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Nuclear decommissioning risk management adopting a comprehensive artificial intelligence framework: An applied case in an Italian site

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ABSTRACT

The increase of nuclear sites entering the decommissioning phase has drawn the attention of governments, regulatory bodies, and industries to decommissioning projects. However, despite the high number of uncertainties and risks of these projects, there is a lack of dedicated risk management frameworks beyond the guidelines established by the International Atomic Energy Agency (IAEA) and the Project Management Institute (PMI). This study aims to propose an integrated framework for managing risks in Nuclear Decommissioning Projects. For the development of the framework artificial intelligence algorithms were employed, integrating models derived from the manufacturing sector capable of assessing risks, identifying an optimal set of risk mitigation actions, and predicting the additional project delay or cost based on a quantitative risk analysis. To demonstrate its validity, the model was applied to a nuclear decommissioning project currently underway in Italy, generating a forecast of the final project delay. The results showed to be promising, as the delay prediction for the analysed phase of the project differs from the current one only by an error of 4.7%. The proposed model can help project managers in managing risks and predicting delays or additional project costs during the preliminary phase. In addition, the framework is equally useful for controlling risks in the progress stages of the project by dynamically updating forecasts.

1. Introduction

In most projects, an accurate risk management process is an essential means of reducing uncertainties and facilitating project success. This is particularly true in projects with a significant degree of uniqueness that are therefore more exposed to complex and previously unaddressed risks. Nuclear Decommissioning Projects (NDPs) represent a relevant case of projects that, due to their high degree of uniqueness, are by their nature challenging to manage, particularly from the risk management point of view. The uniqueness of these projects derives only marginally from their technical and engineering complexities. In fact, the scope of these projects, that is defined by the International Atomic Energy Agency (IAEA) as "*the administrative and technical actions taken to allow the removal of some or all the regulatory controls from a facility, except a repository which is closed and not decommissioned*" (IAEA, 2016), makes them long, expensive and multidisciplinary in nature. In addition, some elements of these projects contribute to increasing their uniqueness (Invernizzi et al., 2017a).

- National regulations may be different and particularly strict, as are the administrative requirements that must be met.
- The long duration of the projects and the remote location of the sites means that important expectations are generated in the community living nearby; the possible inclusion of a waste removal facility can also generate strong social concerns about potential security implications (Invernizzi et al., 2017b).
- These projects have a particular financial structure as there is no cash flow at the end of the project, only conversion to green- or brownfield sites.

The project outcome can therefore be significantly different from case to case, and it is usually not aimed at the achievement of a profit at the end of the execution phase.

However, the interest in nuclear decommissioning projects from governments and institutions is very high. In fact, (i) it is estimated that over the next two decades most nuclear plants will undergo decommissioning, (ii) at the end of May 2021 there were 440 nuclear power reactors operating worldwide but more than 180, including commercial

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power reactors and experimental reactors, have been permanently shut down, resulting in a growing demand for strategies and technologies in the decommissioning phase (Plans for New Nuclear Reactors, 2022), (iii) the upward trend in the number of plants to be decommissioned does not appear to be decreasing, at least during the next decade (Nuclear Energy Agency (NEA) -, 2019).

Despite the interest and relevance of NDP projects, there is not yet a deep knowledge of how they should be managed (Laraia, 2012). This is even more true when it comes to risk management. In fact, the risk management knowledge in nuclear decommissioning projects is mainly limited to (i) the practitioner-based guidelines provided by the IAEA (IAEA, 2008), (IAEA Tech Report 97, 2019) and (ii) the contribution of some academic authors who focused mainly on the risk assessment phase, identifying specific risks and their impact on the project (Jeong et al., 2008), (Jeong et al., 2010), (Awodi et al., 2021).

The need to deepen and study the risk management processes in nuclear decommissioning projects also arises from the evidence of the results of completed NDPs. In fact, in many cases the high degree of uncertainty led to cost overruns and safety concerns that are likely to seriously impact on the projects' success (Awodi et al., 2021), (Laraia, 2012).

From the point of view of the methods proposed for risk management in nuclear decommissioning projects, the IAEA refers to the procedures proposed by the PMI that represent a good, regulated way to manage the possible risks of a decommissioning project. However, as regards the risk analysis phase.

- The pure expert judgement method presents a high degree of subjectivity and low quantitative precision both in the definition phase of probability and impact and in the subsequent phase of allocating risk responses. Such a subjective method can hardly be applied to complex projects as it lacks rationality and precision (Maronati and Petrovic, 2019).
- Parametric models and probabilistic simulations provide greater objectivity and a grounded quantitative approach. However, even a simple probability distribution requires a large amount of risk probability data and the corresponding risk impact values (Love et al., 2012). In most cases this type of information is derived from the data of past projects and their results (Islam et al., 2021a), but this is particularly difficult in the case of NDPs, as their high degree of uniqueness does not allow for an easy comparisons between historical data from past and current projects. In addition, some authors point out that probabilistic simulation methods are widely used in theory but almost unknown in practice (Dikmen et al., 2007), (Baloi and Price, 2003).

Currently, besides the methods mentioned, the existing literature does not present alternative approaches, providing mainly qualitative analysis of the risk assessments phase. The objective of this paper is to provide a quantitative and AI-based framework for a more structured approach to the risk management of NDPs.

In recent years, there have been several efforts to reduce the difficulties of Project Management (PM) activities by using advanced analytical techniques. One of these techniques is Artificial Intelligence, which has a strong potential to improve the quality of PM processes (Fathi et al., 2019), (Wauters and Vanhoucke, 2016). In particular, in the field of risk management the use of artificial intelligence techniques (e.g. the Fuzzy Bayesian Belief Network) can have a positive impact in (i) reducing the uncertainty, vagueness, and subjectivity problems which derives from using expert judgments for risk assessment, and (ii) considering multiple, uncertain, and interrelated project risks for the selection of mitigation action and contingency cost modelling. This paper proposes the use of an integrated framework for the risk management of decommissioning projects that uses AI-based techniques to model the processes of (i) risk assessment, (ii) mitigation action selection, and (iii) contingency cost allocation. The proposed framework combines contributions from several authors, developing an integrated model that is as tailored as possible for NDPs.

The work is structured in the following way: a definition of the current state-of-the-art of risk management in nuclear decommissioning projects is performed; given the absence of quantitative models for the risk management of these projects, the paper performs a review of cross-sectoral AI-based risk management methods adopted in the three main risk management stages, coming to a definition of a proposed integrated framework for NDPs. Finally, to ensure the validity and applicability of the proposed framework, a case study of its application to a nuclear decommissioning project started in 2008 in Italy will be presented. The discussion and the main limitations will highlight the results obtained from the framework application and the potential for its practical use in NDPs risk management.

2. Background

2.1. Nuclear decommissioning projects

To identify an effective risk management model for decommissioning projects, it is first necessary to outline their characteristics, scope, and boundaries. In fact, despite the wide consensus in the existing literature in defining them as long, complex, and expensive processes having a multidisciplinary nature (Invernizzi et al., 2017a), (Invernizzi et al., 2017b), there is no international agreement on the definition of their scope. The lack of clarity about the activity range of these projects stems in part from the semantic use that has been made over the years of the term decommissioning. In some languages (German, Spanish, Russian) the term refers to the definitive end of the operation phase, while in others (French) it is identified with a downsizing of the plant (Laraia, 2012). However, the difficulty in defining this type of project is not only semantic: it also concerns the scope and the objectives of the work to be performed. The IAEA (Decommissioning of Nuclear Power Plants, 1221) identifies three different strategies that relevantly change the possible scope of these projects: the immediate dismantling strategy, the deferred dismantling strategy and entombment. These three strategies lead to significantly different decommissioning projects, from both a technical and a managerial point of view.

