UDRIVE

European Naturalistic
Driving Study

Driver models and risk functions on safety and sustainability

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SEVENTH FRAMEWORK PROGRAMME

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Executive Summary

This report examines the data collected in UDRIVE to investigate how Naturalistic Driving (ND) data and results can be used to improve existing driver models, particularly those related to safety and sustainability. To achieve that, a specific example case was been selected, with the criteria being that it should be relevant highly relevant both for safety and sustainability.

The example case chosen has been selected carefully from a range of possible alternatives. It is driving in horizontal curves on rural and motorways roads, where, given inadequate advance speed adjustment by the driver, there is an elevated risk of loss of control and also unnecessary energy consumption. Driving in the approach to and through curves requires adjustment of both longitudinal vehicle control— speed adaptation to the curve prior to curve entry — and lateral control such that steering input must guide the vehicle through the curve smoothly enough that there are no harsh corrections which could precipitate a loss of control. And of course longitudinal and lateral control are interlinked, in that driving too fast reduces the safety margin for lateral vehicle control, and makes it more likely that harsh steering will cause loss of control, potentially with serious consequences. Single-vehicle crashes, often occurring on curves, account for approximately one-third of fatalities across Europe.

Speed choice on curve approach has significant environmental implications, in that early use of engine braking can reduce energy wastage. Harsh deceleration just prior to curve entry is wasteful of fuel.

Existing traffic micro-simulation models, designed to give road operators insight into how traffic flow and speed is influenced by roadway features, do not consider horizontal road alignment at a detailed level. To examine drivers' lateral control and how it related to curve radius, a model of driver steering behaviour that operates at a far higher level of granularity than the micro-simulation models, has been applied. To investigate energy wastage, a very detailed analysis of driver longitudinal vehicle control in curve approach and in curve negotiation has been carried out. Also investigated has been whether driver behaviour in this longitudinal control can be related to driver attitudes as revealed by the questionnaire administered to the participants in the project.

The results obtained by applying the detailed steering model showed that problematic steering by the UDRIVE participants could be related to curve radius: the tighter the curve, the higher was the incidence of high-amplitude steering input. The resulting distribution showed a negative exponential relationship that is remarkably similar to the known distribution of crash risk for curves of a given radius, where there is a far higher risk for small-radius curves. The insight obtained can not only enhance driver-vehicle simulation models, but also suggests the development of new countermeasures to stimulate greater safety margins in curve driving.

From an eco-driving perspective, the analysis has reinforced the conclusion that energy is being wasted by drivers in the approach to and passage through curves by lack of anticipation of the need to slow down and therefore by over-harsh deceleration. The consequent wastage of energy has been shown to be related to safety-related attitudes and behaviour in the form of self-reported tendency to commit traffic violations.

Suggested further work would be to investigate the correlation between the safety and eco-related behaviours and to further investigate the personal and situational factors that lead to more undesirable behaviours. That would permit the development of models that are more suited to safety and energy consumption predictions than are current micro-simulation models with their focus on the estimation of traffic speeds and flow.

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1 Introduction

The task addressed by this report is to examine how Naturalistic Driving (ND) data and results can be used to improve existing driver models, particularly those related to safety and sustainability. To achieve that aim, a specific example case has been selected, which is highly relevant both for safety and sustainability. The driver behaviour data collected in UDRIVE have then been compared to a pre-existing model of how the driver controls the vehicle. This permits:

1. A verification of whether the drivers observed in UDRIVE actually drive in accordance with the model parameters and model predictions

2. Insight into whether observed deviations from predicted behaviour in vehicle control might be related to sub-optimal safety and energy efficiency.

The example case chosen has been selected carefully from a range of possible alternatives. It is driving in horizontal curves on rural and motorways roads, where, given inadequate advance speed adjustment by the driver, there is an elevated risk of loss of control and also unnecessary energy consumption. Steering behaviour also plays a role, in that attempts to prevent loss of control in a curve by harsh action on the steering wheel, particularly when coupled with harsh braking, may actually precipitate a loss-of-control event. That is one of the major scenarios addressed by Electronic Stability Control (ESC).

Single-vehicle crashes, typically related to improper speed and path, account for approximately one-third of fatalities across Europe (ETSC, 2017). Sixty percent of them occur on rural roads, and younger and less experienced drivers are considerably over-represented in such crashes (ETSC, 2017; Clarke et al., 2010). Although in-depth accident studies (e.g. Reed and Morris, 2012) can shed some light on them, UDRIVE provides the possibility to investigate driver control inputs to the vehicle at the sub-micro level[1], and compare those inputs against the predictions of a vehicle control model which similarly operates at the sub-micro level. As regards sustainability in the form of energy efficiency, the European ecoDriver project identified curve driving and speed choice in advance of curves, as one of the main situations in which driver performance could make a significant contribution to energy savings (Woldeab et al., 2013; Kircher et al., 2013). Analysis techniques used for real-world driving in ecoDriver (Saint Pierre et al., 2016) can be applied to the recorded data from UDRIVE.

Typically micro-level traffic simulation models do not consider horizontal road alignment and hence do not cover curve driving as a special case, since the focus tends to be on optimising traffic flow and hence on vehicle-following parameters. One of the most sophisticated existing simulation models of rural road driving, the VTI RuTSim model (Tapani, 2005; Tapani, 2008) only considers horizontal curves as physical obstacles that reduce vehicle desired speed; it does not model driver/vehicle behaviour in curve approach, curve negotiation and curve exit at a detailed level. The modelling approach investigated here, therefore has the potential to improve those models, particularly for rural-road driving, and allow a greater focus on energy and safety considerations. As discussed later, it may also have real-world application in identifying risky behaviour in real time, so that it could be used to provide feedback to drivers on their driving style.

1.1 Data collection and filtering

In order to investigate driver lateral and longitudinal vehicle control on curves, as recorded for the UDRIVE participants, it was first necessary to identify driving on the road sections of interest. The starting point for the data processing was a random selection of 134 drivers from the UDRIVE database, using all 10 Hz data from these drivers. The models as described in Section 2.1 require a time step of 0.1 s or smaller, so 1 Hz

[1] "Micro" in the context of traffic modelling is normally used to denote behaviour at approximately a 1Hz level. Sub-micro is sometimes called "nano" (e.g., Ni, 2003). It denotes behaviour, e.g. control inputs, at a considerably higher resolution than 1Hz.

data did not suffice. Due to limitations of the central analysis system (in terms of access, disk space and processing speed), data from 82 drivers were initially taken into the analysis.

STEP 1: Started with all data (10Hz) from 82 drivers.

- For each driver, all logged records were processed. First, curves were identified in the data, based on a sequence where:
  - heading was constant (i.e., remaining within a band of 2 degrees for at least 6 s) — this indicated driving on a straight section
  - followed by a change in heading in one direction (changing at least 30 degrees),
  - followed by another phase where heading remained constant (again remaining within a band of 2 degrees for at least 6 s) — indicating another straight section

This step yielded a set of 35,603 curves.

STEP 2 consisted of additional filtering to yield a selection of straight-curve combinations that met the following requirements:

- the speed limit had to remain constant from the start to the end (to avoid changes in speed limit influencing behaviour, as opposed to the characteristics of the curve itself),
- keeping only speed limits of 70 km/h and higher, since curve driving on roads with lower speed limits, typically urban roads, was not of interest
- keeping only curves where the average speed (in the curve and on both straight sections) was at least 50% of the speed limit, to eliminated driving in congested conditions
- and only keeping drivers who contributed at least 50 curves in total

After step 2, the number of curves remaining was 8826 with 39 drivers in total.

STEP 3 consisted of driving conditions that we wanted for our analyses, namely

- free driving (no time headway on both the straight and curve as indicated by the MobilEye sensor)
- the number of steering adjustments larger than 0

After this final step we were left with 1358 straight – curve combinations (S-C combinations) of 31 drivers. The S-C combinations were unequally distributed among drivers of which most drivers contributed with less than 50 curves. However, filtering these out as well would result in a to small sample even for the current purpose which is to demonstrate the possibilities of using the UDRIVE data for modelling and not so much perform a thorough analyses.

The 31 drivers came from five European countries (UK, Germany, Poland, France and The Netherlands). The average age was approximately 42 years (range 23 – 76) and there were 14 women and 17 men in the sample.

STEP 4 consisted of performance indicator calculation and applying the model.

In this step, performance indicators (PI's) were calculated for each curve. These consisted of the following performance indicators and situational variables for each approach and each curve:

- length of the section (m)
- speed limit of the section (km/h)
- average curve radius (m)
- total change in heading through the curve (degrees)
- speed: minimum, maximum, mean, standard deviation (km/h)

- deceleration: minimum, maximum (m/s^2)

The lateral control model described in Section 2.1 was applied to each curve as well. This was initially done for various settings for the Gaussian filter time constant sigma (s): 0.05 s to 0.2 s (in steps of 0.05). Collected model outputs were, for each curve:

- the fraction of problematic adjustments
- the 99th percentile of the error
- the total number of steering adjustments
- the steering adjustment frequency (adjustments per second)
- the mean and the 85th percentile of the steering adjustments in the curve

1.2 Descriptive statistics

This section provides an overview of what is in the dataset that was used in the analyses (so after Steps 1 – 3). As indicated above, the data used for analyses contained 1358 straight – curve passages performed by 31 drivers. It is quite likely that the drivers encountered a particular curve a number of times.

Figure 1-1 shows a scatterplot of curve passages by absolute curve radius (no difference between left or right curve) and speed limit. The speed limits in the sample were 70, 80, 90, 100, 110, 120, 130 and 140 km/h as well as 60 mph (96.6 km/h) and 70 mph (112.7 km/h). Not surprisingly, it can be seen that there is at least some correlation between speed limit and curve radius: higher speed roads tend to have larger radius curves, while smaller radius curves are more frequent on roads with lower speed limits.

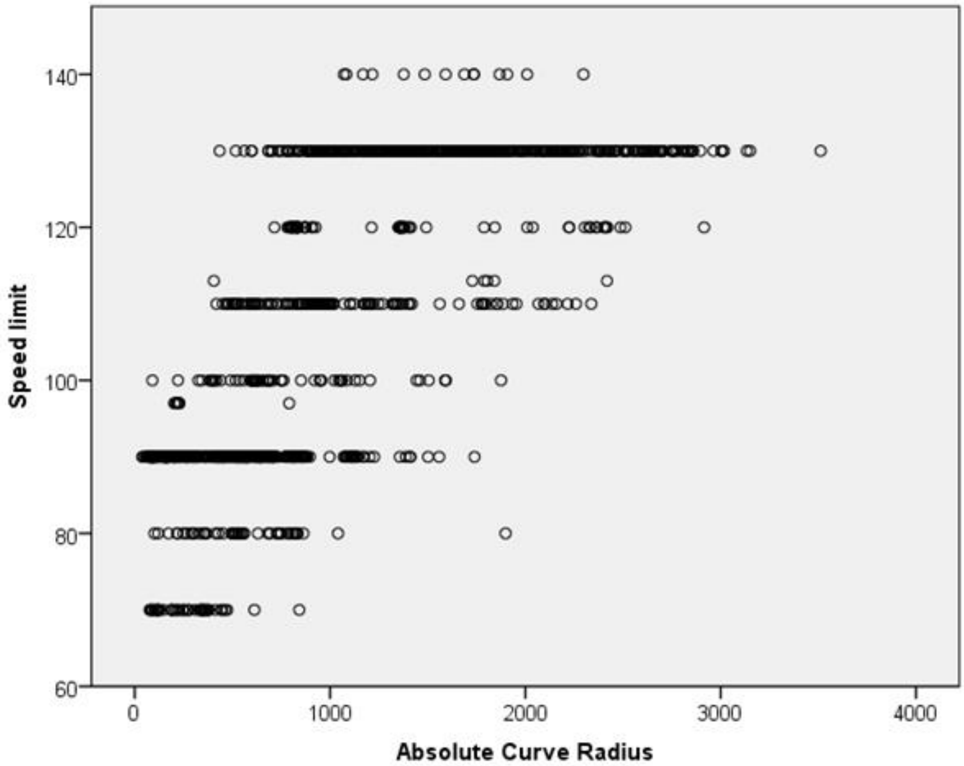

Figure 1-1: Curve passages by curve radius and speed limit

Figure 1-2 provides a scatterplot of average speed for each straight section (the approach to the curve) by speed limit. As might be expected higher speeds are associated with higher speed limits.

