European Naturalistic Driving Study

Potential of eco-driving

Deliverable 45.1

DOI: 10.26323/UDRIVE_D45.1

UDRIVE

European Naturalistic Driving Study

EUROPEAN COMMISSION

SEVENTH FRAMEWORK PROGRAMME

FP7-SST-2012.4.1-3

GA No. 314050

eUropean naturalistic Driving and Riding for Infrastructure and Vehicle safety and Environment

Deliverable No.	UDRIVE D45.1	
Deliverable Title	Potential of eco-driving	
Dissemination level	Public	
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Status	Final	06-06-2017

Please refer to this document as:

Heijne, V., Ligterink, N., & Stelwagen, U. (2017). *Potential of eco-driving.* UDRIVE Deliverable 45.1. EU FP7 Project UDRIVE Consortium. https://doi.org/10.26323/UDRIVE_D45.1

Acknowledgement:

The authors would like to thank Fabio Forcolin (Volvo) and Jonas Bärgman (SAFER) for their valuable comments on previous drafts and Marika Hoeemaeker (TNO) and Nicole van Nes (SWOV) for performing the quality assurance on the final draft.

Disclaimer:

This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no 314050.

Executive Summary

The UDRIVE project collects naturalistic driving data in different European countries in order to assess safety and sustainability. WP4.5 focuses on the analysis possibilities provided by the naturalistic driving data to provide more insight in driving styles and eco-driving. The unique point of this naturalistic driving study for eco-driving is the possibility to analyse driving styles in great detail for particular driving conditions, using the additional recorded parameters, and relate them to actual vehicle emissions. This gives much more insight in the mechanisms that cause fuel consumption than given by studies performed so far. The quantity of the naturalistic driving data was never reached in earlier eco-driving studies. Moreover, with the large quantities of detailed naturalistic driving data made available for safety analyses the addition of eco-driving analysis is very cost-efficient.

Unique to UDRIVE, compared to the generic collection of velocity data of random drivers, such as the Worldwide harmonised Light vehicles Test Procedure (WLTP) database, is the augmentation of the velocity data with driving circumstances, like road type, speed limits, headway, and in-vehicle information. This should allow for placing the driving behaviour in context, and distinguishing personal driving style from behaviour forced by traffic conditions.

The overall objectives are:

- to improve understanding of the variation in driving styles and the contribution of different driving styles to “average” driving behaviour in relation to eco-driving;
- to assess the fuel consumption and the CO_2 emission reduction potential associated with adopting an eco-driving style. Improve insight in the overall net potential for eco-driving at the national and EU level, by studying different parts of the driver population, different road types and traffic situations, and different vehicle applications.

The first aim is to identify different driving styles. This is largely based on continuous time signals and takes account of driver, vehicle and infrastructure. The fuel consumption during a specific trip depends on several aspects:

- infrastructure (traffic lights, round-abouts, lane width, etc.);
- congestion and other road users;
- personal driving style;
- vehicle type and condition (mass, engine size, number of gears, tyre pressure, etc.);
- engine technology;
- fuel type;
- ambient conditions (weather).

To assess the fuel consumption and CO2 emission reduction potential associated with adopting an eco-driving style, it is crucial to separate personal driving style from infrastructure and from congestion while driving. The bandwidth of personal driving style is the bandwidth of the eco-driving. The infrastructure and congestion will be the main influence on the fuel consumption during a trip. In this analysis, the difficult task is to uncover the remainder, which can be improved by a fuel economic driving style. The parameters studied to describe driving behaviour are the speed choice at different speed limits, the loss of energy in braking and gear shifting behaviour. An eco-score per driver is determined to study correlations with driver characteristics.

The UDRIVE dataset used for this analysis contains about 13,500 hours of naturalistic driving data, distributed over more than 150 car drivers. Various approaches are studied to distinguish between different road types, and between free-flow and obstructing circumstances such as congestion and road infrastructure. The statistical noise is expected to be substantial. First the time-series data are evaluated with respect to their averages, deviations, and correlations. Subsequently, the residuals of each driver, road

type, vehicle category, etc. of the general model prediction of the averages are studied. Finally, the significance of the deviation of the residuals with respect to average driving behaviour is determined.

Due to the number of aspects influencing eco-driving, such as velocity, braking, and gear-shifting, and the large number of underlying parameters, such as country, driver, road type, speed limit, and infrastructure, the amount of data, by nature of this complexity, is limited for each specific combination. Just the fact that data was collected in five countries, with their own infrastructure and driver characteristics, already limits the generalizability of the results. Apart from country bias, the small selection of vehicle models included in the data generates another bias, which limits the generalizability of results to extreme driving, possible with high powered vehicles, or dictated by the low engine power of a heavy loaded vehicle. The current study is better suited to generalize the average rather than the bandwidth or spread.

The preferred velocity difference between drivers is up to 20% from the speed limit, both below and above it. The dynamics show an even larger spread, up to 50%. Drivers that keep a larger time headway (either due to personal driving style or due to the absence of traffic), tend to loose less energy in braking. When selecting only straight roads without intersections and without a vehicle in front, the braking energy does not decrease, although the difference between individual drivers increases. This indicates a larger difference in personal driving style, independent of driving circumstances. The difference between better and worse eco-driving behaviour is most easily recognised in the gear shifting analysis. There is a large bandwidth in average engine speed at the gear shifting moment between drivers. The eco-driver advice is to change gear between 2000 and 2500 RPM, but drivers range from 1400 to 3000 RPM, depending on the vehicle type and the gear, but mostly on the driver behaviour.

Braking energy is for most drivers the main energy consumer at low velocities, larger than rolling resistance and air drag. The difference in lost braking energy between the best and worst driver is in the order of 120%, resulting in a difference in energy consumption of up to 10%.

The engine losses are not negligible for passenger cars. Idling in urban areas occurs for 15% of the time, within a bandwidth of 0-50%. The idle CO_2 emission associated with low engine losses is typically 0.3-0.5 g/s. When driving at higher engine speeds, up from idling at 800-1000 RPM, the engine losses increase. Some drivers shift gear much earlier than others, also in the same type of vehicle. This large bandwidth in gear shifting behaviour means there is quite some room for improvement by better eco-driving behaviour. The estimated difference in fuel consumption due to different engine speeds can be up to 20-25%.

Since it is expected that a correction for driving circumstances has a large influence on driving behaviour, a selection is made on free-flow circumstances (based on headway) excluding trajectories with bends and intersections. The distribution of the eco-score per driver varies within a bandwidth of 80%. The ecodriving potential could be described as the difference between the scores of the worst and the best driver, after correcting for driving circumstances. The 80% difference between drivers indicates that eco-driving, as defined by this score, is an observable characteristic of certain drivers. It should be noted however, that fuel consumption does not linearly depend on this eco-driving scoring.

In conclusion, braking, gear shifting and the velocity choice on the motorway can all change the fuel consumption by 10% or higher for a vehicle with traditional technology. This study does not attempt to arrive at a generic number, as it would depend strongly on the vehicle technology. The clustering of drivers by country yields small differences that, due to the limited number of drivers per individual country, are not significant. The same limitation occurs for a clustering per age bin, although there seems to be a trend that older drivers drive more eco-friendly than young drivers. The average ecoscores of men and women are equal. Grouping the results with respect to country, driver age or gender do not yield strong correlations that are with certainty independent of infrastructure, vehicle type and other factors.

Due to sparsity of the data on very specific research questions, correlating different findings must be considered indicative. If there would have been more pronounced results and clear correlations at the base level of separate effects, the higher level research questions could have been answered with more confidence. Eventually, the spread in the base results, which follows directly from the analyses of the data, is a clear indication of the limitations of the meta-study, combining different base results.

The more general the results, such as the velocity distribution around the speed limits on the motorway, the more data can be combined. This yields more robust results which can be generalized to the European average with more confidence. The major drawback of these generalizations is the limited traffic information which may cause an unknown bias. The poor quality of the headway signal is the main culprit to the problems to separate different traffic situations that affect driving behaviour. The generalizations of the result to a European average are therefore partly blind for important aspects which can affect driving behaviour. Specifically, it is based on the assumption that the traffic situations are representative for the European average.

Hence, generalizability of the UDRIVE results to the European average is possible for generic results, but limited for the correlations and underlying dependencies. There is limited information of the bias in the study. However, the large spread in the data and the lack of clustering of results in clear groups, indicate that driver behaviour depends on parameters which are not, or poorly, recorded in this study.

Some recommendations can be made for follow-up research on eco-driving with the current dataset, or future data collection for naturalistic driving studies. The first is to include less homogenous drivers, even if this means that less data is available per driver. Secondly, one should ensure a well-calibrated and continuous headway signal is available, along with other crucial parameters such as road gradient, vehicle payload and road surface.

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1 Introduction

1.1 The UDRIVE project

The UDRIVE project collects naturalistic driving data in different European countries in order to assess safety and sustainability. WP4.5 focuses on the unique analysis possibilities provided by the naturalistic driving data to provide more insight in different (normal) driving styles and eco-driving. The unique point of this naturalistic driving study for eco-driving is the possibility to analyse driving styles in great detail, with the additional recorded parameters, and relate them to actual vehicle emissions, for particular driving conditions. This gives much more insight in the mechanisms that cause fuel consumption than the one given by studies performed so far. The quantity and diversity of the naturalistic driving data was never reached in earlier eco-driving studies. Moreover, with the large quantities of detailed naturalistic driving data made available for safety analyses the addition of eco-driving analysis is very cost-efficient.

The analysis in this work package will be largely based on time series data rather than on safety-critical events. Data from the driver (including driving experience and education) and vehicle is used to distinguish between driver groups. Parameters are partly static and partly dynamic. Dynamic parameters can be incident based or time-history.

Unique to UDRIVE, compared to the generic collection of velocity data of random drivers, such as the WLTP database, is the augmentation of the velocity data with driving circumstances, like road type, speed limits, headway and in-car information. This should allow for placing the driving behaviour in context, and distinguishing personal driving style from behaviour forced by traffic conditions.

1.2 Objectives

The overall objectives of WP4.5 are:

- to improve understanding of the variation in driving styles and the contribution of different driving styles to “average” driving behaviour in relation to eco-driving;
- to assess the fuel consumption and CO_2 emission reduction potential associated with adopting an eco-driving style for different parts of the driver population, on different road types and traffic situations, and different vehicle applications and to improve insight in the overall net potential for eco-driving at the national and EU level.

The first aim is to identify different driving styles. This will be largely based on continuous time signals, and will take account of driver, vehicle and infrastructure. Analysis of the overall dataset of recorded driving patterns will be used to determine the characteristics of:

- average driving behaviour
- most defensive driving styles
- various levels of more aggressive driving styles

These styles are based on driving pattern characteristics (e.g. velocity, acceleration and engine speed) that show correlation with fuel consumption. The braking, gear shifting and free flow velocity all have an important impact on the fuel consumption. The following research questions will be addressed in order to identify driving styles:

- How much do drivers deviate from the speed limit in free flow situations?
- Why do drivers deviate from the speed limit in free flow situations?
- When do drivers brake and is it necessary to brake in each instance?
- Do drivers shift gear to avoid high engine speeds and high fuel consumption?
- Is eco-driving an observable characteristic of certain drivers?

- Are eco-driving and safe driving correlated?

Based on this characterisation, objective figures on driving styles are developed and different driver groups are identified. A driver group is defined as a group of drivers with similar characteristics with respect to driving style. Distinction is made over the driver population and over EU regions. With respect to the drivers, information is collected regarding age, sex, nationality, years of driving experience, etc. These characteristics are correlated with the observed driving behaviour. Possible correlations between driving styles based on fuel-consumption criteria and driving styles based on safety criteria is investigated in WP4.2.

Combining the results of the driving style analysis with fuel consumption measured in other studies (Heijne et al., 2016) allows detailed analysis of the impact of different driving styles on fuel consumption and emissions. The potential for reducing fuel consumption through eco-driving is assessed. Results are also analysed in dependence of driving region and road type. Different driving styles and EU regions are separated to show which driver groups are already adopting eco-driving and which groups do not yet adopt eco-driving. Eco-driving parameters related to braking behaviour, gear shifting and velocity are analysed. This analysis will provide valuable insight in mechanisms that contribute to the current environmental footprint (CO_2) of the EU transport sector.

Based on the current naturalistic driving behaviour, estimations are made on the potential effect of large-scale application of eco-driving. Per driver group, a realistic estimate is given on which part of the group can be influenced towards eco-driving. This analysis will be completed with recommendations on most effective steering mechanisms per driver group.

1.3 Structure of this deliverable

After giving a general introduction to eco-driving, the main objectives of the eco-driving studies within the UDRIVE project are given in chapter 2. A description of the UDRIVE dataset and the definitions used for this specific analysis are discussed in chapter 3, leading to an overview of the main characteristics of this dataset regarding average driving behaviour in section 3.2. The following three chapters cover the main research questions, divided into braking behaviour (chapter 4), personal speed choice (chapter 5) and gear shifting behaviour (chapter 6). The results of these research topics lead to a description of eco-driving as a characteristic of certain drivers in chapter 7. Possible correlations between eco-driving and safe driving are studied in chapter 8, after which the concluding chapter 9 lists the main conclusions.

2 Introduction to eco-driving

2.1 Characteristics of eco-driving

Eco-driving in the context of this study denotes a driving style associated with low fuel consumption. A detailed definition of eco-driving can be found in (Saint Pierre et al., 2016). To summarise, the golden rules of eco-driving are:

- shift gear up as soon as possible: Shift up between 2000 and 2500 revolutions per minute
- anticipate traffic flow (to minimise dynamics and limit braking)
- maintain a steady speed: Use the highest gear possible and drive with low engine RPM
- decelerate smoothly by coasting: release the accelerator in time, leaving the car in gear to use the engine brake

Clearly, these rules on driving style can only be followed if the circumstances allow it. The fuel consumption during a specific trip depends on several aspects:

- infrastructure (traffic lights, round-abouts, lane width, road surface, etc)
- congestion and other road users
- personal driving style
- vehicle type and condition (mass, engine size, number of gears, tyre pressure, etc)
- engine technology
- fuel type
- ambient conditions (weather)

To assess the fuel consumption and CO_2 emission reduction potential associated with adopting an eco-driving style, it is therefore crucial to separate personal driving style from infrastructure and from congestion while driving. The bandwidth of personal driving style is the bandwidth of the eco-driving. The infrastructure and congestion will be the main influence on the fuel consumption during a trip. In this analysis, the difficult task is to uncover the remainder, which can be improved by a fuel economic driving style.

Since fuel consumption is not measured directly in the UDRIVE project, knowledge about the dependency of fuel consumption on several other variables is used as an indicator of fuel consumption. The fuel consumption significantly increases at high engine speeds, high dynamics (both velocity and acceleration) and when losing energy due to braking. To express this more quantitatively, the dependency of emissions on the velocity v and acceleration a of a vehicle is shown in Figure 2-1. The fuel consumption (equivalent to CO_2 emission) is higher for high accelerations and high velocities, and the amount of fuel consumed depends on which area of this figure the driver resides in. For each location in this figure, the following holds:

$$total\ CO_2\ [g] = time\ [s] \cdot CO_2\ concentration[g/s]$$

The total fuel consumption or CO_2 emission for a full trip (e.g. Figure 2-2), which runs over many bins in the velocity-acceleration space, is then expressed as:

$$total\ CO_2\ [g] = \sum_{v,a} time(v,a) \cdot CO_2\ \ concentration\ (v,a)$$

The distribution of time over different velocity-acceleration bins is more commonly described as the driving style during the trip.

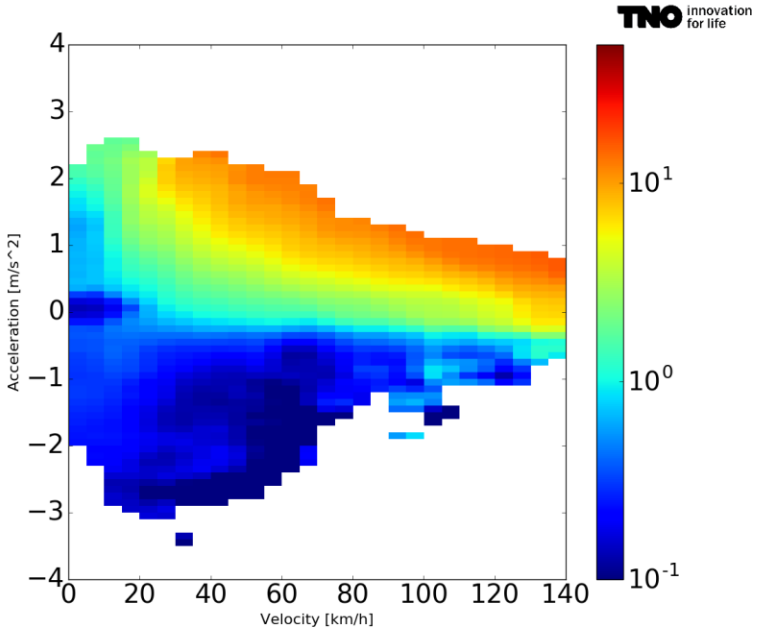

Figure 2-1 CO_2 emissions [g/s] of a Euro-6 vehicle, expressed on a colour scale, in different velocity-acceleration bins

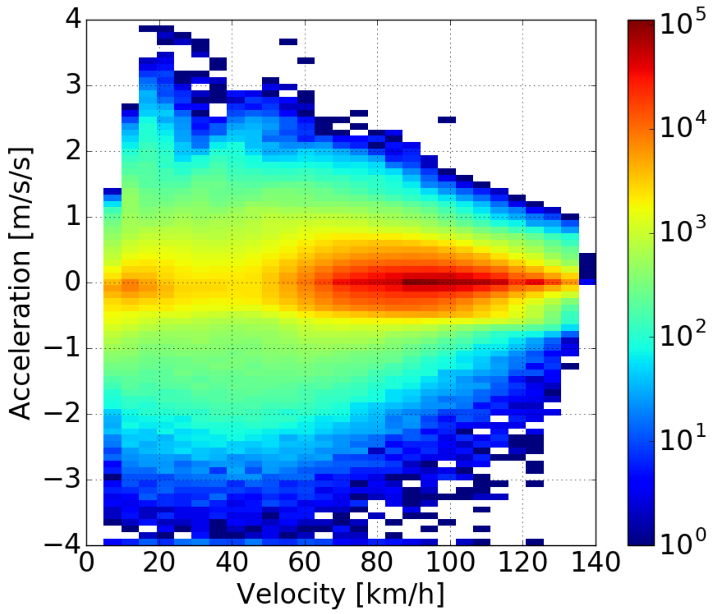

Figure 2-2 Time spent [s] expressed on a coloured scale, in different velocity-acceleration bins, for a random trip

2.2 Eco-driving studies in UDRIVE

The added value of studying eco-driving within the UDRIVE project is substantial, due to the large sample of different drivers, distributed over different EU regions. Another motivation for this analysis is the possibility to study the effect of traffic and infrastructure through the monitoring of the surroundings. The availability of large amounts of continuous 1 or even 10 Hz signals allows for better analysis of correlation between variables, and a lower statistical uncertainty than previous studies. Furthermore, the UDRIVE project, primarily aimed at investigating safety in naturalistic driving, provides a unique opportunity for complementary studies such as this eco-driving analysis.

Varying estimates are quoted for the potential effect of eco-driving on fuel consumption. For example, the ecoDriver project (Saint Pierre, 2016) concludes that on average 4.2% of fuel can be saved by using an ecoDriver system (real-time eco-driving instructions to the driver), ranging from 2.2% on motorways to 5.8% on rural roads. This value depends largely on the baseline and the vehicle technology.

The aspects of driving style that have a large influence on fuel consumption and can be studied within UDRIVE include braking, free-flow velocities and gear shifting. All of these are affected by the three forces underlying driving behaviour: infrastructure, interaction with other road users (e.g. congestion) and personal style. These aspects can be studied independently. However, in the analysis the underlying causes must be investigated conjunctively. For example, if a driver brakes does he (or she) do so because of a traffic light, a vehicle ahead, or because the driver remembered he (or she) left the stove on? Whether the stove was left on cannot be determined, hence personal style is the remainder when all external causes are excluded.
Fuel consumption will vary a lot from driver to driver. Typically, there is a 40% difference between the fuel bill per kilometre of the best and the worst driver driving the same car model (Ligterink and Smokers, 2016a). In part this is caused by driving behaviour, but other causes such as tyre pressure, passengers, luggage, temperature, road surface, etc. also play a role. The large variation and the multitude of underlying causes strain the analysis. Much data is needed to allow for significant and discriminating results. Therefore, all the data is used and the data must be as uniform as possible as well as independent of the aspects not covered in this analysis. Furthermore, the signals must be direct measurements, not derived, in order not to uncover processing artefacts rather than aspects of the driving itself.

