Verification of the HDM-4 fuel consumption model using a Big Data approach: a UK case study

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ABSTRACT

This paper presents an assessment of the accuracy of the HDM-4 fuel consumption model calibrated for the United Kingdom and evaluates the need for further calibration of the model. The study focuses on HGVs and compares estimates made by HDM-4 to measurements from a large fleet of vehicles driving on motorways in England. The data was obtained from the telematic database of truck fleet managers (SAE J1939) and includes three types of HGVs: light, medium and heavy trucks. Some 19,991 records from 1,645 trucks are available in total. These represent records of trucks driving at constant speed along part of the M1 and the M18, two motorways in England.

These conditions have been simulated in HDM-4 by computing fuel consumption for each truck type driving at a constant speed of 85 km/h on a flat and straight road segment in good condition.

Estimates are compared to real measurements under two separate sets of assumptions. First, the HDM-4 model calibrated for the UK has been used. Then, the model was updated to take into account vehicle weight and frontal area specific to the considered vehicles.

The paper shows that the current calibration of HDM-4 for the United Kingdom already requires recalibration. The quality of the model estimates can be improved significantly by updating vehicle weight and frontal area in HDM-4. The use of HGV fleet and network condition data as described in this paper provides an opportunity to verify HDM-4 continuously.

1 Introduction

The Highway Development and Management software (HDM-4) (Kerali, Odoki, *et al.*, 2006) is a powerful decision support tool developed by the World Bank and used by road agencies and managers of road infrastructure in various applications worldwide (e.g. Jianhua et al. 2004; Thube 2011; Valdés et al. 2011; Prasad et al. 2013; Odoki 2016). HDM-4 includes dedicated tools that cover the management processes of highway infrastructures including planning, evaluation of investments, work programming, etc., that helps engineers in decision making at a strategic level. One of the models implemented in HDM-4 aims to estimate the fuel consumption of road vehicles. Recently, several studies (e.g. Zhou & Jin 2017; Rakha et al. 2011; Wang & Rakha 2017; Chen et al. 2017) focused on modelling the fuel consumption of road vehicles, as this represents an important source of greenhouse gas emissions from the road transport industry (EEA, 2017; EPA, 2017a). A better understanding of the phenomena and the ability to estimate the fuel required by road vehicles is essential for optimising operational costs and emissions. Recently, reductions in emissions have been achieved through new engine technologies (NAS, 2015), eco-routing (Zhou, Jin, *et al.*, 2016) and training of drivers (Ferreira, Almeida, *et al.*, 2015; Walnum and Simonsen, 2015; Figueredo, Agrawal, *et al.*, 2017).

However, recent studies highlighted that the fuel consumption of road vehicles can also be affected by the conditions of the road infrastructure due to the effect of rolling resistance related parameters such as unevenness and macrotexture of the road surface (e.g. Sandberg, Bergiers, *et al.*, 2011; Chatti and Zaabar, 2012; Haider and Conter, 2012; Benbow, Brittain, *et al.*, 2013; Ejsmont, Ronowski, *et al.*, 2017). This represents an opportunity for the road agencies to evaluate the performance of their assets in the use-phase and can support decision making in regards to maintenance and rehabilitation (M&R) of the infrastructure.

Although many tools have been proposed recently to estimate the fuel consumption of road vehicles (e.g. Rakha, Ahn, *et al.*, 2011; Chen, Zhu, *et al.*, 2017; Wang, Rakha, *et al.*, 2017; Zhou and Jin, 2017), HDM-4 is still the most widely used in practice. In particular, the model is commonly adopted by engineers in the field of road asset management for conducting road pavement life-cycle cost analyses as it allows an estimate of the socio-economic and environmental impacts that poor condition of the road surface can generate (e.g. Carlson, Hammarström, *et al.*, 2013; FHWA, 2016; Trupia, Parry, *et al.*, 2016). However, before the model can be used with confidence it must be calibrated to local conditions (Bennett and Paterson, 2000).

