An integrated framework for risk response planning under resource constraints in large engineering projects

Abstract

Engineering project managers often face a challenge to allocate tight resources for managing interdependent risks. In this paper a quantitative framework of analysis for supporting decision-making in project risk response planning is developed and studied. The design structure matrix representation is used to capture risk interactions and build a risk propagation model for predicting the global mitigation effects of risk response actions. For exemplification, a genetic algorithm is used as tool for choosing response actions and allocating budget reserves. An application to a real transportation construction project is also presented. Comparison with a Sequential Forward Selection greedy algorithm shows the superiority of the genetic algorithm search for optimal solutions, and its flexibility for balancing mitigation effects and required budget.

Keywords: risk response planning, project management, complexity, design structure matrix, resource constraints, genetic algorithm

Managerial relevance statement

The aim of this paper is to provide managers of engineering projects with an integrated five-step framework to guide the risk response planning process, which is to determine and implement preventive and corrective actions to avoid, reduce or transfer project risks. A series of quantitative methods have also been presented for practical use, e.g., for modeling risks and risk interactions, predicting global mitigation effects of response actions, and optimizing the allocation of constrained budget to candidate response actions. Thus, the framework supports project managers' decision-making process in coping with the complexity of project risks and resource constraints. An example of application to a real industrial project of implementing a tramway system in a medium-sized city in Europe is also provided. The proposed approach is expected applicable to a wide set of engineering projects for risk management.

1. Introduction

Engineering projects require the timely accomplishment of a number of tasks, which are exposed to risks of delay, erroneous or low quality completion, incompletion, etc. The Project Management Institute (PMI) defines a project as "a temporary endeavor undertaken to create a unique product, service or result", and a risk as "an uncertain event or condition whose occurrence affects at least one of the project objectives, e.g., scope, schedule, cost, and quality" [1]. The classical Project Risk Management (PRM) process includes risk identification, risk analysis, risk response planning, risk monitoring & control and lessons learned. In particular, project risk response planning aims at identifying actions that can reduce the threats to the realization of the project objectives at minimum cost. It includes the identification and assignment of one or more persons (the "risk response owner") to take responsibility for each agreed-to and funded risk response action. Risks are addressed by their priorities in terms of their impact on the project. Resources are then assigned to the budget and risk response actions are scheduled in the project plan.

Risks are generally identified using more or less structured methods involving a combination of experience, expertise and information search [2], with classical methods, for example, based on analogy [3], heuristics [4] or analysis [5]. They are generally assessed with respect to their probability and impact [1, 6, 7]. For risk prioritization, a very common tool in risk management practice for projects and other contexts is the 'risk matrix' or 'probability-impact grid' (PIG) or 'probability-impact graph' [8-10]. Top-ranked critical risks are then subject to budget allocation and action planning for prevention or mitigation. The other risks identified are not treated, because the risk is regarded acceptable (in terms of both probability and impact) or the action is too expensive and there is no sufficient budget remaining.

However, engineering projects are growing in complexity, of both structure and context due to the involvement of numerous, diverse and strongly interrelated elements [11-13]. This situation exposes projects to a number of diverse and interdependent risks, which implies that identifying and analyzing their causes and effects is an important aspect. For instance, Failure Modes and Effects Analysis (FMEA) consists in a qualitative analysis of dysfunction modes and their effects [14]. Initially developed for product-related risks, it has been expanded to process-related and project-related risks, where the focus changes, but the principle is the same, consisting in identifying direct causes and effects of a potential failure. Fault Tree and Cause Tree Analyses determine the conditions which lead to an event, and link them through logical connectors in a tree-structure which clearly displays causes and effects of the particular risk analyzed [15, 16]. Some methods have been considered for analyzing the interrelationships among risks, such as Bayesian Belief Networks [17, 18], System Dynamics [19-22], and Influence Diagrams [23].

In addition, risk analysis methods and risk response planning methods do not share the same objectives. Risk analysis methods can help to identify actions (for instance, preventive actions by inferring the causes of a risk from a bow-tie diagram), but they do not indicate how to decide on which actions to undertake or not. Within the risk decision-making process, these methods perform the step of searching alternatives, not the step of sorting / ranking the alternatives. In the end, risk responses must be appropriate, cost effective, and realistic within the project context. Selecting the best risk response from several options is often required. To measure the effectiveness of an action or of a portfolio of actions is not easy, since it affects an uncertain event with the additional uncertainty inherent to the planning and execution of the action itself.

In our work here presented, the complexity underlying the web of interconnections among project risks is modeled and represented in terms of a risk network [24]. Such network representation captures the individual risks and the interactions which may trigger global phenomena, like chain reactions or loops. For instance, a single source risk such as project schedule delay, may impact on the risk of cost overrun, which influences a technical risk, and propagates looping back to amplify the original delay. Then, the effects of response actions designed for mitigating the exposure to one or several risks may impact other parts of the network, so that the overall effects of risk response actions may be very different from the expectation of project managers. The challenge of risk response planning is rendered more difficult by the limitation of resource. As constraints become tighter, balancing risks is more critical and less intuitive. For these situations, reliable analytical methods can help project managers plan risk response actions that optimize resource allocation [25-27].

In this paper, a novel integrated five-step framework is introduced to guide the risk response planning process, which is to determine and implement preventive and corrective actions to avoid, reduce or transfer project risks. A matrix-based method is used to facilitate identifying and assessing risk interactions, and build the representative project risk network. This enables the risk propagation behavior in the network to be analyzed. It is then possible to anticipate the global effects of response actions identified by the project management team. Thus, the framework supports project managers' decision-making process in coping with the complexity of project risks and resource constraints. An example of application to a real industrial engineering project, which consists in implementing a tramway system in a medium-sized city in Europe, is considered.