Some of the key quantities that play a role in the investigation are:

- Power at the wheels (positive or propulsion, and negative or braking): The safe avoidance of braking is a key part in reducing fuel consumption at low velocities, mainly on urban roads. Hence restricting the power at the wheels is an important part of the investigation
- Engine speed: High engine speeds (not associated with high vehicle speed in the highest gear) is the second most important reason for unnecessary energy loss during driving. Engine losses are a significant part of the fuel consumption at low velocities, and these engine losses are approximately proportional with engine speed.
- Degree of congestion: some driving is dictated by other road users. The best available signal is the amount of headway. This signal will be used as a proxy for the degree of congestion. However, headway is also a matter of personal style. These two aspects must be separated.
- Infrastructure: speed limits, traffic lights and bends are basically boundary conditions for driving behaviour. In the case of speed limits of 50 km/h it is not possible to achieve the same fuel efficiency as with an 80 km/h speed limit.

3 UDRIVE dataset and variables

The UDRIVE dataset used for this analysis contains about 13,500 hours of naturalistic driving data. The first section of this chapter gives a more detailed overview of the dataset, drivers and vehicles. Section 3.3 gives an impression of driving parameters over the whole dataset and over different countries. The other two sections discuss different approaches to distinguish between different road types, and between free-flow and obstructing circumstances such as congestion and road infrastructure.

3.1 UDRIVE dataset

In eco-driving research the relationship between driving behaviour and fuel consumption is to be analysed. The research will mainly consist of correlation studies in multi-regression analysis on the continuous data, not that of specific events. Hence the video annotation is less relevant for the eco-driving research questions. Annotations such as start-and-end of congestion could be useful, however those are not currently available. To disentangle the different aspects affecting the driving behaviour, much of the analysis will be meta-analysis on as much of the continuous data as possible. Only in this manner can the personal style be separated from the driving behaviour dictated by circumstances.

The UDRIVE dataset analysed for this deliverable consists of the data available in the car database in April 2017, which contains about 13,500 hours of driving by 154 drivers. A similar analysis could be carried out on truck data, but due to the limited availability of validated truck data in the database the current analysis only covers passenger cars. Table 3.1 gives an overview of the main characteristics of this dataset. Three different vehicle types were used, namely a Renault Mégane and two types of Renault Clios. In some cases, the vehicle type is not registered in the database, hence the column 'other' vehicles. More specific characteristics of the vehicles have not been linked to the database yet, but Table 3.2 gives an idea of the range of mass and engine power available in the vehicles at the German operation site. Some Méganes have an automatic gearbox and some a manual one but this is not listed in the vehicle specifications. The large range (for example in mass) will dilute the results for specific vehicle categories.

Data of vehicles or drivers that could not be identified has been excluded from the analysis. When applying data stratification, for example all data at a certain speed limit, in a certain country or of a certain vehicle type, drivers that drove less than 1 hour under these specific conditions are excluded from the final analysis. This way, when comparing the results per driver, one is certain that all drivers have sufficient statistical coverage.

Table 3.1: Characteristics of the UDRIVE dataset in april 2017

Country	Total time [h]	Total distance [km]	Number of drivers	<v> per driver [km/h]	Number of vehicles			
					MeganeIII	ClioIII	ClioIV	other
United Kingdom	4240	216397	50	56.9	14	28	8	
Germany	903	48047	17	60.9	7	8	2	
The Netherlands	1035	65945	16	62.0			13	3
France	5358	282495	43	63.5	18	4	21	
Poland	2128	114284	28	65.5	14	9	1	4
Total	13665	727169	154	61.3	53	49	45	7

Table 3.2: Characteristics of a subset of the UDRIVE vehicles

Vehicle	Megane III	Clio III	Clio IV
Mass range	1280-1808 kg	1165-1225 kg	1080 kg
Power range	74-195 kW	55-76 kW	66 kW
Max RPM range	3750-6000	5000-5500	5250
Number of gears	5 or 6	5	5

Braking, engine speed and velocity are key variables. Furthermore, drivers should be compensated on their driving behaviour for circumstances such as heavy congestion, bendy roads and traffic lights. A general correlation with headway, bends and infrastructure allows one to compensate for, or at least separate into, different circumstances.

The conditions affecting the driving style must be distilled from the available signals. The relationship between driving behaviour and congestion is well known, but the degree of congestion is difficult to recover from the signals at hand. Headway is an important variable to be used in combination with the velocity and velocity variations. For infrastructure bends, junctions, traffic lights, speed limits and lane width are important aspects to be retrieved from the map-matching data. These affect the driving behaviour, forcing the driver to slow down or even stop. Functional relations between, for example, free-flow velocity, speed limit, road type and headway can be uncovered. Based on these generic relations, the deviations for drivers and circumstances, such as road types, can be uncovered. These are the bandwidths within the data.

The statistical noise is expected to be substantial. There is a need for many proper signals, long time series, and a variety of drivers. Only then can statistical significance be achieved. Hence, first the time-series data are evaluated with respect to their averages, deviations, and correlations. Subsequently, the residuals of each driver, road type, vehicle category, etc. of the general model prediction of the averages are studied. Finally, the significance of the deviation of the residuals is determined.

3.2 Road type definition

Using a combination of speed limits and map variables such as the area type and road classification, a road type definition is developed that suits the needs of the eco-driver analysis.

The raw map matched road types showed too much urban driving and too high velocities for urban driving, which e.g. in emission regulations is defined as all velocities below 60 km/h. Furthermore there is a large percentage of sliproads. Therefore, the definition used for this analysis takes the speed limit as the main indicator of roadtype, after which the map area type is used to define the rural or urban surroundings, and the map road type to define motorways. The motorways are divided into rural and urban motorways, though for most analyses the two are taken as one category, because the interpretation of urban and rural motorways differs per country and per area. The urban motorways only cover a small part of the data. About 10-15% of the data could not be assigned to any road type, because the speed limit and area type are missing. The resulting velocity distributions per road type in Figure 3-1 illustrate that most roads have been assigned correctly.

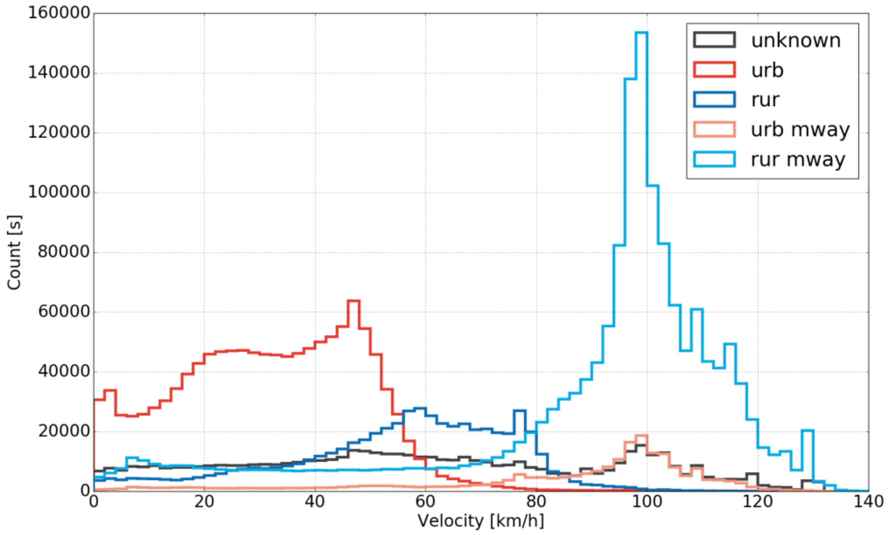

Figure 3-1 Velocity distributions on different road types, for all drivers in The Netherlands

3.3 Average driving behaviour and validation of variables

By looking at distributions per driver and for the whole dataset, the most important variables for the analysis are validated. These include velocity, engine speed, headway, road types, intersections and speed limits.

The average velocities on different road types are given in Table 3.3, along with the percentage of time spent on this road type. This gives an indication of the validity of the road type distinction. A closer look at the distribution underlying the average velocities (see Figure 3-1) shows that indeed the urban roads have velocities lower than 60 km/h, and the rural roads cover about 40-80 km/h. The different peaks in the velocity profiles occur depending on the local speed limits, as can be seen in Figure 3-2. The map matching of the speed limits seems to be reliable. The definition of the road type is derived as described in Section 3.2, and seems to be reasonably valid for all countries.

Table 3.3: Driving behaviour on different road types (road type unknown is not shown)

Country	% distance urban	% distance rural	% distance motorway	<v> [km/h] urban	<v> [km/h] rural	<v> [km/h] motorway
United Kingdom	36%	21%	31%	24	52	91
Germany	40%	20%	36%	28	70	91
The Netherlands	22%	11%	59%	25	52	91
France	37%	30%	27%	25	60	97
Poland	51%	16%	17%	26	78	104
Total	38%	22%	31%	25	60	95

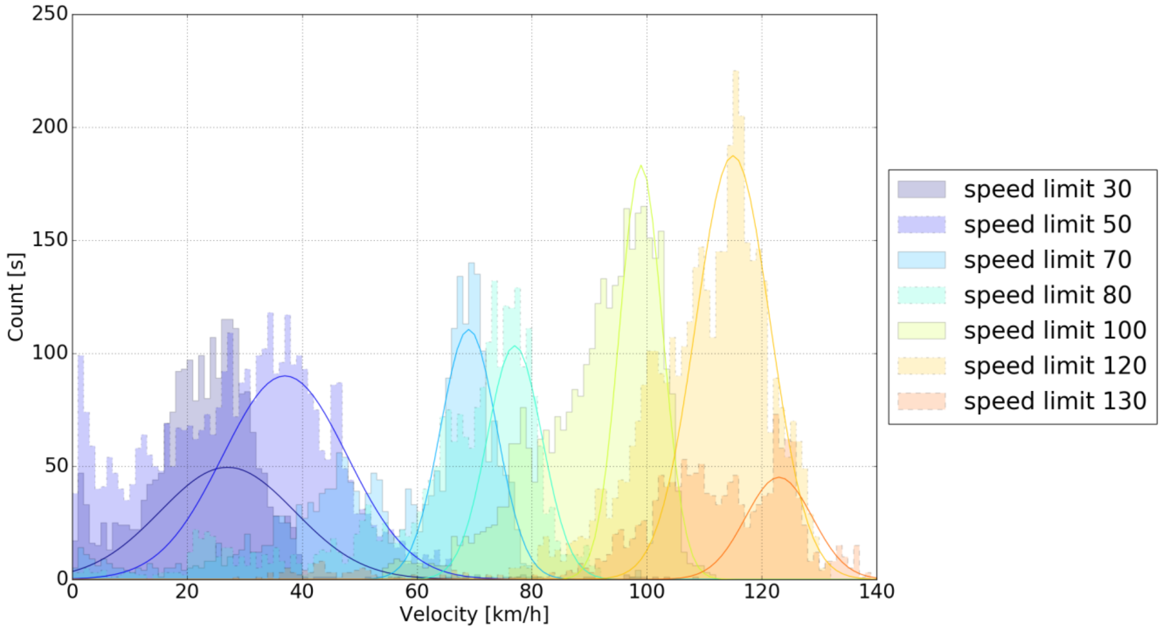

Figure 3-2 Velocity distributions per speed limit for one driver in The Netherlands

The acceleration and velocity distribution gives further insight in the driving behaviour in different countries or at different road types, as can be seen in Figure 3-3 until Figure 3-5. The velocities are higher on motorways, whereas the dynamics (acceleration and deceleration) are lower than in the city and on rural roads. These dynamics have a major influence on the fuel consumption, as was shown in Figure 2-1. It is not the accelerations, but mainly the braking due to those accelerations that causes large energy losses and high fuel consumptions. These figures give a unique insight into driving behaviour for different road types and different drivers.

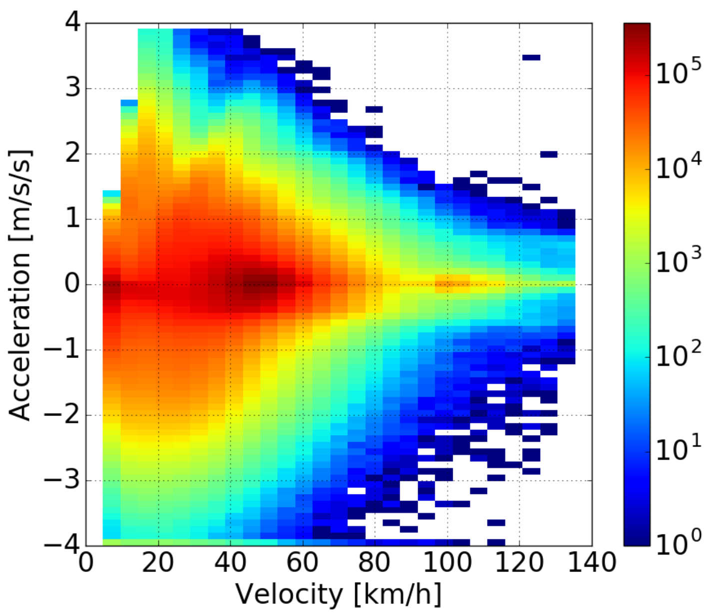

Figure 3-3 Velocity-acceleration distribution on urban roads, for all countries

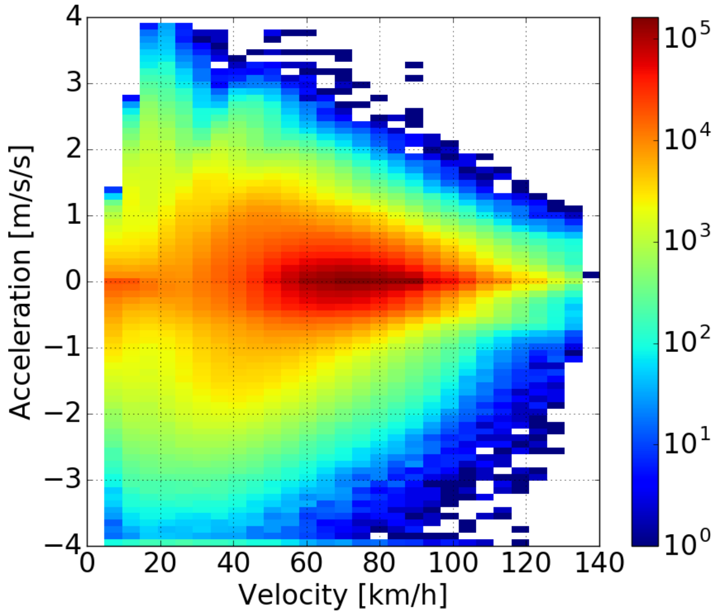

Figure 3-4 Velocity-acceleration distribution on rural roads, for all countries

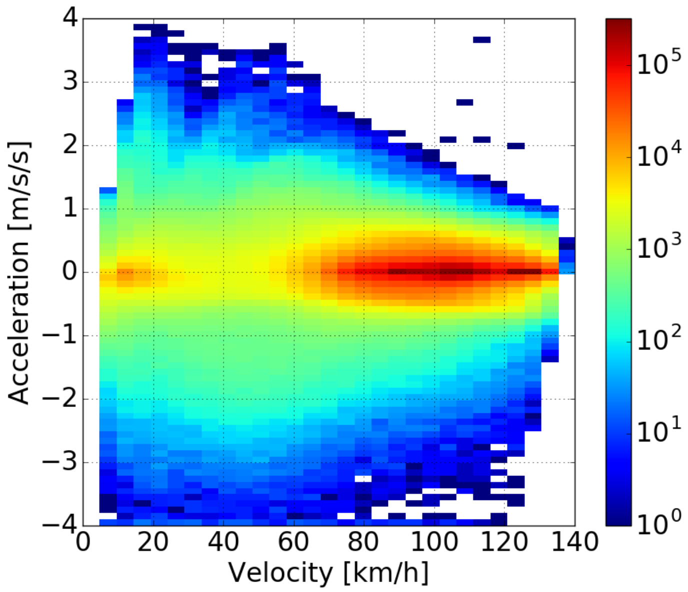

Figure 3-5 Velocity-acceleration distribution on motorways, for all countries

The headway is a crucial variable to determine the driving context. Time headway is measured in seconds, and determines the time it takes the vehicle to cross the distance to the vehicle in front, at its current velocity. The raw headway signal provided by the MobileEye system (expressed in units relative to time, i.e. [10, 15, 20] translate into a time headway of [1, 1.5, 2] seconds) proved to be unusable for analysis, due to its poor resolution. Figure 3-6 illustrates that the steps in the raw signal are too large and the maximal signal too low to gain any insight on real headway. By following separate objects in the list of objects seen by MobileEye, and selecting those objects in front of the vehicle, a more precise headway signal could be derived as follows.

The headway measurement by MobileEye seems to be provided only under certain constraints for speed and range (from empirical trials). The newly derived time headway signal is measured in seconds.

The function that calculates it receives two inputs:

- leading vehicle range: distance in meters from the Leading Vehicle (distance is given by MobileEye)
- subject vehicle speed (from CAN)

the leading vehicle range is a measurement computed using:

- Obstacle1/2/3/4_posX: distance of the 4 detected objects with respect to the subject vehicle
- MatrixTruckOfLeadingVehicleOnEgoLaneInFrontMinDist: it is a 4xN matrix in which each row is an object detected by MobileEye and each column is a time instance. Each element of the matrix tells which of the four objects is recognized as Leading Object by being set to 1 (otherwise 0). One and only one element of the matrix in each column can be set to 1.

The matrix is computed as follows:

1) The matrix is initialized to be 4xN NaNs, where N is the length of the trip, measured in samples.
2) At each time instance, the posY (lateral displacement of the object compared to the camera) of the 4 objects detected by ME is compared to a threshold. The object with the minimum absolute value of posY under the threshold is candidate for being Object Leader. The threshold is set to 0.7 meters (to be checked). This allows having a maximum displacement of about half the width of a vehicle and is able also to get rid of false positives by not detecting an incoming vehicle or parked vehicle on the sides as leader.
3) From the resulting possible leading objects, only the closest in front exploiting the posX measurement (there could be, e.g., two cars in front of each other recognized as leading vehicles) is chosen.
4) A leading vehicle which is classified not as Truck or Car is discarded.
5) Each element of the matrix that fulfills all the above criteria is set to 1.

This algorithm has a limitation in sharp turns. In a sharp turn where the leading vehicle is already in the curve but the ego vehicle is not yet, the algorithm fails to keep track of the vehicle and thus no THW provided. Therefore, before the curve the vehicle is correctly detected as leading vehicle, during the curve is discarded, after the curve it is correctly detected again.

The distributions of this derived time headway are shown in Figure 3-7. The most frequent time headway lies between 1 and 2 seconds, depending on the road type. At first glance they look reliable, but it turns out that the distinctive power of the headway signal to determine whether the vehicle is in a free-flow situation is probably not sufficient. More on this will be discussed in Section 3.4.1.

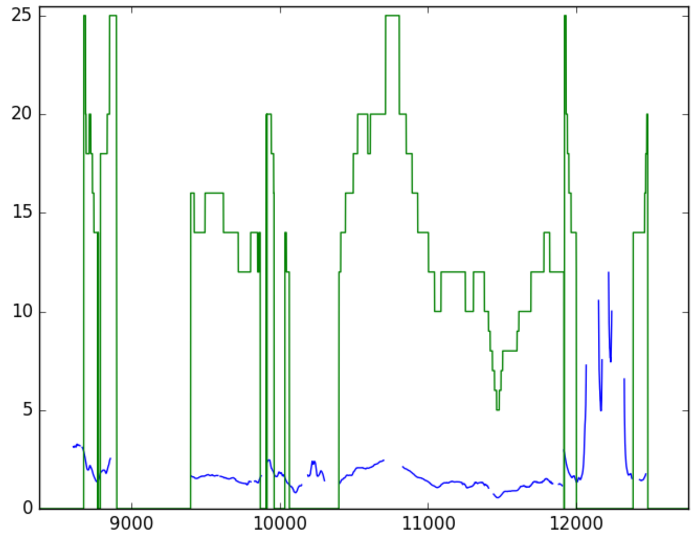

Figure 3-6 Timeseries signals of the headway per second. Raw headway signal in 0.1 seconds (green) and derived time headway [s] (blue) from MobileEye information

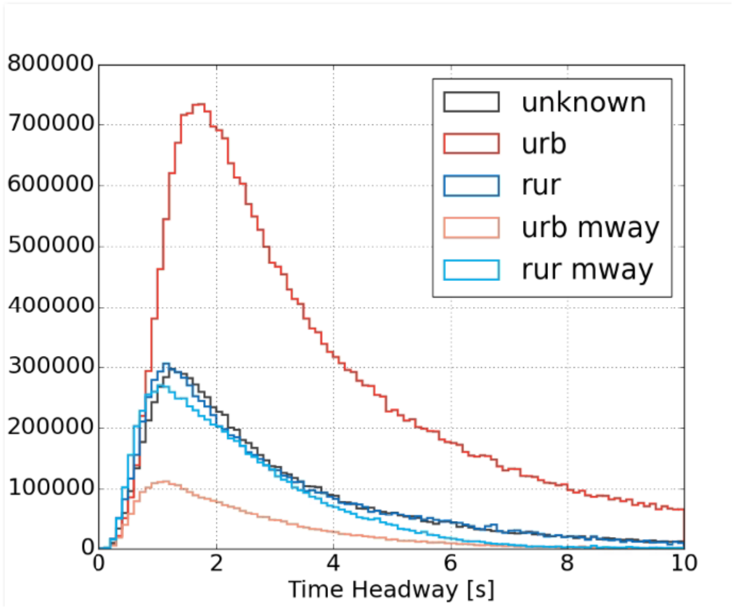

Figure 3-7 Time headway [s] distribution, on different road types, for all data

A vehicle that is idling causes on average 0.4 g/s CO_2 emissions. Reducing idling time, through better infrastructure or less congestion might therefore lower fuel consumption. The idling time in urban areas, defined as the time in which the vehicle is standing still for two or more seconds while the engine is running, varies between 0 and 50% for drivers, as can be seen in Table 3.4. Note that the first seconds of each trip are excluded from data taking, due to hardware limitations or data collection. This creates a bias for the idling time, thereby mainly influencing cold start effects at the beginning of a trip.

