Assessing individual driver's relative performance at curve: applying Data Envelopment Analysis on simulator data

Seddigheh Babaee[1], Yongjun Shen, Elke Hermans, Geert Wets, Tom Brijs, Caroline Ariën

Hasselt University, Transportation Research Institute (IMOB), Belgium

Abstract

This study investigates the performance of drivers at the individual level, at two different curves, using data from a driving simulator in order to identify the best drivers within the sample and to gain insight into the most problematic behavior of each driver. To this end, 34 participants varying in age and gender completed two particular simulator scenarios and their speed, acceleration and lateral position, were monitored at various points. The concept of composite indicators, which combines single indicators into one index score, was employed, and the technique of data envelopment analysis – an optimization model for measuring the relative performance of a set of decision making units, or drivers in this study – was used for the index construction. Based on the results, all drivers were ranked and best performers were distinguished from underperforming ones. Moreover, by analyzing the weights allocated to each indicator from the model, the most problematic parameter and point along the curve were identified for each driver. Finally, the sensitivity of the results was examined.

Keywords: Driver's relative performance; Driving simulator data; Index score; Data Envelopment Analysis.

Résumé

Cette étude examine la performance des conducteurs au niveau individuel, à deux courbes différentes, en utilisant les données d'un simulateur de conduite afin d'identifier les meilleurs pilotes au sein de l'échantillon et de mieux comprendre le comportement le plus problématique de chaque pilote. À cette fin, 34 participants d'âge et de sexe différents ont rempli deux scénarios particuliers de simulateurs ou la vitesse, l'accélération et la position latérale, ont été contrôlés à différents points. Le concept d'indicateurs composites, qui combine des indicateurs simples en un seul score de l'indice, a été employé, et la technique de l'analyse d'enveloppement des données - un modèle d'optimisation pour mesurer la performance relative d'un ensemble de décisions unités ou les pilotes de cette étude - a été utilisée pour la construction d'un indice. Sur la base des résultats, tous les pilotes ont été classés et les plus performants ont été distingués des sous-performant. De plus, en analysant les pondérations attribuées à chaque indicateur à partir du modèle, le paramètre et le point les plus problématiques le long de la courbe ont été identifiés pour chaque conducteur. Enfin, la sensibilité des résultats a été examinée.

Mots-clés: performance relative du conducteur; conduite des données de simulateurs; score d'indice, analyse par encadrement des données.

[1] Tel.: +3211269164 ; fax: +3211269199 .
E-mail address: seddigheh.babaee@uhasselt.be .

1. Introduction

Over the last decade, a lot of research efforts have already been paid to the application of driving simulators for safety issues (e.g., Boyle & Lee, 2010; Montella et al. 2011; Auberlet et al. 2012; Merat & Jamson 2013). In general, the main research questions are related to training programs, fitness to drive (in terms of ageing, medicines, alcohol and drugs), impact of new in-vehicle technologies and the effect of different engineering treatments on driver`s behavior (Fisher et al. 2011). Most of these studies use statistical methods in which the focus is usually on the averages (such as to calculate the mean value and the standard deviation (SD) of a particular parameter for the sample). At the same time, limited research has been carried out based on individual driver risk (Dorn & Gandolfi, 2013; Morris 2013) which is particularly important in the development of proactive driver education programs and safety countermeasures. Within the field of driving simulator research, this study distinguishes itself by focusing on the individual level, and determining the optimal driving performance index score for each individual, resulting in new insights and valuable recommendations.

Recently, various indicators have been combined in so-called composite indicators (CIs) or index (e.g., Al-Haji 2007). Simplistically, a CI synthesizes the information included in a selected set of indicators in one figure (Nardo et al. 2005). In recent years, there has been an increasing interest in the methodology for creating a CI, in which the assignment of weights to each indicator is an essential step (Bax et al. 2012). One of the promising weighting methods is data envelopment analysis (DEA) in which based on the data set the best possible weights are determined for each unit or driver in our case (Hermans et al. 2009; Shen et al. 2010). During the past years, various indexes have been developed by using the DEA technique. The environmental performance index (Färe et al. 2004), the human development index (Despotis 2005) the macro-economic performance index (Ramanathan 2006) and the road safety performance index (Hermans 2009), are examples among others.