In the United Kingdom (UK), calibration of HDM-4 has been performed relatively recently (University of Birmingham, 2011; Odoki, Anyala, *et al.*, 2013). However, not all the calibration factors and parameters of this analysis are currently published. Recently, similar studies have been conducted in the United States with a good level of accuracy (Zaabar and Chatti, 2010; Chatti and Zaabar, 2012; Jiao and Bienvenu, 2015). These studies are based on a limited set of field trials, testing a small pool of vehicles, on selected road segments, considering limited weather conditions, with vehicles driving at a constant speed. However, no validation of these results has been made and findings have been compared only to the test conditions. Therefore, it is not clear whether those estimates reflect the fuel consumption of road vehicles driving across the network under real drive-cycle conditions. In fact, many other countries are performing similar tests to adapt HDM-4 to their local conditions (e.g. Chai, Akli, *et al.*, 2004; Thube, 2011; Valdés, Hidalgo, *et al.*, 2011; Aswathy, Koshy, *et al.*, 2013; Prasad, Swamy, *et al.*, 2013; Odoki, 2016), requiring significant investments and years of analysis to complete. A question regarding this approach is how long the model can be reasonably used after calibration. For example, it is not clear if the model calibrated based on tests performed in the first decade of the century, as in the studies of Odoki et al. (2013), Zaabar & Chatti (2010) and Chatti & Zaabar (2012), using older vehicles, can be used to estimate the fuel consumption of those in use now. It is also unclear if the methodology used to calibrate HDM-4 and similar models, using controlled drive cycles and limited vehicles and test durations, is the most appropriate.

'Big Data' is characterised as being of large volume; from a variety of sources; of often unknown quality or veracity; and being streamed at high velocity (IBM, 2018). Today, a large quantity of information is available regarding the performance of the actual vehicle fleet, owned by heavy good vehicle (HGV > 3.5 t) fleet managers and manufacturers. This truck fleet data, together with the data collected by road agencies to monitor the condition of the infrastructure might be used for calibrating or updating HDM-4, potentially replacing the need for current expensive and time consuming experimental campaigns.

2 Aim & Objectives

The objective of this study is to verify the accuracy of the HDM-4 model, calibrated for the UK, for estimating the fuel consumption of modern trucks. This is done by comparing results of the model with real measurements from a large truck fleet database. We discuss the differences between the model estimates and the available data, highlighting possible effects on strategic decisions of managers of the road infrastructure. Finally, the paper suggests potential improvements to the current calibration of HDM-4 in the UK and a new method for calibration of this and similar analytical models using Big Data.

3 Methodology

3.1 The HDM-4 fuel consumption model

The HDM-4 model is derived from the HDM-III mechanistic model as described in Bennett & Greenwood (2000). The model provides an equation for estimating the amount of fuel consumed as a function of the power required by the vehicle for traction, plus an additional term that describes the power spent by accessories (e.g. air conditioning) and inefficiencies of the engine:

$$IFC = f(P_{tr}, P_{accs} + P_{eng}) = \max(\alpha, \xi \times P_{tot} \times (1 + d_{Fuel})) \tag{1}$$

where *IFC* is the instantaneous fuel consumption (ml/s), P_{tot} the total power required (kW), P_{tr} the power required for traction (kW) (see Equation 2), P_{accs} the power required by accessories in the vehicle (kW), P_{eng} the power required to overcome the internal friction in the engine (kW), α the fuel consumption at idling (ml/s), ξ the engine efficiency (ml/kW/s), and d_{Fuel} the excess fuel consumption caused by congestion (ml/s).

In particular, the P_{tr} component contains the effect of aerodynamics, road geometry, rolling resistance, and inertial forces:

$$P_{tr} = \upsilon \frac{F_a + F_g + F_c + F_r + F_i}{1000} \tag{2}$$

where F_a represents the aerodynamic forces (N), F_g represents the gradient forces (N), F_c represents the curvature forces (N), Fi represents inertial forces (N) and Fr represents the rolling resistance forces (N), estimated by:

$$Fr = CR_2 \times FCLIM \times (b_{11} \times N_w + CR_1 \times (b_{12} \times M + b_{13} \times v^2)) \quad (3)$$

where CR_1 is the rolling resistance factor specific to the tire, *FCLIM* is a factor depending on the driving conditions (presence of snow or water on the road surface), CR_2 is the rolling resistance coefficient specific to the road surface conditions (including roughness, macrotexture, and deflection of the road), N_w is the number of wheels (tires), and b_{11}, b_{12} and b_{13} are coefficients depending on the type and dimensions of the wheels. Further details of the model can be found in Bennett & Greenwood (2000), Bennett & Paterson (2000), Chatti & Zaabar (2012), Kerali et al. (2006), Jiao & Bienvenu (2015) and Odoki et al. (2013).

