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Network analysis-enhanced project risk management for nuclear power plant construction

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ABSTRACT

This paper introduces a comprehensive framework for managing interdependent delay risks in nuclear power plant (NPP) construction by integrating network theory and topological analysis. Spent fuel disposal, nuclear plant safety and nuclear weapons proliferation are known important concerns for nuclear power development, but costs remain the fundamental problem, as NPP projects are plagued by schedule delays that substantially increase total costs. Such complex megaprojects are exposed to numerous risks of different sources that behave interdependently. Most of the studies understand the risks of delay in NPP construction projects in isolation without taking interdependencies into account. The proposed methodology employs a Design Structure Matrix (DSM) to construct a Risk Interaction Network (RIN), enabling a topological assessment to identify critical risks that may cause cascading delays in project tasks. An algorithmic search for these critical risks is conducted, considering the impact of their removal on the RIN's characteristics. We define a bi-objective optimization problem aimed at generating a project schedule that minimizes both the project's makespan and the reachability density of the RIN. The solution is obtained using an evolutionary algorithm. Applied to a Double-Containment Pressurized Water Reactor (DC-PWR) project, this approach effectively uncovers risks neglected by classical analysis and offers scheduling options for different risk attitudes, enhancing decision-making capabilities.

1. Introduction

Expanding the energy portfolio while reducing carbon emissions is one of the foremost challenges of the 21st century [1]. Nuclear power emerges as a viable alternative to increase energy supply and lower greenhouse gas emissions. Historical challenges to nuclear power development such as spent fuel disposal, nuclear plant safety and nuclear weapons proliferation persist, but these issues are comparatively less significant than the uncertainty and escalation in costs, primarily due to construction schedule delays, which remains the main obstacles for advancing nuclear power development [1]. Effective Project Risk Management (PRM) becomes essential in this context to identify, analyze and mitigate risks that contribute to cost escalations and delays. Economic analysis shows that extending construction timelines significantly increases financial risks, with interest during construction accounting for over 40 % of total construction costs in cases of prolonged delays, making nuclear projects financially unviable without reducing these delays [2]. Furthermore, Berthélemy & Escobar Rangel [3] underscores that construction delays are one of the most significant concerns in nuclear projects, exacerbating cost overruns and negatively impacting project viability. Such delays not only increase direct construction costs but also prolong capital lock-in periods, further inflating interest expenses and financial risks for stakeholders [4,5].

Nuclear power plant (NPP) constructions are complex megaprojects, characterized by large scale, substantial financial investments and extended timelines [6]. Portugal-Pereira et al. [7] emphasize that this complexity stems from the interdependence of technical, environmental and regulatory factors, making it difficult to manage them in isolation. As the number of interdependencies grows, managing delays and cost escalations becomes even more challenging, highlighting the need to study these risks in an integrated manner.

Lehtonen [8] argues for studying nuclear project complexities as dynamic, interdependent systems shaped by technical, regulatory, and societal factors. He emphasizes the need for flexible, adaptive approaches to navigate these evolving challenges effectively. Alsharif & Karatas [9] highlight that risks in NPP projects, such as productivity issues and design errors, are interrelated, in a way that a delay in one area can trigger cascading effects throughout the project. Ruuska et al.

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[10] point out that large-scale, multi-firm projects like Olkiluoto 3 and Flamanville 3 are characterized by complex networks of stakeholders, where governance and coordination issues frequently arise. In these projects, challenges in one part of the project can lead to problems in others, as the actions of one firm often affect the entire network of project tasks. For example, in the Olkiluoto 3 project, an error in the welding process required substantial design modifications, which disrupted the project schedule. Similarly, in Flamanville 3, regulatory-driven design changes forced suppliers to adapt to new specifications, further delaying key milestones and complicating the overall project timeline [11]. These cases highlight how the interconnected nature of risks in megaprojects can contribute to delays and cost escalations. Recognizing the multifaceted nature of these interdependent risks, Taroun [12] emphasizes the importance of risk analysis methodologies that account for interdependencies to analyze and assess potential project delays and cost overruns.

From a broader complexity science perspective, nuclear construction projects can be regarded as Complex Adaptive Systems (CAS) due to the nature and behavior of their components and interactions [13–15]. A CAS is composed of heterogeneous, interconnected agents, such as organizations, teams, technologies and regulatory bodies, whose collective behaviors give rise to system-level outcomes that cannot be predicted by analyzing individual components in isolation [16,17]. These agents not only interact with one another, but also with their surrounding environment in a continuous process of mutual influence and coevolution. As agents adapt to changes in the environment, they simultaneously reshape that environment, creating new conditions to which the system must further respond [16,18].

Nuclear megaprojects comprise interdependent tasks linked through technical, logistical, informational and resource-related dependencies [14]. Stakeholder behaviors are shaped by shifting incentives, regulatory pressures and multi-layered governance structures, making project dynamics highly sensitive to context and timing [10]. The tight coupling and nested structure of systems within systems further increase the system's complexity and fragility. The combination of technological and organizational complexity make these projects especially vulnerable to emergent risks that defy prediction or control via traditional, linear project management tools, even when decision makers are highly competent, possess data and have technological means at their disposal [6,19].

Consequently, risks in these environments should not be viewed as isolated threats but as interacting elements within a network. When one risk materializes, it can propagate through interconnections, triggering other risks and producing cascading effects. This systemic behavior highlights the need for a network-based perspective on risk that captures how risks interact and reinforce each other, which traditional risk registers often fail to detect [18].

Given such intrinsic characteristics, it is essential to model interdependent risks to accurately anticipate and manage the cascading effects of risk events [20]. As a matter of fact in recent years, the consideration of risk interdependencies in construction projects has become increasingly established in the scientific and technical literature, with numerous studies highlighting the importance of addressing this complexity to enhance risk management and improve overall project outcomes [21].

This growing academic attention is also reflected in professional standards. The Seventh Edition of the PMBOK® Guide [22], introduced by the Project Management Institute, marks a significant shift from its earlier process-based model, which included sequential steps such as Plan Risk Management, Identify Risks, Perform Qualitative and Quantitative Risk Analyses, Plan and Implement Risk Responses, and Monitor Risks [23], to a more principle-driven and systemic approach [22]. Instead of treating risks as isolated events managed in linear order, the new approach embeds risk considerations across broader performance domains, especially the Uncertainty Domain, which includes concepts such as complexity, ambiguity and volatility. It recognizes that complex projects involve dynamic interactions and emergent behaviors, and it promotes strategies like systems thinking, simulation and iterative learning to navigate such complex environments. However, while the guide encourages this mindset, it does not prescribe formal tools to model risk interdependencies or quantify how they influence project outcomes.

Despite the acknowledged necessity, no existing studies have comprehensively modeled the interdependent risks within NPP construction projects. Kim et al. [24] proposed a comprehensive risk management framework for nuclear power plant (NPP) construction, which highlights the importance of identifying correlations between risks throughout the project life cycle. Although their study introduces the concept of risk paths to illustrate how risks in one area may influence others, it remains focused on risk identification and correlation at a higher level, without offering detailed insights for mitigating the interdependent risks within the project execution itself. On the other hand, traditional risk assessment methodologies often fall short as they tend to evaluate risks in isolation, neglecting the synergistic interactions that can amplify the impact of individual risk events [20]. This underscores the necessity for more sophisticated Project Risk Management approaches that take interdependencies into account and provide a holistic view of project risks.

To address this gap, this paper proposes a network-based framework that explicitly captures, analyzes and mitigates interdependent risks in NPP construction projects. A Design Structure Matrix (DSM) is used to represent the interdependencies among project risks, forming the basis for constructing a Risk Interaction Network (RIN) that maps how risks propagate through overlapping activities and dependencies. To the best of our knowledge, this is the first study to explicitly model and manage risk interdependencies in NPP construction projects. Topological analysis is applied to identify critical risks based on their structural position and influence within the network, and systemic indicators are calculated to quantify the project's exposure to cascading disruptions. To enhance project resilience, a multi-objective optimization approach is employed to identify combinations of risks whose mitigation most effectively strengthens network robustness. Building on this analysis, a bi-objective project scheduling optimization is developed to generate alternative schedules that simultaneously minimize project duration and systemic vulnerability, providing risk-aware planning strategies that explicitly account for risk interactions.

The main contributions of this paper are:

- A network-based framework explicitly modeling risk interdependencies in NPP construction projects.
- Application of topological analysis and systemic metrics to identify and quantify critical risk propagation pathways.
- Development of risk-aware scheduling optimization strategies to enhance project resilience against cascading disruptions.

The proposed methodology is applied to the construction of a double-containment pressurized water reactor (DC-PWR) [25], similar to a Framatome European Pressurized Reactor (EPR), with the goal of identifying vulnerabilities that contribute to cascading delays and cost escalations. The analysis has revealed that critical risks are concentrated in activities with high overlap and dependencies within the task network. A sensitivity analysis has showed that selecting risk mitigation strategies based solely on topological indicators has limitations, whereas optimized identification of critical risk combinations through algorithmic search substantially improves the network's robustness by reducing reachability density and global efficiency. Furthermore, adjusting task sequencing and resource allocation based on risk interdependencies produce alternative scheduling solutions that maintain overall project duration while lowering systemic exposure to disruptions. These findings suggest that incorporating network-based risk analysis into project planning can complement traditional risk assessment methods and provide additional insights for improving project resilience in complex environments.

The paper is structured as follows: Section 2 reviews the literature on the complexity of NPP projects and reference models for the governance of complex systems, on cost uncertainties and risk modeling in NPP construction and on methods to represent risk interactions in large engineering projects, such as Bayesian Networks, Multi-Criteria Decision-Making and DSM; Section 3 outlines the proposed methodology; Section 4 presents the case study; Section 5 discusses the results; and Section 6 concludes the paper with key findings and future research directions.

2. Literature review

2.1. Nuclear construction projects as complex adaptive systems (CAS)

Nuclear construction projects are typically conducted through a EPC (Engineering, Procurement and Construction) contract, that is a turnkey contract where the owner, usually an utility provider, buys a delivery of an operable NPP [26]. Several subcontractors are also involved in these projects, hired directly by the owner, or by the main contractor. Moreover, the work should be approved by a regulatory entity that follows closely the project and should approve not only the design but also the quality of the executed work. This multi-firm scenario without full hierarchical control supports the argument for regarding NPP construction as a CAS [13,15]. As a matter of fact, the Olkiluoto 3 construction involved around 2000 subcontractors, over 17,500 diverse workers, and multiple global supply chains, resulting in an exceptionally complex and interconnected organizational structure. The subcontractor network's structure was not deliberately designed but evolved spontaneously, exemplifying key characteristics of CAS [15].

CAS exhibit several defining characteristics [27,28]:

- Adaptation: Project actors continuously revise decisions and behaviors in response to unfolding events.
- Non-linearity: Small disruptions, such as minor design changes or procurement delays, can propagate and lead to disproportionately large project impacts.
- Feedback loops: Failures in one area of the project can amplify disruptions elsewhere.
- Emergence: New patterns and outcomes result from complex interactions rather than a single cause.
- Self-organization: The system restructures and coordinates itself without centralized command, often leading to unanticipated adaptations.

Reiman et al. [13], focusing on complex adaptive organizations, identified and summarized these concepts by identifying additional characteristics drawn from earlier theoretical work:

- Coevolution: The process of mutual change between a system and its environment.
- History-dependence: The current state of a system is shaped by its unique history of actions and learning, making outcomes non-repeatable across contexts.
- Far-from-equilibrium conditions: Organizations function at the edge of chaos, where the tension between order and disorder enables flexibility, creativity, and continual adaptation.
- Nested systems (recursion): Complex adaptive organizations are composed of subsystems that are themselves CAS.

Understanding NPP projects as CAS implies acknowledging inherent systemic risks and deep epistemic uncertainties that complicate project management. Various scientific frameworks have been proposed to address the challenges posed by these complexities, including Complexity Science, Network Analysis and emerging risk management methods [29]. Within this scope, the Viable System Model (VSM) [30], rooted in management cybernetics, offers significant conceptual and methodological tools aimed at maintaining systemic viability under conditions of complexity and uncertainty. Moreover, the evolution from VSM to Complex System Governance (CSG) further extends the conceptualization and practical applicability of meta-systemic functions, providing structured governance approaches specifically tailored to managing uncertainty and emergent risks characteristic of complex organizations.

