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Using Portfolio Decision Analysis to Select Reinforcement Actions in Infrastructure Networks

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Critical infrastructure networks, such as railway networks, provide essential services whose continuity must be secured. Towards this end, we combine multi-criteria portfolio decision analysis with Probabilistic Risk Assessment (PRA) to construct portfolios of reinforcement actions that contribute cost-efficiently to the attainment of objectives that represent the network's services. Our model admits a range of assumptions about the relative importance of these objectives through incomplete information about the weights associated with the corresponding criteria. It also helps identify which portfolios of reinforcement actions perform best with regard to these objectives at different budget levels. We illustrate our model with a study on the reinforcement of switches at a railway station, which connects several origin-destination pairs with different volumes of planned traffic. If one or more switches are disrupted, some connections may be lost, and the corresponding traffic volume will be affected. We formulate an additive multi-criteria utility function such that the weight of each criterion reflects the planned traffic volume for the corresponding connection. PRA algorithms are used to assess the reliability of these connections. The results help identify the switches where the reinforcement actions should be implemented when the aim is to maximize the station's performance, as measured by the expected enabled traffic volume between the origin-destination pairs.

Keywords: Probabilistic risk assessment, Multi-criteria decision analysis, Portfolio decision analysis, Infrastructure networks, Transportation systems.

1. Introduction

In general, critical infrastructures comprise all the assets, systems, and networks that provide essential functions to society. They are central, for example, in the energy, water supply, transportation, and telecommunications sectors. Because disruptions in these infrastructures can significantly erode public health, safety, security, and economic well-being, they must function adequately to achieve sustainability goals and social development (Yusta et al., 2011).

Europe's railway networks spanned 202,000 km in 2022, with notable growth in high-speed rail. Disruptions in these networks can undermine performance objectives, such as ensuring connectivity between strategic locations or providing reliable transportation for passengers and goods.

Such disruptions can be due to failures caused by the usual wear of technical systems or by vulnerabilities to external hazards, including extreme weather conditions and even intentional attacks. Consequently, there is a need to understand what kinds of disruption can affect the network, what impacts these disruptions can cause, and what actions effectively mitigate them, subject to the constraint that there are limited resources for choosing and implementing these actions. It is pertinent to analyze *portfolios* of these actions, as many are typically implemented jointly. These analyses support allocating resources to cost-efficient portfolios of reinforcement actions to ensure that the network performs effectively relative to their implementation costs (Kangaspunta et al., 2012).

In this paper, we present a multi-criteria portfolio decision analysis approach to (i) assess and aggregate several objectives of infrastructure network performance, measured by corresponding criteria, and (ii) guide the cost-efficient allocation of resources to reinforcement actions that mitigate disruptions. We model the network as nodes (components subject to failure) and edges (connections between components) to identify the nodes (or combinations of nodes) that are most important to network performance.

The remainder of this paper is organized as follows. Section 2 reviews previous approaches to analyzing disruptions and their impacts on infrastructure network performance, focusing on transportation systems. Section 3 develops a multi-criteria portfolio decision analysis approach to quantify the performance objectives of infrastructure networks and to guide the allocation of resources to reinforcement actions to fortify them. Section 4 presents a case study on fortifying switches to improve the reliability of connections at a railway station in Finland. Section 5 discusses the numerical results and outlines directions for future work. Section 6 concludes and outlines potential areas for future research.

2. Background

Early studies on railway networks examined mainly their topological configuration due to data and computational limitations (Erath et al., 2008). Recently, there has been a proliferation of specific models to reduce travel times (Wang et al., 2023), plan new lines (Zhao et al., 2021), and secure track functionality, among others. In many countries, different entities make infrastructure decisions (e.g., ensuring the railway network is safe and functional) and operational decisions (e.g., ensuring that train timetables are maintained). Therefore, infrastructure and operational research efforts have historically been decoupled. In this setting, we focus primarily on the infrastructural analysis of railway networks.

