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Road Safety Resource Allocation Using Interactive Multiobjective Optimization

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Abstract
A model is proposed for allocating safety resources to various hazard sites. Due to budget constraints, allocation of resources for necessary countermeasures is a critical issue in safety improvement programs. Therefore, the Decision Maker needs a tool that can prioritize the identified countermeasures looking at several objectives, the most important of which are: reducing the number of accidents and minimizing the costs. A number of countermeasures could be implemented simultaneously in the same location and this was considered, so that the solution that best optimizes the objectives was selected. Since the considered objectives are not commensurable, a new methodology with interactive multi-objective optimization in the case of 0-1 integer variables was proposed, based on the application of a logical preference model built using dominance-based Rough Set Approach (IMO-DRSA). Finally, an application of the methodology is presented considering a sample of Italian urban intersections and a set of mutually exclusive alternatives at each location.

Keywords: Road Accidents, Road Safety, Budget Allocation, Decision Making, Interactive Multiple Objective Optimization, Dominance-based Rough Set Approach

1. Introduction

The road networks are composed of a large number of road sections, intersections and junctions, often built to outdated design standards applicable at the time of construction. As a result, some sites are no longer able to offer a sufficient level of performance and safety. As the available budget is often limited, good results could be achieved if appropriate countermeasures were taken at these sites. In order to obtain the best combination of safety investments for a given budget, all eligible sites would be systematically analyzed, alternative safety measures would be implemented at each site, the costs and benefits of each possible improvement would be assessed and finally the funds would be allocated according to a mathematical model. Therefore, safety engineers

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need tools that let them to use the available budget more effectively in order to obtain the maximum safety benefit.

The screening of all hazardous sites by crash analysis can be useful to allocate limited funds to achieve the greatest advantages.

Detailed studies of crash types, frequencies and patterns at these sites can help to detect system failure and identify appropriate countermeasures. Anyway, an effective approach for road safety management must also assist the Decision Maker (DM) in choosing and prioritizing projects at sites under consideration while taking into account conflicting objectives and constraints.

The purpose of this research is to give the DM a model for optimizing the allocation of road safety resources at various hazardous sites considering simultaneously different improvement projects. So, a new approach, based on an interactive multiobjective optimization in case of binary (0,1) variables, is proposed. It is used to find the optimal combination of improvements taking into account the budget constraints. The proposed methodology is based on the application of a logical preference model built using the Dominance-based Rough Set Approach (DRSA), which represents an interesting methodology for multiple criteria decision analysis (Greco et al., 2005; Augeri et al., 2011; Augeri et al., 2014; Augeri et al., 2015).

A presentation of this application at a random sample of urban intersections takes into account a number of mutually exclusive alternatives at each site. A real scale application of the methodology would normally evaluate a larger subset of intersections, but a smaller subset is used for demonstration purposes. While here, only low-cost countermeasures and a one-year analysis period are taken into account, the suggested framework is both general and scalable and can be adjusted to include various types of countermeasures, planning period, political choices, and budget.

The main objectives incorporated in the analysis are to lower the number of crashes, to minimize implementation and maintenance costs, and to maximize service life. The option that some countermeasures can be alternatively implemented or combined together at the same site is taken into account.

Since each countermeasure being considered can either be implemented or not implemented, without the possibility of partial implementation, the proposed multiobjective optimization procedure considers integer 0-1 variables (0 for "no implementation of the countermeasure", 1 for "implementation of the countermeasure").

The main difference to other methods in the literature lies in the input and processing of data, as the proposed approach is an exploratory one. Exploration does not allow identifying the absolute optimal strategy because it does not exist, but it helps to sightsee the solution space with the aim to identify the strategy that achieves the best compromise, based on the preferences of the decision maker. Indeed the DM selects a subset of the Pareto frontier and applies a rule that better suits own interests to a part of the Pareto frontier. The use of rules in decision processes is more advantageous than other preference models, because these provide easily comprehensible arguments based on information about preferences, avoiding arbitrary opinions.

Another advantage is that the Decision Maker can return to the process at any time and determine its preferences through a trial-and-error process. The Decision Maker thus gains step by step more knowledge about the relationships between the achievable target values.

Finally, the proposed method uses easy mathematical concepts and not algebraic or analytical models. This approach fits very well to problems of road safety resource allocation where interactions between different stakeholders and experts are indispensable and transparency is an essential requirement.

