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Zheng, Fangfang; Li, Jie; Van Zuylen, Henk J.; Lu, Chao

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Influence of Driver Characteristics on Emissions and Fuel Consumption

Fangfang Zheng[1,4], Jie Li[2,5*], Henk J. van Zuylen[1,2,3,4,5], Chao Lu[1,4]

[1] School of Transportation and Logistics, Southwest Jiaotong University, Western Hi-tech Zone Chengdu, Sichuan 611756, P.R.China

[2] Key Laboratory of Building Safety and Energy Efficiency of the Ministry of Education, Hunan University, Changsha 410082, China

[3] Transport and Planning Department, Delft University of Technology, P. O. Box 5048, 2600 GA Delft, the Netherlands

[4] National Engineering Laboratory of Integrated Transportation Big Data Application Technology, Southwest Jiaotong University, Western Hi-tech Zone Chengdu, Sichuan 611756, P.R. China

[5] Civil Engineering College, Hunan University, Lushan South Road, 410082 Changsha, Hunan Province, P.R. China

[*] ljlj369@msn.com

Abstract: All drivers have individual ways of driving. Still, there are groups of drivers with more or less similar characteristics. In this research, 28 drivers from Chengdu city (P.R. China) participated in an experiment where car following behaviour was measured with GPS devices. In every measured trip there was a leading and a following vehicle both equipped with a GPS device. Drivers are classified based on a Driver Behaviour Questionnaire and observed acceleration and deceleration behaviour. The result shows four distinct classes of drivers: macho drivers, careful/inexperienced drivers, smooth going/professional drivers, and experienced/fast drivers. Drivers in the different classes give different emission of air pollution and fuel consumption. Saturation flows are determined from the trajectories and vary between different driver types. The measured trajectories have been analysed in detail to determine some parameters for the Wiedemann 74 model. Most default parameters in the VISSIM program appear to be unsuited for the simulation of driving behaviour measured in the experiment. The emissions and fuel consumption calculated by a simulation model with default parameters are not consistent with the empirical data. The calibration done for different driver types shows that several model parameters are significantly different for the different driver classes.

1. Introduction

Every driver has his or /her own characteristic way of driving. However, it is practically impossible to have an individual behavioural model for every driver. Most traffic simulations models have one, two or at most three types of drivers of passenger cars and in most studies the difference in behaviour is based on assumptions. The fact that drivers all have passed an examination before they got a driver license makes the driving behaviour uniform to a certain extent. Still, Li [1] found that there are important differences in the way drivers apply the rules of the road, both within a group of Chinese drivers and a group of Dutch drivers. Drivers develop their own driving style based on experience, character, skills, and the context of their journey [2].

One's experience is an important factor influencing the driving style. Novice drivers are often more careful and hesitating than experienced drivers. In many countries, novice drivers have to get sufficient experience of driving in real traffic before they obtain a driving license. In these countries the novice's skills just to operate and control a vehicle are not considered to be sufficient to obtain a driving license.

The research reported in this paper has been done in China with Chinese drivers. In China the situation with respect to drivers, driving licenses and driver experience differs from most Western countries. The driving examination in China is limited to the knowledge of the rules of the road and the skill to operate and control a vehicle. Driving in real traffic is only a minor part of the examination. That has the consequence that novice drivers still have to learn how to drive in real traffic. Furthermore, the percentage of drivers in China who have their license less than 3 years is much higher than that is in a Western country, such as the Netherlands (38% novice drivers in China versus 3.2% in the Netherlands in 2012 [1]). The learning process of novice drivers is not controlled in the sense that they don't learn how to develop a uniform driving style.

It appears that drivers can be categorized in groups of people who have similar driving behaviour. Some researchers have reported on the classification of drivers based on their actual driving behaviour (e.g. [3],[4]) using in-car monitoring systems. These researchers wanted to classify drivers in order to develop driver specific in-car support systems.

Making a distinction in aggressive, average, sensation seeking and cautious drivers (e.g. [5], [6]) requires first of all criteria to classify the drivers. Rather few studies have been done to investigate the relation between driver characteristics and driving behaviour in real life conditions. Brackstone [7] studied the possible relation between psychological types and driving behaviour using instrumented vehicles on a freeway. He referred to previous studies showing that the headway at higher speeds has a relationship with driver's age [8]. Brackstone registered some characteristics of the drivers such as aggressiveness / passiveness and sensation seeking attitudes and found several correlations between psychological traits and driving behaviour. His research was based on a small number of drivers and his statistical analysis has a limited depth.

Nam et al. [9] used a simple aggressiveness characteristic to investigate the impact of this characteristic on emissions. Also, Tang et al. [5] studied the impact of driver characteristics on fuel consumption and emissions. They developed a car following model for three types of drivers (aggressive, neutral and conservative). However, Tang et al. [5] didn't have specific criteria for the classification of drivers and didn't have any empirical data to calibrate their models. Constantinescu et al. [10] used driving characteristics like speeds and accelerations to classify drivers into six groups. Soria et al. [6] classified drivers into three classes based on lane changing behaviour and speeds. They measured car following behaviour by analysing video data from an instrumented car. The speed and distance to the car in front were measured and analysed. They found differences in the calibrated parameters of the CORSIM simulation model for different driving conditions. Ma and Andréasson [11] also used a single instrumented vehicle to record car following behaviour, without considering characteristics of the driver.

Li et al. [12] and Lu et al. [13] analysed videos to extract trajectories of several vehicles. These trajectories were used to calibrate parameters of the car following model in VISSIM. Both Li et al. [12] and Lu et al. [13] observed traffic at urban intersections and they both showed how acceleration, deceleration and speed profiles could be determined from trajectories. However, no information about the drivers was considered in their research.

Wolshon and Hatipkarasulu [14] used GPS data of leading and following cars to measure distance and speeds. They used the data to calibrate CORSIM, but they did not distinguish different driver behaviour. Durrani et al. [15] investigated the effect of the vehicle class on the parameters of the Wiedemann 99 model. They found that the class of the leading vehicle (passenger car or heavy vehicle) has an important effect on the model parameters. Ossen and Hoogendoorn [16] analysed trajectories of vehicles on freeways and concluded that the match between driver behaviour and car following models were variable: the best matching model differs per driver and even the most suitable model for the behaviour of one driver could change in time. Higgs et al. [17] investigated the behaviour of several truck drivers using instrumented vehicles. They calibrated the parameters of the Wiedemann 74 model for each driver separately, assuming that each driver behaves deterministically and mechanically. They optimized all parameters simultaneously. Therefore, no information was derived about the sensitivity of the model performance on the values of the different parameters. Higgs et al. [17] also showed that the boundary values in the Wiedemann 74 model depend on the speed of the drivers and the driver characteristics, which was not considered in the original Wiedemann 74 model. Asamer et al. [18] calibrated parameters of the Wiedemann model for snowy weather conditions. They found that only a few parameters were relevant for the calibration of the model. Also, Li et al. [12] showed that several model parameters did not have a significant influence on the quality of the calculations with the Wiedemann model.

