Models of portfolio decision analysis for mitigating risks in critical networks

Joaquín de la Barra

Aalto University

Aalto University publication series
Doctoral Theses 203/2026

Models of portfolio decision analysis for mitigating risks in critical networks

Joaquín de la Barra

A doctoral thesis completed for the degree of Doctor of Science (Technology) to be defended, with the permission of the Aalto University School of Science, at a public examination held at the lecture hall H304 (Otakaari 1, Espoo, Finland) of the school on 18 September 2026 at 12 noon.

The public defence can also be attended remotely via Zoom.
Link: https://aalto.zoom.us/j/61819835139
Zoom quick guide: https://www.aalto.fi/en/services/zoom-quick-guide

Aalto University
School of Science
Department of Mathematics and Systems Analysis

Supervising professor
Professor Ahti Salo, Aalto University, Finland

Thesis advisors
Professor Ahti Salo, Aalto University, Finland
Professor Steven A. Gabriel, University of Maryland, USA

Preliminary examiners
Professor Enrico Zio, Mines Paris PSL, France, and Politecnico di Milano, Italy
Associate Professor Jose Ramirez-Marquez, Stevens Institute of Technology, USA

Opponent
Professor Enrico Zio, Mines Paris PSL, France, and Politecnico di Milano, Italy

Aalto University publication series
Doctoral Theses 203/2026

ISBN 978-952-64-3340-0 (soft cover)
ISBN 978-952-64-3339-4 (PDF)
ISSN 1799-4934 (printed)
ISSN 1799-4942 (PDF)

https://urn.fi/URN:ISBN:978-952-64-3339-4

PunaMusta Oy
2026

Aalto University

ABSTRACT

Author Joaquín de la Barra

Name of the doctoral thesis Models of portfolio decision analysis for mitigating risks in critical networks

Article-based thesis

Number of pages 159

Keywords critical infrastructures, probabilistic risk assessment, portfolio decision analysis, equilibrium models

Critical infrastructure networks (CINs) are complex systems that provide essential services for society, including energy distribution, transportation, water supply, and telecommunications. They are exposed to natural hazards, technical failures, human errors, or malicious attacks, whose impacts can propagate through interconnected CINs, disrupting multiple services. Infrastructure managers must decide how to allocate limited resources among fortification, maintenance, restoration, and mitigation actions to reduce the frequency and duration of service disruptions. This resource allocation problem is challenging due to the large number of interconnected components, multiple objectives related to service provision, and significant uncertainty about hazards and component failures.

This dissertation develops analytical frameworks to support decision-makers, such as system operators and infrastructure managers, in fortifying and restoring CINs and in selecting mitigation strategies for illicit supply chains that threaten these systems. The proposed frameworks integrate probabilistic risk assessment, portfolio decision analysis, and optimization and equilibrium models to evaluate alternative action portfolios under uncertainty and resource constraints.

First, a framework is developed to identify cost-efficient portfolios of fortification actions for electricity distribution grids. The framework combines reliability models with portfolio decision analysis while accommodating partial information on hazard probabilities and preferences about different grids and reliability indices. Second, multicriteria decision analysis frameworks are proposed to identify critical components in railway systems and to guide the allocation of resources to portfolios of fortification actions that improve reliability and resilience across multiple services. The frameworks are equipped with computational methods to quantify reliability and resilience and determine restoration sequences that minimize cumulative performance loss from service disruptions. Third, a model based on mathematical programming with equilibrium constraints is proposed to determine portfolios of mitigation strategies that reduce trade volume in illicit supply networks while explicitly modeling the objectives and constraints of the network participants.

The proposed frameworks provide systematic decision support for infrastructure managers, system operators, and policymakers by identifying cost-effective portfolios of actions that improve the reliability and resilience of CINs while accounting for incomplete information about relevant parameters, including hazard probabilities and preferences over multiple objectives. Together, they contribute to methodological advances in strengthening CINs and mitigating threats that compromise their operations.

Preface

I remember the acknowledgments of my master's thesis being the most difficult page to write because there was far more to be grateful for than could ever fit on a single page. Years later, I find myself facing exactly the same problem. If anything, the list has only grown.

This thesis was written with the support and influence of mentors, colleagues, friends, and family members who, each in their own way, helped me reach this point. Although I have tried my best to mention everyone, I am certain I have forgotten someone, so my first expression of gratitude is to those whose names are absent but whose impact is not.

To Professor Ahti Salo, for trusting me with the opportunity to come to Finland and for his supervision throughout these four years. Thank you for your commitment to excellence, your high standards in research, and your genuine dedication to your students.

To Professor Steven A. Gabriel, for his academic guidance and for always finding time for a chat despite his busy schedule. Thank you for making learning about equilibrium models such an enjoyable experience.

To Professors Enrico Zio and Jose Ramirez-Marquez, for taking the time to examine this thesis and for their constructive feedback.

To Tuomas Raivio, for all the conversations and discussions while teaching the Risk Analysis course. Teaching has been a challenging but enjoyable part of this journey, and it was a pleasure to work with you.

To Piotr Zebrowski and Stefan Hochrainer-Stigler, for their mentorship during the Young Scientists Summer Program at IIASA; to the SYRR group, for the insightful discussions during our meetings; and to my fellow YSSPers, for a wonderful summer of doing research together and for their enthusiasm and spirit in building a more collaborative research community.

To my co-authors, Leevi Olander, Mahdi Pourakbari, and Kash Barker, for the opportunity to collaborate with them and for their valuable contributions to this thesis.

To my colleagues in the Systems Analysis Laboratory for their peer support and for making my time at Aalto more enjoyable with the tea times and lunches.

To Soroush, Elham, Gulsah, Iman, Kristine, Natalia, Maria, Margarida, Dipesh, Pooja, and Hitesh, for all the laughs, the shared memories, and for being the best support group anyone could ask for during the long Finnish winters.

To Nidia, Tejas, Arttu, Jan, and all the other members of Aallonhuiput, for creating such an important support community, which undoubtedly helped me, especially at the beginning of this adventure in Finland.

To Sebastián, André, Joaquín, and all my other friends in Chile, for making the effort to stay close despite the distance, the time difference, and our sometimes increasingly busy lives.

To my parents, Giovanna and José Luis, and my brother Vicente, for always being there, celebrating every milestone, and making the distance feel a little smaller.

And finally, to Nati, Bagheera, and Oliva, for their love, patience, and for always being my home.

Espoo, August 24, 2026,

Joaquín de la Barra

Contents

List of Publications

This thesis consists of an overview and of the following publications which are referred to in the text by their Roman numerals.

I Joaquín de la Barra, Ahti Salo, and Mahdi Pourakbari-Kasmaei. Choosing Portfolios of Reinforcement Actions for Distribution Grids Based on Partial Information. *Reliability Engineering and System Safety*, 266, 111729, February 2026.

II Joaquín de la Barra, Ahti Salo, Leevi Olander, Kash Barker, and Jussi Kangaspunta. Fortifying Critical Infrastructure Networks with Multicriteria Portfolio Decision Analysis: An Application to Railway Stations in Finland. *Reliability Engineering and System Safety*, 268, 112006, April 2026.

III Joaquín de la Barra, Piotr Zebrowski, Stefan Hochrainer-Stigler, and Ahti Salo. Enhancing Reliability and Resilience in Critical Infrastructure Networks with Multicriteria Portfolio Decision Analysis. *Submitted to Reliability Engineering and System Safety*, 2026.

