How do traffic flow and the emissions they produce vary through the day, week, season and year: evidence from big telematics data

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Abstract

To better estimate and forecast the air quality variation over time, and to improve the efficiency of air quality plans, the temporal variability of traffic emissions warrants further study. This paper presents the analysis of a telematics dataset providing information, sampled at 1 Hz, about 35 000 journeys of a fleet of private vehicles located in the Sheffield area. Variation of vehicle specific power (VSP), which is a good predictor of exhaust emissions, were examined through the day, the week and the year, across different types of day, and against weather and visibility conditions. Whatever the time scale, traffic conditions and the type of the day (regular, weekend, or holiday) were found to affect the value of VSP by up to 30.1% and 56.7%, respectively. Bad weather conditions were found to induce 26.7% lower VSP values whereas daylight was found to induce 8.7% lower VSP values. Consequently, the results suggest that in order to accurately estimate and forecast emissions exhausted from motor vehicle traffic and air quality, ad hoc models should at least take into account the type of day and include diurnal variation. Moreover, the results demonstrate that the influence of traffic on vehicle emissions can be captured qualitatively even in the absence of traffic data.

Keys-words*: exhaust emissions, motor vehicle traffic, diurnal variation, type of day, telematics data.*

Résumé

Afin de mieux estimer et prévoir les variations de la qualité de l'air dans le temps ainsi que d'améliorer l'efficacité des plan de lutte contre la pollution atmosphérique, il est nécessaires d'étudier en détails la variabilité temporelle des émissions routières. Cet article présente l'analyse de données prélevées à une fréquence de 1 Hz sur une flotte de presque 35 000 véhicules particuliers circulant dans la région de Sheffield. Les variations de la puissance spécifique des véhicules (VSP), qui est un bon indicateur des émissions routières, ont été analysées sur la journée, la semaine, et l'année, en fonction du type de journée ainsi qu'en fonction des conditions météorologiques et de visibilité. Quelle que soit l'échelle de temps considérée, il apparaît que le niveau de trafic et le type de journée (normale, weekend, ou vacances) influent sur la valeur de la VSP jusqu'à 30,1% et 56,7%respectivement. Il apparaît que de mauvaises conditions météorologiques induisent une VSP jusqu'à 26,7% plus faible tandis que la lumière du jour induit une VSP 8,7% plus faible. Par conséquent, les résultats suggèrent qu'afin d'estimer et prévoir de façon précise les émissions routières ainsi que la qualité de l'air, les modèles ad hoc devraient au moins tenir compte du type de journée et inclure des variations quotidienne. De plus, les résultats démontrent que l'influence du niveau de trafic sur les émissions routières peut être évaluée qualitativement sans même avoir de données de comptage à disposition.

Mots-clés*: émissions routières, trafic routier motorisé, variation quotidienne, type de journée, données télématiques.*

Introduction

Emissions from motor vehicle traffic are a major contributor to urban air pollution. To help study and design efficient air quality plans, models include traffic emissions based on emission factors aggregated over time (Franco et al., 2013). However, those traffic-related emissions, and exhaust emissions in particular, vary over time with traffic conditions and density, weather conditions, and drivers' behaviour. Moreover, emission regulations rely not only on yearly or daily targets but also on hourly ones. For example, the European legislation for air quality establishes the maximum hourly concentration in nitrogen dioxide (Henshel et al., 2015).

Therefore, to better estimate and forecast the air quality variation, and to improve the efficiency of air quality plans, the temporal variability of traffic emissions needs to be explored in details. The objective of the study presented in this paper was to examine the variation of traffic emissions through different time scales, and with weather and visibility conditions. The paper also aims to demonstrate that telematics data provides an interesting opportunity to study traffic emissions at high time-resolution.

1 Methods

In order to examine the temporal variability of traffic emission, this study relied on the analysis of vehicle tracking data. Based on this data, the vehicle specific power (VSP – used as a proxy for emissions) was computed. Then, the variation of VSP was examined on different time scales (day, week, and year), across different categories of day (business, weekend, and bank holiday day, during or out of school and university terms), and against weather conditions (temperature and rainfall) and visibility conditions (daylight).