In this study, by using the technique of DEA, a CI will be created with respect to driving performance, based on which drivers can be evaluated in terms of their relative overall driving performance tested by means of a simulator, and useful insight in the area of underperformance of each driver can be gained by analyzing the allocated indicator weights. In doing so, two different curve taking scenarios were simulated to analyze the driving performance of individual drivers. Thirty-four drivers drove in the simulator in these scenarios while data on their speed, acceleration and lateral position, were collected as driving performance indicators. The technique of DEA in general, and the multiple layer DEA based CI model in particular, are employed for index construction. We start in Section 2 with the presentation of the data collection and processing. The methodology is discussed in Section 3. Section 4 deals with the corresponding results in terms of a ranking of the drivers based on their index scores, an illustration of the most problematic driving parameter for a particular driver, and a comparison between the performance of the best and the worst driver in two curves. Section 5 concludes the paper and offers some final remarks. Finally, Section 6 discusses about limitations of this study and further research.

2. Data collection and analysis

This study aims to investigate the driving behavior of different drivers in and nearby a curve. Horizontal curves, particularly on two-lane rural roads, have been recognized as a significant safety issue for many years: crash rates are 1.5 to 4 times higher on horizontal curves than on straight road sections, and 25-30% of all fatal accidents occur in curves (SafetyNet, 2009a).

2.1. Participants

Thirty-eight volunteers participated in the study. Four participants were excluded, because two did not finish the experiment due to simulator sickness and two had missing data. Thus, 34 participants (of which 23 men) between 18 and 54 years old (mean age = 26.32; SD = 10.47) remained in the sample.

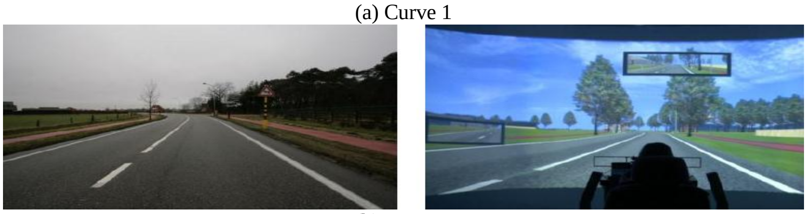
2.2. Driving simulator

The experiment was conducted on a medium-fidelity driving simulator (STISIM M400). It is a fixed-based driving simulator with a force-feedback steering wheel, brake pedal, and accelerator. The simulation includes vehicle dynamics, visual/auditory feedback (e.g. sound of traffic in the environment and of the participant’s car) and a performance measurement system. The visual virtual environment was presented on a large 180° field of view seamless curved screen, with rear view and side-view mirror images. Three projectors offer a resolution of 1024 × 768 pixels and a 60 Hz frame rate. Data were collected at frame rate.

2.3. Procedure

Two different curves in terms of geometry, speed limit and surrounding road environment, were replicated in the driving simulator by means of a procedure called geo-specific database modeling (Yan et al. 2008). The replication of a real-world environment in a simulated virtual world has to be differentiated from simulator research where fictive driving scenarios are used. Blueprints, AutoCAD simulations, and detailed field measurements were used to reproduce the existing curves as detailed and realistic as possible in the simulator. All participants completed two 16.2 km test-drives and their driving performance was monitored at eight different measurement points along the driving scenario. i.e., P1=500m, P2=166m and P3=50m before curve, P4=curve entry, P5=middle of the curve, P6=curve end, and P7=50m, P8=100m after curve. The road width is 2.8m at curve 1, with the posted speed limit of 70 km/h, and at curve 2, the road width is 3.2m and the posted speed limit is 90 km/h (see Fig. 1).

(a) Curve 1



(b) Curve 2

Fig. 1. Real-world vs. simulator images nearby curve entry at (a) curve 1, (b) curve 2.

2.4. Driving parameters

In general, driving behavior comprises the vehicle control in longitudinal and lateral direction. According to the “European Safety Handbook in Secondary Roads” (Gatti et al. 2007), speed, acceleration, and lateral position are the three most commonly used parameters to describe and analyze the behavior of a driver. To use these three measures recorded by the simulator, the raw data have to be processed for each point of each curve, separately. The detailed data processing procedure is elaborated in the following section, using curve 1 as an example.