IV Joaquín de la Barra, Ahti Salo, and Steven A. Gabriel. A Mathematical Programming with Equilibrium Constraints Formulation to Identify Optimal Mitigation Strategies to Reduce Trade Volumes in Illicit Supply Networks. *Submitted to European Journal of Operational Research*, 2026.

Author's Contribution

Publication I: "Choosing Portfolios of Reinforcement Actions for Distribution Grids Based on Partial Information"

De la Barra is the primary author. He and Salo framed the research topic together. De la Barra contextualized the problem, conducted the literature review, and implemented the computational models. De la Barra and Salo wrote the manuscript together. Salo provided methodological suggestions. Pourakbari-Kasmaei provided computational resources and helped revise the manuscript.

Publication II: "Fortifying Critical Infrastructure Networks with Multicriteria Portfolio Decision Analysis: An Application to Railway Stations in Finland"

De la Barra is the primary author. Kangaspunta and Salo proposed and developed the first draft of the manuscript. De la Barra improved the proposal by developing new algorithms, contextualizing the problem for a real application, and updating the literature review. De la Barra and Salo wrote the manuscript together. Olander and Barker provided methodological suggestions and helped finalize the manuscript.

Publication III: "Enhancing Reliability and Resilience in Critical Infrastructure Networks with Multicriteria Portfolio Decision Analysis"

De la Barra is the primary author. He proposed the research topic, developed the mathematical formulations, wrote most of the manuscript, and implemented the computational models. Zebrowski revised the manuscript and provided feedback about the methodology. Hochrainer-Stigler revised the manuscript. Salo helped frame the research topic and finalize the manuscript.

Publication IV: "A Mathematical Programming with Equilibrium Constraints Formulation to Identify Optimal Mitigation Strategies to Reduce Trade Volumes in Illicit Supply Networks"

De la Barra is the primary author. He proposed the research topic, developed the mathematical formulations, implemented the computational models, and wrote most of the manuscript. Gabriel and Salo provided methodological feedback and helped finalize and revise the manuscript.

List of Figures

List of Tables

Abbreviations

CIN	Critical infrastructure network
DSO	Distribution system operator
EPEC	Equilibrium problem with equilibrium constraints
KKT	Karush-Kuhn-Tucker
MCP	Mixed complementarity problem
MCS	Minimal cut set
MPEC	Mathematical programming with equilibrium constraints
MPS	Minimal path set
PDA	Portfolio decision analysis
PRA	Probabilistic risk assessment
RBD	Reliability block diagram
SDG	Sustainable development goal
SPE	Spatial price equilibrium

1. Introduction

1.1 Background

Critical infrastructure networks (CINs) comprise all assets, systems, and networks that provide essential services for society. These infrastructures are crucial in modern economies, supporting sectors such as energy, water supply, transportation, and telecommunications. Due to their roles in the economy, the environment, and society, CINs are considered key to meeting the Sustainable Development Goals (SDGs) (Murray, 2019). Specifically, it has been estimated that CINs influence the attainment of all SDGs, including 72% of their targets (Thacker et al., 2019).

Natural or human-induced hazards jeopardize the integrity of CINs, disrupting their components and potentially interrupting the services they provide. The interconnectedness of CINs amplifies the impact of disruptions (Rinaldi et al., 2001). For instance, the failure of a counterfeit microchip can trigger a false positive in protective equipment at an electrical substation, leading to a power outage that, in turn, paralyzes transportation systems and disrupts water distribution. As the frequency and severity of these hazards have increased (Coronese et al., 2019), safeguarding CINs and enabling their rapid recovery have become increasingly important for mitigating the impact of disruptions (Barker et al., 2013).

Fortification and maintenance actions can reduce the failure probability of components, thereby enhancing the reliability of CIN services, i.e., the probability that services remain operational throughout a specified time period under given operating conditions (Rausand and Hoyland, 2003; Dueñas-Osorio and Vemuru, 2009). Even after implementing fortification actions, components can still fail. This may occur when the magnitude of a forecasted event exceeds expectations or when unforeseen hazards harm the system (Aven, 2015). Moreover, in some cases, the reliability of components is overestimated, and failures are more frequent than expected (Zio, 2009).

In practice, the responsibility for overseeing the CINs lies with infrastructure managers. They design and implement fortification and maintenance strategies and coordinate restoration efforts after disruptions. As resources are typically limited, it is instructive to identify which components are most important to service provision to inform resource allocations for fortification, maintenance, and restoration actions (Chu and Chen, 2016). However, evaluating a CIN's ability to sustain service provision under disruptive conditions and identifying which components most strongly influence this can be challenging, as CINs are typically complex systems comprising numerous components and providing multiple services.

Moreover, identifying important components is further complicated by significant uncertainty in relevant parameters, including the occurrence and magnitude of hazards, their impacts on components, the probability of technical failures, and future demand for CIN's services (Zio, 2016). In this context, probabilistic risk assessment (PRA) is a systematic methodology for addressing such uncertainties by integrating hazard identification, scenario construction, and reliability modeling to quantify the probability and consequences of adverse events (Stamatelatos, 2000).

From a comprehensive perspective, developing a full set of scenarios that captures all relevant uncertainties may be beneficial. This is especially the case for safety-critical systems, whose risk analyses are usually required to be conservative, i.e., the results should err on the side of too much rather than too little caution (Tosoni et al., 2019). For example, because hazards may occur jointly, omitting scenarios depicting their joint occurrence would violate the principle of comprehensiveness, especially if their combined effects exacerbate the impact on the CIN's integrity (Salo et al., 2022).

Once the relevant hazards and associated uncertainties have been identified and their impacts on the CIN quantified, appropriate actions must be selected to reduce these negative impacts and improve service reliability and recovery after disruptions. In this context, fortifying multiple components or subsystems by choosing a coordinated portfolio of fortification actions can yield greater overall benefits than implementing individual actions without accounting for their interactions. By construction, selecting such a portfolio constitutes a portfolio decision analysis (PDA) problem (Salo et al., 2011), as interdependencies among components, resource limitations, and multiple sources of uncertainty must be addressed jointly. This calls for systemic approaches that integrate engineering models, scenario analyses, and expert judgment within a comprehensive framework to assess the cost-effectiveness of alternative portfolios.

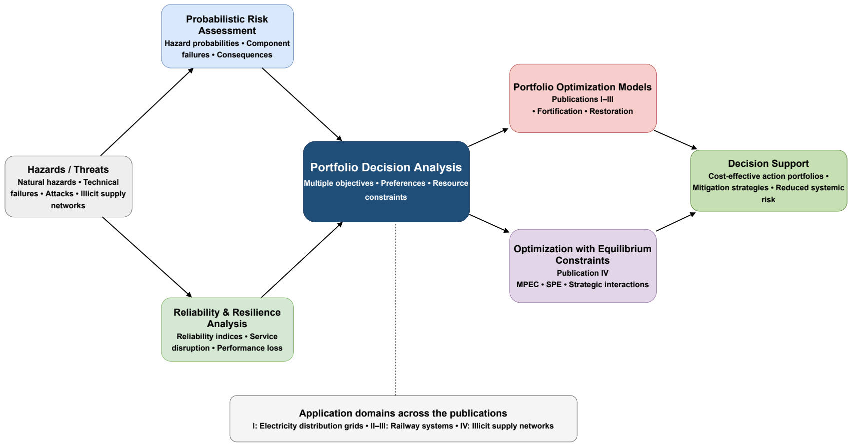

Figure 1.1. Conceptual framework of the dissertation.