2. Literature review overview

There are various studies into the literature on the topic of resource allocation methodology. This review does not claim to be exhaustive, but is merely a report of the main approaches found in the literature. Traditionally, Cost-benefit analysis has been used to determine prioritization in road safety projects, but its application is controversial. Many researchers have developed multiobjective decision support systems that are better suited to this type of decision-making process (Lambert et al., 2003). Some of these methods, applied to various transportation sectors, is reported in a study funded by the Midwest Regional University Transportation Center and the Federal Highway Administration (FHWA, 2001). The optimization techniques used to allocate resources for road safety improvement consist of, for example, linear programming, integer programming, nonlinear programming and dynamic programming, and the proposed models take into account minimization of crashes, maximization of savings in crashes, maximization of benefits, etc.

Pal and Sinha (1998) have formulated the problem as a binary integer optimization model where the total number of crashes is minimized. Other authors have used an interactive multiobjective resource allocation methodology (IMRA), which keeps the objectives in their respective units and provides a set of solutions rather than a single solution (Chowdhury, 2000). Banihashemi (2019) presented an optimization model in conjunction with crash prediction models using a Linear Programming model that optimizes the crash and delay costs of highway networks with implementation costs within a constrained budget. Mishra and Khasnabis (2011) conducted a resource allocation procedure for urban intersection safety improvement alternatives over a multi-year planning horizon. An integer programming technique is used to solve the problem. Mishra et al. (2015) also used a multiple optimal resource allocation strategy that maximizes the safety benefit under budget and policy constraints. The proposed model considers economic competitiveness, equity and relaxation of mutual exclusivity, producing significantly different alternative fund allocations. The resource allocation model is solved using sequential quadratic programming. Murillo-Hoyos et al. (2015) have implemented a decision support system for rural two-lane highway safety improvement programming using constrained network-level optimization. The objective is to maximize the economic value that considers both monetary benefits and monetary costs. Most recently Stipancic et al. (2019) developed a method to prioritize sites based on GPS-derived surrogate safety measures (SSMs) rather than historical crash data. Fancello et al. (2019) compared three multicriteria methods (Concordance Analysis Vikor and Topsis) and showed that the Topsis method performs best in determining a complete ranking of critical road segments and overcomes some negative aspects of the other methods. Some studies have shown that uncertainty due to variance in crash modification factor (CMF), crash frequency, project cost, and prediction of costs and benefits has an important impact on the decision-making process. To account for this uncertainty, Dadashi and Mirbaha (2019) and Sadeghi and Moghaddam (2016) have proposed the use of Data Envelopment Analysis.

Some of the existing methods have weaknesses because they aggregate the objectives into a single value or perform some operations (e.g., averaging, weighted sum, different types of distances, achievement scalarization) that are always arbitrary to some extent.

The IMO-DRSA method proposed in this paper overcomes some of the disadvantages of other approaches.

It has already been successfully applied in the planning of the pavement maintenance with good results (Augeri et al., 2019).

3. Methods

3.1 Structure of resource allocation method

Every safety improvement program has to include a preliminary road crash analysis. Generally, this analysis allows to find out the hazardous sites (aggregated analysis), and to identify the causes that have produced an anomalous repetition and concentration of crashes on these sites (disaggregated analysis). Disaggregated analysis involves the inspection of accident scenes and the analysis of the individual components (i.e., human, vehicle, and road environment). The accident reconstruction approach works backwards from the accident investigation evidence and the remains of the accident to examine the scenario before (pre-crash), during (crash), and after the accident (post-crash). This analysis helps to determine the "how" and "why" of a particular type of accident. It can be said that accident reconstruction goes back to investigate the contributing factors and/or causes behind the accident event based on major and minor physical evidence left at the accident scene (Distefano et al, 2018). After identifying the causal factors of the crash events and obtaining comprehensive information about site characteristics, the next step is to select the most appropriate countermeasure or set of countermeasures according to their potential effectiveness in terms of expected crash decrease. Since they are often limited, the available resources must be optimally used in order to obtain the maximum total advantage in terms of safety. In the literature there are a lot of methods, which could be used to identify hazardous sites and develop the countermeasures (Canale et al., 2015; Montella, 2010; Søresen et al., 2005), but their description is out of the scope of this paper. Instead, the focus of this paper is on the last step, which is the allocation of resources through the development of a model that assists the DM in his or her final decision about safety improvement projects according to his or her preferences and considering some constraints.

