Assessing Emission Benefits of Driver Behaviour Change Programs Using GPS and High Resolution Vehicle Emission Modelling

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Abstract

Road transport is a major contributor to air pollution and greenhouse gas emissions. There is substantial interest in gaining accurate information on vehicle emission levels for policy development and sustainable traffic management. Driver behaviour change programs have become an important strategy in achieving sustainability goals. Evaluating the effectiveness of such programs requires (ideally) detailed information on day-to-day driving combined with accurate measures of vehicle emissions. The current paper reports on a study conducted on 106 Sydney drivers who were monitored for five weeks using a GPS device, exposed to a financial intervention designed to modify driving behaviour, and then monitored again for five weeks. A new vehicle emissions software (P∆P) is then used to evaluate the changes in vehicle emission levels following the intervention. This paper discusses the advantages and challenges of GPS data, methods for imputing missing observations and includes an analysis of the effects of a financial incentive on changes to emissions on average and in particular spatio-temporal environments.

1. Introduction

Driver behaviour change programs have become an important strategy in tackling sustainability issues. While these programmes encompass many types of interventions, the focus here is on modiying driver behaviour using financial incentives based on where, when and how each kilometre is driven (Litman, 2009). Although primarily safety driven, there could also be simultaneous environmental benefits, further strengthening the merits of such programs. This requires detailed information on day-to-day driving combined with more precise estimates of fuel consumption, vehicle emissions and potentially other measures of interest.

With this in mind, this 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). What has not been adequately explored is if these interventions also result in significant environmental benefits. If so, this would increase the potential benefits of a larger-scale program.

To address these types of questions, it is necessary to compute the fuel consumption and emissions from the GPS trace data, which in this study comprised over 80 million second-by-second records. Using new software (P∆P), we examine 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.). This paper outlines the P∆P model and explains how the GPS data were processed and emissions computed for the analysis. An analysis of the changes in CO_2 emissions overall, across time for two drivers and in different spatial situations is then presented. The paper concludes with some final remarks and a summary of future work.

2. The PΔP model

Numerous 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, ARTEMIS), 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, CRUISE), 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.

Vehicle emission models need to reflect local fleet composition, fuel quality, climate and driving characteristics to provide reliable vehicle emission predictions. For instance, 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. This has inspired the development of two complementary vehicle emission models: PΔP and COPERT Australia.

COPERT Australia is an Australian average speed model, which is designed for comprehensive vehicle emission inventories at national level through to more localised scales. The software estimates all types of emissions including hot running, start, evaporative and non-exhaust (tire wear, brake wear). This software has been calibrated with thousands of vehicle emission tests that were conducted in Australia. It links well with output from macroscopic transport models (Smit and Ntziachristos, 2013), but a more detailed model is required for combination with GPS data. It has recently been used to create a national motor vehicle emission inventory for all states and territories in Australia (Smit, 2014).

The PΔP model is a high resolution modal model that 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 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 classification is shown in Table 1.

Table 1: PΔP 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	Uncontrolled; ADR30; ADR70; ADR80/00; ADR80/02-05

* Note that ADRs refer to "Australian Design Rules", which are the emission standards adopted in Australia. They are aligned with the Euro standards.

The PΔP 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. 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. BSFC, mean thermal efficiency). For each vehicle class, one representative vehicle is selected for model development.

Each modal test contains approximately 30 minutes of laboratory-grade second-by-second emissions and speed data based on real-world Australian driving cycles 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.

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:

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

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 α (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 $\beta_0, \ldots, \beta_5$ represent the regression coefficients. An autoregressive-moving average ARMA(p,q) 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.

To use the large empirical bag database, a calibration factor φ is incorporated in the software. It is computed as the total cycle 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:

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

Subsequently, algorithms that predict second-by-second on-road engine power demand are included for each vehicle. 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. Power algorithms have been adopted from Rexeis *et al.* (2005). 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.

