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Selection of projects' primary and secondary mitigation actions through optimization methods in nuclear decommissioning projects

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ABSTRACT

The growing interest in nuclear power has brought attention back to the general condition of nuclear power plants. In fact, according to the main intergovernmental organisations responsible for nuclear energy, more than 150 basic nuclear facilities (in-service reactors, downgraded reactors, fuel fabrication plants, reprocessing plants, and waste storage areas) should be seriously checked for safety reasons, while many others are close to the end of their lifecycles (lasting generally around 50–60 years) – thus, there is an urgent need for research into the management of Nuclear Decommissioning Projects (NDPs). In particular, the high complexity of these projects makes it fundamental to implement strong risk management procedures, aimed at identifying and analyzing all possible hazards, and finding and implementing the appropriate risk response actions. This paper focuses on the selection of mitigation actions and proposes optimizationisation algorithms to select the most time-effective set of risk responses for a nuclear decommissioning project. A single case study of an Italian completed NDP was employed to investigate the application of optimization techniques in the mitigation action selection phase, considering also secondary risks and secondary mitigation action. The results show that the performance that would have been achieved through the optimization algorithm would have been superior, both from the point of view of a reduced time delay, and in terms of a more effective balance between overall risk coverage and implementation costs.

1. 1.Introduction

The period we are facing, influenced by exceptional events having a great impact on energy production and need, is drawing attention to the potential contribution that nuclear energy can make to the overall energy supply.

Although national executives, public opinion, and environmental groups currently debate and sometimes reach agreement on its use and potential, the existing nuclear power supply is limited. According to the IAEA's (International Atomic Energy Agency, 2021) high-case projection, nuclear energy will probably contribute about 12% of global electricity by 2050, with coal remaining the dominant energy source for electricity production at about 37%, data that has changed little since the early 80 s. However, nuclear energy production shows many potentials (International Atomic Energy Agency, 2021):

- The production of greenhouse gases related to atomic energy is virtually zero, which greatly reduces the short-term environmental impact of these plants, allowing also reduced usage of petrol and gas, the supply of which is generally very unstable for geopolitical reasons.
- Nuclear power plants can deliver energy in a constant and controllable way, a characteristic that takes on significance in view of variations in electricity demand.
- Nuclear power plants allow high volumes of energy to be produced at a low cost: a single nuclear power plant can meet the needs of one or more average-sized cities and a modest amount of uranium can power a 1 GW plant, corresponding to the needs of about half a million people (Krishnamurthi et al., 2015).

The growing interest in nuclear power, however, has also brought attention back to the general condition of nuclear power plants: according to some authors around 150 basic nuclear facilities (in-service reactors, downgraded reactors, fuel fabrication plants, reprocessing plants, and waste storage areas) should be seriously checked for safety reasons, while many others are close to the end of their lifecycles (generally around 50 – 60 years) (International Atomic Energy Agency, 2022). Most of the technologies that today provide the energy baseload

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are fossil fuel power plants that will need to be gradually replaced to hit the emissions reduction targets for 2030 and 2050 (Delbeke et al., 2019; 'The Paris Agreement', 2016).

This, and the fact that of the 443 plants in operation worldwide, distributed in 30 countries, more than 65% are over 30 years old, and of these, almost 17% are over 40 years old (IAEA, 2016; International Atomic Energy Agency, 2022), means that there is an urgent need for research into the management of Nuclear Decommissioning Projects (NDPs) (see Fig. 1).

Nuclear Decommissioning Projects aim to assess the degree of radioactive contamination, remove the fuel, decontaminate the facilities, and finally demolish them. The technical and construction diversity of the different plants, the multitude of institutions and stakeholders involved, and the high riskiness of project activities make NDPs highly unique and thus relatively complex to be managed (Invernizzi et al., 2017c; Invernizzi et al., 2017a). The higher the complexity of the projects, the more it is fundamental to implement strong risk management procedures, aimed at identifying and analyzing all possible hazards, finding and implementing the appropriate risk response actions, and finally monitoring project progress after mitigation actions implementation (Qazi et al., 2016).

The current literature on risk management in NDPs offers several frameworks for managing risks: the IAEA (IAEA Tech Report 97, 2019) established the DRiMa project in order to share best practices for procedures and tools already in use among practitioners for the Project Risk Management (PRM) of NDPs; some authors focused on the development of a qualitative assessment analysis of the technical and operational risks of NDPs (Jeong et al., 2008; Jeong, Lee and Lim, 2010), while others proposed modeling alternatives for the identification and management of major risks through Bayesian Networks (Faber et al., 2002).