Since the objectives and the constraints involved are often heterogeneous and conflicting, a multiobjective optimization methodology is proposed. The method is composed of two stages alternating in an interactive procedure (Greco et al., 2008). In the first stage, the Pareto optimal set generates a sample of solutions. In the second stage, the DM indicates relatively good solutions in the generated set, and from this information a preference model expressed in terms of easily understandable "if…, then…" decision rules is induced using DRSA (Greco et al., 2005; Augeri et al., 2011; Augeri et al., 2014; Augeri et al., 2015). In each iteration, the current set of decision rules is presented at DM, with the option to select the one that is most representative. The selected decision rule specifies some minimal requirements it wishes to obtain from the objective functions. This information is translated into a set of constraints that are added to the original problem, limiting the feasible solutions. The process continues iteratively until the DM finds a satisfactory solution. To compare the economic attractiveness of each countermeasure, the following parameters need to be evaluated: 1) the expected reduction of crashes number subsequently the implementation of a safety countermeasure; 2) cost-related parameters, as well as implementation cost, operating and maintenance (O&M) cost, service life. The expected reduction of crashes number at a site after the implementation of a generic countermeasure can be calculated as the difference between the expected number of crashes without countermeasures (n^i) and the expected number of crashes after implementing a countermeasure (n^i_e). The second parameter (n^i_e) can be calculated as a product of the expected number of crashes in the future without the countermeasure and a crash modification factor (CMF) that describes the effect of the planned countermeasure. Numerous studies contain CMFs that show the effectiveness of various countermeasures, based on past and recent assessments of safety improvement efforts (ARRB, 2012; FHWA, 2013; Elvik et al., 2009). The critical issue regarding the use of these data is in the international transferability of CMFs developed in different countries because the effects of countermeasures are highly dependent on the circumstances under which they were developed. For this reason, CMF values should be based on reliable results from safety effect studies conducted in similar conditions to those where the CMFs are used (Peltola et al., 2013). Reliable results can be obtained from before-after studies, including a proper comparison group and controlling for e.g. regression-to-the-mean effect (Hauer et al., 2002). Therefore, the expected safety effect depends not only on the CMF estimate, but also on the expected number of accidents without the implementation of countermeasures, a number that is difficult to estimate. For this purpose, one could use the accidents recorded in the before period, but this would not be correct because the number of accidents in the after period is usually smaller compared to the before period, even if the countermeasures have no effect. This occurs especially if the countermeasure is applied to a site with high numbers of accidents in the before period and is derived from the regression to the mean effect. Regarding the cost estimation, implementation cost includes only the design and building costs. An additional possible measure of the effectiveness of a countermeasure is the difference between the annual average O&M costs before and after project implementation, as a project can reduce overall annual O&M costs.

3.2 Analytical method

Once a list of suitable projects to improve safety at hazardous sites has been drawn up, the question remains as to which projects should be carried out and in what order they are important, considering the objectives to be maximized or minimized and the constraints to be taken into account. The primary objective of this study is to maximize the estimated reduction in the number of accidents following the implementation of specific countermeasures, but other objective functions are also introduced to maximize the efficiency of the investment. Implementation costs are considered as constraints, but they can also be an objective for minimization. In the proposed decision-making process, Decision Maker is not one person, but Expert Panel, which included an engineer from the technical staff of an Italian municipality, two road safety experts and some road users. The final decision was the one that all members of Expert Panel agreed with. In this way, the subjectivity typical of all classic multiobjective methods was mitigated.

The mathematical formulation of the problem is given in the following sections.

3.2.1 Analytical method Interactive multiobjective optimization using dominance-based rough set approach (IMO-DRSA)

In general, in multiobjective optimization problems there is no single solution that is better than any other for all the objectives. Therefore, it is generally impossible to find only one combination of crash countermeasures that maximizes the overall reduction of crashes, maximizes the life of the countermeasures taken, and minimizes their operating and maintenance costs while meeting budget constraints.

A methodology for addressing Interactive Multiobjective Optimization (IMO) (see, e.g., Branke et al., 2008) is presented in this paper to find the solution that best fits the preferences of Decision Maker (DM). Starting from the assumption that all the objective functions must be maximized, the proposed methodology is based on the idea of using some lower bounds (upper bounds in the case of minimization) on the objective functions resulting from a decision model representing the preferences of DM. These bounds gradually limit the feasible solutions, ensuring convergence towards the preferred solution at the Pareto front. In general, an interactive procedure consists of two stages: the computation stage and the dialogue stage. In the first stage, a subset of feasible solutions is computed and presented to DM. Then, in the dialog stage, Decision Maker evaluates the offered solutions and if one is identified as fully acceptable and Pareto-efficient, the process will stop. However, there may be numerous configurations of the solution and so the DM can have difficulties in selecting the best solution.