1.1 Data

The telematics dataset used in this study provided information on the journeys of a fleet of private vehicles equipped with GPS tracking system for insurance purposes. The dataset consisted of GPS vehicle tracking records of 34 425 journeys, sampled at 1 Hz rate. Data provided was anonymised to protect the privacy of drivers following a privacy impact assessment. This included removing any journeys starting or ending in the target region, which were <0.5% of the available vehicle trips. In total, this represents 2 440 580 records and a little more than 15 000 travelled km (i.e. around 440 m per journey). The journeys were collected during one year between 01/05/2014 and 30/04/2015 in the Sheffield city centre over an area of 1.8 km^2. (see Figure 1). An important traffic generator, the University of Sheffield, is found in this area. Because records were available only in the area presented in Figure 1, most of the journeys in the dataset were not complete, i.e. from beginning to end. They were rather the portions of the actual journeys that fall in this area.

For each record, the dataset provided information on the journey from the GPS tracking system (location, time, bearing, and speed) and on the car by post-treatment and coupling with the information from the insurance company (make, model and year). For the purpose of the study, the speed provided by the GPS, which only took a few discrete values, was not accurate enough to capture small variations of speed. Therefore another speed was derived from the successive vehicle positions, calculated as the distance between two consecutive points divided by 1 s. Then, to avoid unrealistic speed values due to GPS errors, the speed was smoothed with the Kalman filter smoothing function available in the "dlm" R package (with a 3rd degree polynomial model).

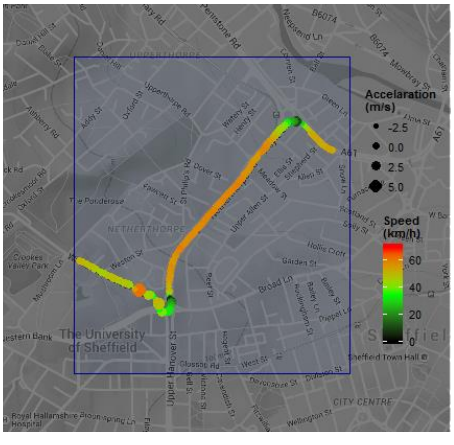

Figure 1. Study area (blue rectangle) and example of an anonymous recorded journey.
Produced with ggmap (Kahle and Wickham, 2013).

1.2 Vehicle specific power

To explore the variation of traffic emissions through different time scale, we first computed the vehicle specific power (VSP) at each second of every journey. VSP is a convenient and good predictor of instantaneous CO_2 vehicle emissions. As such, computing VSP allows one to estimate vehicle emissions without having to run emission models. VSP is used in many studies about instantaneous exhaust emissions (see Moody and Tate, 2016, and Ligterink et al., 2016) and is the primary metric of the motor vehicle emissions simulator (MOVES) of the United States Environmental Protection Agency .

Supposing that all journeys were made with the same average car, VSP was computed with Equation (1), adapted from Jiménez-Palacios (1999), and expressed in kW/tonne:

$$VSP = v \cdot (a \cdot (1+\varepsilon) + g \cdot \sin(grade) + g \cdot C_R) + \frac{1}{2} \cdot \rho_a \cdot \frac{C_D \cdot A}{m} \cdot (v + v_w)^2 \cdot v \qquad (1)$$

where v is the speed of the vehicle (m/s), a the acceleration of the vehicle (m/s^2), ε the mass factor (0.1, dimensionless), g the acceleration of gravity (9.8 m/s^2), $grade$ the road grade (degree), C_R the coefficient of rolling resistance (0.013, dimensionless), ρ_a the ambient air density (1.207 kg/m^3), C_D the drag coefficient (0.328, dimensionless), A the frontal area of the vehicle (2.13 m^2), m the mass of the vehicle (1500 kg), v_w the velocity of the headwind into the vehicle (neglected – 0 m/s).

The speed of the vehicle is the speed computed as described above. The acceleration of the vehicle was derived from the speed and computed as the difference in speed between two consecutive points divided by 1 s.