For this case study, a genetic algorithm is developed to optimize the plan of response actions under given budget constraints. Genetic algorithm (GA) is a probabilistic search method introduced by Holland in 1970s [28]. It is based on Darwin's principle of "survival of the fittest", and has rapidly become a popular evolutionary technique for solving complex combinatorial optimization problems, in a wide range of applications [29]. For example, they have been extensively used for the optimization of system reliability and maintenance [30-33], index fund portfolio management [34, 35], project scheduling [36-38] and machine scheduling problems [39, 40]. The GA results are compared with those obtained by using a greedy algorithm, which is based on Sequential Forward Selection (SFS) [41], where the search for the optimal solution proceeds by making the locally optimal choices at each step, with the hope of finding the global optimum.

The remainder of the paper is organized as follows. Section 2 introduces the integrated framework for risk response planning under resource constraints. Section 3 describes the process of building the project risk network and a risk propagation model. In Section 4, the remaining steps of the framework and the developed algorithms for optimizing the risk response plan are presented in details. Section 5 illustrates the application of the proposed approach to a real industrial project. Finally, we conclude the paper in Section 6.

2. An integrated framework for risk response planning

In this Section, a five-step framework for project risk response planning is presented (Fig.1):

1) Building project risk network;

2) Defining objective function;

3) Identifying budget constraints;

4) Identifying potential response actions;

5) Optimizing risk response plan.

Building the project risk network allows us to follow risk propagation in the project. Potential risk response actions can then be proposed, given the risk management objectives and budget constraints. The effects of these response actions can be traced and anticipated in the risk network model. Embedding these analyses within an optimization algorithm (like the SFS greedy algorithm or the genetic algorithm used in this paper) allows searching for an optimal project risk response plan.

The details of each step of the framework are discussed in the following Sections 3 (step 1, which consists of a few sub-steps) and 4 (steps 2 to 5). In practice, the implementation of the proposed framework requires the involvement of the project management team in each step, to provide the necessary project knowledge and expertise and to take decisions.

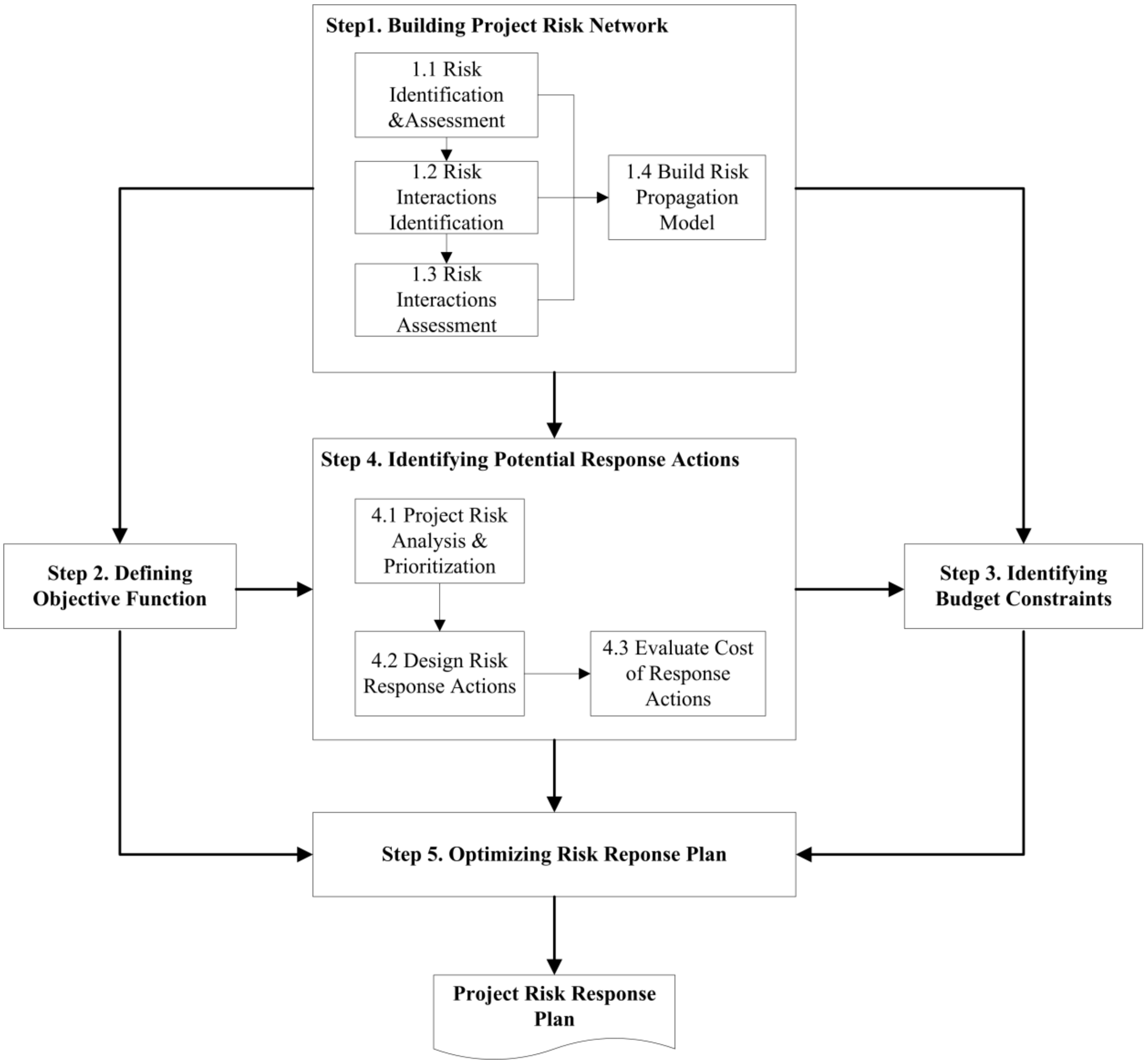

Fig.1. Framework for risk response planning

3. Building project risk network (step 1)

The project risk list containing previously identified potential risks is provided by the project management team (step 1.1). It serves as an input for studying risk interactions in order to build the project risk network.