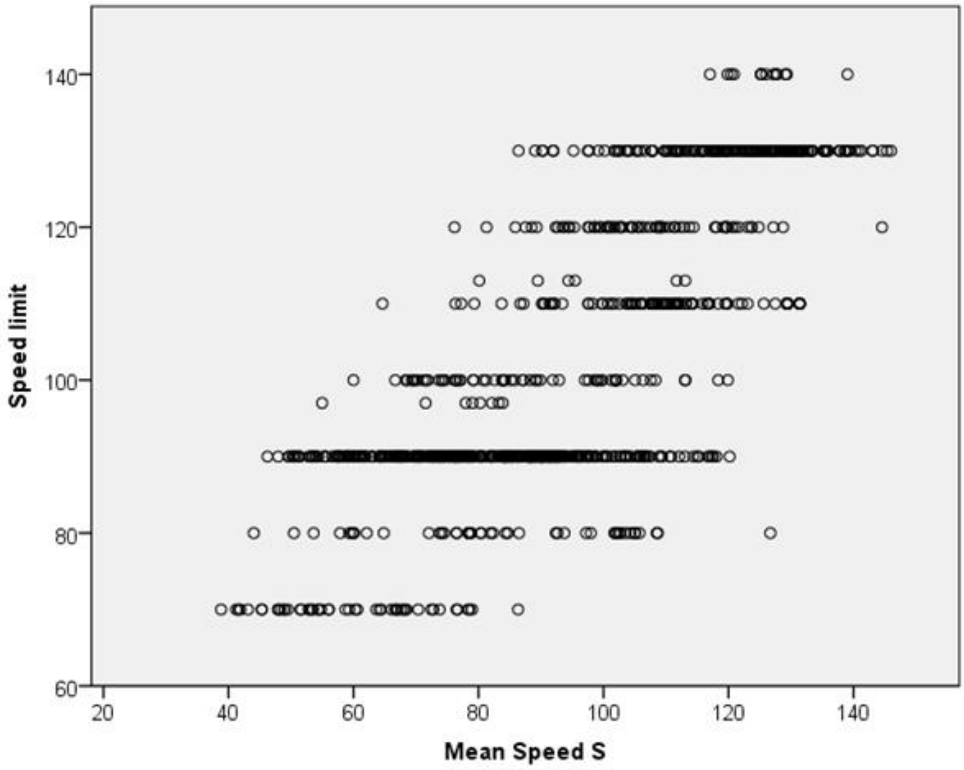

Figure 1-2: Average speed per passage on straight sections by speed limit

Figure 1-3 provides a similar scatterplot for the passages on curves. Again, higher speeds are associated with higher speed limits.

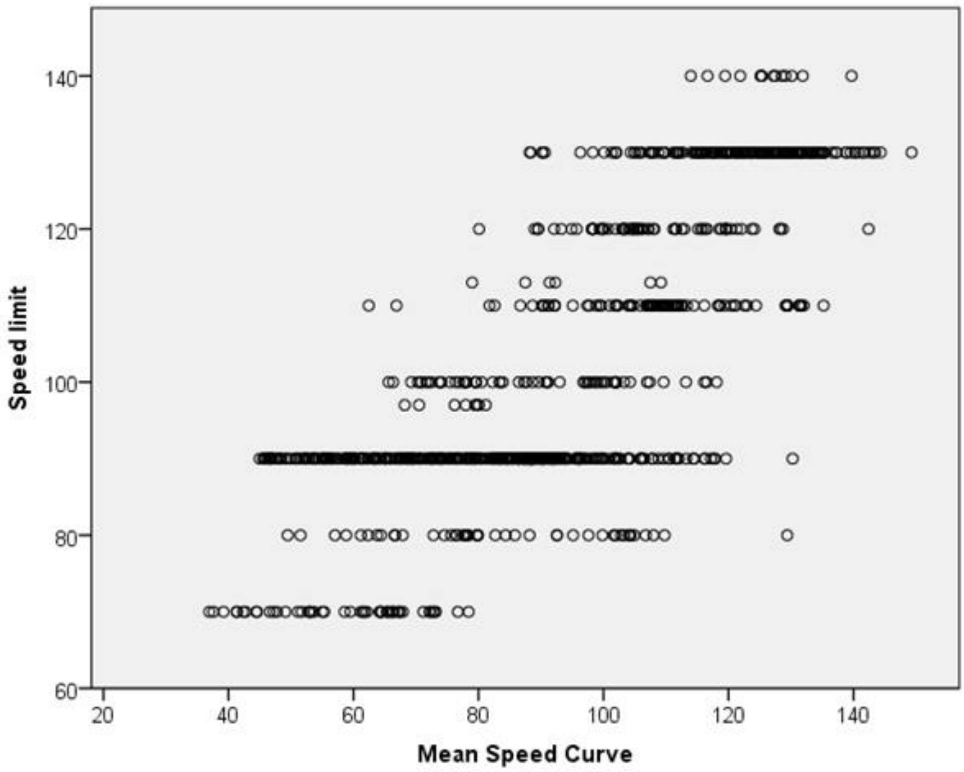

Figure 1-3: Average speed per passage on curves by speed limit

Figure 1-4 shows average speed on the straight sections by curve radius. It can be seen that there is virtually no driving above 130 km/h. There are also indications of increased speed variance for larger radius curves and higher speeds.

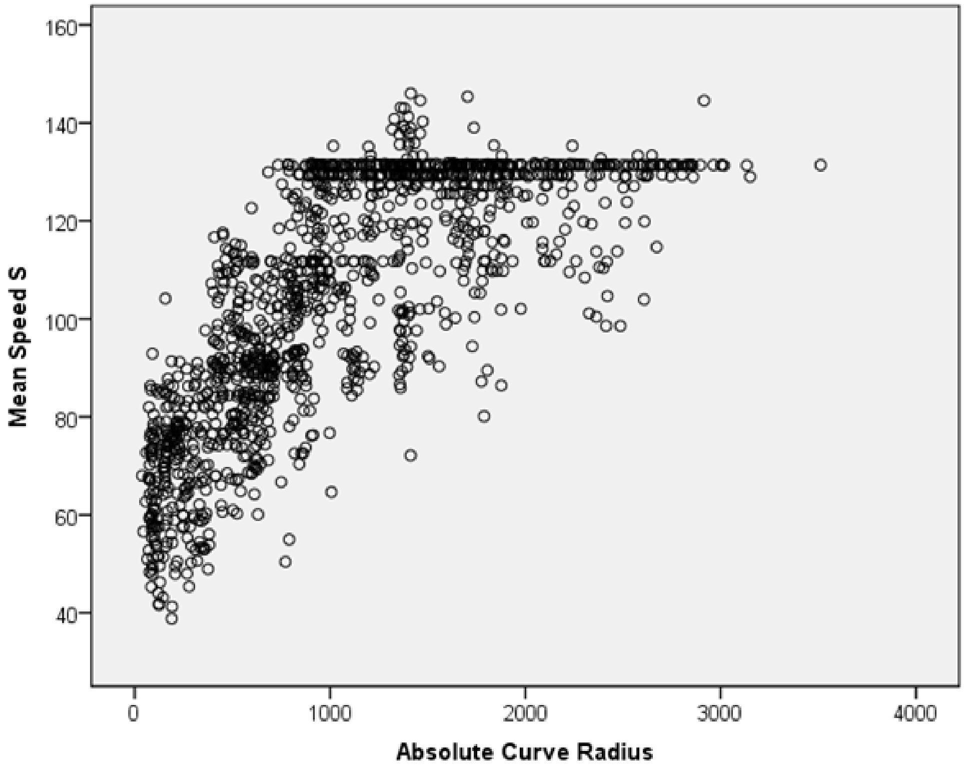

Figure 1-4: Average speed on straight sections by curve radius

2 Safety modelling

2.1 Quantitative modelling of lane-keeping steering

There is a wealth of models of various types describing how drivers steer to stay within their driving lane (see, e.g., the reviews by Plöchl & Edelmann, 2007; Steen et al., 2011; Markkula et al., 2012; Lappi, 2014). A large majority of these driver models describe the driver's steering behaviour as a continuous activity, with steering wheel inputs that change smoothly over time. However, more recently, there has been increasing interest in studying and modelling steering as an intermittent activity. Benderius and Markkula (2014) showed that in a large data set of both naturalistic driving and driving in simulators under various circumstances, driver steering could be accurately described as a sequence of intermittent, discrete steering adjustments, each with a bell-shaped speed profile, something which provides interesting links to neuroscientific accounts of sensorimotor control in for example reaching tasks (Flash and Henis, 1991; Bizzi et al., 2008; Giszter, 2015). The literature on driver steering models assuming control of an intermittent nature is quickly growing (Gordon and Magnuski, 2006; Roy et al., 2009; Benderius, 2014; Markkula, 2014; Gordon and Srinivasan, 2014; Gordon and Zhang, 2015; Johns and Cole, 2015; Boer et al., 2016; Martínez-García et al., 2016; Wu et al., 2016; Markkula et al., subm.), and the UDRIVE data set provides an excellent basis for testing the assumptions of these various models and for learning what insight these models can provide into how driving steering behaviour relates to safety.

All of these models share the same three main types of assumptions on:

1. When drivers apply their discrete, intermittent steering adjustments (including the choice of a perceptual control error quantity)
2. The general shape of the steering adjustments (either fixed or situation-adaptive).
3. The amplitude of the steering adjustments, as a function of the lane keeping situation at hand.

Figure 2-1 shows an example model structure, from Markkula et al. (subm.). It provides an illustration of the model architecture proposed by Markkula et al., replacing the control gain and delay of conventional continuous models with an evidence accumulation mechanism to determine when steering adjustments occur. It also includes a mechanism for prediction of the sensory consequences of steering adjustments, and mechanisms for scaling of individual adjustments with the error in sensory prediction.

