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Data Envelopment Analysis for the assessment of road safety in urban road networks: A comparative study using CCR and BCC models

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Abstract

Nearly 1.35 million people are killed annually on roads around the world and an additional 50 million are injured or disabled. Road traffic crashes are estimated to be the eighth leading cause of death globally for all age groups, the first among children and young people aged 5-29 years. These numbers highlight the urgency of the road safety issue for all governments and administrations. In their efforts to improve safety, road network managers can benefit from decision support tools able to assist them in monitoring and managing road safety interventions. This paper proposes a DEA-based decision support method to assist urban road safety management practitioners in identifying those roads where the needs to improve safety are the greatest. The method is applied to an Italian urban road network to define a hierarchy of hazardous road locations based on safety conditions. The social cost of accidents is used here for the first time as the only output indicator while the average number of conflict points at intersections and traffic flow are used as inputs. Both Constant Returns to Scale and Variable Returns to Scale DEA models, each oriented to input and output, are used. The comparison of the results makes it possible to identify the DEA model that seems best suited to be used as a decision support tool to advise urban road safety management by enabling a more careful definition of targeted priority lists of interventions.

Keywords: Benchmarking Road Safety; Data Envelopment Analysis; Risk Evaluation; BCC and CCR models

1. Introduction

Road accidents are today one of the most critical health and social issues. They are estimated to be the eighth leading cause of death globally for all age groups and the first cause for children and young people aged 5–29 years. According to the latest World Health Organization (WHO) Global Status Report on Road Safety, about 1.35 million people die each year as a result of a road accident while 50 million people are reported to be injured (WHO, 2018). Low- and middle- income countries are the most affected, accounting for more than 90% of the world's road traffic deaths. The road traffic death rate is over three times higher in low-income countries than in high-income countries. Road crashes cause major social costs not only in terms of increased travel times and property damage but above all in relation to the consequent human life losses and serious injuries that place heavy burdens on households as well as on national economies. Every year, road traffic injuries are estimated to cost $518 billion USD worldwide and $65 billion USD in low- and middle-income countries; the latter exceeds the total amount that these countries receive in development assistance (WHO, 2018).

Within this context, an increasing number of countries are taking actions and initiatives to promote road safety and several supporting strategies and programmes have been launched and put into effect in the last years (EC, 2010). The European White Paper on Transport Policy (EC, 2001) targeted the objective of halving the overall number of road deaths in the European Union by 2010. This challenging objective was missed in 2010 (the EU mean value was -35%) but updated and reinforced in the Road Safety Programme 2011-2020. In the Communication of 20 July 2010 "*Towards a European road safety area, policy orientations on road safety 2011-2020*", the EU Commission stated the strategic objectives of the EU to halve the number of road deaths by 2020 compared to 2010 and to move close to zero fatalities by 2050 (EC, 2010). A new interim target of halving the number of serious road injuries by 2030 from the 2020 baseline was then endorsed in the Valletta Declaration of March 2017 (Valletta Declaration, 2017). In 2018, in the framework of an overall road safety strategy, the EU Commission adopted the proposal for a revised directive amending the existing Directive 2008/96/EC on road infrastructure safety management, also known as RISM Directive (EC, 2008). The new Directive 2019/1936, which came into force on 16 December 2019 and has to be transposed into national law by Member States by 17 December 2021 (EC, 2019), intends to address the shortcomings of the previous Directive 2008/96/EC by strengthening road infrastructure safety management procedures and extending the scope beyond the TEN-T network. It recognizes risk-based network-wide road safety assessment as an effective tool to identify road sections that require more attention and to prioritise interventions to improve safety. It also stresses that to improve safety performance of existing roads, investments should be targeted at road sections that show the highest accident concentration and the highest accident reduction potential.

One possible way to monitor and evaluate road safety performance is by using dedicated indicators. The European Transport Safety Council (ETSC) defines safety performance indicators as any measure causally related to accidents or injuries, used in addition to a count of accidents or injuries in order to assess safety performance or understand the process that leads to the accident (Hermans et al., 2009). The importance of setting performance targets was first highlighted in the United Nations General Assembly Resolution A/70/260, adopted in April 2016 (UNGA, 2016). In the same year, the WHO in collaboration with other United Nations agencies and the United Nations regional commissions, started a process of developing voluntary global performance targets on road safety risk factors. A comprehensive set of 12 voluntary global performance targets for road safety was developed in November 2017 by Member States. An informal consultation of Member States on road safety indicators guided by the discussion paper developed by the WHO (WHO, 2017) was convened in February 2018. During the meeting, representatives of more than 35 Member States reached consensus on a set of indicators covering process and outcomes for each of the 12 global targets. Indicator values may vary from country to country depending on the specific policy measures applied concerning, among other things, regulations on the use of alcohol and drugs when driving, speed limits, obligations on protective systems and so on (Safetynet, 2005). Methodologies for estimating safety performance of highways and streets to inform the highway transportation decision-making process are also provided in The Highway Safety Manual (AASHTO, 2010). The latter is a guidance document for incorporating quantitative safety analysis into highway transportation project planning and development processes. It includes, a.o., guidance for the identification of sites with potential for crash or severity reduction, project prioritization, predictive methods for infrastructure improvement project alternative analysis.