The World Nuclear Association states that "the term decommissioning includes all clean-up of radioactivity and progressive dismantling of the plant" and that "for practical purposes it may include defueling and removal of coolant" (Nuclear Decommissioning, 2021). Conversely, the US Nuclear Regulatory Commission strictly defines the start of nuclear decommissioning "after the nuclear fuel, coolant and radioactive waste are removed", with the process involving "decontaminating the facility to reduce residual radioactivity and then releasing the property for unrestricted or (under certain conditions) restricted use" (Decommissioning NRC, 2021).

This lack of alignment among many institutions is not only a problem of definition: it can impact the project scope definition and consequently the estimate of the costs and schedule and many other project management processes of NDPs. For example, spent fuel management (transportation, disposal, and storage) has a strong impact on the NDP budget (Lawless et al., 2014), but not all definitions of a NDP include it, generating misunderstandings and differences between projects carried out in different countries; also, for the project classification stages of risk identification, the inclusion or exclusion of the waste management phase generates significant differences in terms of assessing the impacts of project risks, and the different analysis regarding possible mitigation actions to be activated.

Besides the lack of a precise definition of the scope of NDPs, there is also a problem of lack of expertise in their management. In fact, at the moment of writing, the number of NPDs completed is very few, with only 17 NPPs and a limited number of other nuclear facilities completely decommissioned worldwide (WNA, 2021). As a result, there is very little shared knowledge about how to manage them, both because there is usually a substantial technical difference between the plants being decommissioned, and because the geographical area in which they are located is not the same, which often results in significantly different management styles. Considering that these projects are typically characterised by a long schedule, and a budget of hundreds of billions of dollars (Invernizzi et al., 2017a), the lack of management expertise in the field represents a significant problem.

The challenges arising from the management of these projects are considerable: in fact, they are particularly expensive, considerably more than equivalent decommissioning projects in other sectors. These additional costs relate to the radiological hazards and safety requirements, which can cause significant extra costs of surveillance and maintenance (Selling, 2012), (Invernizzi et al., 2017a). To sum up, "safety factors, the involvement of concerned stakeholders, unforeseen work delays, and inexperienced contractors all contributed to the growing awareness that the closing of a nuclear plant's life cycle is considerably costly" (LaGuardia and Murphy, 2012).

Moreover, since NDPs take place over a long period, they are more susceptible to the impact of possible external or internal changes (for example, a change in the regulatory authorities that may require linked changes in the work items). This results in the need for a project management organisation accustomed to change management and a to a considerable level of complexity (Devgun, 2012).

Increased complexity raises uncertainties and causes a higher number of risks that need to be managed, even more than in the construction of new nuclear power plant projects (Invernizzi et al., 2017a), (Selling, 2012), (Mochida, 2019), (Atyeo and Holdroyd, 2012). The escalating uncertainties also affect decommissioning project cost overrun and safety concerns (Awodi et al., 2021). As a result, the development of an integrated and specific risk-management approach to nuclear decommissioning projects is crucial to meet the objectives set by the decommissioning program and to effectively govern the main project risks.

2.2. Risk management in NDPs

The nature of NDPs requires a particularly detailed risk management approach. It is in fact recognised that the prior identification and management of the main project risk factors facilitates the final achievement of project success: as the number of risks identified during the planning phase increases, the amount of risk occurring decreases in direct proportion (Talabi and Fishchbeck, 2015). Nevertheless, the literature on this subject is rather limited and does not identify many alternative risk management methods to those proposed by practitioners. In particular, the IAEA (IAEA Tech Report 97, 2019), through a shared knowledge process among practitioners, established the DRiMa project in order to share best practices already used for the Project Risk Management (PRM) of NDPs. The recommendation that emerges is to follow a risk management process like that outlined by the Project Management Body of Knowledge (PMBoK) (PMI, 2021), following the steps to identify, assess, monitor and control (mitigate or exploit) the risks associated with the key assumptions of the project plan. However, this process involves mainly qualitative supporting models based on expert judgements. Nevertheless, the IAEA points out that in the risk management process that should be implemented in NDPs there are some unique elements that need to be considered (IAEA Tech Report 97, 2019).

- The planning process can take a long time and be divided into two phases: an Initial Decommissioning Plan (IDP), usually developed when the facility is still in operation, and a Final Decommissioning Plan (FDP) developed following the facility shutdown. Since the IDP may have been developed many years before the FDP, it may contain assumptions of a speculative nature, as it is high-level planning. The consequence is that incorrect or outdated assumptions developed during the IDP can lead to inappropriate strategic decisions that may have negative effects when implementing the decommissioning plan. It is therefore particularly relevant to assess, monitor and control the risks associated with the key assumptions specified in the IDP that will form the basis of the FDP. Thus, there are two parts of the risk management process, the first associated with the IDP assumptions, the second with the decommissioning processes set out in the FDP.
- In addition, the DRiMa project (IAEA Tech Report 97, 2019) emphasises the difference between risk management and safe assessment, highlighting that risk management is about controlling risks to support the achievement of the overall project objective, while safety assessment ensures that decommissioning activities can be carried out safely. The risks identified during the safety assessment process (IAEA, 2008) can become relevant input to the risk identification process.

The contribution of the relevant scientific literature is rather limited in presenting alternative NDP risk management processes and models to those suggested by IAEA. Some studies focus on the development of a qualitative assessment analysis of the technical and operational risks of a specific NDP being studied (Jeong et al., 2008), (Jeong et al., 2010), while others propose modelling alternatives for the identification and management of major risks through Bayesian Networks (Faber et al., 2002). Of particular interest is the contribution of Awodi et al. (2021): their work focused on the identification of risk factors that are shared among many NDPs, focusing on how one or more risk factors may affect the success of the project. Their approach implements interviews with field experts through a questionnaire that aggregates experts' contributions based on their experiences and knowledge. Still, the risk factors identified are considered independent, while it is commonly agreed among the risk management research community that risks are very often dependent on each other. Moreover, they only elicited risk factors, returning a list created with the help of field experts, but they did not apply them to a comprehensive risk assessment framework or to other risk management phases. However, the need to propose alternative methods for risk management processes in NDPs is evident and represents a clear gap not only from the research point of view but also from that of practitioners.

2.3. Gap and scope of the research

As highlighted in the previous paragraph, the risk management models proposed by experts and the scientific literature for the management of NDPs are exclusively qualitative and only analyse the risk assessment phase. Consequently, the authors considered relevant to perform a cross-industry review of the integrated quantitative and AI-based methods used in other sectors, encompassing all the risk management phases (assessment, definition of mitigation actions and contingency allocation). The analysis allowed us to identify a growing trend of using artificial intelligence (AI) tools to model specific risk management phases; however, a multiple-phase risk management process is modelled using AI in only two works: (i) the ProCRiM model developed by Qazi et al. (2016) considers both the Risk Assessment and the Mitigation Actions Selection phases of the PRM process, but the allocation of contingencies, which is critical in NDPs, is not modelled. Furthermore, being grounded in the theoretical framework of Expected Utility Theory and Bayesian Belief Networks, the model requires a large amount of data to be entered as input, which is a recurring problem when using AI algorithms: this is not always possible, especially in the case of unique and complex projects, which are typical of the nuclear decommissioning industry; (ii) on the other hand, Islam et al. (2021b) developed a framework that considers risk assessment and contingencies cost calculation, without defining the selection of mitigation actions to be implemented. However, their model adopts a modified Fuzzy Bayesian Belief Network (FBBN) model, which is an integration of a modified Fuzzy Group Decision Making Approach (FGDMA) and the canonical model that requires less input data to be elicited by experts, making it more suitable for NDPs.