The proposed method is original such as it supports the DM in this step. In other words, the critical evaluation of the proposed solutions is used to build a preference model of Decision Maker and then to compute a new subset of feasible solutions, better matching the preferences of Decision Maker. In DRSA a set of example decisions is received as input and in response a preference model in the form of easy-to-understand "if..., then..." decision rules is provided. Thus, the IMO DRSA method presented in (Greco et al., 2008) provides a preference model expressed in terms of decision rules that explicitly specify the lower (upper) bounds of the objective functions to be maximized (minimized). The proposed interactive method consists of the following steps (Fig. 1) and identifies the considered set of solutions by X and the objective functions to be maximized by f_i: X → R, i = 1,...., m:

- **Step 1**. Generate a representative sample of feasible solutions.
- **Step 2**. Present the sample to the Decision Maker (DM).
- **Step 3**. If the DM is satisfied with one solution of the sample and the solution is Pareto optimal, the procedure stops. Otherwise continue.
- **Step 4**. Ask the DM to indicate a subset of relatively “good” solutions in the sample.
- **Step 5**. Apply DRSA to the current sample of solutions sorted into “good” and “others”, in order to induce a set of decision rules with the following syntax: “*if* $f_{i1}(x)\geq\alpha_{i1}, ..., f_{ip}(x)\geq\alpha_{ip}$... *then the solution is good*” in the case of maximization of the objective functions or “*if* $f_{i1}(x)\leq\alpha_{i1}, ..., f_{ip}(x)\leq\alpha_{ip}$... *then the solution is good*” in the case of minimization of the objective functions
- **Step 6**. Present the obtained rules to the DM in order to choose the most representative one.
- **Step 7**. Add the constraints $f_{i1}(x)\geq\alpha_{i1}, ..., f_{ip}(x)\geq\alpha_{ip}$ coming from the condition part of the rule selected in step 7 to the set of constraints of the optimization problem so as to obtain a more interesting region of feasible solutions, taking into account the preference of the DM.
- **Step 8**. Go back to step 1.

In step 1 (computation stage), any multi-objective optimization procedure that allows to find the Pareto Optimal Set or its approximation can be used. In the dialog stage of the procedure (steps 2 to 6), Decision Maker is required to select a decision rule induced from its preference information that corresponds to the definition of some upper bounds on the minimized objective functions f_i. With respect to sorting the solutions into the two classes "good" and "other" (step 4), note that "good" means better than the rest of the current sample. If Decision Maker refuses to classify a solution as "good", he or she can be asked to provide some minimum requirements of type $f_{i1}\ (x)\geq\alpha_{i1}$,...., $f_{ip}\ (x)\geq\alpha_{ip}$ for "good" solutions. These minimum requirements contain some restrictions that can be used in step 8, such as the analogous restrictions resulting from the selected decision rules.

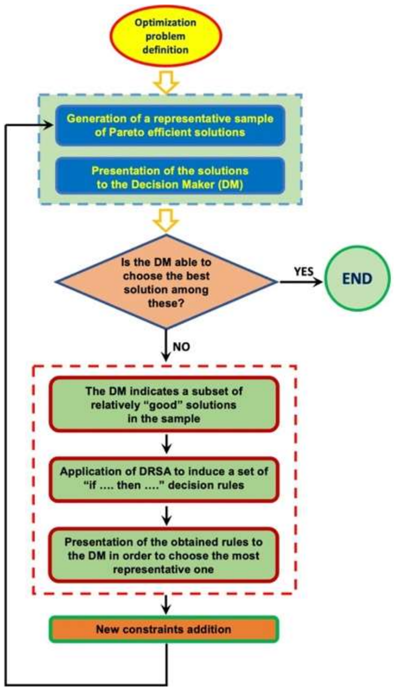

Figure 1: Overview of procedure and steps adopted

If the Pareto optimal set in step 7 is reduced by constraints $f_{i1}\ (x)\geq\alpha_{i1}$,....,$f_{ip}\ (x)\geq\alpha_{ip}$ that result from more than one rule, then the resulting reduced part may be empty. Therefore, before proceeding to step 8, it is necessary to check whether the reduced Pareto Optimal Set is empty. If it is empty, then Decision Maker must revise its selected rules. Decision Maker can be assisted in this task by information about minimal sets of constraints $f_{i1}(x)\geq\alpha_{i1}$ derived from the decision rules under consideration, which must be removed to obtain a nonempty part of Pareto Optimal Set.

