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MEASURING DRIVER'S RELATIVE PERFORMANCE OVER TIME USING DEA AND WINDOW ANALYSIS

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Among different road user types, drivers represent the largest share of road fatalities. As a result, more attention should be paid to the behavior of drivers, especially their behavior over time. By using driving simulator data, this study aims to investigate the relative performance of individual drivers over time. To this end, 20 participants (14 in the end) completed a particular simulator scenario over five days, and their driving performance at various points along the driving scenario was recorded. By taking all this information into account, the technique of data envelopment analysis was applied to assess the relative performance of each driver, and the window analysis was used to measure the variations in performance over time.

1. Introduction

To obtain a clear understanding of driving behavior of different drivers, driving performance evaluation in the manner of constructing a composite indicator (CI) is often applied [1]. It has an advantage of taking the multi-dimension of driving performance into account. However, the variation in driving performance over time is often ignored, which in fact, is of great importance due to the subjective nature of human behavior. For instance, a driver can behave differently when taking the same curve in different days. As a result, the driving performance of a driver should be evaluated not only at a specific point of time but also over a time period.

Horizontal curves, particularly on two-lane rural roads, have been recognized as a significant safety issue for many years [2]. In this study, we aim to evaluate the driving performance of a group of drivers over time when taking a curve, based on data from a fixed-based driving simulator. In doing so, data envelopment analysis

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(DEA), one of the promising benchmarking techniques [3], is applied to measure the relative performance of a set of decision making units (DMUs), or drivers in this study, and window analysis [4] is employed to examine the variations in performance of different DMUs over time. To our current knowledge, it is the first time that these two techniques have been applied simultaneously for driving performance evaluation.

2. Data collection

In this study, an experiment of curve taking was conducted on a fixed-based medium-fidelity driving simulator (STISIM M400) available at Transportation Research Institute (IMOB). The road width around the curve is 2.8m, with a posted speed limit of 70 km/h. In total, 20 volunteers participated in this study. However, six participants were excluded from the further analysis, two due to simulator sickness during the training period and four due to missing data. Thus, 14 participants (8 men) between 18 and 54 years old (mean age=26.32; standard deviation=10.47) remained in the sample. During the simulator driving, all participants completed five same trips of 16.2 kilometers for five different days (the curve was included in the trip), and each day, their driving performance around the curve was monitored along the driving scenario.

According to the European Safety Handbook in Secondary Roads [5], the speed, acceleration, and lateral position are the three most important and most commonly used parameters to describe and analyze the curve taking behavior of a driver. Therefore, amongst various parameters recorded by the driving simulator, the aforementioned three parameters are considered for this study at eight different measurement points along the driving scenario, i.e., P1=500m before curve, P2=166m before curve, P3=50m before curve, P4=curve entry, P5=middle of the curve, P6=curve end, P7=50m after curve, and P8=100m after curve. As a result, 24 indicators (3 parameters × 8 measurement points) in total are used for driving performance evaluation.

3. Methodology

Data envelopment analysis is one of the most commonly used techniques for performance evaluation [3]. It is a non-parametric optimization technique using a linear programming tool to measure the relative performance of a set of DMUs, or drivers in this study. Lately, considerable attention has been paid to the application of DEA in the construction of CIs [6,7]. Suppose that a set of N DMUs is to be evaluated in terms of s indicators (y), the DEA-based CI can be formulated as follows:

$$
\begin{aligned}
& CI_o = \max \textstyle\sum_{r=1}^{s} u_r y_{ro} \\
& \text{s.t.} \\
& \textstyle\sum_{r=1}^{s} u_r y_{rj} \leq 1 \qquad && j = 1, \dots, N \\
& u_r \geq 0 && r = 1, \dots, s
\end{aligned}
\tag{1}
$$

where u_r is the set of weights for DMU under evaluation (i.e., DMU_0).

By solving the above linear programming problem, the best possible indicator weights are determined, and an optimal index score between zero and one is obtained for each unit, with a higher value indicating a better relative performance. In this study, to take the layered hierarchy of the indicators (the 3 parameters are located at the first layer and the 8 measurement points for each parameter are located at the second layer) into account, a multiple layer DEA-based composite indicator (MLDEA-CI) model [8,9] is adopted.