Due to the large amount of data and factors involved, decision-making in the road safety policy context is far from simple (Dell'Acqua et al., 2011). Decision makers often have to make complex decisions regarding the use of public funds in a framework that prioritizes a limited number of interventions within a tight budget. In this regard, a hierarchy of hazardous road sections based on safety conditions can represent a useful tool for supporting decision-making, as it enables transportation managers to establish intervention priorities for future actions. This paper proposes and tests a decision support method based on Data Envelopment Analysis (DEA) to assist road safety management practitioners in identifying those road sections where the needs to improve safety are the greatest. While in the road safety field, DEA has become popular mainly for comparing countries (Hermans et al., 2009) or provinces (Amelian et al., 2017) on the performance of different risk aspects of their road systems, in this study DEA is applied to an urban road network in order to create a list of intervention priorities based on safety conditions. Specifically, the case study concerns the urban road network of a medium-sized Italian city. Four DEA models are tested to identify the one that seems best suited to be included in the decision support tool for defining priority lists in road safety interventions, and thus provide a decision framework to advise urban road safety management. To this end, both BCC (Variable Returns to Scale) and CCR (Constant Returns to Scale) DEA models are used, each oriented to both inputs and outputs. Comparison of the results makes it possible to identify the model that best suits the peculiarities of the application case.

The paper is structured as follows: Section 2 presents a summary table of multi-criteria decision-making methods applied to road safety with a focus on DEA applications. Section 3 provides a basic explanation of DEA and introduces the evaluation model that was designed for the specific case study. Section 4 illustrates the application, the methodology used and the experimentation results. Section 5 discusses and compares the results of the four DEA models applied. Section 6 concludes and, with a view to method transferability, summarizes the basic methodological steps for applying the proposed DEA-based decision support tool to other territorial contexts.

2. An overview of the literature on DEA and other multi-criteria decision-making methods for road safety

Road safety performance are typically based on different criteria related to diverse aspects of the phenomenon. In the past two decades, there has been a growth of interest by policy makers in the use of composite indices for road safety assessment that aggregate in a summary indicator the various parameters at hand (Coll et al., 2013; Chen et al., 2015; Castro Nuño and Arévalo-Quijada, 2018). Most of the available methodologies for assessing road safety composite indicators rely on multi-criteria decision-making (MCDM) methods (Sarrazin and De Smet, 2016), each with its own advantages and disadvantages (El Gibari et al., 2019; Wątróbski, 2016; Velasquez and Hester, 2013). Table 1 summarizes the main strengths and weaknesses of the most common MCDM methods in the light of their application to road safety performance.

Table 1. Synoptic table of the most common MCDM methods applied to road safety performance.

Method	Strengths	Weaknesses	Examples of application to road safety

AHP - Analytic Hierarchy Process	Easy to use. Scalable.	Susceptible to rank reversal. Problems of interdependence between criteria and alternatives. Can be subject to inconsistencies in judgment and ranking criteria.	Agarwal et al., 2013; Khorasani et al, 2013; Yuan et al., 2013
BA - Budget Allocation	Easy to implement.	Primarily based on experts' opinions, can result in biased weightings.	Hermans et al., 2009b
Concordance Analysis	Identifies the best choice ("α problem").	Cannot be used for ranking purposes, unless by forcing the model.	Fancello et al., 2015
DEA - Data Envelopment Analysis	Quantifies efficiency. Rates the efficiency of alternatives against each other. Can handle multiple inputs and outputs.	Assumes that all inputs and outputs are exactly known.	Antić et al., 2020; Ganji and Rassafi, 2019b; Alper et al., 2015; Bastos et al., 2015; Sadeghi et al., 2013; Shen et al., 2011; Hermans et al., 2009
EWM - Equal Weighting Method	Easy to implement.	Implies assumptions of equal importance of the indicators.	Nardo et al., 2005; Saisana and Tarantola, 2002.
ELECTRE	Takes into account uncertainty and vagueness.	Outcomes can be hard to explain in practical terms. The lowest performances under certain criteria are not identifiable. Not useful for ranking purposes involving the allocation of public financial resources (it requires three thresholds defined a priori by the user)	El Mazouri et al., 2019; Fancello et al., 2014; Fancello et al., 2015
MAUT – Multi-Attribute Utility Theory	Takes uncertainty into account. Can incorporate the preferences of the decision makers.	Data intensive. Requires strong assumptions and can be subjective.	Rassafi et al., 2018
PROMETHEE – Preference Ranking Organization Method for Enrichment Evaluation	Easy to use. Eliminates scale effects among alternatives.	Requires the assignment of weights but does not provide a clear methodology to assign values.	Castro-Nuño and Arévalo-Quijada, 2018; Sarrazin and De Smet, 2015.
TOPSIS - Technique for Order Preferences by Similarity to Ideal Solutions	Easy to use. Maintains the same amounts of steps regardless of problem size.	Does not consider attributes correlation. Difficult to weight attributes.	Chen et al., 2015; Rosić et al., 2017; Bao et al., 2012; Qazvini et al., 2016; Fancello et al., 2019
VIKOR	Easy to use.	The ranking-list may not include all the alternatives.	Fancello et al., 2019

Among the existing decision methods for evaluating different alternatives, DEA has been chosen for this study as, in the opinion of the authors, the following features make it an attractive tool for prioritizing road safety interventions in urban contexts:

- while some MCDM methods provide only the best solution (e.g., Concordance Analysis) or a partial ranking-list (e.g., VIKOR), DEA always returns a complete hierarchic list using a detailed score;
- differently from other MCDM methods which require subjective assumptions (e.g., Electre III, BA, MAUT), DEA does not use any subjective parameter;
- while some MCDM models (e.g., TOPSIS and VIKOR) use indicators or algorithms for which the relationship between inputs and outputs may not be immediate, DEA results are easily understood by decision makers;
- differently from other MCDM methods (e.g., PROMETHEE, EWM), DEA does not require obtaining and considering any distribution function and related assumptions;
- DEA allows to consider an input or an output approach, thus supporting decision makers both in maximizing objectives and in minimizing resources;
- the nonparametric nature of DEA, through the identification of the efficiency frontier, allows to identify not only the most efficient units but also their distance from inefficient ones (e.g., this allows to evaluate how many resources must be added for the DMU to reach efficiency);
- in road safety problems, decision makers usually have precise data to be used for inputs, which bypasses one of the DEA's main weaknesses.