The constraints introduced in step 7 are maintained in the following iterations of the procedure, but the DM can remove the set of feasible solutions considered in one of the previous iterations and continue from that point.

3.2.2 *Model formulation*

The proposed multiobjective optimization methodology considers the following variables and data:

- x^i_u: decision variable, representing implementation or non-implementation of countermeasure u^{th}, $u = 1,\ldots s$, on intersection i, $(i = 1,\ldots,q)$; that is $[x^i_u,\ u = 1,\ldots s,\ i = 1,\ldots,q]$; more precisely, $x^i_u = 1$ if the countermeasure is implemented, $x^i_u = 0$ if it is not implemented;
- S_i: set of all possible countermeasures u that might be applied alternatively or simultaneously on site i, $(i = 1,\ldots, q)$;
- n^i: expected number of fatal and injury crashes (hence called crashes) on site i without countermeasure implementation;
- CMF_u: crash modification factor associated to the countermeasure u;

- $n^i_e = n^i$ CMF_u: expected number of crashes on site *i* after implementation of adopted countermeasures;
- $\Delta n^i = n^i - n^i_e$: expected reduction of crashes number on site *i* after implementation of adopted countermeasures;
- c^i_u: implementation cost of countermeasure *u* on site *i*;
- $O\&M_u$: operation and maintenance cost of countermeasure *u*, defined as high (H), medium(M), low (L);
- sl_u: service life of countermeasure *u*, defined as high (H), medium (M), low (L);
- C_{max}: available budget for the implementation of all countermeasures;
- C_{min}: minimum budget to be spent.

The expected number of accidents at site i without implementing countermeasures was calculated as the long-term average accident frequency before treatment, assuming that the number of accidents observed before treatment remains unchanged in the after period if no treatment is implemented. For the reasons described above, this approach is not the most rigorous to estimating accidents without treatment, rather the Empirical Bayes method (Hauer et al., 2002) should be preferred. However, not having suitable data to apply the Empirical Bayes approach, a most simplistic method was used.

Functioning as an illustrative example, the CMFs used for countermeasures assessment were carried out from data in the technical literature, despite knowing the limitations arising from the transferability problem, as better explained in section 3. Unfortunately, this is because CMFs developed under similar condition to our sample were not available.

When multiple countermeasures are implemented at a site, it is common to multiply the CMFs to estimate the combined effect of the countermeasures. However, there are few studies documenting the combined effect of multiple countermeasures. Although implementing multiple countermeasures instead of just one may be more effective, it is unlikely that the full effect of each countermeasure will be realized when implemented simultaneously, especially when the countermeasures target the same type of accident.

Therefore, unless the countermeasures act completely independently, multiplying multiple CMFs is likely to overestimate the combined effect. The likelihood of overestimation increases with the number of CMFs that are multiplied. For this reason, great caution and technical judgment should be used, especially when estimating the combined effect of more than three countermeasures at a given location (FHWA, 2013).

Various models used to evaluate the total CMF that reflects the aggregate effect of the countermeasures are presented in the literature.

In this paper, when two or more countermeasures were implemented simultaneously on the same intersection *i*, the crash modification factor was obtained as follows (Mishra and Khasnabis, 2011; Ogden, 1996):

$$\mathrm{CMF_u} = 1 - [(1 - \mathrm{CMF_{u1}})\cdot(1 - \mathrm{CMF_{u2}})\cdot \ldots \cdot(1 - \mathrm{CMF_{us}})] \qquad (1)$$

It should be noted that this non-linear expression has no influence on the linearity of the proposed model because, if an improvement project implements a set of simultaneous countermeasures, it is considered to be a single element in the set S_i of possible countermeasures on site *i*. In other words, if the countermeasures u_1, u_2, …, u_s are combined in the comprehensive countermeasure *u*, then only countermeasure *u* is present in the set S_i (except for the case in which the possibility that one or more of the countermeasures u_1, u_2, …, u_s are mutually exclusive is also considered).

In this optimization problem, five objective functions quantify the overall benefits and therefore these have to be maximized. They are: a) the number of crashes reduced after countermeasures implementation; b) the number of countermeasures with service life at least medium; c) the number of countermeasures with service life high; d) the number of countermeasures with operation and maintenance costs at most medium; e) the number of countermeasures with operation and maintenance costs low.

The considered constraint is that the implementation overall cost of the countermeasures overall cost of the implementation of the countermeasures does not exceed the available budget (C_{max}). Furthermore, another constraint has to be added in order to specify that no more than one countermeasure for each site can be implemented.