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 (R^2) and sometimes even exhibit improved performance as compared with the results from model verification (Smit, 2013).

In other work, the PΔP has been combined with a microscopic simulation model (AIMSUN) to estimate emissions in Adelaide CBD in morning peak hours (Smit *et al*., 2013). 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 changed over time. Boulter and Smit (2013) used PΔP to assess the emission impacts of variable speed limits (VSL). 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.
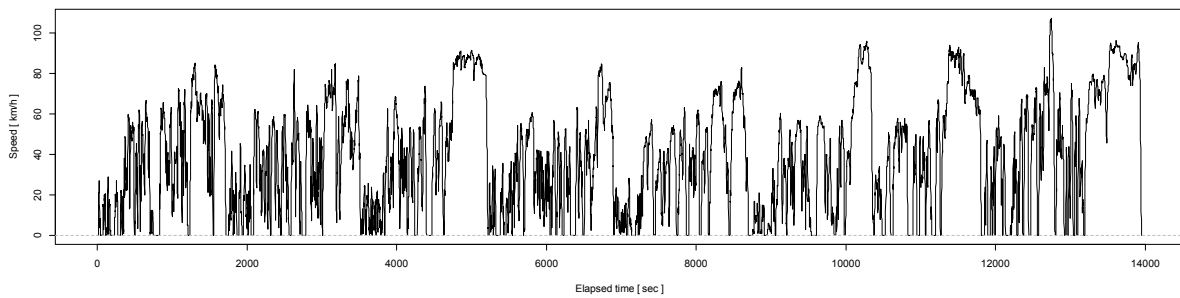

3. GPS data preparation

GPS data from a study of driver behaviour was used as input to examine the impact on vehicle emissions of a pay-as-you-drive (PAYD) financial intervention (see Greaves *et al*., 2011 for more details). In brief, second-by-second GPS data was collected from 106 drivers in Sydney, Australia over two five-week periods delineated by the introduction of the financial intervention. Additional information on drivers and vehicles were collected at recruitment while additional information on trips (driver, number of passengers, etc.) were collected using a web-based prompted recall interface. These data were used to determine the appropriate PΔP vehicle classes and other variables necessary for the estimation of emissions. Of the 106 drivers, 4 drivers provided incomplete vehicle information and were therefore excluded from this analysis.

To prepare the data for input into PΔP, the latitude and longitude of each observation were used to identify the temporal and spatial characteristics of each location. Temporal and Spatial Identifiers (TSI) were constructed in previous work by the authors to identify combinations of temporal and spatial factors (Ellison *et al*., 2013). The temporal and spatial variables used to construct the TSIs reflect factors known to be significant contributors to variability in speeding behaviour. A TSI uniquely identifies a spatio-temporal environment. An example of a TSI is *ST{N-60,TE-D-PH-P0}*. This particular TSI represents an observation that was recorded on a weekday (identified by the absence of W representing weekend trips) during a trip home (PH) with no passengers (P0) driven by the primary driver[1] (D). Spatially, it was on a road with a 60 km/h speed limit (60) and within 10 metres of a non-signalised intersection (N). Observations with exactly the same TSI are considered to be spatially and temporally similar to each other. Although it is beyond the scope of this paper, future work will further examine the emission characteristics of different TSIs. This is briefly discussed in Section 5.

One issue with GPS data is the occurrence of missing observations. This can occur when line of sight is lost to the satellites such as when entering tunnels, going under bridges or in areas with tall buildings. In most cases this occurs only for one or two observations at a time, but in some cases (particularly tunnels or where the vehicle is stopped) longer time periods can be missed. Imputation can be used to fill in these data gaps, but it is important to first understand specifically in which situations imputation errors become unacceptable. To examine this, several Australian real-world drive cycles (1 Hz) were combined into a single input file. The input file contains almost 14 million seconds of real-world driving data. The speed-time data are shown in Figure 1.