Speed (km/h) [1]

Speed is at the core of the road safety problem. Very strong relationships have been established between speed on the one hand and crash risk and severity on the other hand. In fact, speed is involved in all accidents: no speed, no accident. In around 30% of the fatal accidents, speed is an essential contributory factor (SafetyNet, 2009b). Apart from the emergency services, nobody should drive faster than the legal speed limit. As a result, given the posted speed limit of curve 1 in the simulated and real environment (70 km/h), all drivers are first divided into two groups based on their driven speed, i.e., below or equal to 70 km/h on the one hand and above 70 km/h on the other. Next, by using hierarchical cluster analysis in SPSS, each group is further divided into several sub-groups. Finally, all the sub-groups were assigned descending grades starting from 6 (a maximum of 6 sub-groups), illustrating the degree of each driver’s performance, so that the higher the grade, the better the

[1] Also, K-cluster analysis without first making a division between less than or equal to 70 km/h on the one hand, and more than 70 km/h on the other hand, was used for making speed clusters. The ranking result showed that all best and most worst drivers (i.e. driver number 1; 13; 14; 33 and respectively driver number 28; 21 in case of curve 1) detected by the applied method (following the grading as mentioned in Table 1) were also identified as best and worst performers in case of the K-cluster analysis.

performance. This process is carried out in each of the eight points, respectively. Table 1, shows the results of clusters at 500m before the curve (i.e., P1).

Table 1. The threshold of speed clusters at 500m before the curve (P1).

Drivers driving with a speed ≤ 70 Km/h			Drivers driving with a speed > 70 Km/h		
Speed range	Nr. of drivers (%)	Grade	Speed range	Nr. of drivers (%)	Grade
[67.61 , 69.53]	9 (26.47)	6	[70.49 ,74.48]	10 (29.41)	3
[61.88 , 66.50]	6 (17.65)	5	[78.34 , 99.07]	7 (20.59)	2
52.71	1 (2.94)	4	126.42	1 (2.94)	1

Acceleration (m/s^2)

The acceleration is defined as the speed change within a time interval. Regarding the direction of acceleration, there are a longitudinal and a lateral acceleration. The longitudinal acceleration is a value of speed change and lateral acceleration, as a comfort criterion, gives information about how fast a driver changes his/her direction. For this study, we use the resultant of both accelerations, and the hierarchical cluster analysis is applied on the data at different points. As a result, each group is allocated a grade indicating its performance. Again the higher the grade, the better the performance. Table 2 shows an example of grading at curve entry (i.e., P4).

Table 2. The threshold of acceleration clusters at curve entry (P4).

Acceleration range	Nr. of drivers (%)	Grades
[0.273 , 0.691]	17 (50)	6
[0.763 , 1.097]	14 (41.18)	5
[1.410 , 1.918]	3 (8.82)	4

Lateral position (m)

The lateral position is the position of the vehicle within a lane. It can be measured as the distance between the center of the road and the vehicle's longitudinal axis. According to the PIARC Road Safety Manual (2003), the ideal position on a curve is where the center of the vehicle is located on the center of the lane. Since the road width in the simulator scenario of curve 1 is 2.8m, based on the average passenger car dimension, drivers are assigned a grade according to Table 3. A score of 6 indicates best performance because he/she drives in almost the middle of the lane (within a range of ±0.1m from the center-line), while a score of 4 is given to the worst performers because they either pass the center-line or edge-line of the road. Finally, drivers not belonging to these two groups are assigned a score of 5.

Table 3. The lateral position criterion in each point (curve 1).