Mathematically, the problem is defined as follows:

Maximize

$$\Delta n = \sum_{i=1}^{n} \Delta n^i \cdot x_u^i \quad \text{(total reduction of crash)} \qquad (2)$$

$$f_1 = \sum_{slu \geq M} x_u^i \quad \text{(number of countermeasures with service life} \geq \text{medium)} \qquad (3)$$

$$f_2 = \sum_{slu \geq H} x_u^i \quad \text{(number of countermeasures with service life} \geq \text{high)} \qquad (4)$$

$$f_3 = \sum_{O\&Mu \leq M} x_u^i \quad \text{(number of countermeasures with operation and maintenance cost} \leq \text{medium)} \qquad (5)$$

$$f_4 = \sum_{O\&Mu \leq L} x_u^i \quad \text{(number of countermeasures with operation and maintenance cost} \leq \text{low)} \qquad (6)$$

subject to the constraints:

$$C_{min} \leq \sum_{i=1}^{n} c_u^i \cdot x_u^i \leq C_{max} \qquad (7)$$

Expression (7) ensures that the capital investment neither exceeds nor at the same time is too low with respect to the available budget. The following is another constraint considered in the multiobjective optimization problem:

$$\sum_{u \in S_i} x_u^i \leq 1, i = 1, \ldots, q \qquad (8)$$

Expression (8) ensures that no more than one countermeasure for each site can be implemented. Some other objective functions and constraints can be considered according to policy preferences. For example, if at least one countermeasure on site *i* must be implemented, the following constraint can be considered so that a way that at least one x^i_u , $u \in S_i$, must be equal to 1:

$$\sum_{u \in S_i} x_u^i \geq 1 \qquad (9)$$

As mentioned above, in multiobjective optimization problems there is no one solution that is best for all the considered objectives. Therefore, it is generally impossible to find only one combination of crash countermeasures maximizing the total reductions of crashes, maximizing the service life of the adopted countermeasures and minimizing their operation and maintenance cost, while satisfying budget constraints.

4. Case Study

A set of 43 Italian urban intersections is used in order to illustrate the potential advantages of the proposed methodology. These intersections have been identified as highest crash rate locations by a crash analysis. For each intersection, information on crash types and severity are used to define the suitable low-cost countermeasures that could potentially reduce their frequency. For some locations multiple countermeasures are identified as mutually exclusive alternatives. In particular, both very inexpensive countermeasures (signs and road markings) that are on average effective for improving road safety, and more expensive countermeasures such as some traffic calming measures (e.g. road narrowing) were considered. Traffic calming measures, as it is known, are very effective in reducing the speed of approach to intersections and in decreasing accident rates (see e.g., Distefano and Leonardi, 2015; Distefano and Leonardi, 2019; Distefano et al., 2019).

The candidate projects for each site under consideration are shown in table 1.

Table 1: Candidates' projects

INTERSECTION	ALTERN.	COUNTERMEASURES	COST [€]	O & M COST	SERVICE LIFE	Δn
1	a	Road lighting	3.200,00	M	H	2
	b	STOP signs and channelisation	5.530,00	M	L	6
	c	Road lighting, STOP signs and channelisation	8.730,00	H	M	7
2	a	Parking barriers	2.000,00	L	M	3
3	a	Raised pedestrian crossing	13.400,00	M	M	5
	b	Channelisation	16.500,00	M	M	3
4	a	STOP signs (vertical and horizontal)	240,00	M	L	2
	b	Parking barriers	1.000,00	L	M	1
	c	STOP signs (vertical and horizontal) and Parking barriers	1.240,00	M	L	3
5	a	Horizontal STOP signs	30,00	M	L	2
	b	Parking barriers	1.000,00	L	M	1
	c	Horizontal STOP signs and Parking barriers	1.030,00	M	L	3
…………	……	……….	……….	……	……….	…
	……	……….	……….	……	……….	…
37	a	Sidewalk widening, Road narrowing and Rumble strips	8.400,00	M	M	2
38	a	Road lighting	530,00	M	H	1
	b	No parking sign	210,00	L	M	1
	c	Road lighting and No parking sign	740,00	M	M	1
39	a	Road lighting	1.600,00	M	H	1
	b	Horizontal STOP signs	30,00	L	L	1
	c	Road lighting and Horizontal STOP sign	1.630,00	M	M	1
40	a	Channelisation	11.600,00	M	M	4
41	a	Traffic lights changing to turn left	1.000,00	M	M	12
42	a	Horizontal and vertical STOP signs	480,00	M	L	11
	b	Parking barriers	4.000,00	L	M	5
	c	Horizontal and vertical STOP signs and Parking barriers	4.480,00	M	L	14
43	a	Sidewalk widening and Road narrowing	6.000,00	M	M	3

For each project, the decision parameters are as follows: 1) number of crashes decreased on site i subsequently countermeasures realization (Δn^i); 2) implementation cost of each countermeasure; 3) service life; 4) O & M cost.