The research questions of this paper are, whether characteristics of drivers can be classified in uniform groups, whether the different groups of drivers give differences for the parameters of a simulation program, and what the impact of the differences in characteristics is on traffic performance such as saturation flow, speed, fuel consumption and emissions. This paper discusses the results based on the analysis of measurements of trajectories from 56 trips made by 28 different Chinese drivers. Section 2 describes how to classify these drivers into 4 groups. The trajectories were measured on an urban route with 20 signalized intersections in Chengdu city (P.R. China) using GPS devices installed in two cars following each other. Section 3 gives details of these observations. In section 4 the relation between trajectories and fuel consumption and emissions of air pollution is discussed. The trajectories are analysed in section 5, where the research question is whether the typology of the driver has a significant influence on certain characteristics of a trip. In section 6 the relation between driver characteristics and parameters of a simulation model is investigated (the Wiedemann 74 model). The research question is whether one simulation model fits all kinds of drivers. Section 7 concludes the paper with discussion.

In this paper we will use the masculine ('he' and 'his') for drivers, although 21% of the drivers in our test are women. The results apply to all drivers involved in the experiment. Gender appears not to be an important factor in the classification of drivers.

2. DRIVER CLASSIFICATION

Although all drivers have to follow the same rules of the road traffic, there are major differences in their styles of driving. The rules of the road leave considerable opportunities to choose your own way of driving, e.g., the cruising speed – as long as it remains below the maximum speed – the acceleration, lane changing, merging, the reaction time, and the deceleration. Furthermore, drivers may ignore certain rules, for instance in overtaking and choice of lanes. Giving and taking priority is also done according to an individual style. The difference between drivers of passenger cars and truck drivers is evident, but there are also differences between drivers of the first category. Of course, differences in driving style will lead to different traffic behaviour. This has been taken into account in some simulation programs where a distinction can be made between different driving types, e.g. aggressive and cautious drivers.

Even though all drivers are different, it is practically impossible and also unnecessary to have a specific behavioural model for every driver. It appeared that drivers can be categorized in groups of people who have similar driving behaviour. Li et al. [19] used not only the driving behaviour but also the outcomes of a self-assessment to characterize drivers. They investigated the characteristics of 30 drivers in Changsha. By applying factor analysis, they found that the drivers could be classified in 4 groups. Within a group the characteristics of the drivers are similar with respect to acceleration at low, medium and high speeds, cruise speed and aggressiveness, while between the groups there are significant differences. Four factors could be identified that explained 75.9% of the variation in all driving characteristics. This reduction of the driver characteristics to four factors is possible because of the correlation that exists between all characteristics, so that not all characteristics have to be retained.

For the drivers participating in the car-following experiment in Chengdu we followed the same classification procedure. All drivers are Chinese with different background and experience. The drivers were asked to fill in a Driver Behaviour Questionnaire (DBQ) with questions about their personal characteristics, driving behaviour and their history as a driver. The DBQ gave a self-assessment of the drivers. The relation between the answers to the DBQ and real in-car driver behaviour was investigated and the results showed that there was consistency between self-assessed driving behaviour and reality. From the answers to the DBQ an aggressiveness score of the driver was determined. The aggressiveness score is calculated from several items in the DBQ, such as 'crossing stop-line during the red phase', 'offences in the last year', etc. This score appears to be an important explanatory variable for the driving behaviour. The characteristic 'aggressiveness' is much wider than the definition given by the NHTSA [20]. It deals with behaviour that is not necessarily aimed at 'terrorizing' other road users and also includes behaviour that is against the rules of the road. The DBQ answers are combined with characteristics of the driving behaviour such as the acceleration and deceleration rates at different speeds. The characteristics of drivers are described by the following parameters:

- DBQ aggressiveness score,
- Driving experience,
- Mean acceleration and its standard deviation at low speeds,
- Mean acceleration and its standard deviation at higher speeds,
- Mean deceleration and its standard deviation at low speeds, and
- Mean deceleration and its standard deviation at higher speeds.

The characteristics of the drivers (from self-assessment and in-car test) are analysed with factor analysis with the objective to obtain a classification of the drivers in groups with similar characteristics. The factors from the factor analysis are:

F1 related to deceleration and acceleration at low speeds;
F2 related to accelerations at higher speeds;
F3 related to aggressiveness score and decelerations at higher speeds;
F4 related to accelerations at very low speeds and driving experience.

The following typology was identified [1]:

1.Aggressive, macho, unsteady;
2.Conservative, cautious, novice;
3.Professional, smooth going;
4.Experienced, fast driving.

The main characteristics of each group are given in Table 1. The procedure as developed for the 30 drivers in Changsha was also followed in the experiment in Chengdu. Table 2 shows the classification and the main characteristics. The average characteristics of the drivers are similar in the initial data set in Changsha and the group drivers in Chengdu. Therefore, we classified the Chengdu test drivers according to the same four factors as was done with the drivers in Changsha. These four factors explain 67% of the variance of the properties of the Chengdu drivers.

Table 1 Driving type category as determined in the survey in Changsha [1]

Type	Factor	Description	Type Name
1	High F2; High F3	High aggressive score, high acceleration and high deceleration, high speed, and more accidents	Aggressive, macho, unsteady
2	Low F2; Low F3; Low F4	Low aggressive score, short driving experience, low acceleration at all kinds of speed, low deceleration at high speed, and more accidents	Conservative, cautious, novice
3	High F1; High F4	Experienced, high acceleration and deceleration at low speed, more offences registered	Professional, smooth-going
4	High F2; Low F3; High F4	Experienced, low aggressive score, always high acceleration, but low deceleration at high speed, less recorded offences and less accidents	Experienced, fast driving.

Table 2 Characteristics of the DBQ and in-car test sample in Chengdu (The standard deviation of the scores are in brackets)

Item	(n =28)	Note
Mean age (years)	38.04(8.74)	
Males (%)	78.6	
Professional driver (%)	16	
Mean driving experience in years	8.27 (5.00)	
Enjoy driving	8.43(2.04)	{1 = dislike; 10 = enjoy very much}
Self-estimated driving type	4.82(2.36)	{1 = very conservative; 10 = very aggressive}
Others-estimated driving type	4.64(2.31)	{1 = very conservative; 10 = very aggressive}
Self-estimated driving skill	7.46(1.86)	{1 = very poor; 10 = very excellent}
Drivers with offence(s) recorded last year (%)	57.1	
Drivers involved in accident(s) in previous 5 years (%)	42.9	
DBQW Aggressive score	63.07 (12.14)	

Table 3 Classification of the 28 participants of the car following test

Type	Description	Number	Percent
1	Aggressive, macho, unsteady	5	17.86%
2	Conservative, cautious, novice	14	50.00%
3	Professional, smooth-going	5	17.86%
4	Experienced, fast driving	4	14.29%
Total		28	

From further analysis it becomes clear that group 2 represents the novice drivers, young with pleasure to drive. Both type 2 and 4 have few recorded offenses. In the group of type 3 there was one driver who was involved in 4 accidents, the others 0 or 1. Driver type 4 has the lowest aggressiveness score.