1.2 Research objectives

This dissertation develops frameworks to support decision-makers, including system operators, infrastructure managers, law enforcement agencies, and policymakers, in fortifying, maintaining, and restoring CINs. Publication I focuses on integrating multiple information sources, including reliability models and expert judgments, to protect multiple CINs in the electricity distribution sector. Publication II and Publication III develop methodologies to enhance the performance of CINs in the railway sector by improving their reliability and resilience. Finally, Publication IV presents an interdiction model based on supply chain analysis to reduce the trade volume of counterfeit microchips that threaten CINs. Although the four publications are developed in different application domains and decision problems, they share a common decision-support framework. Figure 1.1 illustrates how probabilistic risk assessment, reliability and resilience analysis, portfolio decision analysis, optimization, and equilibrium modeling are integrated across the dissertation.

Publication I develops a framework by combining reliability models for distribution grids with elements of PDA. The framework identifies portfolios of fortification actions that minimize the expected disutility of the distribution system operator (DSO), quantified by the combined unreliability of a group of distribution grids threatened by combined hazards. Additionally, the framework accommodates partial information, providing defensible recommendations even when DSO preferences or expert judgments are only partially specified.

Publication II combines elements of PRA and PDA to develop a multicriteria decision analysis framework that supports the cost-efficient allocation of resources to portfolios of fortification actions, aiming to maximize the performance of the CIN across multiple objectives that represent the different services it provides. The framework accounts for resource constraints and minimum performance requirements on binary objectives.

Publication III combines elements of PRA and PDA to develop a multicriteria decision analysis framework that supports the cost-efficient allocation of resources to portfolios of fortification actions, aiming to enhance CIN's reliability and resilience. Additionally, for a given set of disrupted components, the framework identifies an optimal restoration sequence that minimizes the cumulative performance loss resulting from service disruptions.

Publication IV proposes a mathematical programming model with equilibrium constraints (MPEC) to guide the allocation of resources to alternative mitigation strategies and, specifically, to construct portfolios of such strategies that are cost-efficient in reducing trade volumes of counterfeit microchips in illicit supply networks. The approach can represent different kinds of illicit supply networks, including those in which participants have different objectives and constraints, and in which policymakers can adjust the effectiveness of multiple mitigation strategies through decisions on resource allocation.

2. Methodological background

This chapter outlines the methodological foundations of the dissertation. Section 2.1 introduces key elements of decision theory, with emphasis on PDA, which is employed to support the selection of alternative portfolios under resource constraints. Section 2.2 provides an overview of PRA and discusses how it can be used to quantify system reliability. Section 2.3 discusses complementarity problems and highlights the advantages of MPECs in modeling situations involving multiple interacting decision-makers.

2.1 Decision theory

In this dissertation, the performance of a CIN with respect to criterion j (e.g., the successful provision of a service or the reliability of the CIN) is measured by a criterion-specific utility function $u_j : X \to \mathbb{R}$, where X is a discrete space of consequences for this criterion. Moreover, to account for uncertainty in hazard realizations and component failures, the consequences $x \in X$ are modeled as realizations of random variables. For example, when evaluating the availability of a connection j in a CIN consisting of n components, $x = (x_1, \ldots, x_n) \in X$ denotes the CIN state, where each component state satisfies $x_i = 0$ if component i is disrupted and $x_i = 1$ if it is operational. The function $u_j(\cdot)$ then maps each possible CIN state to 0 or 1, depending on whether connection j is available in that state.

The utility functions $u_j(\cdot)$ can be aggregated with the additive multicriteria utility function in Eq. (2.1) if criteria are mutually preferentially independent and each criterion is additively independent (Dyer and Sarin, 1979). Specifically, in the utility function

$$u(x, w) = \sum_{j=1}^{m} w_j u_j(x) \in [0, 1], \qquad (2.1)$$

the weight of the criterion $w_j \in [0,1], j = 1, \ldots, m$ can be interpreted as the marginal contribution to overall utility when the j-th criterion changes from its worst to its best level. Following the usual convention, these weights are normalized so that $\sum_{j=1}^{m} w_j = 1$.

Under the expected utility paradigm, a rational decision-maker selects among alternative actions in order to maximize expected utility. Evaluating actions in isolation does not reveal how different combinations interact or jointly contribute to maximizing expected utility. In this context, PDA methods support decision-makers in making informed choices among alternative actions by evaluating portfolios of those actions (Salo et al., 2011; Mancuso et al., 2019). Accordingly, portfolios that maximize the decision-maker's expected utility can be obtained by solving

$$\max_{a \in \mathcal{A}} \ \mathbb{E}[u(x,w) \mid a] \ = \ \max_{a \in \mathcal{A}} \sum_{x \in X} p(x \mid a)\, u(x,w), \tag{2.2}$$

where $p(x \mid a)$ denotes the probability of consequence x given portfolio a. Here, z denotes the number of available actions, and $a \in \mathcal{A} \subseteq \{0,1\}^z$ denotes a feasible portfolio of actions, where $a_i = 1$ if action i is selected and $a_i = 0$ otherwise. In practice, the feasible set of portfolios $\mathcal{A}$ is defined by constraints that reflect limited resources, technical requirements, or logical dependencies among actions.

2.1.1 Partial information

The weights in Eq. (2.1) can be obtained through structured elicitation procedures, such as those proposed by (Dias et al., 2018). However, information about weights and other model parameters, including the probabilities of scenarios depicting hazard occurrences, is not always readily available. For example, decision-makers may need to account for priorities across multiple criteria or consult a large group of stakeholders whose preferences do not reach consensus. In other cases, several experts may be consulted to elicit estimates of scenario probabilities or other relevant parameters. Retaining the full range of these assessments within the analysis can be more informative than aggregating them into, for example, a single probability vector. In response to this recognition, and to provide decision support even when complete information is unavailable, the analysis can be conducted over a set of feasible parameter values rather than relying on point estimates. These sets represent *partial information* that can be synthesized using PDA methods (Liesiö and Salo, 2012).

An *information set* $\mathcal{S}$ consists of all the weights that are compatible with the elicited preference statements (Salo and Hämäläinen, 1992). These statements can be elicited by asking the decision-maker to express their views on the relative importance of the criteria. Thus, for example, if criterion 1 is at least as important as criterion 2 but not more than two

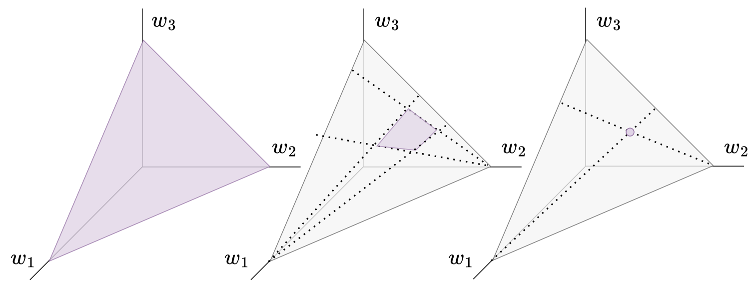

Figure 2.1. Three illustrative information sets (shaded in purple) for the weights w_1, w_2, and w_3.

times more important, the constraint $w_2 \leq w_1 \leq 2w_2$ holds. As most types of such preference statements correspond to linear constraints, the resulting information set $\mathcal{S}$ is given by

$$\mathcal{S} = \{w \in \mathbb{R}^m \mid Aw \leq b\} \subseteq \left\{ w \in \mathbb{R}^m \mid w_j \geq 0 \; \forall j, \sum_{j=1}^{m} w_j = 1 \right\}, \qquad (2.3)$$

where the matrix $A \in \mathbb{R}^{k \times m}$ and the vector $b \in \mathbb{R}^k$ contain the coefficients obtained from k preference statements. Figure 2.1 illustrates three information sets that represent different levels of information regarding the preferences over three criteria. The set on the left is referred to as a non-informative set, since it represents the absence of preference information, or equivalently, it contains no preference statements. In this case, the feasible weights consist of all convex combinations of (1,0,0), (0,1,0), and (0,0,1). The set in the middle incorporates partial information about the preferences, thereby restricting the admissible weight vectors. Finally, the set on the right represents complete preference information, since the feasible region is a single point, yielding a unique weight vector. Although information sets are described here in terms of preferences over criteria, they can also be extended to accommodate partial information about other parameters.