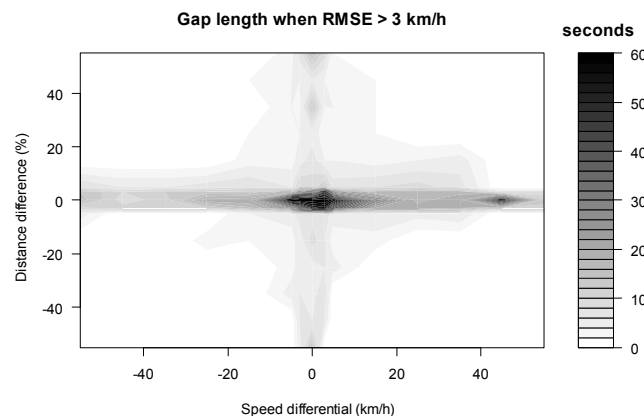[1] In this study, the primary driver is the driver who was exposed to the intervention.

Figure 1: Speed-time input data for examination of imputation errors.

Random "gaps" were created in the speed time data with gap lengths varying between 1 and 60 seconds of duration. For each gap length, 10,000 random 'observed' drive traces were created. For each random driving trace, all speed values between t_1 and t_n were then replaced with linearly imputed values to create a "predicted speed time trace". Note that t_n is computed as as t_1 + gap length +1. This predicted time trace was then compared with the observed time trace and the RMSE of speed (root-mean-squared-error, km/h) was computed for a total of 600,000 speed-time traces.

RMSE (root-mean-square-error) is a frequently used measure of accuracy. It translates the differences between observations and predictions (residuals) into a single measure of predictive power. RMSE is the standard deviation of prediction errors and an estimate of the 95% confidence interval would be approximately 4 times this value. Vehicle exhaust emission standards like the ADR and Euro standards state a "speed tolerance" of ±2 km/h for vehicle emissions testing on chassis dynamometers. This tolerance applies to difference of the test vehicle speed and the required (drive cycle) speed, which requires a professional driver. If this is regarded as a minimum "natural variation" in drive speeds, a value of ±4 km/h could generally apply to the natural variation in speeds of common drivers. This means that an RMSE value of 2 km/h would reflect natural variation in driving speeds. Adding a small margin for acceptable error of 1 km/h results in an acceptable RMSE of ≤3 km/h.

Examination of the results shows that speed prediction error is a function of both the speed difference at t_1 and t_n (Δv: v_n - v_1) and the difference between computed (d_p) and actual distance (d_o), i.e. $\Delta d = (d_p - d_o)/d_o$. Actual distances can be determined from GPS coordinates at t_1 and t_n. When the difference in speed at the start and end time points is small (say between -5 and +5 km/h), then RMSE exceed 3 km/h at time gaps between about 20 seconds or more. However, for large differences in speed (say larger than ±30 km/h), RMSE exceed 3 km/h at time gaps of about 5 seconds or less. Similar results are found for the differences between computed and actual distance. When the difference in distance at both time points is small (for example between ±5%), then RMSE exceeds 3 km/h at time gaps between about 20 seconds or more. However, for large differences in distance (say larger than ±30%), RMSE exceed 3 km/h at time gaps of about 5 seconds or less. The combined effect of Δv and Δd is shown in Figure 2.
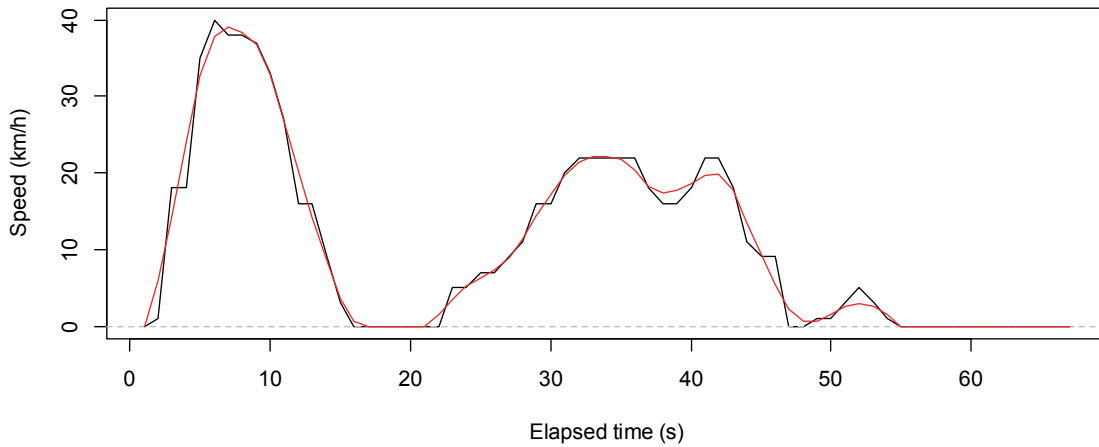