3. In-car test data collection

The driving patterns of these 28 drivers were measured while they were driving as leader-follower pairs in two consecutive driving cars. Test trips were made on a track in the city of Chengdu by drivers using their own ordinary passenger car. The length of the track is 8.390 km (5.25 mi) and is shown in Fig. 1; the track consisted of ordinary urban roads with 22 signalized intersections and the test trips were executed in normal traffic conditions. The maximum speed is 50 km/h. The two drivers of each pair were asked to follow each other in the way as they normally would do. The roles of the driver and follower were interchanged resulting in 56 test drives with duration of on the average 1840 seconds each. This results in more than 51500 observations.

Fig. 1 The route of the test track in Chengdu, the lower left part of the route was used for detailed analysis of emissions and fuel consumption

The data were obtained with portable GPS devices (Garmin 64S) installed in each car. The position and speed were registered with 1 Hz frequency. Other researchers, e.g. Song et al. [21][22][23] and Constantinescu [10] have collected trajectory data for car-following model calibration and driver classification using the same observation method with satisfactory results.

The accuracy of the GPS is determined with the method which is also applied by Ser et al. [24]. The GPS device was placed for a longer time on the same place and the positions were registered once per second. The standard deviation of the position is 1.4 m for the north-south direction and 1.29 m for the east-west direction, and the 95-percentile of the distance to the mean position was 3.17 m (see *Fig. 2*)

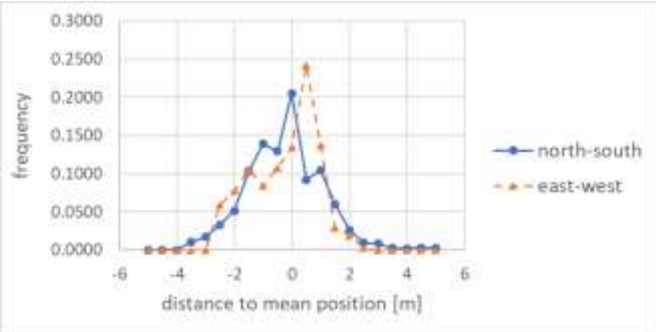

*Fig. 2***.** *Example of histogram of position measured with the GPS on a fixed position*

The changes in position between two measurements can be interpreted as wrongly measured speeds. These errors were not relevant because 95% of these erroneous speeds were less than 0.09 m/s.

The speed measurements by the GPS device were tested by a car driving on a flat, straight road using cruise control with a speed of 100 km/h (27.8 m/s, 62.5 mi/h). The standard deviation of the measured speeds was 0.094 m/s (0.33 km/h, 0.21 mi/h), and 95% of the speeds were within a range of 0.37 m/s (1.33 km/h, 0.83 mi/h). Accelerations have a standard deviation of 0.11 m/s2. These two tests showed that the GPS equipment has acceptable accuracy and can determine the position of the cars within 3 m in 95 % of the measurements.

Another test was made by measuring the distance between two GPS receivers placed in a car on a distance of 3.6 m. After the initial phase (10 minutes) the measured distance between the two devices remains rather constant with a standard deviation of the measured distances of 1.5 m (Fig. 3). The application of a Kalman filter reduces the standard deviation of the measured distances to 1.2 m. The difference between the speeds measured by both devices had a standard deviation of 0.36 km/h and 95% of the measured speeds differences were less than 1.07 km/h.

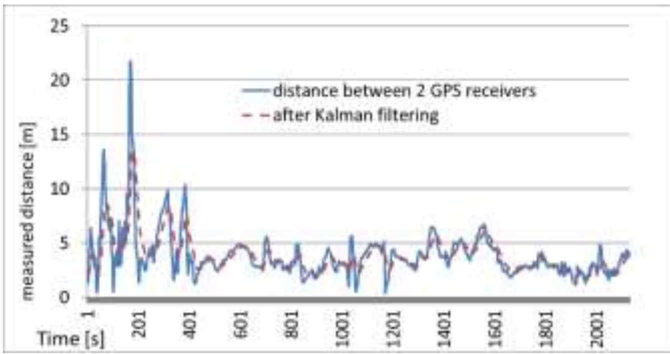

Fig. 3. *Measured distance between two GPS receivers in a car. The real distance was 3.6 m*

The GPS data were collected with a frequency of 1 Hz, which can be considered as sufficient for a car following model calibration [25]. The time scale of processes that were studied is mainly determined by the driver reaction time which is in the order 1 to 2 seconds. The positions measured by GPS were matched to a digital road map and the errors in the positions were reduced by applying a Kalman filter. Situations that another car merged between the leading and the following car were eliminated from the observations. The same was done for moments that the following car didn't drive on the same lane as the leading vehicle. We used the resulting positions to create the vehicle trajectory and to determine the number of stops and waiting time for each test trip.

4. Driver style specific emissions and fuel consumption

From the GPS measurements the trajectories are determined. Fig. 4 shows an example of the trajectories of a leader and a following car. From the trajectories the free driving speed, stops, acceleration and deceleration can be determined. In total 56 trajectories were analysed. The first analysis of the trajectories was made to determine whether driving style has an influence on fuel consumption and the emission of air pollution.

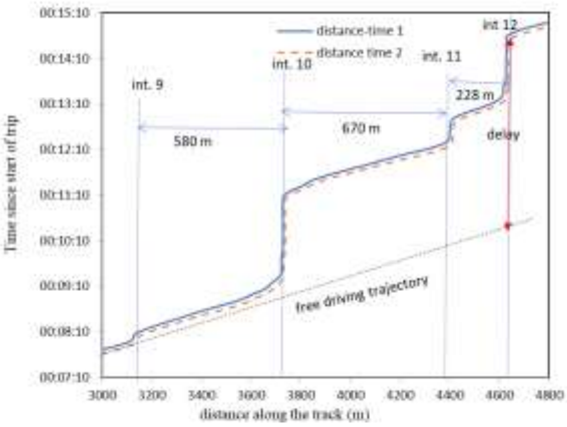

Fig. 4 . Trajectories of a leading (blue) and a following car (red, dashed) on the route shown in Fig. 1

Emissions and fuel consumption of single vehicles can be measured directly by Portable Emissions Monitoring Systems (PEMs) and fuel flow meters. Alternatively, one can use a model to estimate these quantities from the characteristic of the car, the road and the driving pattern.

