Route level analysis of road pavement surface condition and truck fleet fuel consumption

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ABSTRACT: Experimental studies have estimated the impact of road surface conditions on vehicle fuel consumption to be up to 5% (Beuving et al., 2004). Similar results have been published by Zaabar and Chatti (2010). However, this was established testing a limited number of vehicles under carefully controlled conditions including, for example, steady speed or coast down and no gradient, amongst others. This paper describes a new "Big Data" approach to validate these estimates at truck fleet and route level, for a motorway in the UK. Modern trucks are fitted with many sensors, used to inform truck fleet managers about vehicle operation including fuel consumption. The same measurements together with data regarding pavement conditions can be used to assess the impact of road surface conditions on fuel economy. They are field data collected for thousands of trucks every day, year on year, across the entire network in the UK. This paper describes the data analysis developed and the initial results on the impact of road surface condition on fuel consumption for journeys of 157 trucks over 42.6km of motorway, over a time period of one year. Validation of the relationship between road pavement surface condition and vehicle fuel consumption will increase confidence in results of LCA analyses including the use phase.

1 INTRODUCTION

In many countries, environmental questions have become an important part of the decision-making process for design and maintenance of highways (Beuving et al., 2004). Therefore, fuel efficiency and limiting greenhouse gas (GHG) emissions of road pavements has become a central focus of many projects and studies all over the world. Life-Cycle Assessment (LCA) aims at evaluating the impacts associated with all stages of a product's life. This method has been used to estimate the long-term impact of pavements on the environment (Santero et al., 2011), but different methodologies can lead to different conclusions (Trupia et al., 2016). This can be because different studies consider different phases of the life of a pavement in their analyses (Santero and Horvath, 2009, Trupia et al., 2016), because of inadequate information available, or because of different models for estimating the effect of road pavement conditions on vehicle fuel consumption (Zaabar and Chatti, 2010).

In the past many pavement LCA studies omitted the Pavement Vehicle Interaction (PVI) and its effects on vehicle fuel economy. PVI represents the impact of the interactions between pavements and vehicles during the use phase of a road. Although the energy losses due to the PVI can be mainly tracked to the tyre properties, the characteristics of the pavement surface, in terms of roughness and macrotexture, can also significantly affect the rolling resistance and therefore the vehicle fuel consumption (Sandberg et al., 2011).

This area of study is particularly interesting for pavement engineering and road agencies, because of the opportunity to reduce the fuel consumption associated with the road surface condition through conventional maintenance strategies. Pavement condition improvements, based on the reduction of rolling resistance, by controlling pavement roughness and texture depth, can be made rapidly using available technology, and have the potential to generate significant energy and cost savings, and reductions in GHG emissions. By contrast, approaches involving improvements in vehicle technology or traffic reduction can be more complicated and require longer implementation periods.

Calculating the impact of pavement surface properties on the rolling resistance and then on vehicle fuel consumption is complex, although some studies have been performed over the last years (Wang et al., 2012a; Wang et al., 2012b; Hammarström et al., 2012) to analyze this component and its impact in a pavement LCA. These studies, as well as showing the relevance of the impact of surface condition on a pavement LCA, have developed and implemented some models correlating pavement surface properties to vehicle fuel consumption.

A recent study (Trupia et al., 2016) has analyzed the implications of using different rolling resistance models calibrated in different geographical locations for a UK case study. They concluded that some methodological choices and site-specific elements can play a significant role in the development of these models, producing rolling resistance and fuel consumption models that are not suitable for all geographic locations. In addition, the LCA results are sensitive to the chosen model and can generate significantly different findings, reducing confidence in their use for LCA studies. For UK roads, there are not yet any general rolling resistance and fuel consumption models, able to predict the relationship between pavement surface properties and fuel economy, based on local conditions. Further research is needed in this area before introducing this component in the pavement LCA framework with confidence.