3.2 Data requirements

The accuracy required for a model is dictated by the objectives of the analysis. Therefore, Bennett & Paterson (2000) define three levels of calibration dependent on the target accuracy and objective of an analysis:

- *Level I: Basic Application*: this determines the values of basic input parameters, adopts many default values, and calibrates the most sensitive parameters with best estimates based on experience, desk studies and/or minimal field surveys.
- *Level II: Verification*: this involves moderate field surveys and measurement of additional input parameters required to calibrate key relations to local conditions.
- *Level III: Adaptation*: in this calibration major field surveys and controlled experiments are performed for enhancing the current relationships or developing new and locally specific relationships.

Input data required for configuring the HDM-4 model can be summarized as follows (Kerali, Odoki, *et al.*, 2006):

- *Road network data*, including geometry, type of pavement, pavement strength and condition (e.g. measurements of roughness, macrotexture, percentage of cracks, frequency of potholes, etc.).
- *Vehicle fleet data*, including vehicle physical and loading characteristics, utilisation and service life, performance characteristics such as driving power and braking power, and unit costs of vehicle resources.
- *Traffic data*, including details of composition, volumes and growth rates, speed-flow types and hourly traffic flow pattern on each road section.
- *Road works data*, comprising historical records of works performed on different road sections, a range of road maintenance activities practised in the country and their associated unit costs.
- *Weather conditions*, characterising the geographical area considered.
- *Economic analysis parameters*, including the value of time, discount rate and base year.

The reliability of the results obtained depends mainly on how well the data provided to the model represent current conditions and influencing factors, and how well the predictions of the model fit the real behaviour and the interactions between all factors involved, for the variety of conditions to which the model is applied (Bennett and Paterson, 2000).

3.3 Big Data

Modern truck logistics and telematic databases include terabytes of data on vehicle performance. This information is used by fleet managers for making decisions to improve economy and safety, and maximize utilization. The data collected include much of that needed to adapt HDM-4 to local conditions, meaning that level II and level III calibration of the model may be possible using existing data sources. In the UK, data are available regarding road conditions in terms of materials, roughness, macrotexture and strength. For the strategic road network in England, this is stored in the Highways Agency Pavement Management System (HAPMS) database owned by Highways England. The Department for Transport collects statistics about traffic volume and composition of the vehicle fleet driving in the UK, and the Met Office owns historical and real time weather data from hundreds of weather stations distributed across the country.

These represent most of the data needed to calibrate HDM-4 and are already available in the UK, owned and stored in the database of different organisations in various sectors. The present study aims to investigate the use of some of the data available to verify the current state of calibration of the HDM-4 fuel consumption model in the UK and shows that this information can be used to recalibrate the model without performing any further experimental campaign. This new method could find application in other countries where similar data is collected and that in the future, it could become standard for calibration of HDM-4.

Although the accuracy of these data may need to be verified and may not be optimal to calibrate HDM-4 to its maximum level of calibration (level III adaptation), using the large quantity of information available may be a quick, effective, reliable and inexpensive solution compared to expensive and time consuming bespoke data collection programs. Moreover, these data have another significant advantage in comparison with the experimental ones, in that they are collected directly from the field and can be considered representative of what happens at the network level in real conditions.

Although in this paper we consider only a small sample of the data that is continuously collected by companies in England, we refer to this as ‘Big Data’. That is because the data is collected continuously in real-time (high velocity) from vehicles driving all around England (high volume), they come from different sources (variety) and are of different or unstated levels of accuracy (veracity). Additionally, we assume that due to the extent of the road network analysed in the study we can consider the data available are representative of conditions for motorways in England.

In the following sections, further details regarding the description, origin and collection method of the data used in the study are given.

3.3.1 Truck telematic data

According to SAE International (2016) regulations, modern trucks are equipped with sensors that collect data and inform managers on the performance of their fleets allowing them to plan maintenance for their vehicles and training of the drivers. Microlise Ltd, a transport technology and telematic company, collects this type of data to support fleet operators. The data collected by Microlise include the estimated vehicle weight (± 400 kg, calculated by a proprietary algorithm based on engine parameters), the velocity (in m/s), geographical position (in WGS84), the torque percentage and revolutions (in rpm) used by the engine, use of cruise control, acceleration, and fuel consumption (reported to the nearest 0.001 l), among other parameters. Although SAE J1939 sensors and the accuracy of the data collected are not specifically designed to perform calibration of HDM-4 or similar models, advantages of using these data are a) their quantity, meaning that on average they should give reliable figures and b) the fact that they represent what happens at network level under real driving conditions. From sensors, the data flow to an Electronic Control Unit (ECU) which collects and transmits them telematically (SAE International, 2016). This is why fleet managers usually refer to this data as ‘telematic data’. Similar information, from a limited number of trucks tested in carefully controlled conditions, have been used in the past by Zaabar and Chatti (2010) to calibrate the HDM-4 fuel consumption model in the United States