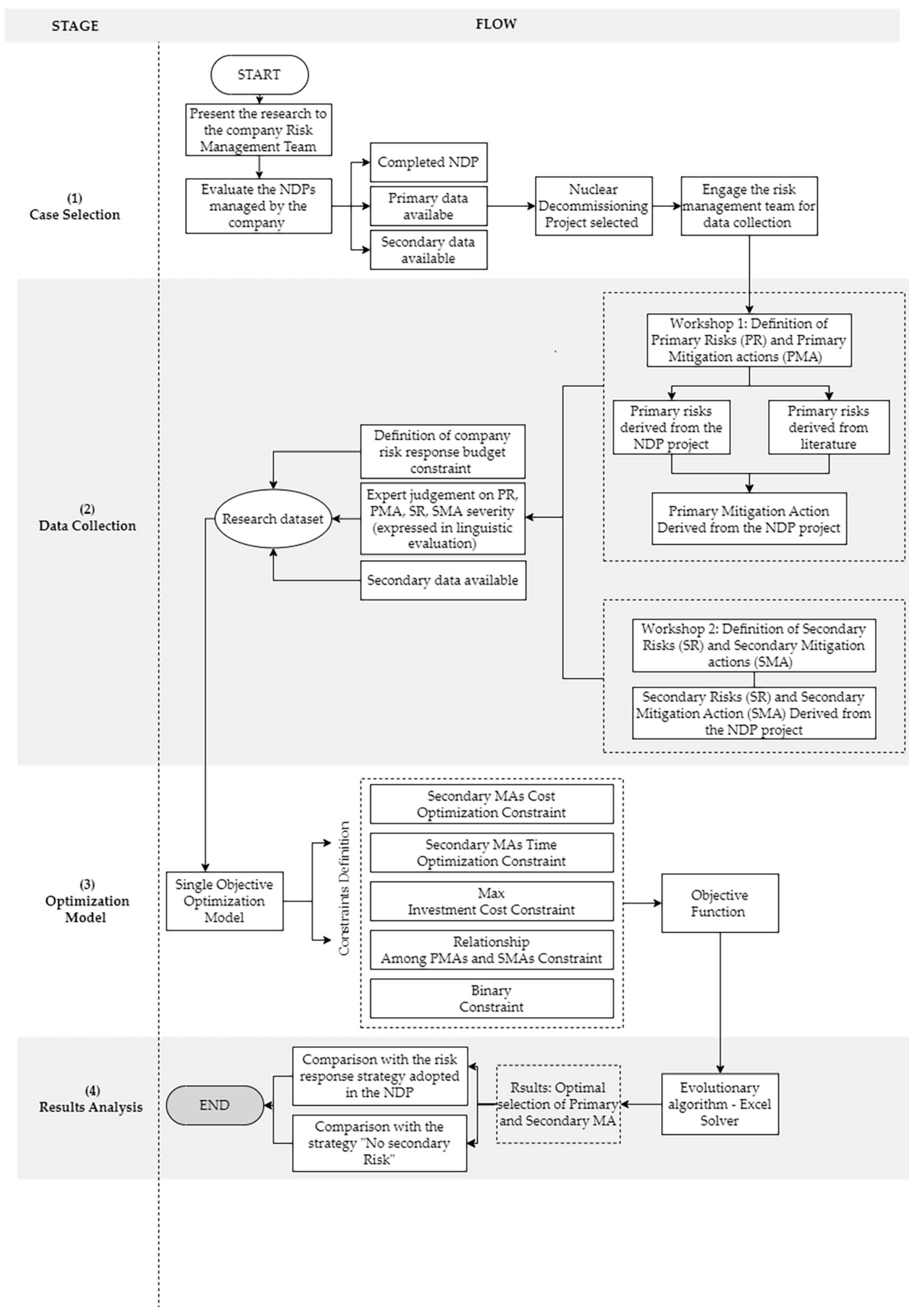

Fig. 1.

The literature provides valuable support for the risk assessment phase, which however is assessed mainly in a qualitative way, relying predominantly on experts' judgement, and considering only primary risks. However, the literature does not provide any examples or cases of the selection of mitigation actions and the contingency allocation, which constitutes the risk response phase.

Mitigation actions are normally taken to reduce the probability of occurrence and/or the impact of the threat on the project, and in NDPs selection of the optimal set of mitigation actions assumes a central role. The high uniqueness of these projects and the complexity of their management often causes them to run over time and over budget (Awodi et al., 2021), and the ability to optimally mitigate project risks can help to promote meeting project constraints.

In order to fill the extant gaps in the literature, the authors investigated the following research question:

RQ1: What are the methods available in the literature employed to select the optimal risk response strategy?
RQ2: What is the most suitable method for an optimal selection of mitigation actions in NDPs?
RQ3: What is the implication of considering secondary risk in the process of mitigation actions selection?

The first research question was addressed by performing an accurate literature review, highlighting the methods found in literature together with limitations and potential for application in NDPs; optimization techniques were reviewed and suggested as suitable methods for performing a quantitative and accurate mitigation action selection. In proposing this method as the preferable way to select mitigation actions in NDPs, the authors suggest to also considering the impact of secondary risks and selecting secondary mitigation actions for a more complete risk response strategy. The paper is organized as follows: the following paragraphs include a description of the methodology used and the results obtained in applying the optimization model to a completed Italian NDP project. The discussions outline the implications of including secondary risks in the analysis, and compare the proposed model application with the actual model implemented by the NDP risk management team.