In this analysis, we have performed an investigation of the latter two assumptions from the list of three assumptions above. This has been done by first applying a signal reconstruction method proposed by Markkula et al. (subm.), to interpret the recorded steering signal as a sequence of intermittent adjustments of a stereotyped, bell-shaped form, thus testing a specific version of assumption (2). As for assumption (3), most of the models referenced above assume that an adjustment amplitude is some kind of function of a lane keeping error at the time of adjustment onset. For example:

$$g_j=-k\cdot\omega_{err}(t_j),$$

where g_j is the amplitude of the jth steering adjustment with onset at time t_j, ω_{err} is the difference between the vehicle current yaw rate and a desired yaw rate to stay in lane, and k is a model parameter. Here, we will assume a simple form for ω_{err}, and investigate (1) to what extent the equation above explains observed steering adjustments, which is a test both of the correctness of the model as such but also of driver ability of applying accurate steering, (2) relative comparisons of goodness of fit between different driver and environment factors, and (3) to investigate how driver steering accuracy varies with these factors (under the assumption that model correctness is largely unaffected by the same factors).

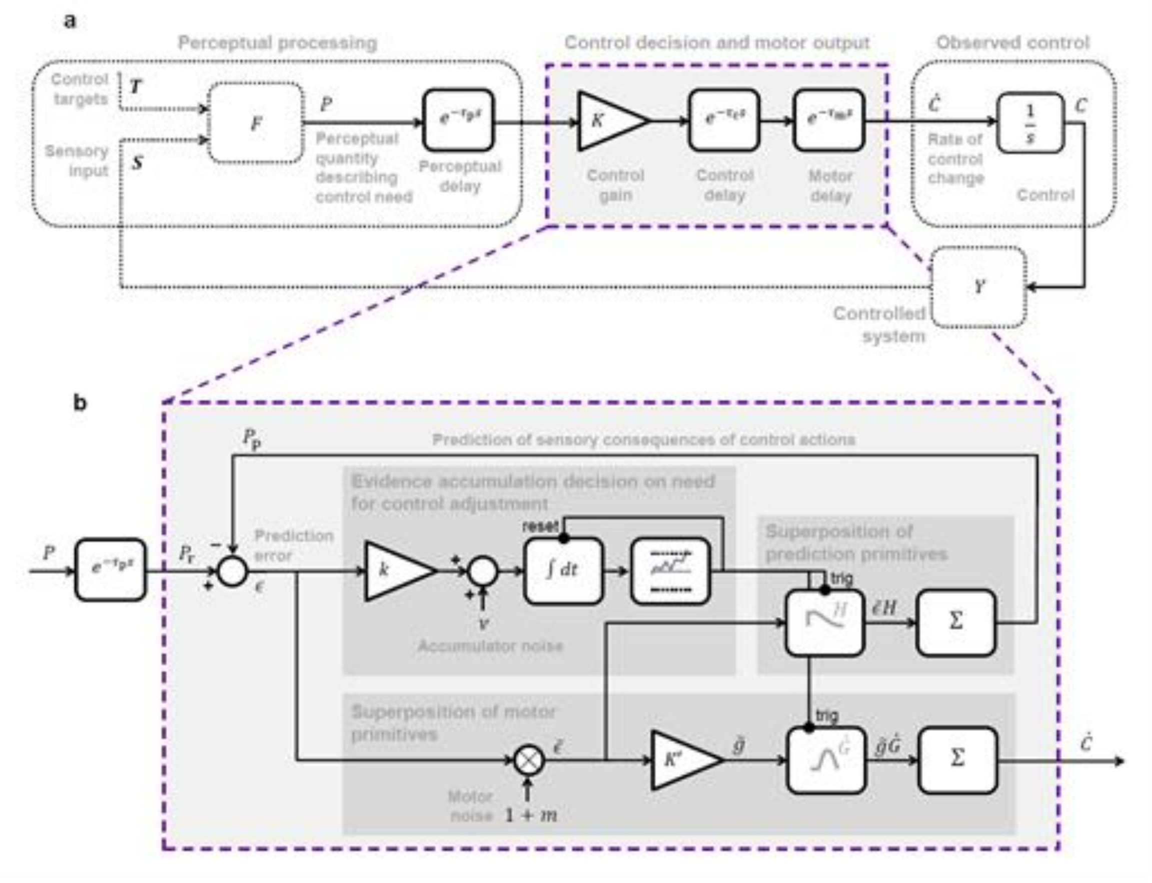

Figure 2-1: Steering model structure

2.2 Model quality

The model has a filter on the steering wheel signal, consisting of a Gaussian-kernel averaging filter with a time constant sigma. As described by Markkula et al. (subm.), the selection of this time constant involves a trade-off:

- Reducing the time constant will yield a larger numbers of steering adjustments and lower reconstruction error (quantified as the 99th percentile of the absolute difference between recorded and reconstructed steering wheel angle).
- At the same time, reducing the time constant too far will result in overfitting: one fitted adjustment of large positive amplitude being followed by one large negative adjustment produce a near-zero reconstructed steering angle. This phenomenon was quantified as the fraction of problematic adjustments.

These quality indicators of the model output are shown in Figure 2-2 and Figure 2-3. As sigma is reduced, the 99^{th} percentile of the error is reduced as well. The fraction of problematic adjustments increases with decreasing sigma. Based on these results, a value of sigma = 0.1 s was selected for the rest of the analysis. Note that this value is identical to the value used by Markkula et a. (subm.) for lane-keeping based on driving simulator data.

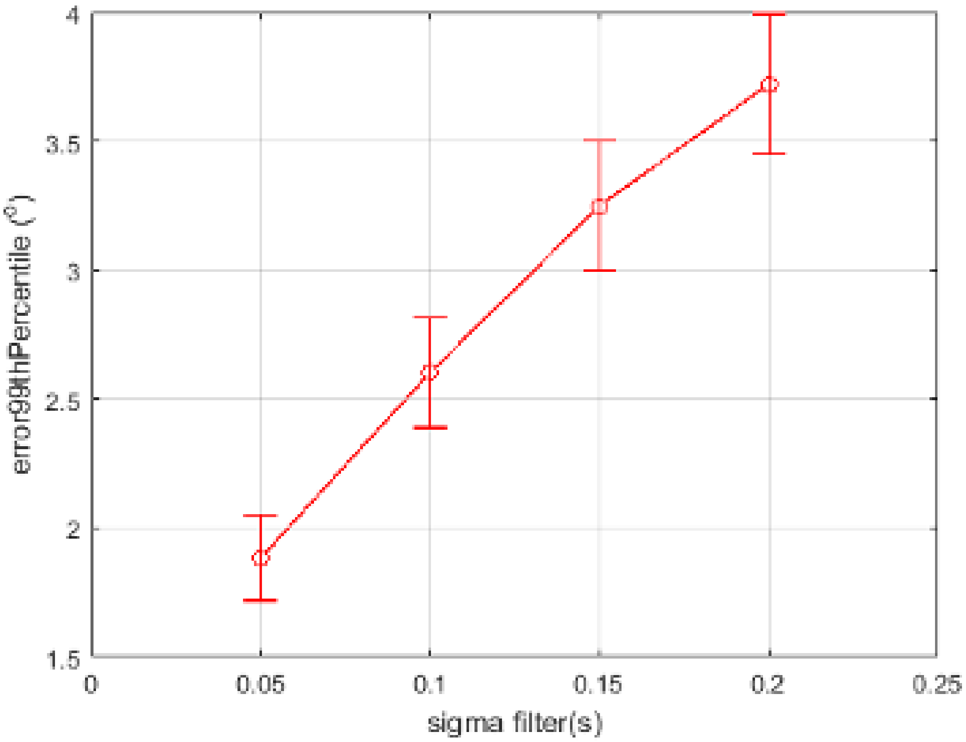

Figure 2-2: The 99th percentile of the absolute difference between recorded and reconstructed steering wheel angle as a function of the time constant sigma

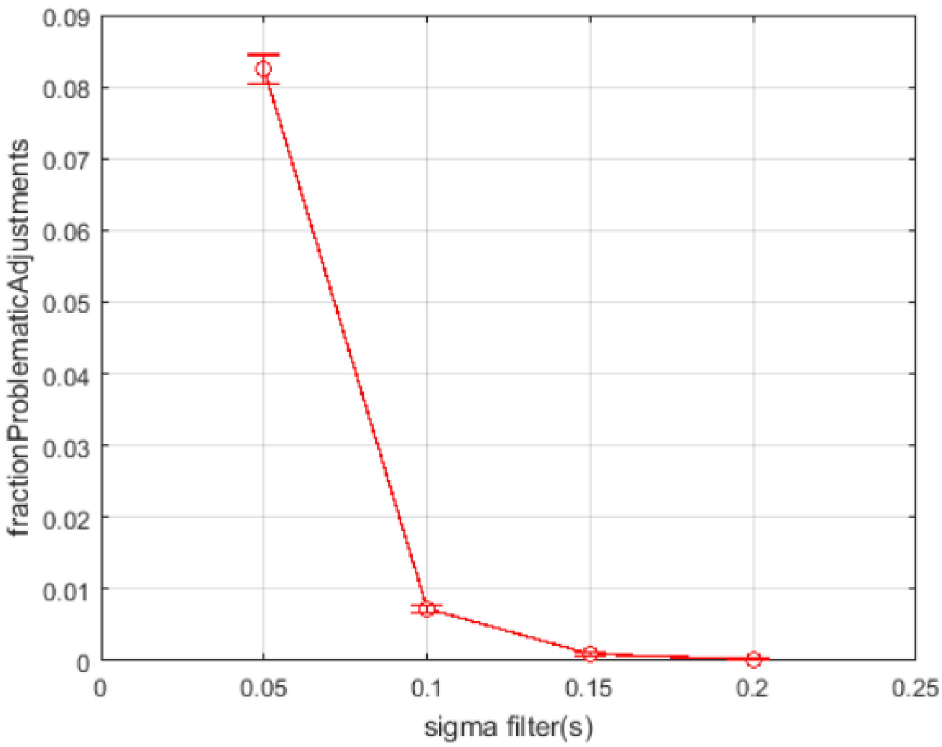

Figure 2-3: The fraction of problematic (overfitting) adjustments as a function of the time constant sigma

2.3 Results

We now turn to the model outputs and in particular to their relationship to safety in lateral vehicle control while driving in curves. Figure 2-4 shows steering adjustment frequency (adjustments per second) in relation to curve radius. There are indications of more frequent adjustments, i.e. more steering effort, on smaller radius curves.