2.1.2 Non-dominated portfolios

When complete information about probabilities and preference weights is available, the expected utility $\mathbb{E}[u(x, w) \mid a]$ is uniquely defined. Since the objective is to maximize expected utility, portfolios can be ranked accordingly.

Definition 1. *Under complete information, a portfolio $a \in \mathcal{A}$ is optimal if* *and only if* $\mathbb{E}[u(x,w) \mid a] \geq \mathbb{E}[u(x,w) \mid a'], \quad \forall a' \in \mathcal{A}$.

Under partial information, $\mathbb{E}[u(x,w) \mid a]$ varies depending on the weights w, and therefore analytical concepts are required to derive defensible recommendations. In such cases, portfolios can be compared using the concept of *dominance* to identify those that outperform others across a range of feasible weights.

Definition 2. *Let $a, a' \in \mathcal{A}$. Portfolio a dominates a' with respect to the information set $\mathcal{S}$, denoted $a \succ_{\mathcal{S}} a'$, if and only if* $\mathbb{E}[u(x,w) \mid a] \geq \mathbb{E}[u(x,w) \mid a'] \quad \forall w \in \mathcal{S}$, *and the inequality is strict for at least one $w \in \mathcal{S}$.*

A rational decision-maker who seeks to maximize expected utility should therefore restrict attention to non-dominated portfolios. The set of non-dominated portfolios depends on both the information set $\mathcal{S}$ and the feasibility constraints defining $\mathcal{A}$.

Definition 3. *A portfolio $a \in \mathcal{A}$ is non-dominated with respect to $\mathcal{S}$ if and only if there is no $a' \in \mathcal{A}$ such that $a' \succ_{\mathcal{S}} a$.*

When multiple non-dominated portfolios exist, the core index can inform decisions about individual actions (Liesiö et al., 2007). Let $\mathcal{A}_{ND} \subseteq \mathcal{A}$ denote the set of non-dominated portfolios. The core index of an action i is

$$CI(i) = \frac{|\{a \in \mathcal{A}_{ND} \mid a_i = 1\}|}{|\mathcal{A}_{ND}|}, \tag{2.4}$$

where $|\cdot|$ denotes the cardinality of the set. The core index (2.4) measures the proportion of non-dominated portfolios in which action i is selected. An action with a core index of 1 can be recommended because it is in every non-dominated portfolio. If the core index is 0, the action can be discarded. If the specification of the partial information becomes more conclusive in the sense that the updated information set becomes a proper subset of the initial one, some previously non-dominated portfolios may become dominated, but no new non-dominated portfolios will be found. Therefore, refining the information set helps to make decisions about the remaining actions.

2.2 Probabilistic risk assessment

PRA is a comprehensive and structured methodology for assessing risks in complex systems. By accounting for temporal variability and uncertainty, it estimates the likelihood and consequences of hazards affecting the systems, thereby supporting cost-efficient improvements in system safety and performance (Stamatelatos et al., 2011). Several PRA methods are based on related representations; for example, reliability block diagrams

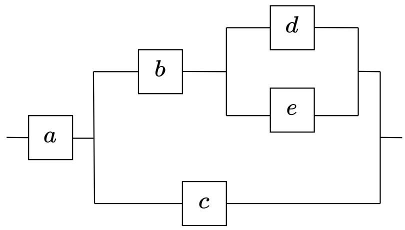

Figure 2.2. Illustrative reliability block diagram of a system with five components.

(RBDs) can often be transformed into fault trees or Boolean expressions, and vice versa. In what follows, selected concepts for estimating system reliability and determining potential restoration sequences are presented in the context of RBDs, as this representation is used mainly in this dissertation. Nevertheless, the same concepts can be extended to other PRA representations.

RBDs represent how the reliability of components or subsystems contributes to the overall reliability of a system (Kim, 2011). The diagram consists of blocks representing components or subsystems, with an associated failure probability or other reliability-related parameters. These components are typically represented as binary states, i.e., operational or disrupted. The system's reliability can be determined by the configuration of the blocks (i.e., how they are connected) and their individual reliabilities. Specifically, for the system to be operational, there must be a path of operational blocks from left to right. For example, in the RBD illustrated in Figure 2.2, if components a and c are operational, there is a path of operational blocks, and therefore the system is operational.

In risk assessments, the system reliability is commonly quantified through the probability of system failure. Given the structure of an RBD, the system failure probability can be expressed as a function of the component failure probabilities. However, for large or structurally complex diagrams, evaluating these expressions can be computationally demanding, particularly when the RBD contains repeated components or configurations that are neither in series nor in parallel. To address these challenges, approximation methods, including minimal cut set based truncations (Sharafat and Ma'rouzi, 2009) or Monte Carlo simulations (Zio, 2013; Ramirez-Marquez and Coit, 2005), can be used to estimate the system failure probability.

2.2.1 Minimal cut sets

A cut set is a set of components (or blocks in the RBD) whose joint failure causes the entire system to fail. For example, in the RBD shown in Figure 2.2, the set of all components $\{a, b, c, d, e\}$ constitutes a trivial cut set, because the simultaneous failure of all components causes the system

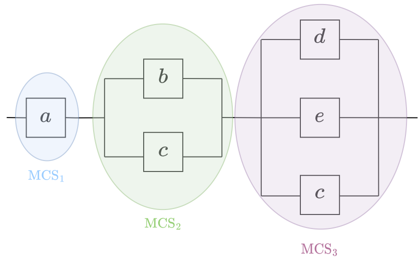

Figure 2.3. Minimal cut set representation of the RBD in Figure 2.2.

to fail. On the other hand, a minimal cut set (MCS) is a cut set that contains no proper subset that is itself a cut set. In the previous example, $\{a, b, c, d, e\}$ is not minimal because it contains $\{b, c\}$, which is already a cut set. In contrast, $\{b, c\}$ is an MCS because none of its proper subsets, $\{b\}$ or $\{c\}$, cause the system to fail.