Threshold for "Lateral Position"	Grades
$1.3 \leq LP \leq 1.5$	6
$0.95 < LP < 1.3$ or $1.5 < LP < 1.85$	5
$LP \leq 0.95$ or $LP \geq 1.85$	4

3. Methodology

Data Envelopment Analysis (DEA), originally developed by Charnes, Cooper, and Rhodes (1978), is a non-parametric optimization technique that uses linear programming to measure the relative efficiency of a set of decision making units (DMUs), or drivers in this study. The focus of DEA is on individual units, in contrast to the focus on the averages. It has become an alternative and a complement to traditional central-tendency analyses and has a number of advantages. As Golany & Roll (1989) pointed out, DEA can be applied to: rank the DMUs, evaluate the effectiveness of programs or policies, identify sources of inefficiency, and create a quantitative basis for reallocating. Lately, considerable attention has also been paid to use DEA in the construction of CIs. By solving a linear programming problem, the best possible indicator weights are determined, and an index score between zero and one is obtained for each unit, with a higher value indicating a better relative performance.

In this study, to evaluate the driving performance of each of the 34 drivers by combining all the 24 hierarchically structured indicators in one index score (see Fig. 2), a multiple layer DEA based composite indicator model

(MLDEA-CI) developed by Shen et al. (2013), which takes the layered hierarchy of indicators into account, is adopted. The main idea of this model is to first aggregate the values of the indicators within a category of a particular layer by the weighted sum approach in which the sum of the internal weights equals to one.

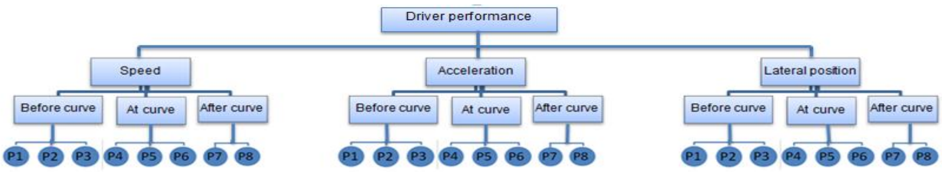


Fig. 2. Hierarchically structured driving performance indicators

Then, for the first layer, the weights for all the sub-indexes are determined using the basic DEA approach. In general, the model assigns the best possible weights to each indicator thereby maximizing the index score for a particular driver while at the same time respecting the following restrictions imposed by the model: (1) The set of weights suggested for each driver must also be feasible for all the other drivers included in the data set; (2) the driving performance during the curve is considered to be more important than before or after the curve. Therefore, a relative weight restriction is given ensuring that the indicators in and along the curve, i.e., at curve entry (P4), middle of the curve (P5) and curve end (P6), receive a higher weight than the other points; (3) to guarantee that all the three aspects of driving performance - speed, acceleration and lateral position - will be represented to some extent in the index score, each of these three factors in the final index score is considered to be of similar importance but with 30% variability to still allow a high level of flexibility.

4. Results

Using simulator data –the values of 24 driving performance indicators for each of the 34 drivers at both curves– and applying the MLDEA-CI model, we obtain the following results: a drivers ranking based on their optimal index scores (4.1), an illustration of the required improvement priorities for a particular driver based on weight allocation (4.2), and a visualization of the performance of some typical drivers (4.3). Each aspect is discussed subsequently.

4.1. Index scores and drivers ranking

By applying the model, 24 driving performance indicators are now combined in an overall index score for each driver by selecting the best possible indicator weights under the imposed restrictions. An index value equal to one identifies a best performer, whereas a score less than one implies underperforming drivers. Apart from distinguishing the best-performing and underperforming drivers, it is possible to rank them based on their calculated index scores (see 2nd and 6th columns of Table 4). While, driver 1 distinguished as best performer and driver 29 as worst-performer at both curves, there are some ups and downs in other drivers ranking. For instance, driver 21 and 28 act as worst performers at curve 1, but they have a relatively better performance at curve 2.

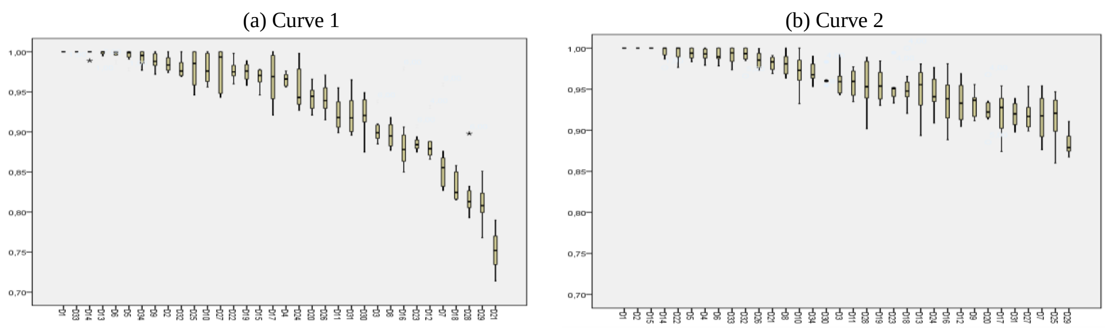


Fig. 3. Boxplot of drivers when eliminating indicators at one point at a time at (a) curve 1 and (b) curve 2.