Figure 2: Contour plot showing gap time length versus Δv and Δd

The above analysis can be used to develop a more complex imputation method, but as an initial assessment, missing observations were conservatively imputed for time gaps less than 5 seconds. Imputed observations represent 3.5 percent of the dataset. This proportion was consistent for the duration of the study. Of the imputed observations, 24 percent had a speed of zero meaning that the previous and/or the next known observations also had a speed of zero. The imputed observations were assumed to have the same spatial characteristics as the previous (known) observation. The speed was calculated as follows.

$$v_i = v_{start} + ROUND\left(\frac{v_{i-1} - v_{end}}{\Delta t - \Delta t^* + 1}\right) \tag{4}$$

Where v_i is the imputed speed (km/h), v_{start} is the previous known speed, v_{i-1} is the previous speed (known or imputed), v_{end} is the next known speed, Δt is the total missing time (s) and Δt^* is the time between the current observation and the previous known observation.

After imputation, smoothing of the vehicle speeds was performed as part of the PΔP simulation using a T4253H filter (running median and Hanning filter). The effect of the smoothing is illustrated in Figure 3.

Figure 3: Smoothing of GPS trace (black) with a T4253H filter algorithm (red)

Additional information for the emissions modelling was included, such as 'before' or 'after' period and the appropriate vehicle class (see Table 1). Generic assumptions were also made here for gradient, loading and the use of air conditioning. Additional road information could be added using the latitude and longitude of each observation and used to identify nearby spatial features. This could include altitude to calculate gradient, the type of road (arterial or residential) and land use characteristics.

The prepared GPS input data file for PΔP contains over 22 million seconds of observed driving behaviour (208,140 km and 6,119 hours of driving). However, since PΔP requires driving patterns to be longer than 100m, any patterns with less than this distance are excluded. There are a number of reasons for the 100m restriction in the software (Smit *et al*., 2014):

- 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; and

- prevent infinite emission factors (g/km) for "idling only" input.

4. Impacts of intervention on CO_2 emissions

The intervention comprised charging drivers for each kilometre driven with higher rates for each kilometre of speeding and night-time driving. To provide an initial indication as to the impact of the PAYD intervention on vehicle emissions, drivers were classified into four categories based on their change in speeding (as a proportion of distance travelled) or total travel (VKT) before and after the intervention. Average figures were calculated for the drivers in each group and the CO_2 emission results are shown in Table 2. The four categories are denoted as an increase in speeding or VKT (SPD+/VKT+) or a decrease in speeding or VKT (SPD-/VKT-). The results for NO_x are presented in Smit *et al.* (2014).