2. Literature review

2.1. Risk response management in nuclear decommissioning projects: A subject in need of exploration

Despite the importance of and interest in nuclear-decommissioning projects, a thorough knowledge of their management is still lacking (Invernizzi et al., 2018). It is in fact far less well understood than the management of building and operation projects for the same facilities because of their long duration and the lack of distribution of the managerial practices used in previous, ongoing, or finished decommissioning projects. When it comes to the risk management process, this is even more true (Awodi et al., 2021). In the case of unique projects such as NDPs, this process requires many different skills in place and effective methods to reach acceptable results in terms of risk identification and management.

Currently, the understandings of risk management in nuclear-decommissioning projects is mainly limited to (i) the guidelines provided by IAEA (IAEA Tech Report 97, 2019), that established the DRiMa project in order to share best practices already in use among practitioners for the Project Risk Management (PRM) phase of NDPs; (ii) a report developed by the European Parliament, that analyses the best practice of selected decommissioning projects and compare those with the management processes adopted in three eastern European nuclear plants shutdown (European Parliament, 2013); (iii) a recent work by (Kim et al., 2022) which adopt the DriMa project's risk family to develop a risk profile suitable for the Kori Unit 1 decommissioning; (iv) a work by (Jeong et al., 2008) that explores the risk assessment phase, which proposes a qualitative identification of risks related to the decommissioning of the Korea Research Reactor-1; and (v) an expert judgment-based risk factor identification and analysis for nuclear-decommissioning projects proposed by (Awodi et al., 2021). The literature on the subject is rather limited and mainly aimed at identifying the risks and proposing a qualitative assessment to better manage the expected threats during the project. To the best of the authors' knowledge, there are no papers that support project managers in identifying suitable methods to manage NDPs risks by showing the impact that risks' occurrence can have on the overall schedule and budget of the project. The risks management process defined by the PMBoK (Project Management Institute, 2021) and the "Managing Risk in Large Projects and Complex Procurements" guidelines (Cooper et al. 2005) identifies two main phases of the procedure: (i) a phase of risk identification, and (ii) and a phase of risk response. While the risk assessment phase deals with risk identification, analysis, and evaluation, the phase of risk response is primarily aimed at selecting the most appropriate risk response strategy. Among the possible responses, the (Project Management Institute, 2021) lists: Avoid Risk, Mitigate Impact/Probability of a Risk, Transfer Risk, Actively/Passively Accept Risk and Escalate Risk. For companies the choice of which risk response to adopt is a complex multi-constrained decision, which often fails in its objectives and causes time delays and increased project costs. Consequently, having in place an accurate and quantitative method to support this decision-making process is a critical success factor for the overall risk management process. A literature review performed by (Shoar and Nazari, 2019) of the extant methods for risk response selection identified five different categories of method: (i) the zonal based method, (ii) the trade-off method, (iii) the Work Breakdown Structure (WBS) – based method, (iv) the Case-Based Reasoning (CBR) method and (v) the Optimization methods:

(i) Zonal based methods involve mapping risks exploiting only two criteria, which are represented in vertical and horizontal axis. The matrix, developed during the risk analysis phase, generally shows on the two dimensions Risk Probability and Risk Impact as evaluation criteria. For each zone of the matrix a type of risk response action, such as transfer, elimination, reduction or acceptance, is recommended (Datta and Mukherjee, 2001; Miller and Lessard, 2001).
(ii) Trade-off methods includes all the decision making procedures applied to risk response selection that are based on keeping a balance between project's time and cost. The decision to choose among different risk responses strategies depends on the way these could ensure the balance set by the project risk management team in terms of respecting projects' delivery schedule and budget (Klein, 1993)
(iii) WBS based methods relate risk response strategy selection to work activities identified in the Work Breakdown Structure (Chapman, 1979). Regardless of the complexity of the process, being a bottom-up procedure there is no possibility to understand if the overall response action selected is the optimal one to meet predetermined management constraints in terms of cost and schedule.
(iv) Case Based Reasoning (CBR) is mostly applied to construction safety risk management for retrieving, reusing, revising, and retaining previous research, and for providing the right solutions for a given problem. In many cases it consists in looking back at previous projects and experiences to search for analogies in the projects that may lead to the application of the same risk response strategy (Fan, Li and Zhang, 2015; Yu et al., 2018).

All the above-mentioned methods present some weaknesses when considering risk response strategy selection for NDPs. The Zonal based method leads to a high-level clustering of risks based on only two dimensions that for large and complex projects would be inaccurate (Wu et al., 2018; Zhang and Fan, 2014). Trade-off and WBS based methods show a deeper level of detail, but they are highly qualitative and thus possibly biased by subjectivity. CBR methods can hardly be applied to NDPs. The limited number of completed projects and their uniqueness limits the knowledge base, resulting in the impossibility of looking at past cases to apply similar strategies (Shoar and Nazari, 2019).

To address this limitation, which can be extended to other industries, some authors have proposed the use of optimization methods as a reliable and quantitative alternative to solve resource constrained problems at both the level of (i) deciding the optimal risk response and (ii) deciding the optimal set of risk mitigation actions to be implemented.