The road grade was derived from elevations retrieved from the 50 cm horizontal resolution digital terrain model (DTM) produced by the UK environment agency. The road grade was computed as the arctangent of the ratio rise/run, where the rise was the difference of elevation between two consecutive points divided by the distance between those two points. When the speed of the vehicle is low and the position of the vehicle moves from one DTM tiles to another, the value of the run may be significantly smaller than the value of the rise, resulting in an overestimation of the grade. To avoid such overestimation, the road grade was computed following the method developed by Wyatt et al. (2014) when the speed of the vehicle falls under 1 m/s. In that case, the road grade at the vehicle position was calculated between the last point where the vehicle was farther than 0.5 travelled meters from the vehicle position considered and the first point where the vehicle was farther than 0.5 travelled meters from the vehicle position considered. Thus, the minimum travelled distance over which the road grade is calculated is 1 m.

2 Results and discussion

VSP values can be either positive when the vehicle needs power to move or negative when it does not. Vehicle emissions levels are low and relative constant for negative values of VSP, e.g. when a vehicle is breaking. Consequently, records with negative values of VSP were discarded from the study, and the results presented below are based on positive values of VSP only.

Whatever the time scale, the results suggest that VSP variation may be explained by traffic conditions (Section 2.1) and by whether it is a typical day or a holiday (Section 2.2). VSP variation may also be observed according to change in the driver’s environment such as change in weather conditions (Section 2.3) or daylight (Section 2.4).

2.1 Variation of VSP over time

VSP was found to vary significantly through the year, week, and day. Figure 2 shows the variation of the mean VSP through the year, the transparency level of each bar reflecting the number observations, and the error bars representing the 5th and 95th percentile of VSP. Overall, VSP appeared to vary by up to 24.5% on average depending on the month. VSP was higher from March to September (5.77 kW/tonne vs 5.19 kW/tonne), with a maximum value in August (6.30 kW/tonne) when many people are on holidays. This may suggest that the driving conditions during this period allowed people to adopt their “natural” driving behaviour, i.e. without being constrained by the bad weather conditions of winter or by heavy traffic conditions.

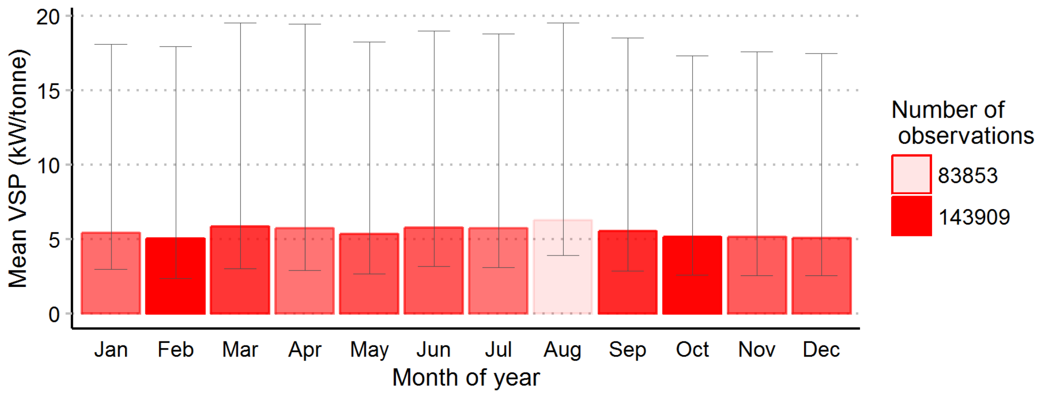

Figure 2. Variation of VSP with the month of the year.

VSP also varied through the week, with higher VSP values during the weekend (6.57 kW/tonne) and lower VSP values on week days (5.29 kW/tonne). Overall, VSP varies by up to 24.1% on average depending of the day of the week. As illustrated in Figure 3, this remained true for every month of the year, supporting the idea that higher VSP values occur in light traffic conditions.