Moreover, to further investigate the robustness of the indexes or the stability in the output (i.e., drivers ranking) given small changes in the indicator set, we considered following 8 scenarios: in scenario 1, point 1 is excluded;

in scenario 2, point 2 is excluded, and so on. In each scenario, the index score of each driver is recalculated and the average of the index scores from the different scenarios is obtained for each driver. The results are presented in Fig. 3, (X-axis: Drivers ID & Y-axis: Index scores) which provide, insight into the sensitivity of each driver's scores with respect to each scenario and indicate driver nr. 1 as a robust, overall best performing driver who obtains an index score of one in all the scenarios at both curves.

Table 4. Drivers ranking based on their driving performance index score.

Curve 1				Curve 2			
ML DEA-CI		Sensitivity Analysis		ML DEA-CI		Sensitivity Analysis	
Driver ID	Score	Driver ID	Ave. Score	Driver ID	Score	Driver ID	Ave. Score
1	1.000	1	1.000	1	1.000	1	1.000
13	1.000	33	1.000	2	1.000	2	1.000
14	1.000	14	0.999	15	1.000	15	1.000
33	1.000	13	0.998	14	0.996	14	0.995
6	0.997	6	0.997	6	0.996	22	0.994
34	0.993	5	0.995	5	0.996	5	0.993
5	0.992	34	0.992	32	0.994	4	0.992
9	0.984	9	0.989	22	0.994	6	0.992
2	0.981	2	0.985	33	0.992	33	0.991
32	0.973	32	0.979	4	0.991	32	0.991
25	0.971	25	0.979	26	0.983	26	0.986
10	0.971	10	0.979	21	0.979	21	0.982
19	0.969	27	0.978	8	0.973	8	0.980
22	0.969	22	0.977	34	0.967	10	0.971
27	0.966	19	0.975	10	0.966	34	0.971
15	0.962	15	0.968	30	0.960	30	0.962
4	0.961	17	0.967	11	0.952	3	0.960
17	0.956	4	0.965	3	0.952	11	0.958
24	0.936	24	0.955	23	0.951	28	0.955
20	0.935	20	0.943	28	0.946	19	0.955
26	0.934	26	0.941	18	0.946	23	0.952
11	0.914	11	0.922	19	0.941	18	0.952
30	0.907	31	0.922	13	0.936	13	0.948
31	0.902	30	0.921	24	0.936	24	0.945
3	0.894	3	0.903	9	0.929	16	0.936
8	0.885	8	0.896	16	0.924	12	0.934
23	0.883	16	0.888	12	0.924	9	0.932
16	0.877	23	0.886	20	0.922	20	0.925
12	0.877	12	0.884	31	0.916	17	0.921
7	0.852	7	0.862	17	0.909	31	0.919
18	0.822	18	0.832	27	0.909	27	0.919
28	0.804	28	0.823	7	0.906	7	0.916
29	0.793	29	0.810	25	0.905	25	0.915
21	0.740	21	0.752	29	0.874	29	0.884

4.2. Weight allocation and required improvement priorities

Since the model not only pursues the optimal index score for each individual, but also guarantees acceptable weights through the imposed restrictions, in addition to the ranking of the drivers, more detailed insight can be gained from the assigned weights which can be interpreted as indications of the importance shares of the corresponding indicator. Fig. 4 shows the assigned weights and shares (the values in brackets) for the case of the driver 28 as a worst performer at curve 1, in the data set. As can be seen, the performance with respect to all three driving parameters is taken into account in the overall score with the share of speed equal to 32.48 %, that of acceleration 25.62 % and that of lateral position 41.90 %. Moreover, the index score is influenced most by the driver's performance at the curve (i.e., P4, P5, and P6) to which a weight of 0.5 or 0.6 is given.