Table 3.4: Percentage idling time per driver, for the full dataset

road type	average % idling	min % idling	max % idling
urban	15%	0%	50%
all	10%	0%	37%

In emission legislation, the product of velocity and positive acceleration at 95 percentile ("vapos") is often used as an indication of how aggressive the driving style was during a trip. Table 3.5 gives the average, minimum and maximum vapos values for all drivers in the dataset. Figure 3-8 gives the values per driver, grouping drivers per country. The upper limit for current Real Driving Emissions legislation, indicated by the red line, lies at 15 m^2/s^3 for the lowest velocity range, and 30 m^2/s^3 for the highest velocity range. The measured vapos values lie mostly within this range. There is no clear correlation between country and vapos but there is a correlation between the vehicle type and this variable, as seen in Figure 3-9. A larger car with more engine power can more easily reach high accelerations at high velocities, which translates in higher vapos values.

Table 3.5: velocity * positive acceleration [m^2/s^3] at 95 percentile per driver, for the full dataset

velocity range	average vapos [m^2/s^3]	min vapos [m^2/s^3]	max vapos [m^2/s^3]
0-60 km/h	14.2	8.1	20.8
60-90 km/h	16.6	8.5	30.2
>90 km/h	14.3	5.6	29.2

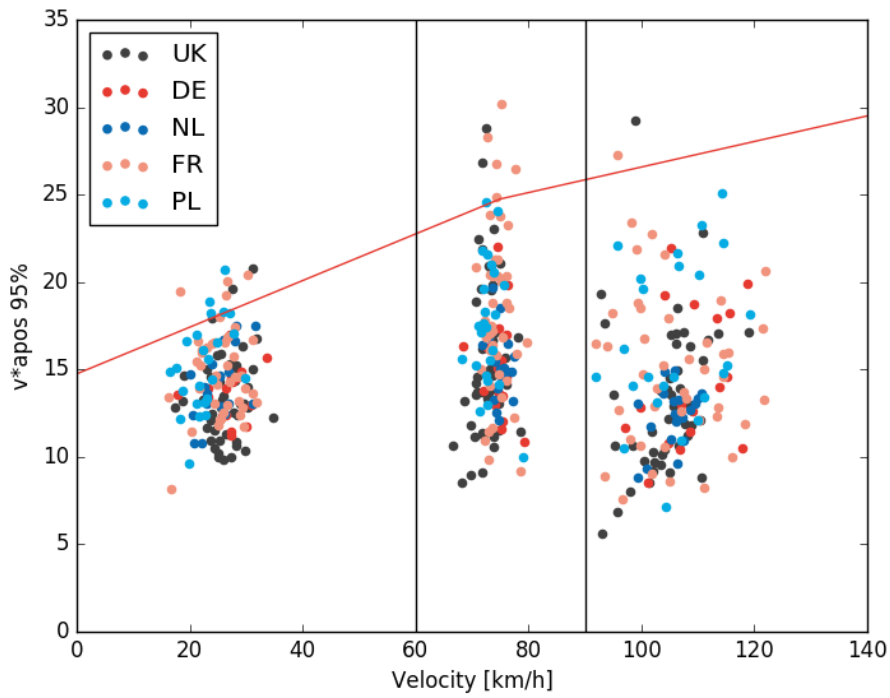

Figure 3-8 v*a positive [m^2/s^3] at 95 percentile in three different velocity ranges, for all drivers per country

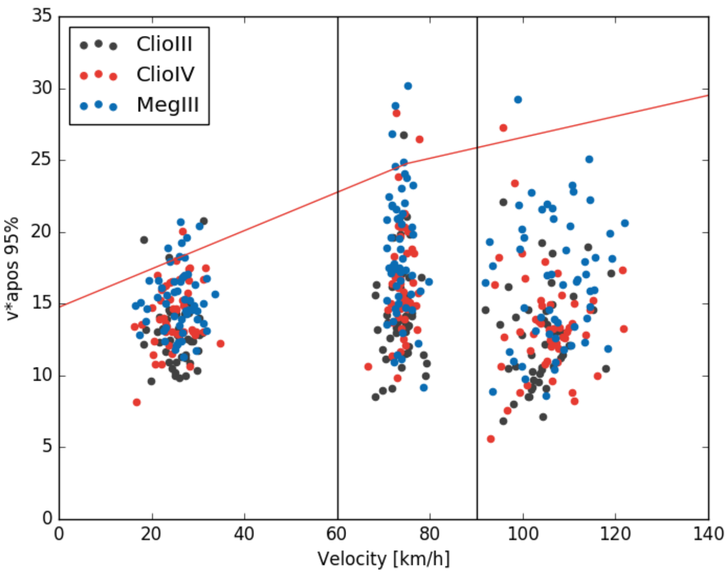

Figure 3-9 v*a positive [m^2/s^3] at 95 percentile in three different velocity ranges, for all drivers per vehicle type

3.4 Freeflow definition

The definition of free-flow situations is complicated, even though the vehicles are equipped with cameras and a MobileEye system to scan the surroundings. Map variables may help to determine obstacles in the road infrastructure, but to get an idea of the congestion level (i.e. whether the vehicle is hindered by any other vehicles in the surroundings), one has to rely on a good headway signal. Note that due to different analytical requirements, for other analysis in UDRIVE (e.g., WP4.2 and WP4.3) the definition of free-flow (and car-following) was less stringent.

3.4.1 Headway per velocity bin

The initial approach to determine free-flow consists of determining the 'preferred' headway of each driver, which depends on the velocity. The average headway for a given velocity bin is given by:

$$< HW\ (v) \geq \frac{1}{N} \sum_{vlow<v<vhigh} HW_v$$

Figure 3-10 illustrates the resulting time headway at different velocity bins for a certain driver, using the derived time headway signal. To define free-flow, one can select all the points where the headway is larger than the median headway at this velocity. This ensures the selection of only those cases in which the vehicle is unhindered by others. For most drivers, the border between hindered and free-flow driving lies around 3 seconds at 50 km/h.

When selecting freeflow traffic in this way, the analysis showed almost no distinction between hindered and unhindered traffic, apart from rejecting a large part of the dataset. Therefore, other methods to determine freeflow were studied, as described in the next sections.

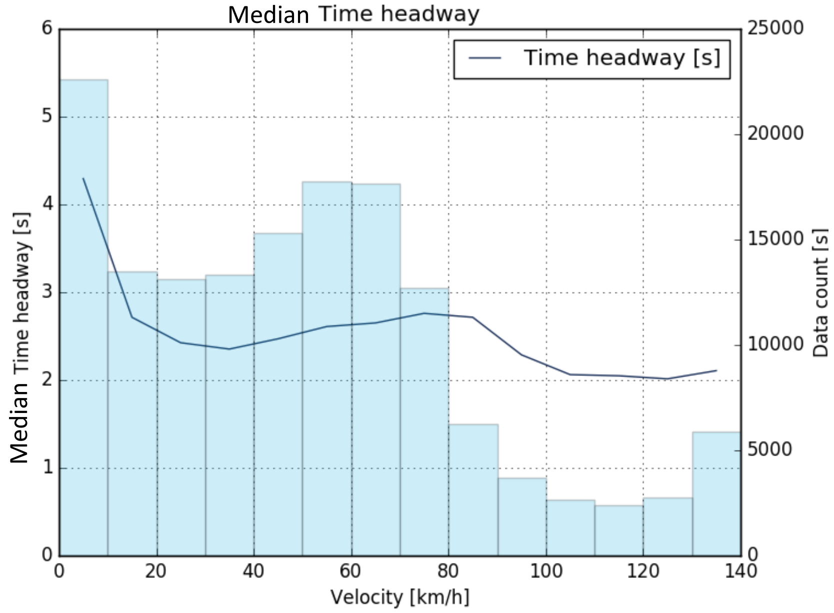

Figure 3-10 Median time headway at different velocities (blue line). The time spent in each velocity bin is given by the underlying histogram

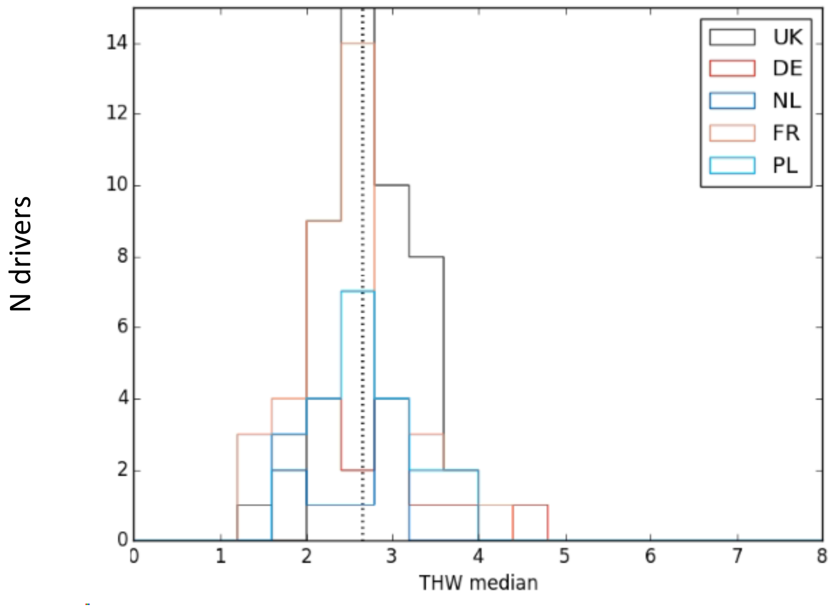

Figure 3-11 Distributions of the median time headway per driver, for all countries

To evaluate the effect of selecting free-flow through headway, the velocity-acceleration profiles of all data and free-flow data can be compared. The difference between the two (expressed as a percentage of the full dataset) is shown in Figure 3-12 until Figure 3-14, for different road types. At constant velocities over 50 km/h, about 40% of the data remains after the free-flow requirement. The data that is rejected at higher velocities mainly consists of dynamic data, i.e. accelerations larger than 0.3 m/s^2. At low velocities however, most data is rejected, both at high and at low accelerations. The rejection ranges from 70% for urban road until 90% for motorways.

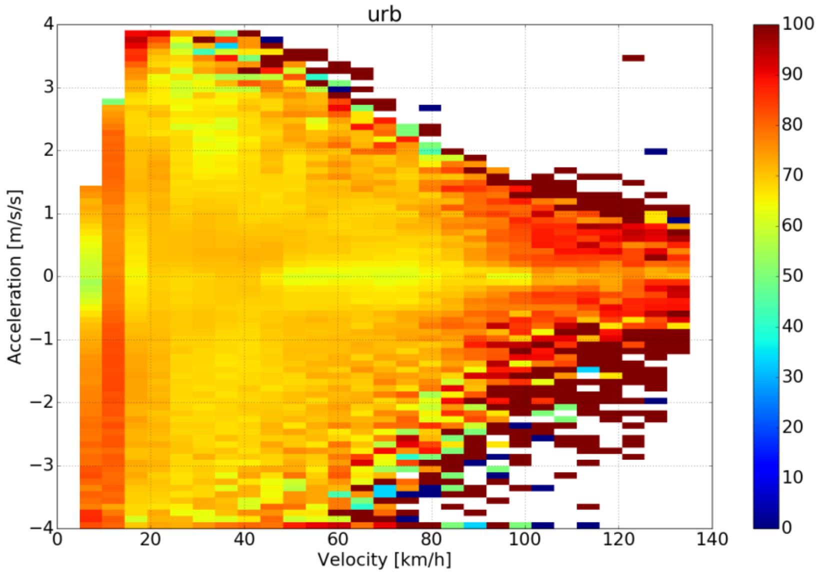

Figure 3-12 Velocity-acceleration distribution of the difference (in percentage) between all data and free-flow selected data for urban roads

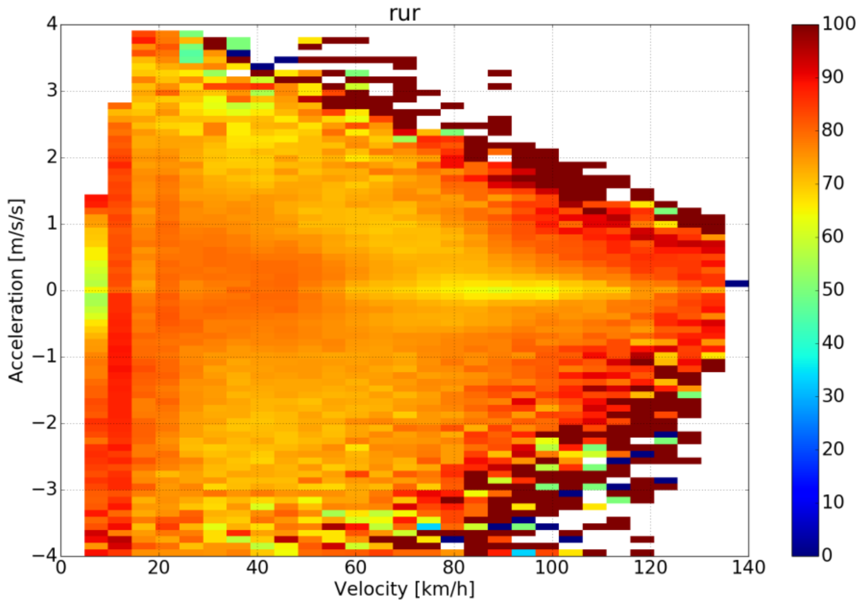

Figure 3-13 Velocity-acceleration distribution of the difference (in percentage) between all data and free-flow selected data for rural roads

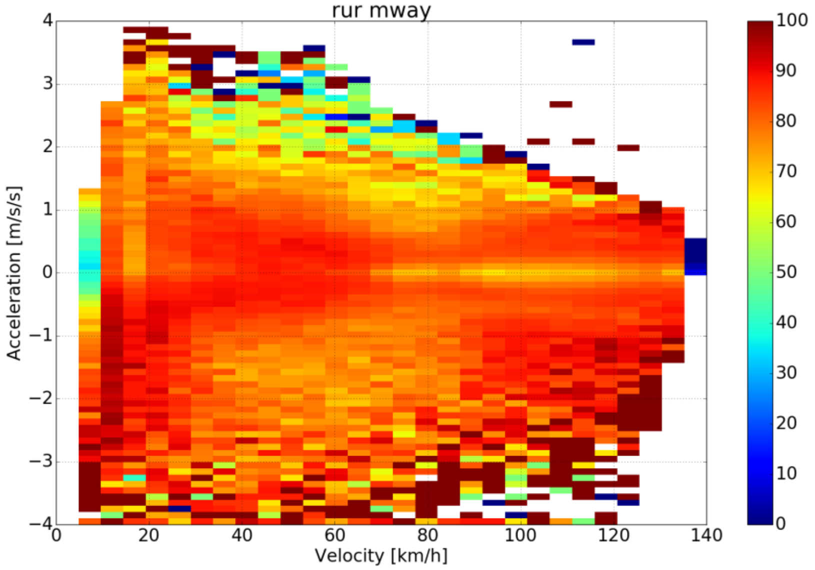

Figure 3-14 Velocity-acceleration distribution of the difference (in percentage) between all data and free-flow selected data for motorways

The free-flow selection used seems to have a predictable effect on the velocity-acceleration profile. However, later chapters will show that the effect on parameters related to eco-driving is not so straight-forward and distinctive. For example, we will see that the braking energy does not significantly decrease in free-flow situations, and the gear changing behaviour does not change at all. Section 3.4.3 gives some conclusions on this and other ways of determining free-flow conditions from the dataset.

3.4.2 Congestion: velocity lower than the preferred velocity per driver

The velocity distribution per speed limit (Figure 3-2) shows that there is usually a peak velocity at which the driver drives most often at this speed limit. This is most likely the free-flow speed of choice. When the velocity is much smaller than this peak, there are other circumstances (congestion or road obstructions such as bends) that prevent the driver from driving around the speed limit. A Gaussian distribution is fitted to the right slope of the peak and mirrored to estimate the left slope. All the data that falls below one standard deviation of the left of the peak is considered non free-flow. Especially on motorways, this procedure helps to distinguish congestion from normal traffic flow. The peaks give an indication of the preferred velocity compared to the speed limit. The width of the gaussian indicates whether a driver always drives at one particular speed, or whether his speed choice varies widely. As can be seen in Figure 3-15, this procedure works best when the peak is rather narrow, which is the case for the higher speed limits.

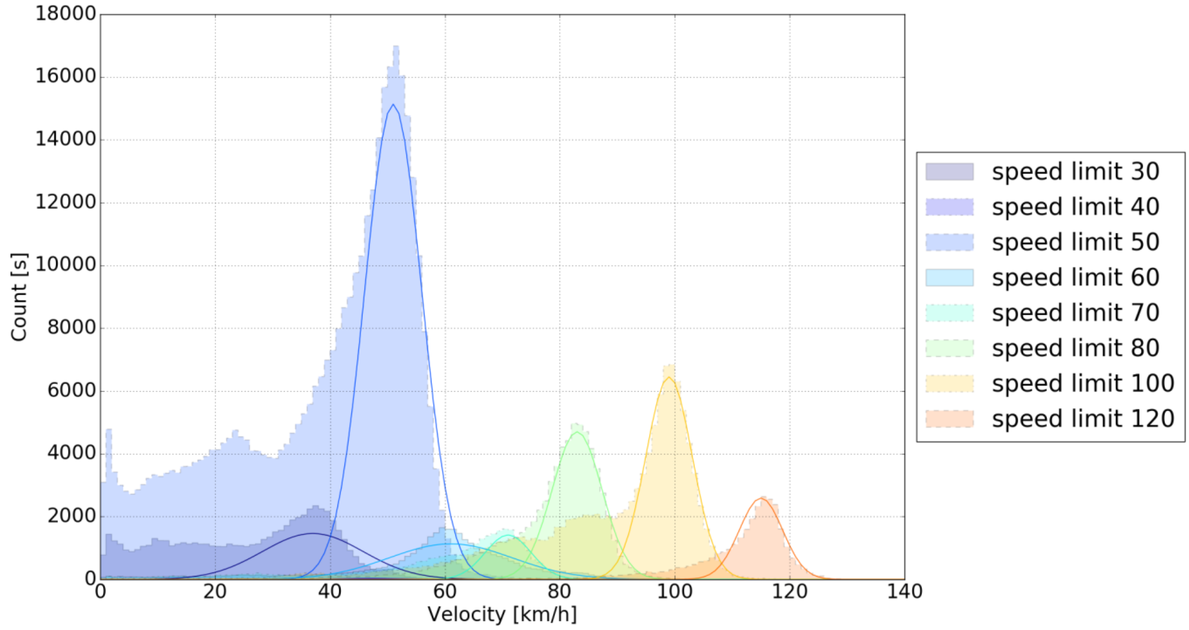

Figure 3-15 Velocity distributions per speed limit for one German driver, with a fit of the most frequent velocity

The percentage of time (or distance) at which the driver drove slower than the peak is listed in Table 3.6. This variable is most reliable for motorways where there are high speed limits and narrow velocity peaks, and gives an indication of the degree of congestion. In Germany, the UK and the Netherlands the congestion on motorways is higher than in France and Poland. When splitting the data further up into specific speed limits, The Netherlands shows much more congestion on the 120 and 130 km/h motorways (Figure 3-17) and less congestion on 100 km/h motorways (Figure 3-16). Figure 3-17 indicates that more than 60% of the time people drive slower than their prefered velocity on 130 km/h roads in The Netherlands.