Recent studies assessed that road surface conditions account for approximately 5% of the total fuel consumption of road vehicles (Beuving et al., 2004 and Zaabar and Chatti, 2010). In England, the 2% reduction in fuel consumption assumed by Zaabar and Chatti (2010), would mean a saving of up to £1 billion a year (considering the current cost of fuel) which corresponds to a quarter of the funding spent in maintenance of local highways (House of Commons, 2011).

Zaabar and Chatti (2010) calibrated their model for US conditions, using a limited number of vehicles tested under carefully controlled conditions (e.g. steady speed) along selected road segments (with selected geometry). This can reduce the range of validity of the study first to the US and second to specific vehicle models and road conditions.

Other studies on the topic (Hammarström et al., 2012) used coast-down measurements (in order to exclude the impact of road gradient on the fuel consumption measurements) or cruise control (no change in direction and vehicle speed) performing the tests only in good weather conditions (e.g. wind speed <4m/s). This controls the variables in an experimental method to improve the repeatability of results but does not reflect what happens at route level under real driving conditions.

Nowadays, truck fleet managers analyse fleet performance to reduce vehicle operating costs by: 1) training drivers and 2) maintaining vehicles. Previous studies (e.g. Atkinson and Postle, 1977, and Evans, 1979 among others) demonstrated the high impact of the driver behaviour and poor maintenance on vehicle fuel economy. Data are collected by sensors that are installed on trucks as standard (SAE International, 2002), and measure the vehicle fuel usage, the vehicle speed, its direction and position, the engine performance, among many other parameters. These data are collected continuously during vehicle use. Road agencies monitor road surface condition for decision making about pavement maintenance. Data are usually collected on an annual basis, including measurements of the pavement surface condition and structural strength, etc.

Using these data, it may be possible to validate the results of experimental studies for specific routes and vehicle types during operation. This is important because for instance, the truck fleet in the US is different to that in Europe. Different payloads are allowed, different tyres are used, different engines are installed, and different speed limits are set. As assessed by many different authors in the past from Sandberg (1990) to Zaabar and Chatti (2010), the impact that these variables can have on fuel economy is much larger than that of pavement surface conditions. Using truck fleet data may allow fuel efficiency models to be calibrated for different geographical areas and fleet composition.

In this paper we report the results of an initial study to test the feasibility of using truck fleet data for a motorway in England, to establish the impact of pavement surface texture depth and roughness on truck fuel efficiency. The results are compared to those of some previous studies and discussed in terms of LCA and its role in decision making for road maintenance strategies.

2 DATA

The truck data are recorded every time an 'event' is triggered at any brake, stop, anomaly, or routinely each 2 minutes (120 s) or 2 miles (~3,219 m). From hundreds of gigabytes of data that each single vehicle's performance database contains, this study considers:

- the vehicle profile, identifying the vehicle and its main characteristics,
- the tracker ID reference for the system of sensors installed,
- the geographical position of the truck, (5 m GPS precision),
- the distance travelled by the vehicle since the previous event (m),
- the time spent by the vehicle to travel to the current position from the previous event (s),
- the total fuel consumed until the current event is recorded (0.001 litres precision, rounded to 0.1 litres for the purpose of reducing database size),
- the air temperature (0.1ºC precision),
- the current gear,
- the current engine torque percentage,
- the engine revolutions (revs/mins).

The Highway Asset Performance Management System (HAPMS) is the database owned and used by Highways England to monitor the condition of the strategic road network in England. The database contains historical information and condition measurements, including:

- a road identifier code,
- a direction code,
- the year of construction,
- the latest date of significant maintenance,
- the construction materials,
- gradient
- roughness measurements (longitudinal profile variance (LPV)),
- texture measurement (sensor-measured texture depth (SMTD),
- skid resistance measurement (not considered in this study),
- deflection measurement (not considered in this study).