Thereafter, to detect the trend in driving performance of each driver over time, the window analysis [4] is employed, which is a method for examining the variations of performance of DMUs calculated from DEA over time. It assesses the performance of a DMU by treating it as a different DMU in each time period. Therefore, the performance of a DMU in a particular period is contrasted with its own performance in other periods in addition to the performance of other DMUs. The procedure of performing the window analysis is summarized here [10]: Consider N DMUs $(n = 1, \dots, N)$ observed over T periods $(t = 1, \dots, T)$, the sample thus has $N \times T$ observations. The window analysis consists of choosing the window length K and then evaluating $N \times K$ DMUs for each window. One who performs the analysis has to determine the length of the window, i.e., K. According to [11], when the time period is odd, the window length could be set to $(T+1)/2$, and when it is even, it is $(T+1)/2 \pm 1/2$. When the window length K is determined, we shift the window forward one period each time until the last period is reached. That is, the data of period $1, 2, \dots, K$ form the first window row, and the data of period $2, 3, \dots, K+1$ form the second row, and so on. In general, a total number of $T - K + 1$ windows exist, and each one comprises a K set of data.

Now we continue based on our data set, in which data are available for 14 $(= N)$ drivers over 5 $(= T)$ daily periods. We therefore perform analysis using a window length of $3\,(= K)$ days. Accordingly, in each window, the number of drivers against which the comparison in terms of driving performance occurs, is tripled because each driver at a different day is treated as an independent unit.

For this study, the MLDEA-CI model is applied first to evaluate the relative performance of all drivers in the same window, and the index score of each driver, $I_{i,j}^{n}$, is entered in the right window position in Table 1.

The procedure is repeated 3 times to obtain the index values in all windows. The average of the 9 index scores is presented in the column denoted “Mean index” and the variance among them is shown in the column denoted “Variance”. The variance is representative of the fluctuation in performance index scores of each driver. A driver with a higher average index score and a smaller variance obtains a better ranking compared to other drivers. For comparing the fluctuations in index scores among the drivers, the column range, $CR_{n,t}$, can be used. For each driver, $CR_{n,t}$ is the difference between the largest and the smallest index scores for driver *n* in period *t.* While, $CR_{n,t}$ can be used to evaluate the stability of the index scores of a driver in each period, CR_n which is the overall column range for driver n, shows the greatest variation in index score of a driver over different periods. Moreover, to understand the stability of a driver over different periods, the total range, TR_n can be used, which represents the difference between the maximum and minimum index score of a driver in all windows. For $CR_{n,t}$, CR_n, and TR_n , the smaller the value, the more stable index score of a driver.

Table 1. Window analysis of driver *n*, with a 3-days window (X: Omitted).

Driver	Period	Day1	Day 2	Day 3	Day 4	Day 5	Mean index	Variance	Column range	Total range
n	W_1	$I_{1,1}^{n}$	$I_{1,2}^{n}$	$I_{1,3}^{n}$						
	W_2		$I_{2,2}^{n}$	$I_{2,3}^{n}$	$I_{2,4}^{n}$					
	W_3			$I_{3,3}^{n}$	$I_{3,4}^{n}$	$I_{3,5}^{n}$				
	$CR_{n,t}$	x	$CR_{n,2}$	$CR_{n,3}$	$CR_{n,4}$	x	M_n	V_n	CR_n	TR_n

4. Results

To assess the driving performance of the 14 drivers over time, we carry out DEA window analysis using the values of 24 driving performance indicators for each driver over 5 days. Table 2 illustrates the results of the best and the worst driver in this group. The column views show the stability of results at the same days, and the row views make it possible to determine the trend of drivers’ performance at different days. Observing the DEA window analysis results in Table 2, driver number 3 with the highest mean index score of 0.9926 is located at the top of the drivers’ ranking, while driver 7, with the lowest mean index score of 0.7654 is ranked at the bottom. The highest mean index score, together with the lowest variance of 0.0001 reveal driver number 3 as the best performer within the group and indicate that this driver has very stable performance over different days. This is also justified by its lower column range (0.0084) and total range (0.0218), compared with that of driver 7.