3.1. Identification of risk interactions (step 1.2)

The Design Structure Matrix (DSM) method introduced in [42] has proven to be a practical tool for representing and analyzing relations and dependencies among system components [43, 44]. For example, it has been extensively used in process modeling and project scheduling problem for design and product development projects, such as in [45-49]. In this work, we use the DSM method to identify risk interactions, for determining the cause-effect relationships among project risks. It provides a simple and concise way to represent the inter-relationships in a complex system. This helps the project manager and the experts focusing on one risk and its dependency with other risks (causes in row and effects in column) during the identification and also the subsequent assessment process, while not getting confused in the complex interrelationships among risks. In addition, the possible existing DSMs representing the interrelations among project objects, such as tasks, actors and product components, can be used to guide the identification of the interactions among the risks associated to these objects. For example, an object-object relationship (whether functional, structural or physical) means that risks, which may be related to product function, quality, delay or cost, can be linked, since a problem on one object may have an influence on another. For instance, the project schedule gives information about task-task sequence relationships; this enables identifying relationships among risks of delay on these tasks.

Moreover, a number of DSM tools and algorithms have been developed to facilitate systemic information acquisition and matrix-based analysis, e.g., in [50, 51]. Although applying these DSM tools/algorithms is not in the scope of this paper, using the DSM methods may provide possible solutions (e.g., in risk grouping and risk owner assignment) for other managerial purposes.

Risk interaction consists of a precedence relationship between two linked risks. We can represent this by the Risk Structure Matrix (RSM), which is a square matrix whose generic element:

$$\begin{cases} RSM_{ij} = 1 & \text{if there is an interaction between risks } R_i \text{ and } R_j \\ RSM_{ij} = 0 & \text{otherwise} \end{cases} \tag{1}$$

Fig. 2 shows an example of a risk structure matrix capturing the relationships in the risk network.

	R1	R2	R3	R4	R5	R6	R7
R1							
R2							
R3				1			
R4	1	1	1				
R5	1			1		1	
R6	1		1	1			
R7		1		1			

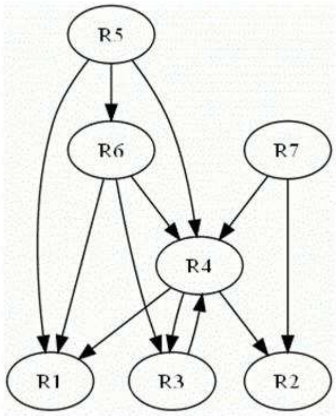

Fig. 2. Risk network and Risk Structure Matrix (adapted from [24])

In the process of building the risk network structure, a sanity check is performed. Suppose we know that R_j has R_i as a cause: if R_i does not have R_j as a consequence, then there is a mismatch. All identified mismatches are studied and solved, like in [52]. Multiple experts are engaged for this task, after being made aware of the possible confusion between direct and indirect interactions among risks, and being asked to concentrate on direct dependencies. For solving mismatches, the two actors involved at each end of the edge are asked to confirm or to deny their initial proposal by discussing together. Generally, people are more easily aware of potential causes that may affect them, rather than potential effects of their own failures. This is why these discussions are mandatory and useful, both for creating a reliable input matrix and for creating links among people.

3.2. Assessment of risk interactions (step 1.3)

In the assessment task, we not only evaluate risk characteristics such as impact and probability, but also assess the strength of risk interactions (interpreted as transition probability between risks). Risk impact may be assessed on a qualitative scale (ordinal or cardinal scale with 5 or 10 levels for instance) or on a quantitative scale (financial loss for instance). Risk impact is assessed by classical methods, based upon a mix of previous experience and expert judgment [1, 53].

For the probability assessment, we make a distinction between the probability of a risk to be triggered by another risk inside the network, and its probability caused by external events or risks which are outside the system. Spontaneous probability can be interpreted as the likelihood of a risk which is not the effect from other activated risks inside the system. On the other hand, transition probability measures the likelihood of direct cause-effect relation between two risks. For the example in Fig. 2, Risk 5 occurs only by spontaneous probability; and Risk 6 may arise from both its spontaneous probability and the transition probability between Risk 5 and Risk 6.

Qualitative scales are often used to express risk probability with 5 to 10 levels (e.g., very rare, rare, unlikely, likely, etc.), which typically correspond to non-linear probability values (e.g., 10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, etc.) [9, 54].

3.3. A risk propagation model (step 1.4)

Some DSM-based work has been done to model the propagation or transmission behavior in the design process. For example, Clarkson and Hamilton proposed a "signposting" model to identify the next design tasks based on the confidence in key design parameters [55]; Smith and Eppinger introduced a work transformation matrix based on the DSM method to model the engineering design iteration process [49]. In the domain of project risk management, a matrix-based risk propagation model has been presented in [56]. This risk network model can be used to predict the global effects of response actions on the entire risk network.

Suppose there are *N* identified project risks in the network. Let vector *s* represent their spontaneous probabilities, i.e. the initial vector of risk probabilities before propagation in the network. Let the *N*-order square matrix *T* denote the matrix of transition probabilities. We make the assumption that a risk may occur more than one time during the project (as witnessed in practical situations). Risk probability is thus cumulative if arising during propagation from different causes or several times from the same cause. After *m* steps of propagation, the probability vector of risks is thus equal to $T^m \cdot s$ and the cumulative risk probability vector *P* is given by the following equation:

$$P = s + \sum_{i=1}^{m} T^i \cdot s = (I + \sum_{i=1}^{m} T^i) \cdot s = (\sum_{i=0}^{m} T^i) \cdot s \quad (2)$$

where *I* is the *N*-order identity matrix. In the limit of infinite propagation steps in the project development,

$$P = \lim_{m \to \infty} (\sum_{i=0}^{m} T^i) \cdot s \quad (3)$$

Multiplying both sides of Eq. (3) by *(I - T)*,

$$(I - T) \cdot P = (I - T) \cdot (\sum_{i=0}^{m} T^i) \cdot s = (I - T^{m+1}) \cdot s \quad (4)$$

It is not guaranteed that the infinite product of the transition matrix *T* would converge to 0, as shown in the following equation:

$$\lim_{m \to \infty} T^m = 0 \tag{5}$$

Sufficient conditions for the convergence of an infinite product of matrices have been given, e.g., in [57-59]. Since in our case *T* is the risk transition matrix, which is usually sparse and composed of transition probability values less than 1, convergence is usually satisfied. Thus, the cumulative risk probability vector can be re-evaluated as:

$$P = (I - T)^{-1} \cdot s \tag{6}$$

Response actions performed on the risk network translate in changes in the values of the parameters of the model, e.g., the spontaneous probabilities in vector *s*, the transition probabilities in matrix *T*. The global effects of these actions in terms of the new values of the risk probabilities in the vector *P* after actions implementation can then be obtained by running the propagation model.