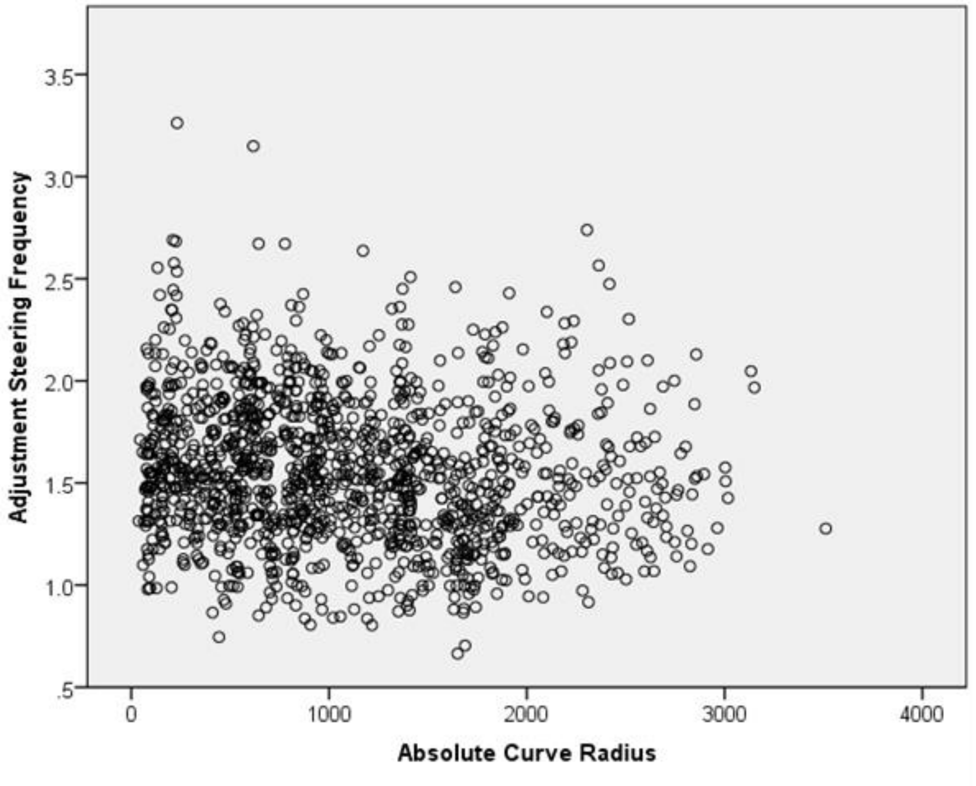

Figure 2-4: Steering adjustment frequency by curve radius

Figure 2-5 shows the mean amplitude of steering adjustments by their relative frequency. It can be seen that there is a tendency for smaller adjustments to be more frequent, with larger adjustments being comparatively rare. Thus control quality is generally good.

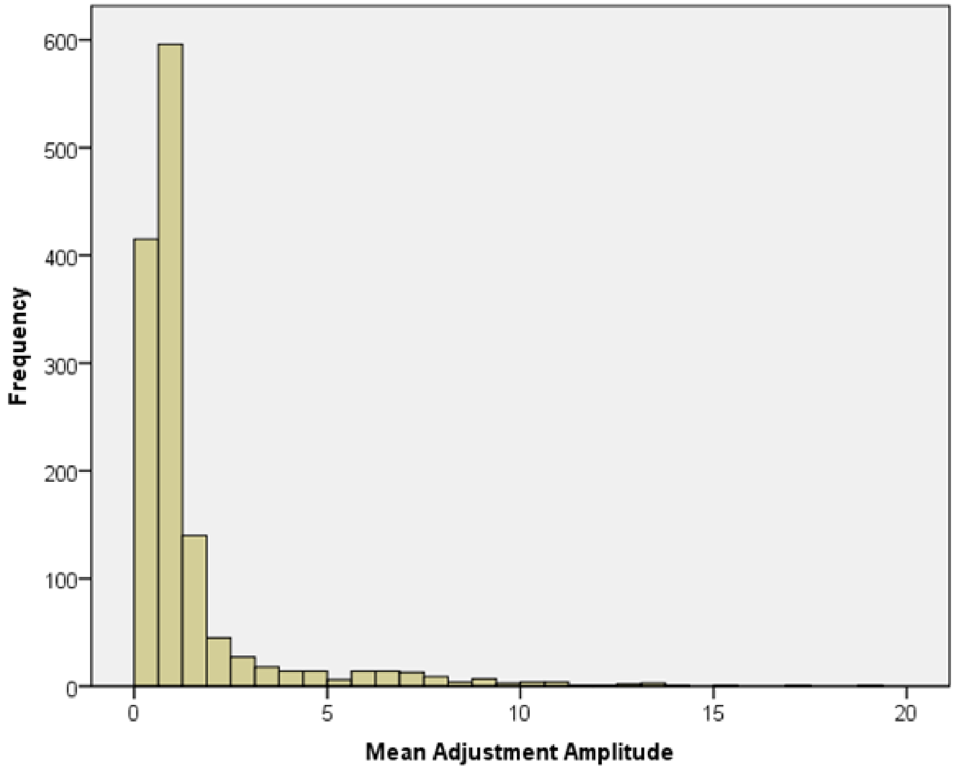

Figure 2-5: Mean amplitude of steering adjustment by frequency

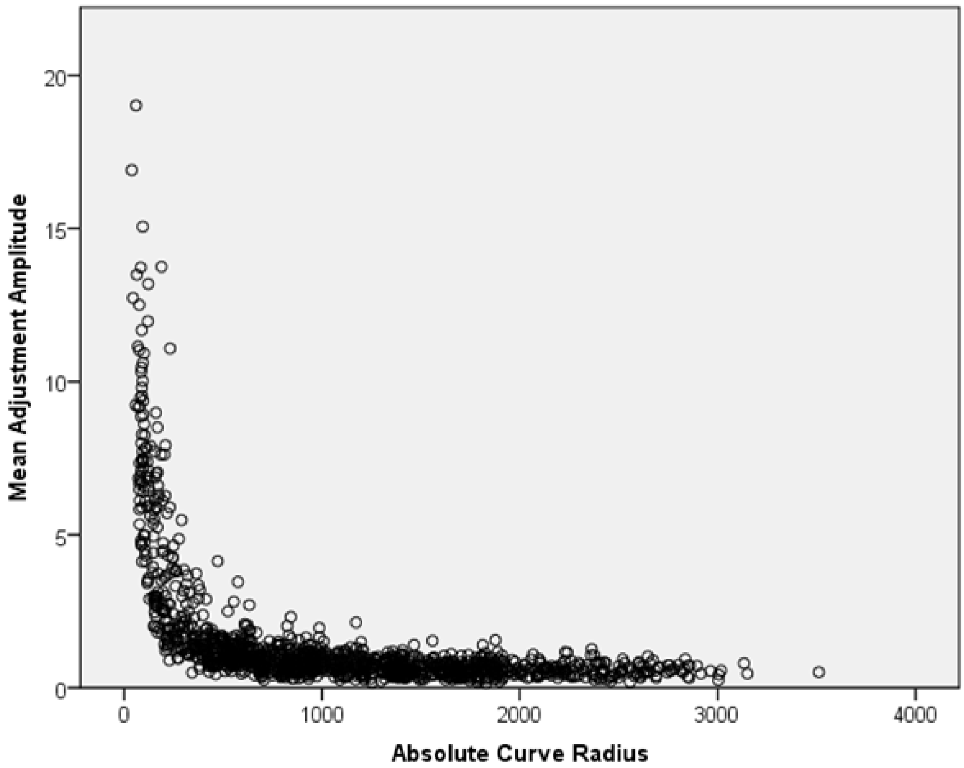

Figure 2-6: Mean amplitude of steering adjustment by curve radius

On the other hand, control quality is by no means even across curve radius. This can be seen from Figure 2-6, which shows the relationship between curve radius and the mean amplitude of steering adjustment. The graph indicates a negative exponential relationship between curve radius and amplitude of adjustment:

large adjustments are far more frequent on tighter curves (see Figure 2-7) which is indicative of unsmooth (jerky) steering on those curves.

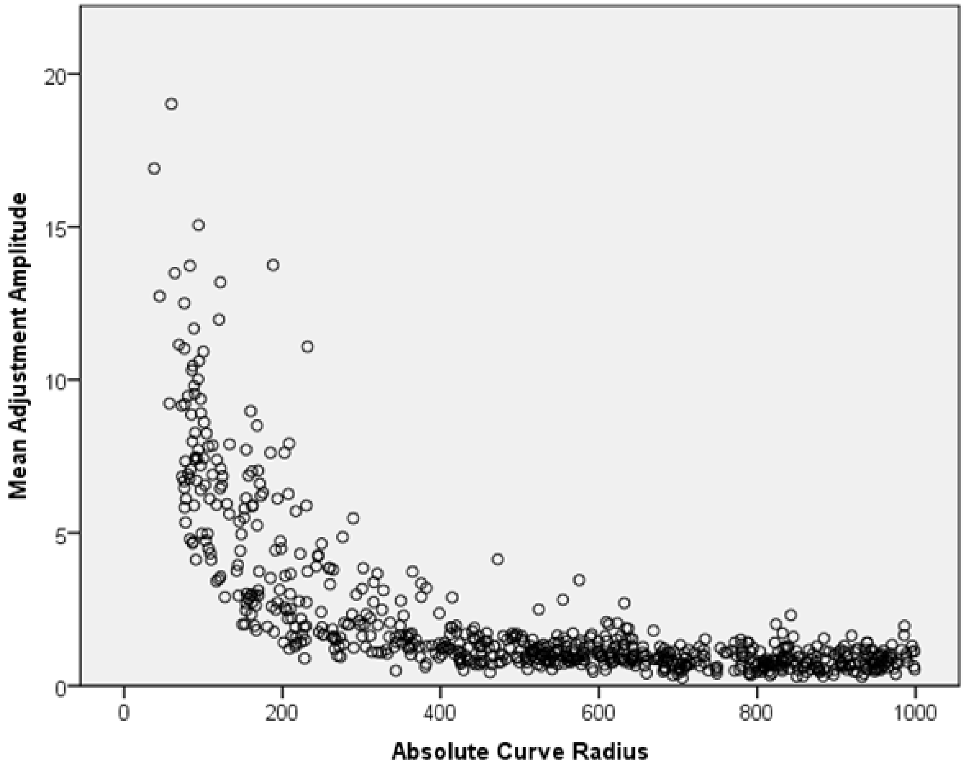

Figure 2-7: Mean amplitude of steering adjustment by smaller curve radii (smaller or equal to 1000).

2.4 Discussion

The application of the steering model to the curve driving data has shown that the quality of driver steering behaviour deteriorates sharply on tight-radius curves as compared to more gentle curves. But the question still arises of whether that deterioration is still manageable, i.e. leaves drivers with sufficient safety margin or whether it is indicative of unsafe performance.

The relationship between curve radius and crash risk has been extensively modelled at the macro level, i.e. for estimating the risk that a passage on a curve of a given radius will result in a crash. The findings from those models are summarised by the European Road Safety Observatory in ERSO (2007), while Gooch et al. (2016) present some of the most recent analysis and come to very similar conclusions. Those findings are illustrated in Figure 2-8. It can be seen that the relationship between curve radius and crash risk is remarkably similar to the relationship between curve radius and amplitude of steering adjustment as modelled from the UDRIVE data.

It can thus be concluded that the poorer steering behaviour that has been found here for small-radius curves is indeed related to real safety outcomes. Higher amplitude is an indicator of greater crash risk. Further work should examine the relationship between speed on curve entry and such poorer-quality steering behaviour. It is perhaps feasible to consider the use of this performance indicator as a trigger of feedback to drivers on the quality of their curve-driving.

