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How do drivers negotiate horizontal ramp curves in system interchanges in the Netherlands?

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ABSTRACT

On interchanges there are higher probabilities of risky situations compared to uninterrupted motorway sections due to increased speed variability and higher frequency of lane-changes. In this study, we focus on understanding and modelling drivers' longitudinal speed behavior when negotiating horizontal ramp curves in interchanges in the Netherlands. For this purpose, detailed trajectory data of free-moving vehicles on 29 different curves from 6 different interchanges were collected from video images taken from a hovering helicopter. Only free-moving vehicles were chosen in order to understand how the road geometric design affects the (unhindered) driving speeds.

The results of the speed profiles analysis show that for each connection, the speed profiles follow certain patterns, despite the large heterogeneity among drivers. These speed patterns were found to be significantly affected by the distance along a connection, the design characteristics of a connection, vehicle type, and drivers' heterogeneity. The impact of the distance along the connection on the speed was found to be significant and non-linear. This indicates that drivers do not maintain constant speeds, but adapt it along the connections.

These models, which describe drivers' speed behavior and adaptation along different connections, are useful for improving current speed behavior models used in different microscopic simulation packages, and provide designers with a tool to estimate the speeds during the design process. The insights from this study, and the identified models, are also useful for enhancing the acceptability of automated vehicles' longitudinal behavior by adapting it to human like behavior.

Keywords:

Interchange, speed behavior, trajectory data, horizontal curves

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1. Introduction

Despite the fact that interchanges can safely and efficiently accommodate high volumes of traffic compared to at-level intersections, they are known to be crash prone areas within the freeway system (McCartt, Northrup, & Retting, 2004). This is due to the high level of turbulence resulting from increased intensity of lane-changes and speed variability. Road horizontal alignment and the design of horizontal curves have a large impact on the driving speeds and on safety due to additional centrifugal forces exerted on a vehicle. Especially at horizontal ramp curves in interchanges, drivers need to adapt their speeds from relatively high driving speeds, allowed on the motorways (120/130 km/h in the Netherlands), to lower speeds, in some cases as low as 50 km/h. This speed adaptation could increase the turbulence intensity on the road and lead to critical situations (van Beinum, Farah, Wegman, & Hoogendoorn, 2016). Therefore, understanding drivers' speed behavior and adaptation when approaching and negotiating horizontal ramp curves in interchanges, and the influence of different design elements on their speed behavior is essential to improve speed predictability and safety. Additionally, the development of models that can realistically simulate drivers' speed adaptation is useful for improving the existing models for longitudinal behavior in microscopic simulation packages, and for developing speed control systems in automated vehicles.

In the literature, there are only few studies that use detailed trajectory data to understand drivers' speed adaptation when approaching horizontal ramp curves in interchanges. Most existing studies used data collected from GPS signals or naturalistic data of vehicle trajectories on curves on two-lane rural roads. For example, (Palmberg, Imberg, & Thomson, 2015) used naturalistic data collected in the euroFOT project in Sweden, and analyzed the speed behavior on seven curves on two-lane rural roads with posted speed limit of 70 km/h. For each trip, speed data was collected for eleven points along each curve. Based on this data the researchers created speed profiles for different drivers and analyzed the speed pattern in the curves. This analysis led to the conclusion that in small radii curves, the speed is reduced significantly within the curvature. The curvature was found to be the most influential factor for the speed reduction. In another study by Othman, Thomson, and Lannér (2014), the authors used the SeMiFOT naturalistic database, including 5,922 trips of 7 Volvo cars driven by 28 experienced drivers to examine the impact of the independent variables: degree of curvature, travel direction, grade, speed limit and road width, on the dependent variables: operational speed, lateral acceleration, yaw rate, and lane-changing. The authors used a general linear model (GLM) technique to model the relationships between the dependent variables and the influencing variables. However, the authors used the mean values of the dependent variables only at three points in each curve: entrance, middle and exit. They did not develop models that take into account the distance along the curve.

Cerni and Bassani (2017) used naturalistic data from vehicles equipped with high accuracy GPS (frequencies L1, L2) in RTK (real time kinematic) mode to estimate and model the curvatures of vehicles' trajectories on two-lane rural roads termed 'operating trajectory', and compared it to the as-built horizontal alignment termed 'designed trajectory'. Based on this comparison the authors evaluated the geometric consistency of the road alignment and the causes that can lead vehicles to diverge from the road alignment. The developed model can assist designers in evaluating and predicting the effects of road alignment on driver lateral behaviour. The authors in this study did not focus on the longitudinal movement and speed change along the curve.

Some researchers used driving simulators to analyze drivers' speed behavior on ramp curves and curves on two-lane rural roads (Bella, 2009; Calvi, 2015; Montella, Galante, Mauriello, & Aria, 2015), where the latter was most frequently subject of research. For example, Calvi (2015) conducted a driving simulator study utilizing the Inter-University Research Centre for Road Safety (CRISS) to evaluate the effects of different curve features on driving speed and lateral positions (trajectories) along a curve on rural roads. He found that the road cross-section, the radius of curve, the visibility condition, and the presence of a transition curve significantly influence driving speeds and the way a driver negotiates a curve in terms of trajectories and consequently the lateral acceleration. Montella et al. (2015) investigated continuous speed profiles of individual drivers by utilizing the VERA high-fidelity dynamic-driving simulator. The results of this study clearly showed that driving speed is not constant along the curve and that the deceleration rates are considerably higher than the acceleration rates. These results also showed that the 85th percentile of the speed reduction experienced by individual drivers is more than twice the difference in operating speed between tangent and curve which emphasizes the importance of analyzing individual speed profiles. While this method indeed provides behavioral insights, it is still limited since drivers might not behave realistically as in real life.

Other researchers used loop detectors to collect real-life driving speed data (Liapis, Psarianos, & Kasapi, 2001). However, this method allows collecting speed data only at specific locations. The assumption in these studies is that drivers maintain constant operating speed throughout the horizontal curves, and that the occurrence of acceleration and deceleration is only on tangents. Previous research (Farah, van Beinum, & Daamen, 2017; Montella et al., 2015) has shown that drivers' speed behavior on curves is not constant, and that part of the deceleration process takes place on the curve.

The main advantage of the data used in this study compared to data used in earlier studies, is that it is field data collected without subjecting drivers to any experimental control. In experiments using instrumented vehicle, despite being conducted in the field, it covers only a limited sample of drivers, who know that they are being observed. In driving simulator experiments, drivers experience no real sense of risk, and the results depend on the fidelity and validity of the simulator. Additional advantage of the data collected in this study is that it is continuous data, so speed profiles can be obtained. In loop detector data, on the other hand, speeds are collected only at specific locations. Therefore, loop detector data have a major limitation when speed profiles are of interest.

The main objective of this study is to analyze drivers' individual speed profiles when approaching and negotiating different ramp curves based on trajectory data collected from the field. By using this data, it would be possible to understand drivers' speed behavior adaptation when negotiating different horizontal ramp curves in system interchanges in the Netherland. In a previous study, Farah et al. (2017), we have used this data to develop an operating speed prediction model. This study, on the other hand, aims to develop longitudinal speed behavior models as a function of the distance along the curve, road geometric design characteristics, vehicle type and drivers' heterogeneity. The road geometric design characteristics will be selected based on previous studies that have shown their significant impact on drivers' speed behaviors on curves.

The rest of the paper is organized as follows, section two presents the research methodology, followed by section three which presents the results of the study. Section four includes the discussion and section five summarizes and concludes the study.

2. Research methodology

This section describes the research methodology that has been used in this study, including the research hypothesis and approach, locations' selection, data collection, and analysis techniques.