(Chatti and Zaabar, 2012). This information, from trucks driving on a daily basis across the road network, could also be used either to calibrate or to update HDM-4 continuously or on a regular basis, depending on the needs of the highway authority. However, the available data (offered anonymized for research purposes by Microlise) are currently standard only for trucks and light duty vehicles, and not for cars or motorbikes. For this reason, this study focuses only on HGVs and specifically on trucks; however, the same methodology could be applied to smaller vehicles if similar data were available. By default, the system used by Microlise triggers a data record every 1 minute or 1 mile (~1,609 meters). However, the frequency of data collection can be changed by modifying the software controlling the telematic unit and depends on the customers' requirements. Each data record includes information regarding the vehicle type, its configuration of axles, performance of its engine (e.g. torque and revolutions), its speed, its GPS location and the cumulative fuel used in 0.001 litres resolution, etc.

3.3.2 Real fuel consumption

For each record, cumulative fuel usage is calculated by the ECU based on a number of sensor readings (e.g. air flow, engine temperature, throttle position, engine speed, etc.) (SAE International, 2016). Then fuel consumption is calculated based on the difference in cumulative fuel usage between consecutive records. Data are then filtered to include only trucks driving at a constant speed between consecutive records. In order for the speed to be considered constant, the absolute difference between the average of the initial and final speeds and the average speed must be lower than or equal to 2.50 km/h. This reflects the assumption of constant speed in the experiments generally used to calibrate HDM-4 (level III adaptation) in previous studies (e.g. Zaabar and Chatti, 2010; Chatti and Zaabar, 2012; Jiao and Bienvenu, 2015).

In total, 19,991 records from 1,645 vehicles driving at constant speed on part of the M1 and the whole M18 during a week in October 2016 were considered. Although selecting a specific month of the year might introduce some bias in the data, in order to minimize the effect of this on the results of the analysis, a month with mean temperature and traffic similar to the annual means was selected.

The whole length of the considered motorway sections is about 300 km. These motorways are in good condition, representative of the Strategic Road Network, which carries over 75% of truck traffic (DfT, 2018) in England, UK.

The data include information from three types of vehicle; 14,281 records from 1,110 heavy HGVs , 5,423 records from 473 medium HGVs, and 286 records from 61 light HGVs. For simplicity, in the following, these are going to be referred as heavy, medium and light trucks respectively. Classes are defined based on the average vehicle weight in line with the vehicle weight classification by EPA (2017b).

3.3.3 Road characteristics

After calibration, the HDM-4 fuel consumption model is able to estimate the impact of road surface condition on vehicle fuel economy (Bennett and Greenwood, 2000). For this task, HDM-4 requires users to input measurements of roughness and macrotexture measured as IRI (International Roughness Index) and MPD (Mean Profile Depth), respectively (Bennett and Greenwood, 2000). HAPMS includes information about construction and maintenance history, road geometry and pavement surface conditions, among other parameters. This is usually collected every 10 metres by a monitoring vehicle and used mostly for quality control and strategic decision making regarding M&R of the infrastructure (The Highways Agency, 2008). The database is accessible online through authorization of Highways England, however, in the UK road roughness and macrotexture are measured as Longitudinal Profile Variance (LPV, in mm^2) at 3, 10 and 30 metres and as Sensor-Measured Texture Depth (SMTD, in mm), respectively. Independent research carried out in the United Kingdom showed that LPV and SMTD are closely related to IRI and MPD (Viner et al., 2006; Benbow et al., 2011). In particular, Benbow et al. (2011) (Equation 4) showed that IRI can be derived from LPV at 3 and 10 metre wavelengths and Viner et al. (2006) (Equation 5) that MPD can be estimated from SMTD measurements:

$$IRI = \max(\sqrt{10 \cdot LPV03m/3} + \sqrt{LPV10m} - 0.1, 0) \quad (4)$$

$$MPD = 1.42 \cdot SMTD^{0.840} \quad (5)$$

These equations, characteristic of UK conditions, have been used to transform the data in HAPMS from LPV and SMTD to IRI and MPD, respectively.The average of IRI and MPD was used to characterize the considered road segments (M1 and M18). Based on Annex 2A of TD 29/08 in the Design Manual for Road and Bridges (DMRB) (The Highways Agency, 2008), which specifies maintenance thresholds in the UK, these results represent a road segment in good condition. Additionally, because the average road gradient on M1 and M18 is approximately zero (with low standard deviation) a flat road segment has been stipulated in HDM-4. In fact, based on the DMRB (The Highways Agency, 2002) the maximum road gradient generally allowed on motorways in the UK is ± 3%. Also, average road radius on M1 and M18 is about 2000 m or more, which can be considered characteristic of a fairly straight road which, again, is reasonable for a motorway in the UK (The Highways Agency, 2002). In consideration of the extent of the road network analyzed, this can be considered representative of motorways in the UK. To summarize, road characteristics have been simulated in HDM-4 by analysing a flat and straight road segment in good condition. It is possible to find full details of the parameters used to characterize the analysed segment of road in Tables 3 and 4 below.

3.4 Application to the UK case study

This study uses the information from the Odoki et al. (2013) calibration to configure the HDM-4 fuel consumption model and obtain estimates of fuel consumption for trucks driving on a motorway in the UK. In the 2011 HDM-4 calibration (University of Birmingham, 2011), two types of trucks described as ‘rigid’ and ‘articulated’ were identified to be representative of the vehicle fleet in the UK. These were modelled in HDM-4 using the fuel consumption models for ‘medium trucks’ and ‘articulated trucks’ types, respectively. However, looking at the available telematic data from Microlise Ltd, three different types of trucks with different average vehicle weight and median fuel consumption can be identified. These are 1) light, 2) medium, and 3) heavy trucks classified, as already mentioned earlier in the text, based on their average vehicle weight (EPA, 2017b) (see Table 1 and Table 2 for details).

Table 1

Qualitative description of the considered vehicle types.

Type	Base type	Measured FC** (l/100km)
Light trucks	Light	15.50
Medium trucks	Medium*	23.33
Heavy trucks	Articulated*	26.50

* as defined in University of Birmingham (2011).

** the median of observed fuel consumption.

Two separate applications of the HDM-4 models have been performed for the UK case study for three types of vehicles. In the first application of the HDM-4 model (Base case), all parameters have been set in accordance with the results of the calibration performed by University of Birmingham, (2011) and Odoki, Anyala, *et al.* (2013) if available (see Table 2, Table 3 and Table 4 for details). The default values have been used otherwise. Because light trucks have not been considered by Odoki, Anyala, *et al.* (2013) all default values have been used for this type of vehicle. In the second application of HDM-4 (Update case), the gross vehicle weight and the frontal area have been updated to the mean values found in the telematic data and technical sheets from truck manufacturers, respectively. These were chosen as previous research (e.g. Saltzman and Meyer, 1999; Hammache, Michaelian, *et al.*, 2001; Coyle, 2007; Franzese, 2011; Woodrooffe, 2014) identified them to be among the most impactful factors on vehicle fuel consumption within the available data. This type of analysis corresponds to a basic application (level I calibration) of the HDM-4 model (Bennett and Paterson, 2000). Calculation of fuel consumption was performed for all the considered types of vehicles without changing the default values for the calibration factors for rolling resistance, accessories and engine power as no information on these is reported in University of Birmingham (2011) or Odoki et al. (2013). In University of Birmingham (2011), the ‘operating weight’ of the vehicle (required by the HDM-4 fuel consumption model) was set to the maximum allowed by law for medium and articulated trucks in the UK (GOV.UK, 2018). However, trucks do not always travel at full payload and because of this their fuel consumption varies. For this reason, in the second application (Update case) of HDM-4 an average vehicle weight from the telematic data, approximated to the nearest ton, was used to update this parameter (see Table 2 for details).

Table 2

Summary of the major parameters used in HDM-4 to characterize the considered fleet of trucks.

Parameter	Light trucks		Medium trucks		Heavy trucks	
	Base case	Update case	Base case	Update case	Base case	Update case
No. of wheels	4	4	6	6	10	10
No. of axles	2	2	3	3	5	5
Wheel type	Radial	Radial	Bias	Bias	Bias	Bias
Operating weight	3.5 t	7.0* t	38.0 t	21.7* t	44.0 t	26.8* t
Frontal area	4.0 m^2	4.5** m^2	5.0 m^2	5.0** m^2	9.0 m^2	7.0** m^2

N.B.: Most of the calibration parameters are set to the default values as these are not publicly available for the UK calibration (University of Birmingham, 2011; Odoki, Anyala, *et al.*, 2013). These can be found in the manuals of HDM-4.

* set as the average gross vehicle weight of trucks in the analysed telematic data.