4. Formulating and solving the optimization problem

4.1. Defining objective function (step 2)

Generally, risk response actions with allocated budget are conducted to achieve two different goals: the local mitigation of particular risks and the global risk exposure mitigation. In this paper, we only consider minimizing the overall risk exposure or expected financial loss in global sense. In this regard, the objective function *OF* can be defined as:

$$OF = \sum_{i=1}^{N} P_i * G_i \tag{7}$$

where P_i and G_i indicate the probability and impact (G for gravity scale or financial value) of Risk i.

4.2. Identifying budget constraints (step 3)

Given the project scope, a budget for project risk management, called B_{RM}, is initially established by the project manager. This budget is dependent on the total budget of the project, the evaluated overall level of risk exposure, and also the risk attitudes of the stakeholders.

The budget B_{RM} is normally comprised of three parts. Besides the expense for performing risk analysis B_{RA} (not significant compared with the other parts) and the reserve for risk contingency B_{RC}, the remaining amount B_{RR} is for the execution of the risk response plan:

$$B_{RR} = B_{RM} - B_{RA} - B_{RC} \tag{8}$$

It should be noted that based on the results of the project risk analysis and of the evaluation of the costs of actions in Step 4 (Fig. 1), the budget for performing the risk response plan B_{RR} can be updated according to the new knowledge acquired with regard to the risk management tasks.

4.3. Identifying potential response actions (step 4)

The identified project risks can be analyzed and prioritized using classical methods or a simulation model based on the risk network [24] (step 4.1). However, it is not the main concern of this paper. Aiming at achieving the objectives defined for risk management, for example, mitigating the global risk exposure as mathematically captured by the OF in Eq. (7), potential response actions can be identified based on the project risk analysis results (step 4.2). The response action list may include different types of risk response actions on risks and their interactions, in terms of risk sharing, risk avoidance, risk mitigation and risk acceptance, etc. These actions are, for instance, adopting less complex processes, conducting more tests, enhancing internal communication, choosing a more stable supplier, etc. From the point of view of the framework of modeling and analysis, conducting the response actions has the effects of changing the values of some of the parameters of the risk network model. For example, a classical response action on a particular risk reduces its spontaneous probability or impact; a complementary preventive action is to cut off the input links or reduce their transition probabilities; blocking the output links can be regarded as the action of confining the further propagation of such risk to subsequent risks.

Risk response actions always consume time, money and other resources. In order to perform the optimization, the cost of each identified action is evaluated by the project management team (step 4.3). Actions should be worthwhile, i.e., more valuable than the expected value of the risk impact. Before the next step of optimization, the response action list shall be examined by the project manager to exclude the unfeasible actions.

4.4. Optimizing risk response plan (step 5)

For each risk response action identified in Step 4, the project manager can decide whether to implement it or not. Given a list of n candidate actions, there are 2^n-1 combinations for the risk response plan aiming at mitigating the overall risk exposure (the global objective function). An exhaustive test of all the combinations is impractical. Considering the resource constraints, heuristic algorithms can be exploited to optimize the portfolio of response actions: here, we provide two examples of such algorithms which are then applied on a real case study in Section 5.

4.4.1. A SFS greedy algorithm

A greedy algorithm based on Sequential Forward Selection is developed for the optimization of a risk response plan under constraints. At each step the action with the best test performance is chosen until the budget is completely allocated. The risk propagation model presented in Section 3.3 can be used to evaluate the mitigation performance of actions in terms of the OF in Eq. (7).

The SFS greedy algorithm is sketched as follows:

Identify the budget constraint B_{RR};
Prepare the action list L;
Create the portfolio of actions $A = \varnothing$;
WHILE $L \neq \varnothing$ **DO**
BEGIN
  FOR each $A_i \in L$
    IF the cost of A_i exceeds the remaining budget B_{RR}: ($C(A_i) > B_{RR}$)
    Remove A_i from L : ($L = L \setminus A_i$);
    ELSE
    Test the global mitigation effects of $A \bigcup A_i$ in the risk network model;
    END
  END
  Choose the best candidate A_i^*;
  Add A_i^* into A : ($A = A \bigcup A_i^*$);
  Remove A_i^* from L : ($L = L \setminus A_i^*$);
  Allocate the corresponding amount of budget ($B_{RR} = B_{RR} - C(A_i^*)$);
END
RETURN A as the optimal portfolio of actions.

Usually such greedy algorithm for optimization under constraints can achieve only a locally optimal solution because it makes commitments to certain choices too early, which prevent it from finding the best overall solution later. For example, choosing at an early stage an action with positive effects but expensive reduces the budget remaining for future actions, with the risk of sacrificing opportunities.

4.4.2. A genetic algorithm

In our work, a genetic algorithm is devised for the optimization of a project risk response plan. The aim is to find an optimal portfolio of actions, whose performance is measured by an objective function (fitness) which integrates the budget constraint. The synergic effects (positive or negative) of the actions in the portfolio are taken into account, because the entire portfolio is tested on the risk network model, while not just the single actions separately.