The VSM is structured around three primary components essential for maintaining system viability amidst complex interactions and environmental perturbations:

- System: Executes core activities, delivering the main operational outcomes.
- Meta-system: Provides regulatory functions ensuring the system's coherence, integration and adaptive capabilities.
- Environment: Denotes external conditions influencing system performance.

Within the meta-system, specific regulatory functions are defined to facilitate dynamic equilibrium:

- Policy (System 5) – Establishes strategic identity and direction, managing external and internal tensions.
- Intelligence and Development (System 4) – Processes external environmental data and strategic foresight.
- Operational Control (System 3) – Ensures operational effectiveness through resource allocation and management.
- *Audit and Accountability (System 3)** – Monitors internal consistency and identifies deviations from expected performance.
- Coordination (System 2) – Manages interactions between system components, reducing variability and preventing instability.

Building on the principles outlined by VSM, Complex System Governance (CSG) [31,32] has emerged as an advanced governance paradigm. CSG explicitly addresses the intentional design and evolution of governance functions to enhance system resilience and adaptability under complex, uncertain conditions.

CSG articulates a set of nine interrelated governance functions, each contributing to the control, coordination, communication and integration required to govern complex systems [32]:

- Policy and Identity (M5): Maintains the system's purpose, vision, and strategic trajectory, ensuring internal coherence and external alignment.
- System Context (M5*): Understands and defines the contextual environment within which the system operates, including enabling and constraining conditions.
- Strategic System Monitoring (M5′): Continuously assesses strategic-level performance indicators, enabling early detection of deviation from expectations.
- System Development (M4): Designs and evolves the system structure to ensure future viability through long-range planning and modeling.
- Learning and Transformation (M4*): Facilitates adaptive learning and system transformation based on feedback, experience and evolving challenges.
- Environmental Scanning (M4′): Detects patterns, trends and shifts in the external environment that may affect the system's present and future state.
- System Operations (M3): Oversees daily activities, ensuring operational effectiveness, consistency and resource efficiency.
- Operational Performance (M3*): Monitors and analyzes system performance to uncover variances and identify improvement opportunities.
- Information and Communications (M2): Ensures consistent information flow and interpretation across functions to support coordinated decision-making.

These governance functions are inherently interrelated and mutually reinforcing. Policy and Identity (M5), for example, shapes the strategic focus of System Development (M4) and Strategic System Monitoring (M5′), whereas the insights gathered from Environmental Scanning (M4′) inform Intelligence and Development (M4) as well as Learning and Transformation (M4*). System Operations (M3) relies on effective Coordination (M2) and robust Operational Performance (M3*) monitoring, supported by clear Information and Communications (M2). The Audit and Accountability (M3*) function serves as a feedback mechanism that enhances transparency, reinforces coordination and informs strategic adjustments across all governance layers. This interconnectedness facilitates coherent and adaptive responses to emerging risks and uncertainties.

The inherent complexity and uncertainty associated with NPP construction projects require attention not only to the presence of governance functions but also to the potential dysfunctions that may emerge when these functions are underdeveloped or misaligned. These dysfunctions, conceptualized as metasystem pathologies, represent systemic weaknesses that undermine viability. Metasystem pathologies may emerge from imbalances, absences or misconfigurations across any of the governance functions, and they often manifest as persistent patterns of underperformance, delayed responses to perturbations or failures in coordination and adaptation [31].

Keating and Katina [31] classify these pathologies into eight interrelated clusters, each reflecting a foundational domain critical to systemic health:

- Understanding: Deficits in human or organizational comprehension of complexity and systems behavior.
- Process: Inadequate internal and external processes that fail to support system development, integration or adaptation.
- Goal: Misalignment or ambiguity of system goals, undermining purposeful governance.
- Regulatory: Insufficient or ineffective control mechanisms to guide systemic responses.
- Resources: Inadequate material, financial or human assets required for sustaining governance and productivity.
- Dynamic: Inflexibility in interacting with other systems and environments, reducing adaptive performance.
- Information: Limitations in creating, transmitting, or interpreting critical information flows.
- Structure: Poorly designed configurations of system elements and relationships, diminishing the system's ability to absorb variety and manage complexity.

Each of these clusters corresponds to potential limitations in the governance framework and points to specific areas where design or operational improvements are necessary. When the system's architecture is unable to absorb the variety generated by internal flux or external disturbances, residual unabsorbed variety accumulates, increasing uncertainty and potentially triggering system degradation or collapse [31].

Designing governance structures capable of absorbing such complexity is, thus, essential. This involves configuring interrelated functions and structures to ensure resilience, robustness, and minimizing fragility. From this perspective, risk management becomes a strategic tool, not as a standalone discipline but as a support function embedded across governance mechanisms, to identify, monitor and mitigate sources of residual complexity. In doing so, it enhances the system's capacity to sustain viability amidst dynamic and uncertain environments.

2.2. Risk assessment of nuclear power plant constructions

Cost uncertainty in nuclear power plant (NPP) construction arises primarily from two key sources: price fluctuations and construction risks. Several studies have identified price fluctuations as a major contributor to cost uncertainty. For instance, Ganda et al. [33] utilized Monte Carlo simulations to quantify uncertainties in key material and labor costs. However, their findings revealed that price fluctuations alone were insufficient to account for the substantial cost overruns observed in actual NPP projects. This suggests that factors such as construction delays and other risks, beyond price variability, play a more significant role in cost escalations. Maronati & Petrovic [34] expanded this analysis by incorporating 18 factors affecting material and labor costs, such as HVAC systems, pumps, and electrical equipment, and demonstrated that when the related uncertainties were combined with schedule delays, their impact on overall project costs became much more pronounced. Their results underscored the critical importance of managing construction timelines to mitigate cost overruns. Despite these refinements, the estimates still fell short of accurately predicting project outcomes, indicating that price fluctuations alone do not fully explain the increases in cost. This discrepancy highlights the dominant influence of construction delays in driving overall cost escalations.

To address this shortcoming, they introduced the concept of "unknown unknowns" into their cost estimation model, bringing their projections closer to real-world outcomes within a reasonable confidence interval [35]. While this approach improved the accuracy of their estimates, construction risks were still not fully accounted for. In response, Stewart & Shirvan [36] expanded the scope of cost estimations by incorporating a broader range of construction-related risks, including supplier delays, human errors and productivity issues due to design changes, called change orders. Their comprehensive analysis provided a more holistic understanding of the uncertainties contributing to cost escalations in NPP construction projects.

A meta-analysis of cost estimations for advanced reactors further supports this perspective, emphasizing that construction risks are a primary driver of delays and cost overruns, particularly for First-of-a-Kind (FOAK) reactors. These risks, including supplier failures, labor inefficiencies and project management challenges, significantly contribute to cost escalations. The report highlights that in FOAK projects, where designs are unproven and construction practices are less mature, such risks tend to compound, further complicating cost control and project timelines [37].

2.3. Methods to model interdependent risks

Methods for representing risk interdependencies in large engineering projects have been developed. These methods include Bayesian Networks, Multi-Criteria Decision-Making techniques, such as the Analytic Hierarchical Process (AHP) and Analytic Network Process (ANP), Design Structure Matrix (DSM) and hybrid methods that combine elements of these techniques. Bayesian Networks offer a probabilistic framework to model uncertainties and dependencies among risks. Lee et al. [38] utilized Bayesian belief networks to analyze risks within the Korean shipbuilding industry. They identified various risks through expert consultations and literature reviews and constructed a network to quantify the probabilistic relationships between risks and the impacts on project outcomes. Similarly, Qazi & Dikmen [39] transformed traditional risk matrices into risk networks using a data-driven Bayesian Belief Network methodology. This approach allows for the aggregation of risks across multiple project objectives, capturing the holistic impact of each risk within an interconnected framework. One limitation of Bayesian Networks is that, as directed acyclic graphs (DAGs), they cannot represent feedback loops. To address this issue, a method has been proposed to eliminate cycles in interdependent risk networks [40,41]. This approach transforms a risk network with feedback loops into a DAG by conducting a topological assessment and selecting a subset of the network, that they called a 'key risk network', being able, then, to evaluate the probability of risk interactions within a Bayesian framework [40,41]. However, this approach may result in significant issues within real-world projects, as these methods are not universally applicable for practical use and sometimes fail to accurately capture the intricate interdependencies among risks [42]. Multi-Criteria Decision-Making methods like AHP and ANP were employed to structure and prioritize risks by considering multiple criteria and their interdependencies. The ANP extends the AHP by overcoming its limitations in representing interactions beyond hierarchical structures, thereby enabling the modeling of interdependent relationships and feedback loops among decision elements [43]. Both methods utilize pairwise evaluations to prioritize risks in alignment with decision-making objectives. Hossen et al. [44] applied a combined AHP and Relative Importance Index (RII) methodology to assess schedule delay risks in international nuclear power plant projects. They organized delay factors into hierarchical levels and evaluated them based on severity and frequency of occurrence. Shin et al. [45] compared the Analytic Hierarchy Process (AHP) with the Fuzzy Analytic Hierarchy Process (FAHP) to assess potential risks at nuclear power plant construction sites. They analyzed the importance and priority of various risk factors classified by process, cost, safety and quality. Boateng et al. [46] adopted the ANP combined with a Risk Priority Index to model and prioritize risks in megaprojects, taking into account complex interrelations among social, technical, economic, environmental and political factors. This method facilitated an interactive prioritization of risks and supported the initiation of timely mitigation strategies.

The Design Structure Matrix (DSM) has been extensively employed to represent and analyze risk interdependencies in large engineering projects. By constructing the adjacency matrix of a graph, DSM effectively models risks as nodes and their interactions as edges, enabling the application of network theory to examine complex risk relationships within projects [47]. This matrix-based representation facilitates the visualization and understanding of intricate risk interrelations, thereby enhancing risk management strategies.

Fang et al. [20] utilized DSM to map and analyze risk interactions within large engineering projects, constructing a Risk Structure Matrix (RSM). They applied topological indicators to identify critical risks based on their network connectivity, thereby improving the comprehension of how interdependent risks can propagate and potentially lead to cascading effects on the various tasks of the project. Building upon this framework, Fang et al. [47] developed a risk propagation model. This model provided insights into the pathways through which risks influence one another, aiding in the identification of key risks that significantly impact project performance. Mok et al. [48] developed a network approach to examine stakeholders concerns in megaprojects, thorough a topological assessment of the concerns network they have identified the key challenges in these projects. Chen et al. [49] developed a hybrid approach combining dialectical systems theory with network theory to identify and analyze construction schedule risks in infrastructure projects. Using dialectical systems theory, a framework was created to capture dynamic interrelations among project components. A risk interaction network was constructed to map these interdependencies and was analyzed using topological metrics.

Nyqvist [50] introduced an Uncertainty Network Model (UNM) for construction risk management using DSM. Their approach converted stakeholders' tacit knowledge into an explicit, systematic representation of project risks and uncertainties. By visually presenting the interconnections and criticality of risks, DSM enabled a comprehensive understanding of networked risks, thereby supporting the implementation of cost-effective risk-control activities. Wang et al. [51] proposed a delay-oriented risk network model for project risk response decisions, incorporating time delays as attributes of edges in DSM. This approach enabled the simulation of how delays in one risk could affect subsequent risks, providing a more precise assessment of risk criticality and informing more effective risk response strategies. Wang et al. [52] advanced Risk Interaction Network (RIN) evaluation and assessment by introducing a simulation-based approach with Conditional Value-at-Risk (CVaR) to evaluate extreme risk scenarios, employing the Best-Worst Method (BWM) for parameter assessment. However, the framework lacked methods for reducing network complexity and exploring trade-offs systematically.