Several models to estimate emissions have been developed (e.g. [26], [27], [28], and [29]). The US Environmental Protection Agency [30] has developed MOBILE6 model for this purpose. The model is based on measurements of fuel consumption and emissions of different cars in a laboratory environment. In 2006 the Comprehensive Modal Emission Model (CMEM) has become available based on MOBILE6, which contains a database of various motor vehicles. This model not only calculates emissions and fuel consumption in different driving conditions, but also simulates the effect of the age of a motor vehicle, the state of maintenance, ambient air temperature etc. [31]. These quantities are given as a function of the Vehicle Specific Power (VSP) which is the power that the engine should deliver for driving at a certain speed v and achieving an acceleration a. In the Comprehensive Modal Emissions Model (CMEM) manual a simplified formula is given. This formula is applicable for the most common passenger cars in the USA (formula 4.1 in the CMEM manual):

$$VSP/ton = 0.132v + 0.000302v^2 + 1.1v \cdot a[kW/ton] \quad (1)$$

Where v is the vehicle speed (in *m/s*) and a is the vehicle acceleration (in m/s^2). The first term, proportional to v can be considered as the rolling resistance, the second one as the air resistance and the third one as the power needed to accelerate the vehicle.

There are some other emission models common in the literature, such as the one developed by Jimenez-Palacios [28] and used by Song et al. [21][22][23]:

$$VSP = 0.132v + 1.1v \cdot a + 0.0003202v^3 \quad (2)$$

The first two terms represent the power for rolling resistance and acceleration; the last term with v^3 is rather peculiar, since the air resistance is generally proportional to v^2.

Because the CMEM is widely available and used by many researchers, we use the formula (1) for the calculation of the VSP and later we use the CMEM software to analyse emissions and fuel consumption.

For the comparison of fuel consumption and air pollution emission between different drivers, we calculated these quantities from their measured trajectories, assuming that they would all drive in the same car. The calculation according to eq. (1) was done for every trajectory and averaged per driver type. The hypothesis is that different driver types will have different values for the VSP. Table 4 shows the comparison between different driver types. The hypothesis H0 that driver type 1 has the same average VSP as type 2 is less probable than 1% and should be rejected, also the hypothesis that type 1 and 3 have the same VSP is less probable than 1% and for the comparison between type 1 and 4 the probability that the VSP values are the same is less than 1%. The difference between driver type 3 and driver type 4 is significant at $P<1\%$. Driver type 2, 3 and 4 are not significantly different from each other [32].

It is noteworthy that this global analysis does not look in detail into the different characteristics of the trajectories. Even though the routes taken by all participants are the same, there might be differences in number of stops and queues per trip. This has been analysed in more detail for the trajectories on the South branch of the test route (see Fig. 1) with 4 signalized intersections. The number of stops, delay, waiting time are estimated from the trajectories. The emission of hydrocarbons [HC], carbon dioxide [CO_2] and nitrogen monoxide and dioxide [NO_x] and fuel consumption per stop are estimated from the trajectories and the CMEM. It is obvious in these results that there are significant differences in the additional air pollution emission and fuel consumption from one stop for different types of drivers. The differences between driver types 2, 3 and 4 are too small to be significant.

Table 4 Comparison of the average Vehicle Specific Power for 56 trips and the standard deviations

Driver type	Number of measured trips	Mean *VSP*, [kW/ton/m]	Standard deviation [kW/ton/m]
1	10	1.632	0.027
2	28	1.571	0.026
3	10	1.598	0.055
4	8	1.571	0.026

Fig. 5 shows the relation between the fuel consumption and the number of stops for different types of driver. Every stop is a sequence of deceleration and acceleration and the acceleration requires more fuel than driving at constant speed. The fuel consumption Fc_i for driver type i as a function of stops on a journey can be written as

$$Fc_i(n_s) = Fc_i(0) + a_i \cdot n_s \quad (3)$$

Where $Fc_i(0)$ is the fuel consumption for the journey without stops for driver type i; a_i is the additional fuel consumption per stop for driver type i and n_s is the number of stops.

The linear relations between fuel consumption and stops are shown in Fig. 5. Each point in the graph represents a trip with the fuel consumption calculated for the trip and the number of stops made. Apparently, the trajectories of driver type 4 do not make difference between driving at a constant speed and making a stop. Table 5 shows also the regression coefficients for the influence of stops on carbon dioxide CO2, carbon monoxide CO, unburned fuel HC, and nitrogen oxides NO_x. The trajectories of driver type 4 do not show any significant influence of stops on emissions. Driver trajectories of driver type 3 don't show a relation between stops and HC and NO_x emissions.

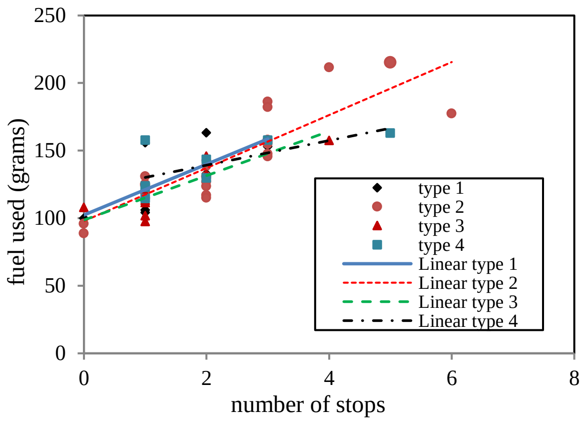

Fig. 5. Fuel consumption as a linear function of the number of stops for the four driver types

Table 5 Estimated fuel/ emission per stop for each driver type (Between brackets the standard deviation)

Driver type	Type 1	Type 2	Type 3	Type 4
Fuel (grams/stop)	18.8 (7.0)	16.5 (2.1)	16.4 (3.5)	Not sig.
HC (grams/stop)	0.07 (0.03)	0.02 (0.003)	Not sign.	Not sig.
CO_2 (grams/stop)	52.6 (21.7)	51.7 (6.6)	53.7 (10.8)	Not sig.
NO_x(grams/stop)	0.09 (0.03)	0.03 (0.005)	Not sig.	Not sig.

Besides, the cruise speed differs per driver type (see Table 6), where driver type 1 has the highest cruise speed and type 2 has the lowest. The t-test of the differences in cruise speed shows that there is no significant difference between type 1 and 3, and between type 4 and 3.