The basic genetic algorithm-based optimization process is described as follows:

1) Basic Scheme

Generation *GEN* = 1;

Create initial population *POP* of individuals *Ind* (each one is a portfolio of actions);

WHILE *GEN* < *GEN** **AND** (Not Terminate-Condition) **DO**

BEGIN

GEN = *GEN* + 1;

Apply each portfolio of actions ($Ind \in POP$) to the risk network model and compute the fitness values for each individual;

Select parents *PAs* from *POP*;

Produce children *CHs* from *PAs* by Crossover;

Mutation operation on children $Ind \in CHs$;

$POP = POP \cup CHs$;

Reduce *POP* by fitness ranking;

END

A risk response plan of n actions A_i ($i = 1, \ldots, n$) is suitable to be encoded as a string of bits $x = \{x_1, x_2, \ldots x_i, \ldots x_{n-1}, x_n\}$ forming a chromosome (individual) in the GA. Each bit $x_i \in \{0,1\}$ indicates whether the corresponding action A_i is chosen in the portfolio or not.

2) Fitness

We integrate the budget constraint into the objective function (fitness) of the optimization problem, aiming at minimizing the value:

$$Fitness\ f = \lambda \sum_{i=1}^{N} (P_i' * G_i') + (1-\lambda)(C / \alpha B_{RR})^{\beta} \tag{9}$$

Here C is the total cost of the action plan; P_i' and G_i' are the probability and impact of Risk i after the implementation of the response plan. The penalty value $(C / \alpha B_{RR})^{\beta}$ significantly increases if the allocated costs C exceed αB_{RR} ($0 < \alpha \le 1$), e.g., 90% of the budget constraint. Thus, breaking constraints is penalized by the decrease of the fitness. The parameter $\beta > 1$ reflects the project manager's degree of aversion to budget overruns. The project manager can adjust the parameter $\lambda \in [0,1]$ to balance the trade-off between budget constraints and mitigation effects.

The details of the GA process are introduced in the Appendix.

5. Application to a real industrial project

The framework proposed has been implemented to a real engineering project aimed at building a tramway infrastructure and associated systems. The project includes the construction and implementation of tramway, equipment, and civil work.

5.1. Build the project risk network (step 1)

An original project risk list has been provided by the project manager. It contains 56 identified risks at the main level, with their names, domains and qualitatively evaluated characteristics, as shown in Table 1. The project risks identified with negative effects belong to different categories such as Technical, Contractual, Financial, Client/Partner/Subcontractor, and Project management on construction site.

Using the DSM-based method introduced in Section 3.1, the interactions among the 56 risks have been identified with the help of the project manager and the team of experts, composed of the 11 risk owners. For each risk, experts were asked to provide information about the potential causes and effects (to explore the row and the column corresponding to the considered risk in the risk structure matrix). The aggregation of local cause-effect relationship identifications enables to build the global risk network.

As anticipated in Section 3.2, the assessment of the identified risk interactions was then performed on a 10-level Likert scale, due to the high expertise of interviewees. This requires the participation of several experts involved in the project, since it necessitates a wide overview of the project elements and stakes. In this case study, four risk owners, including the project manager, were mostly contributing to the data gathering. The other owners and an external risk manager were only solicited to give some specific and local information, and to validate existing data. In the end, the binary risk structure matrix can be transformed into the matrix of the transition probabilities between risks.

Table 1. Tramway project risk list and related characteristics

Risk ID	Risk Name	Risk Domain	Risk Owner	Qualitative Risk Probability	Qualitative Risk Impact	Criticality
1	Safety studies	Technical	1	1	1	1
2	Liquidated damages on intermadiate milestone and delay of Progress Payment Threshold	Contractual	2	7	8	56
3	Vehicle storage in another city	Contractual	1	9	5	45
4	Vandalism on site	Contractual	3	1	3	3
5	Traction/braking function : behaviour in degraded mode on slope	Technical	1	3	2	6
6	New local laws and regulations	Contractual	1	1	3	3
7	Traffic signalling, priority at intersections	Contractual	4	6	5	30
8	Unclear Interface with the Client, for Infrastructure equipment	Contractual	5	1	2	2
9	Delays due to client late decisions	Contractual	5	9	1	9
10	Travel Time performance	Technical	4	1	3	3
11	Limited Force majeure definition	Contractual	2	1	4	4
12	Operating certificate delay	Contractual	2	9	4	36
13	Reliability & availability targets	Technical	4	3	3	9
14	Permits & authorisations	Contractual	2	9	2	18
15	Insurance deductibles	Financial	6	1	3	3
16	Archeological findings	Contractual	2	9	3	27
17	Discrepancies Client / Operator / Concessionaire	Contractual	7	3	5	15
18	Civil Work delay & continuity	Contractual	8	9	4	36
19	Responsibility of client on Civil Work delay	Contractual	2	9	2	18
20	On board CCTV scope	Technical	9	5	1	5
21	Noise & vibration attenuation	Technical	4	3	6	18
22	Potential risks of claim from Civil Work subcontractor	Contractual	2	5	5	25
23	Harmonics level	Technical	5	1	2	2
24	Non compliance contractual Rolling Stock	Technical	1	1	6	6
25	Non compliance technical specifications Rolling Stock	Contractual	1	3	4	12
26	Exchange risk on suppliers	Financial	6	1	3	3
27	Track installation machine performance	Client/Partner/Subcontractor	10	3	2	6
28	Tax risk on onshore	Financial	6	1	2	2
29	Additional poles overcost for Tramway Company	Contractual	5	9	4	36
30	Overcost due to Security requirements for trains	Technical	4	5	4	20
31	Track insulation	Technical	9	1	1	1
32	Delay for energising	Project management, Construction site	5	3	2	6
33	Fare collection requirements	Contractual	7	5	3	15
34	Construction safety interfaces	Technical	3	1	1	1
35	Electromagnetic interferences	Technical	4	1	2	2
36	Exchange risk	Financial	6	1	2	2
37	Risk of partial rejection of our request for EOT (Extension Of Time)	Contractual	2	9	7	63
38	Interface rail / wheel	Technical	4	3	2	6
39	Risk on Certification of our equipement	Country	11	1	2	2
40	OCS installation	Project management, Construction site	3	7	5	35
41	Banks stop financing the project	Contractual	2	7	3	21
42	Costs of modifications not covered by EOT agreement	Contractual	2	1	4	4
43	Return profit decrease	Financial	2	9	8	72
44	Extra trains	Contractual	4	1	6	6
45	Pedestrian zones	Technical	4	1	2	2
46	Train performance	Technical	1	3	2	6
47	Waiting time at stations	Contractual	4	5	1	5
48	Depot delay	Technical	3	9	2	18
49	Error in the Survey (topography)	Technical	4	1	1	1
50	Ticketing design delays	Contractual	7	7	1	7
51	Track installation delay	Technical	3	7	2	14
52	Reengineering / Redesign	Technical	4	9	2	18
53	Slabs pouring delay	Technical	3	5	1	5
54	Initial specifications of CW (Civil Work)	Technical	3	5	1	5
55	Available cash flow decrease	Financial	2	9	7	63
56	Rolling stock delivery delay	Technical	1	3	1	3