Whereas network-based approaches for megaproject management, including risk management, have advanced significantly, few studies have addressed the integration of theory and practice through network control and optimization. Specifically, there is a limited exploration of strategies that balance megaproject value with network efficiency and the implementation of effective network interventions [53]. Existing methods to optimize risk mitigation actions within project risk networks have been proposed. Fang et al. [54] modeled risks using a DSM and compared a Genetic Algorithm (GA) with a Greedy Algorithm for selecting an optimal portfolio of risk response actions within a project, subject to budget constraints. Wang et al. [55] defined a risk interaction model and optimized project risk response decisions using a GA with crossover operator designed and enhanced by a social network analysis (SNA). Zuo et al. [56] developed a bi-objective optimization model not only for selecting a portfolio of risk response actions but also for scheduling risk-related resources, aiming to minimize cost and makespan. Zhang et al. [57] introduced a decision model for project risk response in a multi-project context with uncertain interdependencies, using DSM to map these relationships. However, these optimization approaches do not alter the overall network structure or implement comprehensive network-wide optimization strategies.

3. Methodology

To effectively model and manage interdependent risks in NPP construction projects, this study develops a DSM and performs a topological analysis on the interdependence structure. The proposed methodology is systematically structured into four key steps, with the objective to identifying, analyzing and avoiding risks that could lead to cascading effects resulting in project delays and associated costs.

We build on the work of Stewart & Shirvan [36] with regards to the identification of the risk factors associated with four different NPP designs. Risks are categorized into three categories: Human Errors (H), Change Orders (C) and Supplier Delays (S). The project-specific input data are sourced from the TIMCAT scheduler tool [58,59], and include:

- Task-level information: start and end months, durations in months, planned delay, logical dependencies, number of working hours and staffing levels.
- Activity types: each task is classified as Civil, Mechanical or Electrical.
- Task identifiers: tasks are labeled using the Energy Economic Data Base (EEDB) code of account [60].

Risks are mapped to project tasks by combining risk category and EEDB account. For instance, a human error associated with task A.234 is designated as HA.234.

Given the input information, the development of the methodology, then, proceeds as follows:

3.1. Risk interaction network definition

The first step is the identification of risks and risk interactions, respectively. This step leads to defining a network structure based on the DSM, forming a Risk Interaction Network (RIN).

- Let R_n denote the set of identified risks, where n is the risk index and $n = 1,\ 2,\ \ldots,\ N$ with N being the total number of risks considered.
- Let I_{nk} represent the interaction between risk n and risk k, where $I_{nk} = 1$ if risk n can trigger risk k and $I_{nk} = 0$ otherwise
- Given R_n and I_{nk}, the DSM matrix, D, is constructed as a square $N\ x\ N$ binary matrix, where each element a_{nk} corresponds to I_{nk}

R_n is defined using the previously identified risks from [36], associated with a task and a category, that can be, Human Error, Supplier Delays and Change orders. To define the matrix D a set of assumptions based on previous studies have been considered. Indeed, risk interactions can take various forms. Fang et al. [20] identified cause-effect relationships, where one risk directly triggers another, forming a network of interdependencies. In addition, Wang et al. [55] highlighted three other types of interactions from the literature: work element dependencies, where risks arise from interdependent tasks; primary and secondary risk interactions, which occur when mitigating one risk triggers another; and cross-phase or cross-process interactions, where risks in one phase or process affect risks in subsequent phases or processes.

In addition to the risk interaction types identified by Fang et al. [20] and Wang et al., [55], further studies have highlighted the importance of certain key project factors, or levers, in determining how risks propagate in nuclear power plant (NPP) construction projects. Bolisetti et al. [61] identified design completion, supplier readiness and construction proficiency as critical levers that significantly influence project cost and schedule outcomes. These levers point to interrelated risks that can trigger cascading effects across tasks, making it essential to define interactions in a structured way.

For instance, incomplete designs at the start of construction have been shown to cause frequent rework, licensing amendments and delays, affecting interdependent tasks throughout the project [9]. This demonstrates how design changes in one task can create ripple effects, requiring rework and adjustment in other tasks, supporting the need to define cause-effect relationships between tasks that depend on one another.

Moreover, design changes are closely tied to supplier delays, as highlighted by Bolisetti et al. [61]. Supplier delays are influenced by the design maturity of the components being sourced, with delays being more likely for incomplete or evolving designs that lack an established supply chain. Additionally, the experience of the supply chain determines how quickly these delays propagate. These delays in material delivery, particularly when linked to design changes, can propagate across the project and impact tasks that depend on timely supplies. This supports the rule that supplier failures can cascade through interconnected tasks, exacerbating project risks.

Furthermore, human errors play a critical role in tasks that are performed concurrently. When tasks of the same type (e.g., electrical or mechanical works) are executed simultaneously, they are susceptible to mutual disruptions if errors occur. Incomplete or evolving designs exacerbate this risk, as teams may be working with outdated or unclear information [61].

These insights suggest the need for a systematic approach to identifying and defining risk interactions in NPP projects. By understanding how change orders, supplier delays and human errors interrelate and propagate through the project, a structured framework can be established to model these interactions.

Project tasks in NPP construction projects, and the risks associated with them, are interlinked through multiple dimensions, including physical, informational, material, organizational, geospatial, political, and technological domains. A foundational step in network-based risk analysis is the clear definition of network boundaries [47]. In this work, we focus specifically on schedule-related risks by modeling interactions directly within the project tasks layer, without explicitly representing relationships that extend beyond task-level boundaries, such as stakeholder dynamics.

For each project task, information regarding its type (Civil, Mechanical, Electrical), scheduling attributes (start and finish dates), and precedence dependencies are used to derive interactions. Risk management is founded on the articulation of assumptions about the system under consideration [62]. In this context, we assume that risk interactions emerge from structured dependencies among tasks, identified across four layers: Contractual, Technical, Geospatial, and Temporal.

- Contractual Layer: It is assumed that each type of activity (Civil, Mechanical, Electrical) is executed by a single subcontractor. Tasks of the same type are therefore linked through a shared organizational structure, reflecting potential coordination risks and common exposure to subcontractor performance.
- Technical Layer: Functional task dependencies, as defined by project logic, establish technical interactions. If task B is dependent on the completion of task A, a change or disruption in A may affect B, and vice versa.
- Geospatial Layer: Each task is associated with a specific building or physical location.
- Temporal Layer: Tasks that overlap in execution time and share the same activity type are linked, capturing the heightened likelihood of human error due to concurrent workstreams within the same organizational scope.

These layers are operationalized through observable task characteristics. Together, they define which tasks are linked in the DSM, forming the structural basis for the RIN. The RIN is represented as a directed graph $G(N,\ E)$, where N is the set of risks and E the set of directed edges representing interdependencies.

The task characteristics used for defining risk interactions are:

- The type of task (Civil, Mech, Elect)
- The project timeline and overlapping tasks
- The task dependencies
- The type of risk

First, a definition of interactions within the same risk type is introduced, then, the relationships of different types of risks are defined. Let us consider two tasks A and B:

- Change orders
  - If starting of task B depends on task A, a change on task B may cause a rework on task A.
- Supplier Delays
  - A supplier failure cascades on all other supply chain risks.
- Human Errors
  - Concurrent tasks sharing the same type of resource (Civil, Mech, Elect) have interdependent risk of Human Error, i.e., if A and B are from the same type, $A \rightarrow B$ and $B \rightarrow A$, if they are overlapping.

For the rules between risk categories, the following logic is applied: change orders may cause human errors and supplier delays, if they are associated with the same task. Fig. 1 illustrates these rules: applying them is sufficient to populate the DSM, creating a RIN indicated by D and

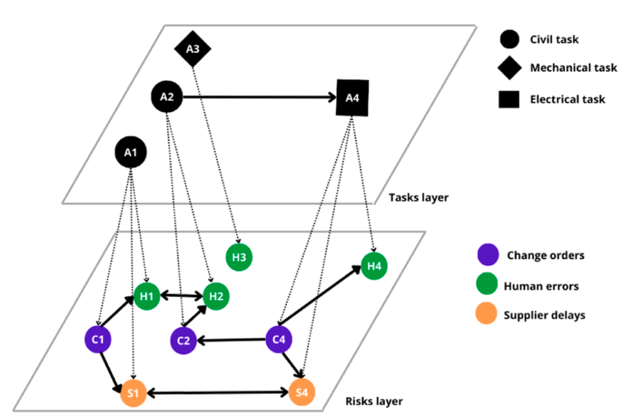

Fig. 1. Illustrative example of rules for defining interactions: Change orders cause human errors and supplier delays within the same task and cause change orders in predecessor tasks. Human errors in concurrent tasks of the same type are interdependent. Supplier delays are all interdependent.

representing the adjacency matrix of a graph described by a tuple $G(N, E)$, where N is the set of nodes and E the set of edges connecting them.

3.2. Topological characterization and indicators

The second step is the characterization of the RIN D from the viewpoint of its topological characteristics. The topological analysis of complex networked systems has been investigated to design reliable networks by means of systematic analyses of the connectivity of the complex wiring web underlying the system structure [63–65].

Indicators like average path length and clustering coefficient, L and CC, can be used to characterize networks. However, these indicators are ill-defined if the network is not fully connected, and if it contains nodes with only one connection [66]. An efficiency measure, ε_{ij}, has been proposed by Latora & Marchiori [66] to extend characterization of networks. They introduced a matrix of shortest paths, where each element d_{ij} of the matrix is the smallest distance between node i to j. In this work, the distance from node i to node j, d_{ij}, is defined as the difference between the start months of the corresponding tasks. The efficiency of the connection between nodes i and j is represented as ε_{ij} and is calculated by:

$$\varepsilon_{ij} = \frac{1}{d_{ij}}$$

The global average efficiency of a network G is then:

$$E_{glob}(G) = \frac{\sum_{i \neq j \in G} \varepsilon_{ij}}{N\ (N-1)}$$

where N is the total number of nodes (risks) in the network

An improvement of this metric has been used to evaluate the reliability efficiency of a network, by considering that flow passes not through the shortest path, but through the most reliable path [67]. For RINs, a Risk Reachability Matrix (RRM) was proposed, with $RRM_{ij} = 1$ if there is at least one path from risk i to risk j [20]. Then, given the RRM matrix, a reachability density indicator, $Rea(G)$, is defined, and it is calculated by:

$$Rea\ (G) = \sum_{i,\ j\ \in G} \frac{RRM_{ij}}{N(N-1)}$$

The identification of risk hubs is crucial for effective risk management in complex networked systems. Passivity and Activity degrees [68] are the number of incoming and outgoing arcs from a node, respectively, and can be used to understand critical risks in terms of direct effect. They are calculated by:

$$Degree_i^{Activity} = \sum_{j \in G} D_{ij}$$

$$Degree_i^{Passivity} = \sum_{j \in G} D_{ji}$$

These indicators are grouped at a higher level of account, given the nested structure of tasks. The degrees are suitable for identification of direct connectivity paths, but they lack capturing indirect effects. To deal with this, the Number of Possible Sources and the Number of Reachable Nodes [20] are computed, for each node. They are calculated by:

$$R_i^R = \sum_{j \in G} RRM_{ij}$$

$$R_i^S = \sum_{j \in G} RRM_{ji}$$

Centrality measures are used to compute edge criticalities, with the aim of identifying important routes to risk propagation. The betweenness centrality of an edge is the proportion of shortest paths that a given edge belongs to in a network [69]. In risk interaction networks, however, it is usually computed by considering all possible paths, not only the shortest, because a risk can be triggered by all possible paths, not only the shortest [20]. However, time is crucial for the reaction of project managers to keep project continuity in front of an unexpected/undesired situation; in light of this, Wang et al. [51] proposed the inclusion of the time delay between risks as an edge attribute; adding a new dimension for criticality. On this basis, betweenness centrality was calculated by taking the occurrence probabilities of risks and time delay between risk interactions. A pure topological viewpoint of analysis can, indeed, be useful to identify critical edges in a connectivity perspective. Temporal networks have been explored for some types of knowledge representation, but to the best of our knowledge, no study has yet quantified the impact of time delays on the connectivity of a risk network in terms of centrality of its elements. To quantify this, in this work we propose a weighed betweenness centrality metric for edges. In other words, a temporal betweenness centrality indicator is introduced to capture the proportion of fastest paths that an edge belongs to.

