Safety Science 51 (2013) 354–360

Contents lists available at SciVerse ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/ssci

A multicriteria knapsack approach to economic optimization of industrial safety measures

Antonio C. Caputo [a,*], Pacifico M. Pelagagge [b], Paolo Salini [b]

[a] University of Roma Tre, Department of Mechanical and Industrial Engineering, Via della Vasca Navale 79, 00146 Roma, Italy
[b] University of L'Aquila, Department of Mechanical, Energy and Management Engineering, Zona Industriale di Pile, 67100 L'Aquila, Italy

ARTICLE INFO

Article history:
Received 30 April 2012
Accepted 7 August 2012
Available online 23 September 2012

Keywords:
Risk reduction
Safety measures selection
Cost minimization
Cost-benefits analysis
Mathematical programming
Knapsack model

ABSTRACT

The selection of safety measures to be applied in an industrial plant to reduce risk to an acceptable level is a critical task for safety engineers. However, to select a portfolio of safety measures is quite hard as a number of different hazards have to be counteracted simultaneously and a wide range of preventive or protective measures can be chosen, including either technical, administrative and managerial actions, within the constraints of a given budget. In this paper a multi-criteria "knapsack" model is described to help safety analysts in selecting the most cost-effective safety measures to be adopted. The problem is formulated as that of maximizing the utility of the portfolio of safety measures subject to a number of constraints including a maximum allowable budget. In the paper at first the problem formulation is given as a knapsack model, then the approach to compute the utility level of a given portfolio of safety measure is described utilizing a multi-criteria method. Finally, an application example is presented and the advantages and disadvantages of the method are discussed.

1. Introduction

Multiple hazards occur simultaneously in industrial plants. In such cases the safety manager has the responsibility of identifying the most critical hazards and properly select safety measures (SMs) in order to obtain the highest risk reduction while complying with enforced regulations and the available safety budget. This may be quite a hard task as a wide range of preventive or protective SMs exist to counteract any given hazard including either technical, administrative and managerial actions. In this context the large number of competing alternatives requires a methodology for prioritizing the candidate SM, so that the benefit within a limited budget is maximized. The choice is made harder by the fact that when multiple SMs exist for a given hazard, a dominant SM may not be easily discernible. In fact, each SM might imply a different overall cost (including capital and operating expenses) but also a different risk reduction potential which even leads to a different expected monetary loss from an accident. This also asks for a multi-criteria analysis and a trade-off evaluation in order to define the most cost-effective portfolio of SMs to be adopted. However, the technical literature is lacking of formalized methods to assist in the selection of safety measures while from the mathematical standpoint this may be considered as a hard to solve combinatorial optimization problem. In practice, it is not possible a thorough enumeration and review of all possible combinations of SMs and usually only one SM at a time is evaluated resorting to a simple cost/benefit analysis. This merely allows to find an economic justification to the candidate SM (Antes et al., 2001). Nevertheless this subjective trial and error approach does not guarantee an optimal choice. Moreover, the safety engineer may not even be sure of having identified the proper set of candidate solutions before carrying out any comparative analysis of the available SMs. Therefore, the SM selection process can be quite inefficient and time consuming.

In the attempt of providing effective methods to assist in this decision making process, a research effort has been undertaken and several possible approaches have been already presented. In a previous paper of the same authors (Caputo et al., 2011) a somewhat advanced computer method for the minimization of total safety-related costs, i.e. the sum of adopted SMs cost and accident cost, was presented. The mix of SMs, able to attain the optimal risk level corresponding to the minimum overall cost, was found by solving the related combinatorial optimization problem resorting to a genetic algorithm. However, although that method proved to be quite powerful, it requires the development of proper stochastic optimization software, which might be unfeasible for the average safety analyst, and relies on fairly detailed knowledge about the characteristics of the hazards and the candidate SMs. Such quantitative information might not always be readily available and require considerable preparatory work to be gathered.

* Corresponding author. Tel.: +39 0657333546.
E-mail addresses: acaputo@uniroma3.it (A.C. Caputo), pacifico.pelagagge@univaq.it (P.M. Pelagagge), paolo.salini@univaq.it (P. Salini).