Table 3.6: Distance driven at velocities lower than the preferred (peak) velocity, indicating congestion or obstruction

Country	% distance lower than peak, urban	% distance lower than peak, rural	% distance lower than peak, motorway
United Kingdom	17%	36%	36%
Germany	22%	36%	34%
The Netherlands	22%	48%	33%
France	15%	28%	22%
Poland	17%	24%	25%

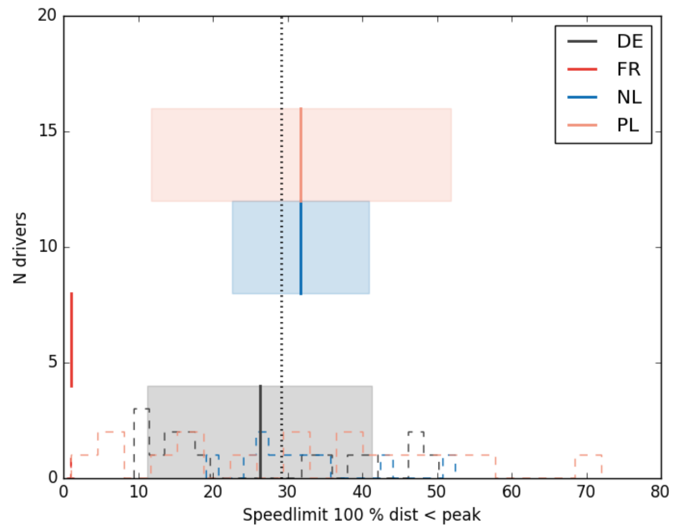

Figure 3-16 Percentage of distance at velocities lower than the most frequent velocity, for a speedlimit of 100 km/h. The average and standard deviation of all drivers in one country are shown by the coloured lines and lightcoloured areas, respectively. The dashed coloured lines are the underlying distributions with one entry per driver

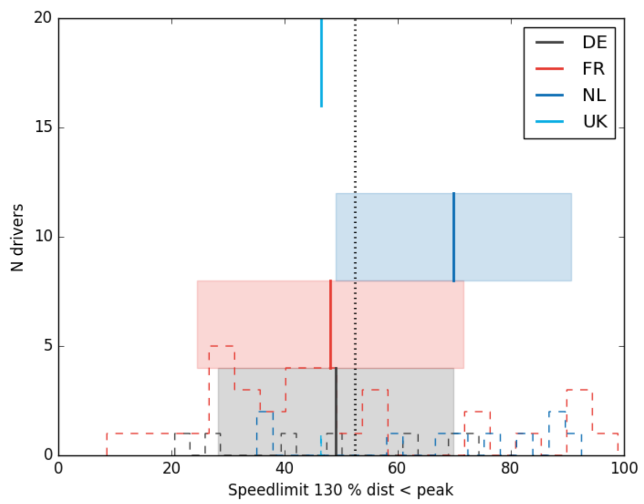

Figure 3-17 Percentage of distance at velocities lower than the most frequent velocity, for a speedlimit of 130 km/h. The average and standard deviation of all drivers in one country are shown by the coloured lines and lightcoloured areas, respectively. The dashed coloured lines are the underlying distributions with one entry per driver

3.4.3 Excluding curves, intersections and traffic lights

In an attempt to better discern between forced actions of the driver, for example by the presence of road curves and turns, and personally chosen driver actions, a scheme is devised to divide each vehicle track into more or less straight sections and non-straight or curved sections. In this scheme the GPS latitude and longitude signals (i.e. GPS_Latitude and GPS_Longitude at 1 Hz) are used to derive the vehicle track. Next, from the vehicle track the road curvature and the time change of the vehicle heading, i.e. the heading rate also known as the yaw rate, are calculated. Finally, by comparing these two derived signals to certain limits (e.g. curvature > 0.001 m while yaw rate > 1 degree/s), the entire vehicle track (1 Hz) can be labeled as curved (1) or straight (0). A visual example of a small part of a vehicle track divided in straight and curved is given in Figure 3-18.

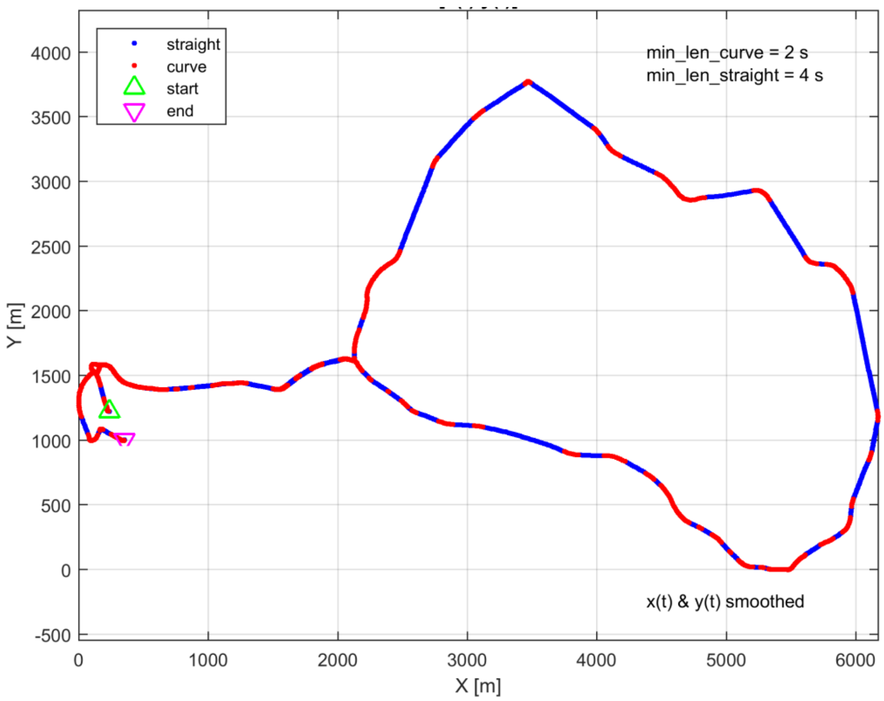

Figure 3-18 Vehicle track translated to x and y coordinates, with curved sections in red and straigth sections in blue.

This derived curve/straight signal is combined with the map intersection signal (i.e. MAP_INTERSECTION at 1 Hz) to select all sections of a vehicle track which were neither curved nor with intersection(s). This is done for all trips of all drivers and used in the analysis of the final results presented in the next chapters.

3.4.4 Conclusion on free-flow determination

The abundance of data per driver enables a good evaluation of average driving behaviour at different road types, different speed limits and in different countries. An estimate can be made of the congestion on motorways for example, which shows significant differences between countries. Evaluating the reasons for these differences in more detail however has proved to be more difficult.

Central to the separation of forced actions of the driver by external circumstances on the one hand and the personal choice of the driver to take certain actions like braking or accelerating on the other hand, is the headway signal. An obstruction in front of the vehicle will force any driver to brake and the headway would provide this information. However, there are concerns to the quality of the raw headway signal, and the reconstructed headway signal. In many cases, factoring the headway into the analysis does not provide the much wanted separation in forced and voluntary actions. Consequently, alternative methods to determine free-flow are also analysed, to little avail. There is limited information to determine the situation around the vehicle which may affect the driving behaviour.

Different ways to select free-flow from normal traffic were evaluated. There is no preferred option that proved to give clearly distinctive and reliable results. Therefore, throughout the next chapters, the full dataset will always be analysed first. After that, a comparison is made between the results on the full dataset and on the dataset with the selection on large headway and roads without intersections and bends.

4 Braking

4.1 Introduction

In many cases braking is necessary and dictated by the driving context. The avoidable braking is the small amount of braking while there is enough headway, no obstruction, no bends or no traffic signals. The filtering of the remaining braking behaviour is the basis for the study of variation in personal style. Another aspect of personal style is the headway kept at each velocity, and its association with braking. Shorter headway, which in many cases may turn out to be unnecessary, will probably lead to more braking.

Research question:

- When do drivers brake and is it necessary to brake in each instance?

4.2 Method

4.2.1 Variables

The braking energy is estimated from the velocity signal (mSpeedCAN), using the total force executed on the vehicle. The signal on brake pressure (mBrakePressure) could not be understood sufficiently well to translate it into the braking energy, therefore an approximation of the energy is derived using the velocity signal and some vehicle parameters. The total force on the vehicle is defined as follows:

$$F_{total} = F_{roll} + F_{air} + F_{inertia}$$

Braking energy is lost only when the deceleration is faster than the deceleration that is caused by the driving resistance. Therefore, the driving resistance force is first defined by defining resistance as the total force minus the force used to accelerate the vehicle:

$$F_{resist} = F_{roll} + F_{air}$$

From this, the deceleration due to resistance can be estimated:

$$a_{resist} = -(g \cdot c_{rr} + v^2 \cdot \frac{1}{2m} c_w \, A \, \rho)$$

which, given the following assumptions,

rolling resistance coefficient c_{rr} = 0.011, gravitational acceleration g = 9.8 m/s^2, drag coefficient c_w = 0.4, frontal area A = 2.2 m^2, air density ρ = 1.2 kg/m^3, vehicle mass = 1500 kg

results in the approximation below, if v is given in km/h and the deceleration in m/s^2:

$$a_{resist} = -(0.11 + 0.00035 \cdot (\frac{v}{3.6})^2)$$

The energy per kilogram kilometer lost in braking, E[J/kgkm], is defined in terms of the velocity and the acceleration (negative deceleration) as follows:

$$E_{braking} = -\frac{1}{dist} \sum_{a < a_{resist}} (a - a_{resist}) \cdot \frac{v}{3.6}$$

where E in J/(kg km), distance in km and velocity in km/h.

The road inclination was not logged by the GPS sensors. A related signal was available from the map matching, but this could not be interpreted into a reliable slope. Other signals on the three-dimensional acceleration of the vehicle (accelerometers Veh_PhidgetSpatial_gyro, Veh_PhidgetSpatial_compass and Veh_PhidgetSpatial_acc) are not sufficiently calibrated compared to the precision of their signals to be of use. Therefore, for this analysis it is assumed that all roads are flat. This should not be of large influence due to the large amount of data that enables an averaging over long distances, resulting in an absolute height difference that converges to zero.

Finally, the free-flow conditions are selected as described in section 3.2.

4.2.2 Analysis

The braking energy can be analysed as a function of velocity. The black line in Figure 4-1 shows the average braking energy per velocity bin of all drivers. At low velocities, the braking energy is higher due to the larger decelerations, combined with a smaller air- and rolling resistance. When selecting only free-flow situations based on the headway signal, the light blue line remains. At very low velocities and above 80 km/h, the free-flow situation seems to result in less braking. When performing the same analysis on roads without intersections or bends, Figure 4-2 shows almost no difference with the previous result, be it that the overall braking energy is marginally lower.

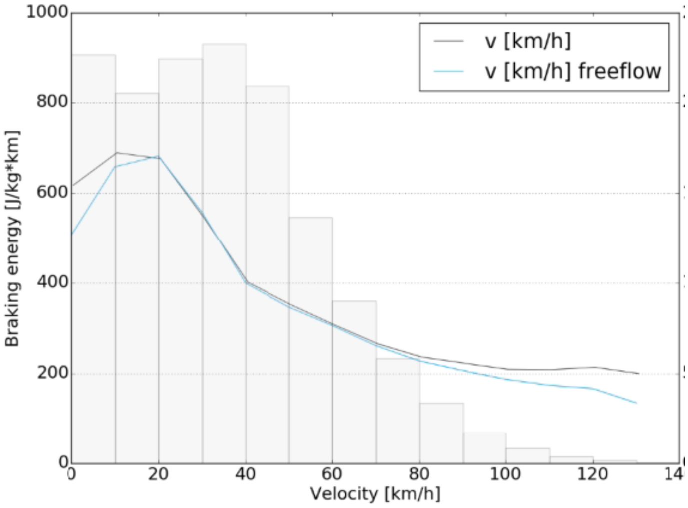

Figure 4-1 Braking energy at different velocities for all data (black line) and freeflow (blue line). The time spent in each velocity bin is given by the underlying histogram

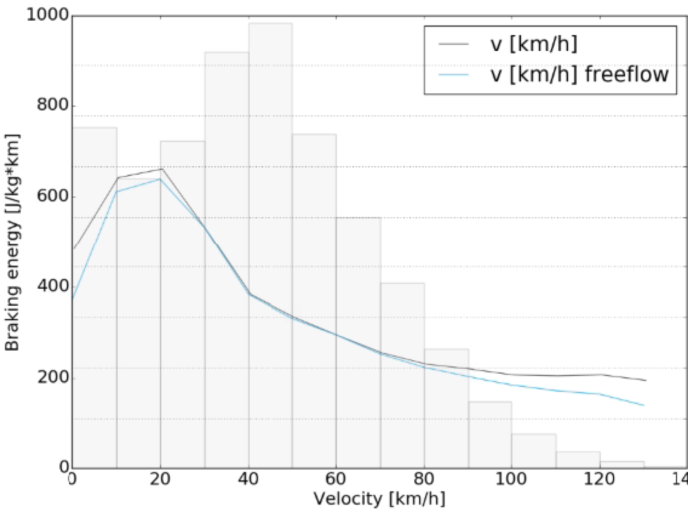

Figure 4-2 Braking energy at different velocities for all data (black) and freeflow (blue). The time spent in each velocity bin is given by the underlying histogram. Straight sections without intersections only

4.3 Results

The braking energy at a specific velocity can differ roughly up to a factor three between drivers. This is visible in Figure 4-3, which shows the braking energy at 50-60 km/h per driver. Excluding bends and intersections, and selecting free-flow based on the headway signal, it results in Figure 4-4. This selection slightly increases the spread between drivers, but also decreases the number of drivers with sufficient data to have at least one hour of driving under those circumstances. There is no difference in the average braking energy between normal and free-flow circumstances.

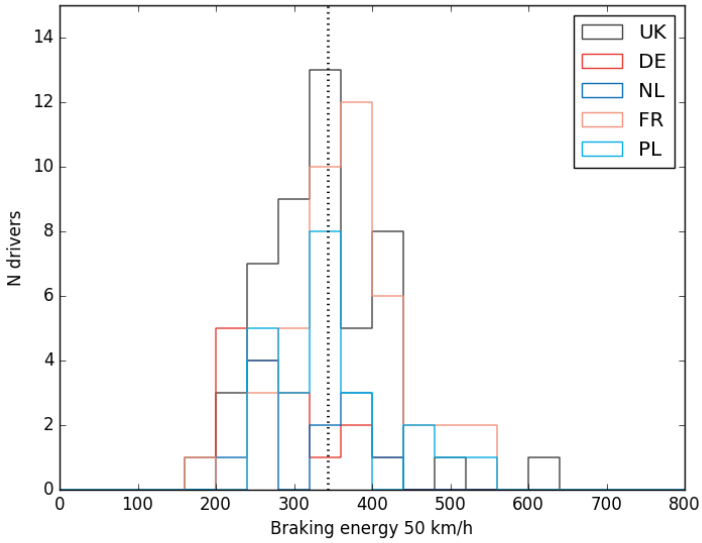

Figure 4-3 Average braking energy [J/kg km] per driver at a velocity of 50-60 km/h

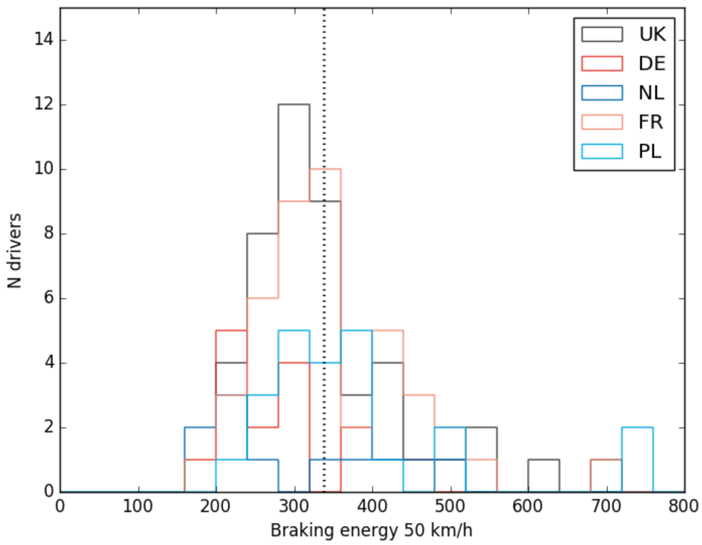

Figure 4-4 Average braking energy [J/kg km] per driver at a velocity of 50-60 km/h, for straight sections and free-flow

One expects that the more headway a driver keeps, the less he needs to brake because he has time to anticipate the traffic. Indeed, Figure 4-5 shows that more headway corresponds with less braking, when comparing the points for one velocity range, e.g. 0-50 km/h. These results are retrieved for one driver after binning the datapoints per trip in three velocity ranges. Each point represents one trip. Also, the higher the velocity, the lower the average time headway and the lower the braking energy. The headway distance, corrected for velocity, is obviously the same or larger for high velocities as for low velocities. The same conclusion can be drawn when comparing braking and headway averages for all drivers, as is done in Figure 4-6, which shows the residuals compared to the average of all drivers in the dataset.

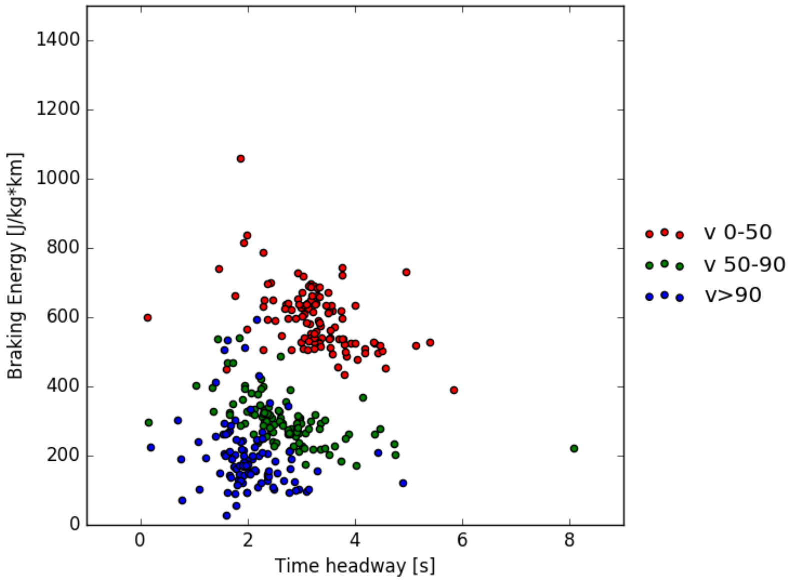

Figure 4-5 Braking energy versus time headway, for three velocity bins. Each point represents a trip. Lower velocities correspond to higher braking energy. Larger headways (in the same velocity range) correspond to lower braking energy

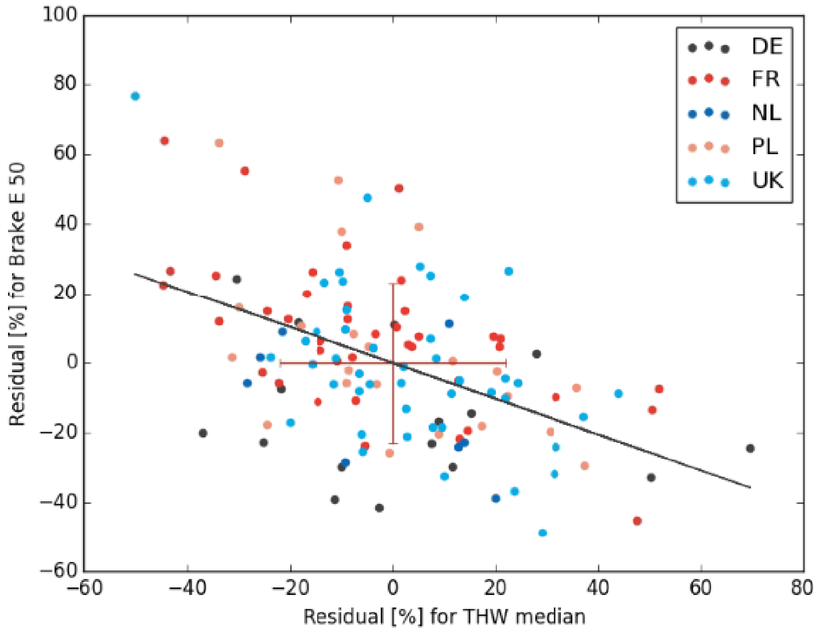

Figure 4-6 Residuals [%] with respect to the average of all drivers, showing braking energy versus time headway per driver. Each point is one driver, and the black line is a fit of all drivers. The red error bars indicate the standard deviation from the mean. Larger headways correspond to lower braking energy

In conclusion, drivers lose most energy in braking at low velocities and in urban driving. The bandwidth between drivers is very large, up to 70% from the average, or 120% between the best and worst driver. Drivers that keep a larger time headway (either due to personal driving style or due to the absence of traffic), tend to loose less energy in braking. When selecting only straight roads without intersections and without a vehicle in front, the braking energy does not decrease, although the difference between individual drivers increases. This indicates a larger difference in personal driving style, independent of driving circumstances.