Table 2: Change in CO_2 emissions between before and after phases*

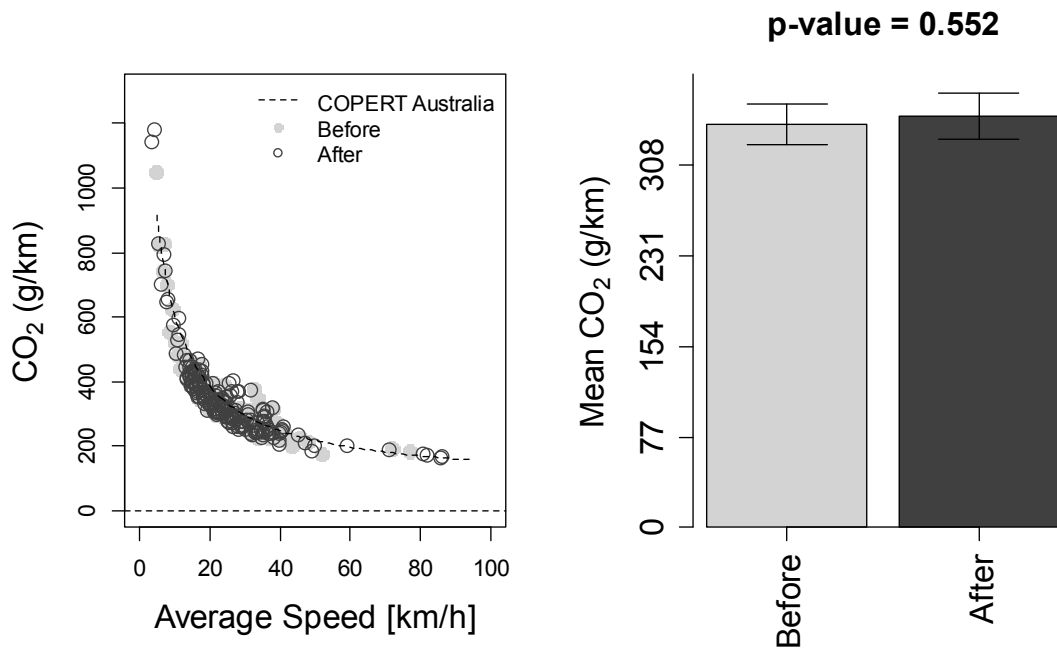| Driver category	n	Distance (km)	Average speed (km/h)	CO_2 emissions (kg)	CO_2 emissions (g/km)
SPD+, VKT+	12	138 (21%)	+1.7 (6%)	30.6 (19%)	-5.2 (-2.0%)
SPD-, VKT+	40	206 (27%)	-0.1 (0%)	42.7(26%)	-1.9 (-0.8%)
SPD+, VKT-	10	-529 (-51%)	+0.0 (0%)	-136.4 (-53%)	-9.9 (-3.7%)
SPD-, VKT-	40	-296 (-26%)	-3.5 (-11%)	-56.9 (-23%)	+8.6 (+3.9%)
Overall	102	-71 (-8%)	-1.3 (-4%)	-15.3 (-7%)	+0.6 (+0.2%)

* Percent change within brackets

Overall, the intervention resulted in significant reductions in VKT, average speed and speeding (see Greaves *et al.*, 2013). In terms of emissions, the reductions in VKT had a substantial impact on reducing emissions of CO_2 as expected. The impacts of changes in average speed on emissions is less clear as (small) increases in CO_2 per kilometre appear to be associated with (small) reductions in average speed. Given the non-linear relationship between emissions and average speed, a possible side-effect of the intervention – which was focused on safety and not emissions – is that, on average, drivers moved to a less efficient point on the emissions curve as a consequence of the intervention.