Table 6 Cruise speed per driver type

Driver class	Cruise speed (km/h)	Standard deviation (km/h)
Type 1	55.8	3.3
Type 2	48.2	3.5
Type 3	54.0	4.6
Type 4	51.1	2.9

This analysis to the trajectories shows that there are differences between drivers of different types. The differences are not always statistically significant. That is due to the limited number of test drivers and possibly because the differences are small. A more detailed analysis is necessary to find out in what way the driving style has an influence on the characteristics of trajectories and the fuel consumption and air pollution emissions. This has been done by analysing the car following behaviour of the different kind of drivers in more detail in the following section. From the observed trajectories some flow characteristics and parameters of a car following model are calibrated for each driver type separately.

5. Trajectory analysis

The differences between the different driver types with respect to the emissions and fuel consumption are visible and for a part statistically significant. Due to the small sample of drivers, not all differences are statistically significant. In the previous section we analysed the trajectories without considering that they are obtained pairwise. In this section we analyse trajectory pairs in order to find out the specific car following features.

First of all, we analyse the space between cars at a stop and the time headway between two cars after a stop. That time headway is an indicator for the saturation flow [33]. The questions to be answered is whether the saturation flows that can be realized and the queueing distance at a stop depend on the type of drivers. Fig. 6 shows the typical trajectories of two cars. The distance *AX* between the cars when they stop behind each other is determined as the mean distance during the time that the vehicles have a speed close to zero (to take into account that speeds are not fully accurately measured). Speeds less than 0.1 m/s are considered as zero speed.

The distance of two cars when stopped is given in Table 7. The table shows also the time headway between the leading and the following vehicle after they drive again after a stop. The saturation flow at intersections is inversely proportional to this time headway [33][32].

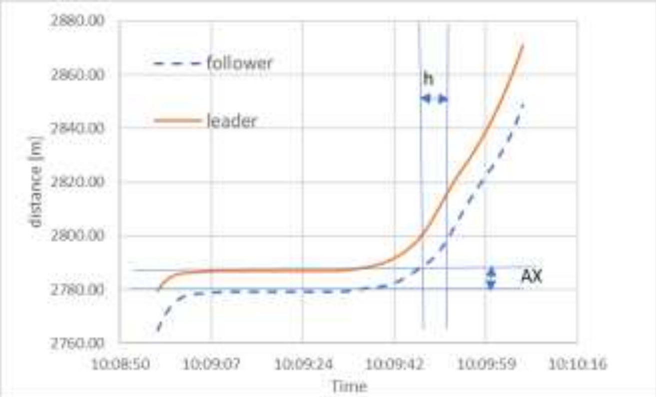

Fig. 6. Example of trajectories of a pair of vehicles stopping, waiting and accelerating.

Table 7 Measured distances between vehicles when stopped and time headway after a stop

Type	Distance AX [m]	St.dev. [m]	Error [m]	Headway [s]	Error [s]
1	8.08	2.79	0.51	2.87	0.33
2	8.99	2.68	0.28	2.86	0.55
3	10.42	2.42	0.55	1.94	0.21
4	8.81	1.29	0.65	2.09	0.18

The distance between two vehicles (including the length of the leading vehicle which is 4.5 m) differs significantly at $p < 5\%$ comparing driver type 1 versus type 3, and type 2 versus type 3. The differences between type 1 versus type 2 and type 3 versus type 4 are significant at the level $p < 10\%$. The differences in (time) headway are significant (at $p < 5\%$ level) between type 1 and type 3, as well as between type 1 and type 4. The differences are significant at 10% level between type 2 and type 3, and between type 2 and type 4. If we take the saturation flow at intersections to be inversely proportional to the time headway, this result gives evidence that the saturation flows for type 1 and 2 are much lower than the standard saturation flow (1800 veh/h) which is observed in most Western countries [33]. This finding confirms the analysis of Li et al. [34] who found that saturation flows at intersections in some Chinese cities are about 30% lower than the values observed on some intersections in the Netherlands. Both the macho (type1) and novice drivers (type 2) have these remarkable longer headways, while the experienced and smoothly driving types have headways and consequently a saturation flow that are similar to what is measured in most Western countries.

The saturation flow is an important factor for traffic control. A low saturation flow gives a low capacity of intersections which could lead to congestion. Congestion increases the fuel consumption for all drivers. Therefore, the low saturation flow has a collective, not an individual effect. Most simulation programs don't have the saturation flow as a model specification parameter, but the saturation flow is the result of the driver model and a correct saturation flow is often used as target for calibration [12], [18].

In the characteristics of drivers, the acceleration and deceleration at different speeds are distinguishing features, as described in Table 1. For the four types of the drivers the relation between speeds and maximum acceleration and deceleration were determined from the 95-percentile of accelerations and decelerations for speeds in bins of 1 km/h. In the Stimulus-Response car following models the assumption is that the acceleration and deceleration of a following vehicle depends on the speed difference and the distance between the leader and the following vehicle [36]. In the next section we calibrate the Wiedemann74 model, where the accelerations and decelerations are assumed to depend on the general status of the following vehicle (e.g. free driving, braking, accelerating) and the characteristic of the driver behaviour, i.e. the maximum accelerations and decelerations. We determine these characteristics according to the measured trajectories. Fig. 7 shows the relation graphically and the linear regression line for driver type 1. The common assumption is that the acceleration is the highest at low speeds. In Fig. 7, it is visible that this assumption is not completely realistic since the accelerations do not fit the regression line well at speeds lower that 5 km/h [17]. Still the regression has significant coefficients for all driver types, as shown in Table 8 and Table 9. The regression relation is given by:

$$b_{max} = p_1 v + p_2 \tag{4}$$

Where p_1 and p_2 are regression coefficients and b_{max} is the maximum acceleration desired by a driver (approximated by the 95 percentile of the observed accelerations). In the same way the relation between the maximum deceleration and the speed is determined.

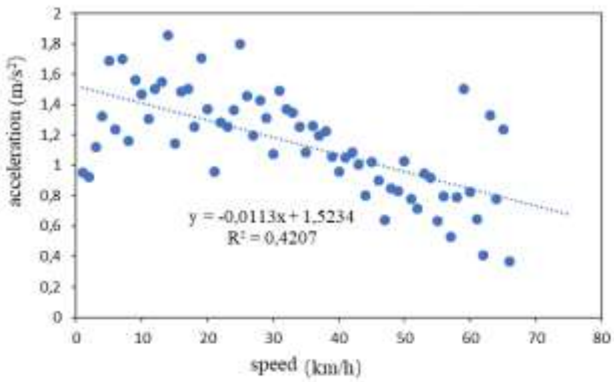

Fig. 7. Relation between speed and 95 percentiles of the acceleration for driver type 1

Table 8 Regression coefficients and their standard deviations of the maximum accelerations b_{max} depending on the speed v

	$b_{max}=p_1*v+p_2$		R^2
type	p_1 (standard dev)	p_2 (standard dev)	
1	-0.011 (0.002)	1.52 (0.06)	0.42
2	-0.016 (0.001)	1.47 (0.04)	0.78
3	-0.016 (0.001)	1.64 (0.07)	0.75
4	-0.019 (0.001)	1.62 (0.04)	0.86

Table 9 Regression coefficients between speed v and maximum deceleration b_{min}

	$b_{min}=p_1*v+p_2$		R^2
type	p_1 (standard dev)	p_2 (standard dev)	
1	0.010 (0.002)	-1.56 (0.08)	0.259
2	0.008 (0.002)	-1.35 (0.07)	0.251
3	0.010 (0.02)	-1.59 (0.09)	0.275
4	0.006 (0.002)	-1.28 (0.07)	0.143

The regression coefficients for deceleration are all significant, but the difference between driver types is not significant.