Thus, what emerges from the literature is that the field of NDPs lacks a quantitative risk assessment model, although a careful and detailed PRM is crucial due to the peculiar nature of these projects. The existing literature highlights that the use of AI-based methods for PRM is becoming widespread, but no study has tested an approach to nuclear decommissioning yet. Also, at the time of writing, there is no AI-based comprehensive framework that considers the entire PRM process carried out during the planning phase of the project, including both mitigation action selection and contingency costs calculation, without requiring a large amount of data to be elicited by experts in the setting up of the model.

The purpose of this paper is therefore to propose an integrated framework that, starting from the contributions of different authors about PRM, can help NDP risk managers to better deal with the Risk Assessment, Mitigation Actions selection and contingency cost calculation phases. The integrated framework adapts some selected methods already existing in the literature and makes them suitable as input/output for the comprehensive PRM process.

3. Proposed framework

The proposed framework is aimed at enabling a more effective PRM for NDPs. Fig. 1 shows the main steps of the implementation process, the discussion of which will be divided according to the three areas of the PRM process: Risk Assessment, Mitigation Action Selection and Contingency cost calculation.

3.1. Risk assessment

The risk assessment phase aims to map the probability and the impact of the project risks, defining a log of risks in order of priority of mitigation. This process is widely modelled in the current literature using Fuzzy Bayesian Belief Networks (FBBN). The FBBN is a combination of fuzzy logic and BBN, which is increasingly used to improve the reliability of models for risk assessment in cases where uncertainty is present (Islam et al., 2017). Fuzzy logic is used to evaluate the verbal opinions of experts and transform them into fuzzy numbers, which are then inserted into the BBN as probabilistic input values, both for the independent nodes and for the Conditional Probability Tables (CPTs). The reason why fuzzy logic is combined with BBN is because the latter employees a single probability value to measure the bonds between nodes: this is not always feasible, as when dealing with expert judgement, fuzzy numbers are easier to collect and organise (Kabir et al., 2016a). The most critical aspect of the FBBN models available in the literature is the generation of the CPTs: they require x^n probabilistic parameters (n and x indicate the number of parent nodes and the variables for each parent node, respectively) for each dependent node (Walls and Quigley, 2001). This would inevitably lead to a huge amount of data to be gathered and organised. This, coupled with the fact that the basic FBBN model works best on large databases, does not suit NDP projects, where the small number of completed projects does not allow for large databases.

Consequently, for the risk assessment phase of NDP projects, the authors suggest the adoption of models like the Fuzzy Bayesian Belief Network (FBBN) Canonical Model algorithm, developed in a series of studies by Islam et al. (2019a). The Canonical Model involves a disjunctive interaction between the risks (the so-called "Noisy-OR gate"): experts provide the probabilistic values for child nodes on a one-to-one basis, instead of determining the joint impact of parent nodes on dependent nodes. It has been proven that this model is able to produce good results even with a small dataset (Walls and Quigley, 2001), and it is possible to significantly reduce the amount of data required to build the network; the only drawback of the canonical model is that each node can have only two states (in this case true or false), while in some cases it would be useful to have available more states (i.e., 50% impact of the risk). The FCM model is composed of two main processes: (i) the Fuzzy Group Decision Making Approach (FGDMA) is used to assess the prior probability of the independent risks, the conditional probabilities between risks (the effect of each parent risk on its child), and the impact of each risk, based on expert judgment. The authors suggest defining different experts' weights considering their professional experience in the nuclear industry. The weights can be calculated considering their current professional position (PP), their working experience in the nuclear decommissioning field (EP), the experience on other NDPs (EO) and the academic qualifications (AQ), which together form the "professional competence" weight (Idrus et al., 2011). The level of professional competence of each individual expert needs to be incorporated in order to increase the data reliability (Kabir et al., 2016b). For the proposed framework it is suggested to compute the weight of professional

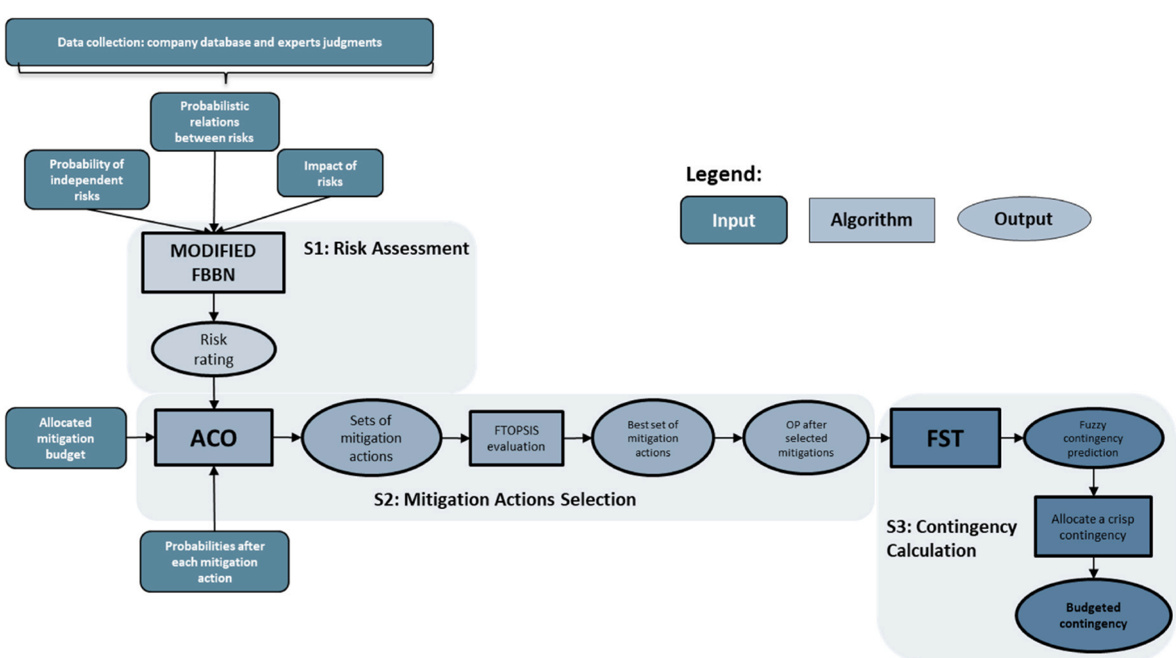

Fig. 1. Proposed PRM framework for NDPs.

competence of a single expert *i* as in (Aboshady et al., 2013). Then (ii) the Canonical Model (i.e., a modified BBN) assesses the probability of the dependent risks in the network (Islam et al., 2019b). The reader may refer respectively to (Islam et al., 2019a) and (Gingnell et al., 2014) for a detail of the calculations to be implemented in the FGDMA and in the modified BBN. The application of these two processes allows to obtain as the output of step 1 (S1) the risk rating of all project risks.

