Article:

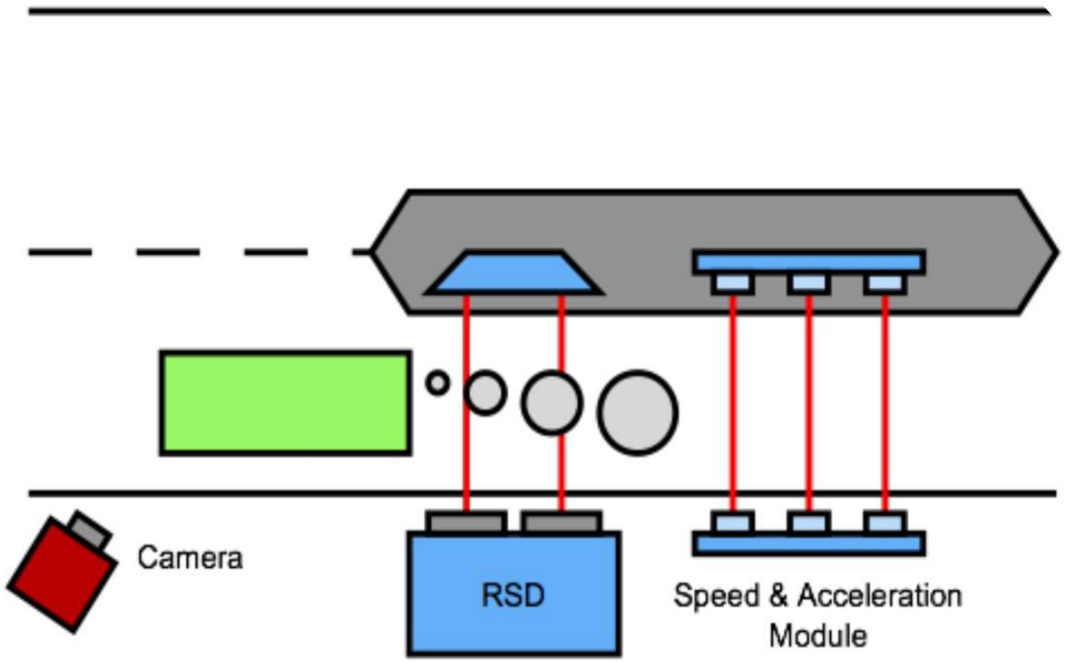
Rushton, CE, Tate, JE orcid.org/0000-0003-1646-6852 and Shepherd, SP orcid.org/0000-0002-4420-3382 (2021) A novel method for comparing passenger car fleets and identifying high-chance gross emitting vehicles using kerbside remote sensing data. Science of The Total Environment, 750. 142088. ISSN 0048-9697

https://doi.org/10.1016/j.scitotenv.2020.142088

*Title Page

A novel method for comparing passenger car fleets and identifying high-chance gross emitting vehicles using kerbside remote sensing data

***Graphical Abstract**



***Highlights (for review : 3 to 5 bullet points (maximum 85 characters including spaces per bullet point)**

- A large number of real driving emission measurements were performed including newly type-approved Euro 6 diesel and petrol passenger vehicles.
- A statistical method was developed for identifying gross-emitter candidate vehicles.
- Under appropriate circumstances it may be appropriate to recommend further investigation to diagnose the cause of these gross-emitter characteristics.

A novel method for comparing passenger car fleets and identifying high-chance gross emitting vehicles using kerbside remote sensing data

Christopher E. Rushton[a,*], James E. Tate[a], Simon P. Shepherd[a]

[a]*Institute for Transport Studies, University of Leeds, 34-40 University Rd, Leeds, LS2 9JT*

Abstract

. The quantification and comparison of NO_X emission from in-situ car fleets, and identification of the highest emitters is an ongoing challenge. This challenge will become more important as new and increasingly complex emissions removal systems penetrate the market. We combine real-world data with new-to-the-field statistical methods to describe fleet-scale emissions behaviours and identify candidate gross-emitter vehicles.

. 19605 passenger cars were observed using a Remote Sensing Device across Aberdeen in 2015. Of these, 736 were Euro 6 Passenger Cars. The distribution of observed pollutant per unit of fuel burnt ratios for most fuel type and Euro standards followed an asymmetrical shape best characterised by the Gumbel distribution. The Gumbel distribution approach was not able to fully replicate the distribution of measurements of petrol or Euro 6 diesel cars due to the presence of a subset of high-emitting outliers, ranging from the 13^{th} percentile for Euro 3 petrol to the 2^{nd} percentile for Euro 6 petrol, with Euro 6 diesel having a 5^{th} percentile outlier value. No outlier fraction was observed for pre-Euro 6 diesels.

*Corresponding author Christopher E Rushton (c.e.rushton@leeds.ac.uk)

. The off-model fractions resembled Gumbel distributed data and in some cases could be modelled as a separate distribution with the fleet behaving as a superposition of them. It is shown that VSP was not directly linked to this behaviour and it is hypothesised that it is caused by the emissions control systems operating sub-optimally. The reasons for sub-optimal operation are beyond the scope of this paper but may be linked to air-fuel mixture sensors, cold-start running and deterioration of the catalytic converter. Larger data-sets with more Euro 6 passenger cars are required to fully test this. Application of this methodology to larger data sets from more widely deployed remote sensing devices will allow observers to identify potentially problematic vehicles for further investigation into their emission control systems.

Keywords: NOx, Vehicle Emissions, Remote Sensing, Real Driving Emissions, Clean Air Zone

---

1. Introduction

1.1. Background and Motivation

. The oxides of nitrogen (typically nitric oxide and nitrogen dioxide, collectively referred to as NOx) have long been known as a major contributor to poor health, with negative outcomes being a result of exposure in most medical domains (EEA, 2017; COMEAP, 2015; Zhang and Batterman, 2013; IARC, 2013; WHO, 2013; Kampa and Castanas, 2008; WHO, 2006). The most significant contributor of NOx to urban environments are mobile oil powered sources, internal combustion driven vehicles (O'Driscoll et al., 2018; Vojtíšek-Lom et al., 2018; Colvile et al., 2001). Attempts have been made to limit the exposure of people to NO_X by stipulating ambient air pollution concentration limit values and vehicle emission standards in the European Union and elsewhere. The current ambient concentration values for NO_X are $40\mu gm^{-3}$ annual average and not to exceed $200\mu gm^{-3}$ hourly average concentration 18 times per year and are stipulated in the EU First Daughter Directive (99/30/EC). The annual limit for hourly exceedance was reached by January in 2018 at Brixton Road in London and Putney High Street broke the exceedance more than 1200 times in 2016 (Guardian, 2018, 2016).

. Vehicle emission standards have been introduced in various stages since 1992, with the Euro 3 legislation in year 2000 first specifying a maximum NO_X emission rate for cars. Significant reductions of NO_X have not been seen in either the concentration in local air (Holman et al., 2015; Ellison et al., 2013; Boogaard et al., 2012) or the real driving emissions performance of vehicles prior to the Euro 6 legislation despite these interventions (Tate, 2016, 2013a,b; Chen and Borken-Kleefeld, 2014; Carslaw and Rhys-Tyler, 2013). Chassis dynamometer measurements made under strictly controlled laboratory conditions have not been representative of the NO_X emissions of in-situ vehicles. Real-world factors including engine management settings, vehicle age, payload, ambient and operating temperature, tyre pressure, road gradient (Wyatt et al., 2014) and a range of other uncontrolled variables are also considered to influence on-road emissions (Rushton et al., 2018; Rushton, 2016)

. Euro 6 is a new set of type approval legislation introduced in 2014 for passenger cars. Euro 6 introduces stricter limit values on NO_X emission compared to Euro 5 and below. A more stringent testing procedure, designed to represent real driving, is to be introduced for later iterations of the legislation. Euro 6 legislation sets the NO_X emission rate at $0.08gkm^{-1}$, half the Euro 5 limit value. Euro 6b report real driving emissions with no limit values and Euro 6c introduces a new drive cycle in the World Harmonised Light Vehicle Test Procedure (WLTP) (Demuynck et al., 2012; Sileghem et al., 2014). Real driving emissions (RDE) rates are reported alongside a conformity factor (CF) with the onset of Euro 6d-temp in 2018 (Mock, 2017). The aim of the more stringent test procedure is to make cycle beating, as observed in the Volkswagen Group emissions scandal, more difficult to achieve. Some initial tests on a small number of vehicles using Portable Emissions Measurement Systems (PEMS) have been performed with results suggesting significantly differing successes between different vehicles (O'Driscoll et al., 2016; Heijne et al., 2016; Weiss et al., 2012, 2011). The impact this regulation will have on real-world tailpipe NO_X emissions is not well understood.