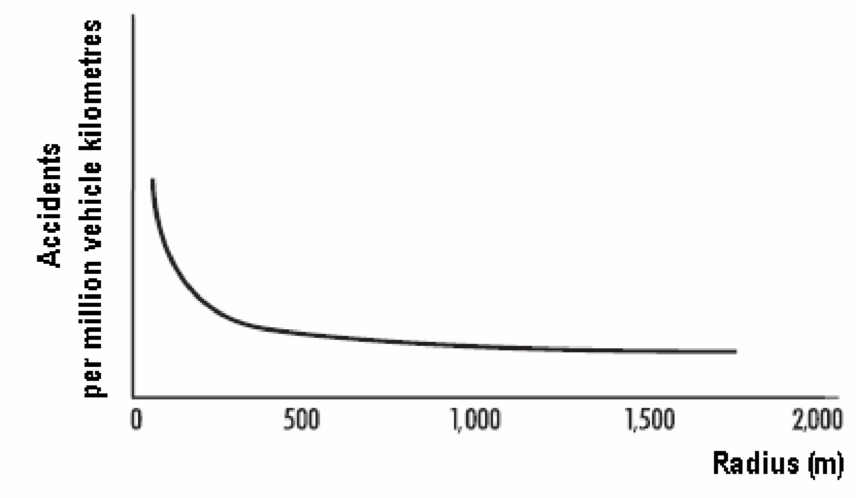

Figure 2-8: Effect of horizontal curve radius on accident risk (ERSO, 2007, based on Hauer, 2000)

3 Eco-driving modelling

3.1 Method

This chapter focuses on how the UDRIVE data can be exploited in the context of models of energy efficiency in driving. Once again, the test case is curve driving.

In the ECOWILL project (CIECA[2], 2013) five Golden Rules of eco-driving are distinguished:

1. Greater Anticipation
   - Anticipate situations and other road users as far ahead as possible.
   - Maintain a greater distance between vehicles in order to avoid unnecessary acceleration and braking and make maximum use of the vehicle's momentum
2. Maintain a steady speed at low RPM
   - Drive smoothly, using the highest possible gear at low RPM
3. Shift up early
   - Shift to higher gear by approximately 2,000 RPM
4. Check tyre pressures frequently, at least once a month and before driving at high speed
5. Remember all ancillary loads add to fuel consumption
   - Electrical equipment and in particular, air conditioning adds significantly to fuel consumption, so use it sparingly.
   - Avoid carrying dead weight and adding unnecessarily to aerodynamic drag e.g.by opening windows at high speed or carrying roof boxes when not in use.

In particular, compliance with the advice to "avoid unnecessary acceleration and braking and make maximum use of the vehicle's momentum" will lead to fuel savings. Drivers should try to use engine braking to slow down (e.g. when exiting a motorway, approaching intersections, approaching sharp curves). The ecoDriver project (see http://www.ecodriver-project.eu) developed driver support systems in which drivers received speed advice to drive as economically as possible, taking a number of environmental constraints into account. One of the main features of the developed systems was to support drivers in more often using engine braking by lifting off the accelerator well in advance of a situation. Based on map data, one scenario for using the engine brake was approaching a curve for which the driver had to slow down (see Woldeab et al., 2014; Kircher et al., 2014). The results of the systems tested on the road in the on-road experiments and naturalistic driving showed positive results for the systems developed and for some of the hypotheses related to the golden rules of eco-driving (see Saint Pierre et al., 2016).

For the analysis here, the UDRIVE data on drivers' approach to curves was examined. The results of these analyses are relevant for improving microscopic traffic simulation models, as these typically do not take effects of curves on driving behaviour into account, beyond a simple constraint on the desired speed of the driver-vehicle unit.

For this work, we mainly looked at strong decelerations and large speed differences and at how these values can be related to driver characteristics. Also we wanted to show the possible potential of the analyses that we have performed to updating driving behaviour models. We did not update a driver model ourselves.

Of the straight – curve combinations that were extracted (see section 1.1, page 6) we calculated the following variables from the data collected

[2] CIECA: The International Commission for Driver Testing

- length (in m)
- maximum speed (in km/h)
- minimum speed (in km/h)
- mean speed (in km/h)
- maximum deceleration (in m/s^2)

For each curve, we knew the radius (in m) and the speed limit (in km/h). Speed limit was used as an indication of road type; all included road types were assumed to be rural or motorway. The golden rule for the approach is to avoid strong decelerations and to use engine braking (coasting) when approaching a curve. Therefore we were mainly interested in maximum deceleration. Since drivers can still adapt their speed in a curve or late in the approach, the maximum deceleration does not have to be on the approach only. Moreover, if in a free driving situation a driver decelerates sharply in the curve, then this is still a 'violation' of the golden eco-driving rule. For that reason, in the analyses the lowest value of the maximum deceleration of the curve or straight was used.

3.2 Results

As a first step in the assessment of the speed adjustment before/in the curve is the magnitude of the speed reduction itself. The radius of the curve plays an important role here, as illustrated in Figure 3-1. It can be seen that mean speed increases with larger curve radius, which is as expected. There are also indications that speed dispersion (speed differences between vehicles) increases with radius: speeds are more constrained when radius is tight.

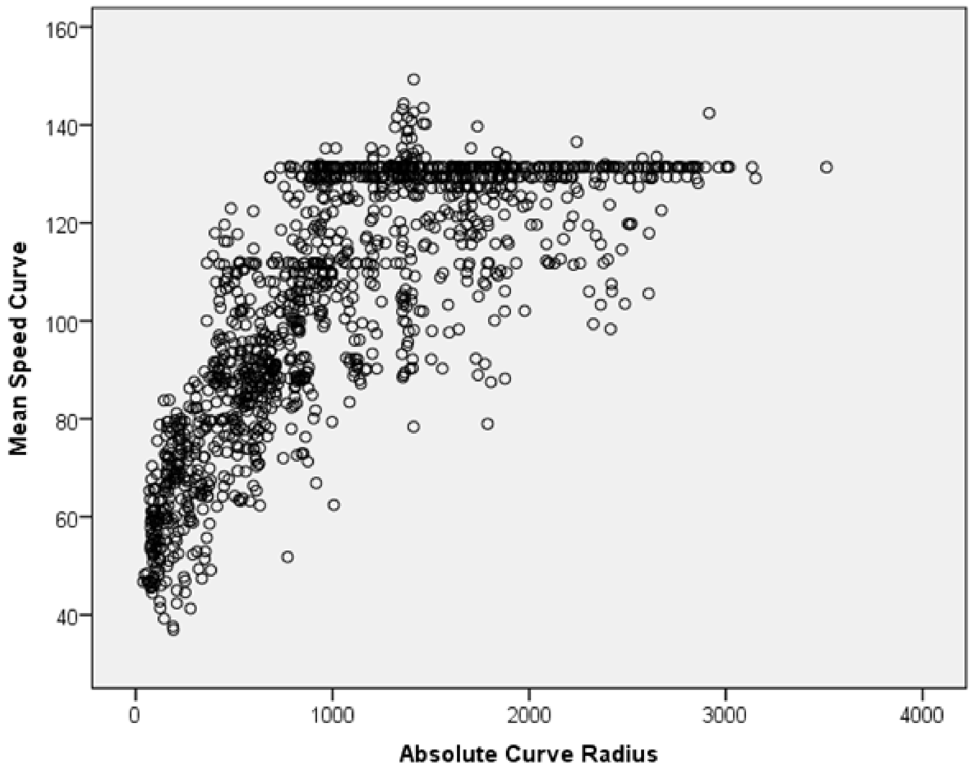

Figure 3-1: Mean speed in the curve as a function of curve radius

Much of the dispersion of the speeds in Figure 3-1 is explained by the approach speed (average speed on the straight section leading to the curve). This is shown in Figure 3-2, where colours are used to visualise the approach speed category (in bins of 10 km/h).

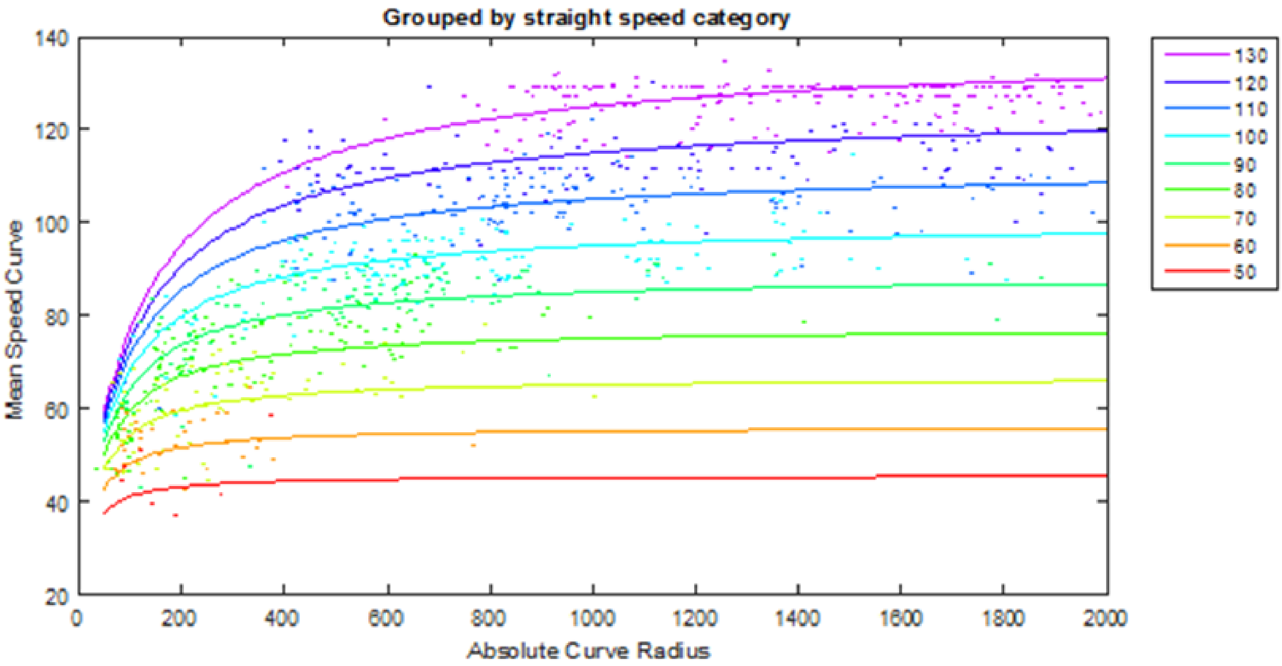

Figure 3-2: Mean speed in the curve as a function of curve radius grouped by approach speed category (km/h)

The solid lines in Figure 3-2 show the curve speed as predicted by the model from Brodin and Carlsson (1986):

$$Vc = \frac{1}{\sqrt{\left(\frac{1}{Va}\right)^2 + 0.15\left(\frac{1}{R} - 0.001\right)}}$$

Where Va is the approach speed (m/s) , Vc is the curve speed (m/s) and R is the curve radius (m).

This figure shows a strong relationship between the curve speed and the approach speed, which in turn will depend on the speed limit, the road category, number of lanes, road width, etc. But it can also be observed that there are some situations in which quite dramatic decelerations are required.

Figure 3-3 shows the same distribution of speed, but now with lines indicating the safe maximum speed for a curve of a given radius. The formula used to calculate that speed is from Papacostas (1987). The black curves denote the maximum speed Vc (m/s) at which a curve can be safely and comfortably negotiated, given the curve radius R (m), the superelevation e (here = 0.055), and the coefficient of side friction f_s:

$$Vc = \sqrt{g * R * (e + f_s)}$$

Here the values of f_s shown are 0.20 for dry roads (shown with the dashed black line) and 0.13 for wet roads (shown with the solid black line). As can be seen in Figure 3-3: Mean speed in the curve as a function of curve radius and of the approach speed category (km/h). Black lines indicate maximum speed to keep the vehicle on the road in dry conditions (dashed) and wet conditions (solid). Figure 3-3 shows that for only a few curves the speed was above the safe maximum speed for dry roads; for wet roads there were considerable more curves above the safe maximum speed. However the road and/or weather conditions were not included in the analyses.