4.4 Discussion

More reliable information on road conditions would enhance the results in this study. The absence of a road gradient signal dilutes the results because all roads are assumed to be flat. Furthermore, resistance forces like tyre pressure, vehicle payload, weather and road conditions etc. influence the coasting variables in the estimation formula for braking energy. With more of this information, it would be possible to perform a second-by-second analysis of braking energy.

The brake pressure signal is not suitable to be used for this analysis, but the calculated braking energy could be determined more precisely by including information on when the driver pressures the brake pedal, and how hard.

5 Personal speed choice

5.1 Introduction

The correlation between local speed limits and the preferred velocity for each driver is central in this research question. In general, lower velocities are beneficial for fuel saving. However, a traffic jam on the motorway, with dynamic driving at low velocities, is in general more fuel-consuming than constant driving at a higher velocity. The free flow velocity, in particular at higher speeds on the motorway, is the most important determining factor for high-velocity fuel consumption. Personal style, lane width, etc. in combination with the speed limit at the location will affect the actual velocity driving. Also, the capabilities of the vehicle can affect the chosen velocity.

Some drivers will have a personal speed limit, others may fluctuate with time of day, routine, or distractions. This will follow from an analysis of the velocity at different speed limits. Once the free-flow conditions are determined from other signals, the personal choice of the driver can also be disentangled from the driving circumstances.

Research questions:

- How much do drivers deviate from the speed limit in free flow situations?
- Why do drivers deviate from the speed limit in free flow situations?

5.2 Method

5.2.1 Variables

The velocity signal is used, along with the speed limits assigned in the map matching. The free-flow conditions are selected as described in section 3.2. Every country has different speed limits on different road types, so a direct comparison between EU regions cannot be made without taking this carefully into account. The speed limits in the United Kingdom are translated to km/h. They often differ a few km/h from limits in other countries, resulting in a multitude of different limits. For some of the analyses, the speed limits are binned in ranges of about 20 km/h.

5.2.2 Analysis

The selection into different speed limit regions is made as described in 3.4.2, based on the map matching variable speed limit, which is assigned on a second-by-second basis.

To answer the research question why drivers choose a specific velocity, not only the amount of deviation, but also the reason for the deviation should be studied. After excluding congestion and infrastructure as reasons for the speed deviation, personal driving style remains. However, there might still be different causes and different characteristics of the deviation. For example, a driver can always drive a fixed but small amount above (or below) the limit, or the driver can go much faster or much slower than the limit depending on his particular mood at that moment. An indicator of these different types of behaviour is the width of the peak of the most frequent velocity (sigma). A wide variation indicates less strict preference, whereas a very narrow peak might for example indicate that someone uses adaptive cruise control.

The average velocity is not used as an indicator of speed choice since very low velocities would largely influence the result, while they are most likely to be caused by driving circumstances. Since the distinction between freeflow and non-freeflow proves to be hard to make, the option of fitting peak velocities is preferred over the average velocity in order to avoid biases from e.g. congestion.

The so-called speed acceleration (VA) histogram of a vehicle trip or a set of vehicle trips for each driver, in combination with other trip signals, may provide a basis to select the so-called ‘free flow’ data. This free flow data may then be used to derive parameters where with the personal driving styles of the various drivers might be identified and within these possibly the eco-(un)-friendly ones. This scheme will be visually explained in the following.

An example VA-histogram for all trips of one single driver is given in Figure 5-1.

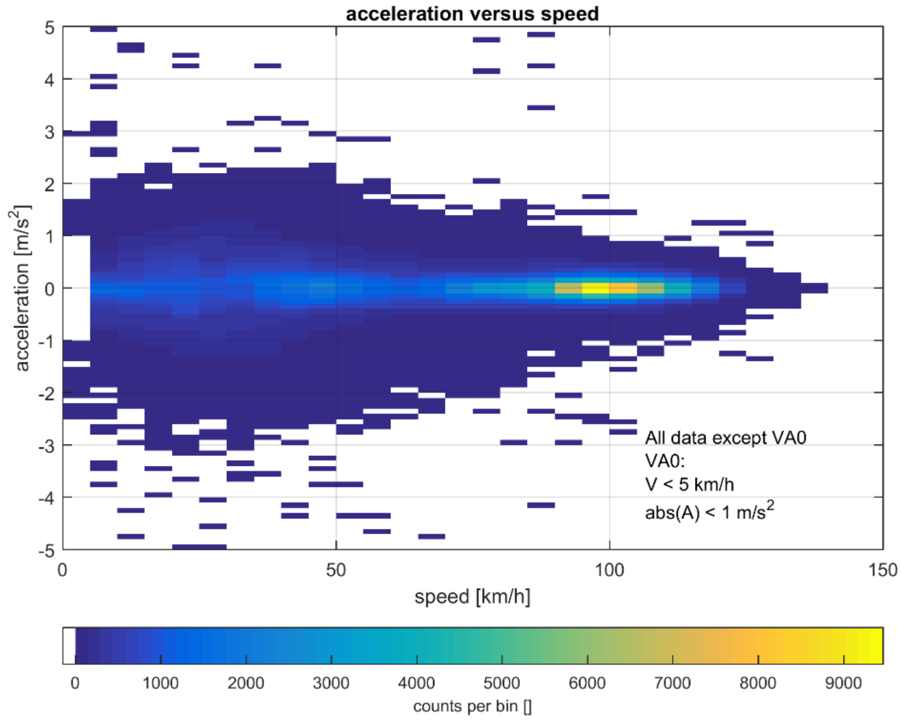

Figure 5-1 Time spent in bins of acceleration versus speed, all trips of one single driver.

For this particular set of trips the total travel time is about 347784 seconds or more than 96 hours. Shown as a color coded intensity are all counts (in seconds) per speed-acceleration bin for all data except for the bins at near zero speed and acceleration (VA0 as indicated), which bin counts were zeroed. This VA0 exclusion was applied for better colour scaling and improved sensitivity of derived parameters.

Next, the same trip set is used for VA-histogramming but only with the VA-data of straight sections without intersections. Ssee Figure 5-2.

Compared with the previous histogram one may observe that the spread in acceleration has diminished. Having eliminated data from curves and intersections one may expect the non-free flow part to have (also) diminished. However, the remaining data may still contain a considerable amount of non-free flow data, e.g. due to congestion which forces drivers to drive more slowly than they would do in a free flow situation. Now, the speed limit signal may be used to further eliminate the non-free flow data. Of course this is under the assumption that drivers pay attention to speed limit signs. This works as follows. Again a VA-histogram is made, but instead of the true vehicle speed signal an adapted speed signal, defined as the difference of the true speed signal and the speed limit, is used for the VA-binning. Then, one may expect the free-flow data to be centered along the speed difference axis around zero km/h. Hence, by limiting the data to a narrow range of the adapted speed around zero km/h, the sought free flow data is finally found. Currently, a range from -25 to +25 km/h for the adapted speed is used to select the free flow data. Ideally, this procedure should (and can) be performed for each unique speed limit available in the data. In the following, however, this was done for three speed limit regions, i.e. Vlim > 55 km/h, 55 <= Vlim < 95 km/h and Vlim >= 95 km/h. See Figure 5-3 to Figure 5-5.

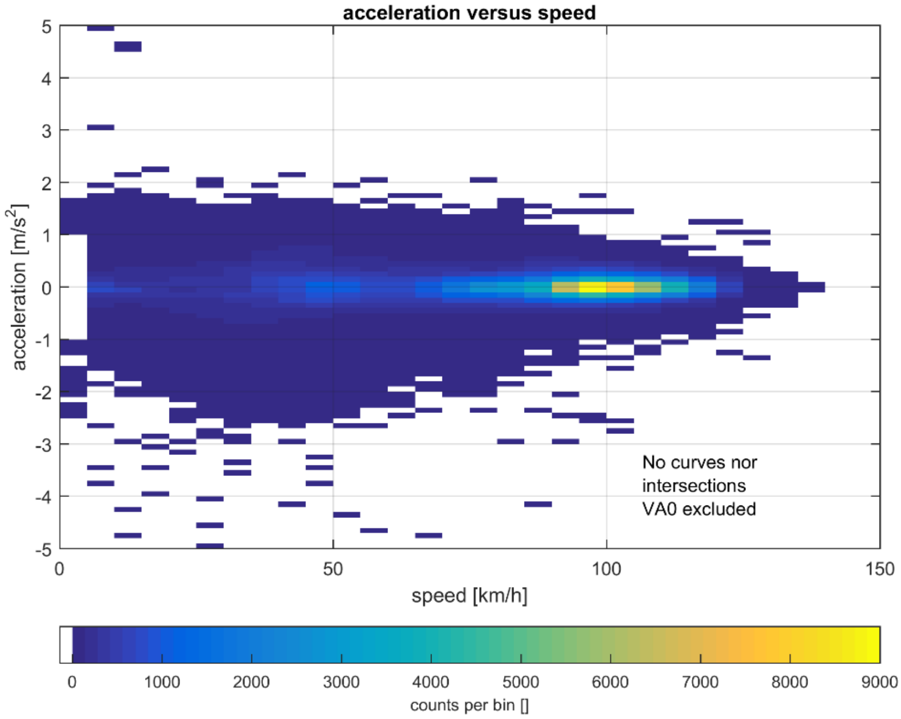

Figure 5-2 Time spent in bins of acceleration versus speed. Same data as in Figure 5-1 (all trips of one driver) but VA-data limited to straight sections without intersections.

From the remaining VA-histogram data, e.g. as shown in Figure 5-3 to Figure 5-5, differrent parameters can be calculated which might be distinctive with respect to driving style. Candidate parameters currently investigated are the (time weighted) mean and standard deviation of the:

- absolute acceleration;
- positive acceleration;
- product of (true) speed and absolute acceleration;
- product of (true) speed and positive acceleration.

The parameter that seems to be the most distinctive for eco-driving, as retrieved from the current analysis, is the mean absolute acceleration. This parameter is larger for lower speed limits, because of the natural distribution of velocity and acceleration. However, after binning per speed limit range (currently three, in the future per unique speed limit), this dependency should be enough reduced to compare the mean absolute accelerations between drivers.

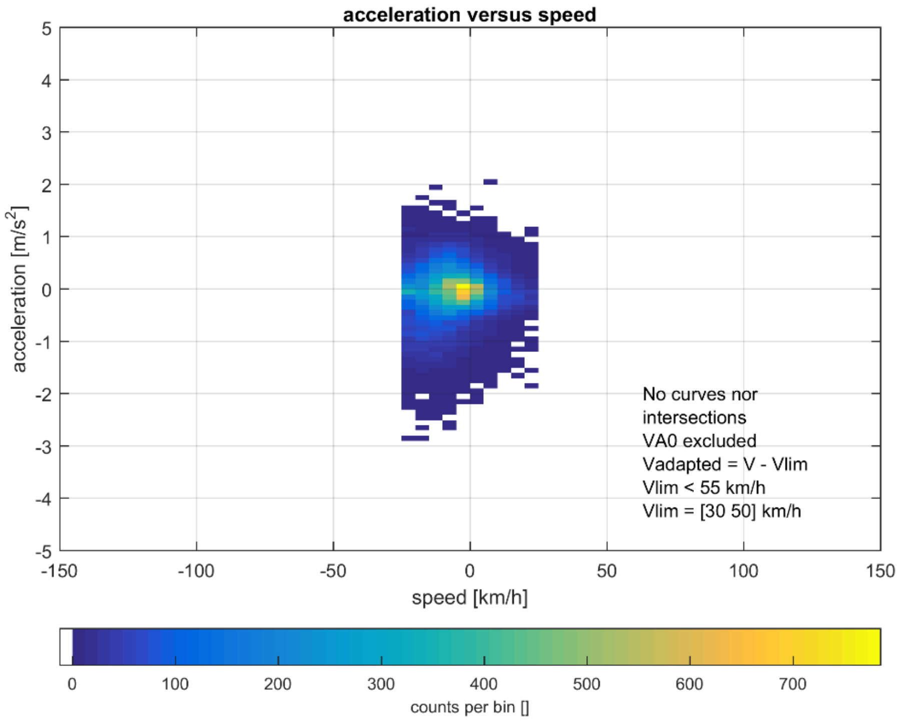

Figure 5-3 Time spent in bins of acceleration versus adapted speed signal, i.e. speed – speed limit. Same data as in Figure 5-2 (all trips of one driver limited to straight sections without intersections) but further limited to speed limits lower than 55 km/h.

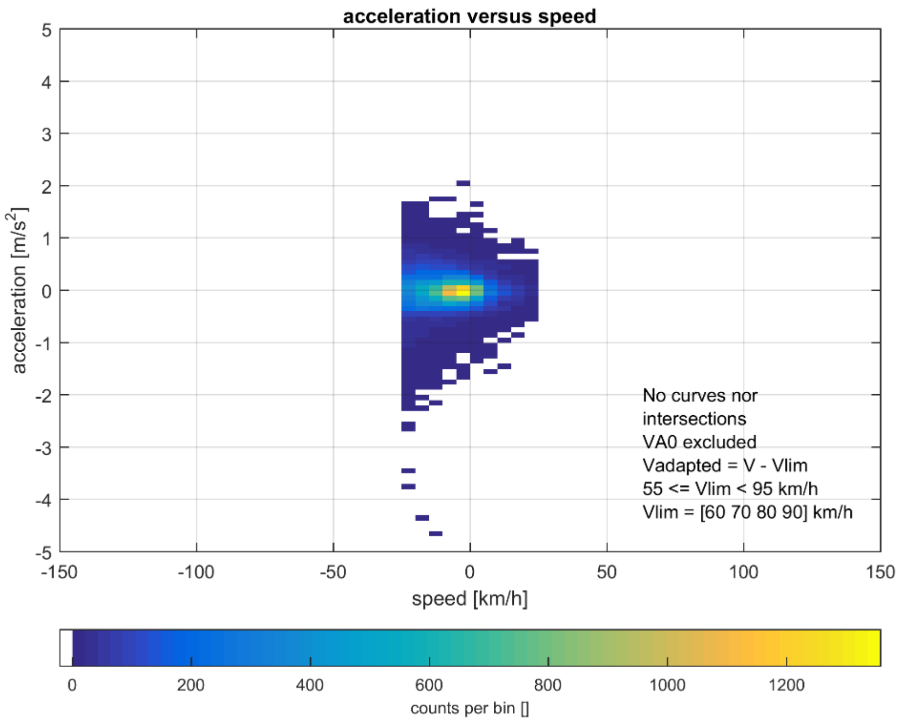

Figure 5-4 Time spent in bins of acceleration versus adapted speed signal, i.e. speed – speed limit. Same data as in Figure 5-2 (all trips of one driver limited to straight sections without intersections) but further limited to speed limits between 55 and 95 km/h.

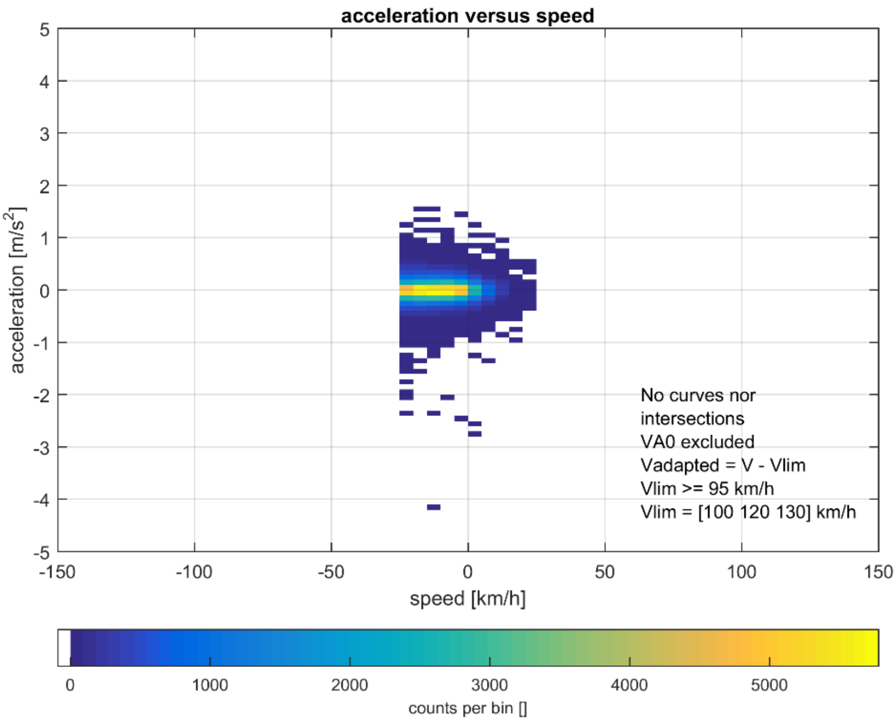

Figure 5-5 Time spent in bins of acceleration versus adapted speed signal, i.e. speed – speed limit. Same data as in Figure 5-2 (all trips of one driver limited to straight sections without intersections) but further limited to speed limits higher than 95 km/h.

5.3 Results

The bandwidth of the most frequent velocity between drivers is up to 20 km/h from the speed limit, both below and above it. This is shown for speed limits 80 and 90 km/h in Figure 5-6 and Figure 5-7 respectively. The variation in velocity, which causes extra fuel-consuming dynamics, varies as much, between 0 and 20 km/h. The two are not clearly correlated for lower speed limits (see Figure 5-8), but for higher speed limits, high velocities correspond to narrower peaks and less dynamics (see Figure 5-9).

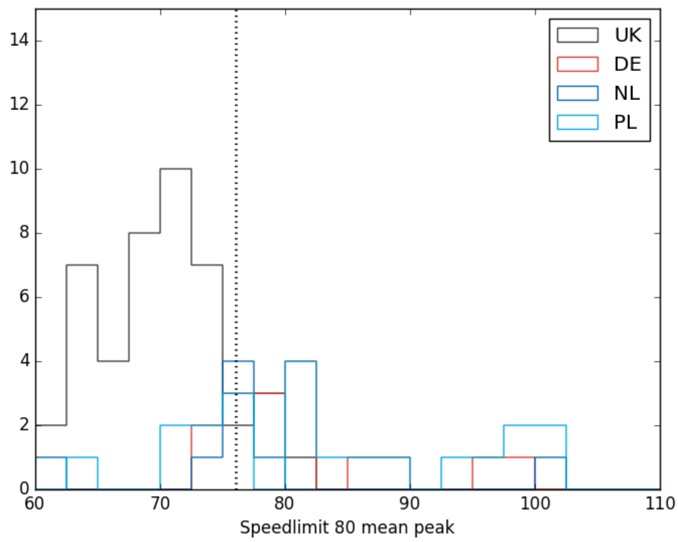

Figure 5-6 Most frequent velocity at 80 km/h speed limit

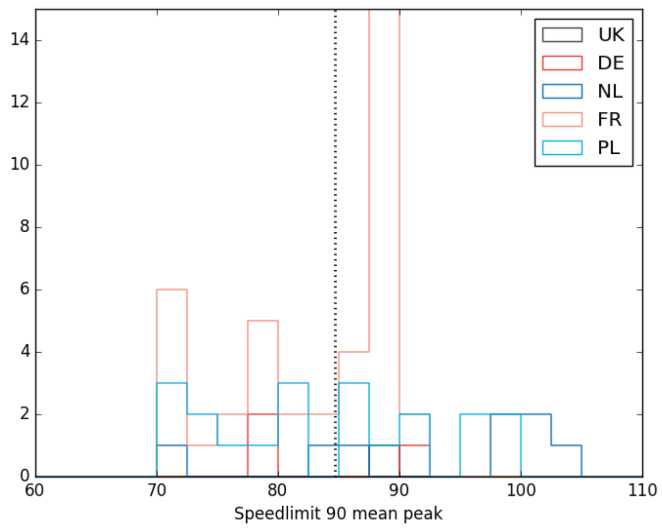

Figure 5-7 Most frequent velocity at 90 km/h speed limit

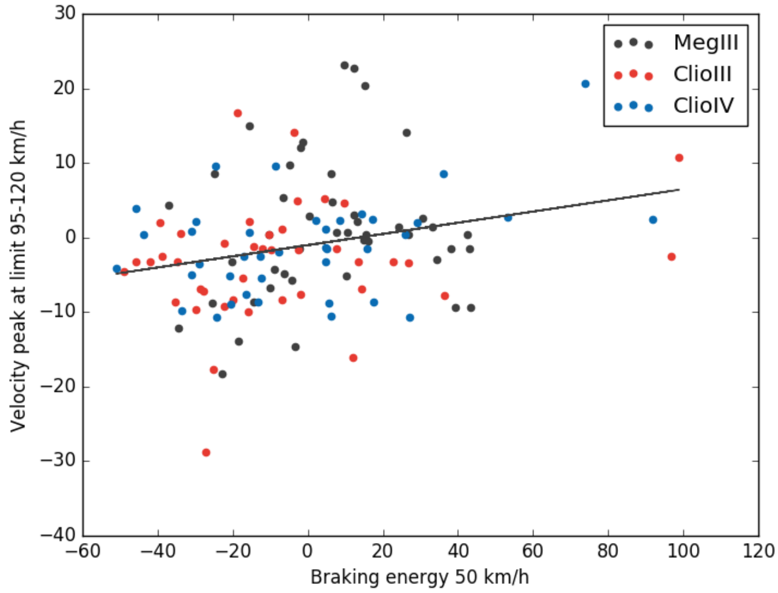

Figure 5-8 Residuals [%] with respect to the average of all drivers, showing the most frequent velocity for speed limits between 95 and 120 km/h versus the braking energy at 50-60 km/h

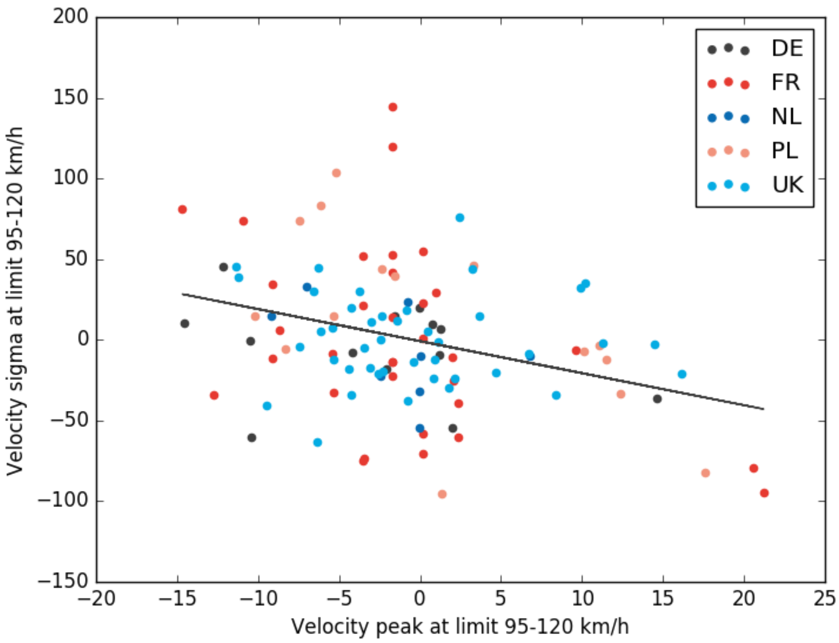

Figure 5-9 Residuals [%] with respect to the average of all drivers, showing width versus peak of the most frequent velocity, for speed limits between 95 and 120 km/h

The analysis of dynamics, or the acceleration at different speed limits using VA histograms, yields the variable abs(acc), the weighted mean of the absolute acceleration in Figure 5-10 for speed limits between 95 and 120 km/h. The spread on this variable is quite large. This becomes visible when plotting its residual value with respect to the average against the most frequent velocity, in Figure 5-11. What also becomes clear from this plot, is that most values of French drivers lie on the lower end of abs(acc). There might be an effect related to the higher speed limits in France (110,120) with respect to other countries (mostly 100,120) that biases this variable. This issue has to be further investigated, and might be resolved by first binning the analysis in separate speed limits, only averaging over a larger collection of limits in the end. For now, this variable is included as it is in the final results in Chapter 7.