. RDE NOx testing using PEMS equipment was first approved for use on heavy-duty vehicles in 2009 (EC 595/2009) and made mandatory for pre-sales type approval in 2011 (EC 582/2011). RDE testing of heavy-duty vehicles has been introduced (EC, 2015a,b) and to tighten the rules on in-fleet light-duty vehicles (EC, 2017). These moves have been formalised in regulation EC 2016/427. The specification of the light-duty RDE test procedure requires between 90 and 120 minutes of driving to be completed. Of this, between 29% and 44% of the distance must be urban (6% to 30% stationary) and 23% to 43% of the distance must be both motorway and extra-urban. Average speeds of $15kmh^{-1}$ to $40kmh^{-1}$ are required in the urban driving section, $60kmh^{-1}$ to $90kmh^{-1}$ in the extra-urban section and greater than $90kmh^{-1}$ in the motorway section, with at least 5 minutes having an average speed greater than $100kmh^{-1}$. Boundary conditions for the RDE test are dynamically set based on average speed per section to ensure that the driving style is neither too aggressive nor too passive (Commission Regulation (EU) 2016/646). The relative positive acceleration ($RPA = \frac{1}{d}\sum_{i=1}^{n}\frac{a_i \times v_i}{3.6}$ for $a > 0$ and $RPA = 0$ for $a \leq 0$) (De Haan and Keller, 2004) must exceed the lower boundary condition. The 95^{th} percentile of the product of speed and acceleration ($v \times a$) over the drive cycle must not exceed the upper boundary. The maximum altitude change is limited to 1200m per 100km, an average gradient of just over 1%. The vehicle mass (M) must satisfy the boundary condition $M \leq M_{90\%}$ where $M_{90\%}$ is 90% of the vehicles maximum mass. (Mock, 2017). Vehicles have to meet a Not To Exceed (NTE) limit defined as the product of the Conformity Factor (CF) and the type approval limit. The CF value is to be determined in EC 2016/427 but is stated as $CF = 2.1$ from 4 years after the introduction of Euro 6 type approval limits, defined in EC 715/2007, (Euro 6d-temp) decreasing to $CF = 1.0$ plus a margin of error in the PEMS device (Euro 6d) of 0.5 in Mock (2017) report and regulation EC 2016/646.

. The inclusion of RDE in the type approval process represents a step change in thinking and process for reducing the emissions from new diesel-powered vehicles. The RDE test may solve many of the issues arising from high NO_X and primary NO_2 emissions in urban environments from passenger cars (Degraeuwe et al., 2016). Real-world monitoring of in-situ fleet vehicles and a robust methodology for comparing both individual vehicles and classes of vehicles is required to validate the benefit of the new legislation. Kerbside remote sensing devices allow for indirect and unobtrusive inspection of vehicles subject to real duty cycles and driven by real drivers in a naturalistic way, with minimal disruption to infrastructure. Short-term surveys (Section 2.1) have laid the ground work for scientific enquiry, however the knowledge contained within these data is yet to be fully discovered. The analysis techniques presented and demonstrated in this paper intend to extend the knowledge and understanding that can be gleaned from remote sensing measurements.

2. Materials and Methodology

2.1. Data Collection

. Remote Sensing Devices (RSDs) have been used in studies across the UK, Europe and world-wide to assess the emissions of in-situ vehicles for a number of years. These studies have shown that there has been little to no change in NO_X emissions from Euro 3 to Euro 5 diesel powered PCs, light commercial and heavy commercial vehicles, despite the incrementally increasing strictness of type approval limit values (Rushton et al., 2018; Carslaw and Rhys-Tyler, 2013; Tate, 2013a,b; Carslaw et al., 2011b,a; Bishop et al., 2003, 2001; Bishop and Stedman, 1996, 1990).

. The RSD was initially developed in 1989 as part of the United States clean air programme (EPA, 1999) to measure Carbon Monoxide (CO) (Bishop et al., 1989) and has been developed further to include Hydrocarbons (HC) (Popp et al., 1999) and NO with prototype Fuel Efficiency Automobile Test (FEAT) devices able to record Ammonia (NH_3) and NO_2 (Burgard et al., 2006). Measurements of the abundance of these species are made by infra-red (IR) and ultraviolet (UV) photometry at frequencies where the species are known to have absorption lines (Bishop et al., 1996). The RSD instrument consists of an open-path non-dispersive IR and dispersive UV light sources tuned to frequencies that interact with NO and CO_2 molecules in the exhaust plume to report a ratio between NO and CO_2. To take a measurement the source and detector module (SDM) directs a multi-frequency beam of light across a single lane of traffic which is reflected back using a corner cube mirror. The SDM calculates the difference in intensity between the sent (I_0) and the received (I) beam. The difference in intensity varies in accordance with the Beer-Lambert law (Lambert, 1760), ($I = I_0 \times e^{-\tau_\nu}$) where τ_ν is the optical depth of the material at frequency ν. The instrument returns the ratio of emissions between CO_2 and NO. The instrument is constantly operating and the pollution background level, subtracted from the observed tailpipe emission, is calculated using the last measurements before the beam is broken. The remaining difference is appointed to the vehicle. Measurement of NO and NO_2 is especially problematic as there are other species with strong absorption lines at similar frequencies to those used to measure NO_2 and have a high potential for interference. The most noticeable source of interference in NO_2 measurements is water (H_2O). Water vapour in the plume, a byproduct of combustion, and also present in the atmosphere, can cause interference. The high spectral resolution of the RSD4600 and RSD5000 instruments allow the impact of interference to be minimised (Jimenez-Palacios, 1998).

. The RSD was deployed for ten days across five sites in the summer of 2015. It was deployed for two days per site and the sites were distributed around central Aberdeen (Tate, 2016). Aberdeen is a port city in East Scotland with a modern economy including research and development into technology and agriculture, and oil due to its proximity to the North Sea. The sites used

Figure 1: Location of RSD sites in Aberdeen

for data collection are identified geographically in Figure 1. The observation sites were pre-selected to represent a range of arterial, circulatory and city centre streets, whilst also meeting practical accessibility constraints such as obstruction of the roads and footpaths. The RSD was deployed from 08:00 to 18:00 where possible to capture the AM, PM, and inter peak periods, and to maximise the sample size of vehicles observed. The number of PC observations per vehicle category are presented in Table 1.

. The RSD was set up in a standard on-road configuration as described in the user manual provided with the equipment (ESP, 2005). An in-depth description of the setup including survey site photographs can be found in Rushton (2016) and Tate (2016). The locations of the sites in Aberdeen are identified in Figure 1. The camera could be placed facing the front or

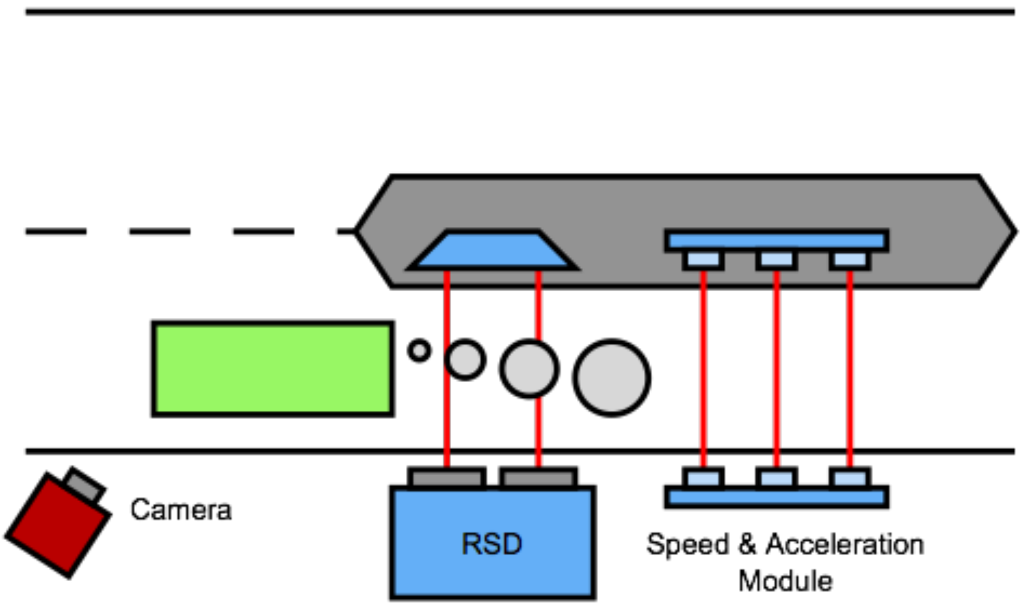


Figure 2: Generalised remote sensing installation schematic with camera facing the front of the vehicle

rear of the vehicle. Figure 2 shows the instrumentation in front facing in the configuration. Front facing cameras result in better capture of HCVs and passenger car licenses but often miss bus license plates. A rear facing camera has a high capture rate for urban busses, but low for both rigid and articulated HCVs that commonly have exhaust outlets after the driver cabin which trigger the camera. Passenger car capture rate is broadly consistent across the two configurations. Typically the decision of front or rear facing camera orientation is dictated by safety and accessibility rather than any traffic derived considerations however if possible the location of the camera can be changed to better capture the most prominent vehicles. A speed and acceleration module (SAM) consisting of three light beams was used to capture the vehicle dynamics. The SAM was placed between 3 and 5 metres before the SDM to ensure that the vehicle dynamics were representative of the emissions being observed. The operation of all the devices was controlled automatically by the RSD. The captured license plate data was converted to vehicle-specific metadata using a lookup service provided by CarWeb (http://www.carweb.co.uk).

