

Imperial College London
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**Analysing the Resilience
of Interdependent Infrastructure Systems
with Network Flow Models**

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for the degree of Doctor of Philosophy
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I hereby declare that this thesis and the work reported herein was composed by and originated entirely from me. Information derived from the published and unpublished work of others has been acknowledged in the text and references are given in the list of sources.

Nils Goldbeck

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Abstract

Critical infrastructure systems form the backbone of modern civilisations and must be resilient against natural and anthropogenic hazards. However, the development of effective resilience strategies is often hindered by the insufficient capability of current analytical methods to capture complex interdependencies between different systems. Such interdependencies give rise to the risk of cascading failures and may delay recovery processes, thus exacerbating the impacts of infrastructure disruption. Advanced modelling and simulation methods are needed to address this problem, especially considering the increasing uncertainty in environmental conditions due to global climate change and additional interdependencies expected as a result of emerging technological trends.

Improving quantitative resilience analysis methods requires the development of models for the stochastic failure and repair of interdependent assets that form a system-of-systems. Moreover, dynamic network effects have to be considered in order to evaluate the impact of component failure on the overall ability of infrastructure systems to meet end-user demand. This thesis presents a novel methodology that combines minimum cost flow assignment models for coupled flows on multiple networks, simulation models for cascading failure and optimisation models for the repair of damaged assets.

The proposed methodology is applied to London's metro and electricity networks to analyse their resilience against flooding. Under certain assumptions regarding hazard exposure and repair resource logistics, the results suggest that doubling the capacity to repair damaged assets could increase resilience by 45 %. In comparison, protecting all vulnerable assets so that they are 50 % less likely to suffer damage would increase resilience by 64 %.

Another case study applies the methodology to a supply chain that relies on transportation infrastructure. Results indicate the optimal investment into supply chain capacities and recovery capabilities. The model predicts cost savings of 17 % if contingency repair resources can be shared between different parts of the supply chain.

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Contents

List of Tables	iv
List of Figures	v
Nomenclature	vii
1 Introduction	1
1.1 Background	2
1.2 Research aim and objectives	4
1.3 Thesis structure	6
1.4 Publications related to this work	8
2 Critical infrastructure protection	10
2.1 Infrastructure resilience	11
2.1.1 From risk to resilience	12
2.1.2 Defining resilience	15
2.1.3 Related concepts	18
2.1.4 Resilience assessment frameworks	20
2.1.5 Measuring resilience	20
2.1.6 Infrastructure system performance measures	24
2.1.7 Need for further research	26
2.2 Interdependency of critical infrastructure	27
2.2.1 Empirical evidence	27
2.2.2 Taxonomies of dependency relations	28
2.3 Modelling and simulation approaches	30
2.3.1 Reliability engineering	30
2.3.2 System dynamics	31
2.3.3 Agent-based modelling	31
2.3.4 Game theory	32
2.3.5 Input-output modelling	33
2.3.6 Graph theory	34
2.3.7 Network flow theory	35
2.3.8 Comparison of modelling approaches	36
2.4 Network flow modelling methods	39
2.4.1 Flow assignment methods	39
2.4.2 Coupling of flows in different networks	42
2.4.3 Dynamic flows	43
2.4.4 Network components	44
2.4.5 Repair processes	45

2.4.6	Preparedness	45
2.5	Summary of gaps in current research	46
3	Modelling principles	47
3.1	Network and asset layer	48
3.2	Minimum cost flow assignment	49
3.2.1	Multiple networks	52
3.2.2	Dynamic flows	53
3.2.3	Coupled flows	54
3.3	Resilience metrics	55
3.4	Cascading failure	58
3.4.1	Deterministic models	58
3.4.2	Stochastic models	60
3.5	Recovery	61
3.6	Preparedness	62
3.7	Concluding remarks	62
4	Stochastic simulation of asset failure and repair	64
4.1	Review of Bayesian Network models	65
4.2	DBN-based asset operability modelling method	67
4.2.1	Global and asset variables	68
4.2.2	Dependencies	68
4.2.3	Damage and repair	69
4.2.4	Failure propagation	73
4.3	Data sources and modelling assumptions	74
4.3.1	London Underground Network	74
4.3.2	London Power Network	76
4.3.3	Flood hazard and recovery resources	76
4.4	Model development	79
4.4.1	Asset operability model	80
4.4.2	Network flow model	80
4.5	Simulation results	84
4.5.1	Asset failure	84
4.5.2	Asset repair	85
4.5.3	Unmet demand	87
4.6	Discussion and concluding remarks	91
5	Optimal recovery strategies	93
5.1	Failure propagation scenarios	94
5.1.1	Time-expanded asset-hazard graph	94
5.1.2	Scenario tree generation	96
5.2	Optimal repair and flow assignment	99
5.2.1	Rolling planning horizon	99
5.2.2	Interdependency	100
5.2.3	Linear programming formulation	101
5.3	Data sources and modelling assumptions	104
5.3.1	London Underground Network	104
5.3.2	London Power Network	107
5.3.3	Repair networks	108