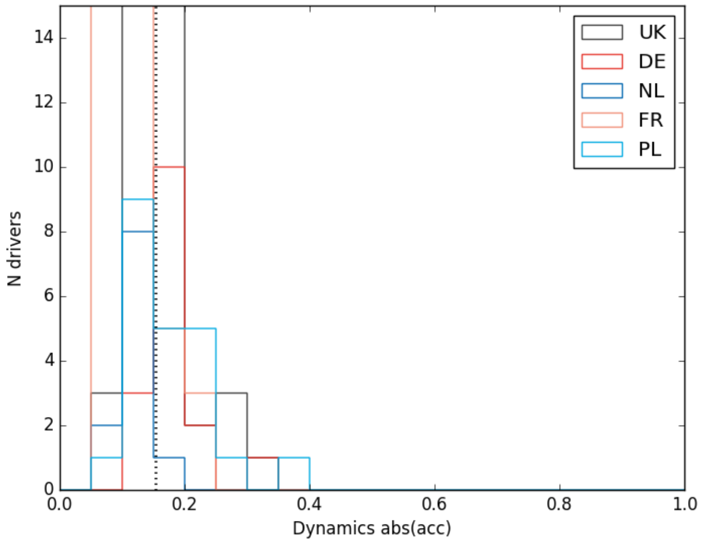

Figure 5-10 Average value per driver of the weighted acceleration for speed limits between 95 and 120 km/h

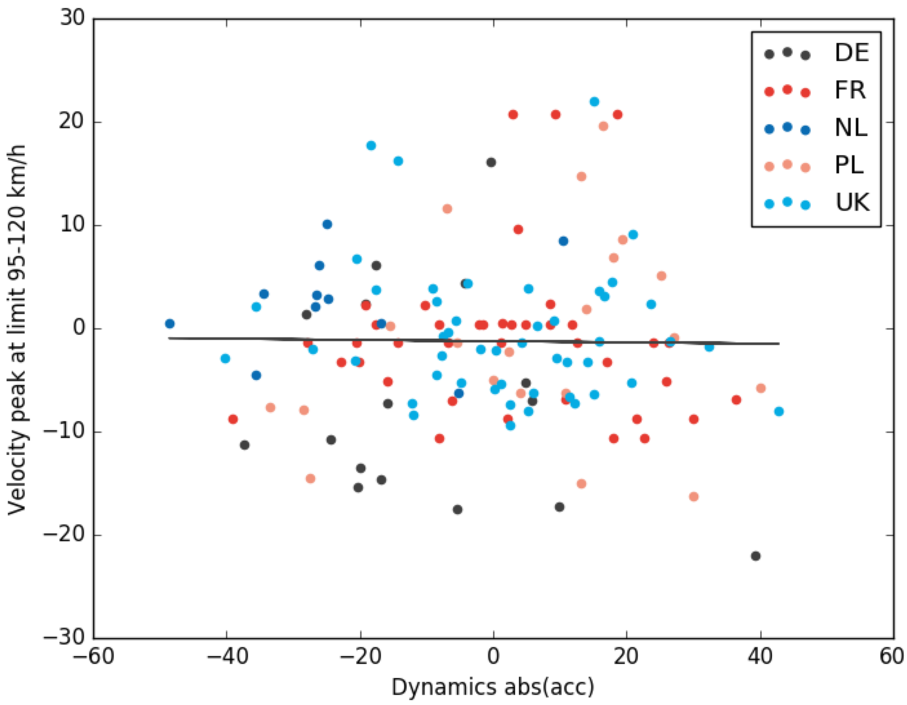

Figure 5-11 Residuals [%] with respect to the average of all drivers, showing peak of most frequent velocity versus weighted acceleration, both for speed limits between 95 and 120 km/h

In conclusion, the velocity difference between drivers is up to 20% from the speed limit, both below and above it. The dynamics show an even larger spread, up to 50%. The selection of straight roads without intersections and without a vehicle in front do not yield significantly different results. The question why drivers deviate from the speed limit remains as yet unanswered, since there is no clear correlation with road obstructions or congestion.

5.4 Discussion

A more reliable definition of free-flow (data excluding of congestion and infrastructual obstructions) would help to give a cleaner free-flow velocity distribution that better represents the driver's personal style.

An additional interesting variable to study is the time of day. It could be used to validate the speed limit (e.g. in The Netherlands, the speed limit on some motorways is 100 at daytime and 130 at night) and definitions of congestion. Furthermore, with the large amount of data available per driver, personal speed choices at different times of the day could be investigated.

The VA histogram analysis to determine dynamics should be binned in different speed limits first, and only averaged over larger ranges of speed limits in the end. This avoids a bias of drivers driving more or less at different speed limits.

The information given by the drivers in the questionnaires would give insight in their reasons to overspeed or to drive slower than the limit. There was unfortunately not enough time in the UDRIVE project to analyse the answers and correlate them with the results in this section. This would be appropriate in a follow-up study.

6 Gear shifting

6.1 Introduction

The part of the driving style which is most clearly distinguishable as personal is gear shifting. It is uncommon for drivers to shift gears as quickly as prescribed. The delay of gear shifting may occur during firm accelerations or congestion with limited headway. Once personal variations in gear shifting with velocities are established, the correlations with circumstances can be investigated further.

Gear shifting behavior is less influenced by the driving context than other eco-driving indicators, but may be affected by the power-to-mass ratio of the driven vehicle. With a higher power-to-mass ratio it is easier to follow traffic in a higher gear. The most persistent eco-driver will always shift gear below a certain engine speed. The subsequent acceleration may be limited by the lack of vehicle drivability. This may not necessarily be a bad thing, as it smoothens the traffic flow. The correlation between engine speed, velocity and transient driving are studied.

Research questions:

- Do drivers shift gear to avoid high engine speeds and high fuel consumption?

6.2 Method

6.2.1 Variables

To be able to study gear shifting behaviour, it is essential to determine which gear the vehicle is in. To determine the gear, the ratio of velocity and engine speed is used. Every gear corresponds to a fixed ratio, while gear shifting or braking results in intermediate v/RPM values. Figure 6-1 shows the relation between engine speed and velocity, clearly showing that this vehicle has five gears, and gear shifting occurs always below 3000 RPM.

The velocity and acceleration just before the gear changing moment are an indication of driving style. Investigation showed that the values two seconds before the gear change are most representative for the driving style. The acceleration at the gear changing moment itself is usually already lower because the driver releases the accelerator pedal to change gear.

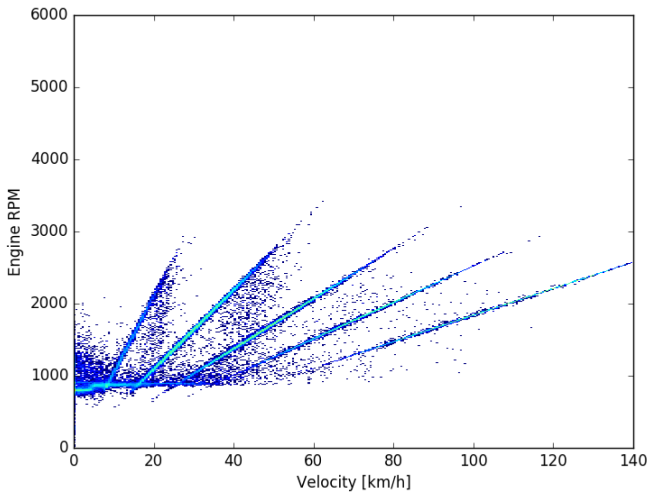

Figure 6-1 Engine speed versus velocity for one driver. This vehicle has five gears

6.2.2 Analysis

Figure 6-2 shows the velocity and acceleration two seconds before the vehicle changed gear. Every point is one gear change moment, and the different colors indicate different gears. A fit is made of the points per gear, indicated by the black line. The average engine speed, acceleration and velocity and the slope of the fit are performance indicators of the gear changing behaviour. These parameters will be considered as eco-driving parameters.

The results are divided into three vehicle categories: Clio III, Clio IV and Megane. Since no more information on mass and power of the vehicles is available, the analysis cannot be further specified as a function of power-to-mass ratio.

Automatic vehicles, though not indicated as such in the database, are easy to recognise in the analysis by the low gear shifting velocities. An example of such a vehicle is shown in Figure 6-2.

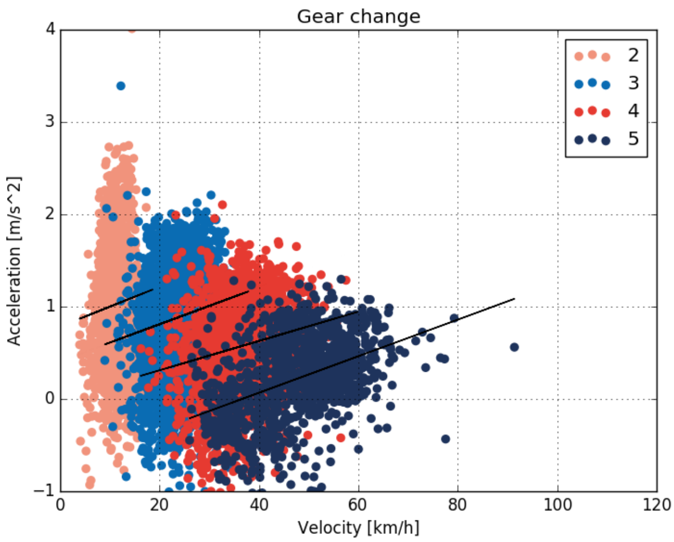

Figure 6-2 Velocity and acceleration at the gear shifting moment. Shifts to different gears are indicated by colours. A fit of the velocity and acceleration points per gear is shown as a black line. Vehicle with automatic gearbox

6.3 Results

The difference between better and worse eco-driving behaviour is easily recognised in the gear shifting analysis. For example, Figure 6-3 shows a driver who shifts gear at low velocities and low accelerations. Third gear is usually entered around 30 km/h. Figure 6-4 on the other hand shows the opposite: a driver who only shifts gear very late, where third gear is only reached at 45 km/h. Both drivers drive the same vehicle: a ClioIV. It is unknown if there are differences in the engine power or weight of the vehicle.

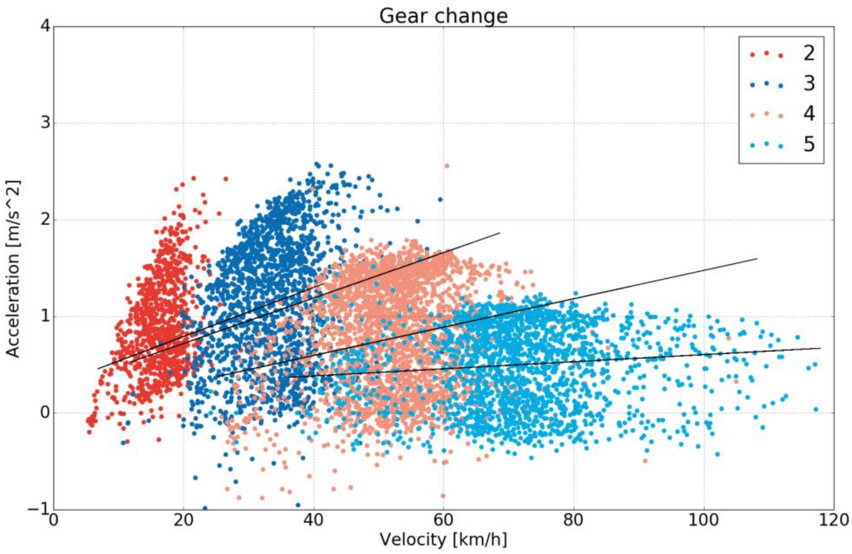

Figure 6-3 Velocity and acceleration at the gear shifting moment. Shifts to different gears are indicated by colours. A fit of the velocity and acceleration points per gear is shown as a black line. Good eco-driving behaviour

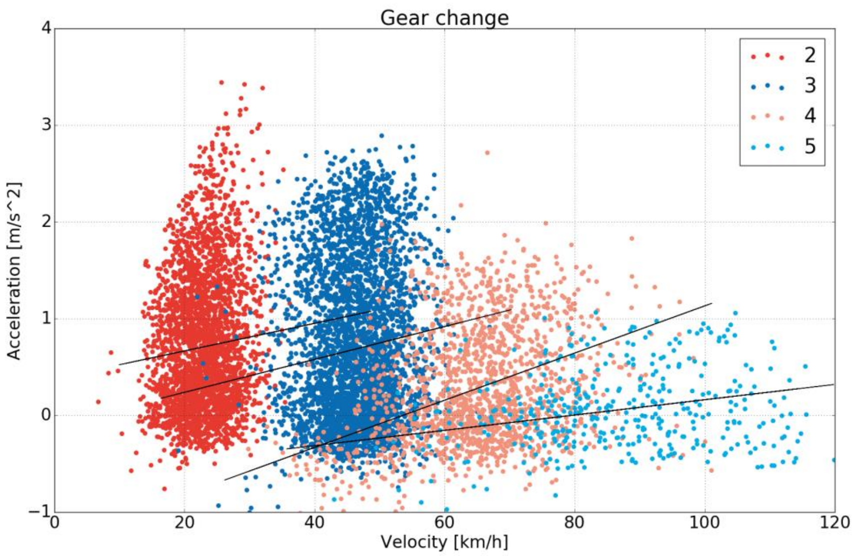

Figure 6-4 Velocity and acceleration at the gear shifting moment. Shifts to different gears are indicated by colours. A fit of the velocity and acceleration points per gear is shown as a black line. Bad eco-driving behaviour

There is also a large bandwidth in average engine speed at the gear shifting moment between drivers. The eco-driver advice is to change gear between 2000 and 2500 RPM, but drivers range from 1400 to 3000 RPM, depending on the vehicle type and the gear, but mostly on the driver behaviour. The bandwidth is shown in Figure 6-5 and listed for all gears in

Table 6.1. This large bandwidth means there is quite some room for improvement by better eco-driving behaviour. In terms of fuel consumption, the lower the RPM the better. A disadvantage of shifting gear at very low engine speeds might be a limited acceleration power (influencing safety) and increased stress forces on the engine that occur mainly for diesel vehicles (influencing the engine lifetime).

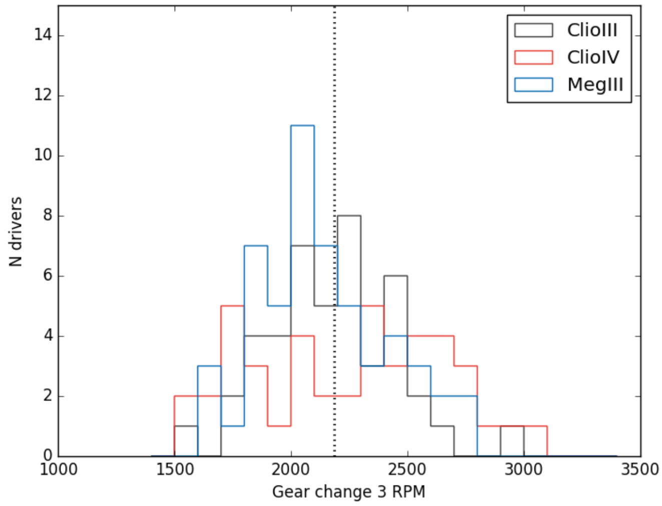

Figure 6-5 Average engine speed per driver at the moment of shifting from second to third gear

Table 6.1: Average parameters at the gear shifting moment, for different vehicle categories

Variable	Gear	Clio III	Clio IV	Megane
<engine speed> [RPM]	2	1987	2034	1952
	3	2169	2196	2127
	4	2167	2115	2108
	5	2127	2074	2012
	6	-	-	1964
engine speed range min-max [RPM]	2	1391-2647	1418-2776	1452-2696
	3	1520-2903	1583-3079	1622-2742
	4	1546-2787	1530-2743	1610-2767
	5	1634-2974	1532-2698	1660-2731
	6	-	-	1543-2813

In conclusion, some drivers shift gear much earlier than others. The average engine speeds differ significantly, also for drivers in the same type of vehicle. The estimated difference in fuel consumption due to different engine speeds can be up to 20-25%.

6.4 Discussion

The gear shifting moment is a clean indicator of driving style and eco-driving. More precision in the results could be achieved by logging not only velocity and engine speed, but also the actual gear from the CAN signals. This way, the gear changing moment could be determined more precisely, which would decrease the noise on the results.

Detailed information on the vehicle parameters is not (yet) available in the database. Therefore, only three common vehicle types could be identified, each with a range of rated powers and masses. The number of gears and whether the vehicle has a manual or automatic gearbox could be derived from the data. A more detailed description of the vehicles in the dataset would improve the analysis results.

Furthermore, it would be interesting to have a more varied sample of vehicle types. Different power-to-mass ratios not only enforce different gear-changing behaviour, but might also correlate with a specific driver personality and driving style. The current dataset contains too few different types of vehicle to investigate this relation.

7 Eco-driving as a characteristic of certain drivers

7.1 Introduction

Several aspects of naturalistic driving behaviour have been studied. The aim is now to relate those aspects to specific drivers, and to correlate them in order to get a judgement of eco-driving behaviour. By doing this, a proposal is made for a definition of an eco-driving score per driver. Besides facilitating a comparison between the drivers, such a score also gives an estimate of the bandwidth of eco-driving behavior and the room that is left for its improvement.

Research questions:

- Is eco-driving an observable characteristic of certain drivers?

7.2 Method

7.2.1 Drivers and clustering

The analysis of variables related to eco-driving is done per driver. The drivers are split in groups according to their country, age and gender, and to the type of vehicle they drive. Subsections of the analysis are made for different road types (urban, rural and motorway), but this distinction is made on a second-by-second basis instead of per driver.

The more selections are made on the data, the smaller the statistical significance of the results. For example, the standard deviation on the data excluding bends and intersections is large because there are less drivers with enough remaining data (at leas one hour is required). This selection of straight roads without intersections excludes more drivers from the final results. In The Netherlands, only 12 drivers remain with enough data to cover all categories for the final result, in the United Kingdom 45, in France 40, in Poland 22 and in Germany 16.