. The RSD was calibrated twice daily, or whenever significant changes were observed in ambient weather conditions (Rushton, 2016), using an internal reference gas cell. Measurements were also audited every hour using blended calibration gas with known concentrations of pollutants broadly representative of what would be expected in the plume of a petrol-powered vehicle. The calibration gas measurements are compared to the known bottle gas concentrations and lock out further measurements if the instrument does not remain within an acceptable tolerance range (ESP, 2005).

2.2. Identifying Extreme Measurements

. A series of events with rare but high value events can be characterised by extreme value distributions. Various forms of extreme value distribution have been applied to many real world scenarios where the distribution of the events' magnitude does not follow a normal distribution. The use of the extreme value distribution extends from finance (Poon et al., 2004; Bensalah et al., 2000) to hydrological data (Martins et al., 2000). There are three different types of extreme value distribution. These are called Weibull, Frechet and Gumbel (Fréchet, 1928; Rosin, 1933; Gumbel, 1941, 1935). It has been previously hypothesised that a small number of vehicles contribute an excess amount of pollution to the overall inventory (Bishop et al., 2016; Zhang et al., 1994). This behaviour is compatible with the behaviours of extreme value distribution functions. This behaviour can be seen in the observed data histograms presented in Figures 3 and 4.

. A suitable distribution function is required to analytically describe population behaviour. A good distribution function for describing vehicle emissions must fit the data well and be parameterised in terms that are easily understandable in a real-world context. The Gumbel distribution meets these criteria and was chosen for use in this study. The Gumbel function is parameterised by the modal (or highest observation frequency in this context) value and a shape parameter that is related to the spread of the data. It is possible to compare both the peak emissions and the spread of the data of different population subsets in an analytical way using these parameters. The Gumbel probability density function $P(x)$ is defined, where $z = \frac{x-a}{b}$, and a and b are the modal value and the shape parameter respectively, in Equation 1. No assumptions or first principles were used a priori to derive a Gumbel or other distribution function therefore it is, at this point, suitable to pick something convenient for analysis. There are other distributions that match the general shape of the observations such as the gamma distribution however their parameters are less intuitive and the distribution itself is less convenient.

$$P(x) = \frac{1}{b} e^{-(z+e^{-z})} \tag{1}$$

3. Results

3.1. Gumbel Distribution Fits

. Each Euro class and fuel type pair were fitted to normal and Gumbel distributions with probability density functions (PDFs) and the theoretical / empirical Quantile relationships were calculated and plotted onto Q-Q Plots (Wilk and Gnanadesikan, 1968). A Q-Q plot demonstrates the relationship between the expected and observed values in a distribution. A well modelled distribution will correlate strongly along the 1:1 line. The distribution fit parameters were estimated using the Maximum Likelihood Estimation (MLE) method from the *fitdistrplus* package in *R* (Wilks, 1938; Delignette-Muller and Dutang, 2015; R Core Team, 2015). The PDF and Q-Q plot types show the difference between the Gumbel and Normal distributions, and the observed data.

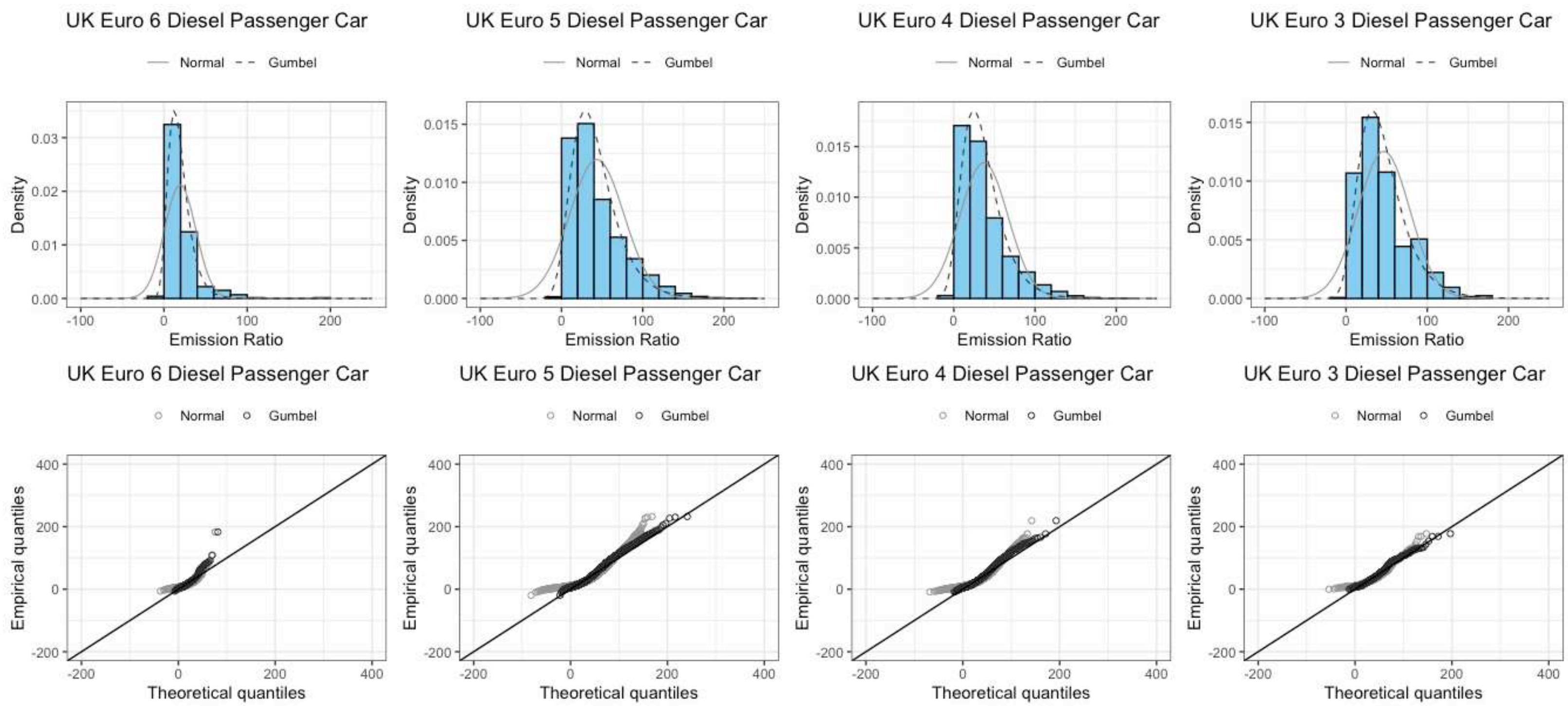


Figure 3: Probability density and quantile-quantile plots for the diesel passenger fleet in the UK. Normal distribution is light grey and solid, Gumbel distribution is dark grey and dashed.