Most railway network analysis draws on network theory to identify critical components, evaluate network performance, and develop strategies to reinforce them (see e.g., Pirbhulal et al., 2021). Latora and Marchiori (2005) present a method to identify critical components in networks represented by nodes and edges. They show how adding edges can improve network performance, measured through topological metrics, i.e., a metric that relies purely on how nodes are positioned and connected in the network. Ip and Wang (2011) propose a methodology to assess and improve the resilience of railway networks using topological metrics, such as the number of independent paths.

Although several studies use topological metrics to assess network performance, few evaluate the quality of these assessments (Haritha and Anjaneyulu, 2024). A key limitation is that topological metrics are not necessarily related to the network's performance objectives. For example, Hao et al. (2023) propose a multiobjective optimization approach to identify critical components in a network, finding that a node's criticality does not often correlate with its topological importance. Similarly, LaRocca et al. (2015) note that topological metrics are limited in assessing the robustness of a power system across scenarios. Alderson et al. (2013) demonstrate that the criticality of a node depends on which other nodes are disrupted.

In evaluating network performance, identifying relevant hazards and their impacts is often challenging. Sometimes, it is unclear what hazards can affect the network or to what extent the network will continue to perform satisfactorily if some occur (Zio, 2016). Zhang et al. (2024) summarize recent studies on quantifying loss of railway functionality due to various hazards.

Several authors proceed by elaborating scenarios and estimating their probabilities. For example, Joshi et al. (2024) and Yang et al. (2024) consider scenarios of rainfall and tornadoes to assess the risks on railway systems in India and China, respectively. Turoff et al. (2016) propose a collaborative, dynamic scenario model based on expert judgments to estimate the cascading effects of infrastructure interactions.

Zio (2016) and Sedghi et al. (2021) call for the development of frameworks that help railway infrastructure managers understand and quantify the complexity of rail networks so that these networks can be better prepared for hazards, thereby ensuring acceptable performance. In this setting, we develop an approach to assess the importance of rail switches and allocate resources to reinforce them in view of multiple objectives that represent the services provided by the network.

3. Proposed Approach for Reinforcing Networks

3.1. *Network Representation*

Let $G(V;E)$ denote a network consisting of a set of nodes $V = \{1,\dots,m\}$ and a set of undirected edges $E \subseteq \{(i,i') \mid i,i' \in V\}$ between the nodes. A path is a sequence of nodes and edges that connect two nodes. The state of each node is either operational or disrupted. If a node is disrupted, none of the paths containing it can be traversed. Thus, using $D \subseteq V$ to denote the set of disrupted nodes, the remaining network after such a disruption is $G(V^D;E^D)$, where $V^D = V \setminus D$ and $E^D = \{(i,i') \in E \mid i,i' \in V^D\} \subseteq E$.

The state x_k of a node k is modeled as a realization of a binary random variable X_k with $x_k = 0$ if node $k \in V$ is disrupted and $x_k = 1$ if it is operational. The state of the network is a realization $x = (x_1,\dots,x_m) \in \mathcal{X} = \{0,1\}^m$ of the random variables that represent the states of m nodes. We assume that the disruption events at the nodes occur independently so that $p_k = \mathbb{P}[X_k = 0]$ is the probability that node k is disrupted. Due to the independence assumption, the probability distribution over the states of the network is characterized by the vector $p = (p_1,\dots,p_m)$.

3.2. *Assessing Network Performance*

When an infrastructure network enables multiple services, its performance in providing such services must be measured considering several objectives. These objectives can be quantified by introducing a corresponding quantifiable criterion for each. Some examples of these objectives are maximizing the probability of having a connection between a given pair of nodes or minimizing the network's restoration time after a significant incident. In what follows, assuming that there are n objectives, we employ the expected utility function so that the performance on the criterion j is given by the normalized utility score $u_j(x), j = 1,\dots,n$ when the network is in state $x \in \mathcal{X}$.