The minimal cut set representation of a system consists of a series connection of its MCSs. For the system in Figure 2.2, this representation is shown in Figure 2.3. Using the minimal cut set representation, the system failure probability $P(Sys)$ can be approximated by the failure probabilities of its MCSs. Let q_i denote the failure probability of component i. Because the components within an MCS must fail simultaneously for the MCS to fail, and assuming that failures are independent of each other, the failure probability of an MCS k is

$$P(\mathrm{MCS}_k) = \prod_{i \in \mathrm{MCS}_k} q_i. \tag{2.5}$$

Since the system fails if any of its MCSs fail, the system failure probability can be approximated from above by summing the probabilities of all MCSs $k \in K$, i.e.,

$$P(\mathrm{Sys}) \approx \sum_{k \in K} P(\mathrm{MCS}_k). \tag{2.6}$$

The right-hand side of (2.6) does not consider higher-order terms associated with the simultaneous failure of multiple MCSs. This approximation is commonly referred to as the *rare event approximation* because the omitted terms correspond to joint events with very low probability when the component failure probabilities are small. The rare event approximation provides an upper bound on the system failure probability.

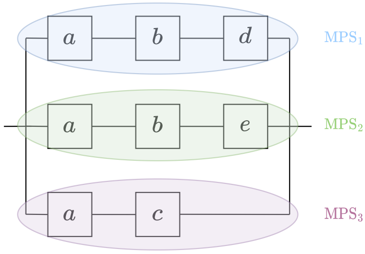

Figure 2.4. Minimal path set representation of the RBD in Figure 2.2.

2.2.2 Minimal path sets

A path set is a set of components whose simultaneous operation is sufficient to guarantee system operation. For example, a trivial path set for the system represented by the RBD in Figure 2.2 is the set of all components $\{a, b, c, d, e\}$, since if all components are operational, the system is operational.

A minimal path set (MPS) is a path set that does not contain any proper subset that is itself a path set. That is, removing any component from an MPS results in a set that no longer guarantees system operation. For example, $\{a, c\}$ is an MPS since it guarantees system operation, whereas neither $\{a\}$ nor $\{c\}$ does. This is because if components a and c are both operational, there is at least one functioning path in the system, while neither a nor c alone can guarantee that. As with MCSs, the system's reliability can be computed from the reliabilities of the MPSs. Moreover, because each MPS contains a sufficient set of components for system operation, MPSs can be used to identify which components to restore first to recover services as quickly as possible after disruptive events.

2.3 Complementarity problems

Complementarity problems are powerful tools for modeling markets because they can represent situations in which one or several decision-makers (or players) interact while optimizing their respective objectives. In the following, the most relevant models for this dissertation are described. For comprehensive reviews, refer to Ruiz et al. (2014) and Gabriel et al. (2012).

In the basic form, the complementarity problem is to solve for a vector of variables x such that $f(x) \geq 0, x \geq 0$ and $f(x)^T x = 0$, where $f(x)$ is a vector-valued function of the same length as x. Using the *perp* symbol $\perp$, this is typically written in a more compact form as,

$$0 \leq x \perp f(x) \geq 0 \tag{2.7}$$

Complementarity problems are closely related to optimization problems in that they can represent the conditions for an optimal solution without explicitly minimizing or maximizing an objective function. For example, let us consider a set of players P, indexed by $i = 1, \ldots, I$, each optimizing its decisions to minimize losses. Each player i solves a problem of the following general form

$$\min_{x_i} \quad f_i(x) \tag{2.8a}$$

$$\text{s.t.} \quad g_i(x_i) \leq 0 : \mu_i \tag{2.8b}$$

$$-x_i \leq 0 : \beta_i, \tag{2.8c}$$

where $x_i \in \mathbb{R}^{n_i}$ is the vector of decision variables of the player i, and $x \in \mathbb{R}^n$ is the vector of decision variables of all players, with $n = \sum_{i=1}^{I} n_i$. The player i's objective function $f_i : \mathbb{R}^n \to \mathbb{R}$ depends not only on the player's own decisions, but also on those of the other players. The inequality constraints $g_i : \mathbb{R}^{n_i} \to \mathbb{R}^{m_i}$ depend only on the decisions of player i. The dual variables associated with the inequality constraints g_i and the non-negativity constraints are contained in the vectors $\mu_i \in \mathbb{R}^{m_i}$ and $\beta_i \in \mathbb{R}^{n_i}$, respectively.

Assuming that the functions f_i and g_i are continuously differentiable, the Karush-Kuhn-Tucker (KKT) conditions associated with the optimization problem (2.8) can be expressed as the equivalent mixed complementarity problem (MCP) (Gabriel et al., 2012),

$$0 \leq x_i \perp \nabla_{x_i} f_i(x) + \mu_i^T \nabla_{x_i} g_i(x_i) \geq 0 \tag{2.9a}$$

$$0 \leq -g_i(x_i) \perp \mu_i \geq 0. \tag{2.9b}$$

If the functions g_i and f_i are convex and a suitable constraint qualification (e.g., Slater's condition) holds, the KKT conditions are necessary and sufficient for optimality (Bertsekas, 2016). Therefore, solving the MCP (2.9) is equivalent to solving the optimization problem in (2.8).

2.3.1 Nash equilibrium

A Nash equilibrium (Nash, 1951) is a combination of decisions by two or more players such that no player can improve its objective by unilaterally modifying its decision. In the context of the optimization problems defined in (2.8), if the I players compete in a non-cooperative setting, a Nash equilibrium can be characterized as a solution of the system formed by the KKT conditions of all players. Under convexity and regularity assumptions, this is equivalent to finding x such that the MCP (2.9) is satisfied for all $i = 1, \ldots, I$.

2.3.2 Spatial price equilibrium

Spatial price equilibrium (SPE) formulations were originally developed to describe markets in which homogeneous commodities are traded among participants or regions (Samuelson, 1952). These models explain regional variation in commodity prices driven by transportation costs and capacity constraints. In equilibrium, supply, demand, and trade volumes are determined so that no market participant can increase its profit by unilaterally changing production, consumption, or shipment decisions.

There are several variations of the SPE that differ in the linearity of the underlying functions, the types of competition, and the number of commodities, among others. For example, Harker (1986) considers a set of regions $r \in R$, each with supply function $s_r(p_r)$ and demand functions $d_r(p_r)$, which depend on the price p_r. Assuming no shipment losses, the balance constraint

$$s_r(p_r) + \sum_{s \in R} x_{sr} = d_r(p_r) + \sum_{s \in R} x_{rs}, \quad \forall r \in R \tag{2.10}$$

must hold. In (2.10), x_{rs} denotes the quantity shipped from region r to region s, and c_{rs} denotes the unit transportation cost. From an economic perspective, a shipment from region r to region s occurs only if the price difference $(p_s - p_r)$ equals the transportation cost. This can be written as the following complementarity conditions,

$$0 \leq x_{rs} \perp p_r + c_{rs} - p_s \geq 0, \quad \forall r, s \in R. \tag{2.11}$$

The balance constraints in (2.10) together with the complementarity conditions in (2.11) define an MCP whose solution characterizes the SPE. The MCP characterizing the Nash equilibrium was derived from the KKT conditions of an optimization problem. As shown by Gabriel et al. (2012), there may be no optimization problem whose KKT conditions are equivalent to an SPE. Therefore, equilibrium models are more general than optimization models, in that they cannot always be derived from the KKT conditions for optimization problems.

2.3.3 Mathematical programming with equilibrium constraints

MPECs are optimization problems in which the feasible set is defined by a combination of constraints and equilibrium conditions, often expressed as complementarity problems (Luo et al., 1996). These formulations provide a framework for modeling hierarchical decision problems, such as Stackelberg games (Yang et al., 2007), in which an upper-level player (leader) optimizes its objective while the decisions of one or more lower-level players (followers) are determined by an equilibrium problem whose parameters depend on the leader's decisions.