5.3.4	Dependency relations	109
5.3.5	Hazard exposure	109
5.4	Model validation	111
5.5	Simulation results	114
5.5.1	Asset failure and repair	114
5.5.2	Unmet demand	115
5.5.3	Value of demand and supply	116
5.6	Sensitivity analysis	118
5.7	Discussion and concluding remarks	119
6	Optimal network capacities	123
6.1	Model overview	124
6.2	Scenario generation using an input-output modelling approach	127
6.3	Multi-stage stochastic programming model	128
6.4	Data sources and modelling assumptions	131
6.4.1	Infrastructure and supply chain network	131
6.4.2	Hazard and failure propagation dependencies	132
6.4.3	Repair network	134
6.5	Simulation results	136
6.5.1	Resilience performance	136
6.5.2	Optimal capacities	138
6.5.3	Cost analysis	141
6.6	Discussion and concluding remarks	142
7	Conclusions and further research	145
7.1	Main findings and contributions	145
7.2	Further research	148
7.2.1	Addressing methodological limitations	148
7.2.2	Addressing further resilience analysis problems	150
7.3	Pathways to impact	151
A	Review of resilience analysis models	153
B	Model parameters used for the case study in Chapter 5	160
C	Copyright permissions	165
	References	166

List of Tables

2.1	Definitions of resilience	16
2.2	Resilience assessment frameworks	21
2.3	Infrastructure performance measures for resilience analysis	25
2.4	Types of dependency relations	29
2.5	Comparison of modelling approaches	37
2.6	State-of-the-art network flow models	40
4.1	Overview of modelling assumptions	79
5.1	Overview of the system-of-systems	105
5.2	Dependency relations	110
5.3	Simulation parameters	114
6.1	Model variables	125
6.2	Node parameters	133
6.3	Link parameters	134
6.4	Random variable parametrisation	134
A.1	Models for analysing the resilience of interdependent infrastructure systems	154
B.1	Parameters for the London Underground Network (LUN) model . . .	161
B.2	Parameters for the London Power Network (LPN) model	162
B.3	Dependency relations	163
B.4	Modelling assumptions	164

List of Figures

1.1	Global socio-economic impacts of disasters between 1998 and 2017 . . .	2
1.2	Overview of key resilience analysis issues	7
2.1	Risk matrix showing extreme weather risks for the London Under-ground syste	14
2.2	Risk matrix showing climate-related risks for the electricity distribu-tion network in London	14
2.3	ISO 31000 risk management process	15
2.4	Resilience loss triangle	18
2.5	Resilience loss triangle concept illustrated with three examples of performance loss and recovery	22
3.1	Basic modelling framework	48
3.2	Fault tree and equivalent hierarchical system of assets	59
3.3	Basic types of recovery models	61
4.1	Graph representation of a Dynamic Bayesian Network (DBN)	66
4.2	Asset operability DBN with two asset types	68
4.3	DBN model for the failure and repair of a generic asset type	69
4.4	DBN model for the failure and repair of one asset with dependency .	73
4.5	Cumulative distribution functions for flood hazard exposure	78
4.6	Asset operability DBN	81
4.7	Number of flood incident	84
4.8	Number of closed metro stations	85
4.9	Asst failure and repair in a typical 30a simulation run	86
4.10	Recovery resource availability in the metro system	87
4.11	Damage probability, repair time and passenger flows for metro stations in the 100a scenario	88
4.12	Total number of journey	89
4.13	Metro network links operating at full capacity	89
4.14	Unmet travel demand	90
4.15	Lost customer hours	90
5.1	Time-expanded asset-hazard graph for the example in Figure 5.3 . . .	95
5.2	Example scenario tree	96
5.3	Example illustrating different types of dependency relations	100
5.4	Map of the critical infrastructure systems	106
5.5	Representation of a metro station with platform nodes, on-train links and walking links	107
5.6	Single-line diagram of a grid supply point with two substations	108