The aggregate results, while providing an overall indication points to a need for a more in-depth analysis. For this purpose, two drivers were selected as case studies for a disaggregate approach:
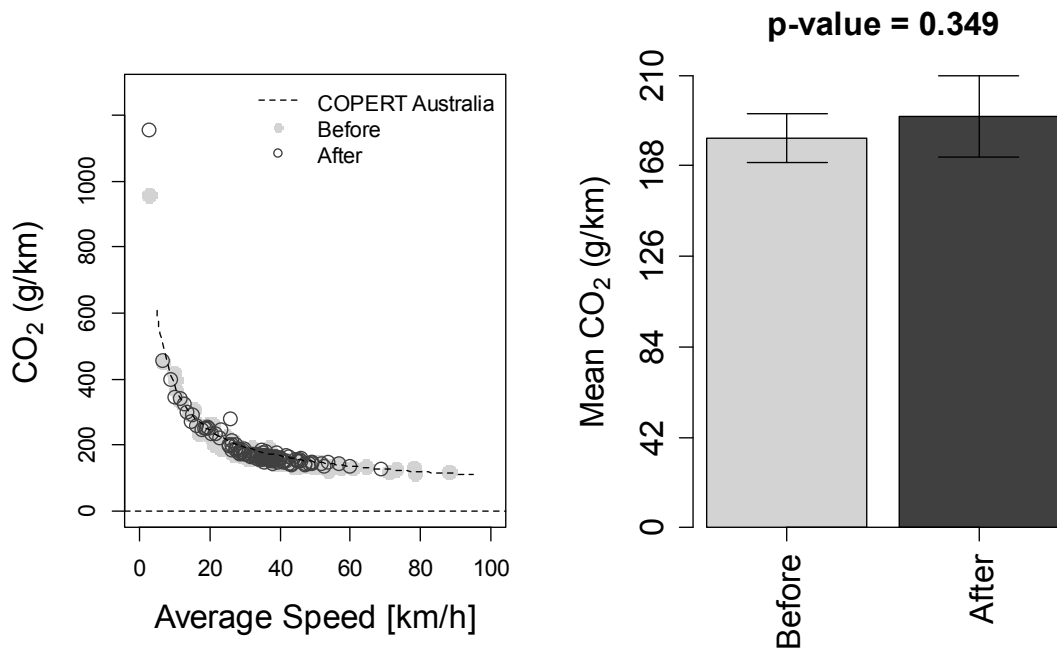
- Driver ID 11111280 who drove a large ADR37-01 petrol passenger car (EURO 1 equivalence). Overall travel (VKT) increased by 33% and average journey speed increased from 26 to 29 km/h (13%). Total CO_2 emissions increased by 24%.

- Driver ID 11111226 who drove a small ADR79-01 petrol passenger car (EURO 3 equivalence). Overall travel (VKT) decreased by 39% and average journey speed decreased only slightly from 37 to 36 km/h (-4%). Total CO_2 emissions decreased by 37%.

These specific drivers should not be considered representative of the sample, but instead are selected to illustrate the potential benefits of a more disaggregated analysis. Obviously, the change in total travel (VKT) largely determines the change in total CO_2 emissions in the before and after scenarios. However, the change in driving behaviour has an additional impact as is shown for driver 11111280.

Figure 4 and 5 (next page) further explore the emissions data that underlie the results for those two drivers. 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. 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. However, changes in CO_2 emission rates (g/km) were not statistically significant for both drivers ($p > 0.05$).

Figure 4: CO_2 emission factors (g/km) for all GPS driving patterns for one selected driver (ID11111280) 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). Vehicle class is PC-L petrol ADR37-01 (EURO 1).