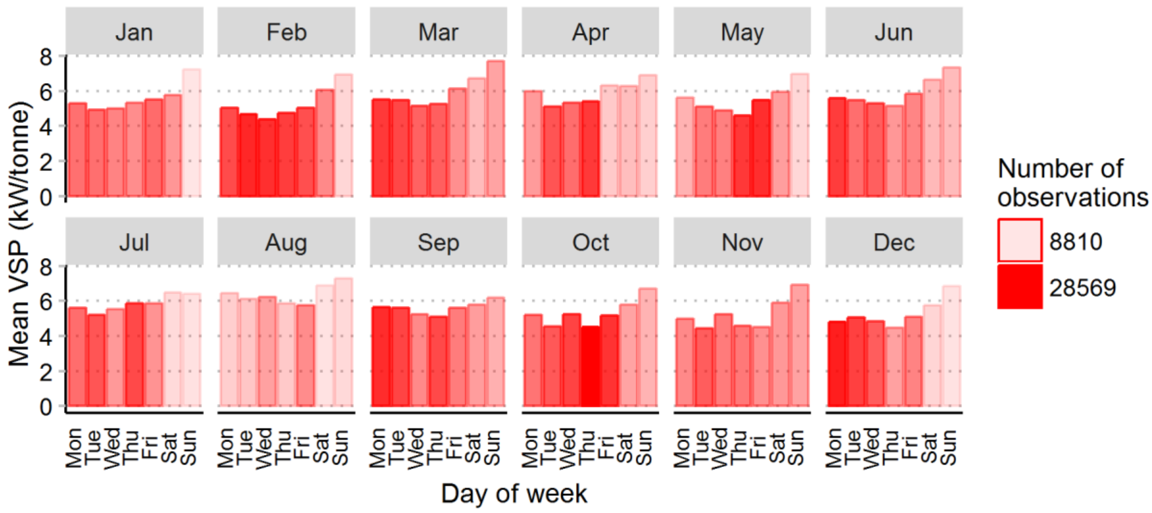

Figure 3. Variation of VSP with the day of the week

VSP also varied through the day. The variation of VSP with the hour of the day is presented in Figure 4. The same pattern was followed across week days. A later, reduced onset of more constrained behaviour occurred on weekend days. On week days, the mean value of VSP was constantly significantly lower (30.1% lower on average) during morning and evening traffic peak periods, i.e. between 7:00 and 9:59, and between 16:00 and 18:59. On weekend days, the variation of the mean value of VSP is not as obvious, explained by the absence of a noticeable traffic peak period.

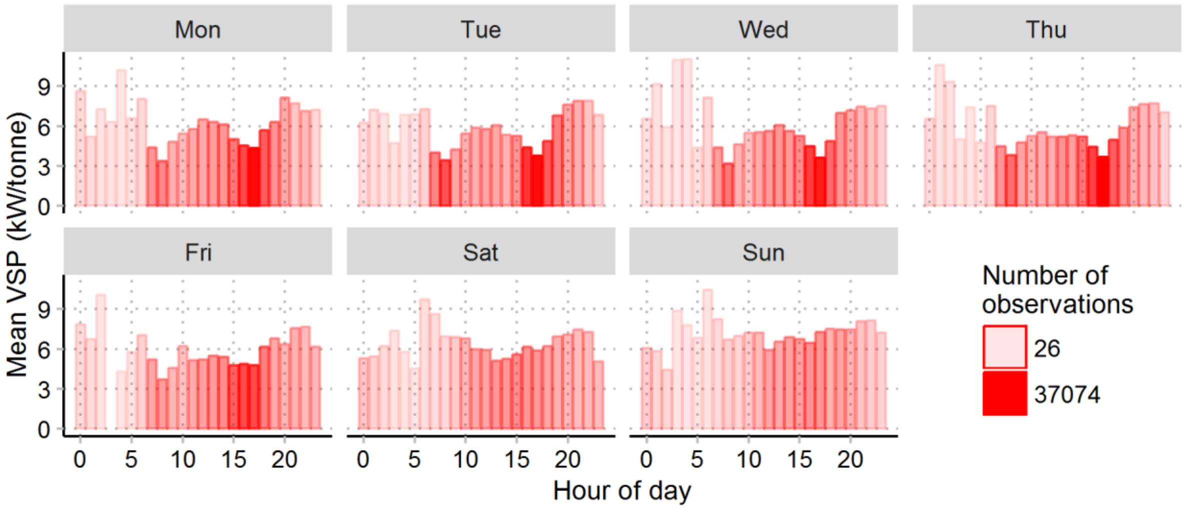

Figure 4. Variation of VSP with the hour of the day.