The utility functions $u_j(\cdot)$ can be aggregated by employing the additive multi-criteria utility function (1) on condition that the criteria are mutually preferentially independent (i.e., preferences for a given criterion do not depend on those for any other criteria), and every criterion is additive independent (i.e., there are no preferences for how the realizations for a given criterion coincide with realizations with other criteria, provided that the probabilities of all realizations on the different criteria remain unchanged) (see Dyer and Sarin, 1979). Specifically, in the utility function

$$u(x,w) = \sum_{j=1}^{n} w_j u_j(x) \in [0,1], \tag{1}$$

the weight of the criterion $w_j \in [0,1], j = 1,\dots,n$ reflects the relative overall utility increase gained as a result of the performance improvement on the j-th criterion when the state of the network changes from its worst state (all nodes are disrupted) to its best state (all nodes are operational). Following the usual convention, these weights can be normalized so that $\sum_{j=1}^{n} = 1$.

Because it can be challenging to specify criteria weights by eliciting point estimates, we characterize these weights with an *information set* $\mathcal{S}$ (Salo and Hämäläinen, 1992). The information set is a subset of all possible weights

$$\mathcal{S} = \{w \in \mathbb{R}^n \mid Aw \le B\} \subseteq \tag{2}$$

$$\left\{w \in \mathbb{R}^n \mid w_j \geq 0\, \forall j, \sum_{j=1}^{n} w_j = 1\right\} = \mathcal{S}^0,$$

where the constraint matrices $A \in \mathbb{R}^{t \times n}$ and $B \in \mathbb{R}^t$ contain the coefficients implied by t preference statements concerning the relative importance of objectives. For example, if criterion 1 is at least as important but no more than twice as important as criterion 2, then the two constraints $w_1 \geq w_2$ and $w_1 \leq 2w_2$ apply.

3.3. *Network Fortification*

The network can be strengthened through reinforcement actions. The expected performance of the network depends on which *portfolio* of actions is implemented. We assume that there is a single reinforcement action per node so that $q_k = 1$ if action k is implemented (i.e., node k is reinforced) and $q_k = 0$ if not. If the action is implemented at node k, its disruption probability is reduced from p_k to p'_k with $p'_k < p_k$.

The portfolio of reinforcement actions is given by vector $q = (q_1, \ldots, q_m) \in \mathcal{Q} = \{0, 1\}^m$. A portfolio is *feasible* if its cost is within the available budget b (that is, $c(q) \leq b$) and satisfies relevant logical constraints (for example, if actions 1 and 2 are mutually exclusive, the constraint $q_1 + q_2 \leq 1$ holds). The set of feasible portfolios is denoted by $\mathcal{Q}_F \subseteq \mathcal{Q}$.

3.4. *Non-Dominated and Cost-Efficient Portfolios*

When maximizing the expected network performance, the objective is to determine which feasible portfolios outperform others for all feasible weights. For further insights, such analyses can be produced at different cost levels comparing portfolios based on the concept of *dominance*.

Definition 3.1. Portfolio $q^1 \in \mathcal{Q}_F$ is dominated by portfolio $q^2 \in \mathcal{Q}_F$ in the information set $\mathcal{S}$, denoted by $q^2 \overset{\mathcal{S}}{\succ} q^1$, if and only if $\mathbb{E}\left[u(x, w) \mid q^1\right] \leq \mathbb{E}\left[u(x, w) \mid q^2\right]$ for all $w \in \mathcal{S}$ and (ii) $\mathbb{E}\left[u(x, w) \mid q^1\right] < \mathbb{E}\left[u(x, w) \mid q^2\right]$ for some $w \in \mathcal{S}$.

If $\mathbb{E}\left[u(x, w) \mid q^1\right] = \mathbb{E}\left[u(x, w) \mid q^2\right] \forall w \in \mathcal{S}$, the expected performance of portfolios q^1 and q^2 is the same, denoted by $q^1 \overset{\mathcal{S}}{\sim} q^2$.