Numerous studies have already recognized DEA as a powerful decision-making method for evaluating road safety performance, a.o., Ganji and Rassafi (2019) and Hermans et al. (2008a). Some selected examples of DEA applications to road safety from the most recent literature (starting from 2008) are discussed below.

The paper by Hermans et al. (2008b) implemented a DEA model to assess road safety performance of 21 EU countries based on the number of traffic fatalities per million inhabitants; in this study all indicators were treated as outputs. This model was further implemented in the paper by Hermans et al. (2009) through an optimal Road Safety Score which minimizes the ratio of weighted sum of outputs (crashes and fatalities) to weighted sum of inputs (speed, trauma management, vehicles, infrastructure, alcohol and drugs and protective systems) to compare road safety performance of 21 EU countries. The study by Shen et al. (2011) applied a DEA model based on the standard input-oriented model to compute the efficiency of 19 EU countries in terms of road safety performance. In this study, authors defined 13 behaviour of road users as the inputs of the model and introduced the number of fatalities, serious injuries and slight injuries per million people and the number of crashes per million people as outputs. Shen et al. (2012) applied DEA to draw an overall picture of the road safety risk in the 27 EU Member States. They used the measures of exposure to risk as the inputs of the model (inhabitants, passenger-kilometres and passenger cars) and the number of road fatalities as output. Egilmenez (2013) applied an input-oriented DEA model to compare road safety of 50 US states using seven inputs, including highway safety expenditure, the number of vehicles, the number of drivers, vehicle miles travelled, road length, road condition and safety belt usage rate, and the ratio of total annual time to the number of fatalities as output. Alper et al. (2015) implemented a DEA model to assess road safety performance of municipalities in Israel based on two inputs (Annual National Road Safety budget allocated to each municipality and total of teaching hours dedicated to traffic safety education) and fourteen outputs related to accidents and persons involved in accidents. A multiple layer DEA technique was implemented by Bastos et al. (2015) to benchmark road safety performance of 27 Brazilian states; mortality rate and fatality were used as the main outputs. Behnood et al. (2014) used an inverted input-oriented CCR model to evaluate a relative inefficiency index for 30 provinces of Iran. They considered as undesirable outputs the number of fatalities per kilometre and the number of fatalities per total road length. A Multi

Criterial Decision Making method for selection of optimal road safety composite index with examples from DEA and TOPSIS method was developed by Rosic et al. (2017) while Shah (2017) proposed a two-stage approach for road safety risk evaluation consisting of DEA in combination with artificial neural networks to assess the risk level of road segments and identify those characterized by high-risk. Sadeghi et al. (2013) incorporated the segmentation procedure into DEA to identify and prioritize accident-prone sections based upon efficiency concept to emphasize accidents with respect to traffic, geometric and environmental factors. Recently, Ganji and Rassafi (2019; 2019b) applied a double-frontier DEA model to assess the productivity of Iranian regional safety programmes in reducing the number of road fatalities.

Almost all the papers analyzed apply DEA as a benchmarking technique for comparing countries, states or provinces on the safety performance of their road systems and related policies: the identification of the efficiency frontier is used to identify both the most efficient units and their distance from inefficient ones. Focusing the analysis on the urban territorial context, this paper proposes and tests a DEA-based decision support tool to assist urban road safety management practitioners in identifying a hierarchy of hazardous roads based on safety conditions. The relative efficiency of each road is measured as the ratio between input and output data computed based on DEA approach.

3. The DEA method

The efficiency of a unit in relation to a group of similar process units was first evaluated by Farrell in 1957 (Farrell, 1957). Broadly speaking, the concept of efficiency is used to characterize the utilization of resources and thus the performance of processes transforming a set of inputs into a set of outputs. The concept of efficiency is relative as it implies that the performance of a unit is compared to a standard. DEA is a performance measurement technique that can be used for evaluating the relative efficiency of decision-making units (DMUs). In the application proposed in this paper, urban roads are identified as DMUs. The first basic DEA model, the so-called Constant Returns to Scale model, also known as CCR, was developed in 1978 by Charnes, Cooper and Rhodes (Charnes et al., 1978). In a typical DEA model, the objective is to compare the efficiency of similar elements based on predetermined inputs and outputs. Therefore, a DMU is considered the element to be compared. For each DMU, the efficiency is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs. A score equal to one indicates an efficient unit. The main advantage of DEA is that it does not require any subjective weighting procedure while benchmarking similar units and an overall performance score for a DMU can be derived as efficiency (Egilmez and McAvoy, 2013). The weights of inputs and outputs are thus not assigned in a subjective way by the decision-maker but attributed by the calculation model so that the efficiency of the DMU is always maximized.

To measure the relative efficiency of any $\mathrm{DMU}\ p$, the traditional DEA model is structured as a linear divisive programming problem (Beasley, 2003):

$$\text{maximize} \qquad Z_{pq} = \frac{\sum_{i=1}^{s} u_{ip} y_{iq}}{\sum_{j=1}^{t} v_{jp} x_{jq}} \tag{1}$$

subject to:

$$q = 1, 2, \dots, n \tag{2}$$

$$0 \leq \frac{\sum_{i=1}^{s} u_{ip}\ y_{iq}}{\sum_{j=1}^{t} v_{jp}\ x_{jq}} \leq 1 \qquad q = 1, \dots, n \tag{3}$$

$$u_{ip} \geq \in \qquad i = 1, \dots, s \qquad (4)$$

$$v_{jp} \geq \in \qquad j = 1, \dots, t \qquad (5)$$

where:

n	number of DMUs being evaluated;
s	number of outputs;
t	number of inputs;
u_{ip}	weight attached to i-th output ($i = 1, \dots, s$) for DMU p ($p = 1, \dots, n$);
v_{jp}	weight attached to j-th input ($j = 1, \dots, t$) for DMU p ($p = 1, \dots, n$);
y_{ip}	value of i-th output ($i = 1, \dots, s$) for DMU p ($p = 1, \dots, n$);
x_{jp}	value of j-th input ($j = 1, \dots, t$) for DMU p ($p = 1, \dots, n$);
z_{pq}	relative efficiency of DMU q ($q = 1, \dots, n$) when evaluated using the weights associated with DMU p ($p = 1, \dots, n$);
$\in$	infinitesimal constant.