0925-7535/$ - see front matter © 2012 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.ssci.2012.08.002

To provide an easier to use method for selecting SMs, an alternative approach based on a set of rating indices was instead proposed in (Caputo, 2008) allowing a rapid screening of potential SMs. The methodology was based on the use of a novel set of easy-to-compute rating indices which allow the analyst to rank the competing safety measures on a cost-effectiveness basis while considering a number of relevant factors which are neglected by traditional cost/benefit analyses. In particular, efficiency, effectiveness, applicability range, the criticality of the affected hazards were also factored in. This allows the safety analyst to adopt a multiple-criteria approach in order to easily define a portfolio of preferred alternatives for direct application or any subsequent more detailed investigation. In fact, the method can assist plant safety practitioners in the practical identification of possible dominant SMs thus solving the implied trade-off conflicts when an adoption decision has to be made.

In this work, instead, the problem of choosing a set of safety measures is framed again in terms of combinatorial optimization, and a mathematical linear programming approach is adopted where the choice of SMs to be adopted is determined by solving a 0–1 linear programming model formulated as a knapsack problem.

In determining the "goodness" of each safety measure the concept of "utility" is adopted which lends itself to a multiple-criteria decision making (MCDM) also allowing the assessment of both qualitative and quantitative performances of the candidate SM.

With reference to the selection of a portfolio of interventions to optimize a performance measure subject to a set of constraint it should be noted that mathematical programming methods have been proposed in the field of civil engineering and buildings renovation, although this approach seems to be new in the field of industrial plant safety.

As an example Brown (1980) utilized a dynamic programming approach to select highway improvement projects, while Farid et al. (1994) utilized an incremental benefit-cost analysis in a similar context. Basing on the multiple choice knapsack problem (Sinha and Zoltners, 1979), Sinha et al. (1981) utilized binary variables to represent various highway improvement alternatives and solved an integer optimization model to select a portfolio of interventions, adopting the total crash rate as the objective function to be minimized. Pal and Sinha (1998) extended this model to consider the effectiveness of the various projects in future years by factoring in the expected growth in traffic. Melachronoudis and Kozanidis (2002) proposed a mixed integer knapsack model to allocate a given budget to highway safety improvements by including either discrete interventions at specific points and continuous improvements over variable lengths of a highway. Gustafsson (1998) utilized a mixed integer linear programming method to select actions in building retrofits. Alanne (2004), finally, adopted a knapsack model to select renovation actions for building retrofit and refurbishment also including multi-criteria rating of alternatives.

The paper is organized as follows. Firstly the methodology is described. Then an application example is presented and the advantages and disadvantages of this decision support method are discussed. Finally, some directions for future research are suggested.

It is believed that this approach can help safety engineers to select the most feasible and cost effective portfolio of safety measures for risk reduction in industrial plants and represents a further valuable tool for the safety analyst who is in charge of risk reduction in industrial plants.

2. The knapsack optimization model

In this work we assume an industrial plant where a set of hazards exist and consider a set of candidate safety measures (i.e. a set of single actions expected to reduce risk) to be possibly implemented. The problem is that of allocating an available budget among these safety measures in order to optimize a safety-related measure of effectiveness broadly defined in terms of utility, which results from a multi-criteria assessment of the safety measures effects. In this respect the problem at hand can be included in the broader area of portfolio optimization.

We adopt an additive knapsack formulation were the objective function to be maximized is expressed in the context of the utility theory as follows

$$\mathrm{Max}\sum_{i=1}^{n} x_i U_i \tag{1}$$

where x_i (x_1, x_2,...x_n) are the decision variables representing the candidate safety measures, with $x_i = 1$ if the i-th safety measure is selected, else $x_i = 0$, and U_i being the utility score achieved by selecting the safety measure x_i.

The problem is subject to the basic constraints

$$x_i \in \{0, 1\} \tag{2}$$

$$\sum_{i=1}^{n} x_i C_i \leqslant C_{\mathrm{MAX}} \tag{3}$$

where C_i is the cost of safety measure x_i and C_{MAX} is the maximum available budget.

Apart from these general constraints, some additional case-specific constraints can be added. In particular when facing safety-related problems the following constraints may be relevant.

- Compatibility constraints, i.e. avoid selecting incompatible safety measures (as an example a water sprinkler and a CO_2 fire fighting system owing to the solubility of carbon dioxide in water) or safety measures acting on the same hazards and having non-additive effects.
- Case-based constraints, i.e. necessary actions dictated by laws and regulations or by case-specific situations.
- User defined constraints, i.e. minimum required risk reduction.

However, no general expression can be given for such constraints as they have to be expressed depending on the specific case at hand. A discussion about the possible formulation of such constraints is given in a subsequent section.

