The Impact of Road Grade on Carbon Dioxide (CO_2) Emission of a Passenger Vehicle in Real-World Driving

David W. Wyatt[a*], Hu Li[b], James E. Tate[c]

[a*] Corresponding author. Doctoral Training Centre in Low Carbon Technologies, University of Leeds, Leeds, LS2 9JT. E-mail address: pmdww@leeds.ac.uk (D.W.Wyatt). Tel.: +44 (0)1133 432556; fax: +44 (0)1132 467310

[b] Energy Research Institute, School of Process, Environment and Materials Engineering, University of Leeds, Leeds, LS2 9JT, UK.

[c] Institute for Transport Studies, University of Leeds, Leeds, LS2 9JT, UK.

Abstract

To accurately estimate real-world vehicle emission at 1Hz the road grade for each second of data must be quantified. Failure to incorporate road grade can result in over or underestimation of a vehicle's power output and hence cause inaccuracy in the instantaneous emission estimate. This study proposes a simple LiDAR (Light Detection And Ranging) – GIS (Geographic Information System) road grade estimation methodology, using GIS software to interpolate the elevation for each second of data from a Digital Terrain Map (DTM). On-road carbon dioxide (CO_2) emissions from a passenger car were recorded by Portable Emission Measurement System (PEMS) over 48 test laps through an urban-traffic network. The test lap was divided into 8 sections for micro-scale analysis. The PHEM instantaneous emission model (Hausberger, 2003) was employed to estimate the total CO_2 emission through each lap and section. The addition of the LiDAR-GIS road grade to the PHEM modelling improved the accuracy of the CO_2 emission predictions. The average PHEM estimate (with road grade) of the PEMS measured section total CO_2 emission (n=288) was 93%, with 90% of the PHEM estimates between 80% and 110% of the PEMS recorded value. The research suggests that instantaneous emission modelling with LiDAR-GIS calculated road grade is a viable method for generating accurate real-world micro-scale CO_2 emission estimates. The sensitivity of the CO_2 emission predictions to road grade was also tested by lessening and exaggerating the gradient profiles, and demonstrates that assuming a flat profile could cause considerable error in real-world CO_2 emission estimation.

Keywords

Vehicle Emissions; Carbon Dioxide; Vehicle Specific Power; Road Grade; Portable Emission Measurement System (PEMS); LiDAR.

1. Introduction

Research has demonstrated that on-board vehicle Portable Emission Measurement Systems (PEMS) can be utilised to provide accurate measurement of vehicle exhaust emissions in real-world driving (Frey et al., 2003; Liu et al., 2010; Ropkins et al., 2007). PEMS instrumentation in such studies are deployed to record the motion, geographical position and exhaust emission of a vehicle driven over a real-world test route, most commonly measured on a second-by-second basis. Utilising the 1Hz PEMS data and values from the test vehicle specification, the engine power output of the vehicle for each second of data can be computed and used as an explanatory variable in predicting fuel consumption and exhaust emission at that instant.

Exploiting the relationship between engine power and exhaust emission, the latest generation of emissions models such as the US Environmental Protection Agency's (EPA) MOtor Vehicle Emission Simulator (MOVES) (Koupal et al., 2004), the Netherlands Organisation for Applied Scientific Research's (TNO) VERSIT+ model (Smit et al., 2007) and the Technical University of Graz's (TUG) Passenger car and Heavy duty Emission Model (PHEM) (Hausberger, 2003) predict vehicle exhaust emission by referencing the calculated engine power output for each second of data to a calibrated mass of exhaust emission at that power, for each emission species.

Derivation of instantaneous engine power output requires a second-by-second measure of vehicle speed, acceleration and road gradient. PEMS can reliably capture vehicle speed, and hence acceleration, during real-world driving, but road grade is very difficult to measure accurately from an instrumented vehicle (Zhang and Frey, 2006).

A number of studies have highlighted the significant influence road grade can have on real-world fuel consumption and exhaust emission (Boriboonsomsin and Barth, 2009; Boroujeni and Frey, 2014; Zhang and Frey, 2006). For test sections with positive road grade, as the gradient increases so must the engine power output to keep the vehicle at a constant speed, due to the increasing force of gravity opposing the motion of the vehicle. This increase in power requires greater fuel consumption resulting in increased CO_2 exhaust emission. Likewise where a vehicle is travelling on a road with negative grade, gravity acts to accelerate the vehicle, reducing the power demand on the engine, which lowers fuel consumption and hence CO_2 emission. Zhang and Frey (2006) recorded an increase in CO_2 emission of 40-90% for three light duty gasoline vehicles over sections of road with gradient ≥ 5% when compared to sections with gradient ≤ 0%, whilst Boriboonsomsin and Barth (2009) measured a 15-20% rise in fuel consumption for a gasoline passenger car between a flat route and a hilly route.

Given the effect of road grade on engine power output and therefore vehicle emission, it is vital for micro-scale emission modelling that instantaneous engine power output is calculated accurately, which necessitates a representative road grade value for each second of test data. There are a number of methods for quantifying road grade proposed in the literature, including; calculation from design drawings; direct land survey measurement; on-board measurement by GPS, accelerometers, barometric altimeters and inclinometers; and mathematical derivation from DTM or DEM (digital elevation maps), each with different characteristics relating to accuracy, precision, scale and price (Boroujeni et al., 2013; Sahlholm and Johansson, 2010; Zhang and Frey, 2006). Zhang and Frey (2006) proposed a LiDAR based methodology concluding that the LiDAR method is advantageous; having relatively few practical and logistical limitations compared with other methods, and can be considered sufficiently accurate for emission estimation.

LiDAR is a mapping technique which quantifies terrain elevation using laser measurement from aircraft. These measurements can be processed to construct highly accurate Digital Terrain Models (DTM) which render a three dimensional representation of the surface topography, describing elevation and position. The availability and cost of LiDAR data have been a citied as a main limitation in its use for road grade estimation (Boroujeni et al., 2013), however, a comprehensive LiDAR 5-metre resolution DTM dataset for the U.K. is available free of charge to academics and students at U.K. institutions through the Landmap Kaia Service hosted at MIMAS based at the University of Manchester (Millin-Chalabi et al., 2011). The advantage of the simple LiDAR-GIS method proposed in this study is that by referencing the measured GPS position to a DTM elevation, a representative 1Hz road grade profile can be quickly generated for a test area without the multiple runs required by GPS measured altitude methodologies (Boroujeni et al., 2013; Sahlholm and Johansson, 2010) and without the detailed roadway analysis and segmentation required in the LiDAR methodology described by Zhang and Frey (2006).

In combination with reducing the fossil fuel dependence of the vehicle fleet through engine efficiency improvements and new vehicle technologies, road traffic management schemes may also deliver CO_2 emission reductions. Mechanisms such as better traffic control systems, which reduce the number of aggressive breaking and acceleration events through a network; eco-driver training, which promotes efficient driving; policies which reward multiple-occupancy of cars or the use of public transport to reduce both the number of vehicle trips and traffic congestion; and improved road geometry design to reduce the impact of road grade can all be used to reduce CO_2 emission from the road transport sector. In order to provide detailed micro-scale assessment of the impact of such strategies, emission estimation models are required that can predict emissions of vehicles in real-world driving conditions with sufficient accuracy and resolution to quantify their environmental benefit and inform the policy decision making process.