Equation (1) maximizes the efficiency of the considered DMU p. Equation (2) defines the efficiencies of all DMUs q with respect to the weights chosen for p, while Equation (3) ensures that all efficiencies are between 0 and 1. Equations (4) and (5) ensure all weights of outputs and inputs are positive.
The CCR model assumes that all the DMUs operate on an optimum scale with constant returns to scale. This means that for a decision-making unit using an input X to produce an output Y, it is feasible to produce αY using αX amount of input (with α scalar).
To estimate efficiencies whether an increase or decrease in input or outputs does not result in a proportional change in the outputs or inputs, Banker et al. (1984) developed the DEA model for variable returns to scale (BCC). Both CCR and BCC models can be oriented to inputs or outputs. In input-oriented models, the objective is to continue producing the same outputs with minimum inputs, in output-oriented models the objective is to maximize outputs using the minimum amount of inputs.

In this study, both input- and output- oriented models are used to compare two different scenarios. The former is used to represent the scenario whose goal is to vary traffic flows and the number of conflict points while maintaining the same number of road accidents. The latter is used to represent the scenario whose goal is to vary the number of road accidents while maintaining the same traffic flows and number of conflict points.

3.1. Definition of the input and output parameters used in this application

This study proposes a decision support tool based on DEA to support public administrations when planning activities and interventions related to road safety. The proposed decision support tool is used to compare the safety performance of a set of urban roads based on several variables related to road safety: traffic flows, number of conflict points at intersections, number of road accidents, number of deaths and injuries in road accidents. Differently from previous studies which used an approach of road segmentation to define road segments based on parameters such as fixed length, distance between two intersections or accident factors (Abdel-Aty and Radwan, 2000; Cafiso et al., 2008; Sadeghi et al., 2013), this application considers whole urban roads as DMUs. This choice responds to the operational needs of local administrators who, in urban areas as the one analyzed, mostly act based on safety assessments conducted at the level of whole roads rather than predefined sections. Identification of urban roads as DMUs is done according to the following homogeneity criteria:

- same functionality level;
- similar capacity level;
- similar traffic flows.

Identified urban roads are treated as production units capable of generating a certain amount of accidents using selected inputs. Factors influencing the occurrence of accident must be carefully chosen to ensure that they are representative and closely linked to the safety performance of the DMUs. Inputs should be selected from among those road safety parameters that can be modified through regulatory and road engineering interventions. Furthermore, to determine the input and output values easily and rapidly, the parameters must be chosen from those already in the possession of local authorities or otherwise readily obtainable through traffic and geometric surveys. In the application proposed, the social cost of accidents is considered for the first time as the only output while the average number of conflict points at intersections and traffic flow are used as inputs. The identification of these variables has been derived from the line of research of the authors in the field of multi-criteria methods applied to road safety (Fancello et al., 2015; Fancello et al., 2019).

The first input parameter (x_1) is traffic flow divided by the length (l) of the urban road (equation 6). The x_1 parameter is calculated as the Average Annual Daily Traffic ($AADT$) divided by the length in meters of the urban road. The $AADT$ is defined as the total yearly volume of vehicle traffic on a road divided by 365 days (Board, 2010). The AADT has been divided by the length of the road in order to have a normalized parameter which allows us to compare fairly homogeneous roads even of very different lengths.

$$x_1 = {}^{AADT}/_{l} \qquad (6)$$

The second input parameter (x_2) is the average number of conflict points at intersections (equation 7). The x_2 parameter is calculated as the sum of the number of conflict points at intersections divided by the number (m) of road intersections. The number of conflict points includes all types of conflict points (diverge, merge and crossing). Let cp_z be the sum of conflict points at intersection z, x_2 can be formulated as:

$$x_2 = {}^{\sum_z^m cp_z}/_{m} \qquad (7)$$

The output parameter (y) is the social cost of accidents (SC). SC represents an aggregate measure of all the costs that road crashes inflict on the community. It includes not only material losses but also pain and suffering as defined in the Italian Legislative Decree n. 35/2011.

Let d be the number of road deaths, f the number of injuries and g the number of road accidents. The value of y is calculated using the equation and coefficients defined in the study attached to Executive Decree n.189 24/09/2012 of the Italian Ministry of Infrastructure and Transport (equation 8):

$$y = SC = 1{,}503{,}990\,€ \cdot d + 42{,}219\,€ \cdot f + 10{,}986\,€ \cdot g \qquad (8)$$

where the average cost for each death is estimated at 1,503,990 €, the average cost for an injury is estimated at 42,219 € and the average general cost of an accident with damage to persons is estimated at 10,986 €. The total SC of accidents in a given road network and in a given time horizon can therefore be calculated by multiplying the average cost per death and the average cost per injury respectively by the number of deaths and the number of injuries from road crashes, to which we add the average general cost per accident multiplied by the number of road crashes with damage to persons recorded in that network in the time horizon considered.