In this work the authors will specifically focus on mitigation actions selection. The reasons for focusing on them as a typical response strategy in NDPs are twofold:

- Nuclear decommissioning projects have high uniqueness characteristics, which make the probability of risks occurring higher (Invernizzi et al., 2017b). At the same time, high standards of regulation and safety make it essentially impossible to accept risks without implementing appropriate mitigation actions (Awodi et al., 2021).
- Risks can have significative impacts on the NDP, not only on the technical side but also on the managerial side (Awodi et al., 2021). The occurrence of one or more risks may result in time delays and/or cost overruns. Consequently, the degree of success in implementing a mitigation action can be effectively measured by considering the reduction in project delay and costs incurred (Jeong et al., 2008).

In this work the authors propose and test an empirical application of an optimization model in mitigation action selection in the context of a real NDP. Although the literature does not identify a method for selecting mitigation actions appropriate to the high uniqueness of decommissioning projects, the authors suggest that optimization algorithms can be a flexible, reliable and easy to implement solution.

2.2. Optimization algorithms for mitigation action selection

In the Oxford dictionary, the verb "to mitigate" assumes the meaning of 'making something less severe', or 'reducing in vigor or intensity an action' (Oxford University Press, 2019). In project management, mitigation action implementation is a strategy to address potential negative risks by reducing their probability and impact. However, the selection of the optimal set of mitigation action is often a challenging decision-making process, which requires a considerable amount of information and data to choose the best option for maximizing the utility in respect to resource utilization constraints. This problem can effectively be solved through optimization technology, which includes the step of mathematical modeling of the problem and the step of solving the same using optimization algorithms. Some authors have already explored using optimization technology to select risk responses, employing different algorithms to solve the mathematical problem.

The existing optimization-solving algorithms can be divided in two categories: deterministic and stochastic. Deterministic algorithms produce consistent outcomes for a given set of inputs, regardless of how many times the model is recalculated (Cavazzuti, 2013). The mathematical characteristics are known in this case. None of them are random, and each problem has just one set of specified values as well as one answer or solution.

The most commonly used deterministic method is Linear Programming (Caine and Parker, 1996), the technique of representing complex relationships between elements by using linear functions to find optimum points. An example of its application is (Zhang, Zuo and Guan, 2020), where after identifying alternative risk responses through case-based analysis, the authors selected an optimal set of mitigation actions for a metro line construction problem by employing linear programming.

However, most real word problems include non-linear constraints, high complexity, and interdependencies across variables requiring the adoption of stochastic modelling, which are used to model any system whose behavior is randomly determined. When solving problems like risk response selection which have many variables and non-linear objective functions, metaheuristic algorithms – a subcategory of a stochastic model – are an effective solution. (Ben-David and Raz, 2001) employed a 'Greedy' algorithm that selected the risk mitigation action, causing a major reduction in the total risk costs for a high-tech company project. (Fang et al., 2013) adopted a genetic algorithm for choosing response actions and allocating budget reserves in a transportation construction project. (Kiliç, Ulusoy and Şerifoğlu, 2008) solved a bi-objective optimization problem in modeling risk mitigation for project scheduling, minimizing both the expected market span and the expected total cost, by employing genetic algorithms. An alternative stochastic optimizer – the Evolutionary Algorithm (EA) – was employed by (Popa and Marcut, 2008) to perform an economic optimization of an abstract state machine; the paper uses the mathematical solution proposed by (Ben-david et al., 2002) to model the optimization problem and solve it through EA, providing good results in terms of the efficiency and adaptiveness of the optimized solution.

A summary of the papers employing optimization models to select risk responses is presented in Table 1.

One of the major pitfalls of the papers listed above is that they only take into account primary risks and primary mitigation actions for the optimization of the risk response, without considering that these actions may cause secondary risks. The next section provides an overview of secondary risks' characteristics and outlines the cases in which they were included in optimization models for the selection of risk responses.

2.3. Secondary risks treatment

Primary risks arise from the vagueness and uncertainties deriving from the activities planned for the development of the project. To cover them, primary response actions can be implemented to mitigate the impact of specific primary risks (Miller and Lessard, 2001). Since these actions have a direct impact on project activities, it is relevant to analyze their effects, as they could lead to further risks, defined as secondary risks. Both primary and secondary risks can have positive or negative impact on the project by acting as a threat or opportunity. "In some cases, the residual secondary risk (the remaining potential negative effects of the secondary risks after implementing the secondary response actions) is greater than the primary risk. Therefore, these secondary risks should be avoided by implementing other response actions" (Tabatabay Asl, Asl and Id, no date).

Chapman (Chapman, 1979) first introduced the concept of secondary risks, developing a comprehensive risk management framework, from risk assessment to treatment. The work is the first that includes secondary risks, pointing out that these should be identified once the primary response action is implemented because secondary risks arise as a direct outcome of implementing a specific risk response. However, the authors do not consider resource constraints, and thus the paper does not provide as output a set of suitable primary and secondary response actions. (Bai et al., 2014) proposed a multiphase framework of risk-management applied to a tunnel engineering project to select mitigation actions. The framework assesses both primary and secondary risks, evaluating whether the emergence of secondary risks could lead to a greater, and therefore undesirable, negative impact. The work, which provides a set of primary and secondary mitigation actions, does not perform the optimization of their choice, meaning that each risk is only individually assessed, without providing an optimal solution.