The purpose of this paper is to develop and demonstrate a simple LiDAR-GIS methodology for calculating a representative 1Hz road grade for use in instantaneous vehicle emission modelling. The sensitivity of CO_2 emission predictions to road grade, in a range of traffic conditions will also tested.

2. Methodology

2.1. Study Design

A fixed lap through Headingley, Leeds was used as a test route for the research. This test lap, shown in Figure 1, comprises a 4.6 km route on mainly single lane urban commuter roads, with a speed limit of 30 mph (48 km/h). The route encompasses one of the main arterial roads into and out of Leeds and is frequently congested.

Figure 1. Headingley Test Lap and Sections (GPSVisualizer, 2013)

The test lap was covered by the same driver in an instrumented vehicle a total of 48 times during a week-long testing period between the 26th February 2007 and the 5th March 2007, with runs conducted between the hours of 07:30 and 21:00 to capture the full range of traffic conditions for this road network. The laps were completed in variety of weather conditions, with sunny, dry, overcast and rainy test laps, in temperatures ranging from 1°C to 15°C.

In order to facilitate analysis at a micro-scale level the Headingley lap was divided into 8 test sections (see Figure 1). These sections were determined by classifying points of latitude and longitude to mark the beginning and end of each section, after which the closest measured GPS points from each run to those selected start and end points were identified. Sections 1 and 8 are the same segment of road but with opposite directions of traffic flow, likewise sections 2 and 4, and sections 5 and 7. Section 3 and section 6 are separate short 'turning' sections.

2.2. Test Vehicle

The instrumented vehicle used in this study was a EURO 4 emission compliant petrol Ford Mondeo with a 5-speed manual gearbox and a port fuel injected 1.8 litre, 4 cylinder, 16 valve spark ignition engine with a maximum power of 92 kW (125 PS) at 6000 rpm. The vehicle was equipped with a Three Way Catalyst (TWC).

The vehicle specifications used for modelling in this study are a kerbweight (with 90% fuel levels, full fluid levels and a 75kg driver) of 1374 kg (Li et al., 2008), a rolling resistance coefficient of 0.013 (Ehsani et al., 2009), an aerodynamic drag coefficient of 0.32, a frontal area of 2.3 m^2 (Doucette and McCulloch, 2011), and an idle engine speed of 850 rpm.

2.3. Test Vehicle Instrumentation

A Horiba On Board emission measurement System (OBS-1300) was used to measure the exhaust flow rate and air/fuel ratio, enabling calculation of CO_2 mass emission from the volumetric measurements. Speed, acceleration and geographical position data were measured and recorded by a RaceLogic VBOX II GPS engine and data logger. All data was recorded at 1 Hz. The OBS set up and its validation over a wide range of engine operating conditions and drive cycles is described by Ropkins et al. (2008).

The OBS and VBOX were time aligned using the vehicle velocity data measured by each instrument. Exhaust flow measurement drift was corrected, where required, using the standard 'on-road' correction method used in other University of Leeds studies, measuring 'zero flow' values before and after each test run and re-calibrating the zero-points, assuming a linear drift over the test (Ropkins et al., 2007). The documented OBS-1300 'pulse effect' overestimation of idle exhaust flow (Daham et al., 2005; Nakamura et al., 2002; Ropkins et al., 2008) was corrected based on the work of Ropkins et al. (2008), which demonstrated an OBS overestimation of idle exhaust flow rate in the order of 40 to 60 percent. A correction factor was applied to the OBS measured exhaust flow rate at all points of vehicle engine idle recorded during the testing.

2.4. Mass Emission Calculation

The exhaust CO_2 emissions as measured by use of the OBS-1300 are captured on a volumetric basis. The CO_2 mass emission rate is calculated from the measured exhaust gas volumetric flow rate, the density of CO_2 and the wet gas concentration of CO_2, using Equation 1.

$$CO_{2\,MASS} = [CO_2]_{t=t+DT} \times MWT_{CO_2} \times [Q_{EX}]_{t=t} \times (273.15/293.15) \times UCF \tag{1}$$

Where, $CO_{2\,MASS}$ is the CO_2 mass emission rate in g/s, standardised to 20°C and 1 atm (293.15K and 101.3 kPa); $[Q_{EX}]_{t=t}$ is the exhaust flow rate in m^3/min at time t; $[CO_2]_{t=t+DT}$ is the percentage concentration of CO_2 associated with $[Q_{EX}]_{t=t}$, which is read after a measurement Delay Time (DT); MWT_{CO_2} is the molecular weight of CO_2, 44.01 g/mol; and UCF are the required Unit Conversion Factors. The Unit Conversion Factors are a multiplication by 1/100 to correct the units of $[CO_2]_{t=t+DT}$ from a percentage volume to volume; a multiplication of 1/60 to change the units of $[Q_{EX}]_{t=t}$ from m^3/min to m^3/s; a multiplication of 1/22.415 to convert MWT_{CO_2} from g/mol to CO_2 density using the ideal gas volume of 1 mole at Standard Temperature and Pressure (STP), with 273.15/293.15 amending the density of CO_2 to that at 20°C and 1 bar

2.5. LiDAR-GIS Methodology for Elevation Profile and 1Hz Road Grade Estimation

The possible error range resulting from instrument imprecision (the VBOX II has a 95% Circular Error Probability (CEP) of 10 metres, meaning that the measured height is within 10 metres of the true position 95% of the time (Racelogic, 2008)) and measurement errors during vehicle transit, caused by GPS signal interference from buildings in urban streets for example, made the raw GPS height measurements recorded by the instrumented vehicle too unreliable to use to generate an accurate elevation profile for the test lap, and insufficiently precise to calculate road grade for each second of data. The test lap elevation profile in this research was instead calculated using a 5m DTM, generated from the LiDAR elevation data, provided through Landmap Kaia (Millin-Chalabi et al.,

2011) . The DTM and the VBOX measured GPS positions for each test run were imported into the GIS software ArcGIS enabling the height at each recorded GPS point to be extracted from the DTM.

The road grade for each second of recorded data was calculated by applying an algorithm to reduce the effect of errors associated with inaccuracies in the measured GPS latitude and longitude position (95% CEP of 3m (Racelogic, 2008)). The errors resulting from GPS absolute position measurement accuracy are especially apparent at points where the vehicle was moving slowly or stationary, as the GPS position appears to shift whilst the vehicle is not moving. As the GPS position changes, so does the elevation estimate extracted from the 5-metre DTM and relatively small changes in GPS position can result in changes in the elevation estimate. Unfeasible erroneous gradients may therefore be calculated where the vehicle travels only a short distance along the test route but due to GPS measurement error there is a significant change in the DTM extracted elevation.