2.1 Research hypotheses & approach

To understand drivers' speed behavior adaptation (individual speed profiles) when approaching and negotiating different ramp curves, detailed trajectory data of *free-moving* vehicles are needed. Only free-moving vehicles were chosen since the main target is to understand how the road geometric design affects the driving speeds, i.e. excluding the impact of leading vehicles. In this study, a free moving vehicle is defined as a vehicle of which its predecessor is at least 100 meters ahead of the tracked vehicle. Assuming a speed of 120 km/h, the distance of 100 meters translates to a time headway of 3 seconds. Previous studies in the literature (Ahmed, 1999; HCM, 2000; Hoogendoorn, 2005) have shown that a headway of 3 seconds is an acceptable threshold for distinguishing free-moving from following vehicles. The following research hypotheses related to road design characteristics impact on speed are tested:

H_1: The distance along the curve has a significant and non-linear impact on driving speeds;

H_2: As the road curvature increases the driving speed decreases (Farah et al., 2017; Montella et al., 2015; Othman et al., 2014; Russo, Antonio Biancardo, & Busiello, 2016);

H_3: Driving speeds on left turning curves are higher than on comparable right turning curves;

H_4: As the road width increases driving speeds increase (Calvi, 2015; Morris & Donnell, 2014). The road width includes the width of the lanes plus the right and left shoulders;

H_5: As the longitudinal slope increases (uphill) driving speeds decrease (Imberg & Palmberg, 2015);

H_6: The impact of the longitudinal slope on heavy vehicles' driving speeds is stronger compared to its impact on cars' driving speeds (positive interaction effect), (McLean, 1978);

H_7: As the super-elevation increases driving speed increases (Quaium, 2010);

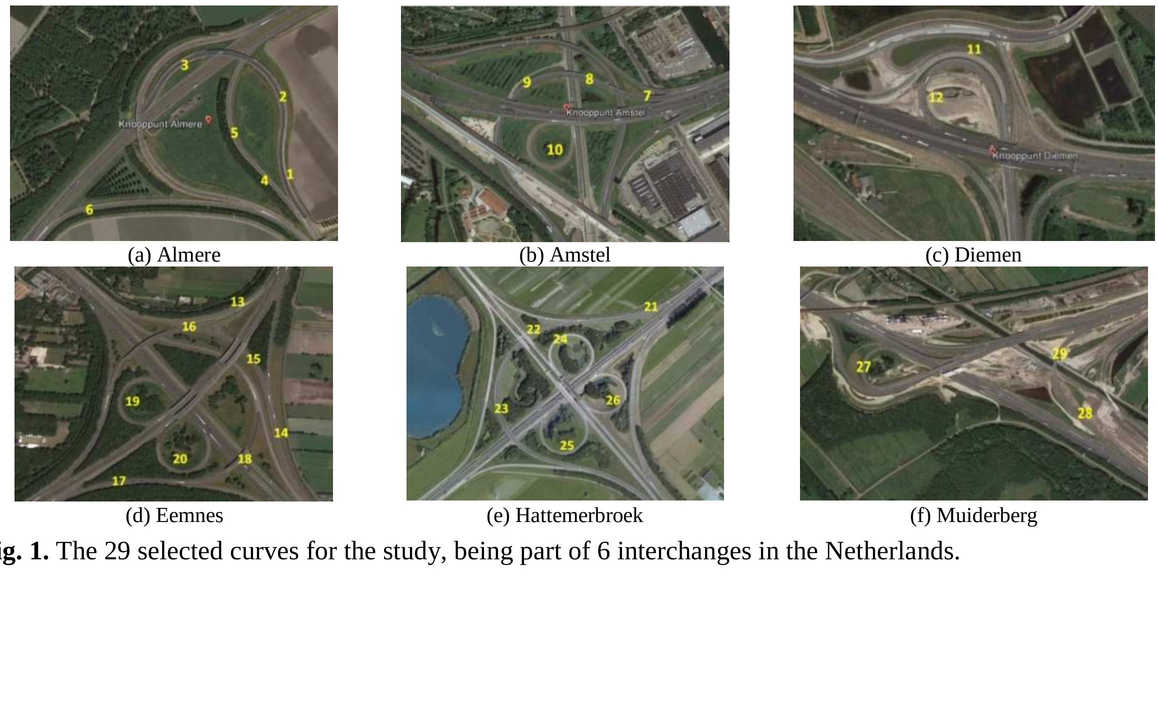
H_8: The impact of super-elevation on driving speeds is stronger on right curves than on left curves (negative interaction effect).

The analysis approach included first an examination of the individual speed profiles. Based on these speed profiles insights with respect to drivers' speed adaptation along the ramps were obtained. Following this, speed prediction models for the different types of connections were developed to test the above mentioned research hypotheses.

2.2 Locations' selection

To investigate the impact of different ramp curves' road design characteristics on drivers' speed behavior, 6 interchanges with 29 different curves were selected. The horizontal curves were part of 9 direct connections (mostly right turning traffic), 12 semi-direct connections (turbines), and 8 indirect connections (loops), as illustrated in Fig. 1.

The numbers (in yellow) on the curves indicate the curve number as specified in Table 1 which summarizes in more detail the characteristics of the selected curves.



(a) Almere (b) Amstel (c) Diemen

(d) Eemnes (e) Hattemerbroek (f) Muiderberg

Fig. 1. The 29 selected curves for the study, being part of 6 interchanges in the Netherlands.

Table 1
Characteristics of the connections.

Curve no.	*Interchange name*[2]	*Interchange type*	*Connection type*	*Design speed (km/h)*	*Radius (m)*	*Turning direction*	*No. of Lanes*	*No. of Observed*	
								cars	*Heavy vehicles*
1	Almere (A27,A6)	Half Turbine	Semi-direct	70	300	R	2	63	2
2			Semi-direct	70	205.1	L	2	57	16
3			Semi-direct	70	205	L	2	60	4
4			Direct	70	2175	L	2	92	8
5			Direct	70	238.5	R	2	42	8
6			Direct	90	222.1	R	2	53	7
7	Amstel (A10, A2)	Turbine-Cloverleaf	Semi-direct	70	225	R	2	47	9
8			Semi-direct	70	230	R	2	108	13
9			Semi-direct	50	174	L	2	50	2
10			Indirect	50	55.7	R	1	40	1
11	Diemen (A9, A1)	Left Trumpet	Semi-direct	70	112.8	L	2	39	4
12			Indirect	50	81.2	R	2	60	4
13	Eemnes (A27, A1)	Turbine-Cloverleaf	Direct	90	447.3	R	1	52	8
14			Direct	90	460	R	2	63	12
15			Semi-direct	70	280	L	2	61	4
16			Semi-direct	70	250.7	L	2	75	6
17			Direct	90	670	R	2	56	2
18			Semi-direct	70	216.6	L	1	56	5
19			Indirect	50	76.6	R	1	33	1
20			Indirect	50	76.9	R	1	68	9
21	Hattemerbroek (A28, A50)	Turbine-Cloverleaf	Direct	90	465	R	3	68	11
22			Semi-direct	90	375	L	2	43	7
23			Semi-direct	70	254.9	L	2	11	0
24			Indirect	50	77.6	R	1	7	1
25			Indirect	50	77.7	R	1	11	1
26			Indirect	50	67.8	R	1	40	9
27	Muiderberg (A6, A1)	Right Trumpet	Indirect	50	77.9	R	1	106	6
28			Direct	90	370	R	1	84	7
29			Direct	70	157.7	R	1	63	2

The type of connection (direct, semi-direct and indirect) and the design speed are largely dependent on the connection’s function in the network and the traffic flow. The design of horizontal curves in ramps of interchanges in the Netherlands is based on the design criteria specified in the Dutch road design guidelines (Rijkswaterstaat, 2015). The road geometry of ramps is determined by the design speed, which is the speed for which the road is considered to provide safe and comfortable driving. The Dutch road design guidelines prescribe three standard design speeds for connectors: 50, 70, and 90 km/h (Broeren, Jong, Uittenbogerd, & Groot, 2015). The posted speed limit is decided based on the operational speed which should normally be the same as the design speed (Rijkswaterstaat, 2015).

Heavy vehicles percentage (based on the observed data) on the selected curves ranged from 0% to 28% (Average= 11%; Std.= 7%). The percentage of heavy vehicles could have a significant impact on the observed speeds, especially on ramps with only one driving lane (i.e., no overtaking possibility).

2.3 Data Collection and Processing

[2] The numbers in between brackets indicate the numbers of the motorways.