2.2 Influence of the type of day on VSP

To examine the influence of traffic conditions on VSP, we compared the mean values of VSP for different types of day for which different level of traffic are expected. Bank holidays dates were retrieved from the UK government website (https://www.gov.uk/bank-holidays). Dates of school and university holidays were retrieved from the holiday calendar of the Sheffield City Council (https://www.sheffield.gov.uk/education/schools/holidays.html) and the University of Sheffield (https://www.sheffield.ac.uk/about/dates) respectively.

Figure 5 illustrates the mean values of VSP for different type of days including regular week and weekend days, bank holidays, and school and university holidays. VSP was found to be higher on days for which light traffic conditions were expected (e.g. during periods with school and university holidays). The highest value of VSP was observed on days which are bank, school and university holidays at the same time (7.82 kW/tonne on average).The lowest VSP value was observed on regular week days (4.99 kW/tonne), when the traffic conditions are expected to be the heaviest. On regular week-end days and bank holidays, VSP values are intermediate at 6.45 kW/tonne and 5.88 kW/tonne respectively. Overall, VSP varied by up to 56.7% depending on the type of day

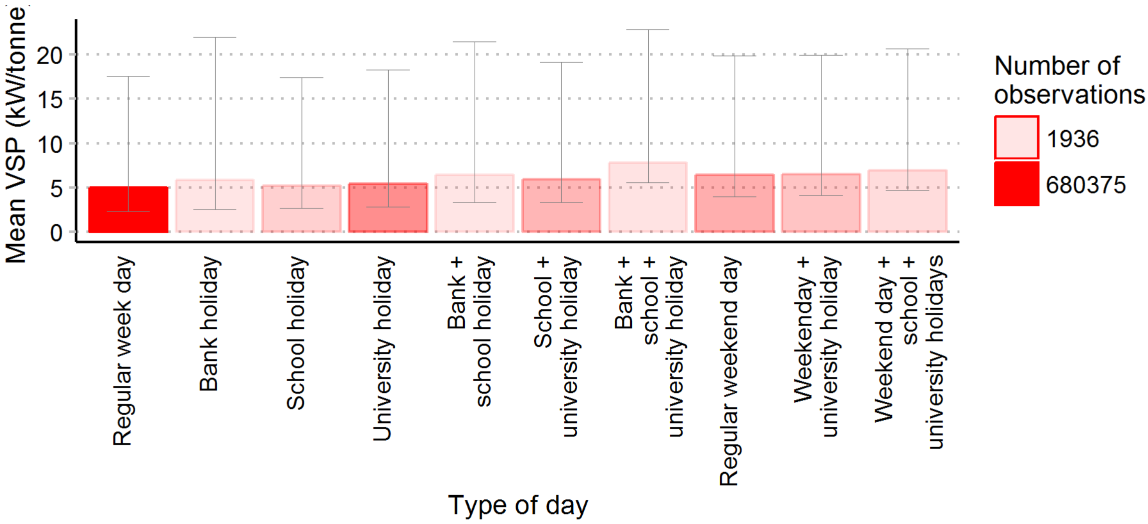

Figure 5. Influence of the type of day on VSP.
Error bars represent the 5th and 95th percentiles.

Coupling the vehicle tracking data with traffic data, when available, would be relevant and could support these findings. However, the results show that, even in the absence of traffic data, the influence of traffic on VSP can be captured qualitatively.

2.3 Influence of the weather conditions on VSP

Bad weather conditions are expected to constrain the drivers' behaviour. In particular, poor visibility due to rain or fog and slippery road due to freezing temperature could induce the driver to be more cautious than usual, resulting in less intense accelerations and decelerations. The driver adapting to weather conditions would thus imply lower VSP, and ultimately lower associated vehicle emissions.

Historical hourly weather data were obtained from the UK Met Office datasets (MIDAS) through the Centre for Environmental Data Analysis (CEDA – http://browse.ceda.ac.uk/browse/badc/ukmo-midas/data). Because no visibility data was available in this database for the study area, descriptors of weather conditions were limited to rainfall and temperature. The data used in this study included hourly temperature and rainfall measured at a station located within the study area. The resolutions of the data were 0.1°C and 0.2 mm respectively.