In this initial study only information about road surface condition is taken from HAPMS. This includes measurements of roughness (Longitudinal Profile Variance, LPV, at 3 and 10 metres in mm^2), texture (Sensor-Measured Texture Depth (SMTD) in mm), skid resistance (SCRIM Coefficient), and road gradient (0.1% resolution). These are the most common parameters used in England for road condition monitoring. Previous studies typically used IRI (International Roughness Index) as a measurement of roughness and MPD (Mean Profile Depth) as a measurement of texture. Benbow et al. (2006) and Viner et al. (2006) established that these roughness and texture parameters are closely related.

3 METHOD

In this initial study, data from trucks driven on M18 (near Doncaster, England) in 2015 where considered. The M18 motorway has been chosen because of its wide range of pavement surfaces, including asphalt and concrete. To the initial 910,591 records available the following filters were applied:

- 3-axle tractor and 3-axle trailer articulated trucks with Euro 5 or Euro 6 engine.
- measurements recorded at the default time or distance (i.e. no other driving event (e.g. harsh braking or cornering) triggered the record),
- speed is steady and set to an average of 85km/h (±2.5km/h),
- no gear change (gear 12, the most commonly used gear at 85km/h was selected).

These filters were applied in this initial study to reduce the effect of other variables and isolate the effect of pavement surface condition on truck fleet fuel economy. Data from 157 articulated trucks driving along the M18 in 2015 remained to be considered in this study. In all, 3677 records are available.

Of these, 1707 data points are for articulated trucks equipped with 12,419cc, Euro 6 engine and 1970 data points are available for the same type of vehicles but with Euro 5 engine.

Based on the literature review the payload and the gradient are two of the most influential variables on fuel consumption (Sandberg, 1990, Beuving et al., 2004). However, no data about the payload is currently available for this study. Therefore, the generated engine torque (as percentage of the maximum) is used instead. In this initial study the impact of the pavement type is not considered. Recent studies have claimed that the differences in fuel consumption between asphalt and concrete pavements is less significant than the impact of surface condition (Beuving et al., 2004). The engine torque percentage, the road gradient, LPV at 3 and 10 metres wavelength and SMTD texture measurements are considered. Performing a backward analysis based on the Aikake Information Criterion (AIC (Aikake, 1973)), a predictive model for fuel consumption (l/100km) has been generated. Among all the possible models, the one that shows the lowest AIC coefficient is considered. Finally the two subsets of data for the two engine types, their distribution, and the generated models are compared.

4 RESULTS

The two datasets (Euro 5 and Euro 6 engine) show very similar mean fuel consumption and standard deviation (see Table 1). However, the fuel consumption data is multi-modal, which probably reflects the resolution of the recorded values. A Kolmogorov-Smirnov two-sample test excludes the hypothesis that the two datasets come from the same population.

Vehicles	Avg Fuel Consumption (l/100km)	Standard Deviation (σ)
Euro 5	28.93	9.58
Euro 6	28.66	9.47

Table 1 - Average and standard deviation for fuel consumption data of Euro 5 and Euro 6 articulated trucks driven on M18 at 85km/h using gear 12.

The following table summarises the range of data included in the analysis:

Statistic	Engine Torque (%)	Road Gradient (%)	LPV10m Roughness (mm^2)	SMTD Texture (mm)
Mean	33.1	0.46	0.87	1.22
Maximum	99.0	3.26	5.62	1.96
Minimum	0.00	-1.85	0.22	0.46
Standard dev.	22.4	0.72	0.36	0.22

Table 2 – Summary of the data included in the analysis. For each value the mean, the maximum, the minimum, and the standard deviation statistics are provided.

Separate backward AIC analyses have been performed on the two datasets. It is possible to see that in both cases the generated models include only the profile variance (LPV) at 10 metres and the texture (SMTD) in the model. Therefore, of those included, they may be identified as the most impactful road condition measurements on fuel consumption. This is a confirmation of previous studies (e.g. Sandberg, 1990, Beuving et al., 2004, Zaabar and Chatti, 2010).