3.2.1. Temporal betweenness centrality

Given a pair of connected nodes, the fastest path is the path that requires the minimum time delay to be completed between the first and the second nodes. The temporal betweenness centrality, $B_e^{temporal}$, for an edge e is calculated by the number of times that an edge is involved in a fastest path, normalized by $n(n-1)$ where n is the number of nodes in the network.

$$B_e^{temporal} = \frac{1}{n(n-1)} \sum_{i,j \in\ E \setminus\ i \neq j\ \neq e} \frac{s_{ij}^e}{s_{ij}}$$

where:

- s_{ij}^e is the number of fastest paths between i to j that passes through edge e
- s_{ij} is the total number of paths from i to j.

The indicator is calculated at both individual and group of edges level, and a bi-objective optimization problem is defined in order to find the largest groups with highest temporal betweenness centrality, in a similar way of Zio et al. [70]. The first objective function of the optimization problem is the group temporal betweenness centrality, indicated by $f_1(x)$ and defined as:

$$\mathbf{f}_1(\boldsymbol{x}) = \frac{1}{(\mathbf{N}-|\mathbf{S}|-1)\ \times (\mathbf{N}-|\mathbf{S}|)} \sum_{\boldsymbol{i,j \in E \setminus\ i \neq j}} \frac{\boldsymbol{s_{ij}^S}}{\boldsymbol{s_{ij}}}$$

where:

- N is the total number of nodes in G
- $S \subseteq E$ is the set of selected edges corresponding to the binary decision vector x
- $|S|$ is the number of selected edges, i.e., $|S| = \sum_{k=1}^{|E|} x_k$
- s_{ij} is the total number of fastest paths between i and j
- s_{ij}^S is the number of fastest paths between nodes i and j that pass through edges in $|S|$
- $x = [x_1,\ x_2,\ \ldots,\ x_{|E|}]$ is a binary decision vector with $x_i = 1$ if edge i is selected into the group S and $x_i = 0$ otherwise

The term s_{ij}^S is computed as

$$s_{ij}^S = \sum_{paths\ \ P_{ij} \supset S} 1$$

The second objective function $f_2\ (x)$ is the number of selected edges to be maximized:

$$f_2(x) = \sum_{k=1}^{|E|} x_k$$

This function counts the total number of edges selected in the group S. Then, the multi-objective optimization problem can be formulated as:

$$\max \mathbf{F}_1(x) = [f_1(x),\ f_2(x)]$$

subject to:

$$g_{1(x)} \leq 0$$

$$g_{2(x)} \leq 0$$

where:

- $g_{1(x)} = \sum_{k-1}^{|E|} x_k - 5$
- $g_{2(x)} = 1 - \sum_{k-1}^{|E|} x_k$

The constraints are defined to limit the number of selected edges to a maximum of 5 and guarantee that at least one edge is selected. A clear difference in this formulation for the one provided by Zio et al. [70] is the direction of optimization of $f_{2(x)}$. In Zio et al. [70], large groups presented high $f_{1(x)}$, as the problem aimed of minimizing the number of selected edges. Here, instead, this logic does not apply due to the high reachability density of the network, creating many possible paths from one node to another. Then, all groups of k size present smaller values of $f_{1(x)}$ than those of k - 1 size. For this reason, we aim at maximizing the objectives.

To deal with this computationally expensive optimization problem, we employed an evolutionary multi-objective algorithm (EMOA), the widely used non-dominated sorting genetic algorithm (NSGA-II) [71] using Pymoo, a python based framework for multi-objective optimization [72]. Given a network with $|E|$ edges, the total number of possible edge group combinations is $2^{|E|}$, which grows exponentially with network size. This makes exhaustive search impractical, particularly when identifying combinations of edges with high temporal betweenness centrality. EMOAs, on the contrary, are well-suited for such scenarios, as they can efficiently explore large, complex search spaces without requiring full enumeration. Evolutionary algorithms are highly sensitive to initial conditions, so warm start is a good way to improve efficiency of the search. In order to find good initial candidate solutions for the warm start, we adopt an associative rule mining sampling strategy, based on the Apriori algorithm [73]. The idea is to find the itemsets with highest support and use them as part of the initial population of the algorithm. The results are compared with a uniform random sampling as warm start.

3.3. Sensitivity analysis

The fourth step aims at disturbing the network to understand the effect of removing nodes (risks) and edges (interactions) from it with the objective of indicating a direction for risk response plans.

Two types of protocols are used to disturb the network. First, based on the results of the topological analysis, we evaluate the removal of network elements by selecting targets to remove. Second, an algorithmic search is performed in which the optimization problem is defined to minimize the reachability density, the global efficiency and the number of removals (here limited to a maximum of 10 removals). The decision vector x is composed of binary variables indicating whether a risk (node) or a risk interaction (edge) is selected for removal:

- For $k = 1,\ \ldots,\ |E|,\ x_k = 1$ if edge k is selected for removal, and $x_k = 0$ otherwise
- For $n = 1,\ \ldots,\ |N|,\ x_{|E|+n} = 1$ if node n is selected for removal, and $x_{|E|+n} = 0$ otherwise

Therefore, the total size of decision vector x is $|E| + |N|$, combining all potential nodes and edges that can be removed from the RIN.

The problem is defined as follows:

$$f_3(x) = Rea(G)$$

$$f_4(x) = E_{glob}(G)$$

$$f_5(x) = \sum_{k=1}^{|E|} x_k + \sum_{n=1}^{|N|} x_n$$

$$g_3(x) = \sum_{k=1}^{|E|} x_k + \sum_{n=1}^{|N|} x_n - 10$$

$$\min \mathbf{F}_2(x) = [f_3(x),\ f_4(x),\ f_5(x)]$$

subject to:

$$g_3(x) \leq 0$$

Given the discrete and high-dimensional nature of the problem, selecting subsets of nodes and edges whose removal minimizes multiple conflicting objectives, the use of a EMOA is well-suited. Among the available methods, NSGA-II was selected due to its proven performance in handling non-convex Pareto fronts, combinatorial search spaces and binary decision variables [65]. The algorithm efficiently explores the solution space without requiring gradient information and maintains diversity across solutions, enabling the identification of multiple mitigation strategies that reflect different trade-offs between systemic risk reduction and the number of interventions. This problem formulation goes beyond typical rank-based approaches by explicitly defining the identification of critical risks as a multi-objective optimization problem. The proposed optimization-based sensitivity analysis represents a novel methodological contribution, enabling the identification of risk mitigation strategies that enhance the structural robustness of the network under constrained removal effort.

3.4. Impact on scheduling

The schedule under evaluation has been derived from an optimization problem aimed at minimizing the overall project duration. The objective of this Section is to determine whether it is possible to adjust the schedule to simultaneously reduce the reachability density of the risk network generated by the schedule, while also minimizing the project's makespan. Consequently, a bi-objective minimization problem is formulated. The TIMCAT scheduler tool is utilized to calculate the project schedule based on a predefined set of tasks durations and dependencies. An additional module has been integrated into the tool to populate the DSM and generate a RIN for each potential schedule. The RIN is subsequently evaluated from a topological perspective to assess the interconnectedness of risks. This routine is employed to calculate the fitness of a given schedule, which is, then, used to define the bi-objective optimization problem.

The first objective function in the optimization problem is the reachability density, $Rea(G)$, which quantifies the degree of risk propagation within the network. The second objective is the project makespan, represented as the square of the project completion months, consistent with the definition used by Stewart & Shirvan [36] for scheduling optimization. Staffing constraints have also been incorporated, with a maximum limit of 4500 concurrent workers and 800 new hires per month. Additionally, the same building constraints from Stewart & Shirvan [36] have been applied in this evaluation. This optimization problem can be classified as a multi-mode resource-constrained project scheduling problem (MRCPSP) with two conflicting objectives, which is well known to be NP-hard [74]. For this reason, we adopt the NSGA-II EMOA to efficiently explore the high-dimensional and discrete solution space and identify a diverse set of trade-off solutions. This formulation integrates network-based systemic risk indicators into the project scheduling process, moving beyond conventional makespan optimization. By including the reachability density of the risk network as an explicit objective, the scheduling problem is extended to account for risk propagation effects. This bi-objective formulation represents a novel approach to construction project scheduling, allowing for the generation of execution plans that jointly minimize project duration and systemic risk exposure.

4. Application to a DC-PWR reactor schedule

To test the applicability of the proposed methodology, we applied it to the scheduling of a project aimed at constructing a FOAK DC-PWR reactor—a large double containment reactor. The project schedule data were obtained from TIMCAT, which provided detailed input necessary for the analysis. For more detailed information about the input data, please refer to Appendix.

By applying the interaction rules to the project schedule, we constructed the RIN and subsequently defined the corresponding graph G. The analysis of network G revealed an average clustering coefficient of 0.5868 and an average (unweighed) path length of 2.14. For comparative purposes, a random graph and a small-world network with similar parameters were also analyzed. The random graph exhibited an average clustering coefficient of 0.0893 and an average path length of 2.49, whereas the small-world network showed an average clustering coefficient of 0.5335 and an average path length of 2.88.

The network presents a short average path length combined with a high clustering coefficient. Additionally, the degree distribution follows a power law with an exponent $\gamma = 3.04$, indicating characteristics of small-world and scale-free networks [75]. These types of networks are typically characterized by the presence of clusters of nodes with high degrees, which act as hubs within the overall network structure. The reachability density of the network was calculated to be $Rea(G) = 0.52$.

These structural properties imply that the network has a high potential for rapid and widespread risk propagation due to the presence of highly interconnected clusters and hub nodes. The short average path length means that risks can quickly spread from one part of the network to another, whereas the high clustering coefficient suggests a high level of local interconnectedness, which can facilitate the cascading of risks within clusters. The scale-free nature of the network, indicated by the power-law degree distribution, highlights the significance of hub nodes that connect different parts of the network and whose failure or disruption can have a disproportionate impact on the entire system. Fig. 2 illustrates the generated project risk network.

4.1. Computation of topological indicators

The analysis focused on identifying critical nodes and edges within the RIN using various topological indicators. Activity and passivity degrees, $Degree_i^{Activity}$ and $Degree_i^{Passivity}$, respectively, the number of reachable nodes and possible sources, R_i^R and R_i^S, respectively, are calculated for all nodes (risks) of the RIN. The temporal betweennes centrality, $B_e^{temporal}$, is calculated for all the network edges (interactions). Then, the nodes and edges are ranked by each indicator.

Table 1 lists the top five nodes based on their activity and passivity degrees. Nodes 'HA.234.' and 'HA.235.' have the highest degrees (both equal to 99), indicating that they are highly active in influencing other nodes and also themselves highly susceptible to influence. Nodes 'HA.231.' and 'HA.233.' follow closely, highlighting their significant role in direct risk interactions. Fig. 3 highlights these nodes in the RIN.

In Table 2, nodes are ranked by the number of reachable nodes, representing the potential scope of their influence. Nodes 'CA.212.15′ and 'CA.221.1′ each reach 185 nodes, indicating their capacity to impact a large portion of the network; although indirectly. They are highlighted in Fig. 4. Table 3 presents nodes ranked by the number of possible sources, highlighting their susceptibility within the network. All top five nodes have 221 possible sources, making them highly vulnerable to cascading effects initiated elsewhere in the network.

Table 4 and Fig. 5 show the top five edges ranked by temporal betweenness centrality. The edge between 'HA.226.72′ and 'HA.231.' holds the highest value (0.018), indicating that it plays a significant role

Table 1
Top 5 nodes by activity and passivity degrees.