Trajectory data of free-moving vehicles were derived from stabilized video images taken with a frame rate of 12 images per second. The camera was mounted under a hovering helicopter for a period of 25-30 minutes above each curve. The camera is a Prosilica's Giga E5 megapixel camera with a Pentax lens. The trajectory data were collected when there was mostly clear weather and the wind direction was north, with a speed of 3-5 m/s. The helicopter hovered at a height between 450 and 550 meters, depending on the size of the interchange. The obtained images were then stabilized using a dedicated tool called 'ImageTracker' developed at the Delft University of Technology. For detailed information on the applied method to stabilize the aerial traffic images and derive the trajectory data see Knoppers et al. (2012).

The trajectory data of the vehicles need to be processed and analyzed to calculate vehicles' individual speeds. Prior to this, a filtering technique was applied to reduce the noise in the data which is caused by inaccuracies in the detection of the vehicles. For this purpose, the Fast Fourier transform algorithm was applied (Brigham & Brigham, 1974). Unfortunately, the tracking was not perfect, so the automated tracking was followed by a manual tracking phase, where the trajectories have been plotted on top of the images and the missing trajectory parts have been added using interpolation and the automated trajectories have been checked for quality. This way, the positions were quite accurate, with a deviation of maximum 1 meter.

Besides the vehicle trajectories, information on the geometric design of the interchanges, and more specifically the curves' features, such as the number of lanes, radius, super-elevation, and longitudinal slopes, were obtained from Civil3D maps acquired from the Dutch National Road Authority (Rijkswaterstaat). The curve radii were measured from the white marking on the left side of the road.

To analyze the speed data as a function of the distance, the geometric features of the road design needed to be calculated for every 10 meters. This was done by measuring all the features of the road design (such as road width, curvature, super-elevation, longitudinal slope) at critical points, i.e. (beginning of transition curve, end of transition curve, mid curve, and end of curve). Then the values in between these critical points were calculated by linear interpolation.

2.4 Speed prediction model formulation

With the chosen data collection method, there are multiple observations for each vehicle on the same curve. As a result, these observations are (serially) correlated. Similarly, since more than one vehicle is observed on each curve, the speed observations of these vehicles might be correlated. Also, since some curves are part of the same connection (for example, curves 1, 2, and 3 in Almere interchange), the speed observations on these curves might also be correlated. This type of data is termed multilevel data (see Fig. 2). To account for these correlations among the different observations at the vehicle level, curve level, and connection level, a Mixed Model (McCulloch & Neuhaus, 2001) with both fixed and random effects was applied. Specifically, the correlation between speed observations is accounted for by including random effects associated with both the clusters (connections, curves and vehicles) and the units of analysis nested within these clusters (speed observations). Random effects allow the residuals associated with the longitudinal measures on the same unit of analysis to be correlated, and therefore, it takes into account the clustering effect. Each connection may have different number of curves, and each curve may have a different number of vehicles observed. The distance or time points at which the dependent variable, in this case the vehicle speed, is measured can also differ for each vehicle. Such data sets can be considered to have four levels. Level 4 represents the clusters of curves in a connection, Level 3 the clusters of vehicles in a curve, Level 2 represents the units of analysis (vehicles), and Level 1 represents the longitudinal (repeated) measures made over distance (observations of speed).

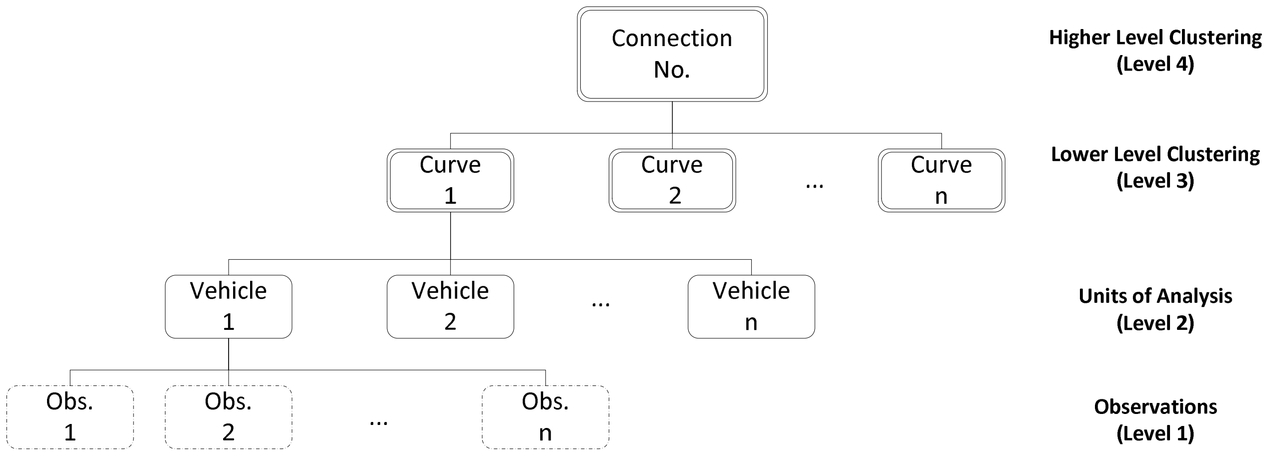


Fig. 2. Multilevel data.

The developed models were estimated using the Mixed Effect Model command in SPSS 22 (SPSS, 2013). The analysis was conducted for each type of connection separately (direct, semi-direct, and indirect). The general specification of the mixed model, follows the defined research hypotheses, and is shown in Eq. (1).

$$Sp_{v,c,cn}(x_c) = \beta_{00} + \beta^1_{Distance} \cdot x_c + \beta^2_{Distance} \cdot {x_c}^2 + \beta^3_{Distance} \cdot {x_c}^3 + \beta_{VehicleType} \cdot \delta_v^{Type} + \beta_{Curvature} \cdot Curvature(x_c) + \beta_{Direction} \cdot \delta_C^{Direction} + \beta_{SuperElev} \cdot SuperElev(x_c) + \beta_{LongSlope} \cdot LongSlope(x_c) + \beta_{RoadWidth} \cdot RoadWidth(x_c) + \beta_{Direction \cdot Curvature} \cdot Curvature(x_c) \cdot \delta_C^{Direction} + \beta_{LongSlope \cdot Vehicle\,Type} \cdot LongSlope(x_c) \cdot \delta_v^{Type} + \mu_{0v} + \mu_{0c} + \mu_{0cn} + \mu_1(x_c) + \varepsilon_{v,c,cn} \quad (1)$$

where;

$Sp_{v,c,cn}$	speed for vehicle ϑ, in curve c, and connection cn as a function of the distance (dependent variable);
β_{00}	average speed for the population;
β	vector of corresponding parameters to be estimated;
δ_v^{Type}	is an indicator with a value of 1 if vehicle v is heavy vehicle, and 0 if car;
$\delta_C^{Direction}$	is an indicator with a value of 1 if it is left curve and 0 if it is right curve;
$Curvature(x_c)$	is a scale variable representing the curvature of the road (1/km.);
$SuperElev(x_c)$	is a scale variable representing the super elevation (%);
$LongSlope(x_c)$	is a scale variable representing the longitudinal slope of the road (%);
$RoadWidth(x_c)$	is a scale variable representing the width of road (m.);
x_c	distance along the curve measured relative to the nose (m.);
μ_{0v}	vehicle-specific residual (effect of clustering at vehicle level), $\mu_{0v} \sim N(0, \sigma_{0v})$;
μ_{0c}	curve-specific residual (effect of clustering at curve level) $\mu_{0c} \sim N(0, \sigma_{0c})$;
μ_{0cn}	connection-specific residual (effect of clustering at connection level) $\mu_{0cn} \sim N(0, \sigma_{0cn})$;
μ_1	is the random effect for the distance variable $\mu_1 \sim N(0, \sigma_1)$;
$\varepsilon_{v,c,cn}$	is the observation specific error term $\varepsilon_{v,c,cn}$~N(0,σ^2);

The vehicle-specific random constant μ_{0v} captures unobserved preferences which affect the speed behavior of the same vehicle (individual driver), (random effect). The curve-specific random effect (μ_{0c})

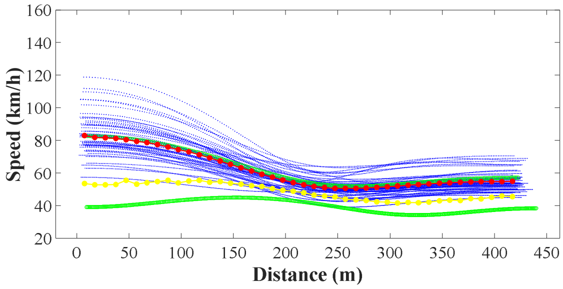
captures unobserved effects related to the fact that the vehicles drove on the same curve, while the connection-specific random effect (μ_{0cn}) captures the unobserved effects related to the fact that several curves belong to the same connection. We tested different polynomial order relationship between the speed and the distance, and found the third order polynomial to fit the best. We also took into account a random effect for the distance variable, to account for different magnitude effects of the speed change along the distance for different vehicles (i.e. drivers).