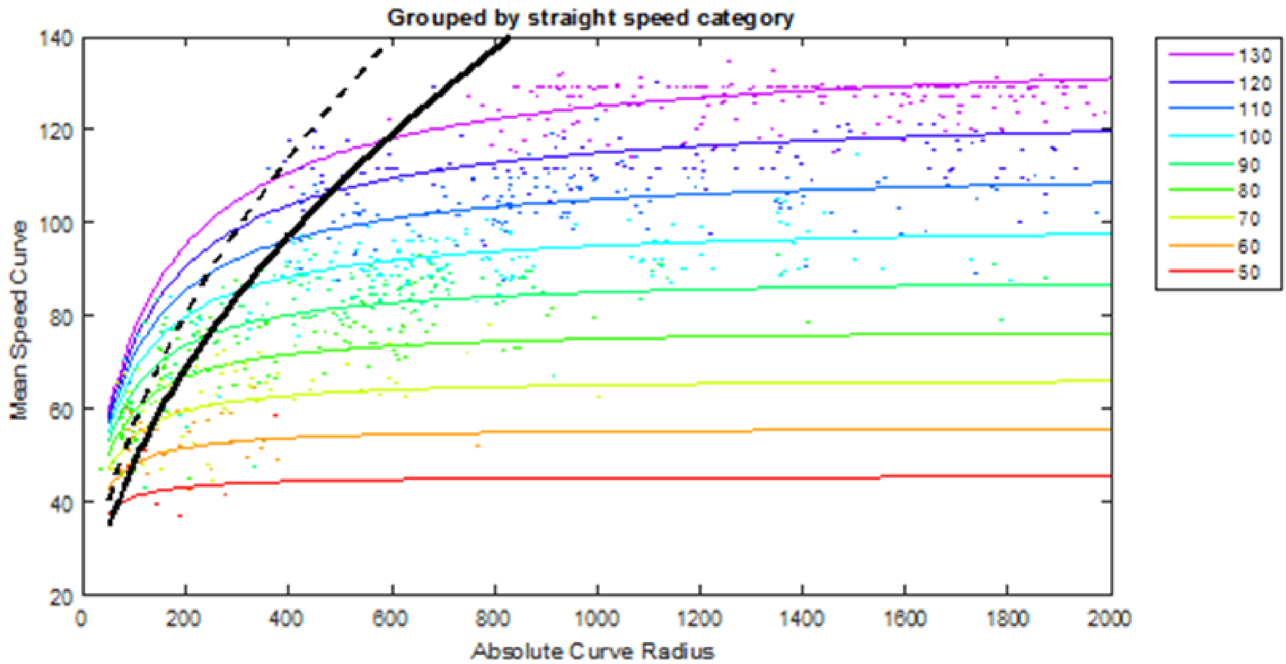

Figure 3-3: Mean speed in the curve as a function of curve radius and of the approach speed category (km/h). Black lines indicate maximum speed to keep the vehicle on the road in dry conditions (dashed) and wet conditions (solid).

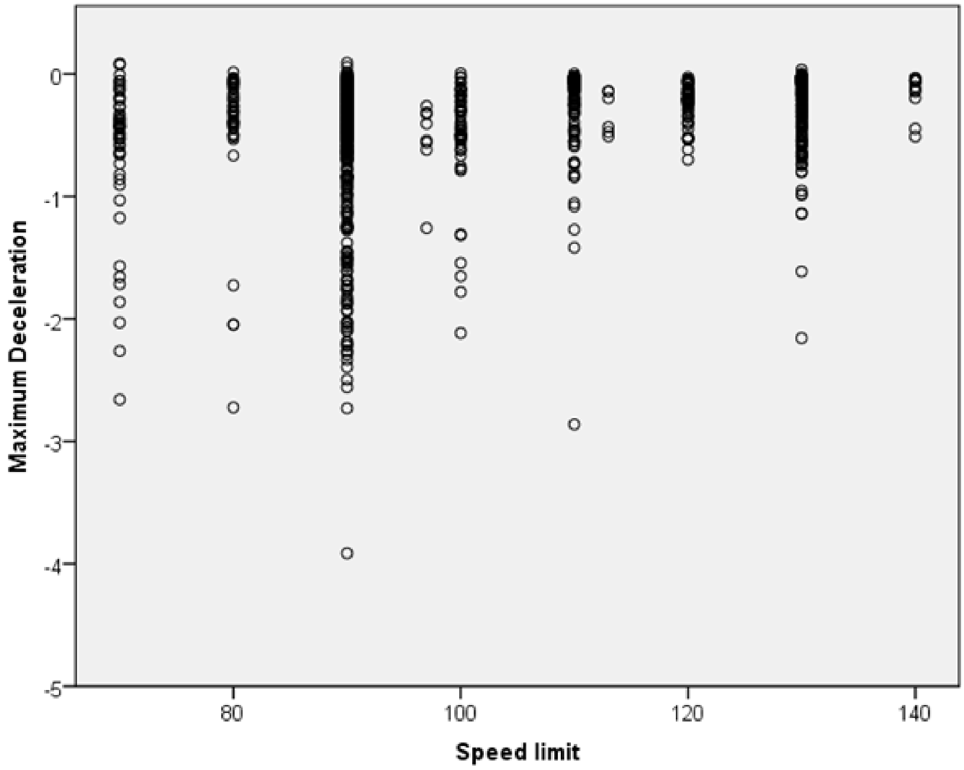

Figure 3-4: Maximum decelerations for the different speed limits in the dataset

Figure 3-4 shows the relationship between speed limit and maximum deceleration. The figure suggests that higher decelerations were on roads with a lower speed limit. This makes sense given that curves with smaller radii are more often found on roads with lower speed limits. This suggestion is reflected in Figure 3-5. The figure shows the maximum deceleration for the different absolute radii (i.e., no distinction between a left or a right curve). The larger decelerations are found with smaller radii.

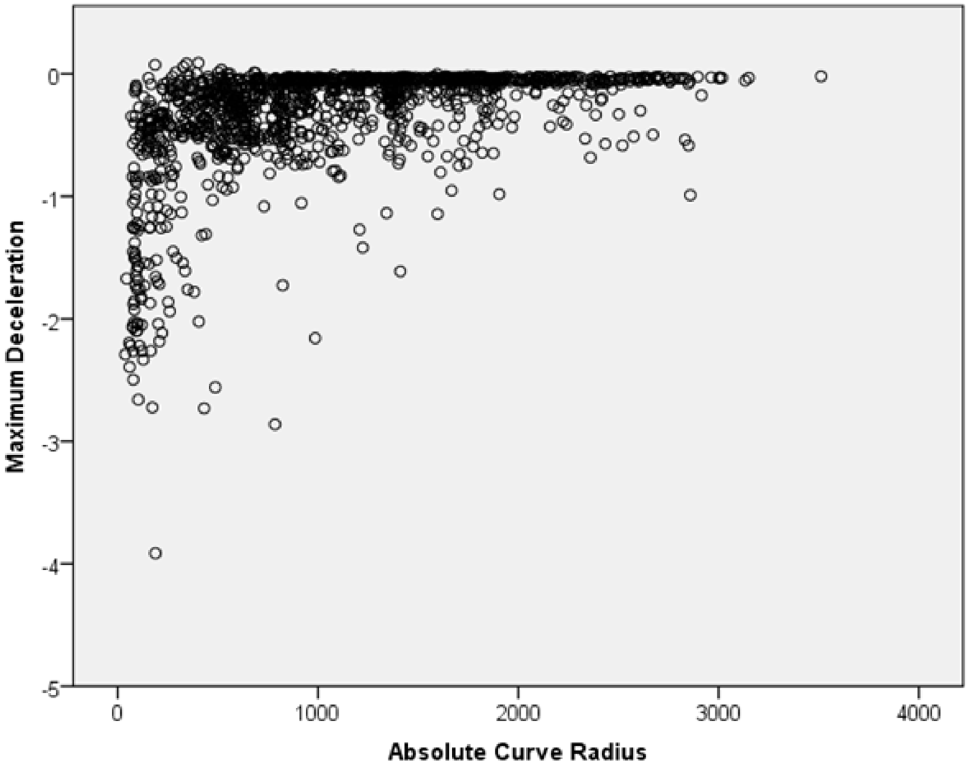

Figure 3-5: Maximum deceleration for different absolute values of curve radii

The difference between the maximum speed and minimum speed was also calculated (in km/h). Given the reasoning above with respect to the maximum deceleration, we used the difference between the highest value of maximum speed on the straight or curve and lowest value of the minimum speed on the straight or curve. This speed change is indicated as 'delta speed'. It makes sense that a similar pattern to that in Figure 3-5 is also found for delta speed. One would expect larger values of delta speed to be found with smaller radii. This is indeed the case as shown in Figure 3-6. Thus large changes in speed are associated with sharper decelerations, which might not be the case if driver were anticipating and therefore using engine braking to slow down.