5.2. Define the mitigation objective and budget constraint (steps 2 and 3)

In this prototype application, the aim is to mitigate the global risk exposure, and for this, the objective function in Eq. (7) is used as the function for which minimization is sought. The impact of risks is assessed in terms of qualitative severity scale (from 1 to 10) for this case study, as shown in Table 1.

We suppose in this case study that the budget reserve for implementing the risk response plan is B_{RR} = 300 k€.

5.3. Build the action list (step 4)

With the help of the project management team, a list of potential risk response actions is proposed, as reported in Table 2. The 21 proposed actions are based on a refined analysis, taking into account interactions between risks and eliminating some unfeasible ones. The actions are intended to mitigate the risk nodes (reduce risk spontaneous probability or risk impact) or the risk interaction edges (reduce transition probability between risks). The local effects of the response actions are estimated (Table 2). The global effects of the actions can be predicted using the risk propagation model described in Section 3.3. The cost for executing these actions is also estimated by the project management team.

Table 2. List of risk response actions

Action ID	Action Name	Cost Estimate (k€)	Evaluated Local Effects (on qualitative scale)
A1	Mitigate R2 by contract update	35	s'(R2)=5 instead of 7
A2	Mitigate R37 by formalizing a procedure for preparing Extension Of Time meetings	10	s'(R37)=6 instead of 9; G'(R37)=6 instead of 7
A3	Mitigate R3 by preventing depot delay (R48)	55	s'(R48)= 5 instead of 9
A4	Avoid consequences of R29 by including flexibility in the contract	20	s'(R29)=0 instead of 9
A5	Mitigate R7 by involving city stakeholders early in the project	20	s'(R7)=3 instead of 6 G'(R7)=3 instead of 5;
A6	Mitigate R40 by preventing bad scope definition (R20) => indirect action	10	s'(R20)=3 instead of 5; s'(R40)=3 instead of 7
A7	Mitigate R22 by signing a Firm Fixed Price contract with Civil Work subcontractor	10	G'(R22)=1 instead of 5
A8	Mitigate R22 by communicating with CW subcontractor and solving problems on a regular basis	20	s'(R22)=3 instead of 5; G'(R22)=3 instead of 5
A9	Avoid R51 by keeping the same track installation machine (R27)	5	s'(R51)=1 instead of 7; s'(R27)=0 instead of 3
A10	Avoid R51 by introducing time buffers on this task, due to the uncertainty	10	T'(R27->R51)=0 instead of 3
A11	Mitigate R48 by prioritizing Civil Work activities and then avoiding propagation R18->R48	20	T'(R18->R48)=0
A12	Avoid R30 by including security in contract definition	20	s'(R30)=0 instead of 5
A13	Avoid R52 by specifying correctly the customer requirements and specificities of the context	60	s'(R52)=0 instead of 9
A14	Confine R10 consequences	40	T'(R10->R13)=0 instead of 3
A15	Mitigate R12 by preventing some of its causes	20	s'(R12)=6 instead of 9
A16	Avoid R12 by decomposing Operating Certificate into smaller components and introducing flexibility in the contract	40	s'(R12)=0 instead of 9
A17	Mitigate R10 by proposing high performance trains	60	s'(R46)=1 instead of 3; T'(R46->R10)=0 instead of 1; T'(R46->R52)=1 instead of 5
A18	Avoid extra trains overcost (R44) by contractual agreement	20	s'(R44)=0 instead of 1
A19	Avoid extra trains overcost (R44) by train performance upgrade	40	s'(R44)=0 instead of 1
A20	Mitigate R13 by early involvement of stakeholders (scope definition)	20	s'(R13)=1 instead of 3
A21	Mitigate R13 by proposing high performance trains	25	s'(R13)=1 instead of 3; G'(R13)=1 instead of 3

5.4. Optimize the portfolio of actions (step 5)

Optimization results obtained using both the SFS greedy algorithm and the genetic algorithm are illustrated and compared in this Section.

5.4.1. Greedy algorithm results

The SFS greedy algorithm devised in Section 4.4.1 has been used to obtain a portfolio of actions, given the budget constraint B_{RR} = 300 k€. The results are reported in Table 3, following the successive iterations of optimal action addition to the portfolio.

The optimal portfolio $\mathbf{A^*}$ contains 11 actions: $\mathbf{A^*}$ **= [A1, A2, A3, A4, A5, A6, A8, A9, A12, A13, A16]**. The total cost is **295 k€** and the value of the objective function, namely the overall risk exposure, has been reduced from **63.128** to **43.599** thanks to the identified actions.