The implementation costs are quantitatively calculated by accurate analysis, while the service life and operation and maintenance cost are evaluated only qualitatively as High

(H), Medium (M) and Low (L). A set of Pareto optimal solutions are calculated and proposed to DM. As the problem under consideration is a Multiple Objective Linear Programming, the Pareto-optimal solutions can be computed using classical linear programming by searching for the solutions that optimize each of the objectives under consideration, or fixing all but one of the objective functions under consideration to a satisfactory value and searching for the solution that optimizes the remaining objective functions. In this problem, the variables are x^i_u , $u = 1,\ldots s$, $i = 1,\ldots, q$, which represents implementation or non-implementation of countermeasure as described earlier. The objective functions considered in the optimization problem are those previously defined in the expressions of (2) through (6).

In addition, two budget constraints are introduced to guarantee that the C investment does not exceed the available budget or be too low at the same time (see expression (7)).

In this example, the budget constraints are:

$$30.000\ € \leq C \leq 35.000\ € \quad (10)$$

where: $$C = \sum_{i=1}^{n} c_u^i \cdot x_u^i \quad (11)$$

Eight different Pareto-optimal solutions were generated fixing the budget constraints and then maximizing *Δn* under the constraint of achieving some objectives.

These solutions, shown in table 2, were submitted to the DM.

Table 2: Sample of Pareto optimal solutions proposed in the first interaction

SOLUTIONS	C [€]	f1	f2	f3	f4	Δn	RATING
s1	31.501	17	6	33	11	129	good
s2	33.481	16	10	31	10	117	
s3	34.373	20	5	27	10	125	good
s4	30.851	15	10	26	10	93	
s5	31.161	19	12	29	12	114	
s6	34.751	20	10	30	10	109	
s7	31.942	15	5	32	12	127	good
s8	30.772	16	8	28	12	111	

Each solution consist of a combination of countermeasures to be implemented at some of the intersections investigated, but the DM might not be able to select the optimal solution to be implemented.

To improve the exploration for a satisfactory solutions, the DRSA was applied to derive decision rules using the preferences of DM. The DM was asked to specify, among those suggested, a subset of solutions "good" listed in the "Rating" column of Table 2. In the present case study, the DM has chosen solutions s1, s3 and s7 as "good".

Considering the classification made by DM of Pareto-optimal solutions into "good" and "other", five decision rules were induced from the lower approximation of the "good" solutions.

The induced rules are listed below (the identification numbers of the solutions supporting the rule are in parentheses):

rule1) if the number of countermeasures to be implemented with operation and maintenance cost “at most” medium is at least 33, then the solution is good; (s1)

rule 2) if the number of crashes reduced after the implementation of countermeasures is at least 129, then the solution is good; (s1)

rule 3) if the number of crashes reduced after the implementation of countermeasures is at least 125 then the solution is good; (s1, s3 and s7)

rule 4) if the total cost is not higher than 34.373 € and the number of countermeasures to be implemented with service life "at least" medium is at least 20, then the solution is good; (s3)

rule 5) if the number of countermeasures to be implemented with operation and maintenance cost "at most" medium is at least 32, then the solution is good. (s1 and s7)

These rules were shown to the DM and he was asked to choose those that most suited his preferences. The DM chose rule 3) that allowed introducing the following constraint:

$\Delta n \geq 125$

This new constraint allowed reducing the feasible domain of the problem and it was used together with the original constraints to compute a new sample of Pareto-optimal solutions. These new solutions, reported in table 3, were presented to the DM.

Table 3: Sample of Pareto optimal solutions proposed in the second interaction

SOLUTIONS	C [€]	f1	f2	f3	f4	Δn	RATING
s1	31.501	17	6	33	11	129	selected
s2	31.261	18	8	33	11	127	
s3	31.261	17	9	33	11	126	
s4	33.642	15	7	31	12	129	

The DM was asked again if one of the proposed Pareto optimal solutions might be satisfactory to him.

In general, two scenarios are possible:

1) The DM is satisfied and the interactive procedure can be stopped.
2) The DM is not satisfied and, in this case, the interactive procedure must be repeated until the DM identifies one satisfactory solution.