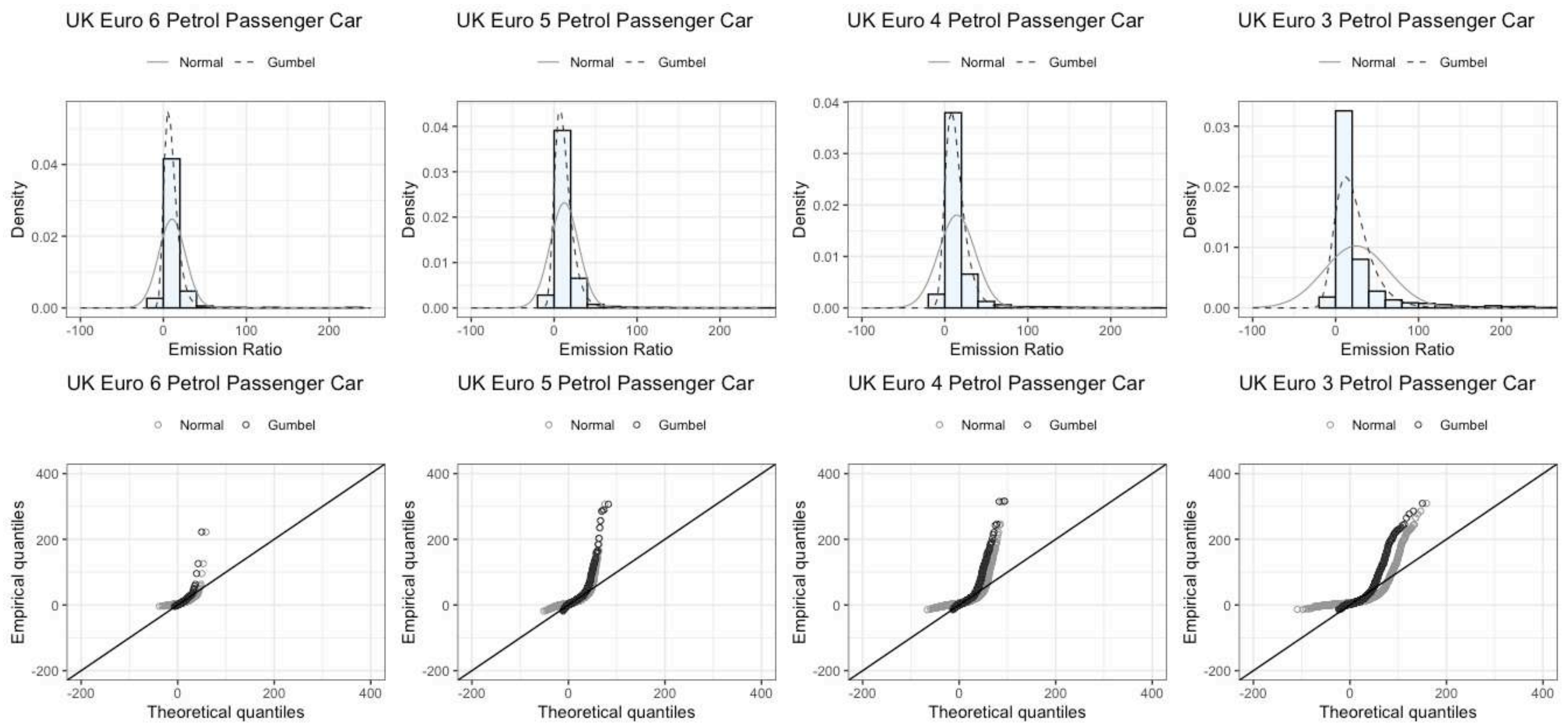


Figure 4: Probability density and quantile-quantile plots for the petrol passenger fleet in the UK. Normal distribution is light grey and solid, Gumbel distribution is dark grey and dashed.

. Figure 3 and Figure 4 show the fits for the fleets of diesel and petrol powered passenger cars respectively. For the diesel powered vehicles the Gumbel distribution fits the data more consistently than the normal distribution showing reasonable agreement across the whole range of percentiles. The normal distribution underestimates both the number of highest emitters and lowest emitters in the population and fails to correctly identify the most frequent value for emissions, suggesting that it is unsuitable for describing the characteristics of vehicle emissions from these vehicle fleet subsets.

. The population of observed emissions ratios for petrol powered vehicles mostly fit the Gumbel distribution. There is a small subset of the population that deviate from the Gumbel distribution. It is hypothesised that this deviation from the distribution function is caused by unusual behaviour by a small subset of the population. This hypothesis was tested by cutting successively larger percentiles from the top of the distribution function and re-fitting the data to the distribution function.

. The higher quantiles side of the distribution begins to depart from the 1:1 line most noticeable in the petrol powered fleets but also in the Euro 6 diesel fleets. It is hypothesised that the majority of the fleet follow the Gumbel distribution and a small percentage of vehicles that do not. The fraction of vehicles that do not follow the Gumbel distribution are termed *'off-model'* and may be interpreted as candidate gross-emitting vehicles.

3.2. Off Model Fraction Calculation

. A goodness of fit measure is required to determine the quality of the representation of the data by the model. The maximal value of this parameter can be used to determine the best model parameters post-hoc. The goodness of the fit between the data and the distribution function is determined by calculating the R^2 value of the relationship between the empirical and theoretical quantiles. Cuts at each integer percentiles starting at 99 were performed to test the hypothesis that the majority of the vehicle population conformed to the Gumbel distribution. The R^2 values calculated for these data sets are shown in Table 1. The highest percentile, maximal R^2 value was chosen as the best model for that fleet subset. This percentile, P_{off}, was reported as the off-model fraction (Table 2). The process was iterated a second time with the off-model fraction to determine the parameters that define the off-model fraction. The variation in R^2 statistic for each cut is shown in Figure 5. The line for $R^2 = 0.98$ is shown as a red dash for comparative purposes. The agreement with the model with well chosen cuts is graphically demonstrated in Figure 6 as the Q-Q line best matches the 1:1 line and agrees with the result generated using the maximising R^2 value approach.

. The real-world applicability of the fit parameters is important when comparison between fleet subsets is to be performed. A model that is representative of reality is important because non-realistic parameters lead to unfair comparisons and wrong conclusions. The normal distribution does not represent the distribution of the observations, suggesting that it is not appropriate for use in this context. The mean and standard deviation are not appropriate parameters for describing the fleet. The Gumbel distribution provides much better agreement with the data and its parameters can be used for comparisons and combined with a well chosen data cut agree with the data at $R^2 > 0.97$ in all cases. The approach outlined in this section creates three

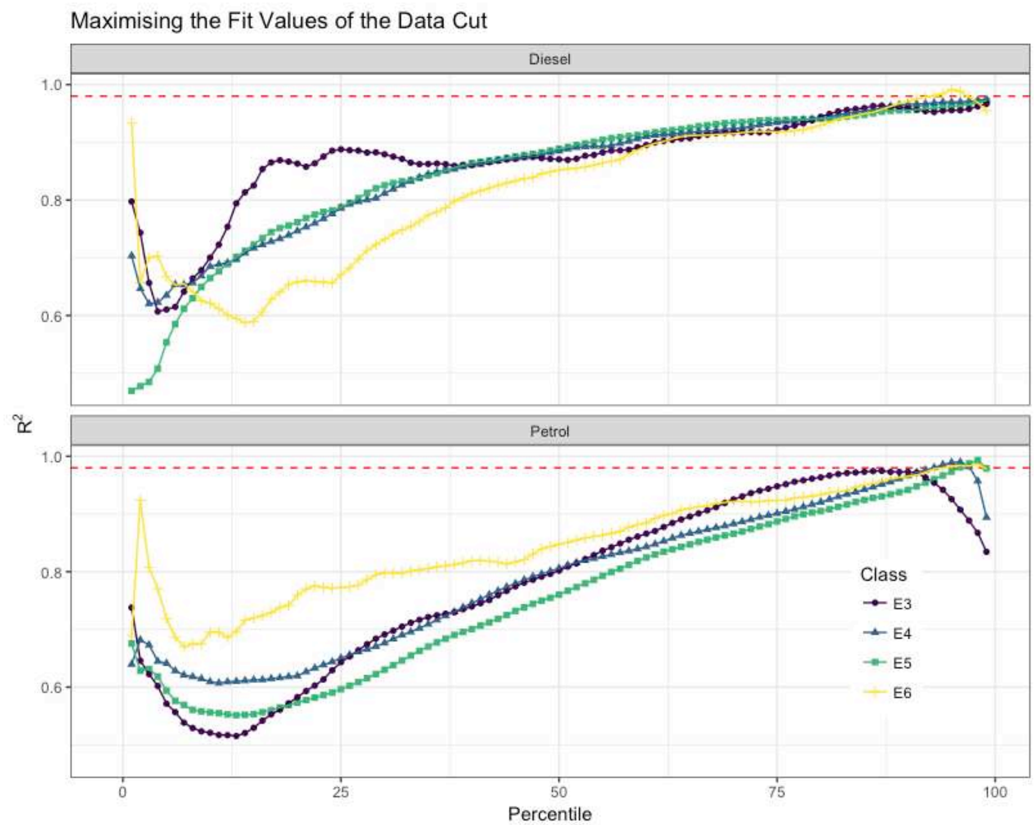


Figure 5: Variation in R^2 for increasing data cuts for the petrol and diesel vehicles. Euro class is indicated by colour and shape with $R^2 = 0.98$ indicated by the dashed red line.