To address this gap, (Parsaei Motamed and Bamdad, 2022) employed a goal programming optimization algorithm to identify the optimal set of mitigation actions, considering both primary and secondary risks. The model was then applied to the risk management phase of an oil and gas project, leading to interesting results in the identification of secondary mitigation actions.

Table 1

Paper	Solution Method	Validation project type	Secondary Risk
(Ben-David and Raz, 2001)	'Greedy' algorithm that operates iteratively and selects, at each iteration, the risk reduction action that produces the greatest reduction in the total risk costs (TRC).	High-tech company engaged in the development of electronic devices used in surveillance missions.	No
(Kayis et al., 2007)	Five heuristic rules – Least Cost First, Highest Risk Factor, Minimum Cost-Risk Ratio First, Random Search, and Genetic Algorithm – are implemented in three simulated scenarios.	New product and process design in Concurrent Engineering (CE) projects	No
(Ben-david, Rabinowitz and Raz, 2002)	An optimal branch and bound algorithm, and two heuristics: a naïve heuristic, based on the principle of maximum net contribution, and a greedy heuristic, based on maximum marginal net contribution.	Test case generated for validation.	Yes, but it does not identify secondary MA
(Kiliç, Ulusoy and Şerifoğlu, 2008)	Heuristic solution approach based on genetic algorithms (GAs)	Test case generated for validation.	No
(Popa and Marcut, 2008)	Evolutionary algorithm	Test case generated for validation.	No
(Sherali, Desai and Glickman, 2008)	Global Optimization Branch-and-Bound Algorithm	A gasline rupture case.	No
(Fang et al., 2013)	A greedy algorithm and genetic algorithm	A tramway construction project	No
(Zhang and Fan, 2014)	Discrete optimizer in LINGO	A ventilation and air conditioning system construction project	No
(Zuo and Zhang, 2018)	Discrete optimizer in LINGO	A road section project.	Yes
(Zhang, Zuo and Guan, 2020)	Linear Programming	A metro construction project.	No

The literature provides limited cases studies on optimized risk response actions which include secondary risks and secondary mitigation action selection. Often the cases present numerical demonstrations which are not case based and, more specifically, the literature does not present any cases applied to NDPs.

This study, building on the available data, aims to provide evidence regarding the managerial implications of taking account of secondary risks and secondary mitigation actions in the NDPs management process.

3. Proposed risk management approach

A single case study was employed to investigate the application of optimization techniques in the mitigation action selection phase of NDPs. Given the substantial lack of previous studies on the same subject, this research is exploratory in nature (Dul and Hak, 2007) and aims to lay the foundation for generalizable managerial recommendations that are included in the Discussion section of this work.

The adopted approach involved selecting a specific NDP, collecting primary and secondary data and information about its projects' risks, and proposing an optimization model to select the optimal set of mitigation actions; to validate the results, the same were compared with the real project data, outlining the advantages and the limitations of employing the proposed approach to select the most appropriate risk response.

The data collected refers both to primary and secondary risk. To give evidence of the strategic relevance of considering secondary risks and secondary mitigation actions, the paper ultimately compares the proposed risk response approach with a "no secondary risks" strategy, outlining the differences in terms of risk coverage and overall project delay. The proposed approach is set out in an extended format in Table 2. The following paragraphs detail the four steps that were followed to answer the research questions (see Table 3).

3.1. Case study selection

The data used in this research were collected in the Italian state company responsible for the decommissioning of the nuclear power plants still present in the country. The research project and its objectives were presented to the risk management team and to the company risk manager. Thus, the research team obtained permission and sponsorship for the data collection. The first step was to identify among the decommissioning projects managed by the company a completed project for which primary and secondary data were available. During a meeting with the project risk manager, the decommissioning project of a nuclear power plant located in the northwest area of Italy was selected; built in the early seventies, the plant was first reconverted after the closing of the Italian nuclear program in 1987 and subsequently permanently closed in 1995. The state company for nuclear decommissioning acquired the plant in 2005 and started the decommissioning activities in 2008. The reason for selecting this specific case for conducting the research are twofold: (i) it is the first fully completed NDP in Italy. All the radioactive waste is currently safely stored in temporary storage at the site. The fact that the project has been completed allows comparisons between the proposed approach and the mitigation action selection strategy adopted in the project; (ii) the NDP was completed in 2021, which allowed collection of recent data, especially those related to the last phase of the project. The company risk management team that oversaw the risk management activities of the decommissioning project is still working in the company and it was consequently possible to collect data and information with the direct support of people that operatively ran the project.