By computing the utility U_i of a safety measure we provide a means to quantitatively express the value that can be expected by a decision maker when paying a certain amount of money to implement that safety measure (Alanne, 2004).

To compute the utility we at first define a set of *Evaluation Criteria* according to which the *Attributes* of a given safety measure will be ranked by assigning a score S_j. Then the overall utility score of a safety measure is computed by aggregating the distinct evaluation criteria scores through a simple additive weighted average.

$$U_i = \sum_{j=1}^{m} w_j S_j \tag{4}$$

being

$$\sum_{j=1}^{m} w_j = 1 \tag{5}$$

In (Eqs. (4) and (5)) m is the number of Evaluation Criteria adopted, w_j is the normalized weight associated to evaluation criterion j, and S_j is the score number corresponding to criterion j which describes the utility associated to the attributes of the considered safety measure respect the evaluation criterion j. To assign the single utility score values S_j in a homogenous manner respect the various evaluation criteria, the procedure suggested by Alanne (2004) is adopted here where

Table 1
Utility values scoring scale.

Score	Utility definition
10	Huge improvement compared with situation before intervention
8	Great improvement...
6	Fair improvement...
4	Moderate improvement...
2	Slight improvement...
0	No improvement compared with situation before intervention
−2	Slight drawback...
−4	Moderate drawback...
−6	Fair drawback...
−8	Great drawback...
−10	Huge drawback compared with situation before intervention

$$S_j = \frac{P_j}{RP_j} RUV_j \tag{6}$$

being P_j the value of the performance measure possessed by the safety measure respect criterion j according to a predefined ranking scale, RP_j is an arbitrary reference value of that performance measure expressed in the same ranking scale, and RUV_j is the utility value corresponding to the reference value RP_j chosen for criterion j. The values of RUV_j can be assigned following Table 1 on a −10 to +10 scale (Alanne, 2004).

3. Evaluation criteria

In this study is proposed that each candidate safety measure is assessed according to the following evaluation criteria, partly adapted from (Caputo, 2008)

- Effectiveness (Score S_1)
- Cost (Score S_2)
- Efficiency (Score S_3)
- Range (Score S_4)
- Applicability (Score S_5)
- Functionality (Score S_6)

The procedure for assigning a score for the six considered evaluation criteria is described in the following.

Effectiveness, i.e whether the SM is able to significantly reduce the risk associated to an hazard (by reducing accident probability and/or the magnitude of consequences).

If we conventionally define the risk level associated to an hazard as the probability of accident p times the magnitude of the consequences M

$$R = pM \tag{7}$$

and we express p and M according to an empirical scoring scale as shown in Table 2 we find that risk can be quantified as a number in the 1–25 range.

Then the effectiveness of a safety measure can be assumed to be proportional to the obtainable reduction of risk scores, i.e. to the difference of risk level before and after the adoption of the safety measure.

$$\Delta R = R_{BEFORE} - R_{AFTER} \tag{8}$$

Table 3
Annual cost of safety measures.

C	Meaning
5	Very high
4	Relevant
3	Average
2	Low
1	Negligible

In case the safety measure can affect multiple hazard the ΔR value can be averaged. Otherwise, for instance, the value corresponding to the highest risk hazard among those affected by the SM can be utilized, according to the analyst's preference. Finally, the *Effectiveness* score can be computed according to (Eq. (6)) by assuming that a huge improvement ($RUV = 10$) is obtained when we have the maximum risk reduction (i.e. $\Delta R_{MAX} = 24$). This means that

$$S_1 = \frac{\Delta R}{24} 10 \tag{9}$$

As an example, if the current risk level is characterized by $p = 3$ and $M = 4$, which gives $R_{BEFORE} = 12$, and by adopting the candidate safety measure we obtain $p = 2$ and $M = 2$, which gives $R_{AFTER} = 4$, we have $\Delta R = 12 - 4 = 8$. Thus

$$S_1 = \frac{8}{24} 10 = +3.3 \tag{10}$$

Obviously, since any safety measure cannot increase the risk level but only reduce it or, at worst, can be not effective, one can only have positive values for S_1.

Cost, i.e. the capability of the SM of being implemented with low capital and operating expenses while maintaining effectiveness and efficiency.

The cost C of a safety measure is to be intended as an equivalent annual cost and can be conventionally evaluated assuming the values of Table 3.