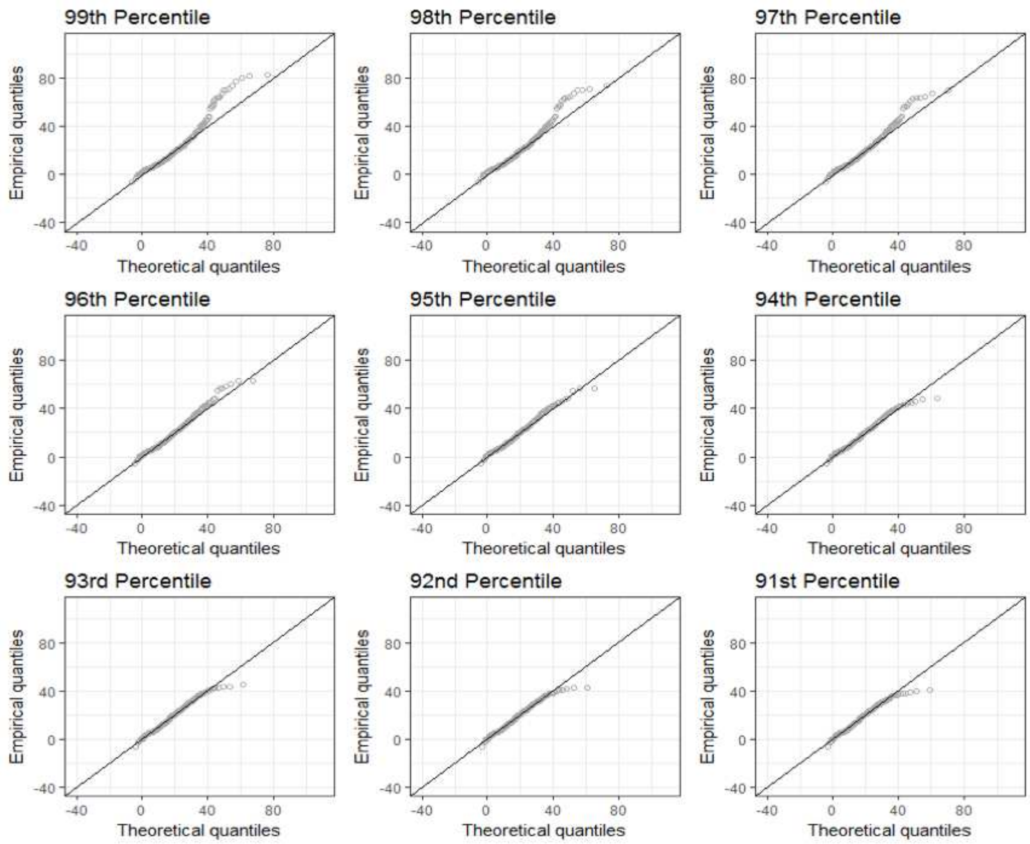


Figure 6: Variation in Gumbel distribution function with changing location and scale parameters for the UK Euro 6 diesel fleet

empirically derived parameters can be used to compare fleet subsets: the two Gumbel parameters and the off-model percentile. These parameters are based on large samples of real vehicles and are more representative of the population and allow for a meaningful and numerical comparison to be made between subsets. This method of analysis allows for a better understanding of the change in emission ratios as they relate to euro class and fuel type. It is possible to demonstrate that there has been a small improvement in the emissions ratios of the petrol fleet from Euro 3 to Euro 6 and that there is evidence of a step-change in emission ratios of the diesel fleet from Euro 3 to 5 and to Euro 6 and to assess the magnitude of these changes. This method can be also applied to vehicles of a specific make, manufacturer, engine capacity or chassis platform given a population sample size of less than 200 vehicle observations (Chen et al., 2019).

Location	Fuel	Euro	n	Off Model Percentile	Fit R^2	Location ($NO : CO_2 \times 10^4$)	Scale
UK	Petrol	3	1701	87	0.975	7.8	8.3
		4	3732	96	0.990	6.7	7.2
		5	4382	98	0.993	6.5	7.3
		6	374	98	0.986	5.5	5.5
	Diesel	3	632	100	0.967	32.0	23.0
		4	2452	100	0.974	24.4	19.8
		5	5522	100	0.972	29.0	22.8
		6*	362	95	0.991	11.2	8.3

Table 1: Summary results table showing the off-model percentage and Gumbel distribution fit parameters for Aberdeen fleet subsections post-cut. The R^2 parameter is the modelled fit between the predicted and the empirical quantiles for each point. *The Euro 6 designations included are those on the road during the data collection and are likely to be Euro 6a.

. The best fit parameters for each of the fleet subsets chosen is presented in Table 1. In all but one case, Euro 3 diesel, cutting the data correctly results in an R^2 parameter greater than 0.97. This result suggests that the majority of the vehicles observed in each class can be parameterised by a Gumbel distribution fitted to appropriately cut data. The implication of this is that vehicle fleets with greater levels of NO_X control exhibit two-type behaviour and that the fleet is comprised of two or more component parts. For the purpose of this paper they can be thought of as normal and grossly emitting vehicles relative to their category.

3.3. Vehicle Specific Power Bias Analysis

. There is a known association between Vehicle Specific Power (Jimenez-Palacios, 1998) and high NO_X emission (Carslaw et al., 2013) and it would be reasonable to expect the gross emitter events to be linked to the highest VSP events. Each fleet subsection (Euro 3-6 petrol and Euro 6 diesel) were split along two dimensions, VSP and emission ratios to link the VSP of a given event to its emissions characteristics. The two VSP derived subsets are referred to as an under-cut and an over-cut population based on their VSP percentile, P_{VSP}. The cut point is defined as the off-model fraction percentile derived from the emissions calculation, $P_{VSP} = P_{off}$. The under-cut subset is the vehicles where $P_{VSP} < P_{off}$ and the over-cut subset is where $P_{VSP} \geq P_{off}$. For example the 98^{th} percentile of emissions was considered the on-model fraction for Euro 5 petrol vehicles and the top 2^{nd} percentile of VSP measurements was considered the over-cut. A high VSP observation is linked to a high emissions measurement if an event is included in the over-cut and off-model sets. A high emissions measurement unrelated to a high

VSP observation would be under-cut and off-model. For example an emission measurement in the top 2^{nd} percentile attached to a VSP measurement in the bottom 50^{th} percentile would be off-model and under-cut however if its VSP measurement was in the top 2^{nd} percentile it would be off-model and over-cut.

. This methodology was applied to all vehicles with off-model components. The results of this analysis are shown in Figures 7 and 8. If VSP was the dominant factor for causing off-model behaviour clustering would be expected in the upper and lower panels. No such clustering is observed and the over-cut VSP follow the trends of the under-cut VSP vehicles. The over-cut, off-model vehicle is the highest in population NO_X emitter in only one case from the current limited sample of six. There is no evidence of strong systematic bias towards high VSP vehicles and off-model behaviour observed in any of these samples. This analysis suggests that whilst the VSP of a vehicle is a contributing factor to its emissions (Carslaw et al., 2013), it is not a systematic dominant factor when considering which vehicles are gross emitter candidates. Gross-emitter candidates appear to be more related to the mechanics of the vehicle, engine, and after treatment systems. In turn this suggests that the solution to the problem of gross-emitter vehicles will be predominantly mechanical rather than behavioural.

3.4. Paramterising Observed Gross Emitter Candidates

. The existence of off-model vehicles presents a problem for modelling the fleet as the modeller cannot simply fit the Gumbel distribution to the data and move on to the next step. The modeller must now understand the nature

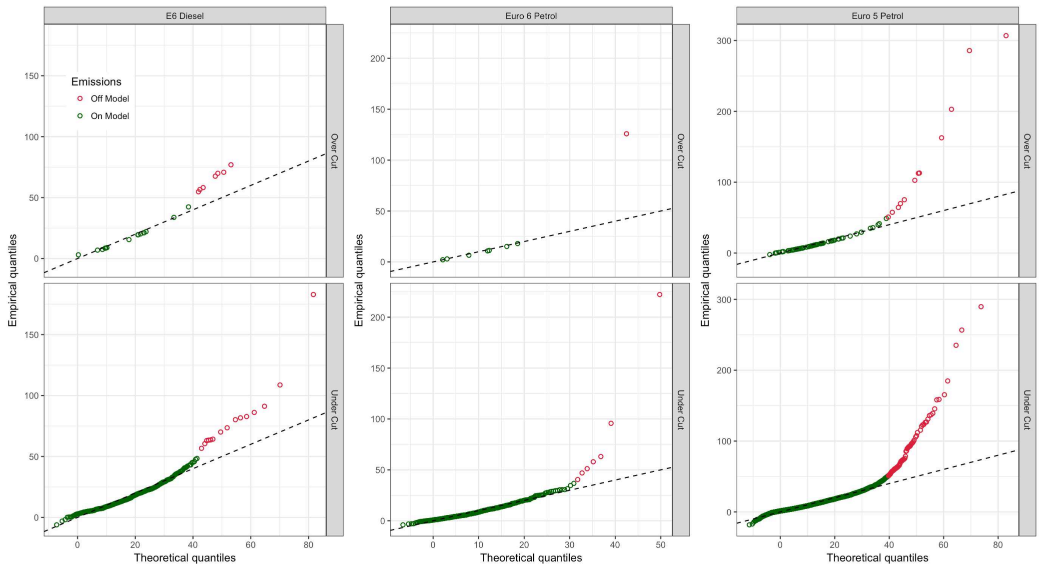


Figure 7: Q-Q plot showing on and off model vehicles split by Euro and fuel, and, under and over cut for VSP. On and off model vehicles are green and red circles respectively

of off-model vehicles or risk not accounting for some of the most important contributors to total emissions. Physically these vehicles might be thought of as having sub-optimal emission control systems due to their higher $NO{:}CO_2$ emissions ratios. There are multiple reasons for why a vehicle's emissions control systems would not perform optimally. Cold-starts, ambient temperatures or defeat devices may all contribute by some degree to the off-model fraction of newer fleets. Catalyst poisoning, sintering or physical damage may all contribute in varying degrees to reduction in catalyst efficiency in older fleets. Kadijk et al. (2018) presents some evidence that failed air-fuel mixture (λ) sensors may be responsible for high emissions from petrol vehicles. Those vehicles exhibiting off-model behaviour were grouped into separate subclasses of their euro and fuel class of vehicles, parameterised in-