Table 3. Optimization results using the SFS greedy algorithm

Iteration	Selected Action ID	Cost (k€)	Objective Function Value	Added Effects	Current Portfolio	Allocated Budget (k€)
Initial Status	-	0	63.128	0.000	[Null]	0
1	A16	40	59.572	-3.556	[A16]	40
2	A5	20	56.521	-3.051	[A16,A5]	60
3	A9	5	54.367	-2.154	[A16,A5,A9]	65
4	A2	10	52.558	-1.808	[A16,A5,A9,A2]	75
5	A4	20	50.777	-1.781	[A16,A5,A9,A2,A4]	95
6	A6	10	49.222	-1.555	[A16,A5,A9,A2,A4,A6]	105
7	A1	35	47.910	-1.313	[A16,A5,A9,A2,A4,A6, A1]	140
8	A8	20	46.641	-1.269	[A16,A5,A9,A2,A4,A6, A1,A8]	160
9	A13	60	45.434	-1.208	[A16,A5,A9,A2,A4,A6, A1,A8,A13]	220
10	A12	20	44.424	-1.009	[A16,A5,A9,A2,A4,A6, A1,A8,A13,A12]	240
11	A3	55	**43.599**	-0.825	**[A16,A5,A9,A2,A4,A6, A1,A8,A13,A12,A3]**	**295**

5.4.2. Genetic algorithm results

In the genetic algorithm, the population size is set to M = 100 individuals. The Roulette Wheel Method is used for selecting the parents for the next generation. The crossover fraction is set to 0.8, and the mutation rate is set to 0.01 by testing. The termination condition is set as either

1) the maximum number of generations GEN^* = 100; or 2) there is no improvement in the best fitness value for 20 successive generations.

For the parameters of the fitness function f of Eq. (9), we set $\lambda=0.9$, $\alpha=0.95$ and $\beta=20$ by experience and testing. We have run the GA for twenty times with different random seeds and selected the best solution among them. In that run performed, the algorithm terminates at the 48th generation and the best individual is the chromosome **$\mathbf{x}^*$ = [1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1]**, corresponding to the decoded optimal portfolio **$\mathbf{A}^*$= [A1, A2, A4, A5, A6, A7, A8, A9, A11, A12, A13, A16, A21]**. The best fitness value is equal to 39.052. The total cost of implementing action plan A^* is **295 k€**. The objective function of global risk exposure in Eq. (7) is reduced to the value of **43.169**.

Comparison with the results of the SFS greedy algorithm (Table 4) shows that in the optimal solution obtained by the genetic algorithm, the action A3 has been replaced by the combination of A7, A11 and A21. In this case, the required budget for the portfolio is the same, but the optimal risk response plan has better effects on the objective of mitigating the global risk exposure.

Table 4. Comparison of the results obtained by the greedy and genetic algorithms

Method	Optimal Portfolio	Number of Actions	Required Budget (k€)	Objective Function Value
SFS Greedy Algorithm	[A1, A2, A3, A4, A5, A6, A8, A9, A12, A13, A16]	11	295	43.599
Genetic Algorithm	[A1, A2, A4, A5, A6, A7, A8, A9, A11, A12, A13, A16, A21]	13	295	43.169

The parameters of the genetic algorithm can be modified to reflect the adjustment of strategy by the risk management. For example, if we set $\lambda = 0.8$ to strengthen the control over the budget, the optimal portfolio becomes **A* = [A1, A2, A4, A5, A6, A7, A8, A9, A12, A13, A16, A21]**. We can see that A11 has been removed from the action plan so that the required budget has decreased to **275 k€**, with an objective function value of **43.443**.

On the other hand, if we increase the balance factor λ to 0.95 for emphasizing the mitigation effects, the optimal portfolio becomes **A* = [A1, A2, A3, A4, A5, A6, A8, A9, A12, A13, A16, A21]**. In this case, A3 has replaced the actions A7 and A11. As a result, the objective function has improved to **42.963**. However, extra budget is required to achieve such result, for a total cost of the risk response plan equal to **320 k€**.

6. Discussion

This study has been motivated by questions and requests by practitioners, who are ready to apply more sophisticated techniques to make decisions about their risk response plans. They were confident in the results of the case study on the tramway construction project, since both algorithms confirmed their priorities.

Apparently, the comparison of the results on the case study indicates that the genetic algorithm provides a superior search for the optimum than the greedy algorithm. The deficiency of the SFS greedy algorithm is that only the effect rather than the cost of actions is considered as the basis for local searches, which may prevent it from finding the global optimal solution. On the contrary, through testing the entire response plans while not individual actions in the risk network model, the genetic algorithm takes into account the synergy or co-effects of different actions for mitigating. Moreover, by adjusting the parameters of the fitness function, the project manager is able to achieve a trade-off between improving risk management results and lowering the budget.

However, the practitioners were attached to the sequence of inclusion of actions in the portfolio by the SFS greedy algorithm, even if in a global optimization algorithm, like GA, this could not have any importance. Specifically, they were confident on inclusion of actions A16, A5 and A9, rather than A13, A12 and A3. On this last action A3, they were ready to include it in their action plan, and both greedy algorithm (since this was the last action included in the portfolio) and genetic algorithm (since it was not included in the optimal portfolio, but embraced after relaxing the budget constraint) proved helpful in convincing them to change their plan in such direction. In general, it is to be expected that the optimization should change only some elements of an action plan, and not make a complete revolution, since decision-makers are capable of identifying the most important and efficient response actions. The optimization work can help in the decisions for actions which are close from inclusion or exclusion, and in the identification of possible big surprises, although less frequent.

One may wonder when to perform this process of data gathering and related analysis. In most cases, the earlier, the better. Indeed, it changes the risk response plan, with its associated budget, resources and actions, so it is recommended to change decisions before they are applied. However, information may be neither available nor reliable at the very beginning of the project, which may result in irrelevant action plans. The decision about the schedule (one or several times during the project) should thus be a balance between the necessities to do it early enough and to have enough reliable information. The best moment depends on the degree of uncertainty on data. If projects are recurrent and some historical data are available, both on risks, risk interactions and risk response alternatives, then this process may be run at the earliest phases. But generally, if the context is new (country, subcontractors), or if the objectives are significantly different, then it is better to wait to have enough and more reliable data. In the case study presented here, the project had already been launched before the beginning of the study. Eight risk review meetings had been conducted before our intervention.