Definition 3.2. The portfolio $q^1 \in Q_F$ is cost-efficient with respect to another portfolio $q^2 \in Q_F$ in the information set $\mathcal{S}$, denoted by $q^1 \overset{\mathcal{S}}{\succ}_C q^2$, if and only if (i) $q^1 \overset{\mathcal{S}}{\succ} q^2, c(q^1) \leq c(q^2)$ or (ii) $q^1 \overset{\mathcal{S}}{\sim} q^2$ and $c(q^1) < c(q^2)$.

Definition 3.3. Portfolio $q^1 \in Q_F$ is cost-efficient for the information set $\mathcal{S}$, denoted by $q^1 \in Q_{CE}$ if and only if $\nexists q^2 \in Q_F$ such that $q^2 \overset{\mathcal{S}}{\succ}_C q^1$.

The set of cost-efficient portfolios can be determined by first computing the utility function at the extreme points of the information set (Liesiö and Salo, 2012) and then using algorithms such as Norm-methods Koski and Silvennoinen (1987) or SAUGMECON Zhang and Reimann (2014) to compute Pareto-optimal solutions.

4. Case Study

The Siilinjärvi train station, depicted in Figure 1, provides connections between its three neighboring stations and beyond in northern Savonia, Finland. We represent the station as a network, where 22 nodes represent the rail switches (the mechanical devices that allow trains to move from one track to another), and edges represent the rail segments between them. Terminal nodes A, B, and C represent the station boundaries from which there are track connections to neighboring stations. Hence, Siilinjärvi has three bidirectional connections: (A,B), (B,C), and (A,C). The connections between terminal nodes are available only if enough switches at the station are operational. Hence, not all switches have to be operational for a given connection, as the connection may be available if some switches are disrupted.

The reliability of switches can be improved through reinforcement actions carried out as part of preventive maintenance. In general, the failure probabilities of switches can be estimated from historical data or simulation models. Still, for this illustrative case, we assume that, before reinforcement, the failure probability of each switch is

$p_k = 0.01$, which is reduced to $p_k' = 0.005$ as a result of reinforcement. All actions have the same cost; thus, the budget spent equals the number of reinforced switches. We study the expected performance of the network as a function of this budget. In particular, we provide guidance for selecting reinforcement actions based on incomplete information about the relative importance of the connections.

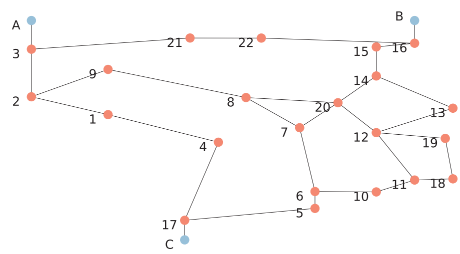

Fig. 1. Representation of the Siilinjärvi station.

4.1. *Network Performance*

The network's performance is evaluated based on the analysis of operational paths for the three origin-destination pairs and, specifically, the reliability of connections (A,B), (B,C), and (A,C). The connection (X,Y) is operational if at least one operational path exists between X and Y (that is, no switch along this path is disrupted). The reliability of a connection is consequently equal to the probability that at least one such path exists. In this setting, the performance of the network relative to the connection j can thus be assessed by employing the utility function (3)

$$u_j(x) = \begin{cases} 1, \text{if connection } j \text{ is operational for state } x, \\ 0, \text{if connection } j \text{ is disrupted for state } x. \end{cases} \tag{3}$$

The expected utility (3) for connection j is $\mathbb{E}[u_j(x)] = 1 \cdot \mathbb{P}[u_j(x) = 1] + 0 \cdot \mathbb{P}[u_j(x) = 0]$ is the reliability of this connection. The utility function (3) can be evaluated by checking whether there is a path for connection j for each network state. However, when the m nodes have binary states, the number of states of the network is 2^m, which can be large. To address challenges arising from the exponential growth of this problem and to support the use of (3) to larger networks, we use the minimum cut upper bound approximation to compute reliabilities for connections (Jung, 2015).