To illustrate the influence of the rain on VSP, rainfall intensity was used to form four categories. No, low, medium, and high rainfalls corresponded to 0 mm, less than 1mm, between 1 and 2 mm and more than 2 mm rainfalls per hour respectively. Moreover, in order to capture the influence of the rain on VSP while minimising influence of other parameters, only records collected during the off-peak period of regular week days (between 10:00 and 14:59) were used. Figure 6 shows that the mean value of VSP remained roughly the same across the first three categories (5.4 kW/tonne) but was 20% lower for rainfall of more than 2 mm per hour (4.5 kW/tonne). This suggests that drivers might adopt less aggressive driving behaviour when the road visibility was reduced by the rain and when the road was wet and slippery.

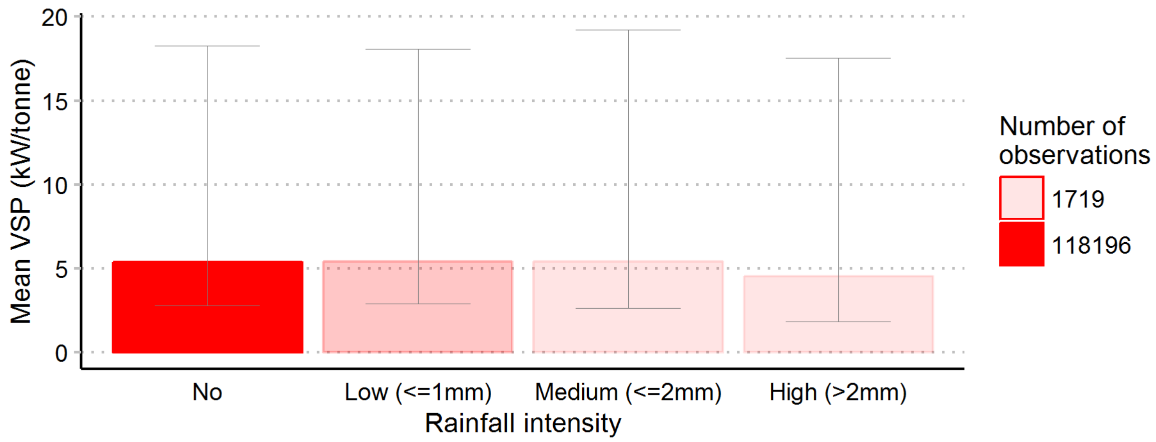

Figure 6. Influence of the rain on VSP.
Error bars represent the 5th and 95th percentiles.

To illustrate the influence of the temperature on VSP, the temperature was categorised into five classes. Negative, very low, low, medium, and high temperatures corresponded to temperatures below 0°C, between 0 and 2°C, between 2 and 7°C, between 7 and 12°C, and above 12°C respectively. Moreover, in order to capture the influence of the temperature on VSP while minimising influence of other parameters, only records collected during the regular week days were used. Because negative to low temperatures are likely to occur during the morning peak period, only records collected during this period (7:00 to 8:59) were used. Figure 7 demonstrates that the mean value of VSP remained relatively constant for temperature above 2°C (between 3.7 and 4.0 kW/tonne) but was clearly lower for low and negative temperature (between 2.9 and 3.1 kW/tonne). This 26.7% difference can be explained by drivers adopting a more cautious driving behaviour, either because of their own perception of the slipperiness of the road or because of the driving assistant warnings.