Rank	Node i	$Degree_i^{Activity}$	$Degree_i^{Passivity}$
1	HA.234.	99	99
2	HA.235.	99	99
3	HA.231.	95	95
4	HA.233.	94	94
5	HA.212.141	84	85

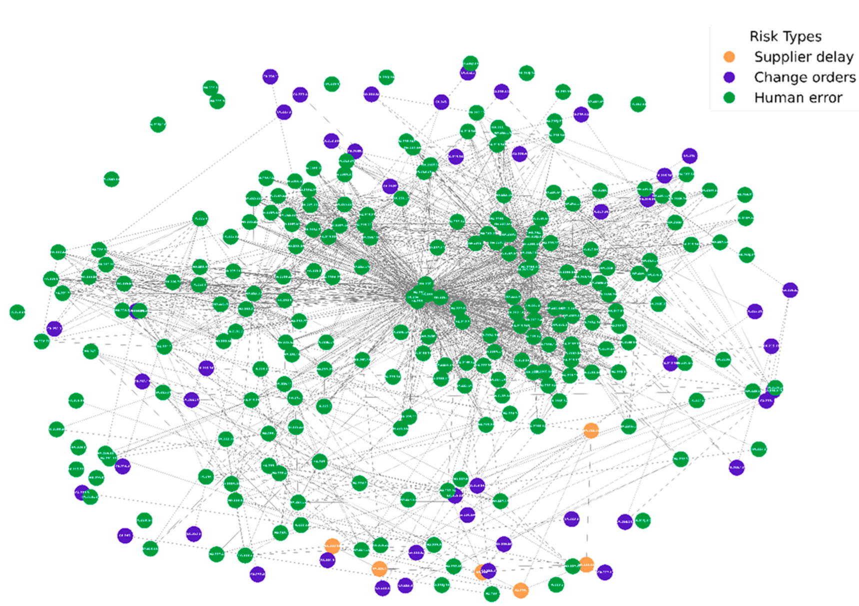

Fig. 2. RIN for the DC-PWR schedule.

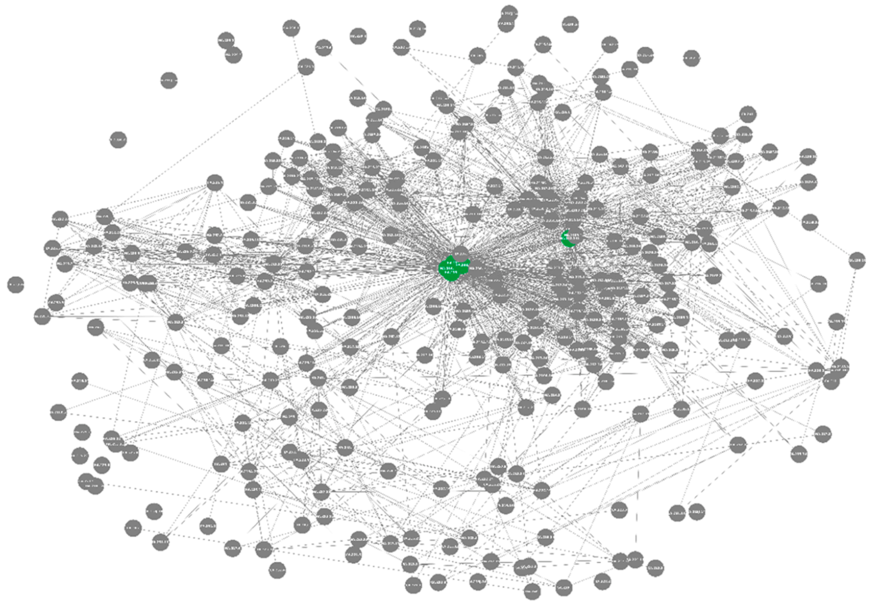

Fig. 3. Visualization of the RIN, highlighting the top nodes that consistently rank highest across three topological indicators: Activity Degree, Passivity Degree and Number of Possible Sources. These nodes are critical under multiple criteria, indicating that they are both highly influential and highly susceptible to influence within the network. Their persistent prominence suggests a systemic role in risk propagation and amplification.

Table 2
Top 5 nodes by number of reachable nodes.

Rank	Node i	R_i^R
1	CA.212.15	185
2	CA.221.1	185
3	CA.216.147	183
4	CA.216.24	183
5	CA.212.140	182

in the fastest information flow through the network. Edges involving nodes 'HA.213.21′, 'HA.234.' and 'HA.213.25′ also exhibit high centrality values, underscoring their importance in potential risk propagation paths.

Regarding the group betweenness centrality indicator, the results of a uniform random sampling and apriori sampling are compared. With a uniform random sampling and a population size of 2000 individuals, convergence was reached after 51 generations; with a population of

Table 3
Top 5 nodes by number of possible sources.

Rank	Node i	R_i^S
1	HA.234.	221
2	HA.235.	221
3	HA.231.	221
4	HA.233.	221
5	HA.212.141	221

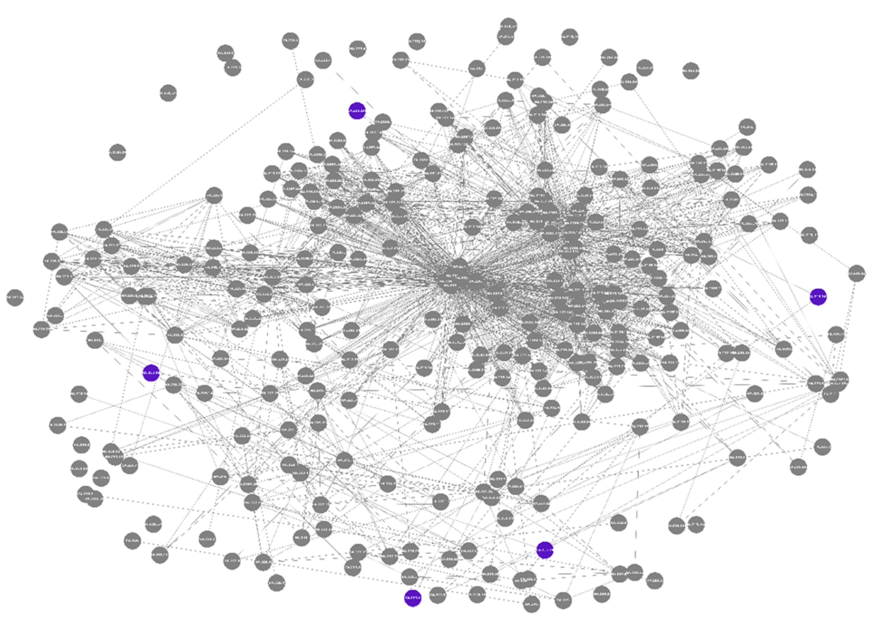

Fig. 4. RIN highlighting the top nodes ranked by Number of Reachable Nodes. This indicator reflects the extent to which a single risk can propagate its effects through the network. Nodes with high reachability are potential sources of wide-scale cascading failures.

Table 4
Top 5 edges by temporal betweenness centrality.

Rank	Edge e	$B_e^{temporal}$
1	('HA.226.72', 'HA.231. ')	0.018
2	('HA.213.21', 'HA.234. ')	0.017
3	('HA.231.', 'HA.226.72')	0.017
4	('HA.213.25', 'HA.234.')	0.016
5	('HA.234.', 'HA.213.25')	0.016

equal size, 51 generations were required also by apriori sampling to reach convergence, but the generated pareto front was superior. Fig. 6 illustrates the obtained pareto front.

4.2. Sensitivity analysis results

To assess the impact of removing specific nodes and edges on the network's reachability and average path length, we conducted a series of manual removal tests. These tests were guided by the results of the topological analysis, focusing on nodes and edges identified as critical within the RIN.

The original network had a reachability density of $Rea(G) = 0.52$ and an average global efficiency of $E_{glob}(G) = 0.49$. Our goal was to observe how targeted removals would alter these network properties, potentially reducing the risk of cascading failures.

Table 5 summarizes the effects of removing selected nodes and edges based on topological indicators. Removing certain nodes can have a more pronounced effect on the network's properties than removing edges, and the specific nodes targeted significantly influence whether

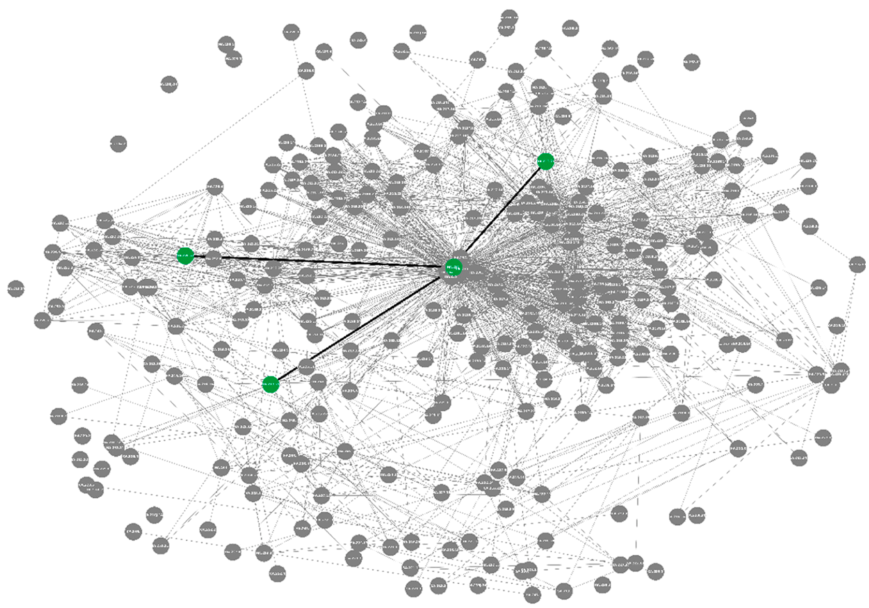

Fig. 5. RIN with top-ranked edges based on Temporal Betweenness Centrality highlighted. This metric identifies the links through which risks are most likely to spread rapidly, leaving limited time for detection and response. These edges represent fast-propagating channels in the network, where early disruption or mitigation is critical to preventing escalation.

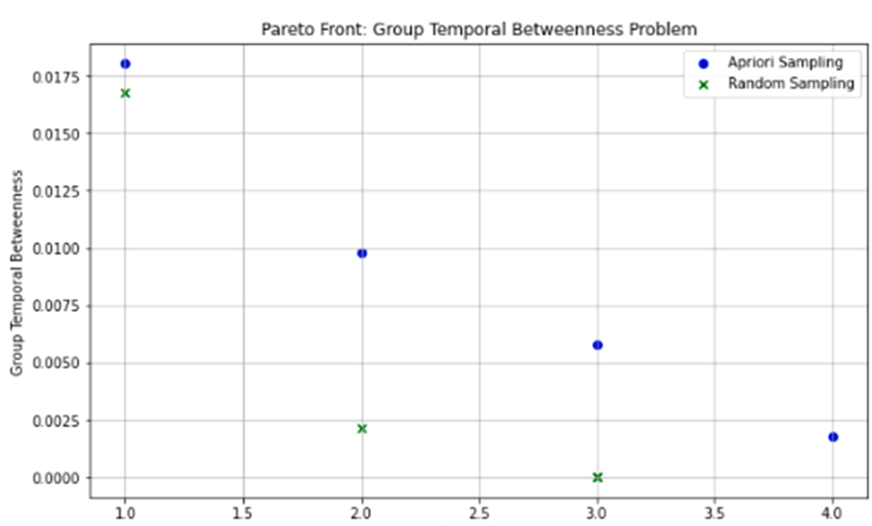

Fig. 6. Comparison of Group Temporal Betweenness Centrality results obtained using two sampling methods: Apriori Sampling (dots) and Random Sampling (crosses). Each point represents the total betweenness centrality of a selected group of nodes of fixed size. Groups identified through Apriori Sampling consistently achieve higher centrality values, demonstrating that the method effectively identifies combinations of risks that are critical for fast and wide risk propagation.

Table 5
Impact of manually removing selected nodes and edges from the RIN, based on topological indicators. The Table shows the number of removals performed and the corresponding percentage variation in reachability density $Rea(G)$ and global efficiency $E_{glob}(G)$, compared to the original network.