Alternatively, in case that actual cost estimates for the SM are readily available one can also quantify C as

$$C = C_{INV\,\mathrm{Max}} \tau + C_{E\,\mathrm{Max}} \tag{11}$$

In (Eq. (11)) $C_{INV\,\mathrm{Max}}$ is the maximum capital investment required to apply the SM, while $C_{E\,\mathrm{Max}}$ is the maximum annual operating cost and τ is the capital recovery factor with T being the safety equipment life span (years) and s the interest rate (%/year).

$$\tau = \frac{s(1+s)^T}{(1+s)^T - 1} \tag{12}$$

Again, according to (Eq. (6)) one can express a *Cost* score S_2 by preliminarily defining a reference cost value and the corresponding utility score. However, it should be noted that since any cost is a drawback for a safety measure, then the expected utility score will be negative.

As an example, let us assume that the candidate safety measure has a cost which is considered "relevant" (i.e. score 4 according to Table 3) and that a measure with a "very high cost" (score 5) would

Table 2
Example of risk ranking parameters.

Likelihood ranking(p)	Level	Reference occurrence frequency (yr^{-1})	Severity ranking (M)	Level	Reference loss value
5	Frequent	>10^{-1}	5	Catastrophic	>10 fatalities
4	Probable	10^{-1}–10^{-2}	4	Critical	1 or more fatalities
3	Occasional	10^{-2}–10^{-3}	3	Relevant	Occasional fatality
2	Remote	10^{-3}–10^{-4}	2	Marginal	Major injuries
1	Improbable	<10^{-5}	1	Negligible	Minor injuries

be considered as a "huge drawback" (utility = −10) then the *Cost* score would be

$$S_2 = \frac{4}{5}(-10) = -8 \tag{13}$$

In case, instead, of a quantitative evaluation, provided that the maximum allowable cost for a safety measure is set at 10,000 € and that the considered safety measure has a cost of 2000 €, then the score would be

$$S_2 = \frac{2000}{10,000}(-10) = -2 \tag{14}$$

Efficiency, i.e. whether the SM is able to affect the most critical hazards.

Let us assume that a preliminary analysis enabled to identify a set of hazards existing in an industrial plant. After computing the risk value R_k for the k-th hazard, it is straightforward to identify the most critical hazard as the one having the highest risk ranking

$$R_{MAX} = \mathrm{Max}(p_k M_k) \tag{15}$$

A relative criticality ranking of the k-th hazard may be then obtained by computing the Hazard Criticality Ranking HCR_k relating R_k to the risk level of the most critical hazard

$$HCR_k = \frac{R_k}{R_{MAX}} \tag{16}$$

This allows to easily identify the most critical hazards.

The *Efficiency* of a safety measure can be then conventionally evaluated assuming the values of Table 4.

Finally, the *Efficiency* score S_3 can be computed according to (Eq. (6)) by assuming that a huge improvement ($RUV = 10$) is obtained when we have a SM affecting mainly the most critical hazards (i.e. $E = 5$). This means that

$$S_3 = \frac{E}{5}10 \tag{17}$$

Given that a SM even if impacting only on a negligible hazard cannot be considered as a drawback, then the expected utility score will be positive.

Range, i.e. the capability of the SM to act on a wide range of different hazards simultaneously.

Similarly to the *Efficiency* and *Cost* scores the *Range* of a SM can be conventionally evaluated assuming the values of Table 5.

The *Range* score S_4 can be computed according to (Eq. (6)) by assuming that a huge improvement ($RUV = 10$) is obtained when we have a SM affecting virtually all hazards existing in the facility (i.e. $RNG = 5$). This means that

$$S_4 = \frac{RNG}{5}10 \tag{18}$$

Given that a SM even if impacting only on a single hazard cannot be considered as a drawback, then the expected utility score will be positive.

Applicability, i.e. an overall judgment about the ease of implementing the safety measure, including possible disruption of productive activities, space requirements, requirements for specific know how, adaptability to existing structures and equipment.

Table 4
Efficiency ranking of safety measures.

E	Meaning
5	The SM affects mainly the most critical hazards
4	The SM affects mainly some relevant hazards
3	The SM affects mainly hazards having average criticality
2	The SM affects mainly hazards having low criticality
1	The SM affects mainly hazards having negligible criticality

Table 5
Range ranking of safety measures.