7.2.2 Residual analysis

Since there is no absolute quantitative definition of ecodriving, the drivers are compared to each other to define whether they are better or worse than average. A residual analysis is performed, where the residual of a variable x is defined as the difference of one driver with respect to the average of all drivers:

$$x_{resid} = \frac{\mathrm{x} - < \mathrm{x} >}{< x >}$$

Starting from a distribution such as the braking energy in Figure 4-3, one can calculate residuals for each driver, expressed in percentages. As an example, Figure 7-1 shows the average values of the braking energy of each driver, and Figure 7-2 shows the corresponding residual values. After grouping those residuals by country, the coloured solid lines are the average residuals per country. By definition, the total residual over all drivers is at 0, indicated by the dotted black line.

An estimate for the uncertainty on this result is made through the standard deviation of the driver results. Instead of propagating the statistical errors of the dataset of each individual driver, only those drivers with more than one hour of data are selected. This way, a driver who drove a long distance will not influence the result more than a driver who covered a smaller distance, and a bias in favour of frequent drivers or people that participated longer in the exeriment is avoided. The standard deviation of the residual is shown in Figure 7-2 by the colored area, and depends on the number of drivers in each country and on the spread of the residuals.

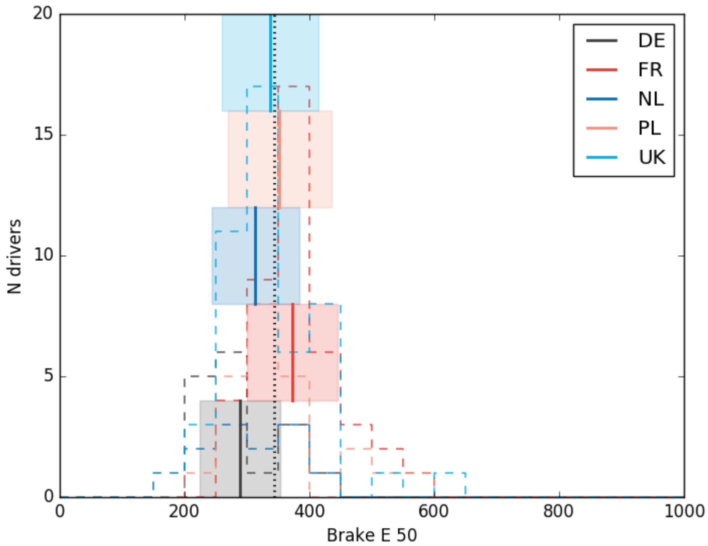

Figure 7-1 Average braking energy per driver at a velocity of 50-60 km/h. The average and standard deviation of all drivers in one country are shown by the coloured lines and lightcoloured areas, respectively. The dashed coloured lines are the underlying distributions with one entry per driver

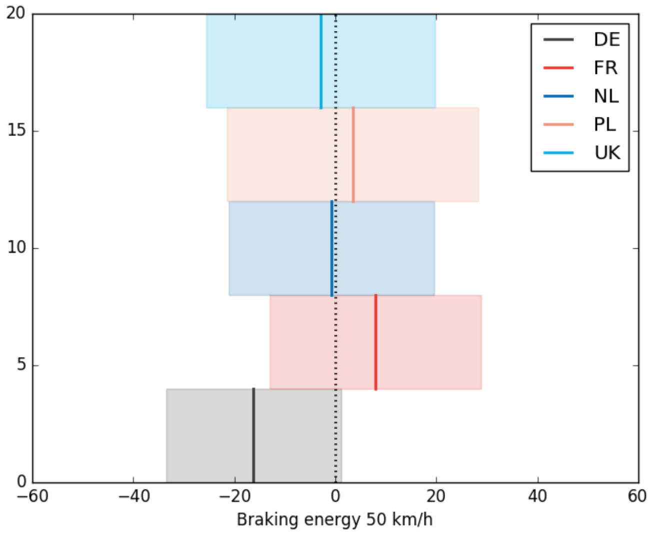

Figure 7-2 Residual braking energy at a velocity of 50-60 km/h per driver with respect to the average. The average and standard deviation of all drivers in one country are shown by the coloured lines and lightcoloured areas, respectively

The same exercise, performed on a more stringent selection, excluding bends and intersections and demanding freeflow conditions, results in Figure 7-3. The bandwidth is larger for a more stringent selection. This could mean that the underlying values lie further apart, suggesting a larger difference between drivers. However, the standard deviation also increases because less drivers meet the threshold for a minimal amount of data.

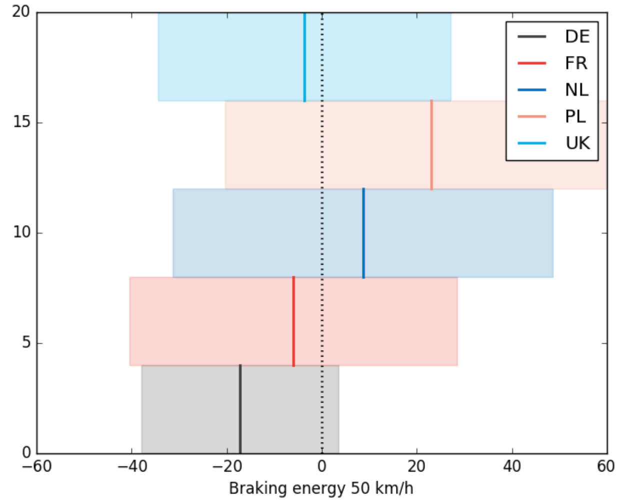

Figure 7-3 Residual braking energy at a velocity of 50-60 km/h per driver with respect to the average. The average and standard deviation of all drivers in one country are shown by the coloured lines and lightcoloured areas, respectively. For straight sections and free-flow

For some variables, one expects to find a correlation with vehicle type. An example is the engine speed at the gear shifting moment. For such purposes, the drivers can also be grouped per vehicle type, as in Figure 7-4 and Figure 7-5. Velocity is not expected to be influenced by vehicle type, and shows indeed no significant difference. The engine speed when changing from second to third gear, in Figure 7-5, does not show a correlation with vehicle type either, although it is expected. Figure 7-6 shows braking energy, with more dependency on vehicle type. The reason for these results is probably the low statistical power due to the low number of drivers per vehicle category, and the lack of knowledge about other influencing parameters such as engine power.

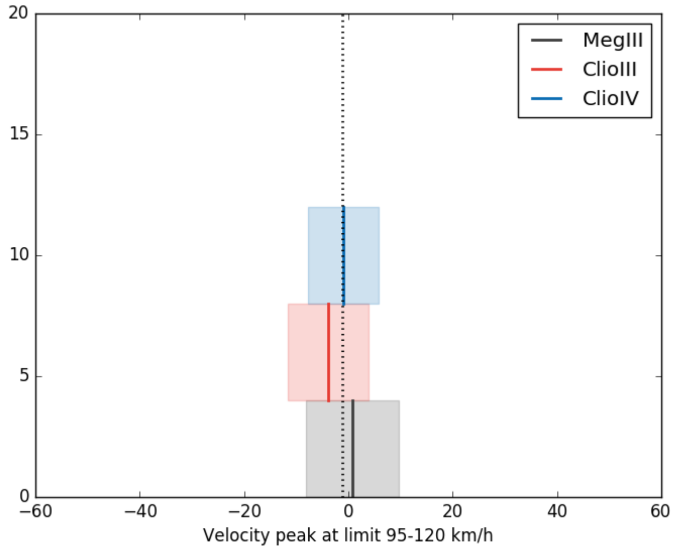

Figure 7-4 Residuals of the peak of the most frequent velocity at speed limits between 95-120 km/h with respect to the average. The average and standard deviation of all drivers with the same vehicle are shown by the coloured lines and lightcoloured areas, respectively

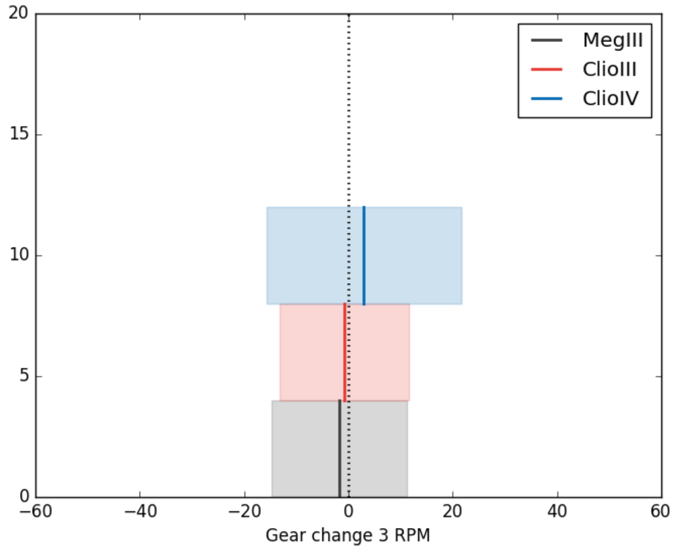

Figure 7-5 Residual engine speed when shifting from second to third gear per driver with respect to the average. The average and standard deviation of all drivers with the same vehicle are shown by the coloured lines and lightcoloured areas, respectively

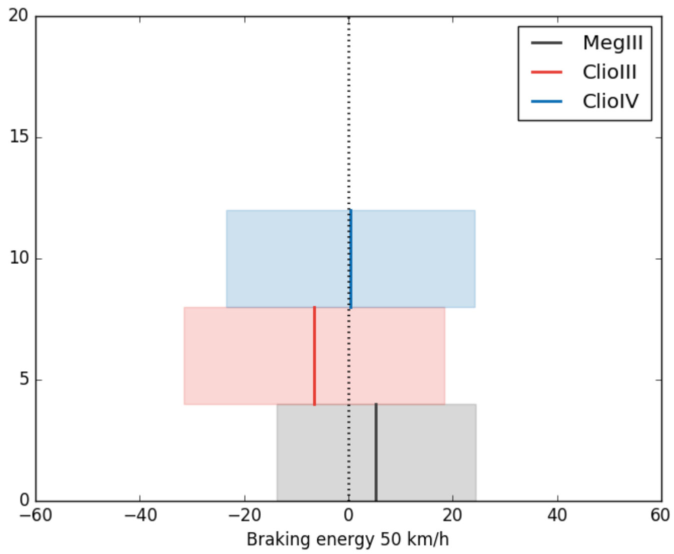

Figure 7-6 Residual braking energy at a velocity of 50-60 km/h per driver with respect to the average. The average and standard deviation of all drivers with the same vehicle are shown by the coloured lines and lightcoloured areas, respectively

7.2.3 Eco-driving score

To define an eco-driving score, a combination should be made of different indicators that correlate with fuel consumption. After calculating the residuals in percentage difference with respect to the average, a simple average of different parameters can be used as such a score. Obviously, all variables should correlate to eco-driving behaviour in the same way. The choice is to define good eco-driving behaviour as a residual smaller than zero (so smaller than the average behaviour), and bad ecodriving behaviour as a residual larger than zero. Scatter plots of the residual values such as Figure 7-7 until Figure 7-9 are used to study the correlation of different variables. Using such plots, a selection was made of the best indicators. Most variables positively correlate to a small extent. Variables that rely directly on the velocity, such as the peak velocity and the braking energy (Figure 7-10) confirm this.

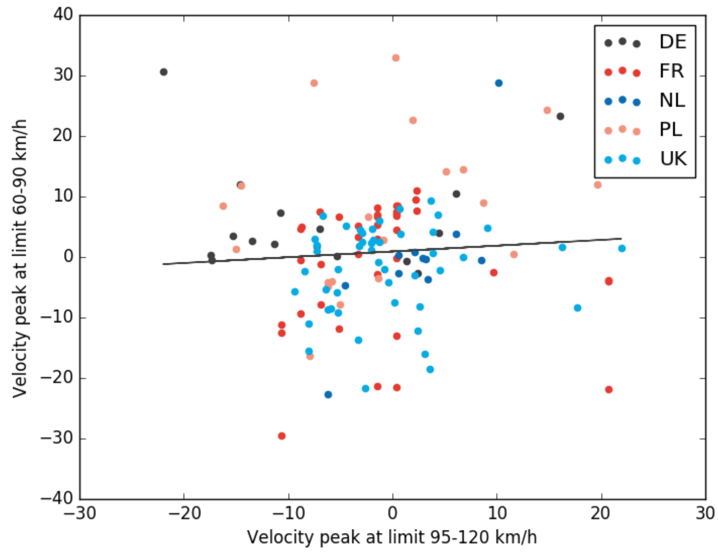

Figure 7-7 Residuals of most frequent velocities at 60-90 km/h and 95-120 km/h speed limits

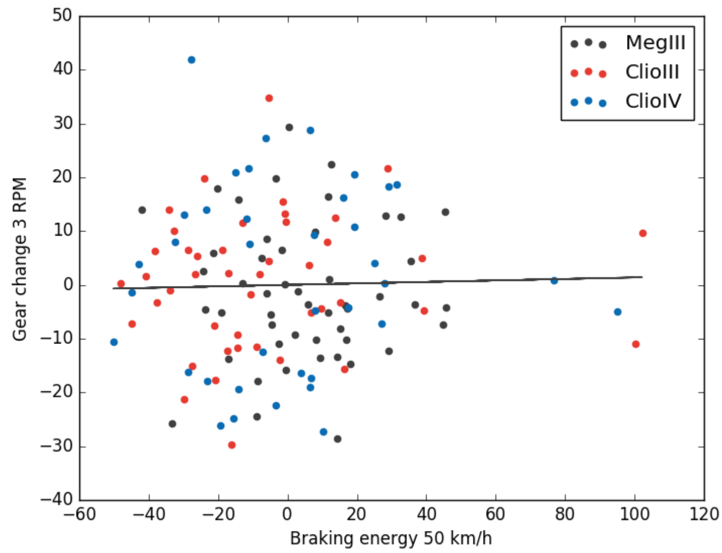

Figure 7-8 Residuals of engine speed at gear shift moment versus braking energy at 50 km/h

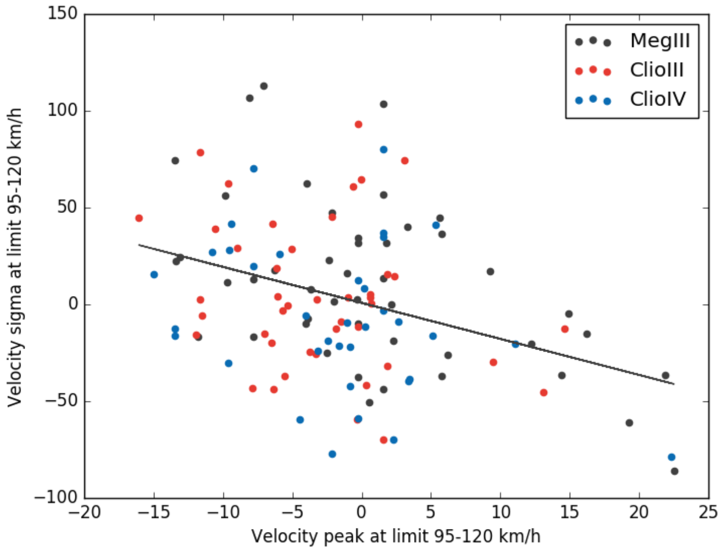

Figure 7-9 Residuals of width versus mean of the most frequent velocity at speed limits between 100 and 120 km/h

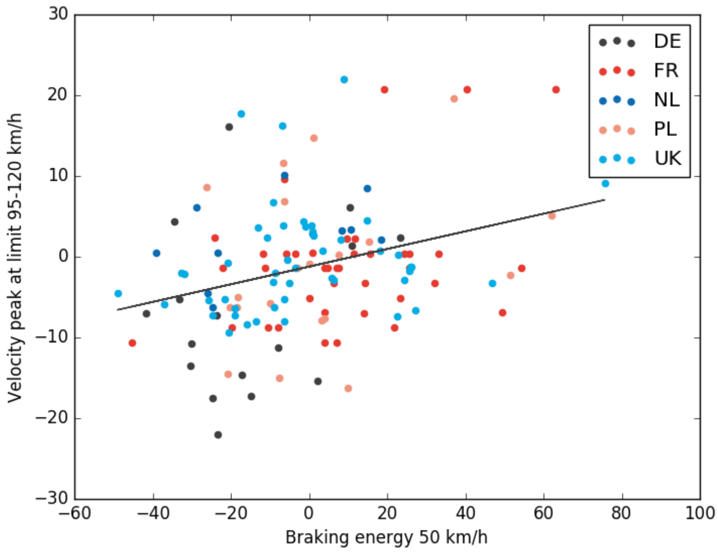

Figure 7-10 Residuals of the peak of the most frequent velocity at speed limits 95-120 km/h and the braking energy at 50-60 km/h

The following residual values are averaged to get an eco-driving score:

- Braking energy at 50-60 km/h
- Engine speed at the gear shifting moment from second to third gear
- Most frequent (peak) velocity at speed limits between 95 and 120 km/h
- Width of the peak around the most frequent velocity at speed limits between 95 and 120 km/h
- Weighted mean of the absolute acceleration at speed limits between 95 and 120 km/h

7.3 Results

The eco-driving scores per driver of the full dataset have a bandwidth of about 30% around the average, or about 60% between the best and worst driver. This is shown in the distribution of ecoscores in Figure 7-11. Note that the lower the score, the better the eco-driving behaviour. Since it is expected that a correction for driving circumstances has a large influence on driving behaviour, a selection is made on free-flow circumstances (based on headway) excluding trajectories with bends and intersections. In that case, the spread and bandwidth are sligthly larger, as shown in Figure 7-12. The eco-score varies within a bandwidth of 80% in this case.

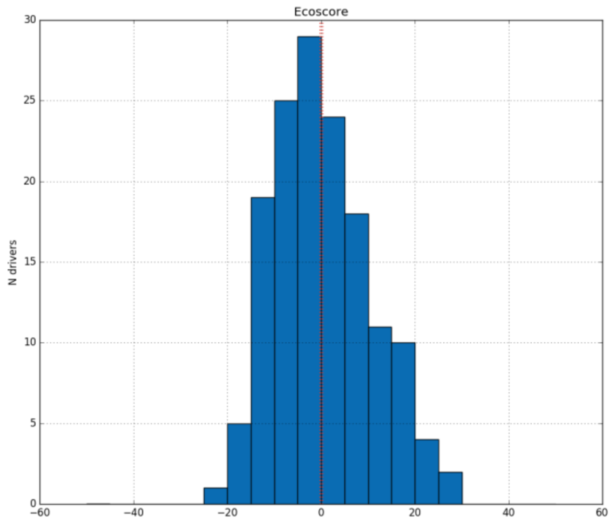

Figure 7-11 Distribution of eco-driving scores of all drivers

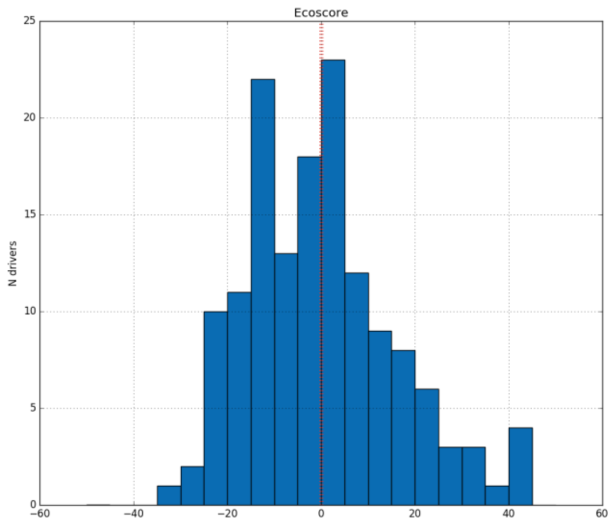

Figure 7-12 Distribution of eco-driving scores of all drivers, for straight sections and freeflow

There is a small difference in the average score in different countries. This can be seen in Figure 7-13. Figure 7-14 also gives the scores for free-flow data excluding bends and intersections. The difference between the two approaches is minimal, and varies for different countries. Overall, one could conclude that the attempt to eliminate external influences from the driving behaviour results in a larger spread between countries. There is also a larger spread between drivers within one country, hence the large bandwidth of the boxes.

France is on the low side, with better eco-driving behaviour, whereas Polish drivers score worse on this eco-driving scale. Note, however, that the underlying data consists of only tens of drivers. Adding data of a few more drivers can significantly change the resulting averages. Since there is not enough data to correct the data per country for underlying effects such as different road types and vehicle types, one cannot conclude that these differences are only due to personal driving style. The concluding chapter will discuss the generalizability of these results in more detail.