Nodes Removed	Edges Removed	Removals	% variation Rea (G)	% var $E_{glob}(G)$
	('HA.221.2', 'HA.226.72'), ('HA.222.12', 'HA.223.1'), ('HA.223.1', 'HA.221.2'), ('HA.226.72', 'HA.231.')	4	0 %	0 %
'CA.212.15', 'CA.221.1', 'CA.216.147', 'CA.216.24', 'CA.212.140'		5	+2 %	0 %
'HA.234.', 'HA.235.', 'HA.231.', 'HA.233.', 'HA.212.141'		5	−2 %	−2 %
'HA.234.', 'HA.235.', 'HA.231.', 'HA.233.', 'HA.212.141'	('HA.221.2', 'HA.226.72'), ('HA.222.12', 'HA.223.1'), ('HA.223.1', 'HA.221.2'), ('HA.226.72', 'HA.231.')	9	−2 %	−2 %
'CA.212.15', 'CA.221.1', 'CA.216.147', 'CA.216.24', 'CA.212.140'	('HA.221.2', 'HA.226.72'), ('HA.222.12', 'HA.223.1'), ('HA.223.1', 'HA.221.2'), ('HA.226.72', 'HA.231.')	9	+2 %	0 %

Table 6
Top 10 solutions selected from the Pareto front generated by NSGA-II, ranked using the TOPSIS method. Each solution corresponds to a set of node and edge removals aimed at simultaneously reducing the network's reachability density $Rea\ (G)$ and global efficiency $E_{glob}(G)$.

Nodes Removed	Edges Removed	Total Removals	% variation Rea(G)	% var $E_{glob}(G)$	TOPSIS Rank
'HA.212.140', 'HA.215.142', 'HA.215.145', 'HA.216.13', 'HA.216.141', 'HA.218D', 'HA.218S.', 'HA.221.3', 'HA.262.12'	[ ]	9	−5 %	−24 %	1
'HA.212.3', 'HA.215.142', 'HA.218D'	[ ]	3	−4 %	−9 %	2
'HA.212.140', 'HA.215.142', 'HA.215.145', 'HA.216.13', 'HA.216.141', 'HA.218D', 'HA.221.1', 'HA.226.3'	[ ]	8	−7 %	−22 %	3
'HA.215.142', 'HA.215.145', 'HA.216.13', 'HA.216.141', 'HA.218D', 'HA.262.12'	[ ]	6	−4 %	−18 %	4
'HA.212.140', 'HA.212.25', 'HA.215.142', 'HA.215.145', 'HA.216.13', 'HA.216.141', 'HA.218D', 'HA.218H', 'HA.221.2', 'HA.262.12'	[ ]	10	−17 %	−23 %	5
'HA.212.25', 'HA.218D', 'HA.221.2', 'HA.221.3', 'HA.234.', 'HA.235.', 'HA.262.12'	[ ]	7	−22 %	−9 %	6
'HA.215.142', 'HA.218D'	[ ]	2	−1 %	−9 %	7
'HA.212.140', 'HA.212.25', 'HA.215.142', 'HA.216.13', 'HA.218D', 'HA.221.1', 'HA.221.2'	[ ]	7	−17 %	−15 %	8
'HA.212.25', 'HA.215.142', 'HA.216.13', 'HA.218D', 'HA.221.2'	[ ]	5	−13 %	−13 %	9
'HA.212.140', 'HA.221.1'	[ ]	2	−5 %	−2 %	10

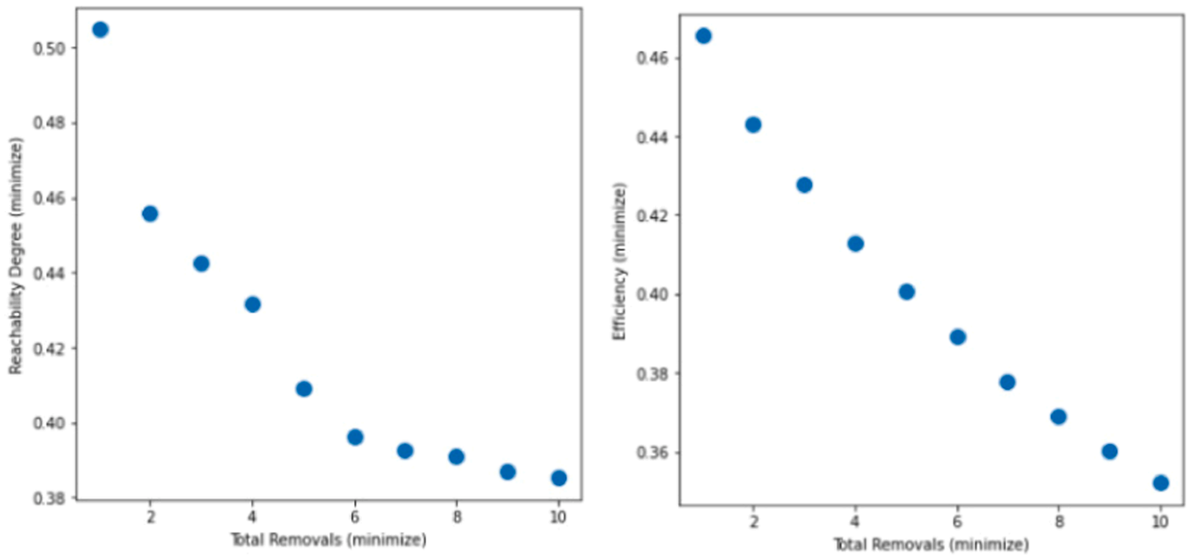

Fig. 7. Pareto fronts for each of the two objectives vs the number of removals.

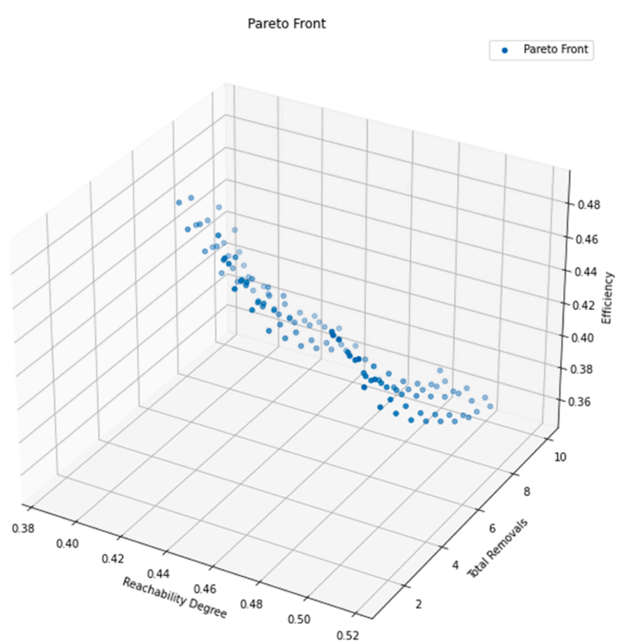

Fig. 8. 3D Pareto front.

the network's connectivity increases or decreases.

To further explore optimal solutions for reducing reachability and average global efficiency, we employed the NSGA-II algorithm. The algorithm was able to find 139 Pareto-optimal solutions, from which we identified the top ten solutions using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [76,77] for ranking.

Table 6 presents the top-ranked solutions.

The NSGA-II algorithm was able to identify solutions that were not apparent through the initial topological analysis alone. This demonstrates the algorithm's effectiveness in handling complex multi-objective optimization problems in the context of network analysis. Figs. 7 and 8 illustrate the obtained Pareto front.

Our findings highlight the potential of using advanced optimization techniques in conjunction with topological indicators to uncover optimal strategies for mitigating risk propagation in complex networks. By identifying and removing critical nodes, we can effectively reduce the potential for cascading risks and enhance the resilience of the network.

4.3. Scheduling problem

We warm started the EMOA with the optimized schedule. The NSGA-II algorithm was able to find solutions that improve both objectives, and many and diverse pareto points found give a large set of options for decision-making with different risk attitudes and can inform the Project Risk Management process. Fig. 9 illustrates the obtained Pareto front at convergence after 315 generations with population size equal to 500 individuals.

5. Discussion

Integrating our empirical results with insights from CAS theory, the proposed RIN effectively captures feedback loops and nonlinear interactions inherent in complex nuclear megaprojects. Specifically, our methodology aligns with CAS principles by using topological analysis to identify emergent, system-level vulnerabilities. In prior research, Stewart & Shirvan [25] identified several critical risks in NPP construction projects through multiple iterations of Monte Carlo simulation, accounting for both probability of risk occurrence and impact on project costs. The critical risks identified for a DC-PWR included CA.245 (FOAK), CA.252.2 (FOAK), HA.244 (FOAK/10-OAK), HA.245 (FOAK/10-OAK), HA.252.2 (FOAK/10-OAK), HA.234 (10-OAK) and HA.235 (10-OAK).

In this work, according to the established interaction rules, criticalities within the RIN emerged from overlapping activities, task dependencies and the involvement of multiple teams. The analysis pinpointed specific nodes and edges as critical based on their quantitative positions within the network.

The nodes HA.234., HA.235., HA.231., HA.233. and HA.212.141 consistently exhibit the highest rankings across various topological indicators. As detailed in Table 2, HA.234. and HA.235. both have activity and passivity degrees of 99, signifying their high influence and susceptibility within the network. HA.231. and HA.233. follow with degrees of 95 and 94, respectively, whereas HA.212.141 have degrees of 84 (activity) and 85 (passivity). These high degrees indicate a substantial number of direct interactions, underscoring the pivotal role of these in potential risk propagation.

In terms of network centrality, each of these nodes possess 221 possible sources and reachable nodes, as presented in Tables 3 and 4, pointing of their centrality within the network. This central position implies that they can both influence and be influenced by the other nodes, thereby increasing their exposition and vulnerability to cascading

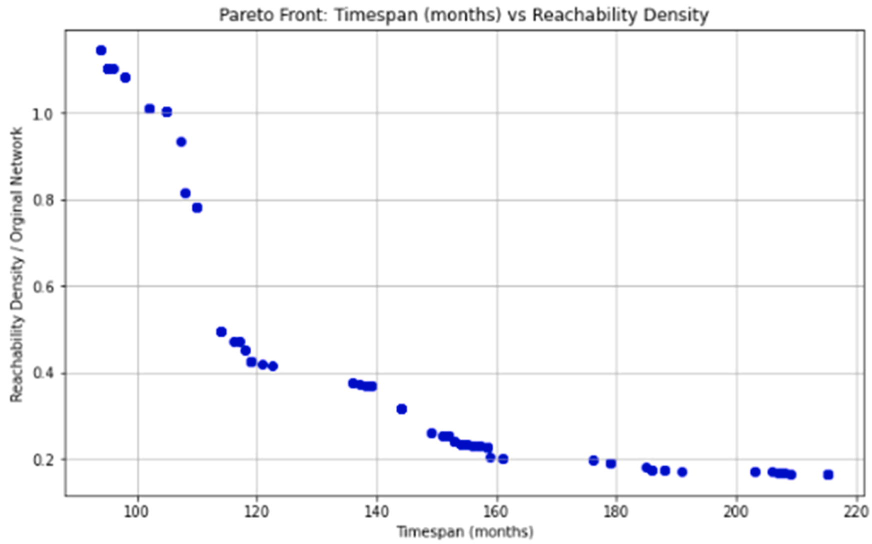

Fig. 9. Final Pareto front generated by the NSGA-II algorithm for the bi-objective scheduling optimization problem. The x-axis represents Reachability Density, normalized by the reachability of the original baseline schedule. The y-axis shows Project Timespan in months. Each point corresponds to a non-dominated solution that balances systemic risk reduction against project duration.

effects.

The criticality of these nodes can be attributed to their specific attributes within the interaction rules framework:

- Overlapping Activities: HA.234. and HA.235. each are involved in 99 overlapping activities, the highest recorded in the dataset. HA.231. and HA.233. are involved in 95 and 94 overlapping activities, respectively, whereas HA.212.141 participate in 84 overlapping activities. A high number of overlapping activities gives the potential for concurrent risks, as simultaneous tasks of similar nature may interact and influence each other.
- Dependencies: Each of the five activities (nodes) above had one incoming dependency. HA.234., HA.235., HA.231. and HA.233. had no outgoing dependencies, whereas HA.212.141 has 14 outgoing dependencies. Nodes with multiple outgoing dependencies are susceptible to risk propagation from several subsequent tasks, rendering HA.212.141 particularly critical in terms of risk vulnerability.
- Task Types: HA.234., HA.235., HA.231 and HA.233 nodes are associated with civil and mechanical tasks, which, according to the interaction rules, exhibit specific interaction patterns. For example, design modifications in one task can necessitate reworking in dependent tasks and overlapping tasks of the same type can result in mutual interactions that increase the risk of human errors.