4.2. *Preferences Regarding Connections*

The relative importance of a connection is assessed based on its annual traffic volume. Since these volumes vary somewhat, we consider two situations. In the first, there is no information about traffic volumes. In this case, preferences about connections are represented by the set $\mathcal{S}^0 = \{w \in \mathbb{R}^3 \mid w_j \geq 0\ \forall j, \sum_{j=1}^{3} w_j = 1\}$. In other words, any one of the connections can be deemed as the one which is of overriding importance and the sole focus of reinforcement actions.

In the second, drawing upon available data about traffic volumes, the connections are ranked based on the traffic volumes such that the volume for the two first connections is at least five times greater than that of the third: (A,B) - 500 trains/year, (A,C) - 500 trains/year, and (B,C) - 100 trains/year. This is represented by the set $\mathcal{S}^1 = \{w \in \mathbb{R}^3 \mid\ w_j \geq 0\ \forall j,\ \sum_{j=1}^{3} w_j = 1, w_2 \geq 5w_1,\ w_3 \geq 5w_1\}$.

4.3. *Results*

4.3.1. *Cost-Efficient Portfolios*

The number of feasible and cost-efficient portfolios for both situations is in Table 1. The number of cost-efficient portfolios is much smaller when there is information about the relative importance of connections. These results highlight how this information makes it easier to produce more conclusive recommendations. Without such information, recommendations could be derived based on decision rules, such as choosing the cost-efficient portfolio to maximize the minimum of reliabilities across connections.

4.3.2. *Switches to Reinforce*

If there is a single cost-efficient portfolio, then the recommended reinforcement actions are the ones that it contains. However, in some cases, there may be many cost-efficient portfolios based on available preference information regarding the

Table 1. Number of feasible and cost-efficient portfolios for the two information sets and size of action portfolios.

Budget	1	5	10	15	20
$\mid \mathcal{Q}_F \mid$	23	35.4k	1.7M	4M	4.2M
S^0	5	163	972	1.7k	1.9k
S^1	2	51	434	673	738

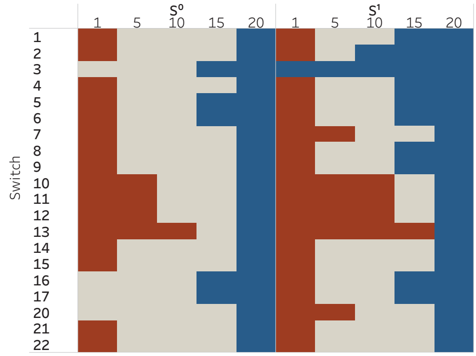

Fig. 2. Core index for reinforcement actions for different information sets and size of action portfolios. Red: exterior action, grey: borderline action, blue: core action.

importance of connections. In such cases, recommendations for choosing reinforcement actions can be based on their *core index*. This metric, proposed by Liesiö et al. (2007), is the relative share of those non-dominated portfolios in which a given action is contained. By definition, all cost-efficient portfolios are non-dominated. We denote by $\mathcal{Q}_{ND}(c)$ the set of non-dominated portfolios of cost c. The core index of an action q_k when the budget is c is given by (4).

$$CI(q_k, c) = \frac{|\{q \in \mathcal{Q}_{ND}(c) \mid q_k \in q\}|}{|\mathcal{Q}_{ND}(c)|} \quad (4)$$

If the core index is 1, the action is a *core action*; if the core index is 0, an *exterior action*, and a *borderline action* otherwise. Core actions can be recommended because they are in every cost-efficient portfolio. Exterior actions can be discarded because they are not in any cost-efficient portfolio. Eliciting additional information about the relative importance of connections typically reduces the number of cost-efficient portfolios and the number of borderline actions.

The core indices of the reinforcement actions for the two information sets and budgets (defined as the size of feasible action portfolios) are in Figure 2. When only a few actions can be implemented, there are no core actions because actions at different switches improve the reliability of paths for different connections, and it is not possible to improve all connections simultaneously. When more information about the importance of these connections is provided, as represented by the change from the information set S^0 to S^1, the number of borderline actions decreases as some become exterior or core actions.