3.2. Mitigation action selection

Step 2 (S2) of the proposed framework introduces an AI-based mitigation action selection phase. For the selection of mitigation actions, only optimisation models consisting of creating a mathematical model to solve the risk mitigation action selection were analysed. Usually, the objective function consists of minimising the cost of implementing the selected strategies, considering constraints that include, but are not limited to, the combination of the acceptable level of loss due to the occurrence of risks and the allocated budget for implementing the actions (Ben-David and Raz, 2001), (Ben-david et al., 2002), (Fan et al., 2008), (Kayis et al., 2007). However, this was not the purpose of this work and, in fact, the nature of NDPs requires a PRM that can effectively limit the overall probability and/or impact of the occurrence of risks, considering a limited budget constraint. The optimal reduction of the probability and/or impact of project risk requires the comparison of potential actions for reducing individual risks. The literature highlights the difficulties associated with using mathematical optimisation on large problems (El-Beltagi et al., 2005), contributing to the development of alternative optimisers, such as genetic algorithms and particle swarm algorithms. The study conducted by (El-Beltagi et al., 2005) compared these alternative optimisers, showing that Ant Colony (ACO) performs better in discrete optimisation problems while being the least demanding regarding processing time. The ACO algorithm is a particle swarm algorithm that is inspired by the social behaviour of ants, which are able to find the shortest path between their nest and a food source (Duan and Liao, 2010). For the proposed framework, the assessment model developed by (Shoar and Nazari, 2019) is proposed in S2, adopting also a Design Structure Matrix (DSM), in order to still consider the interactions among risks. The DSM is a square matrix, in which the risks are placed in the first row and the first column in the same order. The cells in the diagonal are blacked out, as the reflection of risks on themselves is not considered, while off-diagonal cells indicate interactions between risk events. The reader may refer to (Shoar and Nazari, 2019), (Fang et al., 2013), (Seyedhoseini et al., 2009) for details of the calculations to be performed in S2. Note that in the proposed framework, the DSM should be developed using the defuzzified probabilities elicited by experts in S1. After generating the best response action sets by considering the numerical effects of the response actions on the project objectives, the FTOPSIS (Fuzzy technique for order preference by similarity of an ideal solution) method is used to evaluate the solutions obtained. The TOPSIS technique was originally proposed by (Yoon and Hwang, 1981): it assumes that the selected alternative should have both the shortest distance to the positive ideal solution and the farthest distance from the negative ideal solution (Yoon and Hwang, 1981). Thus, the selection of the best set of mitigation actions is a matter of multi-criteria choice, often in NDPs considering one action against another: therefore, the model developed by (Chen, 2000) and later adopted by (Shoar and Nazari, 2019) is proposed in this framework to obtain an overall evaluation of each alternative, using linguistic variables represented by triangular fuzzy numbers. At the end of S2, the risk manager can choose to implement the set of mitigation actions with the highest ranking derived by applying the described process.

3.3. Contingency cost calculation

The literature concerning contingency cost calculation highlights a limited use of regression models, ANN and MCS, which are unsuitable for NDPs due to the difficulty of finding good quality data recorded from similar previous projects. Some studies (Mak and Picken, 2000), (Hammad et al., 2016) tried to adapt an MCS-based model on a subjective dataset, representing a first step towards a lower data requirement. However, the distribution type assumed (i.e., multivariate normal, lognormal, etc.) and the judgement bias are critical limitations of these models. Other studies (Salah and Moselhi, 2015), (Idrus et al., 2011), (Jung et al., 2016) develop a fuzzy experts model to calculate the contingency cost, and are able to account for imprecision and judgement bias, overcoming data limitations. The main problem of these studies is that they do not consider the interrelationships between risks and that they do not account for the difference in experience and knowledge between experts. On the other hand, models like the fuzzy set based approach proposed by (Pawan and Lorterapong, 2016) are able to overcome all the limitations of the previous studies, providing excellent results in defining project contingencies, thus resulting in the best actions to be proposed in this framework in step 3 (S3).

After selecting and implementing the set of mitigation actions found in the previous step, the framework requires the Risk Assessment to be performed again with the FBBN model, to evaluate the probability of occurrence of risks necessary for the contingency cost allocation phase. This is simply performed by modifying the prior probabilities (CPTs tables in the Bayesian Belief Network and impact values created at the beginning of the PRM process) according to the implemented mitigation actions. The obtained risks probability and the corresponding cost (or time) impact in terms of a fuzzy set (triangular) are part of the input to the FST model for contingency calculation. However, the prior probability of an individual risk needs to be weighted to ensure that the sum of the probabilities of all the risks is in unity. Moreover, the posterior probability distribution for the parent risks of a dependent risk (i.e., by distributing the percentage of cost overruns of similar projects based on the posterior probability distribution) can be obtained.

To perform the calculations, it is required to also enter as input the percentage of cost overrun due to each risk factor, which is inherently included in the cost impact of each risk. However, if these are not available, it is still possible to use experts' judgements, accurately aggregated by the FGDMA. Note that it is possible to apply them to contingency in terms of both time (the amount of schedule contingency) and costs. The reader can refer to (Islam et al., 2021b) for the detailed steps that must be applied in order to compute the fuzzy contingency cost for a given risk.

4. Case study

Part of this study consisted of applying the proposed integrated risk management framework to a real-life NDP, with the dual purpose of verifying its structural validity and comparing its outputs against the currently used risk management methodology to evaluate its applicability. To this end, the decommissioning project of a 1970s built plant was selected for the analysis. This "end of life" phase started in 2008, and consequently the decommissioning program of the site is at an advanced stage, with still a few activities left to reach the brownfield phase (defined as "any previously developed land that is not currently in use that may be potentially contaminated" (Alker et al., 2000)). The company serving as the main contractor for the NDP provided the project data regarding risks, and the project risk manager and four of his staff supported the authors in applying the risk management framework to the project risks. To implement the framework, it was first necessary to develop a project-specific risk network, using as input the project Work Breakdown Structure and the activities time plan to map the workflow of the project, identifying individual activities and the links between them. The first draft of the risk network was validated by the risk manager, who was invited to add or remove nodes (i.e., risks or events of risks) and adjust the links among the nodes as he saw fit in respect of the site. The resulting cause−effect relationships network of the NDP project, which were then implemented on *Netica®*, a software suitable for building and modelling bayesian belief networks and influence diagram that offers the possibility of easily manage, modify and update the networks, are presented in Annex 2.

To apply the framework, the inputs required are the elicitation from experts of the prior probability of independent risks, the conditional probability of dependent risks (i.e., the causal relationship between risks) and the time delay impact of risks. The reason why time impacts, and not cost impacts were considered is the intrinsic nature of this NDP: the objective was in fact to achieve the greenfield status in the shortest possible time, in comparison with other past projects that had a longer and overscheduled timeline. The information was elicited through a questionnaire, in which experts were required to assess the probabilities and impacts of risks on a qualitative 7-point Likert scale (i.e., from "none" to "certain" for probabilities and from "none" to "extremely high" for impacts). Tables containing the equivalences between the numeric scale and the linguistic variables are reported in Annex 3.

The questionnaire was composed of three sections: the first section aimed at defining the profile of the experts, asking about their working position, the number of years of experience with NDPs, the number of similar projects they have worked on, and their highest academic title; the second section was devoted to defining the probability of occurrence of independent risk and the one-to-one relationship among risks; finally, the third part was aimed at collecting experts' judgements about the possible impact of the schedule delay of each risk. The experts interviewed had strong experience of risk management in NDPs. In order to evaluate the experience weights of each respondent, the procedure developed by (Aboshady et al., 2013) was employed. In particular, greater relevance was given to the experience gained on NDPs; then, in decreasing order of importance, the experience in similar projects, the work title and the academic title were considered.