In the formulation (2.12), the leader optimizes its decisions y to minimize its objective function $f^L(x, y)$. The constraint $EP(x \mid y)$ represents the equilibrium problem of the followers, with respective decisions x, and whose equilibrium conditions depend parametrically on the leader's decisions y. For example, this equilibrium problem may be formulated as the MCP (2.9) obtained from the KKT conditions of followers $i = 1, \dots, I$ or the SPE in (2.10)-(2.11).

$$\min_{y,x} \quad f^L(x, y) \tag{2.12a}$$

$$\text{s.t.} \quad y \in Y \tag{2.12b}$$

$$EP(x \mid y). \tag{2.12c}$$

3. Contributions

This dissertation develops frameworks and computational algorithms to support decision-makers, such as system operators, infrastructure managers, and policymakers, in making decisions on the fortification, maintenance, and restoration of CINs, as well as on mitigation strategies for illicit supply networks that may harm them. Publication I develops a framework to integrate reliability models with partial information on preferences across criteria and on the probabilities of hazard scenarios to identify portfolios of fortification actions. Publications II and III integrate elements of PRA and PDA to prioritize the fortification of CIN components to enhance reliability and resilience with respect to the multiple services provided by the CIN. Publication IV develops an MPEC formulation to identify portfolios of mitigation strategies to curb trade volumes in illicit supply networks. The contributions are summarized in Table 3.1.

3.1 Publication I

Several models have been proposed to identify fortification actions to maximize the reliability of electricity distribution grids. Nevertheless, most approaches focus on a single grid and consider only a small set of fortification actions and hazards at a time, thereby neglecting potential interactions among them. DSOs typically oversee several grids, and the resources devoted to protecting them are drawn from a common pool. Moreover, fortification actions may enhance the reliability of multiple grids, whereas hazards can simultaneously threaten them. In addition, some actions are more effective against specific hazards. Therefore, from the managerial perspective, integrating multiple grids, hazards, and fortification actions helps identify fortification portfolios that balance investment levels and reliability improvements.

Because hazards may occur jointly, omitting scenarios that depict such joint occurrences can lead to an overestimation of the reliability of distribution grids, especially when combined hazards exacerbate negative impacts. On the other hand, assigning precise probabilities to scenarios can be challenging, particularly for extreme events or scenarios involving multiple hazard realizations with poorly understood correlations.

Publication I develops a framework to determine cost-efficient portfolios of fortification actions that improve the reliability of multiple distribution grids by minimizing several reliability indices. Moreover, by accommodating partial information, the framework provides recommendations for fortification portfolios that perform well across all admissible parameter realizations when complete information from sources such as reliability models, preference elicitation processes, and expert judgments is unavailable.

3.2 Publication II

Identifying critical components based on their contribution to the CIN's performance is essential for prioritizing fortification, coordinating maintenance activities, and replacing components as needed. Many approaches prioritize which components to fortify based on topological metrics, i.e., metrics that depend only on the positions and connections of components in the CIN. However, a limitation of topological metrics is that they are not necessarily aligned with the CIN's objectives and typically do not account for component failure probabilities.

Publication II develops a general assessment approach and accompanying search algorithms to assess the importance of components in a CIN, accounting for component failure probabilities, multiple objectives associated with the services enabled by the CIN, and minimum performance requirements for these objectives. These assessments of component importance are subsequently used to recommend fortification actions that improve the CIN's expected performance. The framework is illustrated by a case study on the fortification of railway switches at a representative railway station to improve the reliability of its connections.

3.3 Publication III

Several approaches have been proposed to enhance the reliability and resilience of CINs, particularly in transportation systems exposed to disruptive events. Fortification actions implemented to protect CIN's components can affect both reliability and resilience, although not necessarily to the same extent. Specifically, by reducing component failures, these actions can reduce service disruptions and the associated expected cumulative performance loss, thereby enhancing reliability and resilience. Previous studies have usually focused on enhancing reliability and resilience separately or relied on topological metrics that do not explicitly account for the services provided by the CIN or the preferences of infrastructure managers regarding those services. There is therefore a need for decision-support frameworks that jointly assess the impact of fortification actions on reliability and resilience while accounting for multiple services and stakeholder preferences.

Publication III develops a multicriteria portfolio decision analysis framework to identify Pareto optimal portfolios of fortification actions that enhance the reliability and resilience of CINs. Since computing reliability and resilience can be computationally intensive, the framework quantifies them using the aggregated service reliability and the expected cumulative performance loss due to service disruptions. In addition, Publication III develops an algorithm to determine optimal restoration sequences for disrupted components, thereby minimizing the expected cumulative performance loss after disruptive events. The framework is illustrated through a case study of the fortification of railway switches at a representative railway station in Finland, demonstrating how infrastructure managers can support decisions on fortification and restoration planning under multiple objectives and operational priorities.

3.4 Publication IV

Optimization approaches, particularly bilevel formulations, have been widely employed in interdiction problems. However, when applied to supply network settings, these approaches typically treat prices as exogenous parameters rather than modeling the price formation through supply–demand interactions. In contrast, equilibrium models can incorporate functional forms for demand and supply and, as a result, have been widely used to model supply networks. Recently, several approaches based on equilibrium models have been proposed to analyze illicit supply networks and identify mitigation strategies to reduce their trade volume. Nevertheless, most of these approaches rely on sensitivity analysis over a discrete, and usually small, set of strategies.

Publication IV develops an MPEC formulation to determine portfolios of mitigation strategies that most effectively reduce the trade volume of counterfeit microchips in an illicit supply network. The formulation combines a well-founded supply network equilibrium model that accounts for participants' objectives and constraints with a classical SPE structure to represent trade volumes and endogenous price formation.

Table 3.1. Summary of publications.

Publication	Objectives	Methodologies	Results
I	To explore the integration of reliability models with PDA in the identification of fortification portfolios for distribution grids.	Partial Information, Decision Programming, Portfolio Decision Analysis	A framework which combines reliability models and partial information about expert judgments and DSO preferences to determine cost-efficient portfolios of fortification actions that maximize expected utility, subject to implementation costs.
II	To identify the components that contribute the most to the attainment of transportation objectives of a railway station, measured by the reliability of the connections that the station enables.	Probabilistic Risk Assessment, Search Algorithms, Portfolio Decision Analysis	A multicriteria portfolio optimization approach for identifying cost-efficient portfolios of fortification actions while accounting for multiple connections and possible minimum reliability requirements on individual connections.
III	To identify fortification portfolios that enhance the reliability and resilience of railway stations.	Optimization, Probabilistic Risk Assessment, Search Algorithms, Portfolio Decision Analysis	A multicriteria decision analysis framework to support the cost-efficient allocation of resources toward Pareto optimal fortification portfolios to enhance the reliability and resilience of railway stations. An algorithm to determine optimal restoration sequences for minimizing the railway station's performance loss.
IV	To explore the application of equilibrium models in determining the portfolios of mitigation strategies that most reduce the trade volume in illicit supply networks.	Spatial Price Equilibrium, Mathematical Programming with Equilibrium Constraints	An MPEC formulation to determine portfolios of mitigation strategies that most effectively reduce trade volume in illicit supply networks.

4. Discussion

This dissertation develops frameworks and computational algorithms to support decision-makers in fortifying and restoring CINs and in mitigating illicit supply networks that may harm them. Publications I, II, and III focus on methodological advances to strengthen CINs by analyzing multiple hazards and performance objectives. These publications integrate PRA and PDA to support the selection of fortification portfolios and the restoration of disrupted components. Publication IV develops an optimization framework to determine mitigation strategies for illicit supply networks that can harm CINs.