More importantly, based on the principle of the MLDEA-CI model, an indicator is assigned a high weight if the driver performs relatively well on that aspect. On the contrary, low weights provide us with valuable information about the aspects requiring most attention for improvement. Therefore, areas of underperformance can be detected, and required improvement priorities can be formulated. Taking the indicators of speed, acceleration and lateral position related to driver 28 as an example, it can be seen that this person is doing relatively well with respect to the lateral position aspect (with the highest share of 41.90%) whereas more attention should be paid to the acceleration parameter (with the lowest share of 25.62 %), especially at P3 before curve, and P7 after curve.

Such a result can be further confirmed by checking the result of this driver at curve 2, in which the share of speed, acceleration and lateral position equal to 35.39%, 25.52% and 39.09%, respectively, verifying that acceleration is indeed the most problematic aspect for this driver.

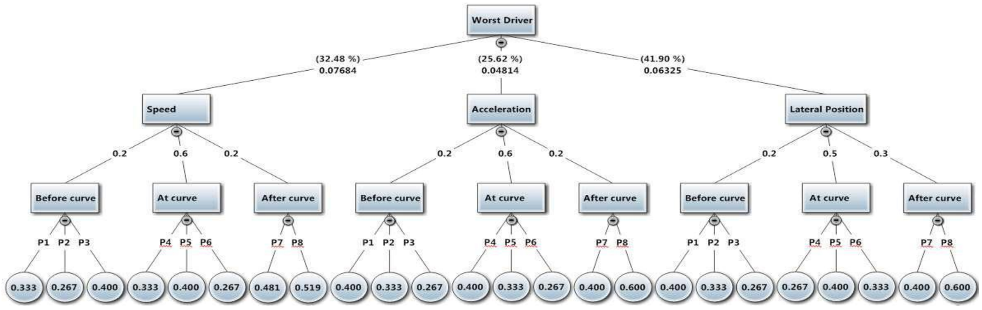


Fig. 4. Assigned weights and shares from the model for the case of driver 28, based on his performance at curve 1.

4.3 *Comparison of typical drivers in terms of driving performance parameters*

In order to make a comparison between best-performing and underperforming drivers, their performance in each aspect is depicted in the following sections.

Speed

Fig. 5 shows the speed of driver 1 as the best-performer versus driver 29 as the worst-performer. The best performer drives smoothly and respects the posted speed limit at both curves. The underperforming driver, on the contrary, can be labeled as worst-performer either because of the high speed or evasive changes along the curve. As can be seen from the graph, the driver needs to correct his performance while approaching and departing the curve. Regarding driver 28, he had a high speed and evasive change while approaching the curve at curve 1, but did relatively good in parallel to best performer and had better speed selection. It can be the proof and a kind of validation why he is at the bottom of ranking at curve 1, but had better position at curve 2.

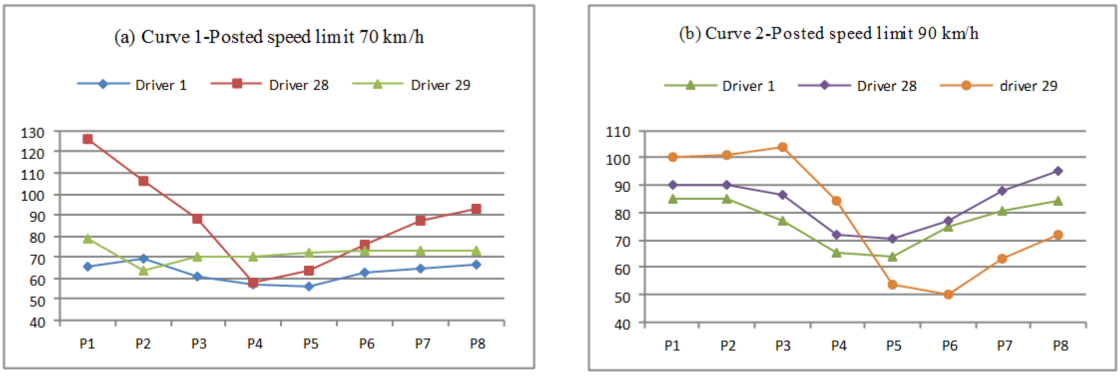


Fig. 5. The speed of driver 1 (the best-performer), driver 29 (the worst-performer), and driver 28.