Table 2. Index scores of the best and the worst drivers using DEA window analysis.

	Day1	Day 2	Day 3	Day 4	Day 5	Mean index	Variance	Column range	Total range
Driver 3									
W_1	0.9820	1	1			0.9926	0.0001	0.0084	0.0218
W_2		1	1	0.9782					
W_3			1	0.9867	0.9864				
$CR_{3,t}$	x	0	0	0.0084	x				
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Driver 7									
W_1	0.7794	0.7520	0.7645			0.7654	0.0003	0.0234	0.0491
W_2		0.7520	0.7643	0.7394					
W_3			0.7860	0.7627	0.7885				
$CR_{7,t}$	x	0	0.0217	0.0234	x				

5. Conclusion

In this study, we introduced DEA and window analysis to evaluate the driving performance of a driver over time. Data from a driving simulator study of curve taking were used for illustration. Specifically, the MLDEA-CI model was applied first to evaluate the relative performance of all the drivers under study in each window and the optimal driving performance index score between zero and one for each driver was determined by combining 24 hierarchical indicators, with a higher value indicating a better relative performance. Next, by performing window analysis, all the drivers were ranked based on their mean index scores calculated from all the windows, and their relative driving performance over time was captured based on the variance, the column range, and the total range of their index scores.

To conclude, this study suggests the DEA window analysis as a promising approach for driving performance evaluation, because it can take into account not only the multi-dimension of driving performance, but also the variation in performance over time. In the next step, the validation of the results will be investigated, other parameters/indicators such as the standard deviation of the lateral position instead of the absolute lateral position will be tested, and the relationship between driving performance and other criteria such as workload will be studied.

References

1 Babaee, S., Shen, Y., Hermans, E., Wets, G., Brijs, T. and Ariën, C., Combining driving performance information in an index score: a simulated curve-taking experiment. *Transport. Res. Rec.*, 2434, 44-51 (2014).

2 SafetyNet, Roads, (2009). Retrieved on July 12, 2011.

3 Charnes A., Cooper W. W. and Rhodes E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.*, 2, 429-444 (1978).

4 Charnes, A., Clark, C.T., Cooper, W.W., and Golany, B., A development study of data envelopment analysis in measuring the efficiency of maintenance units in the US air forces. *Ann. Oper. Res.*, 2, 95-112 (1985).

5 Gatti, G., Polidori, C., Galvez, I., Mallschutzke, K., Jorna, R., Van de Leur, M., Dietze, M., Ebersbach, D., Lippold, C., Schlag, B., Weller, G., Wyczynski, A., Iman, F. and Aydin, C. Safety Handbook for Secondary Roads. Final Report. Contract No. 508164, RIPCORD-ISEREST Deliverable D13 (2007).

6 Hermans, E. A methodology for developing a composite road safety performance index for cross-country comparison. PhD thesis, Hasselt university, Hasselt, Belgium (2009).

7 Shen, Y., Hermans, E., Bao, Q., Brijs, T., Wets, G., and Wang, W., (2015). Inter-national benchmarking of road safety: state of the art. *Transport. Res. C-Emer.*, 50, 37-50 (2015).

8 Shen, Y., Hermans, E., Ruan, D., Wets, G., Brijs, T. and Vanhoof, K., A generalized multiple layer data envelopment analysis model for hierarchical structure assessment: A case study in road safety performance evaluation, *Expert Syst. Appl.*, 38, 12, 15262–15272 (2011).

9 Shen, Y., Hermans, E., Brijs, T. and Wets, G. Data envelopment analysis for composite indicators: A multiple layer model. *Soc. Indic. Res.*, 114, 2, 739-756 (2013).

10 Asmild, M., Paradi, J. C., Aggarwall, V., and Schaffnit, C., Combining DEA window analysis with the Malmquist index approach in a study of the Canadian banking industry. *J. Prod. Anal.*, 21, 67-89, (2004).

11 Cooper, W. W., Seiford, L. M., and Tone, K., A comprehensive text with models, applications, references, and DEA-Solver software. Second edition, New York, Springer. (2007).