It should be admitted that there exist limitations of applying the proposed approach in practice. For example, the difficulties and uncertainties are unavoidable in identifying and quantifying the risk interactions using the DSM methods. First, the issue of a correct risk identification and particularly risk formulation is relevant. In this regard, efforts should be made by the project management team to determine the proper level of details and the way to formulate risks in less ambiguous ways. Second, it is sometimes difficult to differentiate direct and indirect interactions between risks, although the interviewees have been reminded to concentrate on direct dependencies. Third, dealing with project risks, especially the probabilities being used, includes subjective assessment and thus uncertainties. Subsequently, we have to be very careful when manipulating uncertain / unreliable data using optimization algorithms, since the output depends on the reliability of the inputs. One should not apply blindly the optimization results, but should analyze carefully the gap between the proposed solution and its neighbors. Also, we have to be careful when using quantitative data, since we cannot have all the data which are quantitative, so the danger is to mix qualitative and quantitative data.

7. Conclusion and perspective

In this paper, we have presented an original framework for decision support in project risk response planning, and showed how it is applied to a real case study of a tramway construction project. Through modeling risk interactions, the framework makes it possible to analyze risk propagation behavior and thus to anticipate the overall effects of response actions on the global risk network. It can guide the project manager design some non-conventional actions on risk interactions which mitigates risk propagation instead of risk occurrence. For optimally allocating tight resources for risk mitigation, i.e., selecting the best risk response plan from an action list with many options, a Sequential Forward Selection greedy algorithm and a genetic algorithm have been investigated, taking into account budget constraints. The comparison of the results obtained by these two optimization algorithms shows that the genetic algorithm has superior performance. The proposed framework and quantitative methods are expected applicable to a wide set of engineering projects for risk management.

In addition to the limitations of the approach discussed above, for potential improvements, the stakeholders' or the project manager's preferences would be included into the risk response planning process. For example, the mitigation of several particular risks is sometimes mandatory. In addition, the portfolio of actions may be more complex. In practice, for instance, if more funds are allocated on the reinforcement of a component or task, the probability of its failure risk will decrease. In this regard, an action for mitigating risks, for example, A2 can be subdivided into several alternatives (e.g., A2.1, A2.2, and A2.3) with different levels of cost, which will undoubtedly generate different levels of mitigation effects. In this case, we need not only to decide whether to choose an action or not, but also to optimize the level of investment on each action and related risks. Furthermore, the developed DSM-based tools/techniques can be considered for managerial purposes concerning risk management, e.g., in risk grouping and risk owner organization. This work will also be considered for program management of multiple related projects with regard to risk management.

Appendix. The process of Genetic Algorithm for this study

1) Initial population

An initial population of M individual solutions is created randomly. Each individual is a risk response plan, namely a portfolio of actions. Population diversity (i.e., differences in the individuals) is encouraged to investigate more broadly the search space [60].

2) Selection of the parents

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (with lower values of the fitness function) are more likely to be selected. We employ the straightforward Roulette Wheel Selection method [61, 62]: the chromosome x^k is selected if:

$$\frac{\sum_{j=1}^{k-1} f(x^j)}{\sum_{j=1}^{M} f(x^j)} < r \leq \frac{\sum_{j=1}^{k} f(x^j)}{\sum_{j=1}^{M} f(x^j)} \tag{10}$$

where r is the generated random number with $r \in (0,1]$.

3) Crossover and mutation

Crossover allows combining two parents to form a child. We employ a conventional scattered crossover as sketched in Fig. 3 [63]. A random binary vector is created as bit mask. It selects the genes from parent 1 where the mask bit is ‘1’, and the genes from parent 2 where the mask bit is ‘0’, and combines the genes to form the child. It should be noted that in Fig.3 the symbols a~h and 1~8 are replaced by binary bits in the work here presented. A crossover fraction of value in [0, 1] specifies the portion of the individuals in the next generation that are produced by crossover, other than the elite individuals (the number of individuals that are guaranteed to survive to the next generation). Elitism is the process of selecting individuals with a bias towards the better ones, which is based on fitness ranking in the developed GA. Indeed, elitism is important for allowing the solutions to get better over generations.

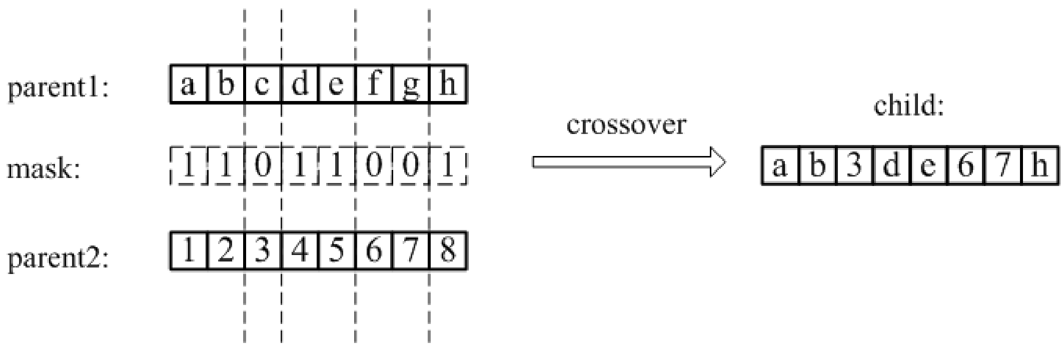

Fig. 3. Illustration of the crossover operation

Mutation inserts small random changes in the individuals of the population, which further favors genetic diversity. It thus enables the GA to extend the search to a broader space. A mutation rate is introduced as the probability that a bit in a chromosome will be reversed (0->1, 1->0). The mutation rate for a single bit is usually taken very low for binary encoded genes [64].

4) Reduction of population for the next generation

We use the conventional GA with fixed population size in this work. In this regard, fitness ranking is used to guide the reduction of the population for the next generation [30]: the individuals with lowest fitness are removed from the enlarged population of parents and children, where the original size *M* is re-established.

5) Termination condition

In this work, the search iterations of the GA are terminated simply when an a-priori fixed number of generations GEN^* is reached, or when the top ranked solution's fitness has stabilized, i.e., a fixed number of successive iterations no longer improve it.

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