3.2. Data collection

The data gathering process followed in the design of this research was aimed to maximize the validity and reliability of the dataset and to enhance the accuracy of the results obtained. To structure the dataset, the authors relied upon a combination of primary and secondary information sources. The primary sources were derived through interviews and structured questionnaires addressed directly to the project risk management team; the data obtained were subsequently verbally cross-validated together with the same team during two research workshops. In parallel, the secondary sources came from the analysis of the provided documentation about the overall risk management process put in place, the internal reports about the project's progress, and the managerial documents about the mitigation action selected. The data gathering process was structured in the following way:

Table 2

Comparison between different approaches to risk treatment

Risk acceptance	1402 days
Mitigation of 80%	586 days
Optimization 'Model SR'	412 days

Table 3

	Considering Secondary Risks ("Model SR")	Considering only Primary Risks ("Model no SR")
Model	Single Objective Optimization Model	Single Objective Optimization Model
Data	PRs, SRs, PMAs, SMAs, PMR, PSMR, SMR, SPRR, Max Cost	PRs, PMAs, PMR, Max Cost
Constraints	1. Secondary MAs Cost Optimization Constraint 2. Secondary MAs Time Optimization Constraint 3. Max Investment Constraint 4. Relationships among PMAs and SMAs Constraint 5. Binary Constraint	1. Max Investment Constraint 2. Binary Constraint
Objective function	MIN (X*tpm + Y*tsm + ppr*tpr + psr*tsr*PSMR*X)	MIN (X*tpm + ppr*tpr)
Results	PMAs = 47 SMAs = 4 Objective function = 441,63 Time delay = 412 days	PMAs = 49 SMAs = 0 Objective Function = 398,75 Time delay = 661 days
Solving method	Evolutionary	Simplex LP
Time to solve	~20 sec	<1 sec
Economic impact	−966 k€	−751 k€

- In a first workshop, the risk management team was invited to consider the primary risk assessment developed by (Awodi et al., 2021), and to extract from the list the risks that were also part of the database of the NDP under consideration. This led to the identification of 22 primary risks; for each of them, the 68 primary mitigation actions identified in the planning phase by the risk management team were extrapolated from the risk management database.
- During the second workshop, the 11 secondary risks identified during the project and the related secondary mitigation actions were extrapolated from the risk management database. At the end of this workshop, the research team defined a project dataset complete with primary risks and primary mitigation actions, and secondary risks and secondary mitigation actions. The dataset – which is reported in Annex 1 - was thus validated by the project risk manager, who confirmed its validity in relation to the actual project data.
- Subsequently, for each identified risk, the risk management team extracted from the company database the probability of occurrence and the relative impact on project's time and costs. Moreover, the impact on time and cost for each primary and secondary mitigation action, and the cost of implementation, were extracted. The values collected from the company database were in the form of 5-point scale linguistic evaluations, ranging through "very high, high, medium, low and very low". The research team agreed on the conversion of the linguistic variables into the numerical ranges that are reported in Annex 1, which properly reflects the values observed in the NDP. The research team also agreed on the value of the maximum mitigation actions implementation budget, set at 1500 k€.

The database, including the probability of occurrence and impact on time and cost of primary risks, primary mitigation actions, secondary risks, and secondary mitigation actions, was finally collectively validated by the risk management team during a third workshop. The final validation of the dataset allowed the proposed model to be applied and tested by the research team.

3.3. Proposed model

Mitigation action selection is a complex multi-constrained selection problem. Considering secondary risks makes the problem intrinsically non-linear, due to the relationship among primary risks, primary mitigation actions, and secondary risks themselves. To deal with this non-linearity issue, a non-linear optimization model was implemented to solve the Single Objective Optimization problem.

The proposed model has been structured with two decision variables, representing the primary and the secondary mitigation actions, and all the data related to primary and secondary risks.

- *First decision variable* = $[X_1, \ldots, X_p]$: binary variable equal to 0 or 1, related to the implementation of the primary mitigation action.
- *Second decision variable* = $[Y_1, \ldots, Y_s]$: binary variable equal to 0 or 1, related to the implementation of the secondary mitigation action.

Data:

- *Primary risk* = $[PR_1, \ldots, PR_{pr}]$*:* described with their probability of occurrence (*ppr*), impact on the time (*tpr*) and on the cost (*cpr*).
- *Secondary risk* = $[SR_1, \ldots, SR_{sr}]$*:* described with their probability of occurrence (*psr*), impact on the time (*tsr*) and on the cost (*csr*).
- *Relationship PMAs and PRs:* a matrix *PMR* defining the relationship among the primary risks and the primary mitigation actions.
- *Relationship PMAs and SRs:* a matrix *PSMR* defining the relationship among the secondary risks and the primary mitigation actions.
- *Relationship SMAs and SRs:* a matrix *SMR* defining the relationship among the secondary risks and the secondary mitigation actions.
- *Relationship PRs and SRs:* a matrix *SPRR* defining the relationship among the secondary risks and the primary ones.
- *Data related to first decision variable*: the impact on the cost *cpm*, the impact on the time *tpm* and the cost of implementation *cipm*.
- *Data related to second decision variable*: the impact on the cost *csm*, the impact on the time *tsm* and the cost of implementation *cism*.

The presence of constraints in the model leads to the non-linearity given by the risks' and mitigation actions' intrinsic relationship. The following constrained were defined:

(1) *Secondary MAs Cost Optimization Constraint:* to optimize the selection of secondary mitigation actions by taking in account the convenience of their implementation due to cost impact.

$$X_p{}^*cpm_p{}^*PMR_{prp} + psr_{sr}{}^*csr_{sr}{}^*PSMR_{srp}{}^*PMR_{prp}{}^*X_p + Y_s{}^*csm_s{}^*SPRR_{prsr} \leq 0$$

(2) *Secondary MAs Time Optimization Constraint:* to optimize the selection of secondary mitigation actions by taking in account the convenience of their implementation due to time impact.

$$X_p{}^*tpm_p{}^*PMR_{prp} + psr_{sr}{}^*tsr_{sr}{}^*PSMR_{srp}{}^*PMR_{prp}{}^*X_p + Y_s{}^*tsm_s{}^*SPRR_{prsr} \leq 0$$

(3) *Max Investment Cost Constraint:* to give a maximum value in terms of the total cost of investment for the project.