Additional critical nodes include CA.212.15, CA.221.1, CA.216.147, CA.216.24 and CA.212.140:

- CA.212.15 and CA.221.1 each have 185 reachable nodes, indicating their extensive influence within the network. CA.221.1 is involved in 55 overlapping activities and has four outgoing dependencies, increasing its complexity and risk exposure.
- CA.216.147 and CA.216.24 both have 183 reachable nodes. CA.216.147 overlapped with critical nodes despite a low number of dependencies, increasing its vulnerability due to the interaction rules related to overlapping tasks.
- CA.212.140 has 182 reachable nodes and is involved in 53 overlapping activities, making it susceptible to risks due to its high connectivity and concurrency.

The sensitivity analysis performed has demonstrated clear differences between the topological indicators and algorithmic search approaches in identifying critical risks within the interaction network. Using topological indicators, the removal of nodes with prominent degrees resulted in a 2 % reduction in reachability density and a 2 % reduction in global efficiency, thereby diminishing the network's connection capacity. Conversely, the algorithmic search approach identified additional critical nodes, such as HA.212.140, HA.215.142, HA.218D and HA.212.3, whose removal led to significant enhancements in network robustness. For example, the second-ranked solution determined by TOPSIS achieved a 4 % decrease in reachability density and a 9 % decrease in the global efficiency with only 3 removals, whereas the first ranked solution resulted in a 5 % reduction in reachability density and a 24 % decrease in the global efficiency, removing 9 nodes. Moreover, certain topological strategies, like the removal of nodes with a prominent number of reachable nodes, caused a 2 % increase in reachability density without changing the global efficiency. These findings underscore the limitations of relying solely on static, local metrics in the context of CAS, where emergent behavior and nonlinear effects demand an integrated, system-level analysis for effective risk mitigation.

In contrast, the algorithmic search approach aligned with both objectives in all ten cases, illustrating its complementary role in optimizing network resilience within the studied risk interaction framework by enabling the identification of systemic vulnerabilities.

The current analysis has allowed identifying several critical risks that were not highlighted in the study of Stewart & Shirvan [25], demonstrating the added value of utilizing network-based analytical techniques alongside traditional simulation methods. Whereas Monte Carlo simulation identified risks such as CA.245, CA.252.2, HA.244, HA.245, HA.252.2, HA.234 and HA.235 as pivotal based on probability of occurrence and impact on project costs, the present study uncovered additional critical risks. These differences indicate that the integration of network-based methods can reveal additional vulnerabilities and provide a more comprehensive assessment of critical risks, enhancing the understanding of network resilience beyond what can be achieved through a simulation-based approach.

The current study both corroborates and extends the findings of Stewart & Shirvan [25] by identifying critical risks within the project network through distinct methodological approaches. Monte Carlo simulation highlighted risks such as CA.245, CA.252.2, HA.244, HA.245, HA.252.2, HA.234 and HA.235 based on their probability of occurrence and impact on project costs. The topological analysis here performed has confirmed the significance of HA.234 and HA.235 as

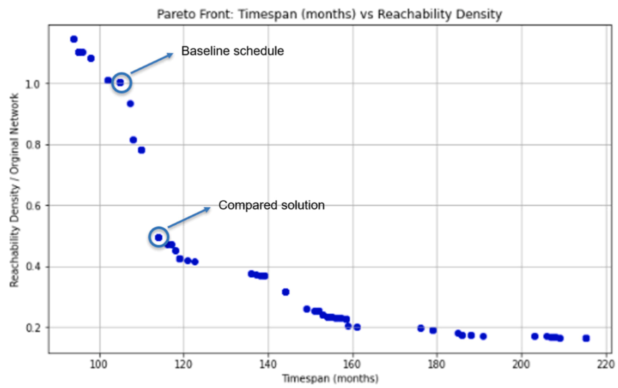

Fig. 10. Indication of the baseline and compared solutions on the Pareto front generated by the multi-objective scheduling optimization.

critical nodes, aligning with the previous identification of these risks. However, employing topological indicators and an algorithmic search approach enabled the detection of additional critical risks, including HA.212.140, HA.221.1, HA.215.142, HA.218D and HA.212.3, which were not deemed significant in isolation. These newly identified risks play relevant roles in the network's connectivity, revealing vulnerabilities that emerge from the interdependencies and interactions among the various project activities. For instance, the removal of 'HA.212.140′ and 'HA.221.1′ resulted in substantial reductions in reachability density and global efficiency, thereby enhancing network robustness in ways not captured by the previous simulation-based analysis. This distinction underscores the advantage of network-based analytical techniques in uncovering risks that are critical due to their position and connectivity within the network, rather than their standalone impact. Consequently, the integration of these methods provides a comprehensive assessment of network resilience, highlighting both overlapping and unique risk factors that influence the overall vulnerability of complex megaproject environments.

Regarding the scheduling problem, the multi-objective evolutionary algorithm employed was able to find several solutions, within a diverse and broad Pareto front for decision making. In order to understand differences between the original schedule, we chose a solution with a low difference regarding the makespan, but which has a Rea (G) value around 50 % lower than the baseline schedule. In Fig. 10 we indicate the selected solution.

The comparison between the baseline schedule and the proposed solution reveals important differences in terms of task durations, start dates and resource allocation, which were adjusted to optimize project flow and minimize risks. A key observation is the adjustment of task start dates for high-dependency tasks. For instance, A.213.141 (Turbine Generator Building Superstructure Concrete) was delayed by 35 months, and this delayed all the other 11 civil tasks of the Turbine Generator Building (A.213) by 40 months. Critical tasks such as A.231, A.232, A.233, A.234, A.235, A.236, tasks of both Civil and Mechanical types related to the Turbine Generator Building, were also delayed by 40 months compared to the original schedule. In addition, A.233 and A.235 had their task lengths reduced by 15 months and 10 months, respectively. On the other hand, reactor building mechanical tasks were brought forward by 23 months, avoiding conflict with the tasks that have been postponed. In terms of reducing task time by allocating more staff, the task relating to Reactor Pressure Vessel Structure + Support (A.221.1) changed the most, from 37 months to 17..

In terms of resource distribution, the proposed solution offers a more balanced approach to staffing compared to the baseline. Figs. 11 and 12 show that, while the baseline schedule exhibited sharp peaks in staffing demands, particularly between months 50 to 80, where labor demands are around 3500 workers, the compared solution smooths out these peaks, distributing labor demands more evenly across the project timeline. This smoothing effect minimizes the risk of resource shortages or overextension, ensuring that labor resources are allocated more sustainably throughout the project.

From a Complex System Governance (CSG) perspective, the proposed methodology supports several key governance functions, while also highlighting areas where further integration could strengthen systemic viability. At its core, the methodology provides analytical input that contributes directly to System Development (M4). By generating alternative project configurations through multi-objective optimization, it enables structured exploration of how temporal sequencing and task interdependencies influence risk propagation. These reconfigurations inform both execution planning and long-term system design, aligning operational decisions with broader development objectives.

The methodology also supports aspects of Strategic System Monitoring (M5′) by quantifying changes in network connectivity, in terms of reachability density of the RIN, across alternative scheduling scenarios. This provides governance actors with warning signals of potential systemic vulnerabilities. Moreover, the availability of Pareto-optimal trade-offs enables scenario-based reasoning, reinforcing the reflective capabilities of Learning and Transformation (M4)**.

In terms of communication dynamics, the methodology implicitly contributes to the Coordination and Planning communication channels by translating strategic constraints into actionable scheduling outcomes. However, it does not currently incorporate real-time learning or feedback mechanisms, which limits support for continuous strategic

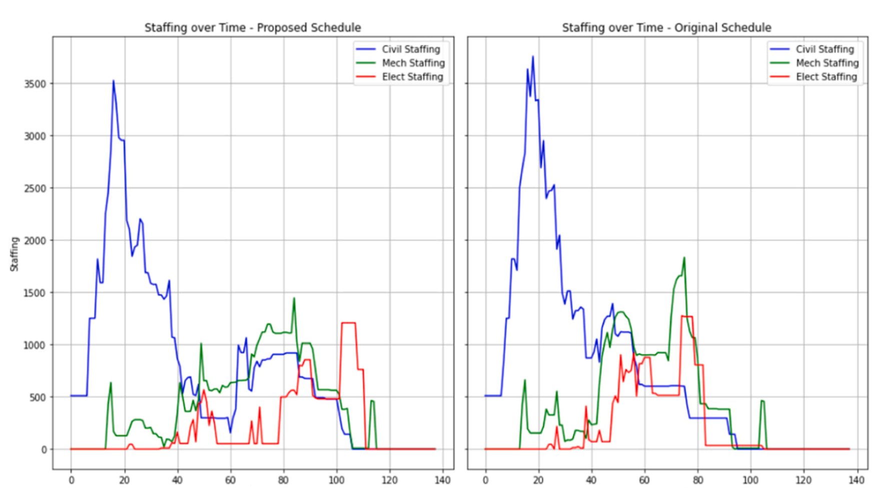

Fig. 11. Comparison of the staffing over time divided by the type of task.

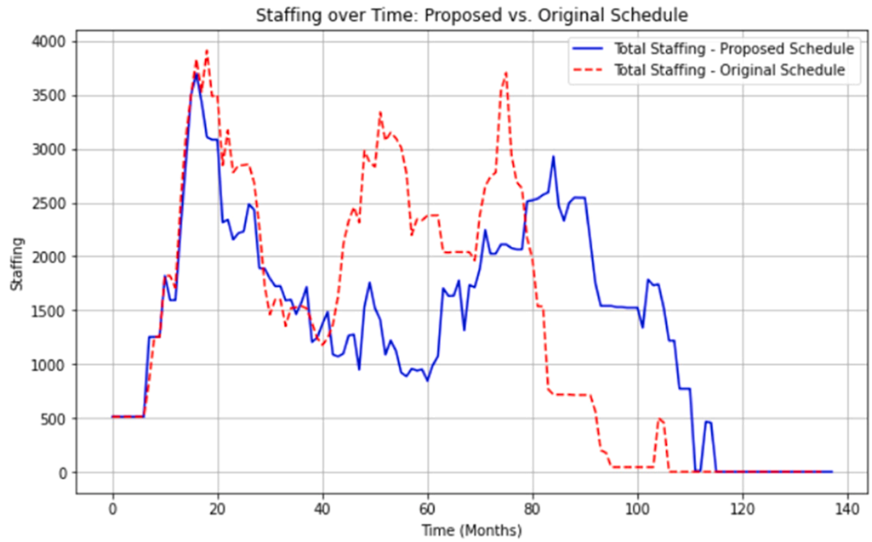

Fig. 12. Comparison of the total staffing over time.

adjustment. Consequently, communication channels such as Monitoring, Interpretation, and Learning Feedback are only partially addressed. Similarly, Environmental Scanning (M4′) and System Context (M5*), which relate to awareness of external influences like regulatory shifts or geopolitical disruptions, are not explicitly represented.

Additionally, these theoretical and methodological connections significantly advance PRM practices as advocated by the PMI to navigate complexity. Whereas traditional PMI approaches historically assessed risks in isolation, the new principle-driven framework emphasizes systemic thinking. Our integrated methodology operationalizes these principles by explicitly modeling systemic interdependencies and nonlinear risk dynamics. The analytical tools introduced enable practitioners to visualize and strategically manage systemic risk propagation, balancing operational execution with long-term strategic adaptability. This comprehensive approach enhances PRM capabilities, improving overall project resilience and reducing vulnerability to complex risk interactions.