The conclusion from the analysis of trajectories for the different driver types is that there is evidence that driver type has a significant effect on headways, stopping distances and acceleration characteristics. The next analysis of the trajectories is on the question which parameters of a car following model depend on the driver type. We have chosen to analyse the Wiedemann 74 model and evaluate the performance of the model with respect to emissions and fuel consumption.

6. Calibration of Wiedemann-74 driving model

The next question is whether the classification of drivers is also relevant with respect to the car following simulation. Several car following models have been developed and published. Brackstone and McDonalds [35] gave an overview

. Car following models can be classified into five categories:

- Safety distance models;
- Stimulus-reaction model or Gazis, Herman and Potts (GHP) model [36]
- Action point models (Wiedemann [37], Fritzsche[38]);
- Fuzzy logic/rule-based models [39],
- Collision avoidance models, Intelligent driving model [40].

The Wiedemann-74 is used as one of the car-following models in the VISSIM microsimulation program. The model assumes that a driver adapts his speed when he has the perception that he drives too close to or too far from the leading vehicle, or when the speed of the follower is higher than his own speed or when he is approaching the leading vehicle too much [37]

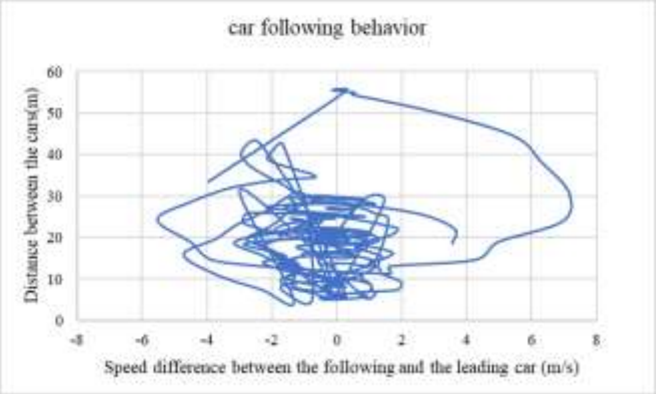

Fig. 8. Representation of car following behaviour

In the driver model of Wiedemann the following driver will adapt his speed in order to get a safe and comfortable position. Furthermore, the model assumes that drivers are not always busy with their driving task. In non-emergency situations they may not always adapt their speeds directly in response to the car in front. In the diagrams of Fig. 8 and Fig. 9 one can observe indeed points in the diagram where the driver changes his (relative) speed, but also areas where he seems to adapt his speed rather randomly, especially when the speed difference is small and the distance is sufficiently large. Wiedemann [37] introduced certain areas with specific behaviour. In Fig. 9 these areas are shown in the background with an example of a real trajectory as observed. The regions are shown in colour with the transition states: *AX* stands for the distance at stops; *BX* stands for the distance at which a driver has to stop for a stopped vehicle in front; *CLDV* is the critical value after which the driver has to decelerate; *SDV* is where the driver becomes aware of the fact that he is approaching the vehicle in front; *OPDV* is where the driver decides to accelerate because the vehicle in front is moving forwards and *SDX* is the distance above which the driver does not see a reason to react on the vehicle in front because it is on a safe distance while under *SDX* and with small differences in speed the driver can change speeds without caring about the distance and differences in speeds.

A first observation of this model of the driver behaviour is that it is rather vague. Both the descriptions of the actions in the different regions of the Δ(speed) – distance space as in the actions, there is a lot of vagueness. As we can see in the real trajectories in Fig. 9 the driver doesn't take actions precisely in a certain area. Wiedemann considered this vagueness in the model by making the boundaries between the regions stochastic. The consequence is that a driver at a certain point in the diagram would react as being in the slow-reaction area, while on a next moment he would be – on the same coordinates – in the area where he has to decelerate. This apparent stochasticity in the driver behaviour makes it difficult to reproduce vehicle trajectories precisely in a simulation. Especially the accelerations calculated from a simulation program have remarkable differences from the observed accelerations at many moments. Still, a traffic simulation model can be calibrated by minimizing the Root Mean Square Error (RMSE) between observed and simulated speeds or accelerations. Several other methods are suitable for the calibration of car following models based on trajectory data (e.g. [41], [42]). For instance, we can use a macroscopic characteristic of trips namely fuel consumption (e.g. [12]) as the calibration objective.

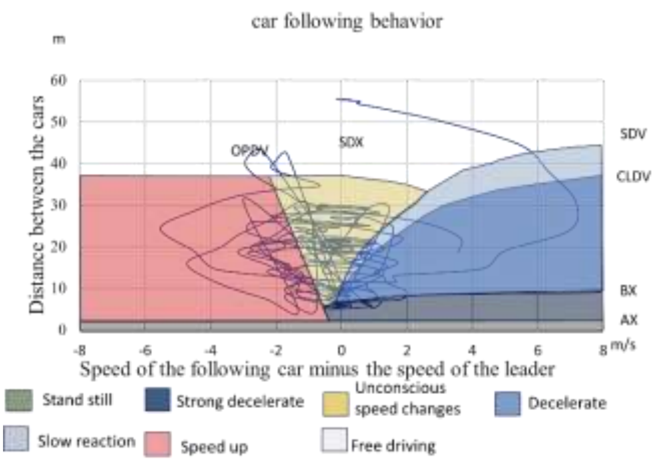

Fig. 9. Driver behaviour areas

Fig. 9 illustrates the different areas in the space of speed difference and distance between the leader and the following car. In the upper part of the diagram the distance between the cars is so large that the following driver can drive at his desired speed. In the lowest part of the diagram the distances between the cars is delimited by *AX* which is the distance at zero speed or the queuing distance. In the right half of the diagram the following car is approaching the leader. If the distance is really short, e.g. shorter than *BX*, the following car has to brake in order to avoid a collision. This braking is assumed to be done with the maximum deceleration. In the diagram there is the area between *BX* and the boundary *CLDV* (Closing Difference in Velocity) where the distance is short and the following car is still approaching the leader. Then the follower has to decelerate quickly. In the area between *CLDV* and *SDV* the reaction doesn't have to be too fast: the follower should know that he should reduce his speed.