(4) *Relationship Among PMAs and SMAs Constraint:* to certify the relationship among the two types of mitigation actions. Indeed, a SMA could be implemented and taken in account if and only if the related PMA has been adopted, otherwise there would be no secondary risk and no need of the secondary mitigation action.

$$Y \leq X$$

(5) Binary Constraint:

$$X = [0, 1]$$

$$Y = [0, 1]$$

All the linear or non-linear programming models seek to maximize or minimize a certain numerical value. Thus, the definition of an objective function is needed to solve the optimization problem and find the optimal value sought. In the proposed case, the function selected was the following:

$$MIN(X*tpm + Y*tsm + ppr*tpr + psr*tsr*PSMR*X)$$

Since the project risk manager claimed that the primary objective of the NDP analyzed was to restore the land upon which the nuclear facilities were built and to hand them over in a "Unrestricted Use" status (International Atomic Energy Agency, 2018) in the shortest time possible, the main criteria followed to structure the entire risk response strategy was to minimize the duration of the whole project. Consequently, to be better able to compare the approach followed in the NDP management with the proposed one, the optimization function was formulated having as a single objective the time optimization.

4. Computational results

The optimization model was solved in Microsoft Excel Solver, through an evolutionary algorithm. After uploading the input data, matrices linking risks and mitigation actions were created. The objective function together with the five constraints presented in paragraph four were reported in a single spreadsheet and subsequently the Evolutionary solver was launched.

The result of the procedure was the optimized sets of primary and secondary mitigation actions, with the relative time delay caused and the necessary budget to be allocated for their implementation.

The mathematical solution of the model allowed the identification of an optimal set of mitigation actions, including 47 primary and 4 secondary ones. Thus, the algorithm allowed to select the 70% of the 68 mitigation actions and the 30% of the 12 secondary mitigation actions identified by the management. This implies that the method enabled to selected most of the primary mitigation actions, allowing for the coverage of both technical related primary risks such as those arising from safty issues, radiation level, plant conditions and nuclear waste management and disposal but also of risks deriving from the managerial side of the project, such as the management of subcontractors, of the personnel in terms of competences and skills, of the legal side of the project and of the data and information gathering.

The results of the mitigation action selection performed by the algorithm are reported in an extended format in Annex 1; this solution led to an overall residual time delay of 412 days.

Once the results were obtained, they were presented to the members of the company's risk management team and compared with two different scenarios: (i) the worst-case scenario consisting in calculating risks' probability and impact absent the implementation of any mitigation actions – which results in 1402 days of delay and (ii) the operational results of the selection of mitigation actions that was applied to the NDP project. The risk management team had adopted a risk mitigation strategy which is often applied in companies, which consists in multiplying the time impact and the occurrence probability of each primary risk, sorting them in descending order and setting a coverage of the risks equal to a predetermined percentage. In this case an 80% coverage was set, leading to a mitigation of the ten most impactful risks (16, 14, 15, 21, 6, 18, 2, 9, 11, and 5, in descending order of severity) – resulting in a total residual time delay of 332 days; an additional time delay of 236 days was then added to consider also the impact of secondary risks.

The comparison among the results obtained is reported in the table below.

Considering the worst-case scenario represented by the 1402 days of delay resulting from not applying any mitigation actions, the implementation of the proposed optimization strategy led to a reduction both of the expected time delay and of the magnitude of expenditure due to covering risk occurrences. However, it was particularly interesting to compare the results obtained through the optimization algorithm with those applied by the risk management team in the NDP project. The selection of the mitigation actions performed through the proposed optimization algorithm shows better performance in reducing days of delays and managing the necessary cost coverage. Considering time constraints, the optimization model provides a selection of an optimal set of mitigation actions which saves about 270 days in respect to the "Mitigation of 80%" strategy. As regards the cost coverage, the management showed interest in the logic of the algorithm, which enables the management team to pass from a strategy of identifying and quantifying the investment needed to cover a certain percentage of risks to a strategy of verifying, given a certain budget, what optimal coverage can be achieved taking account of both primary and secondary risks.

5. Discussion and conclusions

One of the main contributions of this work to the literature, regarding the idea of proposing a quantitative method for the effective management of risk mitigation actions in NDPs, is to highlight the relevance of considering the impact of secondary risks in such complex and unique projects. Thus, a comparison between an optimization model considering only primary mitigation action and the results obtained in the previous step which included secondary mitigation actions was performed, employing in both models the data from the case study. When secondary risks are considered, the problem is non-linear, while when only primary risks are considered, it is possible to solve it through linear programming. Thus, the data related to primary risks and primary mitigation actions were uploaded to Excel and the "simplex LP" solver was launched. In this case only two constraints were implemented: (i) *Max Investment Cost Constraint* – the budget of 1500 K given by the risk management team, and (ii) the *Binary Constraint*. Considering only primary risks and mitigation actions, the model selects the best set of mitigation actions to minimize the impact on the time of the primary risks while respecting the budget constraint. To compare the results obtained from the two models, the impact of the secondary risks related to the primary mitigation actions was added to the value resulting from the "simplex LP" solver. The comparison between the two models is summarized in the table below.