As is known, a DEA model identifies those units that are efficient for a combination of input-output ratios. In this research, the most efficient DMU is defined as the road characterized by the fewest accidents, injuries and deaths with the highest traffic flows and conflict points at the intersections. An efficient road is thus a road that experiences fewer undesirable outputs as a result of more desirable inputs. Therefore, to make data appropriate for the basic DEA model standards and maintain the goal of inputs minimization and outputs maximization, in this study data are modified by inversing values of both inputs (traffic flows and number of conflict points) and outputs (number of road accidents and number of deaths and injuries). A similar inverted approach has been applied in Shen et al. (2012) and Ganji and Rassafi (2019).

4. Application

This section illustrates the application area and data, the methodological steps used to apply DEA to the selected case study and presents the numerical results.

4.1 Application area and identification of DMUs

The case study of interest concerns the urban road network of Villacidro, Sardinia (Italy). Villacidro is a medium-sized town (13.888 inhabitants as of December 31st, 2018) with a dense road network characterized by a high number of intersections and low traffic volumes. The Strategic Plan of the road map of Villacidro was approved in 2015 and, according to analyses on traffic flows and road safety, it identified nine urban roads as being more hazardous. These nine roads constitute the decisional set of the proposed DEA application; they meet the homogeneity criteria defined above:

- they are all urban arterial roadways, as defined in the Villacidro Strategic Plan;
- they are characterized by similar traffic volumes (average AADT > 2,700 vehicles/day);
- they have similar capacity (average capacity > 1,200 vehicles/hour).

Figure 1 shows the road map of the selected urban area; the nine roads of interest are identified through an ID.

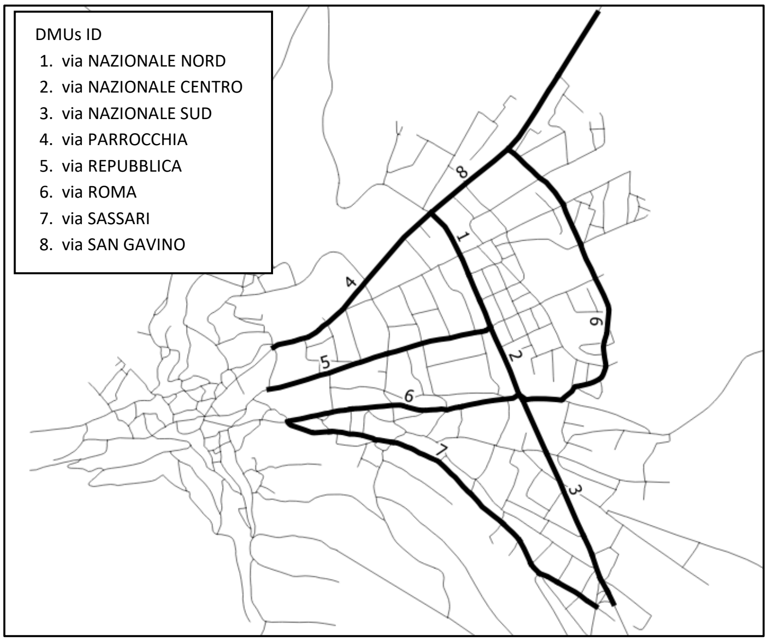

Figure 1. Road map of Villacidro.

4.2 Application data

Input (x_1, x_2) and output (y) values were determined for each road forming part of the decisional set, specifically:

- AADT data (x_1) were taken for granted from the Strategic Plan of Villacidro;
- data on the length of roads (l) were derived from the dwg maps of the Strategic Plan of Villacidro;
- the number of conflict points (x_2) was calculated as the sum of diverging, merging and crossing conflict points at the various intersections;
- the social cost (y) was calculated according to equation (8) using data on road deaths, injuries and accidents from 2009-2013.

Table 2 lists both input (x_1, x_2) and output (y) values for each DMU.

Table 2. Input and output values for the nine DMU's.

DMU ID	$1/x_1 = l/(AADT)$	$1/x_2 = m/(\sum_z^m cp_z)$	$1/y = 1/SC$
1. via NAZIONALE NORD	0.1491547895	0.1190476190	0.0000020344
2. via NAZIONALE CENTRO	0.0619933238	0.1428571429	0.0000102935
3. via NAZIONALE SUD	0.1451540866	0.1200000000	0.0000005715
4. via PARROCCHIA	0.2384041518	0.1139240506	0.0000023399
5. via REPUBBLICA	0.2613524992	0.1571428571	0.0000030126
6. via ROMA	0.5191944619	0.2500000000	0.0000005480
7. via SASSARI	4.4557823129	0.1363636364	0.0000071752
8. via SAN GAVINO	0.2192771084	0.1304347826	0.0000055070
9. via GUIDO ROSSA	0.9726688103	0.0694444444	0.0000133019

4.3 Application methodology

To measure the efficiency score of the nine urban roads, the following four DEA models were applied to the same decisional set:

- CCR model input-oriented (hereinafter CCR-I, test n.1);
- CCR model output-oriented (hereinafter CCR-O, test n.2);
- BCC model input-oriented (hereinafter BCC-I, test n.3);
- BCC model output-oriented (hereinafter BCC-O, test n.4).

4.4 Application results

The experimentation was performed using the DEAP 2.1 freeware software developed by Coelli (1996). Tables 3 to 6 show the results of the four DEA models applied. In all the tests, each DMU was characterized through the following factors:

- score (equal to 1 for efficient DMUs, lower than 1 for less efficient ones);
- general rank (hierarchical position of the DMU);
- projection of the input and output values onto the DEA frontier (the hierarchical position of the projection on the frontier is shown in brackets);

– percentage distance between the actual value of an input (or output) and its projection. The greater the distance, the less efficient the DMU.

Table 3. Results of CCR-I, test n.1.