CINs typically provide multiple services to stakeholders in society. When determining which components or services should be prioritized for fortification and restoration, it may be difficult to reach consensus, as stakeholders may assign different levels of importance to the different services (Aven and Renn, 2010; Keeney et al., 1993). Moreover, CIN performance is typically estimated across several scenarios representing different operational conditions or hazards, the probabilities of which can be highly uncertain. Publication I demonstrates how a systemic framework helps derive defensible recommendations for fortification portfolios while explicitly accounting for partial information about scenario probabilities and preferences over multiple criteria. This framework can also be extended to support proactive decision-making, in which decisions not only mitigate the impact of hazards but may also influence their probabilities (Vilkkumaa et al., 2018).

The frameworks presented in Publications II and III were applied to a representative railway station, demonstrating their practical relevance. Infrastructure managers can use these frameworks to support the planning of maintenance, fortification, and restoration strategies. For instance, by identifying which components contribute most to the reliability of the services provided by the CIN, the frameworks can support maintenance planning based on current demand for those services and the probabilities of component disruptions. They can also support the allocation of monitoring resources by identifying the components most critical to service provision. Furthermore, if maintenance budgets are reduced, the frameworks can help determine which maintenance actions can be postponed with the smallest deterioration in the performance of the CIN.

Although the case studies in Publications II and III focus on a single railway station, the modeling approach can be extended to study larger systems comprising several layers of interconnected networks. Advances in this area can be pursued by building hierarchical models (Gómez et al., 2013; Baiardi et al., 2009) that, for example, subdivide the regional or national railway network into nodes representing railway stations, connected by railway tracks that correspond to edges. In this setting, cost-efficient portfolios of fortification actions at the station level can be aggregated to explore how resources should be allocated more generally to best contribute to the network's overall performance.

Using binary variables to model disruptions assumes that CIN components are operational or disrupted. To model different levels of component functionality more comprehensively, multi-state variables can be introduced to capture intermediate states, for example, allowing components to operate at reduced capacity rather than being simply operational or disrupted (Yingkui and Jing, 2012). A potential challenge with multi-state variables is that the number of CIN's states, defined as combinations of components' states, grows quickly (e.g., if there are three rather than two states at each component in a CIN with n components, the number of CIN's states grows from 2^n to 3^n).

While numerous analytical models have been developed in the context of illicit supply networks, their adoption by decision-makers has been limited. These models are rarely used to guide mitigation strategies because they do not adequately reflect the structure of illicit networks or the resource constraints faced by decision-makers (Price et al., 2022). For example, optimization approaches are often limited in their ability to model endogenous price formation (Murphy et al., 2016). In contrast, equilibrium models are well suited to integrating functional forms for demand and supply that determine prices endogenously, thereby providing greater flexibility to represent situations involving multiple participants (Gabriel et al., 2012). Publication IV shows how equilibrium models, particularly MPEC formulations, can be used to identify portfolios of mitigation strategies to reduce trade volumes in illicit supply networks. The formulation accounts for different structures of illicit supply networks and several mitigation strategies, and therefore can be applied to a wide range of contexts. However, the current formulation cannot yet account for the presence of different hierarchical structures within illicit supply networks. To account for more complex structures, one possible extension is to develop additional equilibrium models, such as equilibrium problems with equilibrium constraints (EPECs) (Ruiz et al., 2014). EPECs can model more complex situations, such as cases in which illicit traders are motivated not only by profit, but also by competition with law enforcement agencies. Nevertheless, EPECs are generally harder to solve than MPECs due to the non-convexity of their feasible region, which may require the development of more efficient algorithms (Leyffer and Munson, 2005).

The illustrative cases presented in this dissertation consider a single CIN type each. Although the framework proposed in Publication I can be extended to account for interdependent CINs, such an extension can be challenging. First, the interdependencies among infrastructures must be explicitly modeled, including physical, cyber, geographic, and logical dependencies (Rinaldi et al., 2001; Buldyrev et al., 2010). For example, accounting for cascading failures across networks can lead to more complex models. Second, CINs often operate on different temporal scales. For example, an electrical failure in a distribution grid can propagate within seconds, whereas disruptions in transportation or water systems can take longer to affect other systems. Integrating such heterogeneous time scales into a single framework requires accurate modeling of dynamic interactions and restoration processes (Pant et al., 2014; Ouyang and Wang, 2015). Third, CINs may be overseen by multiple decision-makers with potentially conflicting objectives and information asymmetries (Rangrazjeddi et al., 2024).

Building on the above discussion, future research can extend the methods presented in this dissertation in several directions. Accounting for interdependent CINs remains an important avenue, requiring appropriate modeling of potential physical, cyber, and administrative dependencies, as well as the representation of failures propagating across CINs operating on different time scales. In addition, incorporating multi-state component representations would enable a more detailed characterization of CIN performance, but these representations can increase computational time, which calls for the development of approaches, such as decomposition methods, to solve the models in a reasonable time.

Further developments in equilibrium-based models of illicit supply networks are needed to account for hierarchical settings, such as those in which illicit traders compete with law enforcement agencies. In this context, exploring cross-disciplinary approaches can help develop more realistic representations of network structure, participant behavior, and the impacts of mitigation strategies. Finally, closing the gap between methodological developments and their practical use is a challenge. Future research can focus on developing methodologies to collaborate with decision-makers, improve transparency, and promote the adoption of decision-support tools.

References

Terje Aven. Implications of black swans to the foundations and practice of risk assessment and management. *Reliability Engineering & System Safety*, 134: 83–91, 2015.

Terje Aven and Ortwin Renn. *Risk Management and Governance: Concepts, Guidelines and Applications*. Risk, Governance and Society. Springer Berlin Heidelberg, 2010.

Fabrizio Baiardi, Claudio Telmon, and Daniele Sgandurra. Hierarchical, model-based risk management of critical infrastructures. *Reliability Engineering & System Safety*, 94(9):1403–1415, 2009.

Kash Barker, Jose Emmanuel Ramirez-Marquez, and Claudio M. Rocco. Resilience-based network component importance measures. *Reliability Engineering & System Safety*, 117:89–97, 2013.

Dimitri Bertsekas. *Nonlinear Programming*, volume 4. Athena Scientific, 2016.

Sergey V. Buldyrev, Roni Parshani, Gerald Paul, H. Eugene Stanley, and Shlomo Havlin. Catastrophic cascade of failures in interdependent networks. *Nature*, 464(7291):1025–1028, 2010.

James C. Chu and Shih-Chi Chen. Optimization of transportation-infrastructure-system protection considering weighted connectivity reliability. *Journal of Infrastructure Systems*, 22(1):04015008, 2016.

Matteo Coronese, Francesco Lamperti, Klaus Keller, Francesca Chiaromonte, and Andrea Roventini. Evidence for sharp increase in the economic damages of extreme natural disasters. *Proceedings of the National Academy of Sciences*, 116(43):21450–21455, 2019.

Luis Dias, Alec Morton, and John Quigley. *Elicitation: The Science and Art of Structuring Judgement*. Springer, 2018.

Leonardo Dueñas-Osorio and Srivishnu Mohan Vemuru. Cascading failures in complex infrastructure systems. *Structural Safety*, 31(2):157–167, 2009.