On the other half of the graph the situation is that the leader is increasing the distance by accelerating. The follower will accelerate and try to reduce the speed difference and keep close to the leader. In the middle area delimited by *OPDV* (Opening Difference in Velocity), *SDX* and *SDV* the follower can adjust his speed and distance gradually, without the need to modify his position and speed with respect to the leader. Changes in speed and distance are rather random.

Table 10 Definition of the model parameters for the boundaries of the Wiedemann 74 model

Model parameters	Expressions	Explanations
AX	L_{n-1}+AXadd+RND1n*AXmult	AXadd and AXmult are parameters to be calibrated, L_{n-1} is length of the leading car
BX(v)	(BXadd+BXmult*RND1n) *$v^{0.5}$	BXadd and BXmult are parameters to be calibrated v =min (v_n ,v_{n-1})
SDX	AX+EX*BX	EX = EXadd+EXmult*(NRND-RND2n), EXadd and EXmult are calibration parameters
SDV(Δx)	$((\Delta x-L_{n-1}-AX)/CX)^2$	CX = CXconst*(CXadd+CXmult*(RND1n+RND2n)) CXconst, CXadd and CXmult are calibration parameters
CLDV	$((\Delta x-L_{n-1}-AX)/CX_2)^2$	CX_2 is a calibration parameter
OPDV	CLDV*(-OPDVadd-OPDVmult*NRND)	OPDVadd and OPDVmult are calibration parameters

In Fig. 9 the real trajectories are not exactly according to sharp boundaries. Drivers may have different behaviour in two situations with the same physical condition. Wiedemann introduced random terms in the boundary formulas to deal with the diversity in behaviour.

Table 10 provides the expressions for the boundaries of the Wiedemann 74 model.

The quantities NRND, RND1n, and NRD2n are random numbers, specific for a driver. These random numbers represent the variation of behaviour between drivers. The variation of behaviour of one driver who reacts differently at different moments is not represented in the Wiedemann model. Therefore, the calibration of the model for one single driver can be done while the random terms are ignored [17].

Apart from the model parameters described in Table 10 the acceleration and deceleration behaviour of the drivers has to be specified when they are in one of the four areas. Wiedemann assumes that the maximum acceleration and deceleration depends linearly on the speed. When a driver comes in the free-driving region he will accelerate with acceleration rate b_{max} according to

$$b_{max} = BMAXmult * (v_{max} - v * FactorV) \qquad (5)$$

where *BMAXmult* and *FactorV* are calibration parameters and v_{max} is the maximum speed.

When the driver in the free-driving region passes the *CDV* threshold, his deceleration will be

$$b_n = \frac{1}{2} * \frac{(\Delta v)^2}{ABX-(\Delta x - L_{n-1})} + b_{n-1} \qquad (6)$$

where *ABX* is a calibration parameter and b_{n-1} is the deceleration rate of the leading vehicle. In the emergency braking area (distance Δx less that *BX*) the deceleration is

$$b_n{}' = \frac{1}{2} * \frac{(\Delta v)^2}{ABX-(\Delta x - L_{n-1})} + b_{n-1} + b_{min} * \frac{ABX-(\Delta x - L_{n-1})}{BX} \qquad (7)$$

where b_{min} is the maximum deceleration of the driver.

In the region of the unconscious speed changes (speed differences between *OPDV* and *SDV*), the following driver accelerates with a rate b_{nul} when he approaches *OPDV*, and decelerates with $-b_{nul}$ when he approaches *SDV*.

The Wiedemann car following model has a very large number of parameters. Most of them are shown in Table 11. For most purposes it is not necessary to calibrate all parameters ([12] and [18]). Some parameters have a small, even negligible, influence on saturation flows, fuel consumption, and emissions.

Table 11 Parameters for the Wiedemann 74 car following model

Parameter	Default value	Suitable value for the four driver types
L_{n-1}	4.5 m	4.5 m
AX_{add}	1.25 m	3.58 / 3.49 / 5.94 / 4.31 (Table 7)
AX_{mult}	2.5 m	2.79 / 2.68 / 2.42 / 1.29 (Table 7)
BX_{add}	2.0 m	-
BX_{mult}	1.0 m	-
EX_{add}	1.5 m	-
EX_{mult}	0.55 m	-
CX_{const}	40	40
CLDV	-	-
OPV_{add}	1.5	-
OPV_{mult}	1.5	-
B_{NUL}	0.1	-
B_{MAX}	3.5-3.5v/40	-
v_{max}	-	60 km/h
v_{des}	80 km/h	Cruise speed 55.8 / 48.2 / 54.0 / 51.1 km/h
$BMIN_{add}$	-20+1.5v/60	-

The parameters that determine the boundaries between the different areas in Fig. 9 are *AX*, *ABX*, *CLDV*, *SDV*, *SDX*, and *OPDV*. In the previous section the distance at a stop, *AX*, is directly calibrated from the trajectories. The cruise speed and acceleration and deceleration behaviour depending on the speed have also been calibrated directly from the trajectories. These model parameters depend significantly on the driver type.

The parameter *SDX* is determined by *BXadd*, *BXmult*, *EXadd*, and *EXmult* and *AX* (which has been determined directly). The other possibly important parameter is *CX* which determines the transition *SDV* between free driving and closing in / deceleration. These parameters are difficult to calibrate directly from trajectories.

For the calibration of the model parameters *CX* and *SDX* we use the Vehicle Specific Power (*VSP*) of the following vehicles as the characteristic of a trip and try to minimize the difference between the simulated and observed *VSP*. This is analogous to the method used by Song et al. [23] – apart from the facts that they don't consider a leading vehicle and do not distinguish different driver types and they apply the formula (2) instead of the CMEM formula (1).

Some authors use random search methods to calibrate all parameters of the Wiedemann model simultaneously (e.g. [43] and [17]). Since we already calibrated some parameters directly from trajectories and also wanted to calculate the estimation error of the calibrated parameters, we have calibrated two model parameters one by one. Interaction effects have been negligible since the estimated value of the first parameter did not differ from the default value. By this procedure we could determine the significance of the differences in the estimation of the calibrated parameters between the different driver types as illustrated in Fig. 10.

The calibration of *SDV* was done by searching for the best fit of the trip VSP by modifying these parameters. The Root Mean Square Error (RMSE) of the simulated versus the observed VSP is calculated.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - T_i)^2}{n}} \qquad (8)$$

S_i is the simulated value of VSP at time step *i* and T_i is the *VSP* calculated from the observed speeds and accelerations; *n* is the number of time steps of the observations. The simulation is done by a Matlab simulation based on the specification of Wiedemann, where parameters are varied. The parameters are optimized with the objective of minimizing the RMSE. This was done for the observations for each driver types.