For the Euro 5 dataset the following equation has been obtained:

$$FC = 19.18 + 0.066T\% + 6.85g\% + 1.91LPV10 + 2.77t \quad (1)$$

where, FC = predicted fuel consumption [l/100km]; $T\%$ = engine torque percentage [%]; $g\%$ = road gradient [%]; $LPV10$ = Longitudinal Profile Variance at 10m wavelength [mm^2]; t = texture depth [mm].

In this case, the correlation coefficient (r) between the predicted and the measured fuel consumption is 0.54 (Figure 1).

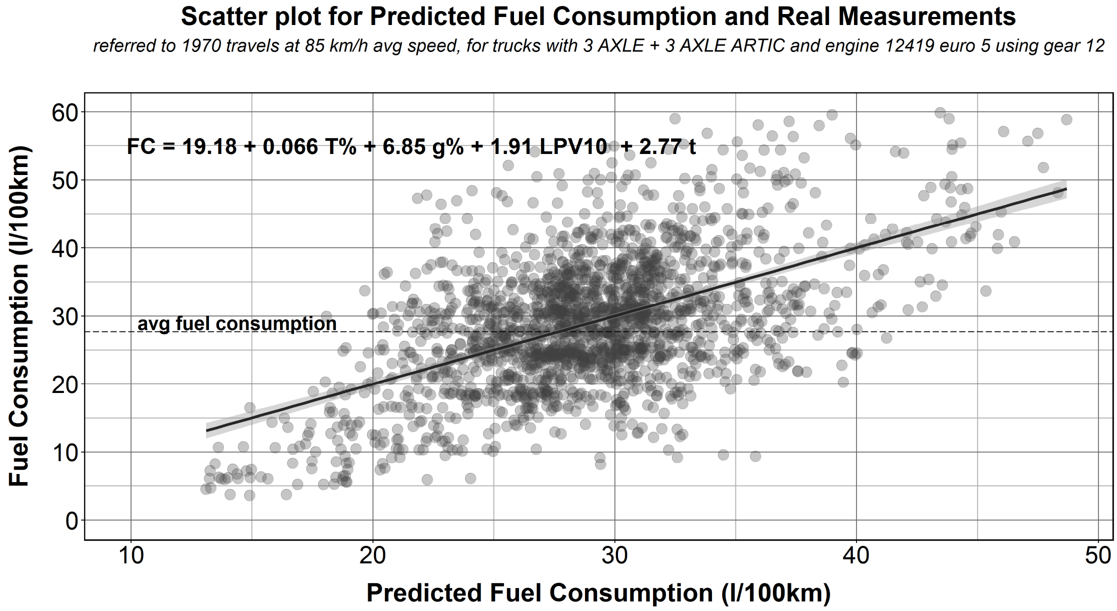

Figure 1 – Comparison between predicted value and fuel consumption measurements for articulated trucks, equipped with 12419cc engines Euro 5 driven at 85km/h using gear 12 only.

For the Euro 6 dataset the following model has been generated:

$$FC = 17.17 + 0.067T\% + 7.57g\% + 1.40LPV10 + 3.10t \quad (2)$$

The correlation coefficient (r) between the predicted and the measured fuel consumption is 0.66 (Figure 2).