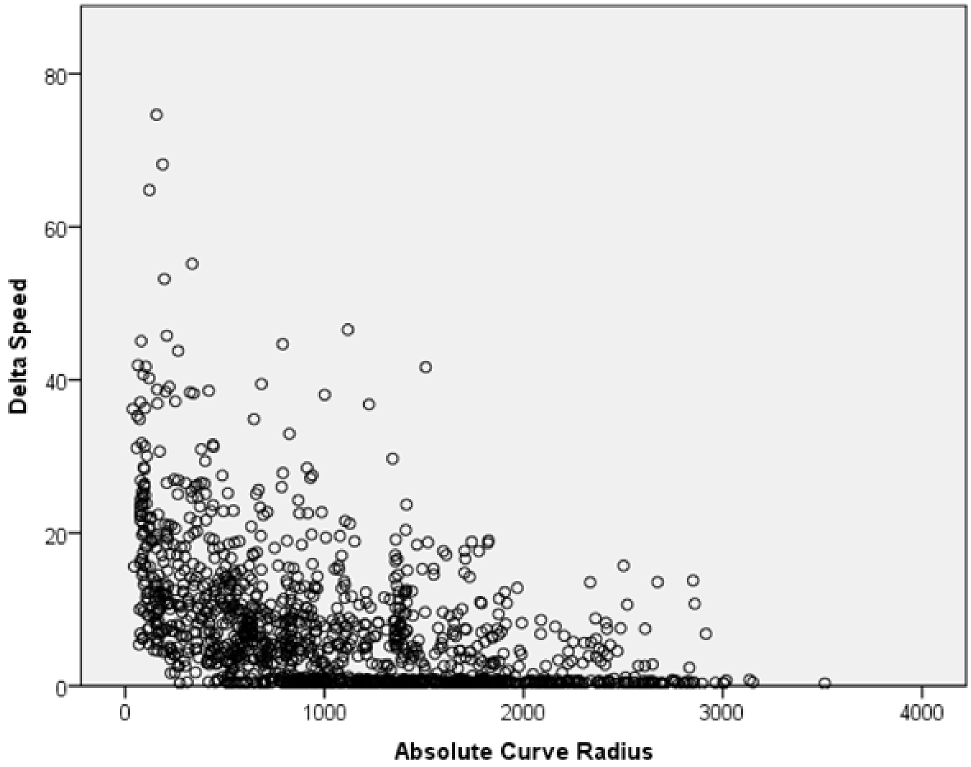

Figure 3-6: Delta speed for the different values of curve radius

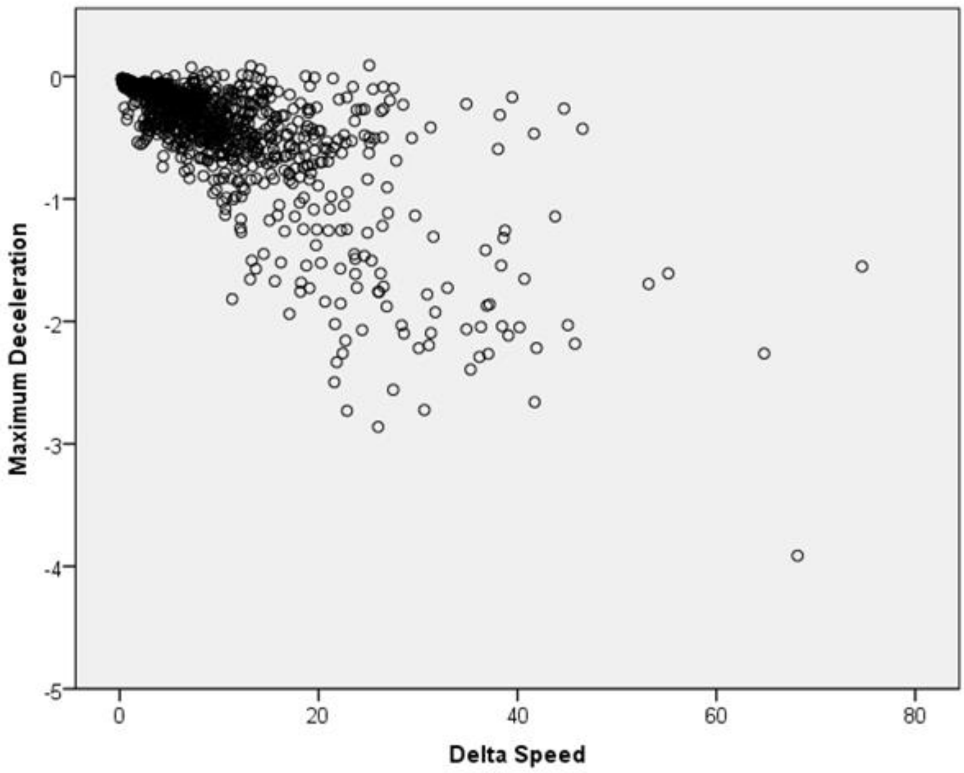

Figure 3-7: The relation between maximum deceleration and delta speed

The relationship between the maximum deceleration and delta speed for curves is presented in Figure 3-7. The figure indicates that, for most of the curves, drivers slowed down in accordance with the golden rules. Some of the curves may have provided undisturbed passages where there was hardly any need to decelerate. Other curves may have required some deceleration, but one that could easily be achieved with coasting. Here we have defined decelerations between 0 and −0.5 m/s^2 as coasting. Between −0.5 m/s^2 and −1 m/s^2 is seen as gentle braking.

Both Figure 3-5 and Figure 3-6 show that for curves with radii above 1000 m the deceleration is very small as is the delta speed. For that reason the analyses were focussed on radii smaller or equal to 1000 m. Adding this selection criterion to criteria already in place results in 719 straight-curve combinations unequally distributed over 31 drivers. The resulting maximum decelerations for the curves with radii of 1000 m or less are shown in Figure 3-8.

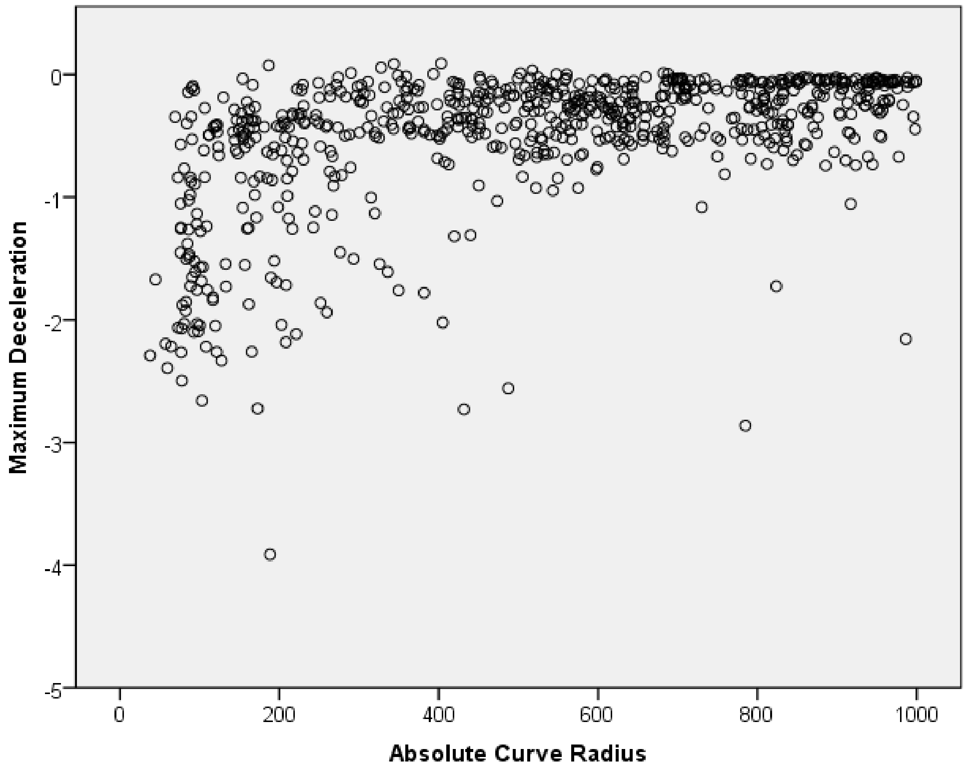

Figure 3-8: Maximum deceleration for the different absolute value of curve radii (<=1000)

One relevant question here is how driver factors and in particular personality and risk-taking propensity influences eco-driving behaviour. If such factors are significant, then models of energy consumptions might have to be adapted to cater for the effects of personality and driving style. UDRIVE provides data to look at this issue. On being recruited as participants, drivers filled out the Driving Behaviour Questionnaire (DBQ; see, e.g., Reason, Manstead, Stradling, et al, 1990) and the Arnett Inventory of Sensation Seeking (AISS; see, e.g., Arnett, 1994).[3] A higher overall AISS score denotes a higher level of sensation seeking and a higher DBQ violation score indicates a greater propensity to commit violations. Visually there was no clear relationship between the total AISS score and maximum deceleration (see Figure 3-9) or between the total DBQ violation score and maximum deceleration (see Figure 3-10).

[3] Not all drivers filled out the questionnaire or filled out the questionnaire completely. Of five drivers we miss the AISS score, of four drivers we miss the DBQ Aggressive Violations score, of six drivers we miss the Ordinary Violations score, and of seven drivers we miss the DBQ All Violations score. So these drivers are excluded from the analyses with respect to the AISS and DBQ.

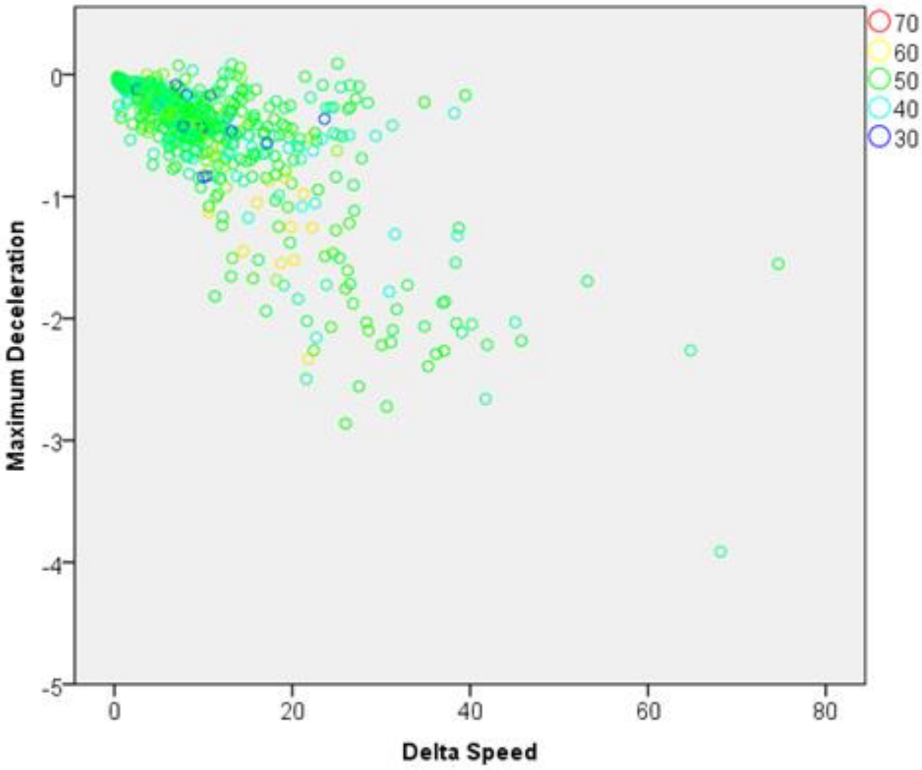

Figure 3-9: Maximum deceleration and delta speed and overall AISS score (in colour)

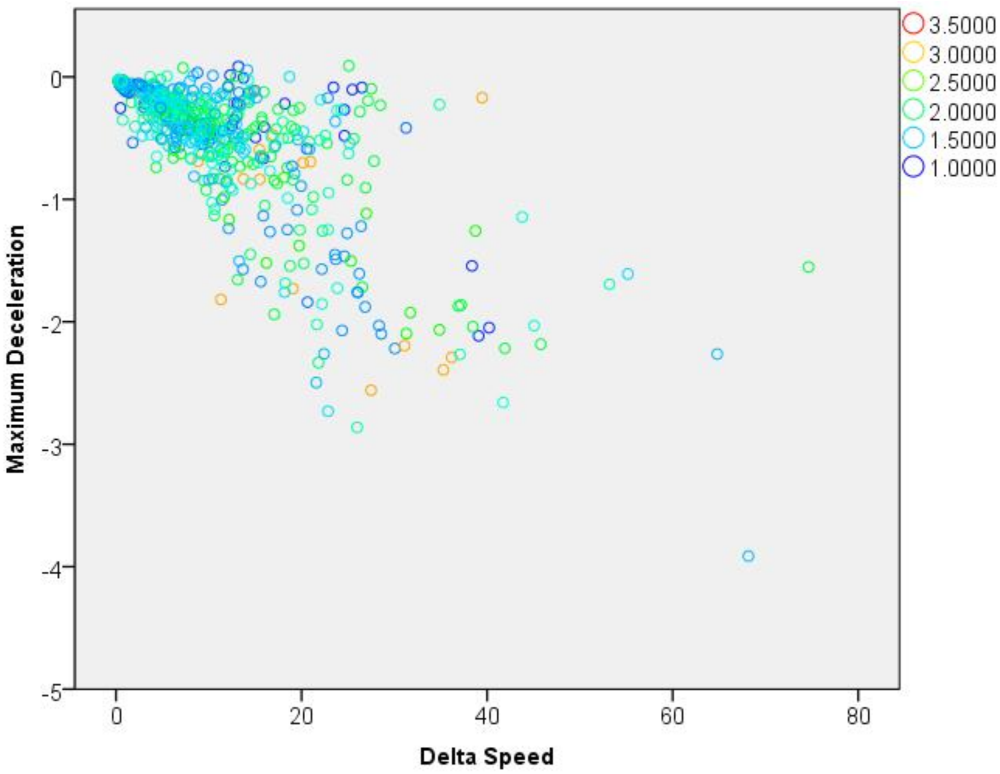

Figure 3-10: Maximum deceleration and delta speed and overall DBQ score (in colour)

However, Figure 3-9 and Figure 3-10 are based on a number of straight-curve combinations and these are not equally distributed over the drivers. Therefore we calculated the median maximum deceleration over all straight-curve combinations for each driver. Next, these were combined with their AISS and DBQ scores.