5. Results and case discussion

5.1. Risk assessment

The questionnaire results were elaborated by the FGDMA algorithm that was used to compute the fuzzy prior probabilities of the independent risks, the conditional one-to-one relationships between the risks, and the impact of each of them. After having calculated the experts' weights, it was possible to obtain the crisp values for the likelihood of the occurrence of risk and the impact on the project schedule, which could then be given as input to the FBBN.

The crisp defuzzified probability values returned by the FGDMA model were then given as input to the modified FBBN model. *Netica*® was used to compute the CPTs, based on the weights of the parent risks directed to the dependent risk using a "Noisy-Or" distribution, a very common canonical model (Islam et al., 2019b). The canonical model was built in the software environment after reproducing the risk network, resulting in a model with 10 independent and 24 dependent risks, with a total of 74 links among them.

The software generated the CPTs among the different risks in the network using the Noisy-Or model. Based on the findings of (Gingnell et al., 2014), a 20% leaky probability in Noisy-Or was implemented to compute the Conditional Probability Tables. The leaky probability means there was a 20% chance that a schedule overrun occurs beyond the risks covered in this work (Islam et al., 2019b). The weight of each risk was given as input of the CPT of the child risk that it affected in *Netica*® (Annex 4).

To ensure the theoretical and practical validity of the model, a validation step was required before moving on with the application of the FCN to the project. Methods such as benchmarking, an extreme scenarios test, and sensitivity analysis are frequently used to validate Fuzzy Bayesian Belief Networks (Yang et al., 2008). Benchmarking analysis is used to demonstrate the superiority of the model adopted over more conventional approaches in finding the same outcomes more precisely and quickly. However, a full quantitative validation of benchmarking was not possible due to the lack of a standard method that considers correlations between risks for NDPs. Therefore, an extreme condition test and a scenario test (Yang et al., 2008) were conducted with the aim of validating the proposed canonical model and to fine-tune some parameters, if necessary.

In particular, two extreme condition tests (i.e., 100% risk probability and 0% risk probability for all the input variables) were conducted, each time changing the leaky probability, such as 0%, 5%, 10%, and 20%. The aim of extreme condition tests is to monitor if the model responds logically in the case of extreme conditions (Islam et al., 2019b). For example, the Noisy-Or distribution produced a 68.3% probability of project end delay when all the input variables are true (100% probability), representing a condition which is unrealistic, as it is expected that the probability of project delay is 100% when all its input probabilities have a certain probability of occurrence. This result led us to modify the conditional probability tables of all the dependent risks to achieve a more realistic outcome (100% delay probability). On the other hand, when all the input variables had 0% probability of occurrence, the probability of final project delay was predicted to be 43%. This outcome was due to the leaky probability of the Noisy-Or distribution, as it still considered a 20% probability buffer for the given risk to occur. However, 43% was considered a probability too high for this scenario.

One of the advantages of the model is that it can be fine-tuned by experts to achieve a more reliable and realistic outcome. Moreover, the initial CPTs produced by the Noisy-Or condition can be revised after the initial elicitation of probabilities (Islam et al., 2019b). Therefore, the CPTs can be fine-tuned to reach the desired outcomes, still without modifying the overall validity of the model. So, due to the poor results obtained with a 20% leaky probability, different input probabilities scenarios were tested (Yang et al., 2008) to investigate how the model behaved in each scenario with a different leaky probability and different CPTs. The results of running different scenarios are presented in Fig. 2.

The Noisy-Or with 10% and 20% leaky probability failed the extreme condition test. With a low probability of input parameters, the model still predicted a schedule delay for the project of 24%–43%. This shows that in a condition of no risk, the project could still experience a significant level of delay. At the other end of the spectrum, extreme cases of input variables (i.e., probabilities up to 100%) provide a very low prediction (60%–67% probability). Contrarily, the Noisy-Or distribution with no leaky probability (0% leaky) returns a satisfactory outcome up to 40% probability of all the input parameters. Nevertheless, this model fails when employed in higher input probabilities: for example, when the input probabilities have 100% probability of being true, the predicted delay probability is only 52.9%.

However, if the CPTs provided by the experts and calculated in the previous step (FGDMA) are slightly changed, the Noisy-Or leaky model with 0% leaky probability can provide a very fit outcome among the entire range of scenarios. It also reflects very well the fuzzy range used by experts in eliciting probabilities: when all the input parameters have a probability of occurrence between 20% and 40%, the chance of incurring a final time overrun for the project is between 17% and 32%, while if the probability of the input parameters is 40%–60%, the probability of delay ranges from 32% to 46%, and so on.

Following the outcomes of the previously described scenario analysis, to predict the probability of the project being late, the best performing model is used, which was the 5% leaky Noisy-Or with modified CPTs. The risks addressed by the experts who responded to the questionnaire are left unchanged, only modifying slightly some of the CPTs. Finally, the model calculated the probability of time overrun of the project to be 42.2%, which represents a medium probability of delay. Fig. 3 shows the risk analysis output for the case study generated in *Netica* ®.

Once the likelihood of the occurrence of each risk in the network was calculated, it was possible to complete the Risk Assessment phase of the PRM process by calculating the rating of each risk. The risk score was calculated as:

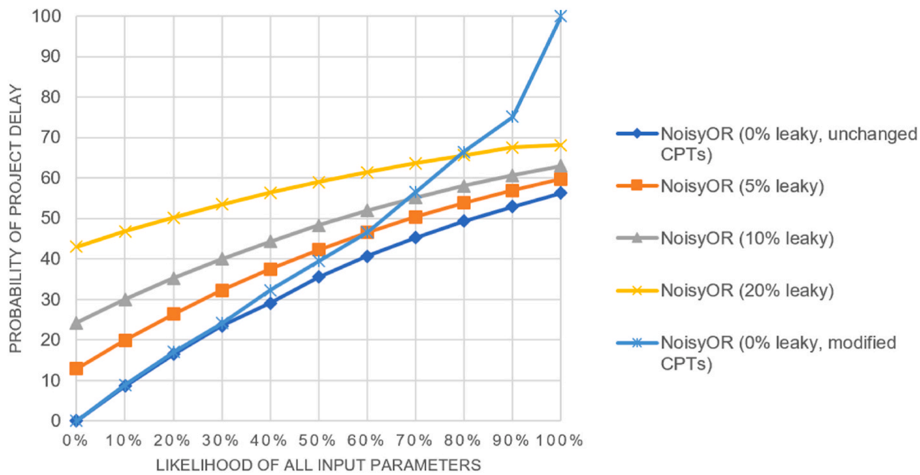

Fig. 2. Comparative scenario analysis using different distributions of CPTs.