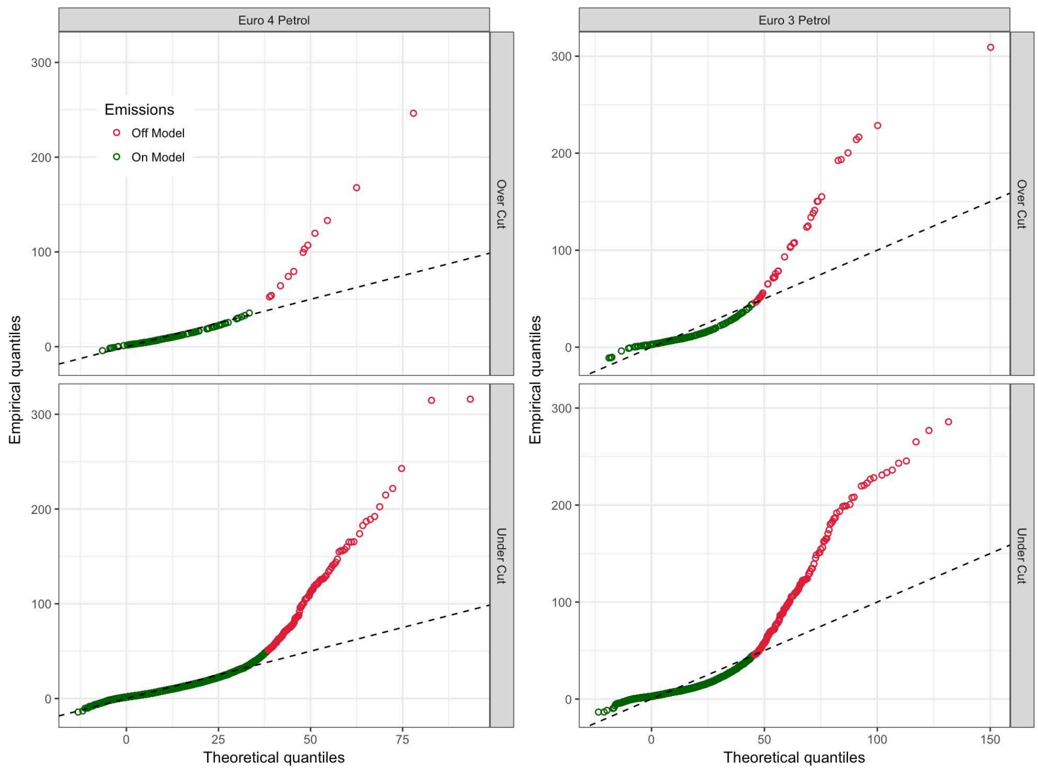


Figure 8: Q-Q plot showing on and off model vehicles split by Euro and fuel, and, under and over cut for VSP. On and off model vehicles are green and red circles respectively

dependently, and their contribution was added to the on-model component of the fleet.

. There is some logic to the increased off-model percentile of petrol vehicles however the following assertion is presented with the caveat that determining the underlying cause of a vehicle's emission characteristics is beyond the scope of this paper. The 2% of observed off-model vehicles in Euro 5 and Euro 6 petrol vehicles may be caused by cold starts because it is unlikely that the vehicles in this fleet subset contains many failed three-way catalysts or λ-sensors. As these components age and fail there is an increased fraction of vehicles falling into the off-model subset and this is observed by an increased off-model percentile. Regarding the diesel vehicles it is likely that all vehicles are high emitters and the only variation is in the Euro 6 subset.

. The off-model fractions of the Euro 3 and Euro 4 passenger car petrol fleet subsets were chosen for initial parameterisation because they had the largest sample sizes of 222 and 150 respectively. Euro 6 diesel is included despite the small sample size of 19 as they are the most relevant vehicle class to this analysis and the observed distribution was assessed to be qualitatively similar to a Gumbel distribution. The Euro 5 and 6 petrol vehicle subsets with identified off-model contributions did not contain enough off-model vehicles to fit distribution functions to with any degree of confidence.

. The functions for the on and off model components were plotted and normalised then overlaid on the data. The off-model fraction is small for both the Euro 4 petrol and Euro 6 diesel fleets so an additional and exaggerated off-model component has been added to the data. The exaggerated component

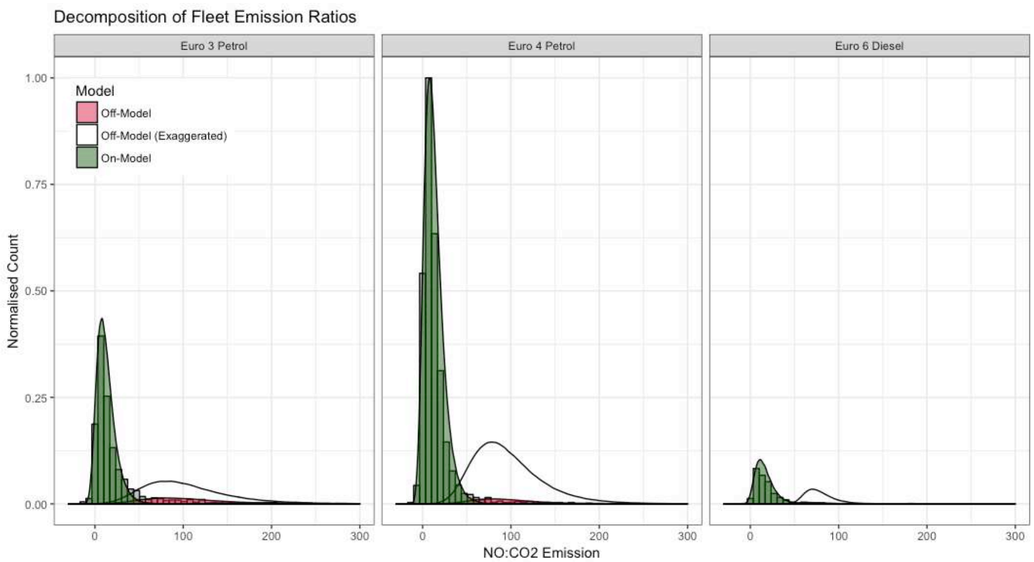


Figure 9: Decomposition of the fleet subsets into their off-model (red) and on-model (green) fractions and overlaid on the observed data (grey histogram). An indicative and exaggerated off-model component has been added, without, that shows the magnitude of the Gumbel function if the fleet was 50% off-model.

Type	Sample	Location	Shape
Euro 3 Petrol	150	80.9	38.7
Euro 4 Petrol	222	78.2	31.1
Euro 6 Diesel	19	70.5	13.1

Table 2: Off-model Gumbel distribution parameters for petrol powered Euro 3 and Euro 4 UK fleet subsections

was calculated based on the assumption that 50% of the vehicles in the fleet were off-model and is for illustrative purposes only. These distributions are shown in Figure 9. Two-sample KS tests were performed on the function and the data to determine the similarity between the model predictions and the data. The p statistics for the Euro 3 petrol vehicles were $p = 1.69 \times 10^{-3}$ and for the Euro 4 petrol vehicles were $p < 2.2 \times 10^{-16}$. The p-values generated suggests that there is good agreement between the predicted distribution of both the normally emitting vehicles and the gross-emitters, suggesting that this methodological approach can provide useful insight to distribution of emission ratios in these fleets. The number of vehicles in the Euro 6 diesel category was not large enough to generate a reliable p-value however the qualitatively successful application of this methodology suggests that given a bigger data set this feature could be replicated in a more robust statistical manner.

4. Conclusion and Discussion

4.1. Conclusions

. The method developed in this paper provide a framework for comparing vehicle fleet subsets from remote sensing data. This approach has been used to demonstrate the magnitude of impact that a legislative change has had on the emissions ratios of nitric oxide. Further application of this methodology will allow for almost immediate appraisal of new legislation Euro 6c+ vehicles as they enter the fleet when new data becomes available. This methodology can also be used to investigate other subsets such as vehicle make and model.