Topological metrics such as *degree* or *betweenness* are usually used to quantify the relevance of nodes in a network. For example, Ghorbani-Renani et al. (2021) identify candidate nodes to be reinforced in interdependent networks based on five centrality metrics. Yet, a concern with relying solely on centrality metrics is that they are not necessarily linked to network performance. In contrast, the priorities for the reinforcement actions at the nodes that represent switches depend explicitly on how these actions improve the reliability of connections and how important these connections are. For example, switch 10–which has a high ranking according to some centrality metrics (closeness 2nd, degree 3rd, and betweenness 6th)–should only be reinforced if the budget allows for the reinforcement of many switches.

4.3.3. *Station Performance*

The reliabilities of the connections for all cost-efficient portfolios containing five reinforced switches are in Figure 3. Given that the traffic volume of connection (B,C) is at least five times smaller than that of connections (A,B) and (A,C), the reinforcement actions are focused primarily on the connections that involve terminal node A.

Because the set of cost-efficient portfolios for the weight set S^0 contains those that lead to the greatest reliability improvements on any given connection, these portfolios can be scrutinized to gain insights from the perspective of reliability

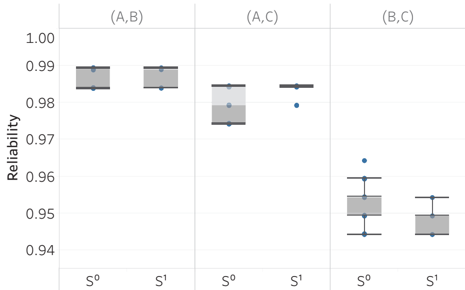

Fig. 3. Reliability of the connections for different cost-efficient portfolios and information sets. Budget: five switches.

analysis. For example, if only five actions can be implemented, then the maximum reliability of the connection (B,C) obtained by implementing reinforcement actions is around 0.965.

5. Discussion

Our model assumes that the disruption events at nodes occur independently of each other. In some situations, there may be dependencies such that the probability of disruption of one node depends on the disruptions at other nodes. This would be the case, for example, if the failure of a given node increases the load on another to the extent that the disruption probability of the latter becomes higher. Such interdependencies can be analyzed using Bayesian analysis (see e.g., Langseth and Portinale, 2007), even if such analyses call for a much higher number of parameter estimates about conditional probabilities. To alleviate the difficulties of working with such estimates, incomplete probability information could be admitted, for example, by asking experts to express statements on verbal scales and mapping such statements to interval-valued probabilities (see, e.g., Toppila and Salo, 2013).

One could extend the proposed approach by building scenarios to characterize external conditions affecting the network's performance. For example, if node disruption probabilities depend on the weather, specifying scenarios representing various weather conditions can be instructive in permitting the identification of portfolios that perform well across all scenarios or at least some of them (see, e.g., Liesiö and Salo (2012)).

The use of binary variables in the modeling of disruptions assumes that nodes are operational or disrupted. This assumption could be relaxed by introducing multi-state variables to capture restrictions arising from partial (but not complete) loss of node performance.

6. Conclusion

In this paper, we have developed a model that combines multi-criteria portfolio decision analysis with probabilistic risk assessment to guide the selection of cost-efficient combinations for reinforcement actions in infrastructure networks that may be disrupted due to natural hazards, technical failures, or intentional attacks. In contrast to previously proposed measures, such as topological centrality metrics, our model accounts for multiple objectives representing the network's services and admits incomplete information about the relative importance of the criteria attached to these objectives. The computational results also convey useful information about the budget levels (measured by the size of the feasible action portfolios) for which specific reinforcement actions should be carried out.

Our research also opens avenues for further methodological and applied work on analyzing critical infrastructures and selecting reinforcement actions. For example, although we have focused on a single network, the simultaneous consideration of multiple interdependent networks, such as energy, transportation, or communication systems, calls for further methodological extensions.

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