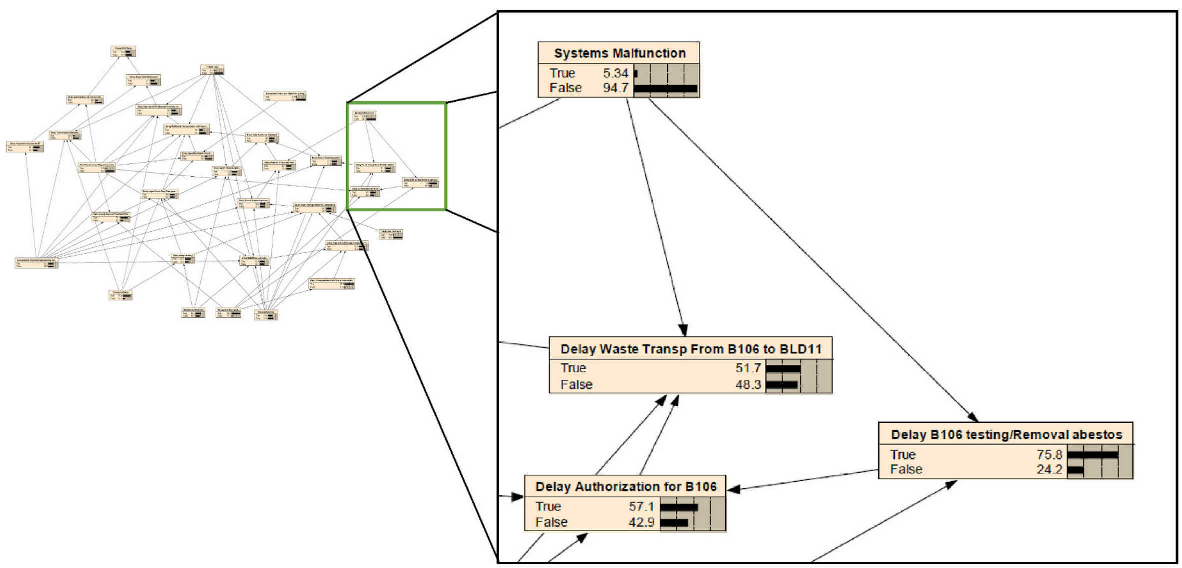

Fig. 3. Risk Network in Netica ® - 2-column fitting image.

$(FRS_r)_{L,M,U} = (\sqrt{FS^r_{RL,} * FS^r_{I_j}})_{L,M,U}$ where FS^r_{RL} and $FS^r_{I_j}$ are the fuzzy scores for respectively the risk probability (Likelihood) and Impact, and *L,M,U* stand for low, medium and high, respectively, considering the triangular fuzzy number, which is later defuzzified with the usual formula for FTNs:

$$(FRS_r)_{Deff.} = \frac{(FRS_r)_L + 4\,(FRS_r)_M + (FRS_r)_U}{6}$$

The calculated risk rating levels are shown in Annex 5: in the opinion of the experts involved, the calculation of the risk rating performed as in the proposed framework is fundamental to effectively identify the risks that require the most attention in being managed. Also, it is the starting point for the selection of the best mitigation actions to employ to reduce the overall risk exposure of the project.

However, as concerns the considered project and all the other NDPs carried out by the main contractor, all the mitigation actions that are applied are selected compulsorily by the regulatory body; thus, with the data not being available, it was not possible in this case study to test the mitigation action selection phase of the proposed model.

5.2. Contingency cost calculation

The risk assessment phase concluded that the four most probable risks were the in obtaining the authorisation for the transportation of solid radioactive waste, the risk of delays by the regulatory body, the risk of delay due to contractors' inability to adhere to the schedule (contractor delay), and the risk of delayed testing of the radioactive waste deposit "A". However, since the risks authorisation for the transportation of solid radioactive waste and delay in testing the deposit had no impact on the project schedule, other high-probability risks were considered. Therefore, those most probable to have a significant impact on project delay were, in decreasing order of the probability of occurrence, the risk of delays by the regulatory body (R_1), the risk of contractor delay (R_2), the risk of delay in obtaining approval for the liquid radioactive waste treatment plan (R_3), and the risk of delay during the preparation of drums of solid radioactive waste for transportation to supercompacting (R_4). Each of these risks showed a predicted impact on the project schedule, elicited by the experts in the questionnaire, which was then inputted in the FST model created for the contingency calculation phase, as adopted in (Islam et al., 2021b).

The computational outcome of the risks' prior probabilities, posterior probabilities, and the impact on the schedule of each risk in the form of a triangular fuzzy set, which serve as input for the contingency calculation phase, is given in Table 1. Note that the contingency amount is already weighted based on experts' weights and is given on a decimal scale. For the transposition from decimal scale to time measurement, please refer to Annex 3. Moreover, only the four most probable previously described risks are reported here for the sake of simplicity in representing the required inputs.

In order to correctly evaluate the outputs of the model based on the current PRM practice and outcome, the process of contingency calculation is performed first of all for achieving the brownfield state, as few remaining activities are required and, at the time of writing, the milestone has already been achieved, so actual time delay data are available.

For each single risk, the predicted contingency amount is obtained by multiplying each triangular element by the posterior probability of the considered risk. It must be highlighted that, in this case, to obtain the posterior probability of the risks, it was considered that the probability of delay of the waste transportation from deposit "X" to "Y" is 100%, as it is the last remaining activity before reaching the brownfield state.

The following step consisted in calculating the contingency amount for the dependent risks, which is obtained by summing the contingency amount of the parent risks. This step also demonstrated that the experts were able to match their judgements to the predicted amount. Table 2 shows the numerical steps required to generate the contingency prediction for achieving the brownfield phase.

The last row of Table 2 shows the fuzzy contingency amount calculated by the FST model. Then, it is possible to obtain the defuzzified value. The result for the predicted amount is 0.805, which, as shown in Annex 3.2, lies in the "Very High" range, which in defuzzified numbers ranges from 0.7 to 0.9, considering delays from 250 to 360 days. It is possible to convert the crisp number into a more relatable quantity, expressed in days: with the application of a simple linear approximation in the considered range (250–360 days), the delay is predicted to be about 308 days.

5.3. Error analysis

The predicted contingency amount was compared with the actual time delay of the project by error analysis (330 days estimated by the PRM team). The team's predicted delay lay in the same range as the model prediction and, with the same linear approximation used before, it was possible to obtain the associated crisp number (0.845), to compare it with the output of the model. The percentage error in this scenario between the predictions of the model and of the PRM team is 4.73%. Considering that a maximum of 20% error in the prediction of the schedule contingency amount based on subjective judgements is supported by (S. A. A. and RobinsonA. S. M., 2007) and (Fidan et al., 2011), it can be concluded that this outcome demonstrates the validity of the model in predicting the schedule delay contingency amount to be considered for the project.

However, these findings from the fuzzy contingency amount model need to be justified before being applied to the entire project and to future projects, so the next step is to perform and discuss a detailed error analysis, with the Fuzzy Quality Index (FQI) and Agreement Index (AgI) analyses, to justify the model outcomes. The presence of differences in judgements among the different experts may cause inconsistencies in the evaluation of the risks. This is due to judgement bias and vagueness in their understanding of project risks. Therefore, it is necessary to evaluate the fuzzy quality index of the measured schedule contingency amount. The FQI can be explained by the fuzziness of a fuzzy set A. This indicates the degree of precision of a fuzzy contingency amount for the project.

On this occasion, the experts are required to evaluate the impact of risks on the schedule using a Likert scale; then their judgements are grouped in a fuzzy triangular number. The quality of the fuzzy number (the FQI) is therefore measured as:

$FQI = \frac{F(A)+AG(A)}{2}$ where $F(A) = b - a - \int_a^b |2A(x) - 1| dx$ represents the fuzziness of a given triangular fuzzy set $A(x)$, $x \in [a,b]$, and

$AG(A) = \frac{(a_3 - a_2)+(a_2 - a_1)}{6}$ is the ambiguity for a triangular fuzzy number (a_1, a_2, a_3).

A higher level of fuzziness indicates a wider data set (the difference among fuzzy numbers is large), while a lower level of fuzziness is associated with a narrow data set; on the other hand, the ambiguity of a fuzzy number measures the precision level of the measured values: a higher value of ambiguity is a symptom of imprecision in the dataset (Islam et al., 2021b).

Table 3 shows the triangular fuzzy number of the predicted contingency amount for the brownfield phase of the project (FCAg), the predicted (defuzzified) schedule contingency amount, the actual time delay of the phase conclusion, the percentage error between the predicted contingency amount and the actual delays, the corresponding fuzziness, ambiguity and FQI.

