effect on vehicle emissions, e.g. emissions increase less than would be expected on the basis of the increase in total travel. The exception is NO_x for driver D where the change in emissions is larger (-78%) than the change in VKT (-56%).

Figure 5 and 6 further explore the emissions data that underlie Figure 4. (Driver B, NO_x and Driver D, CO_2 are taken as random examples). These figures show the computed emissions (g/km) for all GPS driving patterns in the before and after phases for each driver as a function of average (travel) speed, as well as the mean normalised emission levels in both phases, the confidence intervals and the *p*-values.

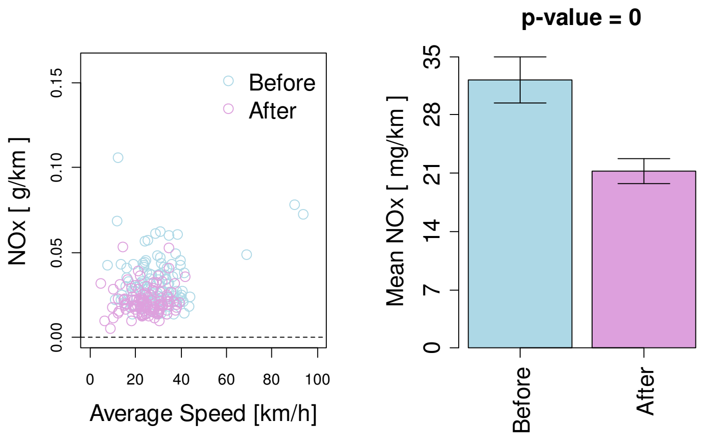

Figure 5: Normalised NO_x emissions (g/km) for all GPS driving patterns for Driver B as function of average speed (left) and the mean emission factors in the before and after phases including 95% confidence interval and p-value (right).

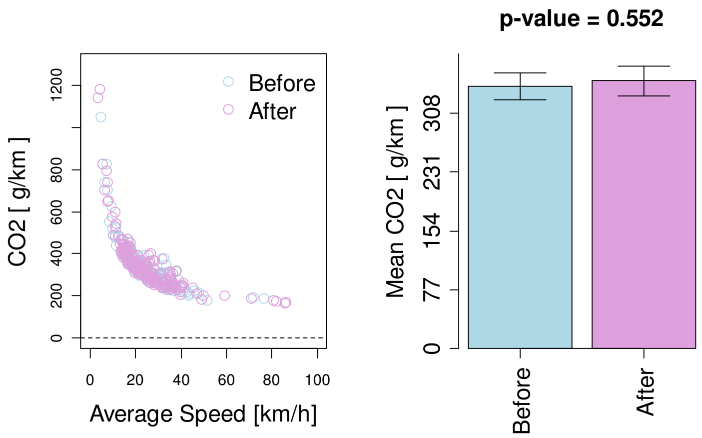

Figure 6: Normalised CO_2 emissions (g/km) for all GPS driving patterns for Driver D as function of average speed (left) and the mean emission factors in the before and after phases including 95% confidence interval and p-value (right).

These initial results indicate emissions of individual GPS driving patterns are variable, in particular for NO_x. Changes in emission rates (g/km) can be statistically significant (Figure 5) or not (Figure 6). It also shows that the overall emission change is a function of a large number of individual driving patterns in the before and after phase, each with their own unique sequence of idling, acceleration and speeds. Further work is required to expand the imputation method and simulate emissions for driving patterns smaller than 100 m, then analyse the full database in more detail and determine if changes in “fleet” emissions are statistically significant and what are the main factors driving the changes.

CONCLUSIONS

This paper has presented preliminary results of a comprehensive analysis of the emission impacts of an intervention program where 106 Sydney drivers were monitored for five weeks using a GPS device. The program exposed drivers to a financial intervention to improve driving around safety outcomes. Assessment of the emissions impacts requires a computationally-efficient tool that can readily use millions of second-by-second records as input.

A new Australian software (PΔP) was employed in conjunction with GPS data for four drivers to explore the feasibility of this approach. It is concluded that the tool can readily be used after necessary GPS data preparation, which mainly involves imputation of missing records and speed smoothing. Analysis of the emission results for four drivers before and after the intervention demonstrates that changes in VKT and changes in driving behaviour both impact emissions. The preliminary results indicate that VKT is the main factor driving the change in CO_2 emissions in particular, whereas driving behaviour changes can result in statistically significant changes in NO_x emissions. Analysis of the full GPS database will provide better and more robust information in this respect.

While it has become increasingly easy to collect disaggregate driving behaviour information, it is still complex to quantify emissions. The tool presented here greatly simplifies this computation process, while still maintaining a sufficient level of disaggregation in the results to identify the key components affecting emissions. In terms of the wider policy implications, quantifying potential environmental benefits adds to the increasingly compelling safety arguments for PAYD-type interventions focused around improved driving behaviour.

REFERENCES

- Atjay, D.E., Weilenmann, M., Soltic, P., 2005. Towards accurate instantaneous emission models, Atmospheric Environment, 39, 2443-2449.
- Greaves SP, Fifer S and Ellison R 2013 'Exploring Behavioral Responses of Motorists to Risk-Based Charging Mechanisms', *Transportation Research Record: Journal of the Transportation Research Board (Special Issue: Safety Data, Analysis, and Evaluation 2013)*, vol.2386, pp. 52-61.
- Litman, T. Pay-As-You-Drive Pricing For Insurance Affordability. Available for download from http://www.vtpi.org/payd_aff.pdf Accessed Jun. 1, 2009.
- 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., McBroom, J., 2009. Use of microscopic simulation models to predict traffic emissions – Technical Note, Road and Transport Research, 18 (2), 49-54.
- 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., 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, 4, 336-345.
- Smit, R., Casas, J., Torday. A., 2013. Simulating fuel consumption and vehicle emissions in an Australian context, Australasian Transport Research Forum 2013 Proceedings, 2 - 4 October 2013, Brisbane, Australia.
- Boulter, P., Smit, R., 2013. The effects of intelligent transport systems on CO2 emissions - an Australia perspective, Proceedings of the CASANZ Conference, Sydney, 7-11 September 2013.

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