DMU ID	Score	Rank	Projection of $1/x_1$	Distance (%)	Projection of $1/x_2$	Distance (%)
1. via NAZIONALE NORD	0.2156	7	0.032 (7)	-78.441	0.025 (7)	-78.441
2. via NAZIONALE CENTRO	1	1	0.061 (4)	0	0.142 (1)	0
3. via NAZIONALE SUD	0.0604	8	0.008 (9)	-93.963	0.007 (8)	-93.963
4. via PARROCCHIA	0.237	5	0.056 (6)	-76.298	0.027 (6)	-76.298
5. via REPUBBLICA	0.2313	6	0.060 (5)	-76.868	0.036 (5)	-76.868
6. via ROMA	0.0253	9	0.013 (8)	-97.467	0.006 (9)	-97.467
7. via SASSARI	0.2747	4	0.524 (2)	-88.225	0.037 (4)	-72.53
8. via SAN GAVINO	0.5085	3	0.111 (3)	-49.153	0.066 (3)	-49.153
9. via GUIDO ROSSA	1	1	0.972 (1)	0	0.069 (2)	0

Table 4. Results of CCR-O, test n.2.

DMU ID	Score	Rank	Projection of $1/y$	Distance (%)
1. via NAZIONALE NORD	0.2156	7	9.4E-06 (9)	363.844
2. via NAZIONALE CENTRO	1	1	1E-05 (6)	0
3. via NAZIONALE SUD	0.0604	8	9.5E-06 (8)	1556.33
4. via PARROCCHIA	0.237	5	9.9E-06 (7)	321.912
5. via REPUBBLICA	0.2313	6	1.3E-05 (4)	332.301
6. via ROMA	0.0253	9	2.2E-05 (2)	3847.26
7. via SASSARI	0.2747	4	2.6E-05 (1)	264.032
8. via SAN GAVINO	0.5085	3	1.1E-05 (5)	96.669
9. via GUIDO ROSSA	1	1	1.3E-05 (3)	0

Table 5. Results of BCC-I, test n.3.

DMU ID	Score	Rank	Projection of $1/x_1$	Distance (%)	Projection of $1/x_2$	Distance (%)	Projection of $1/y$	Distance (%)
1. via NAZIONALE NORD	1	1	0.149 (7)	-0.001	0.119 (8)	-0.001	2E-06	0
2. via NAZIONALE CENTRO	1	1	0.061 (9)	0	0.142 (3)	0	1E-05	0
3. via NAZIONALE SUD	1	1	0.145 (8)	-0.001	0.120 (9)	-0.001	5.7E-07	0
4. via PARROCCHIA	0.998	5	0.237 (3)	-0.198	0.113 (5)	-0.198	3.2E-06	38.853
5. via REPUBBLICA	0.7446	7	0.194 (6)	-25.54	0.117 (7)	-25.54	3E-06	0
6. via ROMA	0.4552	9	0.236 (4)	-54.482	0.113 (6)	-54.482	3.2E-06	488.926
7. via SASSARI	0.5093	8	0.972 (2)	-78.171	0.069 (2)	-49.075	1.3E-05	85.385
via SAN GAVINO	0.9286	6	0.203 (5)	-7.14	0.121 (4)	-7.14	5.5E-06	0
via GUIDO ROSSA	1	1	0.972 (1)	0	0.069 (1)	0	1.3E-05	0

Table 6. Results of BCC-O, test n.4.

DMU ID	Score	Rank	Projection of $1/x_1$	Distance (%)	Projection of $1/x_2$	Distance (%)	Projection of $1/y$	Distance (%)
1. via NAZIONALE NORD	0.9997	3	0.14915	0	0.11905	0	2.035E-06 (9)	0.032

2. via NAZIONALE CENTRO	1	1	0.06199	0	0.14286	0	1.029E-05	(6)	0
3. via NAZIONALE SUD	0.2382	8	0.14515	0	0.12	0	2.399E-06	(8)	319.811
4. via PARROCCHIA	0.6913	4	0.2384	0	0.11392	0	3.380E-06	(7)	44.646
5. via REPUBBLICA	0.2751	7	0.26135	0	0.12679	-19.317	1.095E-05	(4)	263.547
6. via ROMA	0.0464	9	0.51919	0	0.106	-57.599	1.180E-05	(3)	2054.16
7. via SASSARI	0.5394	5	0.97268	-78.17	0.06945	-49.074	1.330E-05	(1)	85.388
8. via SAN GAVINO	0.5093	6	0.21928	0	0.13018	-0.196	1.081E-05	(5)	96.353
9. via GUIDO ROSSA	1	1	0.97267	0	0.06944	0	1.330E-05	(2)	0

A number of considerations can be drawn by comparing the general DMUs ranking with the ranking of the projections:

- Table 3 - CCR-I model: the ranking of the $1/_{x_1}$ projection shows only three common positions with the general DMUs ranking (1st, 3rd and 7th place) while the ranking of the $1/_{x_2}$ projection maintains six common positions (1st, 3rd, 4th, 7th, 8th and 9th place). It means that x_2 contributes to the general DMUs ranking more than x_1. Some examples can help to understand: the DMU called "via Nazionale Centro", which ranks fourth in the $1/_{x_1}$ projection and first in the $1/_{x_2}$ projection, keeps the top also of the general DMUs ranking. Conversely, "via Sassari", which ranks second when considering the $1/_{x_1}$ projection and fourth when considering the $1/_{x_2}$ projection, maintains fourth place also in the general DMUs ranking.
- Table 4 - CCR-O model: only one common position (8th place) emerges from the comparison between the general DMUs ranking and the ranking of the $1/_y$ projection. Three DMUs are in the first five places in both rankings: "via Guido Rossa", "via Sassari" and "via San Gavino" rank respectively first, fourth and third in the general DMUs ranking and third, fifth and first in the ranking of the $1/_y$ projection.
- Table 5 - BCC-I model: when comparing the general DMUs ranking, with the rankings of the $1/_{x_1}$ and $1/_{x_2}$ projections, it emerges that only two DMUs are in the first five places: "via Guido Rossa" ranks first in all rankings and "via Parrocchia" ranks fifth, third, and fifth respectively.
  Moreover, some DMUs ("via Nazionale Nord", via Nazionale Centro" and "via Nazionale Sud") which are on the top of the general DMUs ranking, are on the bottom of the two projection rankings (7th, 9th, 8th place in the $1/_{x_1}$ projection rank and 8th, 3rd, 9th place in the $1/_{x_2}$projection rank). It means that there is not a strong objective correlation between the relative efficiency and the inputs used to calculate it.
- Table 6 - BCC-O model: only one common position (8th place) emerges from the comparison between the general DMUs ranking and the ranking of the $1/_y$ projection. Two DMUs are in the first five places in both rankings: "via Guido Rossa" and "via Sassari" rank respectively first and fifth in the general DMUs ranking, and second and first in the ranking of the $1/_y$ projection. Even in this case, these differences show that there is not a strong objective correlation between the relative efficiency and the output used to calculate it.

Figures 2 to 5 show graphically the positioning of each DMU with respect to the relative distance between the real value of the data and its projection onto the efficiency frontier. The closer the point is to the origin of the axes, the greater the efficiency of the DMU. For example, looking at Figure 2, "via Roma" and "via Nazionale" are the most efficient DMUs being both very close to the origin while the most distant "via Guido Rossa" and "via Nazionale Centro" are the less efficient ones.

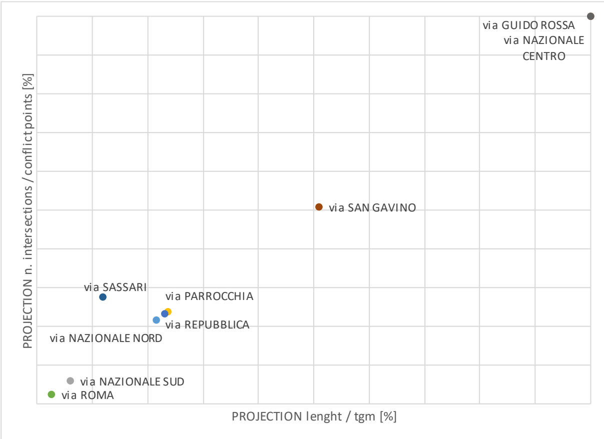

Figure 2. CCR-I, test n.1.

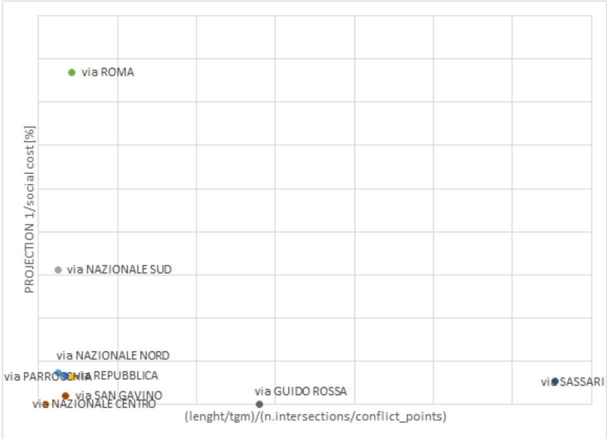

Figure 3. CCR-O, test n.2.

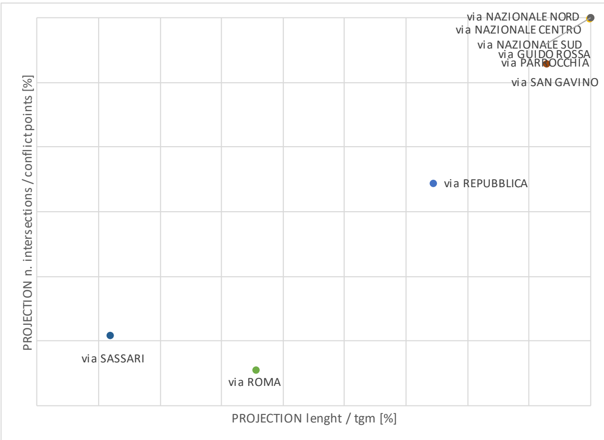

Figure 4. BCC-I, test n.3.

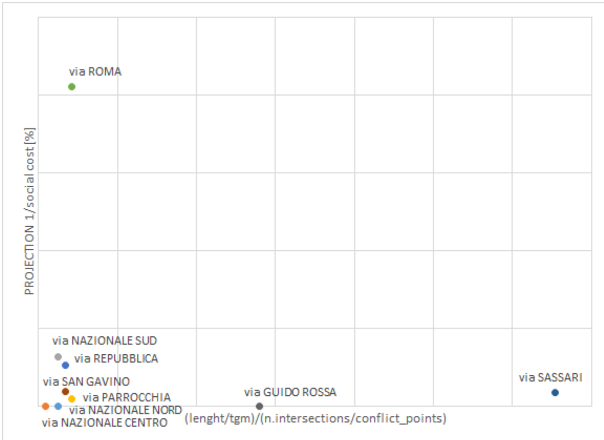

Figure 5. BCC-O, test n.2.