It should be noted that, by using the defuzzified values on a scale from 0 to 1 instead of the equivalent value in days for the delay, it is possible to turn the numbers into percentages, which are easier to understand and evaluate. The error is far below the 20% boundary, allowing us to conclude that the predicted contingency amount provides a significant indication of the level of accuracy in the prediction of schedule delay. On the other hand, the fuzziness value is slightly above 20%, which is high, while the FQI is 18% of the predicted schedule contingency amount, due to the large fuzziness of the fuzzy number, which may be caused by the propagation of fuzziness along the risk network, thus increasing its impact on the outcome. As the error of fuzziness originates from uncertainty, vagueness, and imprecision in the expert judgements in the risk assessment phase, both the prediction error and fuzziness can be reduced by repeating the risk evaluation with field experts, applying a three-round fuzzy-Delphi technique.

5.4. Agreement index

To calculate the agreement index, the actual delay in reaching the brownfield phase is considered as the budgeted amount, as data from the initial budgeted amount are not available. Fig. 4 represents the area used for the calculation of the Agreement Index, which is calculated as:

$$AgI(FCC_g, BCC) = \frac{(area\ FCC_g \cap BCC)}{area\ FCC_g} * 100(\%)$$

The calculation returns an Agreement Index of 75.4%, which is a satisfactory level, considering the findings of (Islam et al., 2021b). In order to obtain a better understanding of the value, it should be stated that a high Agreement Index means a higher chance of avoiding a project cost overrun (S. A. A. and RobinsonA. S. M., 2007). Therefore, assuming that the PRM team budgeted the schedule contingency amount as the same amount of time as the actual experienced delay, this would cover the brownfield delay with a 75.4% probability. In other words, in the described scenario there is a 100–75.4 = 24.6% probability that achieving the brownfield phase would be delayed despite the budgeted contingency allowance.

Once the model has been employed, evaluated, and discussed in detail for the phase of the project that leads to achieving the brownfield state of the site, it is scaled up to calculate the schedule contingency amount for the entire project, which ends with the release of the site to

Table 1
Inputs for the contingency calculation phase.

Risk	Prior probability (p_i)	Posterior probability (α_i)	Fuzzy contingency amount		
			a	b	c
R_1	0.883	0.888	0.511	0.711	0.895
R_2	0.788	0.824	0.117	0.281	0.481
R_3	0.741	0.781	0.702	0.865	0.964
R_4	0.620	0.650	0.180	0.364	0.564

Table 2
Calculation for the contingency amount prediction for achieving brownfield state.

Independent risk	Posterior probability (α_i)	Fuzzy contingency amount predicted			Fuzzy contingency amount		
		a	b	c	a x α_i	b x α_i	c x α_i
Regulatory body delays	0.920	0.511	0.711	0.894	0.469	0.654	0.823
System malfunction	0.065	0.196	0.396	0.596	0.013	0.026	0.039
New requests from regulatory body	0.112	0.481	0.681	0.854	0.054	0.076	0.096
Site interferences	0.519	0.60	0.324	0.524	0.083	0.168	0.272
Dependent risk	**Posterior probability (αi)**	**Fuzzy contingency amount predicted**			**Fuzzy contingency amount (calculated)**		
		a_p x α_i	b_p x α_i	c_p x α_i	a x αi	b x αi	c x αi
Delay in deposit "A" testing/asbestos removal	0.789	0	0.	0.079	0.483	0.680	0.862
Delay in authorisation for deposit "A"	0.942	0.551	0.740	0.878	0.469	0.654	0.902
Delay in waste transportation from X to Y	1	0.585	0.785	0.932	0.553	0.822	0.990

Table 3
Schedule contingency amount prediction and fuzziness test results.

FCA_g			CA_p	CC_{actual}	Error (%)	Fuzziness F(A)	Ambiguity AG(A)	FQI
a_1	a_2	a_3						
0.552	0.822	0.991	0.805	0.845	4.73	0.22	0.073	0.145

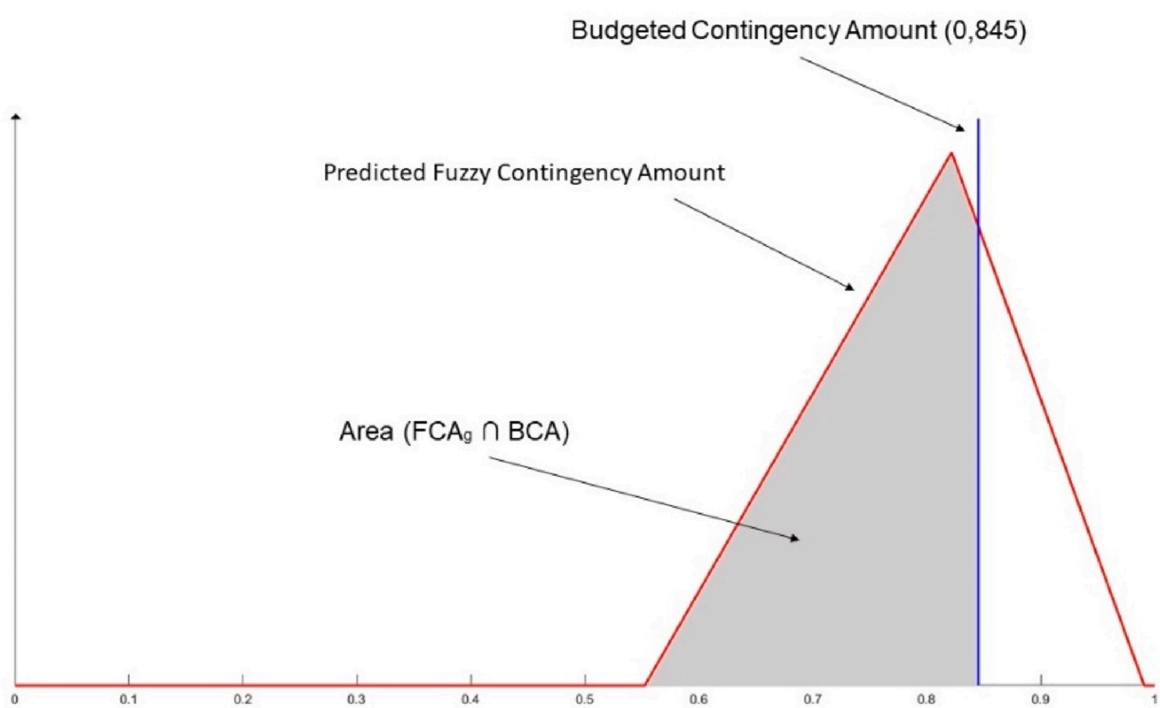

Fig. 4. Agreement Index between the predicted and budgeted contingency amount for the brownfield phase.

the greenfield state.

To obtain the predicted amount and to allocate a crisp contingency amount for the project, the same steps carried out in the brownfield achievement phase were performed. The outcome of the calculations revealed that the predicted schedule delay contingency amount for the entire project is 1075 days. However, this value cannot be compared to the current prediction of the PRM team of the project, as they still have not evaluated it (achieving greenfield status is expected in 10 years).

To evaluate the quality of the prediction, the Fuzzy Quality Index is calculated: the fuzziness and the ambiguity of the predicted contingency amount for the entire project turn out to be 2.28 and 84 days, respectively, returning a FQI of 43.2 days. Considering the order of magnitude of the prediction, it can be stated that this is accurate.