In order to determine a representative gradient on a second-by-second basis an algorithm was therefore applied to smooth out the errors resulting from GPS absolute position measurement imprecision. For each second of data, when the vehicle was travelling at greater than 10m/s then the gradient was calculated by dividing the distance travelled in the measured second by the change in height in that measured second. Where the vehicle was travelling at less than 10m/s, rather than calculating the gradient over 1 second, the gradient is calculated over the period from where the vehicle was at least 5 metres before the start of that measured second to the point where the vehicle was at least 5 metres past the end of the measured second. This ensures that the minimum length of road section over which the gradient is calculated is 10 metres.

The Bluesky LiDAR height data utilised in this study have an accuracy of up to ±10cm (Bluesky, 2013), however the resolution of the DTM does have an influence on the accuracy of LIDAR based elevation estimates. In this study, the 5-metre resolution DTM presents a map of LiDAR calculated elevations at the intersection points on a horizontal 5 metre grid covering the test area. The height of any GPS point within that grid is calculated by linearly interpolating between the nearest grid intersection points, by the GIS software. However as a result of interpolation, surface features such as bridges, underpasses and steep road side banking, where there is an abrupt non-linear change in surface elevation within a 5-metre grid square, can produce errors in the height estimation. In these cases the modelled linear change in surface height does not reflect the abrupt real-world change. Manual correction of physically unfeasible road grade estimates could be undertaken utilising geo-referenced photographic images. In this study no manual adjustments of the estimate road grade were necessary, as the Headingley test lap contained no surface features that required correction.

2.6. Vehicle Specific Power

Vehicle Specific Power (VSP) is employed in this research to estimate the power per unit mass for the vehicle for each second of recorded data. The VSP of the test vehicle was calculated for each second of test data, from the 1Hz vehicle speed data, recorded by PEMS measurement, and the 1Hz road grade estimate generated by the LiDAR-GIS methodology. The general form of the VSP equation (Jimenez-Palacios, 1999) is described in Equation 2.

$$VSP = v \cdot (a \cdot (1 + \varepsilon_i) + (g \cdot grade) + (g \cdot C_R)) + (0.5\rho_a ((C_D \cdot A)/m) (v + v_w)^2 \cdot v) \quad (2)$$

Where VSP is vehicle specific power (kW/tonne); v is vehicle speed (m/s); a is vehicle acceleration (m/s^2); ε_i is the gear-dependent "Mass factor" (tonne), which is the equivalent translational mass of the rotating components of the powertrain; g is the acceleration of gravity ; grade is road grade (dimensionless); C_R is the coefficient of rolling resistance (dimensionless); ρ_a is the ambient air density (kg/m^3); C_D is the drag coefficient (dimensionless); A is the frontal area of the vehicle (m^3); m is the mass of the vehicle and v_w is the velocity of the headwind into the vehicle.

For this study the simplified VSP equation for a typical light duty vehicle (Jimenez-Palacios, 1999) was employed, with the rolling resistance term coefficient $(g \cdot C_R)$ of 0.128 and aerodynamic drag term coefficient $(0.5\rho_a (C_D \cdot A)/m)$ of 0.000318 calculated to correspond to the test vehicle used in the research.

$$VSP_{EURO4} = v \times [(1.1 \times a) + (9.81 \times (\sin(\mathrm{atan}(grade))) + 0.128] + (0.000318 \times v^3) \quad (3)$$

2.7. Modelling in PHEM

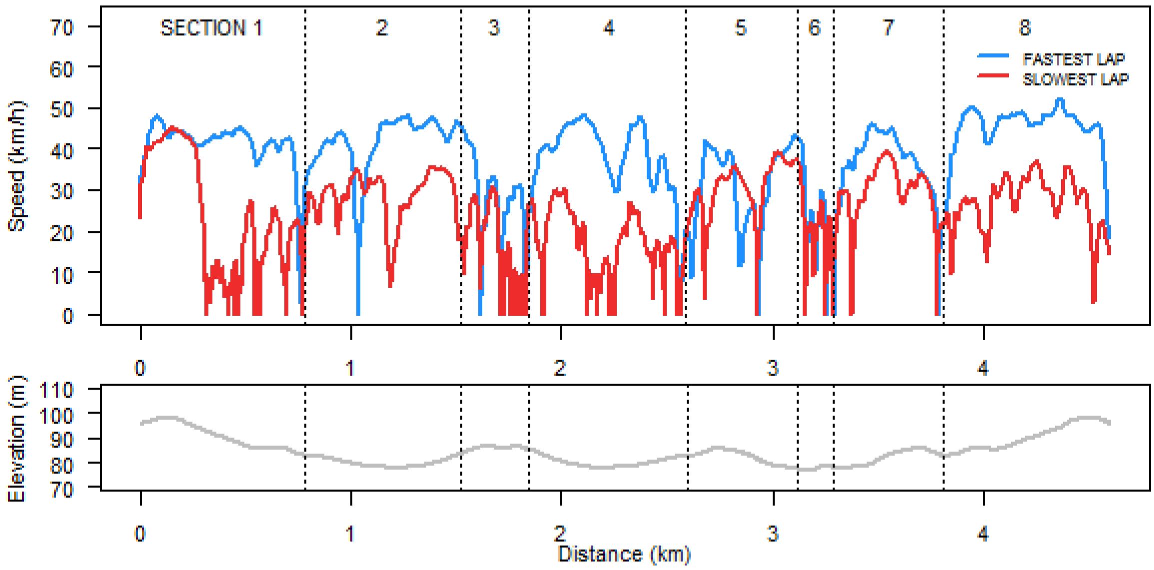
Vehicle emission estimation in this research was conducted using the power-instantaneous emission model PHEM (Hausberger, 2003). The PHEM model enables micro-scale calculation of vehicle second-by-second fuel consumption and exhaust emission in any reasonable driving conditions. PHEM requires a 1Hz speed profile with associated road grade measurements and data describing the test vehicle to calculate, for each second of test data, the engine speed and power output of the vehicle. These speed and power values are then referenced to an engine emission map, specific to the test vehicle's fuel type and certified EU emission standard, to estimate the second-by-second vehicle fuel consumption and emission values (Hausberger et al., 2010).

For this study the 1Hz speed profile from the PEMS was used with LiDAR-GIS calculated road grades. The specification data (as described in Section 2.2) for the EURO 4 Mondeo test vehicle were used to parameterise PHEM, with an estimated loading of 150 kg for the PEMS system. The PHEM engine-emission map used during the modelling was that for a comparable EURO 4 petrol vehicle.

3. Analysis of PEMS Measurements over the Headingley Test Lap

The median time to complete the test route over the 48 test laps was 19 minutes 50 seconds, however the lap times ranged from 10 minutes 14 seconds in free flowing conditions to 28 minutes 37 seconds in congested traffic. The average lap speed was 14.2 km/h (range 9.6 km/h to 27 km/h). Plotting the distance - speed profile for the slowest lap, recorded at 8.20am in peak morning rush hour traffic against the fastest lap, recorded at 8:36pm in free flowing traffic conditions, highlights the variation in vehicle operation which can occur over the same lap and road segments. The speed profile for the congested lap, marked in red in Figure 2, displays recurrent periods of very low speed, where the vehicle frequently stops and starts. Even outside of these periods, congestion hinders the vehicle from reaching the 48 km/h speed limit for the road. The distance - speed profile for the fastest lap, marked in blue, shows that whilst there were points where the vehicle was stationary, there were noticeably fewer stationary points than during slowest lap, and upon restarting the vehicle was able to accelerate back up to the speed limit of the road.