The "model no SR" results in a higher number of PMAs selected; this is for two reasons. The first is that in this case the optimization was performed considering only primary risk, and thus the whole budged was optimally distributed in order to cover only them. Second, the "model SR" has more constraints, so many PMAs cannot satisfy them. Some of the PMAs or SMAs should be implemented in terms of time minimization, but they are not selected. This happens because the model is also optimizing the initial investments necessary for implementing the mitigation actions; thus, the non-selection is due to the fact that their implementation costs is too high for the maximum budget constraint. In other cases, conversely, as in PMA 2, 44, 54, 62, and 64, the impact of the secondary risk is higher than the lowering effect of the primary mitigation action plus the one of the secondary mitigation actions (-12–80), and thus the "model SR" does not select them, while the "model no SR" does. From the point of view of the economic impact, both the cost impact and the cost for implementing the mitigation actions were considered through the imposed constraints. Thus, besides the maximum budget value for the MAs, which was set to 1500 and was equal in both the models, the budget savings resulting from the mitigation actions selection strategy can also be outlined. The cost impact due to risk occurrence is higher in the "Model no SR" because more primary actions – linked to several secondary risk – are selected; budget savings are calculated as the difference between the impact that mitigation actions have on mitigating risks (negative sign) and their implementation costs (positive sign). The "Model SR", considering also secondary risks, shows better performance in terms of mitigating the cost impact of risks while minimizing the implementation costs, saving around 215 k€. Finally, regarding the solving algorithms, the "Model no SR" and "Model SR" were both solved with the Excel solver, but using two different solving methods (respectively the "Simplex LP" and the "Evolutionary"). The computational speed using the "Simplex LP" proved to be lower (<1 sec) than the in the case of using the “Evolutionary” one (~20 sec); however, in both cases the Excel solver proved to be a reliable and user-friendly tool for solving the optimization problems.

Nuclear decommissioning projects are characterized by a high degree of complexity, long duration, and high economic and social impact. For these reasons it is necessary to manage them with due care and through a well-structured process of risk management (Awodi et al., 2021). Despite being such a relevant topic, the literature fails to propose effective methods for managing nuclear decommissioning risks properly, offering only studies of qualitative risk assessments. Moreover, the literature concerning decommissioning projects does not provide any study of risk response selection, selection of mitigation actions, or definition of contingencies to cover risks. This work presents a Single Objective Optimization Model aimed at optimizing the selection of mitigation action and minimizing risk exposure, considering also secondary risks.

The contributions of this work to the research are twofold. Firstly, the paper integrates the literature concerning the risk response selection phase carried out by means of optimization algorithms, proposing them as an effective method for the quantitative selection of mitigation actions; to prove the model’s effectiveness the authors applied it in a case study of an Italian NDP already completed. The results obtained from the application of the model were then compared with those coming from the real risk mitigation action selection strategy adopted in the project. The results show that the performance that would have been achieved through the optimization algorithm would have been superior, both from the point of view of a reduced time delay, and in terms of a more effective balance between overall risk coverage and implementation costs.

Secondly, the paper contributes to the research concerning the selection of risk responses in light of secondary risks, which is still little dealt within the literature. The paper shows that, especially in projects with high complexity, the consideration of the risks induced by the implementation of primary mitigation actions can lead to different and more comprehensive risk response strategies that also consider secondary mitigation actions. In keeping with other works where secondary risks are included in the analysis, like (Parsaei Motamed and Bamdad, 2022; Zuo and Zhang, 2018), this work has been developed through a single-objective model aimed at minimizing delay to the fixed schedule. This was crucial in order to compare the results obtained with those coming from the real case, given that in the studied NDP project the whole strategy was based on minimizing time delay. The optimization model was then solved through a stochastic solving method in order to consider the randomness present in the real world.

The results obtained are also remarkable from the practitioners’ perspective. The optimization model proposed is flexible, easy to implement, easy to interpret and unlimited in the number of criteria and objectives that can be considered. Given the NDP’s uniqueness, project managers need to have at their disposal flexible and easy-to-update models able to select risk responses for many customizable criteria. The proposed model provides a good example, which also suggests that managers should be prepared to manage secondary risks.

Despite the contributions mentioned above, there are still some limitations to the study, which also represent possible future research steps that need to be outlined. First, in order to simplify the proposed model and highlight the relevance of secondary risks, the projects risks were considered independent of each other. In this sense a possible future development of the proposed work could consist in structuring a modelled risk assessment phase outlining interdependencies among risks, both primary and secondary. Second, the information on the model inputs related to primary and secondary risks and primary and secondary mitigation actions were collected in the form of experts’ judgements. In order to obtain more accurate results that take into account the uncertainty involved in expressing a judgement, fuzzy logic could be applied to the data collected in the risk management team, developing a structured risk assessment phase.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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