Table 10 describes the relation between *SDV* and *CX*. Varying *CX* shows that this parameter has a small influence on the RMSE. The difference between the values found by the optimization and the default value 40 is not significant as shown in Table 12. The differences between the various driver types is not significant as well.

Table 12 The optimum value of CX for different driver types

	type 1	type 2	type 3	type 4
Optimum value (m)	34.25	41.16	50.65	39.84
Standard deviation (m)	65.39	19.33	120.36	28.92

The influence of *SDX* on the trip *VSP* is clearer: the simulated *VSPs* becomes closer to the observed ones for optimum values of *SDX*. Table 13 shows the values that have been found for the different driver types. They appear to differ significantly for some cases. Driver types 2 and 4 have values that are not significantly different, while differences between other types (e.g., type 1 and 2, type 1 and 3, type 1 and 4, type 2 and 3, type 3 and 4) are significant.

Table 13 Calibrated values for *SDX*

	Type 1	Type 2	Type 3	Type 4
Optimum value (m)	77.62	65.42	85.63	65.69
Standard deviation(m)	17.57	11.59	13.60	10.11

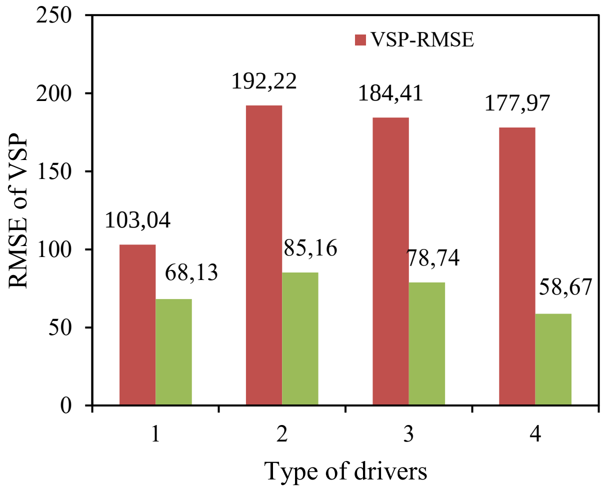

Fig. 10. Result of VSP-RMSE after calibration of SDX

Fig. 11 shows the probability distribution of the measured *VSP* and VISSIM simulated *VSP* with calibrated *SDX*, *AX*, and acceleration / deceleration parameters. The variation of the other boundaries *ABX*, *CLDV* and *OPDV* shows that they don't have a significant influence on the *VSP*.

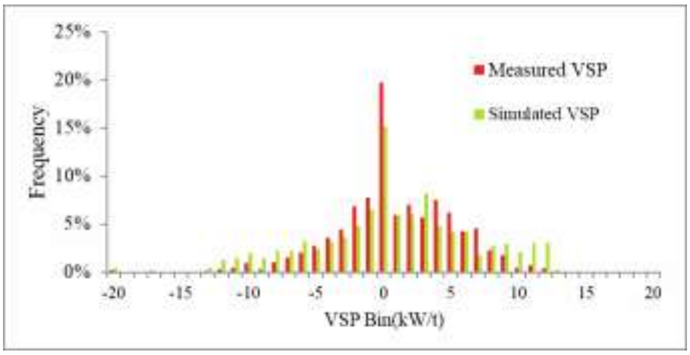

Fig. 11. Distribution of the measured and simulated VSP for driver type 2, after calibration of SDX, AX, and acceleration / deceleration parameters

7. Conclusions and discussion

Drivers have their characteristics in driving style and attitude. No driver is the same but some drivers are more similar than others (analogue to the famous statement of Orwell [44]: "All animals are equal but some animals are more equal than others"). Drivers with similar characteristics can be united in homogeneous groups. The drivers are classified in four types (from type 1 to type 4 as discussed in section 2) based on their self-assessment and acceleration behaviour. This was done for two groups of Chinese drivers in two cities, Changsha and Chengdu. The results show that the characteristics of drivers of these two cities are similar.

The group drivers that were studied consists of 28 persons. The numbers of drivers per type were rather small. Only the number of the cautious type 2 drivers is larger (14 persons). The small number of persons per driver type made it necessary to be very careful with the statistics of the observed characteristics. Several differences that we found are not sufficiently significant to distinguish between driver types. Important, significant differences between the driver types were found for

- fuel consumption and emissions,
- cruise speed,
- acceleration characteristics,
- distance in a queue,
- time headways when accelerating from the queue, and
- the transition distance that drivers start to accelerate.

The fuel consumption and emissions for stops are lowest for the cautious type 2 drivers, while for type 4 drivers no significant relation could be found between fuel consumption / emissions and the number of stops. The cruise speed of cautious drivers type 2 is about 6 to 12% lower than that of drivers of the other types.

The time headways for type 3 and 4 drivers are significantly lower than those for other driver types and similar to the headways observed in the Netherlands. The time headway of type 1 and type 2 drivers (aggressive and cautious drivers) is about 40% higher than the headway of 2 seconds that is commonly used in capacity calculations for signalized intersections. This is a confirmation of the earlier finding that saturation flows at several intersections in Chinese cities are much lower than the saturation flows in Western countries. The reason behind this difference is probably that experienced and smooth drivers are better able to predict what a driver in front will do so that they can better anticipate that and drive with a shorter headway.

For the dependence of the maximum acceleration on the speed, it appears that a type 1 driver does not accelerate much less when driving at high speeds than at low speeds. Drivers of type 4 have a reduced acceleration rate at higher speeds. Since in the VSP model (equation 1) the third term contains the product of speed and acceleration, the acceleration strategy of driver type 4 is more fuel saving.

Some parameters of the Wiedemann 74 model have been calibrated and most of them are different for the different types of drivers. This makes it obvious that microscopic simulation programs of traffic should have the possibility to represent different types of drivers and it should be possible to compose the traffic as a mixture of different kinds of drivers. Specifying each driver type can be done as described in several publications, e.g. [12][18][29].

This experiment was executed in China with Chinese drivers. The group of novice drivers (with less than 3 years driving experience) is much higher in China than those in most countries with a longer history of motorization [1]. Furthermore, the examination for a driver license in China concentrates on the skills to operate and control the car instead of the skills to drive in traffic. Novice drivers feel themselves uncertain and hesitating when they have to drive in real traffic. That can be observed in the result for driver type 2. The development of the driver population in the future will probably change the quantitative results shown in the paper. Still the main conclusions will hold: drivers with different characteristics have to be modelled with different models and their performance on the road will be different.

The direct practical application of this research for the situation in China is that the Chinese road authorities should reconsider the requirements for a driver license and include a test of driving in real traffic. That will reduce the number of type 2 drivers who give a bad traffic performance.

8. Acknowledgments

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