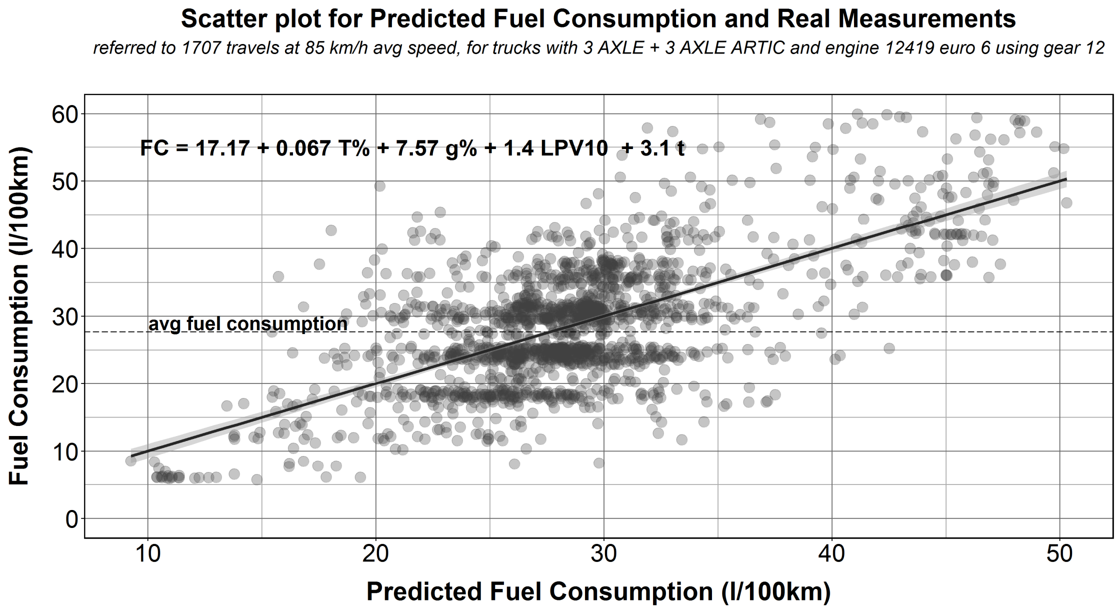

Figure 2 – Comparison between predicted value and fuel consumption measurements for articulated trucks, equipped with 12419cc engines Euro 6 driven at 85km/h using gear 12 only.

5 DISCUSSION

The two generated models (equations (1) and (2)) show similar results. Both the models tend to overestimate low fuel consumption and underestimate high fuel consumption, however the same behaviour was obtained by Zaabar and Chatti (2010). The model for the Euro 5 trucks shows that up to 4.5% of the fuel consumption depends on the level of roughness along the M18. On the other hand up to 4.1% of fuel consumption depends on roughness along the M18 for the considered Euro 6 trucks. Zaabar and Chatti (2010) claimed that the roughness can affect approximately 5% of the fuel consumption. The fact that the first results of this study agree with those of previous studies (Beuving et al., 2004, Zaabar and Chatti, 2010) gives us confidence in using the Big Data approach. While these two initial models have identified the same pavement surface condition measurements as the most significant from those tested, the correlation coefficients between the measured and predicted fuel consumption show the models are far from explaining all the variability in the data. This may in part be due to the influence of unmeasured factors, including for instance, the pavement type, or meteorological factors like the air temperature or the wind speed and direction, among others. It is also probably due to the lack of a direct measure of payload and the use of engine torque as a surrogate. Further work will attempt to address this factor by estimating the payload using a physical-mechanical model. It may be possible to validate such a model for a limited number of trucks using fleet manager's information about delivery schedules or with limited trials of trucks with measured payloads. It may also be possible to record more frequent and precise fuel consumption data for a limited number of trucks. More sophisticated techniques for modelling and noise reduction will also be tested. It is hoped that using these approaches, better predictions will be obtained providing further confidence in the use of Big Data to estimating PVI fuel consumption.

Previous research (Sandberg, 1990, Beuving et al., 2004, and Zaabar and Chatti, 2010, among others) has shown that the impact of PVI on fuel consumption is also significant for smaller vehicles. However, at the moment, the study considers only 3-axle tractor and 3-axle trailer articulated trucks due to the fact that they are the most common type in the dataset of the considered fleet.

The initial results obtained in this paper demonstrate the feasibility of using the Big Data approach to make a fleet and route level analysis to estimate fuel consumption due to PVI. The further work that is planned is intended to generate estimates that will be suitable to be introduced into pavement LCA studies, including the use phase, for UK case studies. A similar approach should be possible in other countries. Assessing this impact at a more general level using a Big Data approach will represent an important step in the development of consistent and accurate PVI fuel consumption models. Further research, to extend this approach to all types of vehicles is necessary to improve confidence in introducing the PVI component into road pavement LCA studies.

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