3. Results

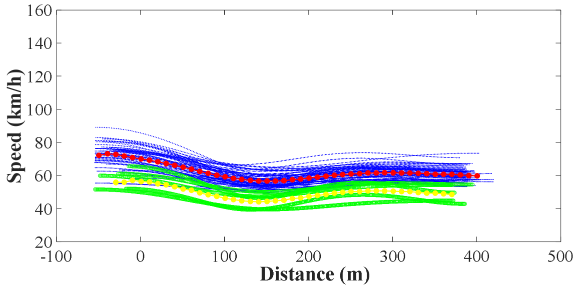
This section presents the results of the speed profiles first, to illustrate the changes in the driving speeds of observed vehicles, both cars and heavy vehicles, when approaching and negotiating different curves. This is in order to understand the relation between speed and distance. Then this is followed by the estimated models to test the research hypotheses presented earlier.

3.1 Speed profiles analysis

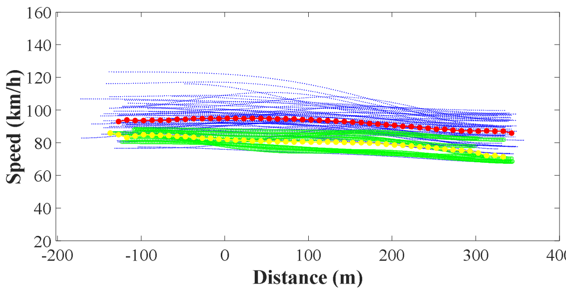
Fig. 3 presents several examples of the speed profiles analysis. The 0 m - point refers to the beginning of the ramp nose.



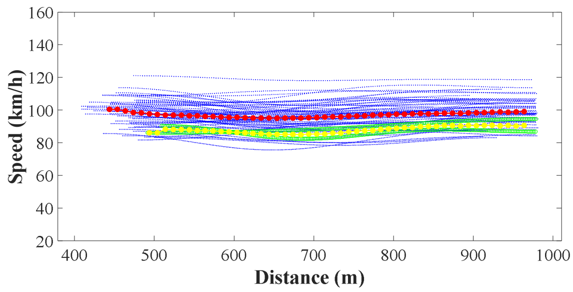
(a) Amstel indirect connection (curve 10; radius 55.7 m)



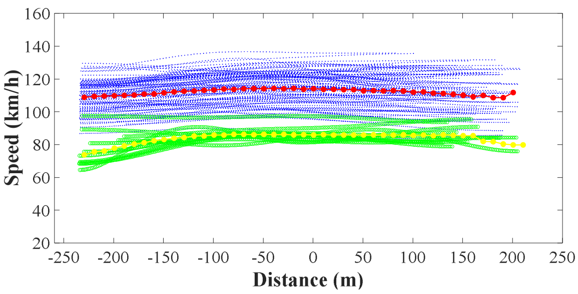
(b) Eemnes indirect connection (curve 19; radius 76.6 m)



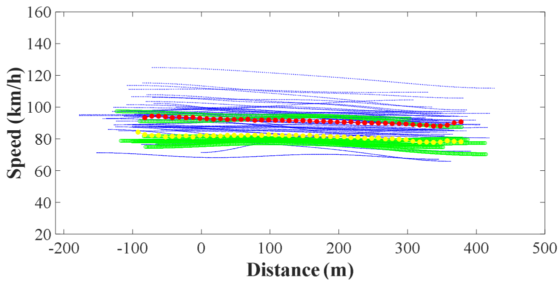
(c) Amstel semi-direct connection (curve 7; radius 225 m)



(d) Eemnes semi-direct connection (curve 18; radius 216.6 m)



(e) Almere direct connection (curve 4; radius 2175 m)



(f) Eemnes direct connection (curve 14; radius 460 m)

Fig. 3. Vehicles' speed profiles on different curves (blue lines represent speed profiles of individual cars; green lines represent speed profiles of individual heavy vehicles; red and yellow dotted lines represent the average driving speeds for cars and heavy vehicles, respectively, calculated every 10 meters).

It can clearly be seen that the speeds of heavy vehicles are lower compared to the speeds of cars as expected. It is also clear that for each connection, despite the large heterogeneity among drivers, there are certain patterns characterizing the speed profiles.

Fig. 3(a) and 3(b) present the speed profiles of indirect connections at the Amstel and Eemnes interchanges in the Netherlands, while Fig. 3(c) and 3(d) present the speed profiles of semi-direct connections, at the same interchanges. In an earlier paper by Farah et al. (2017) it was found that the absolute change of speeds of vehicles travelling on indirect connections is larger compared to that on semi-direct connections. This can be clearly seen in these figures. The authors associated this to the curvature, and also to the number of lanes. An increased number of lanes was found in the literature to increase driving speeds (Kockelman & Ma, 2010).

Fig. 3(e) and 3(f) present the speed profiles of vehicles driving on direct connections. Here the changes in drivers' speed profiles when negotiating these curves are relatively small. The reason is that these curves have usually larger radiuses.

We investigated the driving speeds at the nose (the location where drivers are no longer allowed to change lanes), which, according to the step theory (Rijkswaterstaat, 2015) applied in the Netherlands, the design speed at the nose should be one step lower than the design speed for the motorways (120 km/h), i.e. 90 km/h. By gradually decreasing the advisory speed, abrupt changes in speed can be prevented, creating safer motorways. Fig. 4 presents the results, which clearly show that the median speeds at the nose on the semi-direct and direct connections are higher than the design speed of 90 km/h at the nose. Furthermore, the speed variability on these connections is higher compared to the indirect connections. Notice that in Fig. 4 the number of connections is 14, as the semi-direct connections and some of the direct connections are composed of two or three curves with one nose, as shown in Fig. 1.

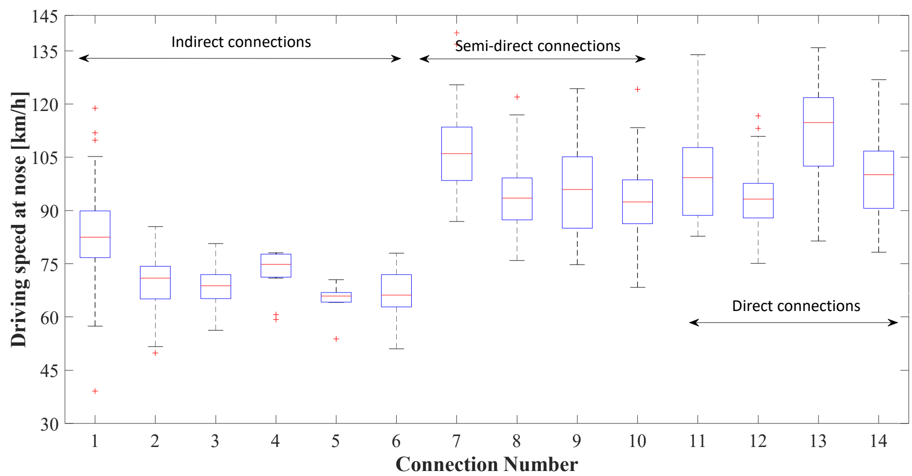


Fig. 4. Boxplot of the driving speeds at nose (km/h) of the different connections (the red line represents the median speed, the bottom and top of the box indicate the 25th and 75th percentiles respectively, the T-bars are the whiskers, and the red plusses are outliers).