RNG	Meaning
5	The SM affects virtually all hazards existing in the facility
4	The SM affects most hazards existing in the facility
3	The SM affects multiple hazards existing in the facility
2	The SM affects only a few hazards existing in the facility
1	The SM is focused on a single hazard existing in the facility

Functionality, i.e an overall judgment about the reliability, usability and acceptance by workers including any negative interaction with productive activities, possibility of expanding/upgrading/updating the safety measure.

Both the *Applicability* and the *Functionality* judgments can be given in a qualitative manner and the corresponding utility score can be assigned by referring directly to Table 1 values. Scores S_5 and S_6 can have both positive or negative values.

After having assigned scores S_1–S_6 to the safety measures and weights w_1–w_6 to the evaluation criteria, it is straightforward to calculate the overall utility score of the safety measure resorting to (Eq. (4)). As an example let us imagine that a candidate SM has obtained the following scores: $S_1 = 7$, $S_2 = -4$, $S_3 = 2$, $S_4 = 3$, $S_5 = -5$, $S_6 = 6$, and that the analyst is mainly concerned with risk reduction, cost and functionality so that he assigns the following weights: $w_1 = 0.3$, $w_2 = 0.3$, $w_3 = 0.05$, $w_4 = 0.05$, $w_5 = 0.1$, $w_6 = 0.2$. The utility of the candidate safety measure would be computes as $U = (0.5 \times 7) + [0.3 \times (-4)] + (0.05 \times 2) + (0.05 \times 3) + [0.1 \times (-5)] + (0.2 \times 6) = 3.5 - 1.2 + 0.1 + 0.15 - 0.5 + 1.2 = 3.25$.

4. Additional constraints

In this model the decision variables are assumed to be binary, i.e. a safety measure is applied or not. However, in many cases a given type of safety measure can be applied to a variable extent instead of simply as "yes" or "no". As an example if one plans to install a sprinkler system for fire extinguishing then this can be applied into a single department, into several departments or in the entire plant. If one plans to introduce an emergency squad this can be composed of a variable number of operators. To handle such cases one should introduce continuous decision variables as well. While this is certainly possible resorting to mixed integer linear programming techniques, in the present model it is made the position that alternative manners of applying the same safety measure at different degrees of intensity are considered as distinct candidate safety measures.

However, being alternative ways of implementing the same measure incompatible, a further constraint is required in the model so that no more that one implementation option of a similar measure is allowed (i.e. we cannot choose to install a sprinkler system in a single department AND in the entire facility).

If we assume that S is a subset of mutually exclusive safety measures composed by alternative ways of applying the same type of measure at different degrees, then the following constraint holds

$$\sum_{k \in S} x_k \leqslant 1 \tag{19}$$

A similar constraint can be included in the model to avoid simultaneous selection of other kinds of mutually exclusive safety measure such as distinct but non-additive measures aimed at obtaining the same effect, technically incompatible measures (i.e. CO_2 and water sprinkler fire extinguishers in the same room) or conceptually meaningless measures (i.e. switching to an inherently safer ambient pressure process occurring inside an explosion resistant vessels). In this case we can define an $n \times n$ compatibility matrix CM where the generic element cm_{ij} (with i and $j = 1$–n) is

Table 6
Utility values computation table.

	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8	SM9	SM10
ΔR	8	4	10	8	20	13	3	6	5	18
Effectiveness (S_1)	**3.33**	**1.67**	**4.17**	**3.33**	**8.33**	**5.42**	**1.25**	**2.50**	**2.08**	**7.50**
$C_{INV\ \mathrm{Max}}$ (€)	24,000	14,000	10,000	12,000	32,000	26,000	14,000	2400	32,000	22,000
$C_{E\ \mathrm{Max}}$ (€/yr)	1000	800	800	1000	2200	500	300	300	2000	1800
C (€/yr)	4905.9	3078.4	2427.5	2952.9	7407.9	4731.4	2578.4	690.6	7207.9	5380.4
Cost (S_2)	**−5.45**	**−3.42**	**−2.70**	**−3.28**	**−8.23**	**−5.26**	**−2.86**	**−0.77**	**−8.01**	**−5.98**
E	3	3	2	1	2	2	1	3	2	1
Efficiency (S_3)	**6**	**6**	**4**	**2**	**4**	**4**	**2**	**6**	**4**	**2**
RNG	3	3	2	1	4	4	3	4	1	2
Range (S_4)	**4.3**	**4.3**	**2.9**	**1.4**	**5.7**	**5.7**	**4.3**	**5.7**	**1.4**	**2.9**
Applicability (S_5)	**−2**	**2**	**−4**	**−6**	**5**	**−2**	**−1**	**8**	**9**	**−5**
Functionality (S_6)	**9**	**−2**	**6**	**3**	**−3**	**4**	**−5**	**0**	**2**	**8**
U	**1.82**	**0.33**	**1.45**	**−0.08**	**1.74**	**1.46**	**−1.08**	**2.78**	**1.49**	**1.90**