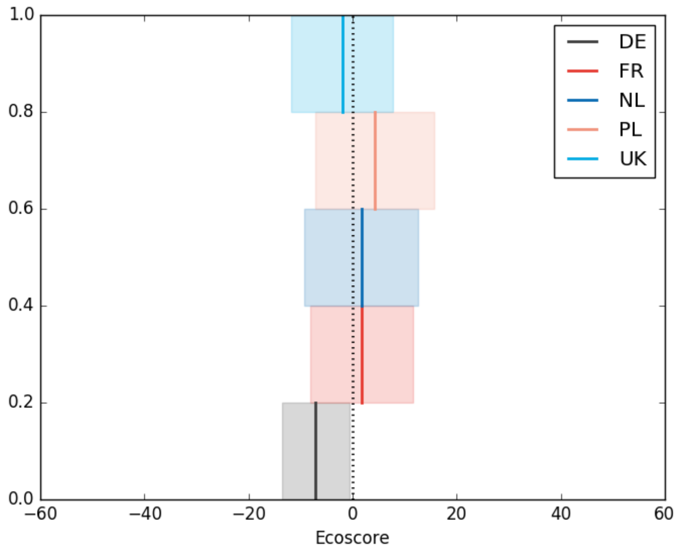

Figure 7-13 Residual ecoscore with respect to average of all drivers, full dataset

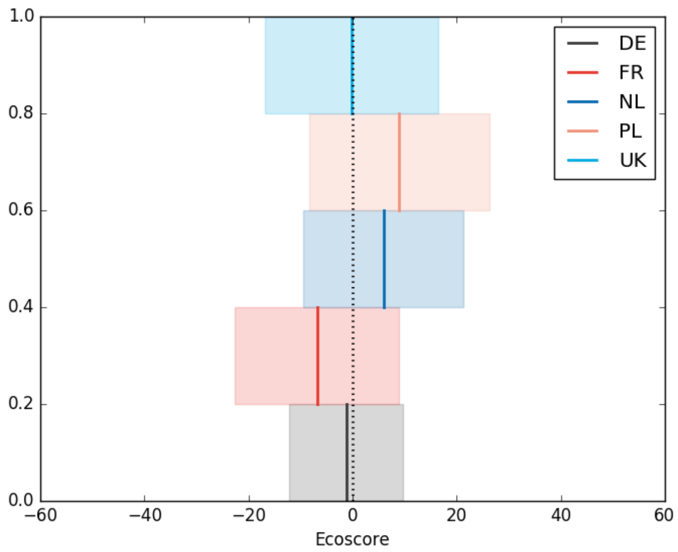

Figure 7-14 Residual ecoscore with respect to average of all drivers, for straight sections and freeflow

When grouping the results not by country but by vehicle, Figure 7-15 is retrieved. The Renault Megane performs slightly worse than the Clios. This can either have to do with different driving behaviour in those vehicles, or with the larger engine and vehicle size. To distinguish the two, one should make subgroups of countries per vehicle type. Since most vehicle types were only used in one country, the number of remaining drivers would usually be lower than 10, which reduces the statistical power so much that no conclusions can be drawn from the remaining sample.

The same analysis is performed grouping the drivers by gender, which does not yield a significant difference, as can be seen in Figure 7-16. The clustering per age group (per 10 years) in Figure 7-17 shows that young drivers perform slightly worse on this eco-driving scale than older drivers. Again, the underlying data of some groups is very small, for example the age groups below 20 years and above 80 years have only one participant. .

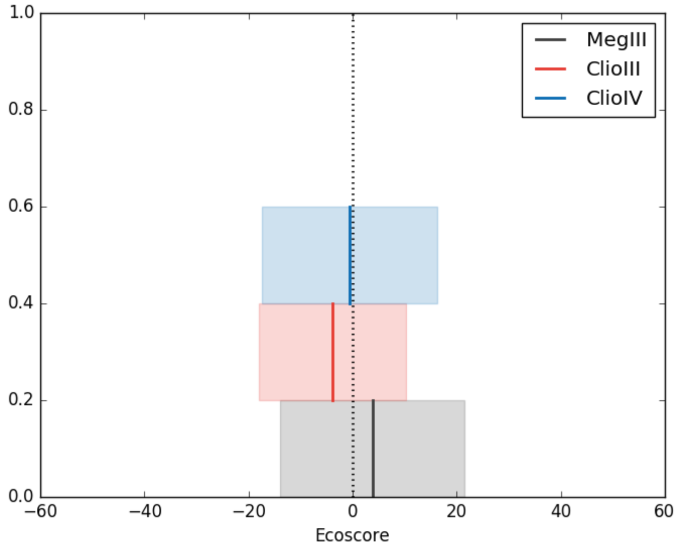

Figure 7-15 Residual ecoscore with respect to average of all drivers, grouped per vehicle type, for straight sections and freeflow

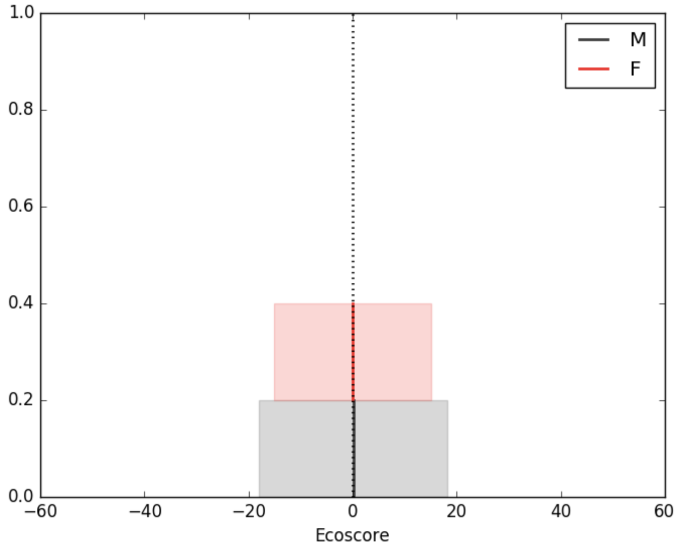

Figure 7-16 Residual ecoscore with respect to average of all drivers, grouped by gender, for straight sections and freeflow

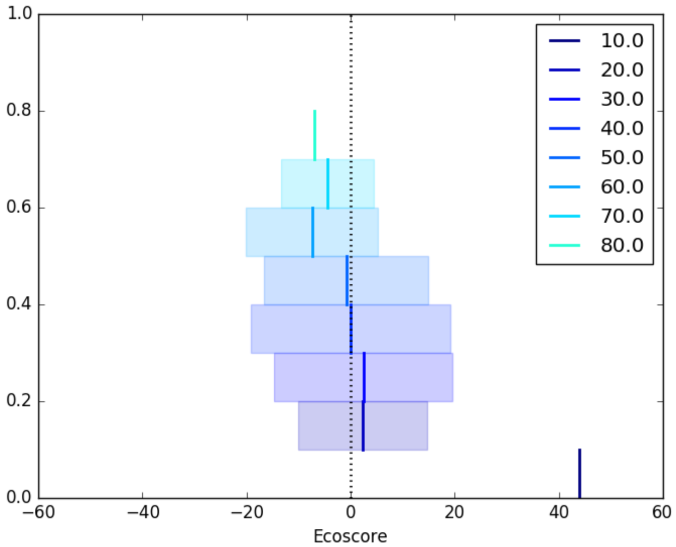

Figure 7-17 Residual ecoscore with respect to average of all drivers, grouped per 10-years age group, for straight sections and freeflow

The ecodriving potential could be described as the difference between the scores of the worst and the best driver, after correcting for driving circumstances. The histogram in Figure 7-11 gives the values of all remaining 120 drivers. There is a factor 2.5 (80% difference) between the outer values. One could therefore conclude that eco-driving, as defined by this score, is an observable characteristic of certain drivers. It should be noted however, that fuel consumption does not linearly depend on this eco-driving scoring.

7.4 Discussion

Even without splitting the data into different road types, the amount of data underlying the results is insufficient to draw definite conclusions. Having more different drivers would enable a better characterisation of different driver groups, and maybe more drivers that behave in a similar eco-driving manner. Furthermore, having more different vehicle types per country would enable an analysis independent of vehicle type.

8 Correlation between safe driving and eco-driving

8.1 Introduction: Safe and eco-driving

The scoring of drivers on eco-driving styles and safety driving styles is the basis to establish a correlation between the two. However, the scoring on eco-driving styles can only be done once external influences are corrected for. These can be established by filtering out average velocity and necessary slowing down and stopping for bends and traffic lights. The remainder is then analyzed for additional fuel consumption for braking, driving in a low gear and driving at a high velocity. The amount of coasting (i.e. slowing down without braking and with gear engaged) is another good measure for eco-driving. If this is combined with a reduced amount of hard braking, it is a clear signal for a combination of safe driving and eco-driving.

It is to be expected that a driver who anticipates the traffic situations ahead will be both a safe and a fuel-efficient driver. Sudden hard braking is erratic behaviour related to unsafe driving, i.e., it is considered an indicator for safety critical events. Sudden braking is also related to additional energy loss and variations in velocity. Variations, or dynamics in driving, are generally a sign of more energy usage and fuel consumption for the same distance and duration.

Research questions:

- Are eco-driving and safe driving correlated?

8.2 Method

Safe driving can be defined in many ways, some of which are addressed in the other work packages in the UDRIVE project. Ideally, one could correlate a 'safe driving' score with the ecodriving score developed here. However, no definition of such a safe driving score was available when writing this deliverable. Therefore an estimate of safety is made through the variable shown in Figure 3-8 in Section 3.3: velocity times positive acceleration (vapos). This variable is commonly used for validating the driving behaviour in emission testing. The driving behaviour should neither be too aggressive nor too tame in order to pass the test definition requirements. A correlation is made of the safe driving variable and the ecoscore per driver.

8.3 Results

The correlation between the driving behaviour value vapos and the ecoscore is significant. Low vapos values, often associated to tame or safer driving behaviour, correspond to better ecoscores.

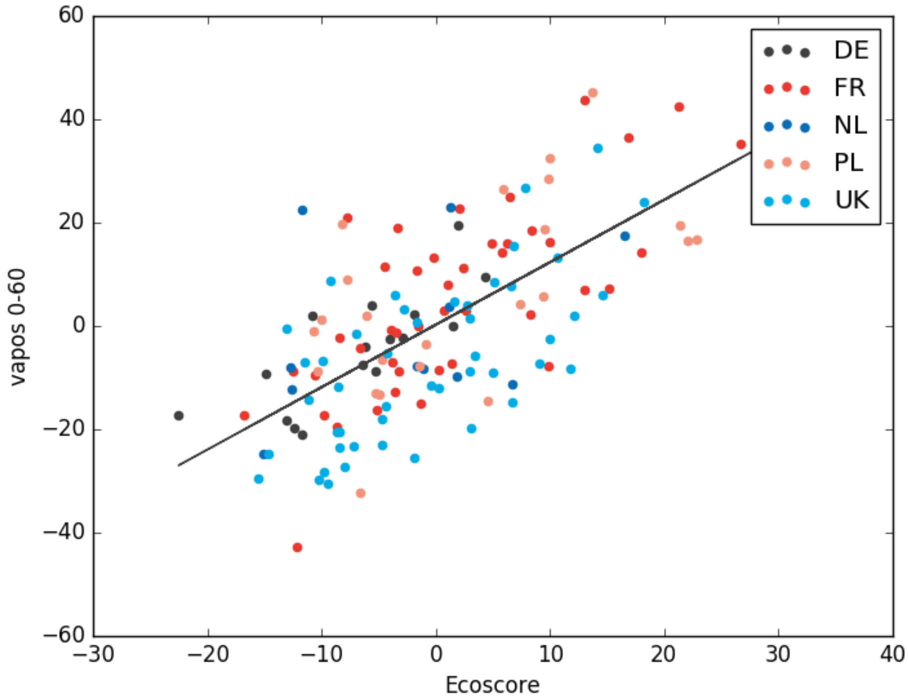

Figure 8-1 The residuals of the variable vapos [m^2/s^3] at velocities between 60-90 km/h versus the ecoscore

8.4 Discussion

Anticipation is key in smooth driving. Hence it is to be expected that if driver can be classified as a smooth driver in a variety of circumstances, it is a common feature that quantifies the quality of anticipation. But to place this anticipation in perspective, it must be corrected for the levels of congestion encountered, and the infrastructural obstructions to smooth driving, like traffic lights and bends. With the poor quality of the headway signal, there is little hope to perform this correction with confidence. This restriction on the data plagues this aspect most of all. Moreover, a similar classification for generic safe driving, i.e., not separate events but as a continuous, measurable quality, is so far absent. Hence, although it is expected there is a strong correlation between fuel efficient and safe driving via anticipatory behaviour, it turns out to be very difficult to quantify this aspect.

9 Conclusions

9.1 Conclusions

This study focuses on the driver aspects of fuel efficiency that are unrelated to the vehicle technology. The energy consumption through braking, the additional air drag forces at high velocities, and the higher engine losses with higher engine speeds are the three main types of energy associated with additional fuel consumption for the same mobility demand. These aspects are invariable, whereas other effects on fuel consumption may change with technology.

Actual vehicle technologies may limit the effects of certain driver behaviour. For example, an automatic transmission will remove the driver influence in engine losses almost completely. The recuperation of braking energy will reduce the braking losses to some extent. The higher velocities, above 100 km/h, are always associated with additional air drag and fuel consumption, almost independent of the vehicle technology.

The braking energy is a significant contribution to the total energy consumption at low velocities. The rolling resistance and air drag form about 200-300 kJ/km in urban driving with average passenger cars. This means that braking energy, in the order of 300-800 kJ/km, is for most drivers the main energy consumer at the wheels.

The engine losses are also not neglible for passenger cars. The idle CO_2 emission associated with low engine losses is typically 0.3-0.5 g/s. At 36 km/h, these minimal losses are associated with a substantial 30 -50 g/km. At higher engine speeds, up from idling at 800-1000 RPM, the engine losses increase. It is expected that losses increase more than proportionally with engine speed, and that a 200 RPM higher engine speed will increase the engine losses with 10%-20%. This results in effects in the order of 10 g/km increase in fuel consumption, dependent on vehicle and engine technologies. In most extreme cases, where drivers are instructed to drive very aggressively or very eco-friendly, poor gear shifting can add up to 25% in fuel consumption in urban driving. The natural bandwidth among naturalistic drivers in this study is only slightly smaller.

The recuperation of braking energy may reduce the energy losses, but the conversion to electric energy and back, needed for storing the braking energy, is associated with substantial losses. Hence, lower braking energy is always associated with some fuel efficiency benefits, but probably half or less for a hybrid vehicle compared with a vehicle with mechanical brakes only.

The clustering of drivers by country yields small differences that, due to the limited number of drivers per individual country, are not significant. The same limitation occurs for a clustering per age bin, although there seems to be a trend that older drivers drive more eco-friendly than young drivers. The average ecoscores of men and women are equal.

In conclusion, the three aspects braking, gear shifting and the velocity choice on the motorway, all have effects on the fuel consumption of 10% or higher for a traditional vehicle. This study does not attempt to arrive at a generic number, as it would depend strongly on the vehicle technology. Very likely, in the last twenty years the influence of the driver on the fuel consumption has decreased significantly with technology improvements. It is very likely this trend will continue. On the other hand driver behaviour does not evolve quickly over time, safe for changes in the capabilities of the vehicle and in the traffic rules.

9.2 Generalizability

Due to the number of aspects of eco-driving, such as velocity, braking, and gear-shifting, and the large number of underlying parameters, such as country, driver, road type, speed limit, and infrastructure, the amount of data, by nature of this complexity, is limited for each specific combination. From other studies (e.g. Marotta et al., 2012, Ligterink et al., 2017), it is also clear there is a substantial variation in driving behaviour from country to country. Hence, zooming in on particular details and specific correlations, the results may not be generalized to the European average. Just the fact that data was collected in five countries, with their own infrastructure and driver characteristics, already limits the generalizability of the results. Apart from the country bias, the small selection of vehicle models included in the data generates another bias, which limits the generalizability of the results to extreme driving, possible with high powered vehicles, or dictated by the low engine power of a heavy loaded vehicle. Hence, the current study is better suited to generalize the average than the bandwidth or spread.

Due to sparsity of the data on very specific research questions, correlating different findings, e.g., eco-driving and safe driving must be considered indicative. If there would have been more pronounced results and clear correlations at the base level of separate effects, the higher level research questions could have been answered with more confidence. Eventually, the spread in the base results, which follow directly from the analyses of the data, is a clear indication of the limitations of the meta-study, combining different base results. Simply said, with four different driver groups, combining three different aspects of driving behaviour, each in simple “low-medium-high” classes, most of the 108 combinations will have no underlying data, because there are “only” 154 drivers. At least about 20 drivers per driver group would be needed to gain draw more definite conclusions.

The more general the result, such as the velocity distribution around the speed limits on the motorway, the more data can be combined. This yields more robust results which can be generalized to the European average with more confidence. The major drawback of these generalizations is the limited traffic information which may cause an unknown bias. The poor quality of the headway signal is the main culprit to the problems to separate different traffic situations that affect driving behaviour. The generalizations of the result to a European average are therefore partly blind for important aspects which can affect driving behaviour. Specifically, it is based on the assumption that the traffic situations are representative for the European average.

The generalizability is limited by the final issue of missing data. The road gradient, vehicle payload, rough road surfaces, speed bumps, pot holes, etc. are not, or poorly, recorded in the UDRIVE data. However, they may affect the driving behaviour in a significant matter. For example, a driver may live in a rural area with poor road maintenance and may take great case to avoid damages to the car a lot of time. Such dependencies are likely to exist and they will affect the driving behaviour significantly. Some of the spread in the data will be the result of such effects. Given that different drivers are driving in different areas and use the car for different reasons, it is impossible to separate such effects.

Hence, generalizability of the UDRIVE results to the European average is possible for generic results, but limited for the correlations and underlying dependencies. There is limited information of the bias in the study. However, the large spread in the data and the lack of clustering of results in clear groups, indicate that driver behaviour depends on parameters which are not, or poorly, recorded in this study.

9.3 Recommendations

The following recommendations can be made for follow-up research with the current dataset, or future naturalistic driving studies:

- Include more different drivers, even if this means that less data is available per driver
- Ensure a well-calibrated and continuous headway signal
- Include more countries
- Perform the same/similar analysis on truck data
- Evaluate influence of driving experience on eco-driving

References

Heijne, V.A.M., Kadijk, G. et al. (2016). NOx emissions of fifteen Euro 6 diesel cars: Results of the Dutch road vehicle emission testing program 2016. TNO report R11177.

Ligterink, N.E., Smokers, R.T.M. (2016). Real-world fuel consumption of passenger cars based on monitoring of Dutch fuel-pass data. TNO report R11258.

Ligterink, N.E., Spreen, J.S., Cuelenare, R.F.A. (2017). Chase car study: driving behaviour in the Netherlands, Belgium, France and Germany. TNO report R10436.

Marotta, A., Tutuianu, M., Martini, G. (2012). Task 7 Europe-centric light duty test cycle and differences with respect to the WLTP cycle. JRC technical report.

Saint Pierre, G., Brouwer, R., et al. (2016). D43.1 Eco driving in the real-world: behavioural, environmental and safety impacts. ecoDriver project.

List of Abbreviations

WLTP: Worldwide harmonised Light vehicles Test Procedure

UDRIVE : eUropean naturalistic Driving and Riding for Infrastructure and Vehicle safety and Environment

RPM: Rounds Per Minute (engine speed)

List of Figures

List of Tables

Appendix A Review report template; checklist for reviewers

A.1 Overall judgement: readibility, structure and format

		Yes	No	N/A
	Does the deliverable reflect the content described in the Description of Work?	X		
Comments				
	Is the deliverable sufficiently understandable: did you fully understand it (even if slightly off topic for you)?	X		
Comments				
	Does the deliverable include learning from mistakes/challenges encountered and does it stimulate to further research?	X		
Comments				
	Is the document template applied properly?	X		
Comments				
	Is the structure of the deliverable easy to follow? Do you suggest any changes to the structure to make the deliverable more accessible?	X		
Comments	No changes are required.			
	Is the English in the deliverable good? Is it clear and accessible?	X		
Comments				
	Are the figures and tables understandable and refered to in the text?	X		
Comments				

A.2 Scientific judgement

		Yes	No	N/A
	Is the issue which is being researched clearly and simply stated?	X		
Comments				
	Are the objectives as described in the deliverable in line with the Description of Work (description of the Task)?	X		
Comments				
	Is the quality of the study design sufficient, are the methods/procedures as well as their actual application appropriate/correct?	X		
Comments				
	Do the results match the objectives as described in the Description of Work?	X		
Comments				
	How are the findings and results of the work described in the deliverable? Does the conclusion chapter reflect all described main important issues in the report and are the conclusion well based? Are the conclusions clearly stated? Are the conclusions relevant and applicable?	X		
Comments				
	Does the report include the relevant and necessary references? If relevant, is the necessary wider view on the field of work properly given?	X		

Comments				
	Other comments		x	