In this case, the DM was satisfied with s1, so the procedure was stopped.

5. Discussion and conclusion

This paper presents a methodology for prioritizing improvements in road safety and for the optimal allocation of resources. To this end, an interactive optimization procedure based on a Decision Rule Preference Model (IMO-DRSA) was used to support the interaction with the DM. Any multi-objective optimization method that finds the Pareto-optimal set or its approximation is usually a good complement to the IMO-DRSA.

Indeed, one of the main complications in a prioritization problem is that there are many feasible solutions, and this makes it difficult for DM to choose the most satisfactory solution of all. The method presented in this paper can support the DM at this stage of the decision process.

The DM provides preference information classifying some of the solutions into two categories ("good" and "other") and the result is a preference model in the form of "If..., then..." decision rules, which is suitable to reduce the Pareto-optimal set by an iterative process, until DM is able to selects a satisfactory solution.

The input information are converted into the preference model in a clear and traceable way and for this reason the proposed method can be considered as a "glass box", as opposed to the "black box" effect typical of many methods that do not provide a clear explanation of how the result is achieved.

This is because the decision rules explain the final decision, which is not the result of a simple application of a technical method, but is obtained from a decision process based on the active participation of the DM.

The Decision Rule Preference Model is well suited for decision support providing the rationale for preferences in a logical form that makes it understandable to DM since it does not resort to technical terms such as utility, trade-offs, scaling functions, reference points, etc.

Note that the decision rules are based only on ordinal properties of the objective functions. Unlike any method that involves some degree of scalarization (almost all existing interactive methods), the proposed method does not aggregate the objective functions into a single value at any step and avoids operations (such as averaging, weighted sum, different types of distances, power scalarization) that are always arbitrary to some degree. To demonstrate the application of the method, an example was presented, which was carried out on a sample of Italian city intersections. The application to a case study pointed out the suitability of the proposed methodology to prioritize projects in such a way that maximum safety benefits are achieved by reducing traffic accidents.

The results obtained show that the decision-maker's decisions depend on his own sensitivity to accident reduction and budget constraints.

Moreover, these results confirm that IMO-DRSA is a useful tool in multi-objective optimization problems because it assists the DM to select the best solution from a large number of feasible solutions.

In the example, only cost-effective countermeasures were considered, but different types of countermeasures were considered depending on the security strategy adopted.

In fact, due to its versatility, the proposed methodology can be adapted to any road safety strategy, taking into account different types of countermeasures, planning period, policy options and budget (annual or total).

Let us conclude this section with a brief discussion of the possible limitations of the proposed methodology. They mainly relate to calculation aspects and are of two types:

- limitations related to the induction of decision rules;
- limitations related to the generation of points in the Pareto front.

In both cases, the constraints are largely theoretical, with no real impact on concrete decision-making processes. As far as the induction of decision rules is concerned, the problem of discovering all decision rules is indeed exponential in the number of attributes. However, the number of attributes corresponds to the number of objective functions to be considered, and only a limited number of objective functions can be considered, since, as stated in the celebrated article by Miller (1956) "The Magical Number Seven, Plus or Minus Two: Some Limits on Our Capacity for Processing Information", due to the limits of one-dimensional absolute judgement and the limitations of short-term memory, the number of objects that the human brain can process is 7 ± 2.

Furthermore, in the case of a larger number of objective functions and consequently attributes, very efficient algorithms based on intelligent heuristics have been successfully proposed (see e.g. Blaszczyński et al., 2013). Again, concerning the problem of point generations in the Pareto front, 0-1 linear programming is theoretically a NP hard problem, but in fact there are a lot of efficient algorithms to solve the problem efficiently (see e.g. Schrijver, 1998; Wolsey, 1998).

Another problem could be related to the large number of inducible decision rules, which obviously cannot all be presented on Decision Maker, since the required cognitive effort carries the risk of reducing the quality of the final decision. Again, this is a rather theoretical problem, since there are a number of measures that are of interest for decision rules (see e.g. Greco et al., 2004; Greco et al., 2012), and there are algorithms that focus on the discovery of the most interesting decision rules (see e.g. Blaszczyński et al., 2013).

Finally, the subjectivity, which is typical of all classical multiobjective methods and which could be a weakness of the proposed method, was mitigated by an Expert Panel that supported Decision Maker in the decision process. Different bodies could also be used to evaluate different criteria. For example, an Expert Panel could consist of members of the managing authority, road safety experts, road users, government delegates, etc.

A future area of research is to consider a multi-year analysis period with the aim of implementing a program to improve safety over a planning horizon.

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