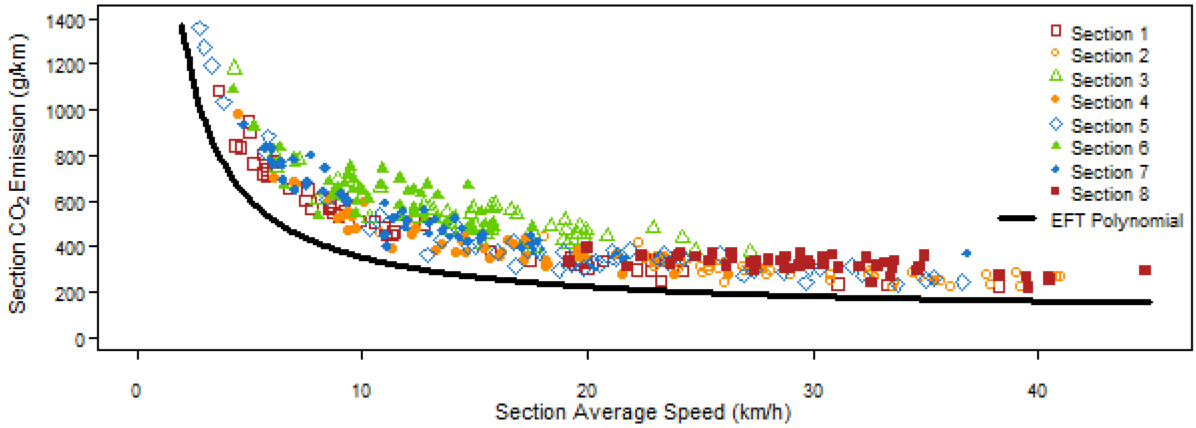
Figure 2. (a) Vehicle Distance - Speed Profiles for the Fastest and Slowest Recorded Laps and (b) Elevation Profile



The specific traffic conditions experienced during each of the real-world test runs influenced both the driver input (and as a result engine load) and the total time to complete the lap. The variability of these conditions resulted in a wide range of average CO_2 emissions per km for the 48 test laps (313 gCO_2/km to 586 gCO_2/km). The median emission over the 48 laps was 438 gCO_2/km, which is more than double the rated CO_2 emission for the vehicle of 182 gCO2/km (Ford, 2005).

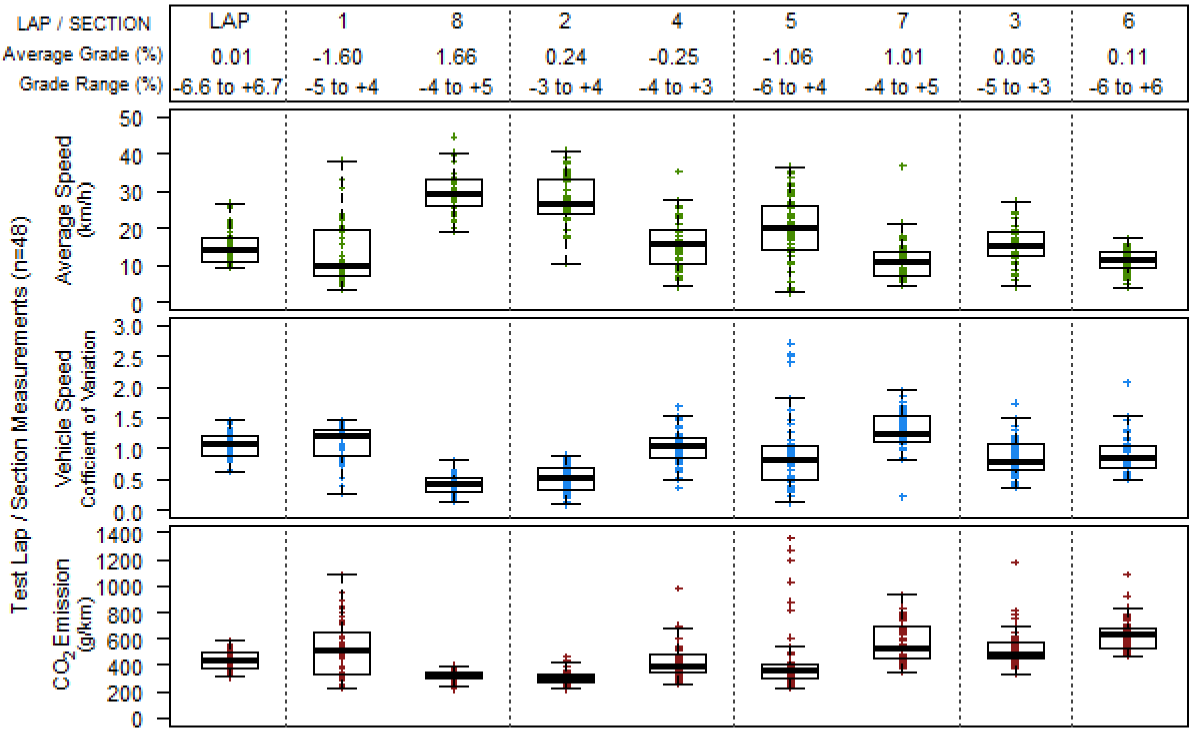
Figure 3 compares the PEMS measured gCO_2/km for each of the road sections. Although the section emissions roughly follow the curve of the EFT function, for this vehicle the function underestimates the emission generated in every section. It is also clear from the graph that at each speed the real-world measurements show a wide spread of possible emission rates, indicating that CO_2 emission assessment through an average speed function may not provide a reasonable estimate for real-world CO_2 emission in all situations.

Figure 3. PEMS Measured Section CO_2 Emissions versus Section Average Speed (n=384). EFT Polynomial is the Emission Factor Toolkit (EFT) average speed emission function for the vehicle type (R012, Car <2.5 t, Petrol, 1400-2000 cc, Euro 4) (DEFRA, 2009)



The coefficient of variation (CV) is the ratio of the standard deviation to the mean, is a measure of the relative dispersion of vehicle speeds from the average speed, and describes the consistency of the vehicle speed through a lap or section. A low CV indicates a relatively constant speed and a high CV shows a wide dispersion of vehicle speeds. Sections 2 and 8 had the lowest rate of CO_2 emission and also the narrowest spread of emission values (see Figure 4). These were the sections with consistently high average speeds and relatively consistent vehicle speed. In these sections traffic flow was not greatly hindered by increased traffic density in the network during peak traffic periods. Conversely the data for sections 1 and 7 present a wide spread of CO_2 emission values. During free flowing conditions these sections could be completed relatively quickly, at relatively low gCO_2/km emission rates. However, during rush hour periods, the queuing times over these sections increased, raising the vehicles gCO_2/km emission rate because the stationary vehicle's idle CO_2 emissions increase the total CO_2 emission whilst the vehicle is not moving.