. The results presented in this paper suggest that the the vast majority (87% to 100%) of NO_X remotely sensed emission ratios for vehicles in any given euro or fuel subset can be described using a well-fitted Gumbel distribution function. In fleet subsets where significant work has ben done to reduce NO_X emissions a small number of gross-emitter candidate vehicles can be observed in their deviation from this model. For the normally behaving vehicles the fitted parameters from the Gumbel distribution function can be used to compare and contrast fleet emission rates in a more precise way. This new methodology allowed the level of Euro 6 emissions to be tested and compared to other Euro and fuel-type fleet subsets for the first time ignoring high emitters. It can now be shown that a new Euro 6 diesel vehicle is likely to emit slightly more NO:CO_2 than a Euro 3 petrol powered vehicle when passing through a remote sensing device. This is approximately half the emission of a Euro 5 or 4 diesel vehicle. Given that a Euro 3 petrol powered vehicle is not an ultra-low emission zone (ULEZ) compliant vehicle there should be some concern that the introduction of ULEZ into city centres may not lead to a significant reduction in ambient NO_X concentration. No significant change was observed between Euro 3, 4 or 5 diesel cars as might be expected with step-changes in the legislation.

4.2. Discussion

Remote sensing studies have previously demonstrated their value in observing the differences between in-situ vehicles, and laboratory and PEMS based testing environments. The results and methodologies demonstrated in this paper build on this work, showing that an appropriate function to parameterise this data is a Gumbel distribution. The use of the Gumbel distribution to describe the observation improves the investigative capacity that RSD observations can generate. Some simple cases of application have been demonstrated and results have been presented and it has been confirmed that the difference between Euro 3, 4 and 5 diesel passenger car emission rates is minimal. This methodology allows for more naturalistic and granular descriptions of the fleets to be produced which both account for the natural variation in emissions between similar vehicles and those vehicles with abnormally high emission rates.

. The new method using the Gumbel distribution can be used to make strong assessments about the differences between fleet subsets at any level of granularity. This paper investigated the variation between different Euro class and fuel types. The difference between cities or sub-regions within cities and temporal differences may also be assessed. The variation between make, marque, year of first introduction, level of WLTP or RDE compliance if not stated explicitly, engine size or other parameters can be analysed/ in the same way given a large enough data-set. Chen et al. (2019) indicates that this number may be less than 200 vehicles per subset, well within the capability of an RSD campaign.

. The characterisation of the on-model and off-model fleets mean that an observer can now assess the likelihood that a vehicle is operating in a sub-optimal way. With appropriate underlying infrastructure the vehicles that are performing within the expected window can be identified using a real-time, big-data approach that compares each vehicle observed to every other vehicle. Vehicles suspected as having SCR emulators (OEM defeat devices or customer fitted) may be identifiable. This may provide a useful tool for compliance monitoring in the future.

. Improving the statistical framework around individual vehicle emissions and how they are positioned within the fleet presents a further use case related to clean air zone enforcement. It may be desirable in the course of enacting and enforcing future clean air zones to penalise drivers of excessively highly emitting vehicles on a case by case basis. One-off individual measurements may struggle to identify the worst emitters and may be further confounded by idiosyncrasy in vehicle emission control systems and driver behaviour. Repeated measurements of the same vehicle may be able to identify those vehicles that are consistently emitting higher than the rest of the fleet. Repeated measurements of the same vehicle become more likely if remote sensing devices are more widely deployed in the future. Targeted schemes to remove the most highly emitting vehicles would become more realistic. This methodology, coupled with the correct infrastructure, could provide a useful tool for identification of candidate gross-emitter vehicles. These vehicles could then be flagged as a gross emitter candidate, potentially triggering a more thorough emissions test at next routine inspection. This type of fleet surveillance and targeted intervention, when coordinated with more targeted RDE testing by type approval, could give authorities some of the tools they need to reduce the number of high emitting new diesel cars on the road whilst minimising the disruption to those vehicles that are performing at a level consistent with the requirements of the legislation.

5. Future Work

. Further important use cases of this methodology include assessing the effectiveness of emissions reduction systems on Euro 6c, 6d-temp and 6d vehicles as they enter the fleet. Each of these legislative changes are changes to the test procedure with Euro 6d-temp and Euro 6d requiring real driving emissions tests to be within a conformity factor of legislation ($CF_{d-temp} = 2.1$ and $CF_d = 1.5$) and this is expected to result in real-world reduction in tailpipe emission. Using the methods developed in this paper a more representative and useful comparison could be made between these new type approval classes, each other, and those currently on the road. These comparisons could be completed reasonably quickly after the vehicles are introduced to the fleet as a sample size of the order 100 will give statistics that are comparable to the current Euro 6 fleet.

. Different manufacturers and platforms solve the NO_X emissions problems in different ways. Whilst the sample sizes presented in this paper are too small to assert with any confidence that a particular manufacturer, make, model or platform is performing better or worse than another, as the number of observations increase, the data can be cut into smaller, more specific, subsections allowing for more targeted investigation to be performed. Extended and longitudinal remote sensing studies, ideally with a time period greater than one year, will provide the number of measurements required to assess these differences or similarities in a statistically robust way, providing useful information to local authorities, vehicle manufacturers and the car-buying public about the emissions of their choice of vehicle. Additionally the longitudinal study approach will allow identification of any temporal and seasonal changes to vehicle emission rates. Of special interest is the impact of ambient temperature on emissions due to changes in cold starts and cold running as the wording of the Euro class legislation allows for emissions control systems to be switched off if ambient temperatures are not within a specified operational window. The interdependence of multiple factors could be analysed in some depth given a large enough sample size.

. Light commercial vehicles are an untested segment of the fleet and an important avenue for future investigation. Understanding the impact of light commercial vehicles is critical to assessing the impact and effectiveness of ULEZ introduction. At the time of data collection there were no Euro 6 diesel LCVs observed in the UK so no analysis could be performed. At the time of writing the penetration of Euro 6 light commercial vehicles will have increased to the point where general surveys are likely to contain enough vehicles to perform useful statistical tests for comparison. Data has been collected for Euro VI HCVs however given the difference in legislation surrounding these engines and the complexities relating to engine specification and after-treatment systems further work is required both to understand, assess and implement this methodology for these vehicles.

Bensalah, Y., et al., 2000. Steps in applying extreme value theory to finance: a review. Bank of Canada.

Bishop, G., Stedman, D., 1996. Measuring the emissions of passing cars. Accounts of Chemical Research 29 (10), 489–495.

Bishop, G. A., Burgard, D. A., Stedman, D. H., 2003. On-road remote sensing of automobile emissions in the la brea area: Year 3, october 2003.

Bishop, G. A., Morris, J. A., Stedman, D. H., Cohen, L. H., Countess, R. J., Countess, S. J., Maly, P., Scherer, S., 2001. The effects of altitude on heavy-duty diesel truck on-road emissions. Environmental science & technology 35 (8), 1574–1578.

Bishop, G. A., Starkey, J. R., Ihlenfeldt, A., Williams, W. J., Stedman, D. H., 1989. Ir long-path photometry: a remote sensing tool for automobile emissions. Analytical Chemistry 61 (10), 671A–677A.

Bishop, G. A., Stedman, D. H., 1990. On-road carbon monoxide emission measurement comparisons for the 1988-1989 colorado oxy-fuels program. Environmental Science & Technology 24 (6), 843–847.

Bishop, G. A., Stedman, D. H., Ashbaugh, L., 1996. Motor vehicle emissions variability. Journal of the Air & Waste Management Association 46 (7), 667–675.

Bishop, G. A., Stedman, D. H., Burgard, D. A., Atkinson, O., 2016. High-mileage light-duty fleet vehicle emissions: Their potentially overlooked importance. Environmental science & technology.

Boogaard, H., Janssen, N. A., Fischer, P. H., Kos, G. P., Weijers, E. P., Cassee, F. R., van der Zee, S. C., de Hartog, J. J., Meliefste, K., Wang, M., et al., 2012. Impact of low emission zones and local traffic policies on ambient air pollution concentrations. Science of the total environment 435, 132–140.

Burgard, D. A., Dalton, T. R., Bishop, G. A., Starkey, J. R., Stedman, D. H., 2006. Nitrogen dioxide, sulfur dioxide, and ammonia detector for remote sensing of vehicle emissions. Review of scientific instruments 77 (1), 014101.

Carslaw, D., Beevers, S., Westmoreland, E., Williams, M., Tate, J., Murrells, T., Stedman, J., Li, Y., Grice, S., Kent, A., et al., 2011a. Trends in nox and no2 emissions and ambient measurements in the uk. Defra, London.

Carslaw, D., Rhys-Tyler, G., 2013. Remote sensing of no2 exhaust emissions from road vehicles. A report to the City of London Corporation and London Borough of Ealing, Version 16th July.

Carslaw, D. C., Beevers, S. D., Tate, J. E., Westmoreland, E. J., Williams, M. L., 2011b. Recent evidence concerning higher no x emissions from passenger cars and light duty vehicles. Atmospheric Environment 45 (39), 7053–7063.

Carslaw, D. C., Williams, M. L., Tate, J. E., Beevers, S. D., 2013. The importance of high vehicle power for passenger car emissions. Atmospheric Environment 68, 8–16.