5. Discussion

Table 7 shows and compares the general rank of each DMU in the four tests. Looking at the results, it emerges that the rank of DMUs sometimes varies with the specific model (CCR or BCC) and approach (input- or output-oriented) used. Several considerations can be drawn from the analysis of the ranks and projection data:

- the Constant Returns to Scale (CCR) model produces the same ranking when using input- and output-oriented approaches. This is a major advantage for the application of the CCR model in road safety as it allows authorities to consider different perspectives, depending on the objectives (input- or output-oriented), while obtaining the same result;
- in the CCR input-oriented model (Table 3) the ranking seems more influenced by the "number of conflict points" variable (x_2) than by the "AADT" (x_1). It could be explained through the features of the road network examined, which is characterized by low traffic volumes and high number of road intersections. As for the CCR output-oriented model (Table 4), it is not possible to prove a direct relationship with the "social cost" output (y), being the general ranking of DMUs different from the ranking of the projections in almost all cases;

- the Variable Returns to Scale (BCC) model produces different results when using input- and output-oriented approaches. When the input-oriented approach is used, 4 DMUs out of 9 are positioned on the frontier and can be considered as equally efficient. Such a result is not useful for the purpose of the study as the model does not differentiate adequately between efficient and inefficient DMUs, thus providing a non-practical hierarchy;
- by comparing the rankings provided by the BCC input-oriented and BCC output-oriented models, it emerges that 5 DMUs out of 9 have the same rank. In the remaining cases, models can sometimes yield very different results. An example is "via Nazionale Sud", which is in first place in the BCC input-oriented test and in eighth place in the BCC output-oriented test;
- by comparing the rankings provided by the CCR (both input- and output-oriented) and BCC output-oriented models it emerges that only four DMUs out of nine maintain the same rank in the three tests.

Table 7. General rank of the DMUs in the four tests.

DMU ID	**CCR Input-oriented (Test 1)**	**CCR Output-oriented (Test 2)**	**BCC Input-oriented (Test 3)**	**BCC Output-oriented (Test 4)**
1. Via Nazionale Nord	7	7	1	3
2. Via Nazionale Centro	1	1	1	1
3. Via Nazionale Sud	8	8	1	8
4. Via Parrocchia	5	5	5	4
5. Via Repubblica	6	6	7	7
6. Via Roma	9	9	9	9
7. Via Sassari	4	4	8	5
8. Via San Gavino	3	3	6	6
9. Via Guido Rossa	1	1	1	1

These results prove the usefulness of the CCR model, both input- and output-oriented, as a convenient decision support tool for hierarchical analyses in road safety. The CCR model can indeed provide a robust hierarchy both in the case of an input or output approach. Conversely, the variability of the hierarchical results provided by the BCC model with the two approaches (input and output) makes it unsuitable for prioritizing road safety interventions, as the hierarchy provided is less stable. This is further confirmed by the impossibility to identify an objective relationship between the relative DMUs efficiency and the input and output values, as highlighted by the ranking of their projections.

6. Conclusions

This paper has proposed a DEA-based decision support procedure that could provide a decision framework to advise urban road safety management. The proposed procedure has been applied to an Italian urban road network in order to identify a list of intervention priorities based on the safety conditions of its roads. The designed evaluation model considers the social cost of accidents as the only output indicator and the average number of conflict points at intersections and traffic flow as inputs. To assess the suitability of the various DEA models to provide a robust hierarchy to be used by decision-makers for prioritizing road interventions, both BCC (Variable Returns to Scale) and CCR (Constant Returns to Scale) DEA models were applied, each oriented once to inputs and once to outputs.

The application results have made it clear that to ensure the validity of the DEA method for decision-making purposes, particular attention must be paid to the choice of the specific model to be applied. According to the application results, the CCR model seems to provide a robust hierarchy for both the input and output approaches, whereas the BCC model leads to different hierarchical results, depending on the approach used. The CCR model seems to provide a more objective and general assessment of the DMUs performance, while the BBC model appears to mainly explore the DMUs "behaviour" in terms of technical and scale differences. The CCR model may be more suitable for the definition of priority lists considering that road network practitioners usually need a general hierarchy of hazardous road locations based on safety conditions. The outcomes of the study thus confirm the usefulness of the DEA approach as a road safety decision support tool and indicate that CCR models seem better suited than BCC models to be used by road managers for defining priority lists in road safety interventions.

As for the input and output variables, the results of the application on the case study have shown that the number of conflict points at the intersections seems to affect road safety performance more than traffic flow. This may indicate that in urban contexts similar to the one analyzed (medium-sized towns characterized by dense road networks and limited traffic volumes) greater attention must be paid by road managers to reducing conflict points rather than limiting traffic.

The basic methodological steps for applying the method on other urban contexts can be summarized as follows:

1. Selection of DMUs within the urban road network based on the following homogeneity criteria (it implies the availability of data for all DMUs):
   - functionality level;
   - road capacity;
   - traffic volumes;
2. Measurement of inputs and outputs:
   - inputs: average number of conflict points at intersections and traffic flow;
   - output: social cost of accidents;
3. Choice of the approach, depending on the objectives of the analysis:
   - input-oriented: if the decision maker wants to maximize traffic flows and the number of conflict points while maintaining the same number of road accidents;
   - output-oriented: if the decision maker wants to minimize accidents while maintaining the same traffic flows and number of conflict points;
4. Application of the DEA CCR model and validation of the ranking-list.

A final consideration concerns an inherent limitation of DEA methods related to the selection of the input and output variables. As DEA is a nonparametric method that measures relative efficiency by comparing it with the possible production frontiers of DMUs with multiple inputs and outputs, its validity strongly depends on the proper choice of the input and output variables. The latter must be carefully chosen using data mining techniques to ensure that they are representative and closely linked to the safety performance of the DMU. In this study, the selection of the social cost of accidents as the only output and the average number of conflict points at intersections and traffic flow as inputs were derived from a careful data mining process conducted by the authors in previous studies.

As a future development of the research, further analyzes will be implemented to compare the performance of the CCR input-oriented and CCR output-oriented model so as to confirm their validity as a decision support instrument and highlight any differences and application specificities.

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