$cm_{ij} = 0$ when measure i is compatible with measure j otherwise $cm_{ij} = 1$. Obviously $cm_{ii} = 0$. Then, for each safety measure i a check has to be made that no other incompatible measure j has been selected, as represented by the constraint

$$\sum_{j=1}^{n} x_j \; cm_{ij} < 1, \forall i \tag{20}$$

When introducing the compatibility matrix CM approach, constraint (20) can absorb constraint (19).

If a safety measure i is a precondition to apply another safety measure j then this condition can be expressed by the constraint

$$x_i \geq x_j \tag{21}$$

A similar constraint would represent the situation when measure i is required in case measure j has been already applied.

Finally, if a safety measure i is compulsory according to existing regulations, the following constraint applies

$$x_i = 1 \tag{22}$$

5. Application example

In order to demonstrate the practical application of the proposed method a fictitious example is described here.

Let us assume that to rate the candidate safety measures the following values are assumed, $RP_1 = 24$, $RP_2 = 9000$, $RP_3 = 5$, $RP_4 = 7$, $RUV_1 = 10$, $RUV_2 = -10$, $RUV_3 = 10$, $RUV_4 = 10$, $w_1 = 0.3$, $w_2 = 0.2$, $w_3 = 0.05$, $w_4 = 0.05$, $w_5 = 0.2$, $w_6 = 0.2$. The values of RP_5, RP_6, RUV_5, RUV_6 are withheld because an utility value will be directly assigned for those scores based on the analyst's judgment.

Based on the evaluation of the characteristics of safety measures, with reference to the hazards existing in the considered fictitious plant, their ranking scores and corresponding utility values are computed as shown in Table 6, where cost data are evaluated assuming $s = 10\%$/yr; $T = 10$ yrs; $\tau = 0.16$. In Table 6 the bold numbers are final scores and utility computed according to the model, while the other numerical values are input data, values assigned by the analyst or intermediate computations. A sensitivity analysis has been then carried out by changing the annual budget available for safety measures. Table 7 shows the optimal set of safety measures for each budget level and the corresponding overall utility value obtained.

The table also shows the actual cost of selected safety measures (which is obviously within the budget) and the ratio of incremental utility to the incremental cost. This latter information is also plotted in Fig. 1 along with the graph of incremental utility to the incremental budget.

Finally, Fig. 2 shows the trend of utility/cost ratio with increasing budget. All of the above information apart from indicating the optimal set of safety measures to be selected for any given available budget, also allow the decision maker to determine the most cost-effective budget level to be allocated to risk reduction in the considered plant.

6. Discussion of the model

The selection of safety measures in industrial plants is typically an iterative process where designers manually generate alternatives which are then evaluated one at a time to be accepted or rejected and the process is repeated until a satisfactory, although not necessarily optimal, overall solution is obtained. The adoption of the proposed optimization model with a personal computer allows to "fully automate" either the generation and the evaluation of alternatives and allows an optimal portfolio of interventions to be determined by evaluating a large number of mutually compatible or non-compatible solutions also accounting for conflicting preferences and evaluation criteria. This supports the human decision making process by providing rapid assessment of solutions which otherwise would have not been considered, especially in case of conflicting criteria and constraints.

In the proposed method at first the candidate solutions are evaluated resorting to a multi-criteria approach. Then the results are

Table 7
Sensitivity analysis.