From the results presented in Fig. 3 and Fig. 4, it can be summarized that drivers mostly follow the same speed profile pattern (i.e. decelerate and accelerate approximately at the same locations) but start from different initial driving speeds. Heterogeneity among drivers have a large impact on the absolute speed profile. Therefore, the speed prediction model that will be proposed should take drivers' heterogeneity and the non-linear form of the speed profile into account. The variation in the initial speeds (at 0 m – ramp nose) chosen by different drivers when negotiating curves could be used for the development of personalized active safety systems, such as curve speed warning systems (Palmberg et al., 2015).

3.2 Speed prediction model estimation results

The following subsections present the estimation results of the speed prediction models for each type of connection, separately. We start with presenting the results of the speed prediction model for the indirect connections (*3.2.1*), followed by the semi-direct connections (*3.2.2*), and the direct connections (*3.2.3*). Table 2 summarizes the dataset that was used for the models' estimation. Curve number 4 was excluded from the direct connection estimation model since it has a very large radius compared to the other curves, and it is the only left turning curve among right turning curves.

Table 2
Dataset used for the models' estimation.

Connection type	No. of curves	No. of vehicles	No. of observations
Indirect	8	270	16724
Semi-direct	12	798	28672
Direct	8	627	24989
Total	29	1774	73485

The data were analyzed using a mixed effect model with maximum likelihood (ML) estimation (Raudenbush & Bryk, 2002). Following a stepwise strategy suggested by Singer and Willett (2003) and Shek and Ma (2011), several models were tested. These included (1) an unconditional model which examines any mean differences in the speed across individuals, (2) an unconditional speed model (that served as a baseline model) to explore whether the speed curves are linear or curvilinear, (3) second order (quadratic) polynomial model, and (4) third order (cubic) polynomial model to determine if the rate of change in speed accelerate or decelerate with distance, (5) adding additional explanatory variables related to the road design and vehicle type, and (6) examination of two additional covariance structures beside the Unstructured (UN), which are the Compound Symmetric (CS) and First-Order Autoregressive (AR1). The UN covariance structure requires no assumption in the error structure (Singer, 1998), is commonly used in longitudinal data and often offers the best fit. The CS structure allows to examine whether the variance and correlation between each pair of observations are constant across the distance points. Finally, the AR1 covariance structure assumes the variance to be heterogeneous and the correlations between two adjacent distance points to decline across measurement occasions. In the first four models the UN covariance was assumed. The intercept and linear slope of the distance were allowed to vary across individuals. Missing data were handled through pairwise/likewise deletion. The results in terms of the Akaike's Information Criterion (AIC) and Schwarz's Bayesian Criterion (BIC) are presented in Table 3. The model with the lowest AIC and BIC was chosen as the best model. From the results in Table 3, it is clear that the models with the UN covariance structure outperformed the other types of covariance structures. The subsections below go in detail in each selected model.

Table 3
AIC and BIC for the different models and different connections.

	Indirect connections		**Semi-direct connections**		**Direct connections**	
	AIC	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
(1)	123779.4	123794.9	163105.0	163121.5	157984.2	158000.3
(2)	105260.2	105291.1	138428.9	138462.0	120881.9	120914.4
(3)	91310.8	91341.6	138452.9	138486.0	117801.9	117834.4
(4)	91348.1	91379.1	138471.8	138504.8	116625.0	116657.5
(5A) UN	89536.3	89567.2	135895.7	135928.7	115258.9	115291.4
(5B) CS	93285.1	93308.2	145909.6	145934.4	122171.3	122195.7
(5C) AR1	93285.1	93308.2	145909,6	145934.4	122171.3	122195.7

3.2.1. Speed prediction model for indirect connections

The speed prediction model estimation results for the indirect connections are presented in Table 4. The vehicle-specific residual was found to be statistically significant. This accounts for individual heterogeneity between drivers within the model. In other words, each driver has an individual intercept which deviates from the mean intercept of the group. This approach estimates a single variance parameter which represents how spread out the random intercept is around the common intercept (following a Normal distribution). The vehicle-specific residual, as shown in Table 4, has a very large value compared to the observation specific error term. This mean that the variance resulting from the drivers' heterogeneity is much larger than the variance resulting from the explanatory variables. The curve-specific residual (level 3) was not found to be statistically significant. This could be explained by the fact that several characteristics of the curves are already included in the model as covariates and they capture the between curve variation. Therefore, we can conclude that any correlation in the speed observations of different vehicles driving on the same curve are captured by the curve characteristics. The connection-specific residual (level 4) was also found to be insignificant. This indicates that drivers do not adapt their driving style to a specific connection.

Table 4
Speed prediction model estimation results for indirect connections.

Fixed Effects		***Estimate***	***Std. Error***	***t***	***Sig.***
β_{00}	Intercept (mean)	101.361	4.4864	22.593	<0.0001
$\beta_{Vehicle\ Type}$	Vehicle type (1=car, 0=heavy vehicle)	3.8714	2.9953	1.292	0.197
$\beta_{Curvature}$	Curvature (1/km.)	-0.3550	0.0087	-40.550	<0.0001
$\beta_{RoadWidth}$	Road width (m.)	0.1490	0.0353	4.216	<0.0001
$\beta_{LongSlope}$	Longitudinal slope (%)	-0.4820	0.1066	-4.520	<0.0001
$\beta^1_{Distance}$	Distance (m.)	-0.1516	0.0065	-23.196	<0.0001
$\beta^2_{Distance}$	Distance^2 (m.^{2})	0.000165	2.7452E-6	60.241	<0.0001
$\beta^3_{Distance}$	Distance^3 (m.^{3})	3.2066E-8	2.0783E-9	15.429	<0.0001
$\beta_{Vehicle\ Type\ *\ LongSlope}$	Interaction effect (%)	0.48082	0.1070	4.493	<0.0001
Random Effects		***Estimate***	***Std. Error***	***Wald Z***	***Sig.***
μ_{0v}	VehicleID: intercept (var)	3368.8261	296.311	11.369	<0.0001
μ_1	Distance (var)	-5.9570	0.53157	-11.206	<0.0001
$\varepsilon_{v,c,cn}$	Residual	9.8067	0.10907	89.913	<0.0001

As expected, and confirming the research hypotheses described in section 2.1, there is a significant negative effect of the curvature and the longitudinal slope (uphill) on the speed, and a positive effect of the road width on the speed. The type of the vehicle was not found to be statistically significant, however, the interaction effect between the vehicle type and the longitudinal slope was found to be positive and significant, indicating that the effect of the longitudinal slope on heavy vehicles is stronger compared to cars. Furthermore, and opposite to previous studies who suggested constant speeds on curves, the distance along the curve was found to have a significant and non-linear relation with speed. All indirect connections were right turning curves and therefore, it was not possible to test the impact of the curve direction variable on speeds. All variables, except for vehicle type, were statistically significant at the 95% confidence level. The random effect of the distance is statistically significant ($p < 0.0001$), suggesting that the impact of the distance on the speed varies significantly between vehicles (i.e. drivers). In terms of effect size, considering the estimates and the influencing factors' values, the distance, vehicle type and longitudinal slope have the biggest impact on speeds, followed by the second order of the distance, curvature and the road width, and lastly the interaction between the vehicle type and the longitudinal slope, and the third order of distance.

3.2.2. Speed Prediction Model for Semi-Direct Connections

Table 5 presents the speed prediction model estimation results for the semi-direct connections.

Table 5

Speed prediction model estimation results for semi-direct connections.