James S. Dyer and Rakesh K. Sarin. Measurable multiattribute value functions. *Operations Research*, 27(4):810–822, 1979.

Steven A. Gabriel, Antonio J. Conejo, J. David Fuller, Benjamin F. Hobbs, and Carlos Ruiz. *Complementarity Modeling in Energy Markets*, volume 180. Springer Science & Business Media, 2012.

Camilo Gómez, Mauricio Sanchez-Silva, Leonardo Dueñas-Osorio, and David Rosowsky. Hierarchical infrastructure network representation methods for risk-based decision-making. *Structure and Infrastructure Engineering*, 9(3): 260–274, 2013.

Patrick T. Harker. Alternative models of spatial competition. *Operations Research*, 34(3):410–425, 1986.

Ralph Keeney, Howard Raiffa, and David Rajala. *Decisions with Multiple Objectives: Preferences and Value Trade-Offs*. Cambridge University Press, 1993.

Man Cheol Kim. Reliability block diagram with general gates and its application to system reliability analysis. *Annals of Nuclear Energy*, 38(11):2456–2461, 2011.

Sven Leyffer and Todd Munson. Solving multi-leader–common-follower games. *Optimization Methods and Software*, 20(4–5):525–540, 2005.

Juuso Liesiö and Ahti Salo. Scenario-based portfolio selection of investment projects with incomplete probability and utility information. *European Journal of Operational Research*, 217(1):162–172, 2012.

Juuso Liesiö, Pekka Mild, and Ahti Salo. Preference programming for robust portfolio modeling and project selection. *European Journal of Operational Research*, 181(3):1488–1505, 2007.

Zhi-Quan Luo, Jong-Shi Pang, and Daniel Ralph. *Mathematical Programs with Equilibrium Constraints*. Cambridge University Press, 1996.

Alessandro Mancuso, Michele Compare, Ahti Salo, and Enrico Zio. Portfolio optimization of safety measures for the prevention of time-dependent accident scenarios. *Reliability Engineering & System Safety*, 190:106500, 2019.

Frederic Murphy, Axel Pierru, and Yves Smeers. A tutorial on building policy models as mixed-complementarity problems. *Interfaces*, 46, 2016.

Sarah Murray. The critical role of infrastructure for the Sustainable Development Goals. Technical report, The Economist Intelligence Unit, 2019.

John Nash. Non-cooperative games. *Annals of Mathematics*, 54(2):286–295, 1951.

Min Ouyang and Zhenghua Wang. Resilience assessment of interdependent infrastructure systems: With a focus on joint restoration modeling and analysis. *Reliability Engineering & System Safety*, 141:74–82, 2015.

Raghav Pant, Kash Barker, and Christopher W. Zobel. Static and dynamic metrics of economic resilience for interdependent infrastructure and industry sectors. *Reliability Engineering & System Safety*, 125:92–102, 2014.

Ashleigh N. Price, Kevin M. Curtin, Nicholas R. Magliocca, Daniel Turner, Penelope Mitchell, Kendra McSweeney, and Diana L. Summers. A family of models in support of realistic drug interdiction location decision-making. *Transactions in GIS*, 26:1962–1980, 2022.

Jose Emmanuel Ramirez-Marquez and David W. Coit. A Monte-Carlo simulation approach for approximating multi-state two-terminal reliability. *Reliability Engineering & System Safety*, 87(2):253–264, 2005.

Alireza Rangrazjeddi, Andrés D. González, and Kash Barker. Game-theoretic algorithm for interdependent infrastructure network restoration in a decentralized environment. *Risk Analysis*, 44(7):1630–1650, 2024.

Marvin Rausand and Arnljot Hoyland. *System Reliability Theory: Models, Statistical Methods, and Applications*, volume 396. John Wiley & Sons, 2003.

Steven M. Rinaldi, James P. Peerenboom, and Terrence K. Kelly. Identifying, understanding, and analyzing critical infrastructure interdependencies. *IEEE Control System Magazine*, 21, 2001.

Carlos Ruiz, Antonio J. Conejo, J. David Fuller, Steven A. Gabriel, and Benjamin F. Hobbs. A tutorial review of complementarity models for decision-making in energy markets. *EURO Journal on Decision Processes*, 2(1):91–120, 2014.

Ahti Salo and Raimo P. Hämäläinen. Preference assessment by imprecise ratio statements. *Operations Research*, 40(6):1053–1061, 1992.

Ahti Salo, Jeffrey Keisler, and Alec Morton. *An Invitation to Portfolio Decision Analysis*, pages 3–27. Springer New York, 2011.

Ahti Salo, Edoardo Tosoni, Juho Roponen, and Derek W. Bunn. Using cross-impact analysis for probabilistic risk assessment. *Futures & Foresight Science*, 4(2): e2103, 2022.

Paul A. Samuelson. Spatial price equilibrium and linear programming. *The American Economic Review*, 42(3):283–303, 1952.

Ahmad R. Sharafat and Omid R. Ma'rouzi. All-terminal network reliability using recursive truncation algorithm. *IEEE Transactions on Reliability*, 58(2): 338–347, 2009.

Michael Stamatelatos. Probabilistic risk assessment: what is it and why is it worth performing it. *NASA Office of Safety and Mission Assurance*, 4(05), 2000.

Michael Stamatelatos, Homayoon Dezfuli, George Apostolakis, Chester Everline, Sergio Guarro, Donovan Mathias, Ali Mosleh, Todd Paulos, David Riha, and Curtis Smith. Probabilistic risk assessment procedures guide for NASA managers and practitioners. Technical report, National Aeronautics and Space Administration, 2011.

Scott Thacker, Daniel Adshead, Marianne Fay, Stéphane Hallegatte, Mark Harvey, Hendrik Meller, Nicholas O'Regan, Julie Rozenberg, Graham Watkins, and Jim W. Hall. Infrastructure for sustainable development. *Nature Sustainability*, 2(4), 2019.

Edoardo Tosoni, Ahti Salo, Joan Govaerts, and Enrico Zio. Comprehensiveness of scenarios in the safety assessment of nuclear waste repositories. *Reliability Engineering & System Safety*, 188:561–573, 2019.

Eeva Vilkkumaa, Juuso Liesiö, Ahti Salo, and Leena Ilmola-Sheppard. Scenario-based portfolio model for building robust and proactive strategies. *European Journal of Operational Research*, 266(1):205–220, 2018.

Hai Yang, Xiaoning Zhang, and Qiang Meng. Stackelberg games and multiple equilibrium behaviors on networks. *Transportation Research Part B: Methodological*, 41(8):841–861, 2007.

Gu Yingkui and Li Jing. Multi-state system reliability: A new and systematic review. *Procedia Engineering*, 29:531–536, 2012.

Enrico Zio. Reliability engineering: Old problems and new challenges. *Reliability Engineering & System Safety*, 94(2):125–141, 2009.

Enrico Zio. *The Monte Carlo Simulation Method for System Reliability and Risk Analysis*. Springer, 2013.

Enrico Zio. Challenges in the vulnerability and risk analysis of critical infrastructures. *Reliability Engineering & System Safety*, 152:137–150, 2016.

Business, Economy

Art, Design, Architecture

Science, Technology

Crossover

Doctoral Theses

Aalto DT 203/2026

ISBN 978-952-64-3340-0
ISBN 978-952-64-3339-4 (pdf)

Aalto University
School of Science
Department of Mathematics
and Systems Analysis
aalto.fi