Budget (€/yr)	U	SM	C_{tot}	$\Delta U/\Delta C$	Budget (€/yr)	U	SM	C_{tot}	$\Delta U/\Delta C$
4000	4.24	3,8	3118	0	15,000	7.96	1,3,8,10	13,404	0
5000	4.24	3,8	3118	0	16,000	7.96	1,6,8,10	15,708	0
6000	4.61	1,8	5596	0.037	17,000	8.29	1,2,3,8,10	16,483	0.033
7000	4.68	8,10	6071	0.007	18,000	8.29	1,2,3,8,10	16,484	0
8000	5.69	3,6,8	7849.4	0.101	19,000	9.42	1,3,6,8,10	18,136	0.113
9000	6.13	3,8,10	8498.4	0.044	20,000	9.42	1,3,6,8,10	18,137	0
10,000	6.13	3,8,10	8498.4	0	21,000	9.69	1,3,5,8,10	20,812	0.027
11,000	6.5	1,8,10	10,977	0.037	22,000	9.75	1,2,3,6,8,10	21,214	0.006
12,000	7.5	1,8,10	10,978	0.1	23,000	9.75	1,2,3,6,8,10	21,214	0
13,000	7.52	1,3,6,8	12,755	0.002	24,000	10.02	1,2,3,5,8,10	23,891	0.027
14,000	7.96	1,3,8,10	13,404	0.044	25,000	10.02	1,2,3,5,8,10	23,891	0

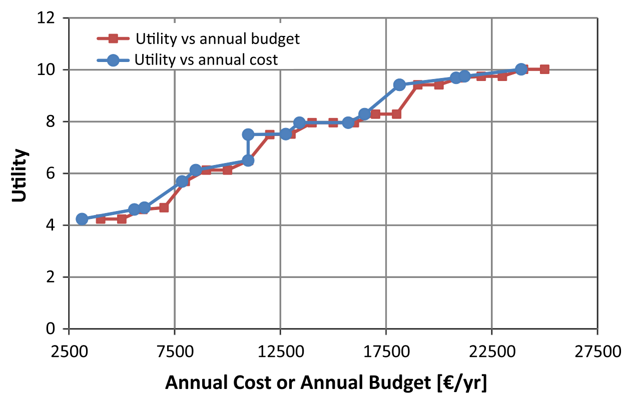

Fig. 1. Trend of utility vs annual cost or annual budget.

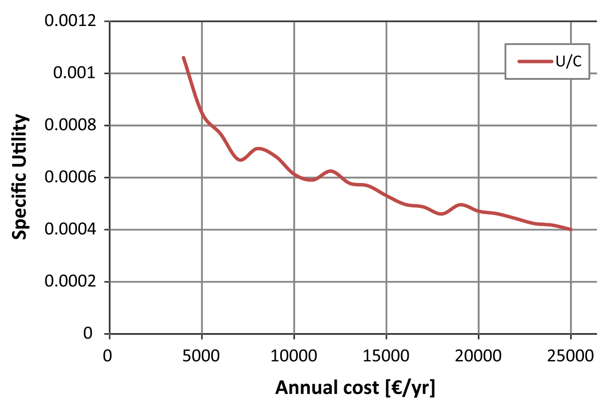

Fig. 2. Trend of specific utility (UC) vs annual cost.

used as inputs to the knapsack model which maximizes the sum of utilities brought by single options into a portfolio subject to given maximum allowable cost. Obviously this benefit is fully gained when there are a large number of solutions to be examined. In case, instead, of a limited number of possible portfolios then a simple multi-criteria analysis or the utilization of an index-based method (Caputo, 2008) would suffice.

Another advantage of the method is that it can be easily utilized resorting to common office automation software. In fact, the knapsack model can be solved using, for instance, the Solver function of MS Excel. In general knapsack problems can be rapidly solved with Branch and Bound techniques which are based on progressive elimination of dominated solutions. However, the passage to a nonlinear model, required to account for the non-additive features may make the approach more computationally intensive so that efficient solution methods should be developed.

The method is inherently additive. This means, at first, that a simple additive weighting model is applied to aggregate scores to get a single score representing the utility of an option, and then that the utility score of a safety measure is merely added to the scores of the other selected safety measures in order to compute the overall utility. While this can be appropriate in most cases, it may happen, especially when multiple safety measure affect the same hazards, that the effects of safety measures are not additive. In this case a non-linear utility model accounting for mutual interactions among safety measures would be required. However, this would make the model much more complex. An easy solution to this problem is to add incompatibility constraint, as shown above, which prevent choosing safety measures which interact negatively or in a non-linear manner. Moreover, while some quantitative performance measures can be additive, the same cannot be generally said for qualitative contributions to the overall utility. Another problem may arise if the set of criteria has been defined so that overlapping evaluations become possible. Care should be given, therefore in the proper selection of evaluation criteria. The additive model is also compensatory, meaning that strengths of an option respect one criterion may compensate for weaknesses respect another criterion. For instance, a safety measure having the maximum risk reduction potential but also the maximum cost would have a null utility score if both evaluation criteria adopt the same weight. Additional studies are therefore required to fully explore the implications of additivity hypothesis and to manage the cases of non-additivity.