Acceleration

The total acceleration can be decomposed into longitudinal acceleration and lateral acceleration. The longitudinal acceleration, indicating how fast a driver changes his/her speed, is shown in Fig. 6 (a,c). According to Lamm & Chouriri (1987), the observed deceleration rates when approaching horizontal curves should not be significantly different from -0.85 m/s^2. Others proposed higher acceptable values up to -1.34 m/s^2 and -1.8 m/s^2 (Hu & Donnel, 2010). It can be seen that the worst-performer exceeded dramatically the maximum threshold when approaching the curve. The result is consistent with the priorities we stated in Section 4.2. for driver 28. In addition, the lateral acceleration - indicative of how fast a driver changes its direction- shown in Fig. 6 (b,d) confirms inappropriate driving behavior of the driver 29 and driver 28.

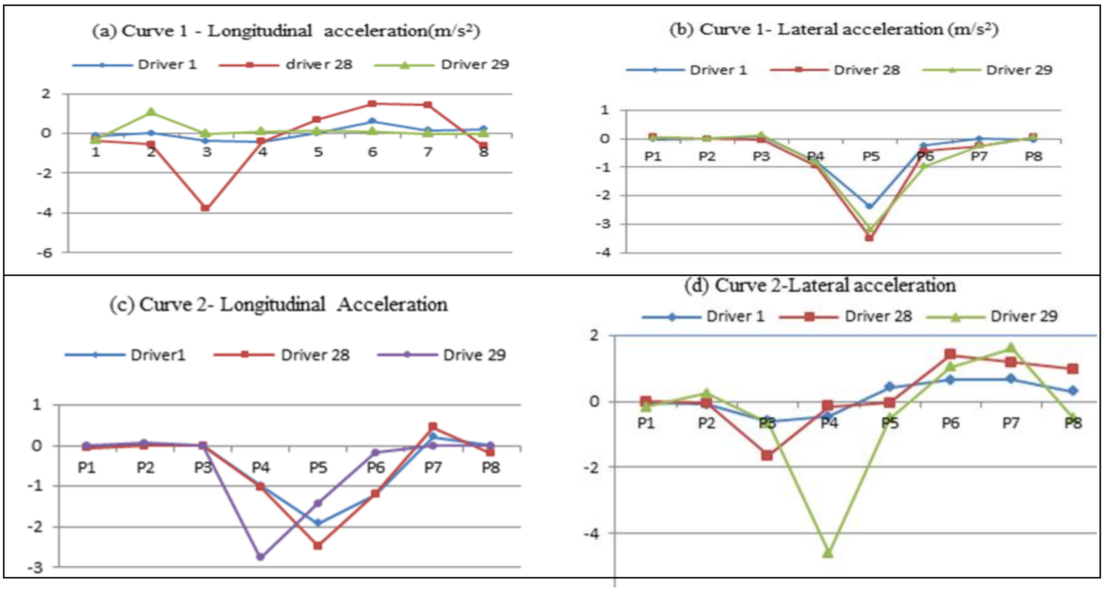


Fig. 6. The acceleration of driver 1(the best-performer), driver 29 (the worst-performer) and driver 28.

Lateral position

When driving, it is commonly accepted that the higher the variability in the lateral position of a vehicle, the less safe a driver (COST, 1999). By comparing the performance of the best-performer and the worst-performer with respect to their lateral positions in this experiment, as shown in Fig. 7, it can be noted that the worst performer, i.e., driver 29, was involved in more dangerous situations. However, according to the threshold of lateral position indicated in Table 3, it should be mentioned that although the best-performer in this experiment was doing better than the other two drivers, he was still not doing perfect, and improvement is still needed.