** set as found in technical sheets of truck manufacturers.

In regards to the road characteristics, these have been defined in HDM-4 in order to reflect the conditions of motorways in the UK. Because the data considers only trucks driving at constant speed, the effect of traffic congestion has not been considered and the traffic flow pattern set to ‘free-flow’. A full list of the considered road network characteristics simulated in HDM-4 can be found in Table 3 and Table 4. These parameters have been set as described by University of Birmingham (2011).

Table 3

Summary of the major parameters used in HDM-4 to characterize the analyzed road segment simulating the characteristics of a motorway in England, UK.

Characteristic	Value	Units
Type of road	Primary or trunk	[-]
Climate Zone	England local*	[-]
Traffic flow pattern	Free-Flow	[-]
AADT (daily traffic)	12,500*	[vehicles]
Flow direction	One-way uphill	[-]
Surface class	Bituminous	[-]
Speed flow type	SF5	[-]
Accident class	AC3	[-]
Length	1.0	[km]
Carriageway width	16.0	[m]
Shoulder width	1.0	[m]
Rise + Fall	0.0	[%]
Speed limit	85**	[km/h]
Average horizontal curvature	3	[deg/km]
Qualitative conditions	‘Good’***	[-]
Drainage	‘Excellent’	[-]

* climate and distributions of traffic are defined in Table 5.

** average vehicle speed on M1 and M18 for the considered fleet of trucks (telematic data).

*** see Table 4 for further details.

Table 4

Summary of the major parameters used in HDM-4 to characterize the performance of the pavement (M1 & M18, in England).

Characteristic	Value	Units
Roughness (IRI)	1.6	[m/km]
Macrotexture (MPD)	1.1	[mm]
Cracks	0	[%]
No. potholes	0	[No./km]
Mean rut depth	2.5	[mm]
Skid resistance	0.5	SCRIM 50km/h

N.B.: These values have been used in both applications of the model. These have been taken as the average values measured in 2016 (HAPMS) and to reflect conditions of a pavement in 'Good' condition (as defined in the HDM-4 manual).

Table 5 gives a summary of the climatic parameters (weather conditions) characteristic of the UK (University of Birmingham, 2011).

Fuel consumption estimates made by HDM-4 for the Base and Update case have been compared to the mean of the observed distribution (real measurements from the telematic database). However, as it is possible to see in Figure 1, the observed distributions seem to be slightly right skewed. From the analysis of Cullen-Frey's graphs (Cullen and Frey, 1999) (these have not been reported for brevity) we assume that it is possible to approximate the observed distributions as log-normal. For this reason the non-parametric Wilcoxon one-sample t-test (Wilcoxon, 1945) is used to compare the performance of HDM-4 in the Base and Update case at the 95% confidence level. This is to test the null hypothesis that the true mean of the observed distribution is equal to the value estimated by HDM-4 and is checked for each truck type and for both applications Base and

Update case. A p-value smaller than 0.05 rejects the null hypothesis in favour of the alternative, meaning that estimates are not significantly similar to the median of the observed distribution. This will be used to evaluate the reliability of the estimates made by HDM-4 calibrated by Odoki et al. (2013), for the United Kingdom, in comparison to the telematic measurements. Finally, the Interquartile Range (IQR) (75% quartile - 25% quartile) is used as a reference and for comparison between HDM-4 estimates and the observed median fuel consumption.

Table 5

Summary of the climatic parameters (weather conditions) characteristic of the UK. Adapted from University of Birmingham (2011).

HDM-4 Climatic Parameters	Values
Moisture classification	Humid
Moisture index	0*
Duration of dry season (as fraction of a year)	0.25
Mean monthly precipitation	70 mm
Temperature classification	Temperature cool
Mean annual temperature	9 ℃
Mean monthly ambient temperature range	7.5 ℃*
Number of days when the temperature exceeds 32℃	0*
Freezing index (C-day)	55*
Percentage of time vehicle driven on snow covered roads	2**
Percentage of time vehicle driven on water covered roads	9**

* HDM-4 default values for humid condition.

** Estimated values used in University of Birmingham (2011).

4 Results

Table 6 reports the measured median fuel consumption (FC) and estimates computed by HDM-4 for each type of vehicle in the Base and Update cases. The table also reports the IQRs and p-values from the Wilcoxon one-sample t-tests.

Table 6

Results of the data analysis with the estimated and observed fuel consumption for light, medium and heavy trucks.