Figure 4. Box Plots of the Test Sections gCO_2/km, Average Speed and Vehicle Speed Coefficient of Variation measurements, over the 48 Test Runs



4. Evaluation of the LiDAR-GIS method for Road Grade Estimation.

As demonstrated in other studies (Coelho et al., 2009; Song and Yu, 2009; Zhai et al., 2008), CO_2 emission increases approximately monotonically with positive VSP and has a consistently low CO_2 emission rate with negative VSP. To evaluate whether the LiDAR-GIS road grade values enhanced the calculation of VSP, the Pearson Correlation Coefficient (r) between VSP and CO_2 emission was calculated for each of the 48 test laps, for VSP calculated both with (VSP_G) and without (VSP_0) the LiDAR-GIS 1Hz road grade.

Table 1. Summary of the Pearson Correlation Coefficient (r) values between VSP and PEMS measured CO_2 emission for each of the 48 test laps. VSP calculated both with (VSP_G) and without (VSP_0) road grade.

		VSP_0		VSP_G	
Test Route	**Number of Runs**	**Ave r**	**r Range**	**Ave r**	**r Range**
Headingley	48	0.76	0.72 - 0.80	0.79	0.74 - 0.84

To assess if there was a significant increase in the strength of the linear association between VSP and CO_2 emission with the addition of road grade the Williams' t-test for comparing two non-independent correlations was used (Howell, 2013; Williams, 1959) . Both VSP calculation methods show a relatively strong linear correlation between VSP and CO_2 emission (see Table 1), however the strength of the linear relationship between VSP and CO_2 emission increased for each of the 48 test laps with the addition of the LiDAR-GIS road grade. In each instance, at a significance level of α =.05 (two-tailed), the correlation using VSP_G proved significantly greater than the correlation calculated with VSP_0, which suggests that the LiDAR-GIS method provides a reliable representative 1Hz gradient.

5. Instantaneous CO_2 Modelling with and without LiDAR-GIS generated Road Grade.

The PHEM instantaneous emission model was used to calculate the second-by-second CO_2 emission estimates for the EURO 4 test vehicle on the Headingley test laps. In order to test the LiDAR-GIS road grade methodology, CO_2 emission estimates from PHEM were calculated for each test run with the test area modelled as flat with all road grade values set as zero ($PHEM_0$), and modelled with the calculated LiDAR-GIS road grade values ($PHEM_G$).

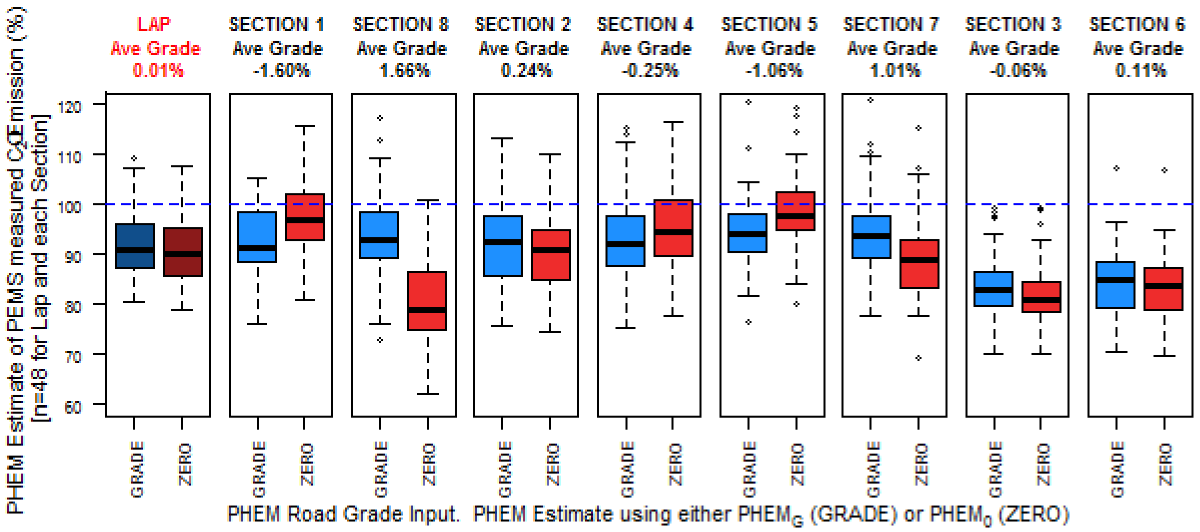
PHEM was configured for the specific EURO 4 test vehicle (as described in Section 2.2) with a 150kg loading and emission estimates determined from the recorded (PEMS) speed profile for each test run under the two road grade conditions specified in $PHEM_0$ and $PHEM_G$. For each of the 48 test laps and sections the $PHEM_0$ and $PHEM_G$ modelled CO_2 aggregate emissions were compared with the corresponding PEMS measurements (illustrated in the Figure 5 boxplots). Modelling each of the 48 test laps, the average $PHEM_G$ estimate of the lap total CO_2 emission was 91% of the real-world PEMS measured CO_2 emission, with a range from 81% to 110% (with 50% of the $PHEM_G$ estimates between 87.4% and 96.1%).

Although $PHEM_G$ modelling appears to underestimate the real-world vehicle CO_2 emission, which may result from the PHEM EURO 4 petrol average engine emission map not being specific to the test vehicle and/or possible disparity in the timing of the modelled and real-world gear changes, much of this discrepancy is likely to be caused by factors not included in the modelling such as day-to-day variation in ambient temperature, starter battery state of charge and use of the vehicles air conditioning and heating systems, each of which can have a significant effect on vehicle fuel consumption (Mock et al., 2012). Inaccuracy of the simulated vehicle weight may also have had an influence on the modelled rate of CO_2. Although the test vehicle's kerbweight is recorded in the vehicle's specification, and the vehicle loading was estimated, the actual weight of the test vehicle was not directly measured. Future modelling would be improved by an accurate measure of the test vehicle weight, since an underestimation may result in lower modelled than measured CO_2 emission.

The average $PHEM_0$ estimate (without road grade) of the lap total CO_2 emission was 90% of the PEMS recorded valued, with a range from 79% to 108% (with 50% of the values between 85.8% and 95.3%). The results for the test lap are similar to those attained with $PHEM_G$, with only a slight improvement in PHEM CO_2 emission estimation over the test lap using the LiDAR-GIS road grade. The Headingley test lap starts and ends at the same point, therefore the average road grade over the lap is approximately zero. As a result, $PHEM_0$ overestimates of CO_2 emission on downhill road segments are partially offset underestimation on uphill road segment. The overestimation / underestimation by $PHEM_0$ can be seen in the Figure 5 test section box plots. Whilst the average $PHEM_G$ estimate of the PEMS CO_2 emission in Sections 1, 2, 4, 5, 7 and 8 (excluding the turning sections) range between 91% and 94%, the $PHEM_0$ estimates of PEMS CO_2 emission are greatly influenced by the road grade in the section and vary from 79% to 98%.