The method is particularly flexible, as the analyst has freedom to modify the existing evaluation criteria as he wishes and also can add any other criterion he considers to be relevant in a specific application. Moreover, in order to keep the model easy to use, a simplified expression of S_j scores has been adopted in this paper. Nevertheless, the analyst can choose any other more detailed expression. As an example, the rating indexes proposed by (Caputo, 2008), which are fairly more elaborate, can be adopted as well.

Another degree of freedom comes from the possibility of changing the values of weights w_j to account for different attitudes or interests of the decision maker.

Finally, it should be pointed out that the method lends itself to be fully utilized in the framework of a sensitivity analysis to assess the robustness of the solution to changes in the maximum allowed budget or in the weights assigned to the evaluation scores. This would also allow to evaluate the marginal utility variation when progressively increasing the allowed budget, in order to define the most cost-effective budget level.

7. Conclusions

Plant safety is a major concern for industrial activities considering the involvement of human lives and the risk of relevant economic losses. Plant managers are thus asked to develop a portfolio of safety measures able to significantly reduce risk in a cost-effective manner. However, this is a complex task given the large number of hazards occurring on the workplace and the very large number of safety measures available, spanning from managerial interventions to technology-based options. This gives rise to a combinatory explosion in the number of possible portfolios of safety measures to be evaluated. In the paper a multi-criteria linear programming knapsack model has been developed to assist the safety manager in the ranking and selection of safety measures portfolios to mitigate a given set of hazards in industrial plants subject to budget constraints. The model is easy to apply and rapid to solve on a personal computer. Moreover, it allows to account for conflicting preferences and evaluation criteria, while the simple structure enables to implement additional constraints to manage non-compatibility issues. The model is easy to apply because detailed quantitative knowledge about risk levels and safety measures costs or performances is not strictly required. Another benefit implied by the method is that an attempt to formalize the rating and selection process of safety measures has been provided within a framework offering guidance to the analyst. This would eliminate much of the guess-work allowing the analyst to make more informed decisions. The possible limitations of the method appear the degree of subjectivity still implied in the multi-criteria evaluation as well as the additivity hypothesis underlying the model. However, the first can be mitigated by asking a panel of experts to perform the multi-criteria analysis so that a consensus can be obtained, while the proper formulation of solution alternatives and the adoption of proper constraints can help in reducing the non-additivity concerns. It is believed that the safety practitioner can utilize the presented approach to better focus the safety measure selection process while reducing cost and time spent in the analysis.

References

Alanne, K., 2004. Selection of renovation actions using multi-criteria "knapsack" model. Automation in Construction 13, 377–391.
Antes, M.K., Miri, M.F., Flamberg, S.A., 2001. Selection and design of cost-effective risk reduction systems. Process Safety Progress 20 (3), 197–203.
Brown, D.B., 1980. Use of dynamic programming in optimally allocating funds for highway safety improvements. Transportation Planning and Technology 6, 131–138.
Caputo, AC., 2008. A novel set of ranking indices for effective selection of safety measures. In: Proc. 26th International System Safety Conf. (ISSC 2008). Vancouver, Canada, August 25–29.
Caputo, A.C., Palumbo, M., Pelagagge, P.M., 2011. Economic optimization of industrial safety measures using genetic algorithms. Journal of Loss Prevention in Process Industries 24 (5), 541–551.
Farid, F., Johnston, D.W., Laverde, M.A., Chen, C.J., 1994. Application of incremental benefit-cost analysis for optimal budget allocation to maintenance, rehabilitation and replacement of bridges. Transportation Research Record 1442, 88–100.
Gustafsson, S.I., 1998. Mixed integer linear programming and building retrofit. Energy and Buildings 28, 191–196.
Melachronoudis, E., Kozanidis, G., 2002. A mixed integer knapsack model for allocating funds to highway safety improvements. Transportation Research Part A 36, 789–803.
Pal, R., Sinha, K.C., 1998. Optimization approach to highway safety improvement programming. Transportation Research Record 1640, 1–9.
Sinha, P., Zoltners, A.A., 1979. The multiple choice knapsack problem. Operations Research 27, 503–515.
Sinha, K.C., Kaji, T., Liu, C.C., 1981. Optimal allocation of funds for highway safety improvement projects. Transportation Research Record 808, 24–30.