Results of a regression analysis revealed a significant relationship between the median maximum deceleration level and the three DBQ violation scores, indicating that harder braking corresponded with higher DBQ violation levels (see Figure 3-11, Figure 3-12 and Figure 3-13. In the regression analyses with the AISS scores, no significant effects were found [all $p>0.3$].

Therefore, the hypothesis that energy consumption in the form of over-aggressive deceleration, is related to violation was confirmed. Thus there is an overlap between drivers' general safety related behaviour, as indicated by their self-reports, and their eco-driving behaviour.

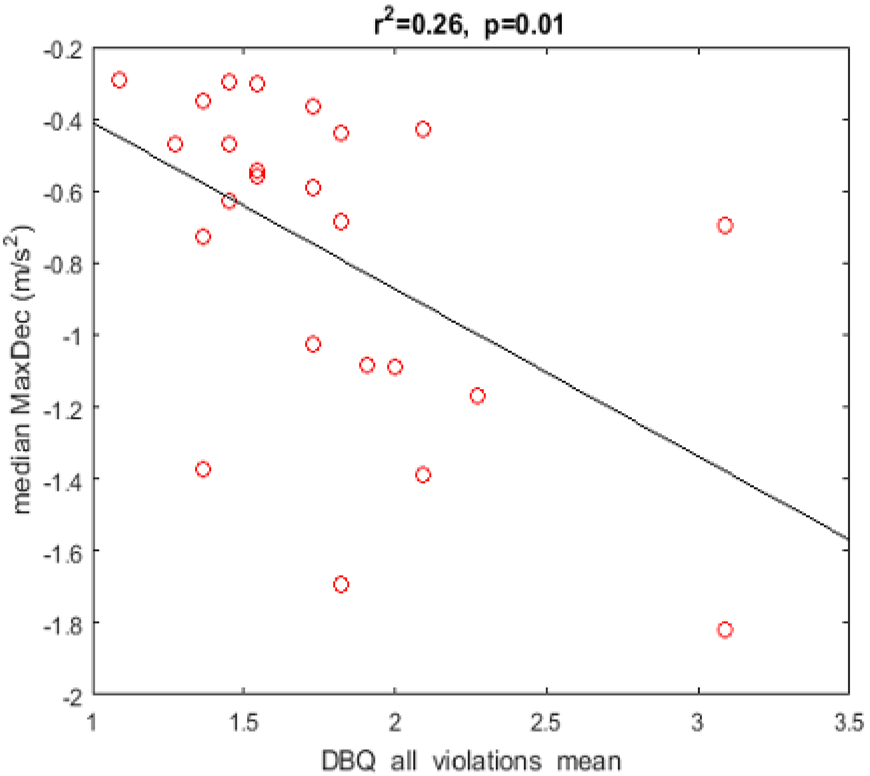

Figure 3-11: Median maximum deceleration as a function of DBQ all violations score

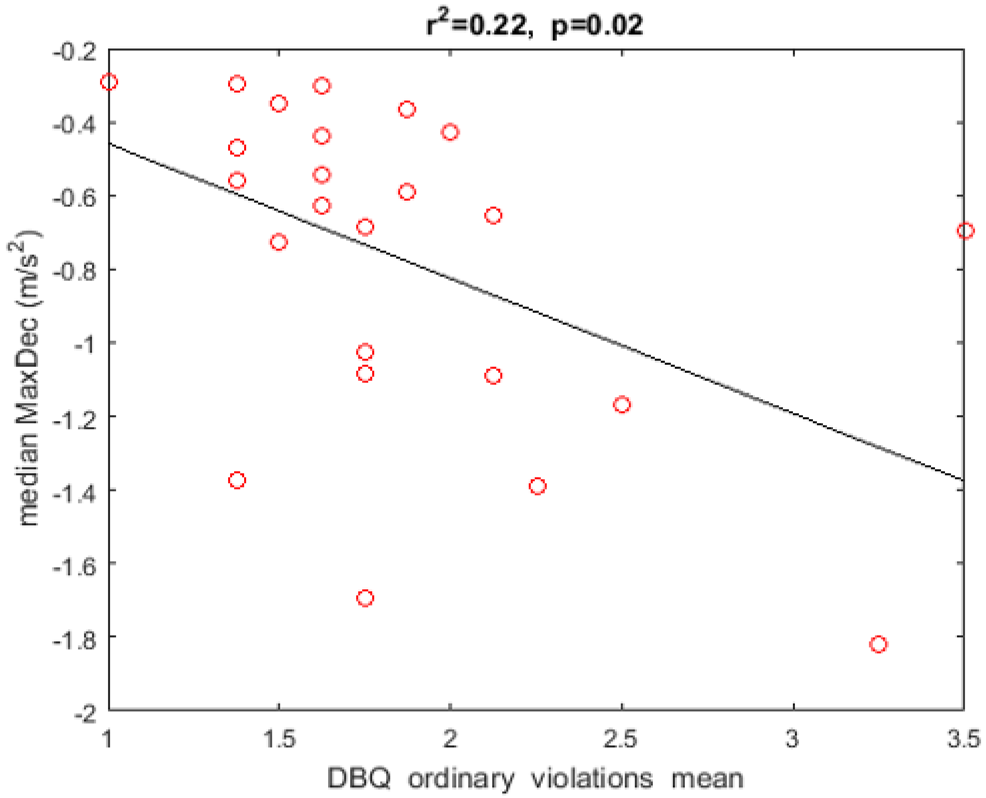

Figure 3-12: Median maximum deceleration as a function of DBQ ordinary violations score

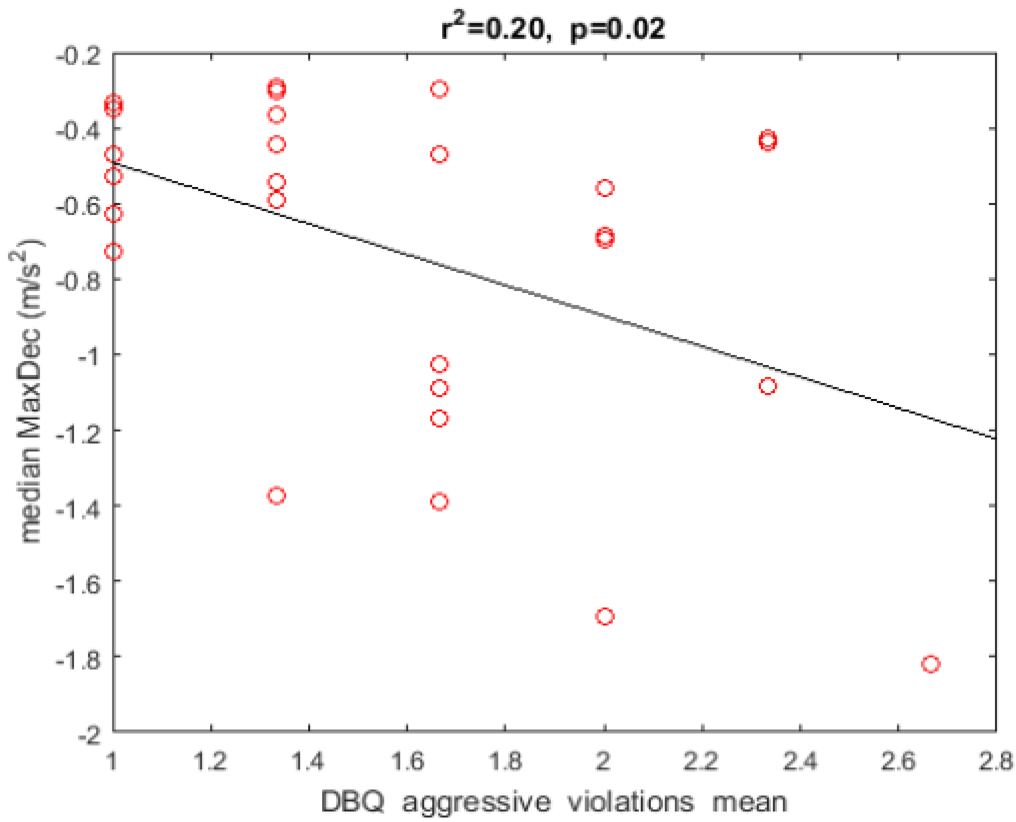

Figure 3-13: Median maximum deceleration as a function of DBQ aggressive violations score

4 Conclusions

The values of the UDRIVE data for the improvement of models of traffic and driver behaviour has been shown both for safety-related behaviour and for energy consumption. Analysis of curve driving at the sub-micro (nano) level has been applied to examine how driver input into vehicle lateral control varies by curve radius. It has been shown that amplitude of input varies systematically by curve radius, with larger corrections being systematically more common on tighter curves. The resulting distribution showed a negative exponential relationship that is remarkably similar to the known distribution of crash risk, with far higher risk for small-radius curves. The insight obtained can not only enhance driver-vehicle simulation models, but also suggests the development of new countermeasures to stimulate greater safety margins in curve driving.

From an eco-driving perspective, the analysis has reinforced the conclusion that energy is being wasted by drivers in the approach to and passage through curves by lack of anticipation of the need to slow down and therefore by over-harsh deceleration. The consequent wastage of energy has been shown to be related to safety-related attitudes and behaviour in the form of self-reported tendency to commit traffic violations.

Suggested further work would be to investigate the correlation between the safety and eco-related behaviours and to further investigate the personal and situational factors that lead to more undesirable behaviours. That would permit the development of models that are more suited to safety and energy consumption predictions than are current micro-simulation models which are generally most suited to estimation of traffic speeds and flow.

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List of abbreviations

DBQ: Driving Behaviour Questionnaire

AISS: Arnett Inventory of Sensation Seeking

List of Figures

Appendix A Review report template; checklist for reviewers

A.1 Overall judgement: readability, 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	x	
Comments	No with respect to mistakes/challenges; yes with respect to further research			
	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				
	Is the English in the deliverable good? Is it clear and accessible?	x		
Comments				
	Are the figures and tables understandable and referred 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	x		

	necessary wider view on the field of work properly given?			
Comments				
	Other comments			