Type of truck	Measured median FC (l/100km)	IQR (l/100km)	HDM-4 Base case (l/100km)	p-value Base case	HDM-4 Update case (l/100km)	p-value Update case
Light	15.50	7.37	13.35	$6.4 \cdot e^{-10}$	15.20	0.27
Medium	23.33	14.67	33.79	$2.2 \cdot e^{-16}$	26.72	$2.2 \cdot e^{-16}$
Heavy	26.50	16.50	69.67	$2.2 \cdot e^{-16}$	55.90	$2.2 \cdot e^{-16}$

Figure 1 shows the HDM-4 estimation of the Base case and Update case and compares results with the distribution of real fuel consumption measurements from the telematic database, along with the log-normal approximation of the observed distribution.

Results of the study show that a basic application of HDM-4 calibrated for the case study of the UK (University of Birmingham, 2011; Odoki, Anyala, *et al.*, 2013) (Base case) does not give realistic estimates compared to real measurements for medium and heavy trucks.

By updating the operating vehicle weight and the frontal area based on telematic data and manufacturers' information, better estimates can be obtained. That represents a significant improvement and highlights the importance of estimating correctly the operating vehicle weight and the frontal area of the considered vehicles. These impact the gradient forces, the internal frictions, rolling resistance and aerodynamics (see equations of the HDM-4 fuel consumption model (Kerali, Odoki, *et al.*, 2006)), and they can be easily evaluated and updated in the HDM-4 model by analysing the large quantity of data owned by fleet managers without performing any field tests.

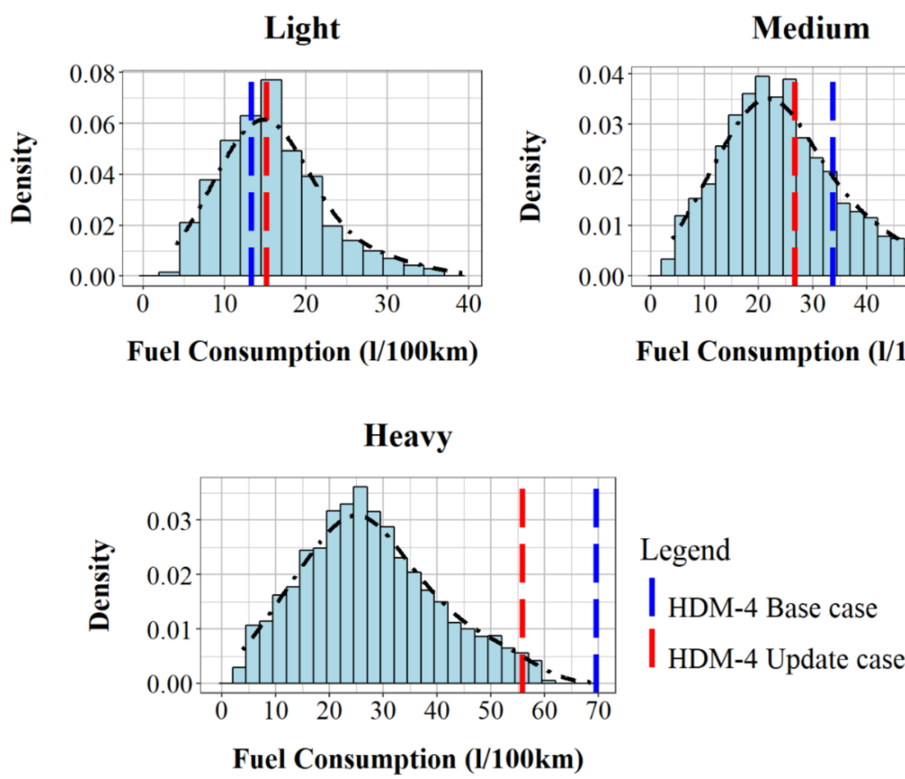

Fig. 1. Comparison of HDM-4 estimates ('Base case' and 'Update Case') with measured fuel consumption distributions for light, medium and heavy trucks.

Although closer to the observed values, results of the Update case remain, for medium and heavy trucks, outside the 95% confidence interval with p-values lower than 0.05, indicating that the results are not comparable. However, from Table 6 it is possible to see that for light trucks in the Update case the computed p-value (p-value = 0.27) shows that updating the operating weight and frontal area for this vehicle type is enough to make the estimates made by HDM-4, comparable with the median of the observed distribution at the 95% confidence level.