Fixed Effects		***Estimate***	***Std. Error***	***t***	***Sig.***
β_{00}	Intercept (mean)	66.2747	1.2894	51.398	<0.0001
$\beta_{Vehicle\ Type}$	Vehicle type (1=car, 0=heavy vehicle)	19.0837	0.8545	22.333	<0.0001
$\beta_{Curvature}$	Curvature (1/km.)	-0.80107	0.02062	-38.845	<0.0001
$\beta_{CurveDirection}$	Curve direction (1=left; 0=right)	9.4251	0.8462	11.138	<0.0001
$\beta_{LongSlope}$	Longitudinal slope (%)	-0.4159	0.0436	-9.522	<0.0001
$\beta_{Superelevation}$	Super-elevation (%)	1.003	0.0538	18.641	<0.0001
$\beta^1_{Distance}$	Distance (m.)	0.0031	0.0013	2.288	0.022
$\beta^2_{Distance}$	Distance^2 (m.^{2})	-4.2655E-6	1.5065E-6	-2.831	0.005
$\beta^3_{Distance}$	Distance^3 (m.^{3})	1.9937E-9	0.0000	2.749	0.006
$\beta_{Vehicle\ Type * LongSlope}$	Interaction effect (%)	0.3798	0.0451	8.413	<0.0001
$\beta_{Direction * Superelevation}$	Interaction effect (%)	-0.8316	0.0565	-14.705	<0.0001
Random Effects		***Estimate***	***Std. Error***	***Wald Z***	***Sig.***
μ_{0v}	VehicleID: intercept (var)	394.774	20.6893	19.081	<0.0001
μ_1	Distance (var)	-0.3529	0.0228	-15.439	<0.0001
$\varepsilon_{v,c,cn}$	Residual	4.888	0.0421	116.107	<0.0001

The variables vehicle type, curvature, longitudinal slope and the interaction between the vehicle type and the longitudinal slope have a statistically significant impact on the speeds, and the direction of impact is similar as in the speed prediction model for the indirect connections. The road width was not found to significantly impact the speeds, while the super-elevation was found to have a significant positive impact on the speeds. In other words, higher super-elevation leads to higher driving speeds. This is logical, since higher super-elevation support to counterbalance the lateral acceleration the driver feels when negotiating a horizontal curve. The direction of curve was also found to be statistically significant. Drivers drive faster on left turning curves. A negative interaction effect was found between the direction of curve and the super-elevation, indicating that the influence of higher super-elevation is lower on left curves. Finally, the distance along the curve was found to have a significant and non-linear impact on the driving speeds, similarly as for the indirect connections.

In terms of effect size, considering the estimates and the influencing factors' values, vehicle type and curve direction have the biggest impact on speeds, followed by the curvature, longitudinal slope, super-elevation, and the interaction effects. Lastly, the first, second and third order of distance have the least impact on the speeds. This is also apparent from Figure 3 (c) and (d).

3.2.3. Speed Prediction Model for Direct Connections

The speed prediction model estimation results for the direct connections are presented in Table 6. The results show that the variables vehicle type, curvature, distance and road width are significant predictors of speeds. The effect of the longitudinal slope on speeds was not found to be statistically significant. In terms of effect size, the vehicle type has the largest impact on speed followed by the distance, curvature and road width, and lastly by the second and third order of distance.

Table 6

Speed prediction model estimation results for direct connections.

Fixed Effects		***Estimate***	***Std. Error***	***t***	***Sig.***
β_{00}	Intercept (mean)	93.9915	0.6246	150.474	<0.0001
$\beta_{VehicleType}$	Vehicle type (1=car, 0=heavy vehicle)	6.5964	0.2702	24.407	<0.0001
$\beta_{Curvature}$	Curvature (1/km.)	-0.7309	0.0227	-32.171	<0.0001
$\beta_{RoadWidth}$	Road width (m.)	0.1278	0.0161	7.897	<0.0001
$\beta^1_{Distance}$	Distance (m.)	-0.03299	0.00136	-24.225	<0.0001
$\beta^2_{Distance}$	Distance^2 (m.^{2})	3.095E-6	1.5819E-6	1.956	0.050
$\beta^3_{Distance}$	Distance^3 (m.^{3})	5.226E-8	2.0119E-9	25.978	<0.0001
Random Effects		***Estimate***	***Std. Error***	***Wald Z***	***Sig.***
μ_{0v}	VehicleID: intercept (var)	189.5456	10.8295	17.503	<0.0001
μ_1	Distance (var)	-0.2430	0.02054	-11.831	<0.0001
$\varepsilon_{v,c,cn}$	Residual	4.3574	0.04001	108.899	<0.0001

3.2.4. Comparison of the estimated models for the three types of connections

Table 7 summarizes and compares the estimates of the influencing factors (*fixed effects*) for the three types of connections following the estimated models in the previous section. The values in bold are the three most influencing factors in terms of size effect.

Table 7

Comparison of the estimates of the influencing factors (*fixed effects*) for the three types of connections

Fixed Effects		***Estimates***		
		Indirect	***Semi-direct***	***Direct***
β_{00}	Intercept (mean)	101.361	66.2747	93.9915
$\beta_{Vehicle\ Type}$	Vehicle type (1=car, 0=heavy vehicle)	**3.8714**	**19.0837**	**6.5964**
$\beta_{Curvature}$	Curvature (1/km.)	-0.3550	**-0.80107**	-0.7309
$\beta_{RoadWidth}$	Road width (m.)	0.1490	**-**	**0.1278**
$\beta_{CurveDirection}$	Curve direction (1=left; 0=right)	**-**	**9.4251**	**-**
$\beta_{LongSlope}$	Longitudinal slope (%)	**-0.4820**	-0.4159	**-**
$\beta_{Superelevation}$	Super-elevation (%)	**-**	1.003	**-**
$\beta^1_{Distance}$	Distance (m.)	**-0.1516**	0.0031	**-0.03299**
$\beta^2_{Distance}$	Distance^2 (m.^{2})	0.000165	-4.2655E-6	3.095E-6
$\beta^3_{Distance}$	Distance^3 (m.^{3})	3.2066E-8	1.9937E-9	5.226E-8
$\beta_{Vehicle\ Type\,*\,LongSlope}$	Interaction effect (%)	0.48082	0.3798	-
$\beta_{Direction\,*\,Superelevation}$	Interaction effect (%)	-	-0.8316	-

It can be seen from Table 7 that for the three types of connections, vehicle type has a large impact on the speeds, with the largest impact on the semi-direct connections. For the indirect connections the distance and the longitudinal slope are the most influencing factors besides vehicle type, while for the semi-direct connections, it is the curvature and curve direction, and for the direct connections it is the distance and the road width. It can also be noticed from Table 7 that the road width, longitudinal slope, and super-elevation are significant for some of the connections' types. This could be the result of the factors' range of values and their variability for the different connections. For example, the range of values of the longitudinal slope for the direct connections (-0.911, 2.698) is much smaller than for the semi-direct (-12.444, 4.600) and indirect connections (-4.198, 11.089), and therefore, this factor is not significant for the direct connections. The impact of the distance is most dominant at indirect connections. This is also confirmed by the speed profiles presented in Figure 3. Therefore, the distance is an important factor, especially at the indirect connections. The second order of distance has also a relatively considerable impact on driving speeds at indirect connections, while the third order has a relatively small but significant impact on the driving speeds at the three types of connections.

Table 8

Comparison of the estimates of the *random effects* for the three types of connections

		Estimates		
Random Effects		***Indirect***	***Semi-direct***	***Direct***
μ_{0v}	VehicleID: intercept (var)	3368.8261	394.774	189.5456
μ_1	Distance (var)	-5.9570	-0.3529	-0.2430
$\varepsilon_{v,c,cn}$	Residual	9.8067	4.888	4.3574

As shown in Table 8, in all three speed prediction models it is clear from the variance explained by the random effect of the intercept compared to the residuals, that the heterogeneity among drivers has a much stronger impact on the variability in speeds compared to the road design characteristics. It can also be seen that this variability between drivers is more dominant for the indirect connections, followed by the semi-direct connection, and lastly by the direct connections.

3.2.5. Impact of influencing factors on the driving speeds

Fig. 5 illustrates the impact of the influencing factors included in the models on the driving speeds. These figures were created by varying each time a selected factor of interest, while holding all other influencing factors constant. The values of the influencing factors were chosen to reflect their mean.