For example over Section 1, a primarily downhill section with an average road grade of -1.6%, the average $PHEM_G$ and $PHEM_0$ estimates of the section total CO_2 emission were 91% and 97% PEMS measured emission respectively. In this instance the $PHEM_0$ appears to provide the most accurate estimate of the real-world CO_2 emission. However over Section 8, the corresponding uphill section (the opposite traffic flow to Section 1) the average total section CO_2 emission estimate from $PHEM_0$ is 79% of the PEMS measured value, whereas for $PHEM_G$ it is 93%. Whilst the calculated $PHEM_0$ CO_2 emissions for the downhill sections (1, 4 and 5) are closer to the PEMS measured emission, the stability of the $PHEM_G$ estimates over all sections irrespective of average road grade demonstrates the addition of the LiDAR-GIS data in PHEM delivers consistently more reliable micro-simulation CO_2 emission estimates.

Figure 5. PHEM modelled CO_2 emission as a percentage of the PEMS measured emission for each of the 48 test laps and sections, under the two road grade scenarios $PHEM_0$ and $PHEM_G$.

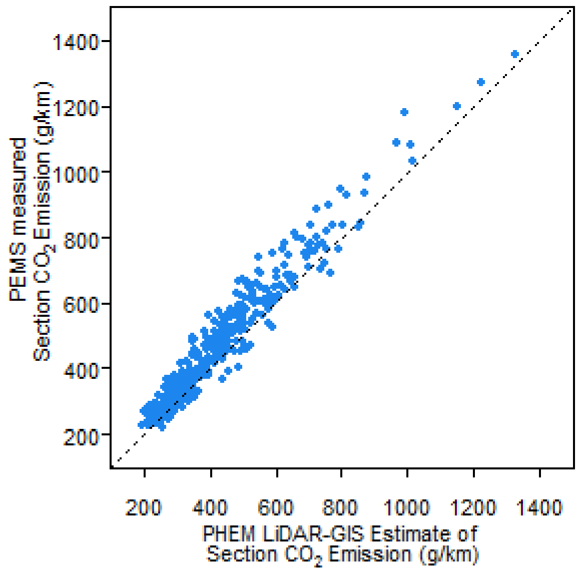


The PHEM CO_2 emission estimates of the real-world emission through the short 'turning' sections 3 and 6 are perceptibly less accurate than for the longer test sections. The decrease in the accuracy of PHEM in these sections is likely to be due to the driver gear selections in these short stop start sections not being characteristic of the gear shift patterns under normal driving conditions and hence not being adequately represented in the model.

The stability and accuracy of the $PHEM_G$ estimates when compared to the measured PEMS CO_2 emission at this micro-scale section level suggests that both the LiDAR-GIS method for generating road grade provides a representative 1Hz gradient profile and that reliable micro-scale simulation of CO_2 emission over real-world networks is possible utilising the PHEM power-instantaneous emission model.

The scatter plot of $PHEM_G$ CO_2 emission estimate versus the PEMS measured CO_2 emission for each section (n=348) (see Figure 6) demonstrates the strength of the $PHEM_G$ model in estimating the real-world vehicle CO_2 emission over the Headingley test sections.

Figure 6. $PHEM_G$ Calculated gCO_2/km Emission versus PEMS Recorded gCO_2/km Measurements for the Headingley Test Sections.



6. Sensitivity of CO_2 Emission Estimates to Road Grade

The sensitivity of the CO_2 emission predictions to road grade was tested by lessening and exaggerating the gradient profiles. PHEM CO_2 emission estimates for the test vehicle were calculated using the real-world PEMS measured speed profiles under five road grade scenarios, where coefficients of 0, 0.5, 1, 2 and 3 were applied respectively to each second of LiDAR-GIS calculated road grade. The zero road grade coefficient ($PHEM_0$) models the test area as totally flat. With the 0.5

coefficient ($PHEM_{0.5G}$), the model uses half of the calculated LiDAR-GIS value at each second. For $PHEM_{0.5G}$ 96.79% of the 1Hz road grade estimates were between ±2% with 99.61% between ±3%. For $PHEM_G$ 99.46% of the 1Hz road grade estimates were between ±6% and 94.4% were within the range of ±4%. Doubling the road grade at each section with the road grade coefficient of 2 ($PHEM_{2G}$), 76.24% of the 1Hz road grade estimates were between ±6% and 97.46% were within the range of ±10%. With a road grade coefficient set to 3 ($PHEM_{3G}$) 80.93% of the 1Hz road grade estimates were between ±10% and 96.26% were within the range of ±14% Whilst it is likely that in real-world driving the steeper road grades would have an impact on the speed profile of the vehicle, to enable comparison, the modelling in this section of the study assumes the same speed profiles (as measured by the PEMS system) for the vehicle at every road grade coefficient.

Table 2 details the PHEM modelled CO_2 emission results for the 48 test runs over each lap and section for the 5 road grade scenarios. The average lap CO_2 emission under $PHEM_0$ is 400 gCO_2/km with a range over the 48 test runs from 276 – 513 gCO_2/km. The average lap CO_2 emission increase by 1.4% when the LiDAR-GIS road grade ($PHEM_G$) is considered. For $PHEM_{2G}$ the average CO_2 emission change over the lap compared to $PHEM_0$ is 4.0% higher, rising to +7.6% for the $PHEM_{3G}$ scenario. As this test lap starts and ends at approximately the same point, the average lap road grade is zero. This modelling suggests that it is incorrect to assume that over a test route with an average flat road grade but which experiences change in elevation over the length of its profile, that the increase in CO_2 emission in uphill sections will be offset by the decrease in CO_2 emission in downhill sections. The PHEM modelling indicates that for such test routes CO_2 emission increases with increasing steepness of road grade.

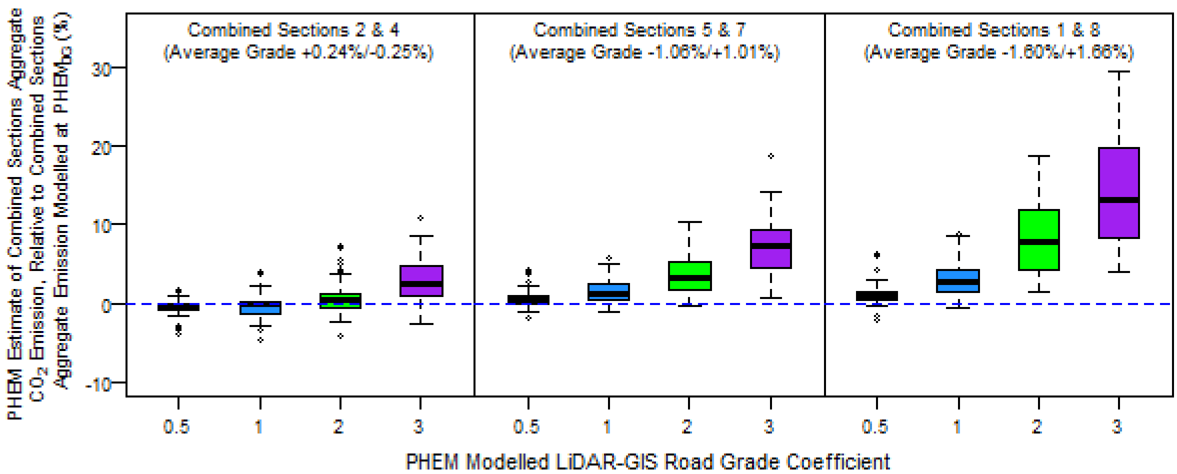
Analysing the PHEM calculations at the section micro-scale suggests that road grade is a very important factor in establishing CO_2 emission over short road sections. Over Section 8, a relatively fast free flowing uphill section (with an average road grade of +1.66% from the LiDAR-GIS elevation profile), the average increase in CO_2 emission from $PHEM_0$ to $PHEM_G$ is 17.2% with a range in CO_2 emission increase for the section of between 8.5% and 43.2%. Over the same section under $PHEM_{3G}$, with a hypothetical tripling of 1Hz road grade, the CO_2 emission increase range is from 32.3% to 102.1%. This suggests conducting micro-scale modelling without establishing accurate road grade would cause the CO_2 emission estimates to vary considerably from the real-world CO_2 emission.