Moreover, it is possible to suggest a budgeted schedule contingency amount for the project, considering an Agreement Index of 80%. After performing the inverse calculations of those carried out to obtain the agreement index for the brownfield phase of the project, the suggested budgeted contingency amount is 1165 days. This can be considered as the number of days to be added to the schedule to close the project within the deadline with 80% probability.

6. Conclusion and future development

The proposed framework proved to be a good fit for the NDP analysed. In fact, the risk assessment phase returned as output a medium probability of delay of the project, which was similar to the findings of the risk management team for the project. Moreover, for the first phase of the project, obtaining the brownfield state for the site (which is the most detailed and recent one), the contingency calculation performed by the framework showed a time delay very similar to the actual one, with an error of only 4.73%. Also, the framework is able to consider cause–effect dependencies between risks and activities, whereas the actual risk management process being used by the company did not consider them. Carrying out such a cause–effect analysis of project risks can foster good risk management by identifying the root causes of the project delay during the preliminary phase of the project.

In general, the framework is demonstrated to be suitable for the risk management of NDPs: (i) it can easily be implemented in different NDPs by changing the input probabilities and the CPTs, according to the peculiarities of the given project, and (ii) it is flexible and dynamic also during project execution when managing schedule risks. In the case of schedule delay during the execution of the project, the PRM team will just need to re-assess the root causes of the delay and their impact on corresponding risks. For the risks that have occurred, it is sufficient to assign a 100% probability of occurrence and the corresponding impact will be determined accordingly. Also, the framework allows initial risks that can no longer influence the project to be deleted and newly identified risks in the risk network during execution to be added. Finally, (iii) new risk can be added during execution: it is necessary to identify the immediately dependent risk(s) and the subsequent dependent risks that propagate throughout the network.

However, it should be mentioned that the initial model inputs, the prior probabilities, the posterior probabilities, and the impact on project schedule delay can vary significantly, as they are expert judgements. The accuracy level of the risk assessment results can have a significant impact on the predicted contingency amount and on the correct selection of mitigation actions. Furthermore, the proposed model, despite requiring less input data than most other FBBN models, is of limited value if experts have insufficient knowledge to evaluate the risks and their impacts (Islam et al., 2019b). A possible solution to this problem may be the use of a fuzzy-Delphi technique, with the aim of consolidating the different expert opinions (Nasirzadeh et al., 2014).

In S1 the use of a canonical model for the FBBN has a drawback: it allows each node to have only two states (in this case true or false), while in some cases it would be useful to have more states available (i.e., 50% impact of the risk). Moreover, additional discussion is required in relation to the use of the modelling software, *Netica* ®. The risk assessment phase is carried out with the condition that the Noisy-Or node is Boolean (i.e., true or false). This implies that, instead of using the triangular fuzzy probabilities directly for the independent risk and the one-to-one relationships among risks, the defuzzified (single value) probabilities are given as input. A future development of this work could be to introduce the triangular probabilities as three different input values (i.e., the “least likely”, the “likely” and the “most likely”), which requires the model to be run in three different states.

The application of the model is hindered by the fact that the risk network is strictly tied up with the individual characteristics of the project, making possible adaptations long and tedious for practitioners. However, a possible future work can employ the risk factors listed by (Awodi et al., 2021) to create a risk network that can be applied to the entire nuclear decommissioning industry. Finally, a possible development of this work could be to apply the proposed model to a larger NDP, such as the decommissioning of a nuclear power plant, in which it would also be possible to use the available data to perform the selection of the mitigation actions 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 authors do not have permission to share data.

Annex 1. Acronyms

NDP	Nuclear Decommissioning Project
PRM	Project Risk Management
FBBN	Fuzzy Bayesian Belief Network
FGDMA	Fuzzy Group Decision Making Approach
BBN	Bayesian Belief Network
ACO	Ant Colony Optimisation
FTOPSIS	Fuzzy technique for order preference by similarity of an ideal solution
ANN	Artificial Neural Network
MCS	Monte Carlo Simulation
FST	Fuzzy Set Theory

Annex 3. Equivalences between the numeric scale and the linguistic scale

Occurrence probability	Description
0	Impossible - Event never occurs
1	Very Unlikely - Events are highly unlikely to occur
2	Unlikely - Events are unlikely but possible to occur
3	Even Chance - The occurrence likelihood of possible events is an even chance
4	Likely - Events are likely to occur
5	Very Likely - Events are highly likely to occur
6	Certain - Events are expected to occur with absolute certainty

Annex 3.1. The seven-point linguistic scale for assessing occurrence probabilities of risks

Magnitude of impact	Description	Schedule delay
0	Impacts on project schedule can be nearly ignored/negligible effects	0 days
1	Very Low - Potential for causing slight impacts on project schedule	Up to 15 days
2	Low - Potential for causing minor impacts on project schedule	From 15 to 85 days
3	Medium - Potential for causing moderate impacts on project schedule	From 85 to 165 days
4	High - Potential for causing substantial impacts on project schedule	From 165 to 250 days
5	Very High - Potential for causing critical impacts on project schedule	From 250 to 360 days
6	Extreme - Impacts on project performance are catastrophic	360 days or higher

Annex 3.2: The seven-point linguistic scale for assessing magnitude of impact of risks.
Annex 4: Example of Conditional Probability Table for the risk of delay of Building 1 (BLD1) Characterisation.

Annex 5. Risk Rating for Dependent and Independent Risks

Independent Risks	Probability	Impact	Rating	Score
Regulatory body delays	0.883	0.708	0.791	VH
Site interferences	0.436	0.330	0.379	M
Unexpected findings	0.556	0.725	0.635	H
Contractor delay	0.788	0.287	0.476	M
Unavailability of planned engineering resources	0.502	0.214	0.328	M
New requests from regulatory body	0.094	0.677	0.253	L
Incomplete listing of criteria and objectives	0.053	0.828	0.210	L
Tender delay	0.094	0.596	0.237	L
System malfunction	0.053	0.396	0.145	L
Delay obtaining ISIN clearance	0.075	0.591	0.210	L
Dependent Risks				
Delay in “A” testing/asbestos removal	0.758	0.017	0.112	L
Delay in authorisation for “A″	0.571	0.776	0.666	H
Delay in waste transportation from “X” to “Y″	0.517	0.776	0.633	H
Delay in sample testing	0.625	0.017	0.102	L
Delay in authorisation of solid waste transportation	0.907	0.017	0.123	L
Delay in “Z” characterisation	0.509	0.017	0.092	VL
Delay in preparation of transportation of solid waste drums for supercompacting	0.620	0.367	0.477	M
Delay in drums transportation to supercompacting	0.493	0.374	0.430	M
Delay in drums supercompacting	0.525	0.287	0.388	M
Delay in “H” characterisation	0.538	0.017	0.095	VL
Delay in solid materials characterisation	0.497	0.099	0.222	L
Delay in “F” characterisation	0.527	0.880	0.681	H
Delay in solid rad waste treatment	0.549	0.880	0.695	H
Delay in approval of liquid waste treatment plan	0.741	0.854	0.796	VH
Delay in liquid waste transportation preparation	0.499	0.720	0.599	H
Delay in liquid rad waste treatment	0.247	0.428	0.325	M
Delay in rad waste transportation to national repository	0.345	0.637	0.469	M
Delay in deposits “A” decommissioning	0.385	0.502	0.440	M
Delay in conventional demolitions	0.289	0.615	0.422	M
Delay achieving greenfield phase	0.373	0.921	0.586	H
Delay in dossier preparation (Art 57)	0.602	0.396	0.488	M
Delay in authorisation for site release	0.221	0.813	0.424	M

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