Fig. 5(a) illustrates that the driving speeds on an indirect connection with a radius of 300 meters, road width of 9.15 meters (including one driving lane, right shoulder and left shoulder), and longitudinal slope of 6%, decrease up to a distance of approximately 350 meters downstream of the nose, and after this point the speeds increase again. The relationship is not-linear, but polynomial of the third order (i.e. cubic). It can be noticed that the speeds of cars are higher than the speeds of heavy vehicles, as would be expected. Fig. 5(b) illustrates the interaction effect between the longitudinal effect and the vehicle type, and as a function of the curvature. It can be seen that as the curvature increases the driving speeds decrease. The impact of the longitudinal slope of the indirect connection on the speeds of cars is almost negligible compared to the impact of the longitudinal slope on the speeds of heavy vehicles.

Fig. 5(c) presents a comparable analysis to Fig. 5(a) but for the semi-direct connections. As can be clearly seen in the results, the changes in the speed as a function of the distance measured relative to the nose are much more smaller compared to that for the indirect connections. It can also be noticed that there is a slight increase in the speeds, although very mild. As expected, the driving speeds of heavy vehicles are lower than those of cars. The speed limit for heavy vehicles on motorways in the Netherlands is set to 80 km/h. The driving speeds on left curves are higher than the driving speeds on right curves. Fig. 5(d) illustrates the interaction effect between the super-elevation and the curvature direction for both cars and heavy vehicles. The impact of the increase in super-elevation is stronger on right curves than on left curves. As the super-elevation increases the driving speeds also increase.

Fig. 5(e), similar to 5(a) and 5(c), shows the changes of the driving speeds as a function of the distance relative to the nose on direct connections. It is clearly a non-linear relationship. The changes in the speeds are, however, milder compared to the indirect connections, but more prominent than the semi-direct connections. This is counter intuitive, as one would expect a consistent decreasing effect. In Fig. 5(f) the impact of the curvature on the driving speeds is also illustrated. We can see a decrease in the speed as the curvature increases.

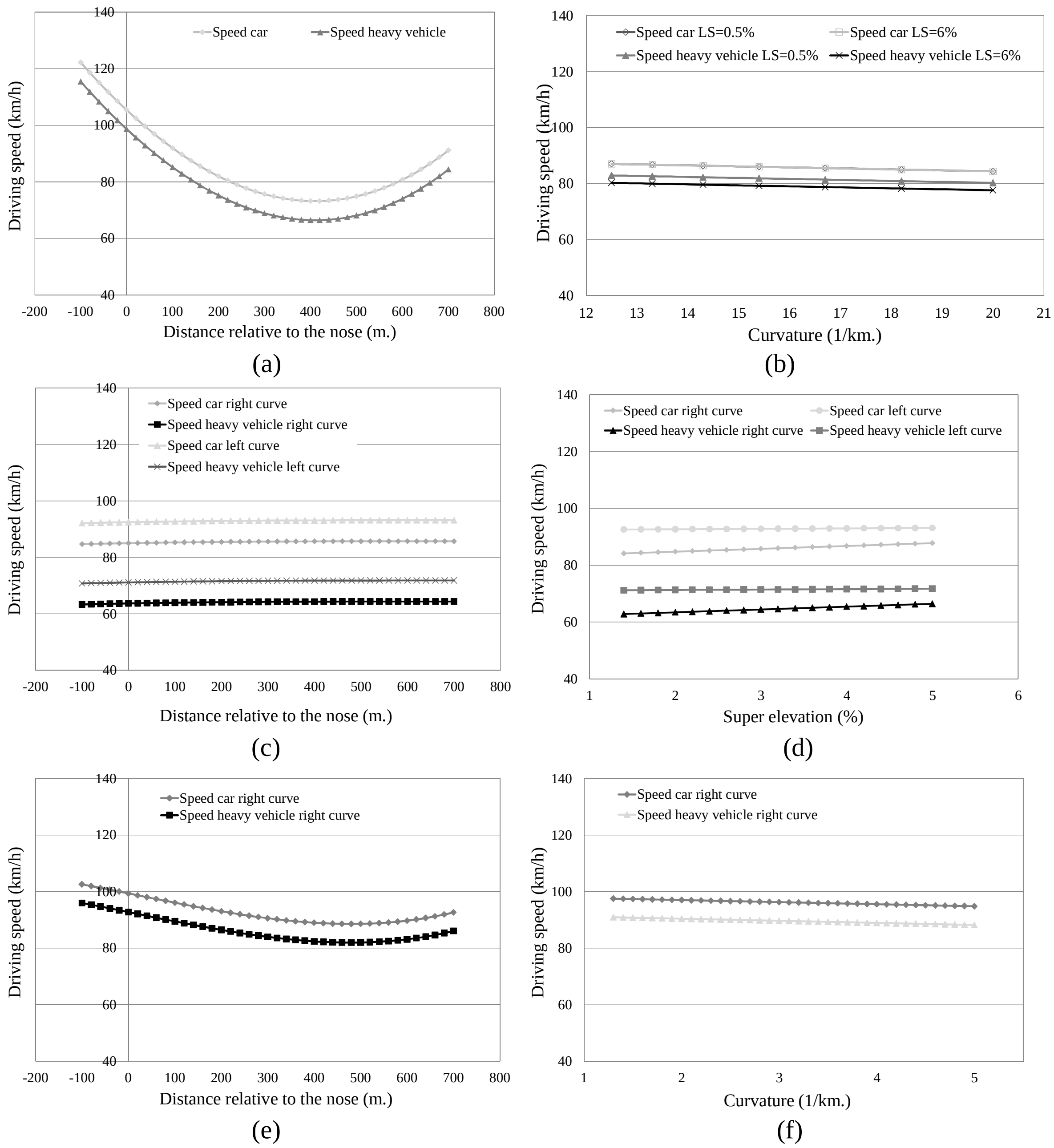


Fig. 5. Impact of various influencing variables on the driving speeds on indirect connections (a, b); semi-direct connections (c, d); and direct connections (e, f).

4. Discussion

Using trajectory data for 29 ramp curves, drivers' individual speed profiles and speed behavior adaptation were analyzed. Furthermore, longitudinal speed behavior models were developed. In the developed speed prediction models for the three types of connections, different polynomial orders were examined, and a cubic relation (third order polynomial function) was found to best fit the speed data as a function of the distance along the curve (measured relative to the nose, the reference point). This confirms the first hypothesis (H_1), and clearly proves that drivers do not maintain constant speeds when negotiating curves, especially on indirect connections, but continuously adapt their driving speeds supporting the conclusions of previous studies (Farah et al., 2017; Montella et al., 2015; Montella, Pariota, Galante, Imbriani, & Mauriello, 2014). The curvature and direction of curve were found to significantly affect the driving speeds. As the curvature increases, driving speeds decrease confirming the first research hypothesis (H_2) as well the findings of earlier studies (Farah et al., 2017; Montella et al., 2015; Othman et al., 2014; Russo et al., 2016). It was also found that the driving speeds on left turning curves are higher compared to comparable right turning curves (confirming H_3). This result contradicts previous findings by Othman et al. (2014) and Calvi (2015) who did not find significant differences in the driving speeds between left and right turning curves. One possible explanation for the higher speeds on left curves, is the sight distance which is larger on left turning curves compared to right turning curves, which allows drivers to make larger anticipatory eye movement (Lehtonen, Lappi, Koirikivi, & Summala, 2014) leading drivers to feel safer with higher driving speeds. This is in line with earlier research by Shinar, McDowell, and Rockwell (1977) who found that the search patterns on right and left curves are not symmetrical: visual excursions to the right on right curves are greater than eye movements to the left on left curves. The road width was found to increase significantly the driving speeds (confirming H_4) on the indirect and direct connections, but not on the semi-direct connections. For all indirect connections, there is only one driving lane per connection which widens as the curvature increases. For the semi-direct and direct connections, this can vary between 1 and 3, with most cases with 2 lanes. Further research should investigate why the road width in semi-direct connections does not affect drivers' speed similarly as the indirect and direct connections. The longitudinal slope (H_5) and the interaction between the longitudinal slope and the vehicle type (H_6) significantly affect the driving speeds of vehicles on the indirect and semi-direct connections, but were not found to significantly affect the speeds on the direct connections. This is, however, expected as the mean value and especially the variance of the longitudinal slopes of the direct connections (0.25%, 0.59%) are much smaller compared to the indirect (-0.82%, 8.94%) and semi-direct connections (0.44%, 3.19%). The impact of steeper longitudinal slopes on heavy vehicles' speeds are larger than on passenger vehicles as reflected in the direction of impact (positive) of the interaction effect. Finally, curves with higher super-elevation values lead to higher driving speeds (H_7) on the semi-direct connections. Super-elevation was not found to be statistically significant for the direct and indirect connections using the dataset in this study. Further research is needed into the forces that act on a vehicle when negotiating these connections to better understand the reasons behind these results. The negative interaction effect between the curve direction and super-elevation for the semi-direct connections indicates that the increase in speeds as the curve super-elevation increase is larger on right turning curves compared to left turning curves. This indicates that drivers are more sensitive to super-elevation values on right curves compared to left turning curves (H_8). This might be because on left curves drivers have larger sight distance than on right curves, and therefore can adapt their driving curvature to reduce the centrifugal force acting on them. On right turning curves, on the other hand, the sight distance is shorter, which averts drivers from taking risks by increasing their driving curvature and encroaching into the adjacent lane or shoulder.