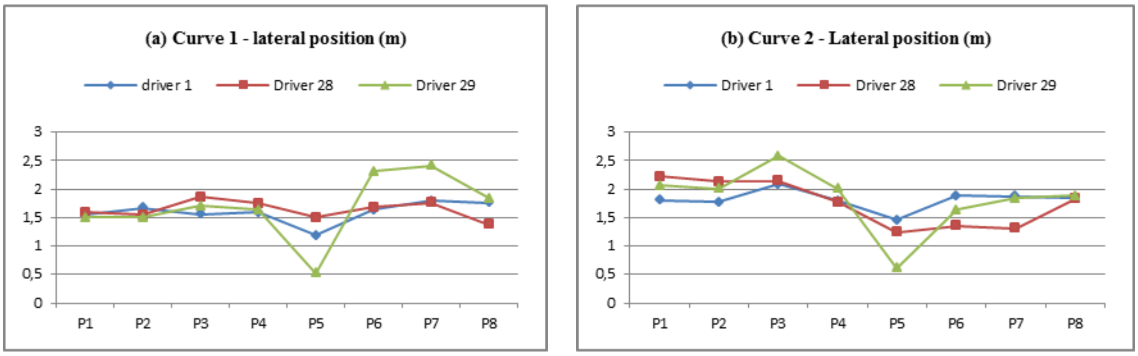


Fig. 7. The lateral position of the best-performer versus the worst-performer

5. Conclusion

In this study, we developed an overall driving performance index for drivers' evaluation at the individual level. In doing so, a multiple layer DEA-based composite indicator model was applied on a hierarchy of driving performance indicators, deduced from a driving simulator experiment. Based on this model the most optimal driving performance index score for each of the 34 drivers was determined by combining all the 24 hierarchical indicators. Apart from identifying the best-performing and underperforming drivers, all drivers were ranked based on their calculated index scores, and their relative performance respecting to speed, acceleration, and lateral position was attained. In addition, based on the principle of the MLDEA-CI model, an indicator is assigned a high weight if the driver performs relatively well on that aspect. On the contrary, low weights indicate the aspects requiring most attention for improvement. Therefore, areas of underperformance were detected, and required improvement priorities formulated. It should be mentioned that the focus of this study was on the methodological contribution in this phase. it's a data-driven approach and more attention will be paid with respect to the classification and grading in the future. Based on the research, we can conclude that the MLDEA-based CI methodology is valuable for driver's evaluation at the individual level and for the identification of the most problematic aspects of driving, which in turn is helpful for more customized training purposes; drivers can be trained in specific tasks in the simulator, according to each driver's weakness, thereby improving driving abilities and the level of road safety. Also, regarding the future usefulness of the results, there are opportunities in terms of selecting candidates for driving jobs, identifying high risk drivers, improving the rating process and rewarding low risk drivers.

6. Limitation and future resarch

The issue of external validity is often raised when discussing the results of research employing driving simulations. Although moving base simulators provide a more correct rendering of real driving behavior and a greater degree of realism (Bella, 2009), there are strong indications that geometric design issues are examinable in a fixed-base driving simulators in a perfectly adequate way (e.g., Bella, 2008; Calvi, 2012). In addition Bella (2008) and Godley et al. (2002) concluded that speed parameters can be validated as dependent measures for research using a driving simulator. Moreover, the simulator used in this study is equipped with a 180° field of view, which satisfies the prescribed minimum of 120° field of view for the correct estimation of longitudinal speed (Kemeny & Panerai, 2003). Furthermore, Mayhew et al. (2011) suggest that on-road performance and performance on the simulator are significantly related. Their findings prove that the simulator can be used as a valid measure for assessing driving performance for research purposes and are consistent with other research (Bella, 2008) that has found simulation can provide a valid index of driving performance. Although this literature provides a good indication for the reliability of a driving simulator for this research, future research would involve the validation of the speed and lateral position measurements on the road in the same curve configurations. Moreover, future research on the composite driving performance index can be done concerning the data, i.e. adjusting the model in order to allow the use of raw data instead of assigned grades to different indicator clusters. In addition, different road types and speed limits or other sections of road (e.g., intersections) would be worthwhile to consider. Furthermore, in the future, beside the data of driving simulator performance, personality and psychometric tests and driver's crash records, would be useful to combine in order to construct optimal driving performance index scores.

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