Figure 5: CO_2 emission factors (g/km) for all GPS driving patterns for one selected driver (ID11111226) 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). Vehicle class is PC-S petrol ADR79-01 (EURO 3).
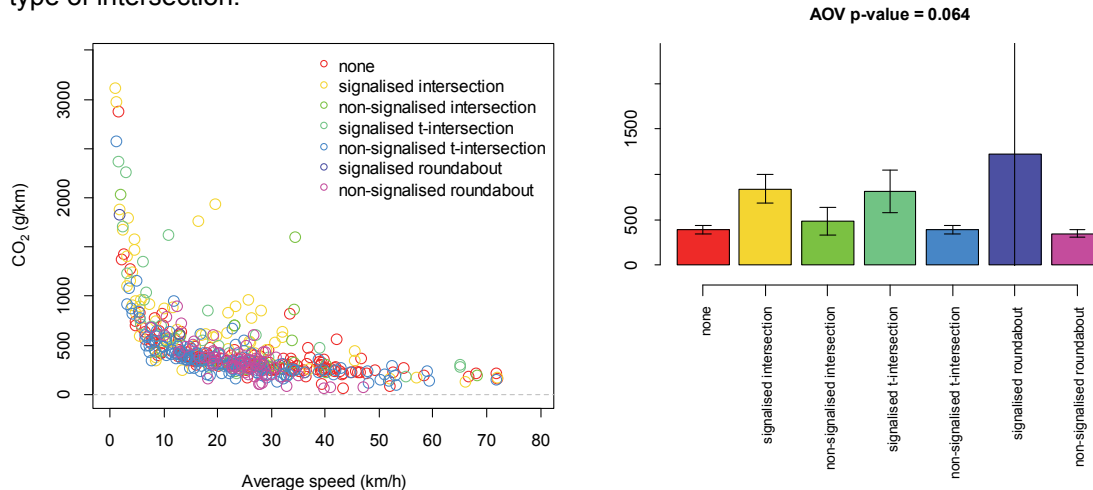
The charts also show the average speed emission factors as predicted by the COPERT Australia software (Emisia, 2014) for the corresponding vehicle class of the Australian fleet. The simulation results generated with P∆P shows good agreement with COPERT Australia. The variation around the COPERT line is generated by differences in driving profiles with the same average speed.

5. Using GPS data to develop emission factors for specific traffic situations

GPS data can be used to develop specific emission factors for a wide range of traffic situations, represented either by individual variables or a TSI (see Section 3). The benefit of GPS data is that a substantial amount of land use and road environment characteristics can be linked to the speed-time data since each observation has a latitude and longitude position. This process can be done during or after data collection. An example of this is shown in Figure 6 where the type of intersection is used to classify GPS data of a single driver and subsequently compute mean CO_2 emission factors for each type of intersection.

Figure 6: CO_2 emission factors (g/km) for all GPS driving patterns classified by traffic situation for one selected driver (ID11111305) as a function of average speed (left) and the mean emission factors for each traffic situation including 95% confidence interval and AOV p-value (right)

Adding data from the other 101 drivers will greatly increase the sample size and therefore confidence intervals for the emission factors since some intersection types – signalised roundabouts for example – are uncommon.

The number of traffic situations can be easily expanded to include other variables. This includes factors associated with particular locations, such as land use characteristics, or with particular points in time, such as weather. The variables that have been incorporated into TSIs (Ellison *et al*., 2013) are the presence of a school zone, rain, intersection type, speed limit, time of day, weekend/weekday, trip purpose and the number of passengers. Other variables have also been incorporated into the dataset. This includes a rudimentary road type variable and a proxy for congestion. Using Geographic Information System (GIS) layers, it is possible to expand these to include any number of spatial characteristics. Land use is the most obvious aspect to include but the number of lanes, road width, presence of pedestrian crossings and the locations of bus stops and train stations can all be incorporated, provided the data are available in a format that provides latitude and longitude positions.

6. Conclusions

This paper has presented preliminary results of a comprehensive analysis of the emission impacts of an intervention program where 102 Sydney drivers were monitored for two 5 week periods 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 two drivers to explore the feasibility of a disaggregate approach. The aggregated results compare well with the emissions software, COPERT Australia.

Use of the tool requires appropriate preparation of the input data. Primarily, this revolves around the GPS data preparation, which mainly involves imputation of missing records, smoothing of speed-time data and incorporation of spatiotemporal variables.

Analysis of the emission results for 102 drivers before and after the intervention demonstrates that changes in total travel (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, whereas driving behaviour changes also affect emissions although they may not always be statistically significant.

While it has become more feasible 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.

Finally, GPS data can also be used to develop fleet average emission factors for a large range of traffic situations. This will be particularly useful for more localised emission assessments where more accurate and situation-specific analysis is required.

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