5.1. Limitations and future research

Although the proposed approach offers a valuable framework for capturing structural complexity and interdependencies in NPP construction projects, certain limitations should be acknowledged. The model focuses primarily on task-based and schedule-driven interactions and does not explicitly incorporate systemic drivers such as human and organizational behavior [29], architectural and engineering proficiency [61], or the safety culture of subcontractors [15,26]. These factors can influence not only the occurrence of risks, but also the nature and strength of interdependencies across tasks. Moreover, external systemic factors, including regulatory pressures, supply chain disruptions and black swan events, are not explicitly represented, although they can have significant impacts on project dynamics. In addition, the current analysis is based on a static network structure, which assumes that risk interactions remain fixed throughout the project. However, these relationships coevolve as the project progresses and external conditions shift. Future research could build on this foundation by integrating time-dependent models, incorporating organizational and environmental dimensions, and enabling scenario-based simulations to capture the dynamic, uncertain nature of large-scale project environments. Additionally, this methodology can be extended to other nuclear technologies, such as Small Modular Reactors (SMRs) and Generation IV reactors, to evaluate its adaptability and performance across varying project configurations. It also holds potential for application in project portfolios involving multiple units, where the interaction of risks across concurrent or sequential projects introduces additional complexity.

Regarding model construction, this study adopted generalized rules to construct the Design Structure Matrix (DSM) due to the scale of the problem. With 278 risks identified, a full pairwise evaluation would require 77,006 comparisons, making manual elicitation impractical. Future studies could investigate the use of data mining or machine learning techniques to infer interactions from historical data or structured project knowledge bases, thereby enhancing the efficiency and scalability of the approach.

Finally, incorporating a probabilistic dimension into the modeling of risk occurrence and propagation could further improve the robustness of the framework, allowing for a more nuanced understanding of uncertainty and cascading behavior.

6. Conclusions

This paper aims to advance the field of nuclear project management by proposing the integration of Design Structure Matrix (DSM) and topological analysis. By applying this approach to nuclear power plant construction, this work demonstrates the benefit of enabling to effectively capture and mitigate interdependent risks, which are often the cause of significant delays and cost overruns in such complex projects. The proposed methodology allows for a deep understanding of how risk interactions propagate through a project, leading to informed decision-making and its management.

Through the application of the DSM framework to a DC-PWR reactor project, this research highlights how the methodology can identify critical risks and optimize project schedules. The analysis of risk propagation using topological metrics provides insights into the most vulnerable areas of a project network, enabling targeted mitigation strategies. This is especially valuable in the context of nuclear power plant construction, where delays can have significant financial and operational impacts.

Future work could build on this foundation by integrating time-dependent models, incorporating organizational and environmental dimensions, and enabling scenario-based simulations to capture the dynamic, uncertain nature of large-scale project environments. In particular, advancing the framework with a probabilistic dimension would support the modeling of uncertainty in task perturbation and cascading effects.

The methodology can also be applied to other nuclear power plant designs, such as Small Modular Reactors (SMRs) or advanced Generation

IV reactors, to show its generalization capability and effectiveness across different nuclear technologies. It can be also employed to analyze the risks of a portfolio of projects, such as the construction of several units, accounting for how the risk networks of the different projects in the portfolio interact among each other. This work has simplified the construction of the DSM by applying generalized rules across all activities. Performing pairwise evaluations is unfeasible due to the extensive number required; in the case study explored in this work, with 278 identified risks, 77.006 evaluations would be necessary. Future work could explore data mining techniques to identify potential risk interactions more efficiently [78–80]. Overall, the methodological framework offers a comprehensive tool for managing the inherent complexities and risks of nuclear power plant construction projects.

CRediT authorship contribution statement

André L.N. Casotti: Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation. **Enrico Zio:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Conceptualization.

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.

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Appendix

From Project Schedule to Risk Interaction Network

For completion, this appendix deep dives on the input schedule data, and the process to create the RIN given its information. Stewart & Shirvan [36] leverage on the EEDB code-of-accounts to define the tasks of each specific design in the TIMCAT scheduler tool. The EEDB categorizes costs using a code-of-accounts system. At the highest level, costs are divided into Direct Costs (Account 2) and Indirect Costs (Account 9), with each main category further broken down into sub-categories identified by additional indices. For instance, Direct Costs included: Account 21 for Structures & Improvements, Account 22 for Reactor Plant Equipment, Account 23 for Turbine Plant Equipment, Account 24 for Electrical Plant Equipment, Account 25 for Miscellaneous Plant Equipment, and Account 26 for the Main Condensing Heat Rejection System. Each sub-category could also be divided into more specific accounts by appending additional numbers to the main account label, following the same hierarchical structure. For the scheduler tool Stewart & Shirvan [36] adapted the cost subdivision of EEDB, considering them as tasks, by enriching their model with construction related information. Given so, a task is indicated by its related Account.

Let us consider the Reactor Building tasks as an example. In Table 7 we provide information about the type of task, the dependencies along with the fraction, the number of hours required for completion of the task, obtained from TIMCAT.

Table 7
Reactor Building tasks characteristics.

Account	Header	Description	Civil	Mech	Elect	Dependency	Fraction	Hours
A.211.	Yardwork	Yardwork	1	0	0	None	0	1143,329
A.212.13	Reactor building	Substructure	1	0	0	A.211.	0.5	260,196.3
A.212.140	Reactor building	Interior concrete	1	0	0	A.212.141	0.5	1018,795
A.212.141	Reactor building	Superstructure concrete	1	0	0	A.212.13	0.9	806,054.2
A.212.142	Reactor building	Structural & Misc steel	1	0	0	A.212.141	0.5	65,328.44
A.212.149	Reactor building	Painting	1	0	0	A.212.141	0.9	289,630.6
A.212.15	Reactor building	Containment liner	1	0	0	A.212.141	1	687,725.3
A.212.21	Reactor building	Plumbing & Drains	0	1	0	A.212.141	1	22,499.44
A.212.22	Reactor building	HVAC	0	1	0	A.212.141	1	1607.125
A.212.23	Reactor building	Safety HVAC	0	1	0	A.212.141	1	91,920.56
A.212.24	Reactor building	Lighting & Service power	0	0	1	A.212.141	1	73,734.13
A.212.25	Reactor building	Elevator	0	1	0	A.212.141	1	2207.23
A.212.3	Reactor building	Passive cooling pool	1	0	0	A.212.141	1	370,008.6
A.219.	Reactor building	Shield building	1	0	0	A.212.141	1	1026,824

The optimization process in the scheduler tool defines a duration for a task, called task length, and the delay on the start. The delay is a parameter to delay the start of task from the period this task could has been started. Both task length and delay are month units. In other words, a task length of 10 means 10 months to execute the task. With these variables defined, the staffing required to complete the task in the specified duration is calculated. Table 8 shows a defined schedule for the Reactor Building tasks, used in this work.

Table 8
Task length and delay definition leading to the schedule consolidation.

Account	Task Length	Delay	Start	Actual Start	Finished	Staffing	Type
A.211.	15	0	0	0	15	476.387	Civil
A.212.13	5	0	8	8	13	325.2454	Civil
A.212.140	36	1	28	29	65	176.8741	Civil
A.212.141	30	0	13	13	43	167.928	Civil
A.212.142	34	1	28	29	63	12.0089	Civil

(*continued on next page*)

Table 8 (*continued*)

Account	Task Length	Delay	Start	Actual Start	Finished	Staffing	Type
A.212.149	19	3	40	43	62	95.27323	Civil
A.212.15	45	22	43	65	110	95.51741	Civil
A.212.21	39	19	43	62	101	3.60568	Mech
A.212.22	20	28	43	71	91	0.502227	Mech
A.212.23	16	1	43	44	60	35.90647	Mech
A.212.24	55	6	43	49	104	8.378878	Elect
A.212.25	59	3	43	46	105	0.233817	Mech
A.212.3	43	20	43	63	106	53.78031	Civil
A.219.	45	22	43	65	110	142.6145	Civil

Finally, Stewart & Shirvan [36] have also identified associated risks with the schedule tasks. The identified risks related to the Reactor Building tasks are indicated in Table 9.

Table 9
Identified risks of the reactor building tasks.

Account	Risk
A.211.	Change orders
A.212.13	Change orders
A.212.140	Change orders
A.212.141	Change orders
A.212.15	Change orders
A.212.3	Change orders
A.212.15	Supplier delay
A.219.	Supplier delay
A.211.	Human Errors
A.212.13	Human Errors
A.212.140	Human Errors
A.212.141	Human Errors
A.212.142	Human Errors
A.212.149	Human Errors
A.212.15	Human Errors
A.212.21	Human Errors
A.212.22	Human Errors
A.212.23	Human Errors
A.212.24	Human Errors
A.212.25	Human Errors
A.212.3	Human Errors
A.219.	Human Errors

Given the information reported in these tables, we have the necessary input data to build the network of risks, RIN. The rules defined in Section 3.1 are applied, and the resultant network is provided in Fig. 13.

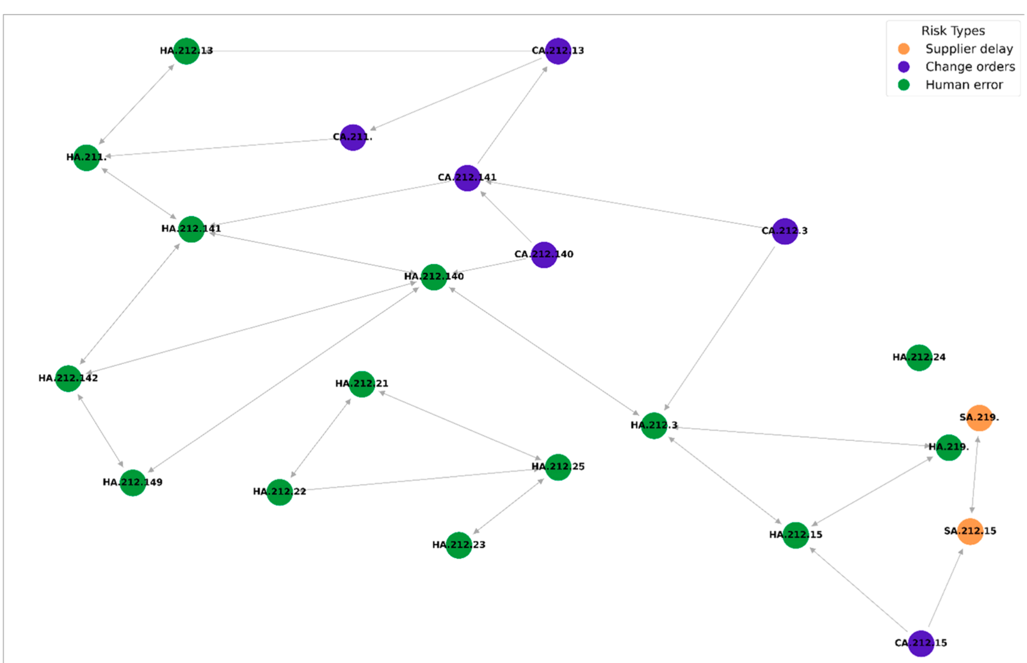

Fig. 13. RIN of the reactor building.

The RIN of the Reactor Building highlights the division in two sub-networks, one composed by the human errors risks of mechanical tasks (HA.212.21, HA.212.22, HA.212.25, HA.212.23), and the other involving the civil tasks and their possible causes of delay, with a well-connected structure. The human error risk of task A.212.24 is isolated because it is the only electrical task of this building. The change orders rules for interactions aims at representing the cascading effects of design changes in a project. For example, a required change in the Superstructure concrete may require further evaluation in the Substructure, that can lead to reinforcements, for instance. This is represented by the edge connecting CA.212.41 to CA.212.13. The same idea is valid for the other structural elements that have a dependence relationship, and their interactions are represented in the RIN. The human errors risks are based on the idea of shared resources. If two tasks are of the same type, the resources used to advance in one could be used in another, in most cases. Supplier delays are considered also with an interdependence relationship following the same logic of activities provided by similar or same resources. So, a delay in one component could affect the performance of a supplier in delivering also the other components.

Data availability

Data will be made available on request.

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