These results have implications on multiple aspects, including road design guidelines and road safety, development of automated vehicles' controllers and systems, and development of microscopic simulation platforms. The following paragraphs further elaborate on these different aspects.

Implications for road design guidelines and road safety

The conclusion that drivers' speeds along ramp curves are not constant has considerable implications for road safety and road design guidelines. The road design and drivers' speed selection should be compatible to increase road safety. In this study, it was found that median speeds at the nose on semi-direct and direct connections are higher than the design speed of 90 km/h at the nose. Entering and negotiating curves with speeds higher than the intended design speed and higher speed variability on curves increase the likelihood of accidents (Abdel-Aty & Radwan, 2000). Higher speeds cause higher side friction demand and longer stopping distance, which requires curves with larger radius and higher super elevation in order to provide safe roads (Imberg & Palmberg, 2015). Almost all considered interchanges' ramp curves in this study were built and designed in the seventies or eighties. Vehicle technologies have greatly developed during the last three decades enabling vehicles to drive with higher speeds and higher stability than before. This could partly explain the gap found between the design speeds of these ramp curves and the actual driving speeds of vehicles. When further investigating the existing road signs on these curves in the field, it was found that about one third of the curves do not have any posted speed limit or advisory speed limit signs, one third of the curves had advisory speed signs, and the remaining curves had posted speed limit signs. The literature on advisory speed signs is contradictory (Comte & Jamson, 2000), indicating that drivers may or may not adhere to these advisory speeds. Based on the speed observations of this study, no clear trend could be identified between the speeds and the advisory and speed limit signs. In an earlier study it was found that advance warning signs by themselves are not as effective at reducing speeds as when they are used in conjunction with chevron sight boards and/or repeater arrows (Charlton, 2007). It was also found that drivers take curve radius into account rather than speed limit (Othman et al., 2014). Therefore, improving curve design guidelines by considering drivers' actual speed performance and improving horizontal curve signing practices are both crucial to increase the compatibility between the design speeds and actual driving speeds (Mattar-Habib, Polus, & Farah, 2008; Polus, Pollatschek, & Farah, 2005). Infrastructure and technological countermeasures, such as variable message signs, transverse bars, variable and mandatory Intelligent Speed Adaptation (ISA) systems, and in-car advice using infrastructure-to-vehicles communication can contribute to reducing the gap between the actual driving speeds and the speeds intended by the actual road design (Carsten & Tate, 2005; Comte & Jamson, 2000).

Implications for the development of automated vehicles

What becomes apparent from the speed profiles and the estimated models is that the speed variability among drivers (i.e., inter-individual differences) is much larger than the speed variability along the curves for the same driver (see for example Fig. 2(e)): the variability explained by the random intercept for VehicleID is much larger compared to residual variance in all of the three models. These larger inter-driver differences indicate that different drivers have different comfort levels and preferences when negotiating horizontal ramp curves. This is relevant when, for instance, developing automated vehicles' controllers and control strategies. It is expected that the acceptance of automated vehicles by drivers would increase if the vehicle is programmed to drive more similarly to the preferred driving behavior and driving style of each driver (Basu, Yang, Hungerman, Singhal, & Dragan, 2017; Scherer et al., 2015). Additionally, in the first phase of integrating automated vehicles in mixed traffic, composed of automated and traditional vehicles, when the penetration rate is still relatively low, programming automated vehicles to drive similarly to other traffic, and thus reducing speed variability among vehicles, is expected to be beneficial for safety (Aarts & Van Schagen, 2006).

Implications for microscopic simulation models

The developed models can be used to further enhance and validate the existing models in microscopic simulation platforms for determining the driving speeds of simulated vehicles on curves. Microscopic simulation models, such as VISSIM (Fellendorf & Vortisch, 2010) and AIMSUN (Barceló & Casas, 2005), are largely used by the engineering community to assess different road design alternatives in terms of traffic operations. Therefore, improving the models that simulate the speed behavior of vehicles is an important building block. In VISSIM (Fellendorf & Vortisch, 2010), for example, it is possible to define a reduced speed area. Following the VISSIM manual once the vehicle reaches the beginning of this area it is assigned a new desired speed from within the speed distribution assigned to its vehicle class, which can possibly also be a higher speed. The deceleration process is initiated according to the user-defined deceleration value (PTV, 2011). By using the developed models in this study that take into account the distance along the curve, it would be possible to predict the speed of the vehicle along the curve and the speed behavior adaptation.

Another potential improvement of the existing speed models in microscopic simulation platforms is a further refinement of the stochastic behavior of drivers by the inclusion of driver heterogeneity. This is important as this study has shown that there is a large variability among drivers in their speed adaptation when negotiating curves.

5. Conclusions & future research

The detailed analysis of the speed profiles of vehicles traversing different curves shows that drivers' deceleration and speed adaptation do not occur only on tangent road sections, as some previous studies have assumed, but continues into the curve. This confirms the findings by Montella et al. (2014) and Farah et al. (2017). It was found as well that despite the variability among drivers, there is a certain pattern describing how drivers adapt their driving speeds. Speed prediction models for each type of connections (indirect, semi-direct and direct) were developed using third order polynomial function for the distance. It was found that the distance along the ramp (measured relative to the nose area) affect significantly the driving speeds and has the largest impact on indirect connections. We also found that the curvature, the super-elevation, the longitudinal slope, road width, and the vehicle type significantly affect the driving speeds.

This study demonstrated that this type of data has a large potential to reveal insights into drivers' behavior when negotiating curves. Developing such models, which utilize disaggregate data to describe more realistically drivers' speed behavior and speed adaptation along different connections, are useful for improving simulation models and defining the specifications of automated vehicle controllers. The results of this study also have implications on the existing design guidelines and the proposed measures to reduce the gap between actual driving speeds and the design speeds. Advances in technology, such as, Intelligent Speed Adaptation (ISA) systems, and in-car advice using infrastructure-to-vehicles communication can contribute to reduce this gap.

The main drawback of this study is the lack of insights into drivers' characteristics and relevant human factors that are expected to play an important role in the determination of the speeds drivers chose to drive. Future research should focus on understanding the determinants of different driving speed entry of drivers, and the implications on the probability of road accidents. Such insights can be applied, for example, in personalization of risk warning systems.

This study collected speed data in good weather conditions; future research should as well collect similar data in poor weather conditions (e.g. rain, fog), to better understand the impact of weather conditions on driving speeds (also in relation to the roadway surface). Also road friction is an important factor when investigating curve design, future research should include measurements of side friction (Donnell, Wood, Himes, & Torbic, 2016), and take this factor into account. The impact of the turning direction of the curve on the driving speeds was only tested for the semi-direct connections, and not for indirect and direct connections. This is because of lack of left turning curves in the sample of the direct and indirect connections. Future research should also investigate the impact of the turning direction of the curve on indirect and direct connections.

Extracting lateral position data of a vehicle path when negotiating a curve was possible from the recorded trajectory data, however measurements' noise was relatively large and thus requires further investigation. Curve negotiation strategy, corner cutting, and steering corrections are also important to understand vehicle lateral dynamics when negotiating curves and further research into this is essential to improve curve design and safety.

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