Particular attention is required in the case of heavy trucks. For this type of vehicle, despite updating the operating vehicle weight and the frontal area, the HDM-4 model gives a very different estimate of fuel consumption, when compared to real data. This may be because, during the last decade, there has been considerable technological innovation for road vehicles (EPA, 2018), including heavy duty vehicles (NAS, 2010; Sharpe and Muncrief, 2015; Delgado, Rodríguez, *et al.*, 2017); and the default parameters used in HDM-4 for the engine speed, the transmitted torque, the aerodynamics factor and the rolling resistance parameters may need a complete re-evaluation, for this type of vehicle in particular.

Traditionally, a level II (calibration) or III (adaptation) recalibration of the parameters of the model (Bennett and Greenwood, 2000; Bennett and Paterson, 2000) would include performing new experiments, testing the effect of improvements in the efficiency of modern engines, differences in the vehicle weight (including variations of the payload), and new ‘fuel’ types (e.g. GLP, methane, or electric vehicles). Another possibility may be offered by the ‘Big Data’ approach and the large quantity of data available in the truck telematic database. Using these data to update the HDM-4 fuel consumption model may be one way to save in testing and improve precision and reliability of the estimations.

5 Conclusions

This paper presents a verification of HDM-4 fuel consumption estimates by comparing these to real world measurements from a large dataset from truck telematic and road agency databases. The data were obtained for a large fleet of trucks that can be considered representative of modern trucks driving on motorways in real conditions of weather, traffic, etc. Some 85% of the UK truck fleet was registered after 2000, when the SAE J1939 standard for sensors was introduced and approximately 10% of the fleet is renewed each year (DVLA and DfT, 2018). This method could therefore, be applied to the majority of the UK HGV fleet. While the analysed dataset represents modern and therefore, the most fuel efficient trucks, the replacement rate means it is representative of the truck fleet of the near future.

First an application of the HDM-4 (Base case) model calibrated for the UK using the parameters published (University of Birmingham, 2011; Odoki, Anyala, *et al.*, 2013) has been performed and the measured fuel consumption data have been used for comparison. In a second application, the model has been updated using vehicle weights and truck frontal areas for the trucks in the dataset (SAE International, 2016).

Results of the study show that the latest calibration of HDM-4, performed in UK less than 10 years ago and tested in the Base case, is not able to estimate the fuel consumption of the considered fleet of trucks. The study also shows that for this case study of the UK, a simple update of the operating vehicle weight and frontal area of the considered vehicles can improve the accuracy of the estimations. This confirms the findings of studies that identified vehicle weight (e.g. Coyle, 2007; Franzese, 2011) and aerodynamic characteristics (e.g. Saltzman and Meyer, 1999; Hammache, Michaelian, *et al.*, 2001; Woodrooffe, 2014) to be among the most influential variables that affect vehicle fuel consumption.

Results represent a significant improvement and have been obtained by using data available in the telematic database and that come from standard sensors installed on all modern trucks. An advantage of using these data is that the information comes directly from the real world and therefore, is representative of real driving conditions, while data collected by performing experiments may not be. However, analysis shows that updating just vehicle weight and frontal area may not always be enough to produce reliable estimates from HDM-4, with differences that exceed the relevant IQRs.

The authors suggest that, in order to use HDM-4 at a strategic level in road asset management, a full recalibration (level III, (Bennett and Paterson, 2000)) of the model should be performed for the UK as poor estimates may lead to wrong decisions in terms of budget allocation . That should include a re-evaluation of vehicles, engines, traffic and pavement related parameters. In this regard, recent studies showed that telematic data can be used to directly model the fuel consumption of modern trucks accurately (e.g. Perrotta, Parry, *et al.*, 2017). Others have used telematic data for analysing driver behaviour for optimization of the operational costs of large fleets of trucks including fuel consumption (e.g. Figueredo *et al.*, 2017).

The present study focused on roads in good condition representative of the Strategic Road Network, which carries 75% of truck traffic. Further work is required to investigate the effect of poorer road conditions on vehicle fuel consumption, which should be considered within the scope of the suggested full recalibration of the HDM-4 model in the UK.

In conclusion, the present work shows that analysis of the ‘Big Data’ available in the telematic database of fleet managers, along with the database of road managers and others, can help in updating HDM-4 without performing new experiments and can represent a valid alternative to the traditional approach. This should be tested first for heavy trucks as for this type of vehicle errors in the estimates made by HDM-4 seemed to be very large. Future standardization of sensors for cars would make it possible to extend the applicability of this methodology to a wider range of vehicle types and make full calibration of HDM-4 possible from the large quantity of data available.

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