Table 2. PHEM CO_2 Emission Calculation under five road grade scenarios.

Section		CO_2 Emission Comparison at Modelled Road Grade Coefficients									
		$PHEM_0$		$PHEM_{0.5G}$		$PHEM_G$		$PHEM_{2G}$		$PHEM_{3G}$	
#	Ave. Grade (%)	Ave. (g/km)	Range (g/km)	Ave. (% Change from $PHEM_0$)	Range (% Change from $PHEM_0$)	Ave. (% Change from $PHEM_0$)	Range (% Change from $PHEM_0$)	Ave. (% Change from $PHEM_0$)	Range (% Change from $PHEM_0$)	Ave. (% Change from $PHEM_0$)	Range (% Change from $PHEM_0$)
1	-1.60	509	210 - 1037	-2.7	-9.3 – 0.3	-4.8	-11.7 – -3.9	-8.0	-17.5 – -3.9	-9.9	-22.2 – -4.5
8	1.66	258	170 - 336	8.5	4.0 – 32.0	17.2	8.5 – 43.2	37.1	18.5 – 67.7	57.1	32.3 – 102.1
2	0.24	274	203 - 503	0.5	-4.7 – 3.7	2.0	-3.8 – 11.0	4.8	-1.7 – 13.9	8.7	1.0 – 17.5
4	-0.25	409	236 - 876	-1.4	-6.3 – 2.7	-2.0	-6.7 – 5.3	-2.3	-7.1 – 7.6	-1.5	-6.7 – 8.3
5	-1.06	434	246 - 1322	-2.4	-7.5 – 1.1	-4.1	-9.7 – 2.3	-7.4	-17.8 – 0.7	-9.1	-20.7 – 3.3
7	1.01	515	257 - 856	3.2	0.9 – 12.9	6.0	2.0 – 17.2	12.1	5.1 – 28.2	20.1	8.3 – 41.0
3	0.06	436	273 - 986	0.7	-1.1 – 2.6	1.7	-0.5 – 6.3	3.9	0.0 – 8.9	7.0	0.5 – 14.3
6	0.11	524	344 - 957	0.4	-3.5 – 3.9	0.9	-3.3 – 2.0	2.4	-2.3 – 6.5	4.4	-0.4 – 9.4
LAP	0.01	400	276 - 513	0.5	-0.8 – 2.3	1.4	-0.3 – 3.9	4.0	1.4 – 8.9	7.6	3.2 – 15.8

In order to assess how the magnitude of CO_2 emission varies with road grade over a road segment with two-way traffic flow, the total CO_2 emission over paired sections 1 and 8, 5 and 7, 2 and 4 were calculated. The total CO_2 emission was calculated over each combined section for each of the 48 test runs under the five road grade scenarios. As these section pairs cover the same road segment there is no net change in elevation, so the average grade of each of the combined sections is zero. In Figure 7, the combined sections aggregate CO_2 emissions for each of the road grade coefficients (0.5, 1, 2 and 3) are referenced against the aggregate CO_2 emission over the same combined section with $PHEM_0$. The results indicate that the higher CO_2 emissions on uphill sections are not offset by the lower emission rates on downhill sections. The discrepancy over the combined sections tends to rise as the road grade coefficient applied in the PHEM modelling increases. The magnitude of the increase in emission is greatest where the average road grades of the two sections of opposing traffic flow are steepest.

Figure 7. Percentage Change in the PHEM Aggregate Total CO_2 Emission between $PHEM_{0G}$ and $PHEM_G$ modelled with each Road Grade Coefficient, over the Combined Sections.



It should be noted that the traffic conditions in the road sections that make up the combined pairs can be quite different for each direction of traffic flow, as traffic control measures and traffic volume can cause different levels of congestion, resulting in a wide range of CO_2 emission values in each section (as illustrated in Figure 4). However the results in Figure 7 present the calculated emission from real-world speed profiles recorded throughout the day, and thus these combined emissions should reflect the likely range of CO_2 emission for the test vehicle on these real-world road segments.

7. Summary and Conclusions

Analysis of the PEMS data revealed a wide spectrum of traffic flow conditions captured by the instrumented vehicle repeatedly driving through the urban traffic network, with measurements taken both during peak rush hour congestion and in free flowing traffic conditions. A wide range of CO_2 emission values were recorded (PEMS) over the test lap, ranging from 313 gCO_2/km to 586 gCO_2/km. The measured CO_2 emission values were consistently higher than those predicted by the UK EFT average speed emission curve. The spread of the CO_2 emission values at each speed demonstrates why average speed based emission models may not reliably predict CO_2 emission estimates for short road segments/ sections as they fail to correctly account for acceleration, road grade, drag, rolling resistance and engine speed.

This study has shown that in order to accurately estimate vehicle CO_2 exhaust emissions at a micro-scale in real-world conditions, a representative road grade profile for each second of the test data is needed. The straightforward and quick LiDAR-GIS method proposed in this study provides a methodology for determining road grade for each second of a vehicle journey, and improved the modelling of CO_2 emission for this PEMS data set. The research demonstrates that using the PHEM instantaneous emission model with LiDAR-GIS calculated road grade is a viable method for generating accurate real-world micro-scale CO_2 emission estimates. The results also show that it is incorrect to assume that the increase in emission on uphill sections will be offset by the decrease in emission on paired downhill sections.

The research shows that failing to account for even a relatively modest road grade, when modelling micro-scale vehicle emission, could potentially result in highly inaccurate estimates of real-world emission. Transport management and urban planning projects should be incorporating road grade into their analysis where prediction of vehicle emissions is required.

With the proposal for a PEMS element in Euro 6c type approval from September 2017 (Delphi, 2013) the development of a robust yet practical road grade estimation methodology for PEMS analysis will be very important to assist the analysis of on-road test data and quantify the relationship between power output and exhaust emission. Whilst this research focused on CO_2 emission, it is expected that road grade will have an even greater influence on the emission of other exhaust pollutant such as NO_x where a higher proportion of emissions are related to high power events (Carslaw et al, 2013).