Chen, Y., Borken-Kleefeld, J., 2014. Real-driving emissions from cars and light commercial vehicles–results from 13 years remote sensing at zurich/ch. Atmospheric Environment 88, 157–164.

Chen, Y., Zhang, Y., Borken-Kleefeld, J., 2019. When is enough? minimum sample sizes for on-road measurements of car emissions. Environmental Science & Technology 53 (22), 13284–13292.

Colvile, R., Hutchinson, E., Mindell, J., Warren, R., 2001. The transport sector as a source of air pollution. Atmospheric environment 35 (9), 1537–1565.

COMEAP, 2015. Statement on the evidence for the effects of nitrogen dioxide on health.

De Haan, P., Keller, M., 2004. Modelling fuel consumption and pollutant emissions based on real-world driving patterns: the hbefa approach. International journal of environment and pollution 22 (3), 240–258.

Degraeuwe, B., Thunis, P., Clappier, A., Weiss, M., Lefebvre, W., Janssen, S., Vranckx, S., 2016. Impact of passenger car nox emissions and no2 fractions on urban no2 pollution–scenario analysis for the city of antwerp, belgium. Atmospheric Environment 126, 218–224.

Delignette-Muller, M. L., Dutang, C., 2015. fitdistrplus: An R package for

fitting distributions. Journal of Statistical Software 64 (4), 1–34.
URL http://www.jstatsoft.org/v64/i04/

Demuynck, J., Bosteels, D., De Paepe, M., Favre, C., May, J., Verhelst, S., 2012. Recommendations for the new wltp cycle based on an analysis of vehicle emission measurements on nedc and cadc. Energy Policy 49, 234–242.

EC, 2015a. European commission - press release commission welcomes member states agreement on robust testing of air pollution emissions by cars.
URL http://europa.eu/rapid/press-release$_{I}P - 15 - 5945_{e}n.htm$

EC, 2015b. Faq air pollution standards.
URL http://europa.eu/rapid/press-release$_{M}EMO - 15 - 5705_{e}n.htm$

EC, 2017. Agreement on commission proposal to tighten rules for safer and cleaner cars.
URL http://europa.eu/rapid/press-release$_{I}P - 17 - 5131_{e}n.htm$

EEA, 2017. Exceedance of air quality standards in urban areas. Tech. rep.
URL https://www.eea.europa.eu/data-and-maps/indicators/exceedance-of-air-quali

Ellison, R. B., Greaves, S. P., Hensher, D. A., 2013. Five years of londons low emission zone: Effects on vehicle fleet composition and air quality. Transportation Research Part D: Transport and Environment 23, 25–33.

EPA, 1999. Nitrogen oxides (nox), why and how they are controlled.

ESP, 2005. RSD 4600 Operator's Manual Edition 3.0.

Fréchet, M., 1928. Sur la loi de probabilité de l'écart maximum. In: Annales de la societe Polonaise de Mathematique. [sn].

Guardian, 2016. London takes just one week to breach annual air pollution limits.
URL `https://www.theguardian.com/environment/2016/jan/08/london-takes-just-one`

Guardian, 2018. London reaches legal air pollution limit just one month into the new year.
URL `https://www.theguardian.com/uk-news/2018/jan/30/london-reaches-legal-air-`

Gumbel, E., 1935. Les valeurs extrêmes des distributions statistiques. In: Annales de l'institut Henri Poincaré. Vol. 5. pp. 115–158.

Gumbel, E. J., 1941. The return period of flood flows. The annals of mathematical statistics 12 (2), 163–190.

Heijne, V., Ligterink, N., Stelwagen, U., 2016. 2016 emission factors for diesel euro-6 passenger cars, light commercial vehicles and euro-vi trucks. Tech. rep., TNO.

Holman, C., Harrison, R., Querol, X., 2015. Review of the efficacy of low emission zones to improve urban air quality in european cities. Atmospheric Environment 111, 161–169.

IARC, 2013. Outdoor air pollution a leading environmental cause of cancer deaths.

Jimenez-Palacios, J. L., 1998. Understanding and quantifying motor vehicle emissions with vehicle specific power and tildas remote sensing. Ph.D. thesis, Massachusetts Institute of Technology.

Kadijk, G., Elstgeest, M., Ligterink, N. E., van der Mark, P. J., 2018. Emissions of twelve petrol vehicles with high mileages. Den Haag: TNO.

Kampa, M., Castanas, E., 2008. Human health effects of air pollution. Environmental pollution 151 (2), 362–367.

Lambert, J. H., 1760. Photometria sive de mensura et gradibus luminis, colorum et umbrae. Klett.

Martins, E. S., Stedinger, J. R., et al., 2000. Generalized maximum-likelihood generalized extreme-value quantile estimators for hydrologic data. Water Resources Research 36 (3), 737–744.

Mock, P., 2017. Real-driving emissions test procedure for exhaust gas pollutant emissions of cars and light commercial vehicles in europe. Tech. rep.
URL `https://bit.ly/2uJnoaw`

O'Driscoll, R., ApSimon, H. M., Oxley, T., Molden, N., Stettler, M. E., Thiyagarajah, A., 2016. A portable emissions measurement system (pems) study of nox and primary no2 emissions from euro 6 diesel passenger cars and comparison with copert emission factors. Atmospheric Environment 145, 81–91.

O'Driscoll, R., Stettler, M. E., Molden, N., Oxley, T., ApSimon, H. M., 2018. Real world co2 and nox emissions from 149 euro 5 and 6 diesel, gasoline and hybrid passenger cars. Science of the total environment 621, 282–290.

Poon, S.-H., Rockinger, M., Tawn, J., 2004. Extreme value dependence in financial markets: Diagnostics, models, and financial implications. Review of financial studies 17 (2), 581–610.

Popp, P. J., Bishop, G. A., Stedman, D. H., 1999. Development of a high-speed ultraviolet spectrometer for remote sensing of mobile source nitric oxide emissions. Journal of the Air & Waste Management Association 49 (12), 1463–1468.

R Core Team, 2015. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. URL `https://www.R-project.org/`

Rosin, P., 1933. The laws governing the fineness of powdered coal. J. Inst. Fuel. 7, 29–36.

Rushton, C. E., 2016. Measuring and modelling vehicle nox emissions using a remote sensing device.

Rushton, C. E., Tate, J. E., Shepherd, S. P., Carslaw, D. C., 2018. Interinstrument comparison of remote-sensing devices and a new method for calculating on-road nitrogen oxides emissions and validation of vehicle-specific power. Journal of the Air & Waste Management Association 68 (2), 111–122.

Sileghem, L., Bosteels, D., May, J., Favre, C., Verhelst, S., 2014. Analysis of vehicle emission measurements on the new wltc, the nedc and the cadc. Transportation Research Part D: Transport and Environment 32, 70–85.

Tate, J., 2016. Vehicle emission measurement and analysis - aberdeen city council.

Tate, J. E., 2013a. Vehicle emission measurement and analysis - cambridge city council.

Tate, J. E., 2013b. Vehicle emission measurement and analysis - sheffield city council.

Vojtíšek-Lom, M., Beranek, V., Klír, V., Jindra, P., Pechout, M., Voříšek, T., 2018. On-road and laboratory emissions of no, no2, nh3, n2o and ch4 from late-model eu light utility vehicles: Comparison of diesel and cng. Science of The Total Environment 616, 774–784.

Weiss, M., Bonnel, P., Hummel, R., Manfredi, U., Colombo, R., Lanappe, G., Le Lijour, P., Sculati, M., 2011. Analyzing on-road emissions of light-duty vehicles with Portable Emission Measurement Systems (PEMS). Publications Office.

Weiss, M., Bonnel, P., Kühlwein, J., Provenza, A., Lambrecht, U., Alessandrini, S., Carriero, M., Colombo, R., Forni, F., Lanappe, G., et al., 2012. Will euro 6 reduce the nox emissions of new diesel cars?–insights from on-road tests with portable emissions measurement systems (pems). Atmospheric Environment 62, 657–665.

WHO, 2006. Who air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide: global update 2005: summary of risk assessment.

WHO, 2013. Review of evidence on health aspects of air pollution: Revihaap project: final technical report.

Wilk, M. B., Gnanadesikan, R., 1968. Probability plotting methods for the analysis for the analysis of data. Biometrika 55 (1), 1–17.

Wilks, S. S., 1938. The large-sample distribution of the likelihood ratio for testing composite hypotheses. The Annals of Mathematical Statistics 9 (1), 60–62.

Wyatt, D. W., Li, H., Tate, J. E., 2014. The impact of road grade on carbon dioxide (co 2) emission of a passenger vehicle in real-world driving. Transportation Research Part D: Transport and Environment 32, 160–170.

Zhang, K., Batterman, S., 2013. Air pollution and health risks due to vehicle traffic. Science of the total Environment 450, 307–316.

Zhang, Y., Bishop, G. A., Stedman, D. H., 1994. Automobile emissions are statistically gamma distributed. Environmental science & technology 28 (7), 1370–1374.