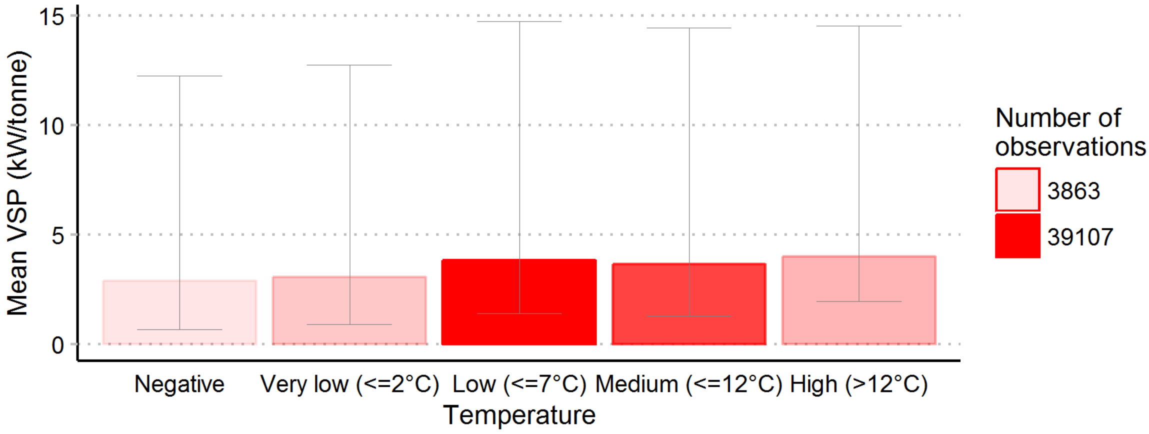

Figure 7. Influence of the type of day on VSP.
Error bars represent the 5th and 95th percentiles.

2.4 Influence of the daylight on VSP

Road visibility is not affected by weather conditions only. Daylight is likely to affect road visibility and consequently influence the drivers' behaviour in the same way weather conditions do.

The sunrise and sunset functions of the "maptools" R package enabled us to determine whether each record was collected during daytime or night time, depending on the day of the year and the time of the day. In the study area, the earliest and latest times at which the sun rises were 04:53 and 08:21 respectively, while the earliest and latest times at which the sun sets were 15:47 and 21:37 respectively. To capture the influence of daylight on VSP while minimising influence of other parameters, only records collected during those two periods of the day were used.

Figure 8 shows the mean values of VSP during daytime (over 296 513 observations) and night time (over 444 303 observations). The 0.4kW/tonne (8.7%) difference in mean VSP was statistically significant (p-value < 0.001) and proved that daylight had an impact on VSP. This impact could appear counterintuitive as VSP was lower during daytime than during night time, implying that drivers' behaviour was more aggressive during night time despite the reduced visibility. An explanation of this finding could lie in the hypothetical drivers' preference to drive in daylight. This preference would induce relatively heavier traffic conditions in daytime, constraining the drivers' behaviour and, in turn, lowering the mean value of VSP.

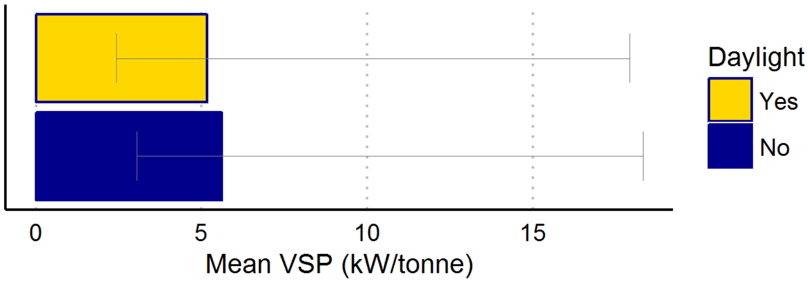

Figure 8. Influence of the daylight on VSP.
Error bars represent the 5th and 95th percentiles.

Conclusion

Exploring big telematics data from Sheffield city centre, it was found that the average vehicle specific power (VSP) varies significantly through the year, week and day. Also, differences in VSP were observed depending on the type of day, whether normal, holiday or weekend. The results suggest that heavy traffic conditions constrained drivers' behaviour so that associated VSP values remained low. Similarly, it was found that bad weather conditions induced low VSP values. VSP being a good predictor of vehicle exhaust emissions, it would be expected that the same results would have been found with emissions.

Therefore, the results suggest that to accurately estimate and forecast air quality and emissions, ad hoc models should take into account the type of day and should include diurnal variation. Most advanced models should include the influence of the weather and daylight as well. Moreover, those results demonstrate that the influence of traffic on VSP, and consequently on vehicle emissions, can be captured qualitatively even in the absence of traffic data. Further work is underway to directly capture the variation of emissions (instead of the variation of VSP). To this end, PHEM will be used to model vehicle emissions from the telematics data.

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