Acknowledgements

David Wyatt is supported by the Doctoral Training Centre in Low Carbon Technologies at the University of Leeds funded through the UK EPSRC. Thanks go to Bob Boreham for his help in the instrumentation of the test vehicle and driving. The PEMS data used in this research was recorded as part of the EPSRC research grant, GR/S31126/01, for the RETEMM (Real-world Traffic Emissions Measurement and Modelling) Project.

References

Bluesky,2013. LiDAR Height Data. http://www.bluesky-world.com/products/lidar/, 05/11/2013.

Boriboonsomsin, K., Barth, M., 2009. Impacts of Road Grade on Fuel Consumption and Carbon Dioxide Emissions Evidenced by Use of Advanced Navigation Systems. Transportation Research Record(2139), 21-30.

Boroujeni, B.Y., Frey, H.C., 2014. Road grade quantification based on global positioning system data obtained from real-world vehicle fuel use and emissions measurements. Atmospheric Environment 85(0), 179-186.

Boroujeni, B.Y., Frey, H.C., Sandhu, G.S., 2013. Road Grade Measurement Using In-Vehicle, Stand-Alone GPS with Barometric Altimeter. Journal of Transportation Engineering-Asce 139(6), 605-611.

Coelho, M.C., Frey, H.C., Rouphail, N.M., Zhai, H., Pelkmans, L., 2009. Assessing methods for comparing emissions from gasoline and diesel light-duty vehicles based on microscale measurements. Transportation Research Part D-Transport and Environment 14(2), 91-99.

Daham, B., Andrews, G.E., Li, H., Ballesteros, R., Bell, M.C., Tate, J., Ropkins, K., 2005. Application of a Portable FTIR for Measuring On-road Emissions. SAE International.

DEFRA,2009. Emission Factors Toolkit for Vehicle Emissions. http://laqm.defra.gov.uk/review-and-assessment/tools/emissions.html#eft., 11/10/2013.

Delphi, 2013. Worldwide Emission Standards: Passenger Cars and Light Duty Vehicles 2013/2014. delphi.com/emissions-pc.

Doucette, R.T., McCulloch, M.D., 2011. Modeling the CO2 emissions from battery electric vehicles given the power generation mixes of different countries. Energy Policy 39(2), 803-811.

Ehsani, M., Gao, Y., Emadi, A., 2009. Modern electric, hybrid electric, and fuel cell vehicles : fundamentals, theory, and design, 2nd ed. ed. CRC ; London : Taylor & Francis [distributor], Boca Raton, Fla.

Ford, 2005. Ford Motor Company Limited. The New Ford Mondeo. Brochure. Published by Ford Motor Company Limited, Brentwood, Essex, England; May 2005.

Frey, H.C., Unal, A., Rouphail, N.M., Colyar, J.D., 2003. On-road measurement of vehicle tailpipe emissions using a portable instrument. Journal of the Air & Waste Management Association 53(8), 992-1002.

GPSVisualizer,2013. GPS Visualizer Website. http://www.gpsvisualizer.com/, 07/10/2013.

Hausberger, S., 2003. Simulation of Real World Vehicle Exhaust Emissions. VKM-THD Mitteilungen; Heft/Vol 82; Verlag der Technischen Universitat Graz 2003, ISBN 3-901351-74-4.
Hausberger, S., Rexis, M., Zallinger, M., Luz, R., 2010. PHEM User Guide for Version 10. Technische Universitat Graz.

Howell, D.C., 2013. Statistical methods for psychology, Eighth edition, International edition. ed.
Jimenez-Palacios, J., 1999. Understanding and quantifying motor vehicle emissions with vehicle specific power and TILDAS remote sensing. , Doctoral Dissertation, Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Koupal, J., Nam, E., Giannelli, B., Bailey, C., 2004. The MOVES Approach to Modal Emission Modeling. Presented at the 14th CRC On-Road Vehicle Emissions Workshop, San Diego, CA.

Li, H., Andrews, G.E., Savvidis, D., Daham, B., Ropkins, K., Bell, M., Tate, J., 2008. Study of Thermal Characteristics and Emissions during Cold Start using an on-board Measuring Method for Modern SI Car Real World Urban Driving. SAE Int. J. Engines 1(1), 804-819.

Liu, H.A., Barth, M., Scora, G., Davis, N., Lents, J., 2010. Using Portable Emission Measurement Systems for Transportation Emissions Studies Comparison with Laboratory Methods. Transportation Research Record(2158), 54-60.

Millin-Chalabi, G., Schumm, J., Gupta, B., Tun, Y., Kandeh, J., Kitmitto, K., 2011. The Landmap Service: Reaching New Horizons in Data Management and E-Learning. RSPSoc Annual Conference 2011, Bournemouth University, UK.

Mock, P., German, J., Bandivadekar, A., Riemersma, I., 2012. Discrepancies between type-approval and “real-world” fuel-consumption and CO2 values. Assessment for 2001-2011 European passenger cars. ICCT Working Paper; April 2012. Paper no 2012-2.

Nakamura, H., Kihara, N., Adachi, M., Ishida, K., 2002. Development of a Wet-based NDIR and Its Application to On-board Emission Measurement System. SAE International.
Racelogic,2008. VBOX II Lite 5Hz GPS Data Logger User Guide. http://www.racelogic.co.uk/_downloads/vbox/Manuals/Data_Loggers/RLVB2L_Manual.pdf, 30/06/2014.

Ropkins, K., Quinn, R., Beebe, J., Li, H., Daham, B., Tate, J., Bell, M., Andrews, G., 2007. Real-world comparison of probe vehicle emissions and fuel consumption using diesel and 5% biodiesel (B5) blend. Science of the Total Environment 376(1-3), 267-284.

Ropkins, K., Tate, J.E., Li, H., Andrews, G.E., Hawley, G., Bell, M.C., 2008. Chassis Dynamometer Evaluation of On-board Exhaust Emission Measurement System Performance in SI Car under Transient Operating Conditions. SAE International.

Sahlholm, P., Johansson, K.H., 2010. Road grade estimation for look-ahead vehicle control using multiple measurement runs. Control Engineering Practice 18(11), 1328-1341.

Smit, R., Smokers, R., Rabe, E., 2007. A new modelling approach for road traffic emissions: VERSIT+. Transportation Research Part D-Transport and Environment 12(6), 414-422.

Song, G.H., Yu, L., 2009. Estimation of Fuel Efficiency of Road Traffic by Characterization of Vehicle-Specific Power and Speed Based on Floating Car Data. Transportation Research Record(2139), 11-20.

Williams, E.J., 1959. The Comparison of Regression Variables. Journal of the Royal Statistical Society Series B-Statistical Methodology 21(2), 396-399.

Zhai, H.B., Frey, H.C., Rouphail, N.M., 2008. A Vehicle-Specific Power Approach to Speed- and Facility-Specific Emissions Estimates for Diesel Transit Buses. Environmental Science & Technology 42(21), 7985-7991.

Zhang, K.S., Frey, H.C., 2006. Road grade estimation for on-road vehicle emissions modeling using light detection and ranging data. Journal of the Air & Waste Management Association 56(6), 777-788.