5.7	Infrastructure assets in the two impact zones of the hypothetical flooding incident	111
5.8	Actual and predicted link flows (passengers per hour) in the London Underground Network (LUN)	112
5.9	Total asset inoperability and changes in asset operability	115
5.10	Geographic distribution of disruption impacts zero, two and four hours after the beginning of the flooding incident	116
5.11	Value of demand (VoD) and expected value of supply (VoS)	117
5.12	Value-based system performance index	118
5.13	RLT area for 12 parameter configurations	119
6.1	Two example scenarios of loss and repair of production capacity at a node	126
6.2	Example supply chain network	132
6.3	Repair network	135
6.4	Supply chain performance for 100 scenarios and individual repair resources	137
6.5	Cumulative probability function for the RLT area	137
6.6	Optimal capacities in the supply chain network	139
6.7	Optimal capacities in the repair network	140
6.8	Cost compared to the no-disruption scenario	141

Nomenclature

Sets

A	Assets
A^P	Parallel system assets
A^S	Series system assets
D	Dependencies
D^F	Failure propagation dependencies
D^I	Input dependencies
D^L	Logic dependencies
D^U	Asset utilisation dependencies
E	Links
E^{MC}	Links in multi-commodity networks
E^{SC}	Links in single-commodity networks
H	Hazards
OD	Origin-destination pairs
$P_{o,d}$	Shortest paths between $(o, d) \in OD$
$Q_{i,j}$	Paths that include link $(i, j) \in E$
V	Nodes
V^{MC}	Nodes in multi-commodity networks
V^{SC}	Nodes in single-commodity networks

Variables

$\bar{f}_{i,j}$	Nominal flow capacity of link $(i, j) \in E$
$\bar{g}_i$	Nominal network in-flow capacity at node $i \in V$
$\bar{h}_i$	Nominal storage capacity at node $i \in V$
$\tilde{f}_{i,j}$	Available flow capacity of link $(i, j) \in E$
$\tilde{g}_i$	Available network in-flow capacity at node $i \in V$
$\tilde{h}_i$	Available storage capacity at node $i \in V$
$f_{i,j}$	Flow on link $(i, j) \in E$
g_i	Network in-flow at node $i \in V$
h_i	Inventory at node $i \in V$
u_i	Network out-flow at node $i \in V$

v_i	Network out-flow at node $i \in V$ due to dependencies
w_k	Utilisation of asset $k \in A$
x_k	Damage of asset $k \in A$
y_k	Repair of asset $k \in A$
z_k	Operability of asset $k \in A$

Parameters

$\check{f}_{o,d}$	Demand for OD pair $(o, d) \in OD$
$\check{u}_i$	Demand at node $i \in V$
$\hat{f}_{i,j}$	Maximum flow capacity of link $(i, j) \in E$
$\hat{g}_i$	Maximum network in-flow capacity at node $i \in V$
$\hat{h}_i$	Maximum storage capacity at node $i \in V$
$c_{i,j}^f$	Cost for flow on link $(i, j) \in E$
c_i^g	Cost for generation at node $i \in V$
c_i^h	Cost for inventory at node $i \in V$
$c_{o,d}^{MC}$	Value of satisfying demand between OD pair $(o, d) \in OD$
c_i^{SC}	Value of satisfying demand at node $i \in V$
$\bar{c}_{i,j}^f$	Cost for flow capacity on link $(i, j) \in E$
$\bar{c}_i^g$	Cost for generation capacity at node $i \in V$
$\bar{c}_i^h$	Cost for inventory capacity at node $i \in V$
$t_{\max}$	Length of simulation period
t_p	Length of planning horizon
t_h	Time at which hazard event $h \in H$ occurs

Derived metrics

MSP	Minimum system performance
RL	Resilience loss
TLD	Total length of disruption
VoD	Value of demand
VoS	Value of supply

Chapter 1

Introduction

Civil infrastructure networks are largely responsible for maintaining the security, well-being and prosperity of modern societies. While infrastructure milestones, such as the opening of a new bridge or metro line, receive widespread public attention, the ubiquitous infrastructure systems that people use in their daily lives remain mostly unnoticed – until they fail to function as expected. Then societies become painfully aware of the many ways in which they rely on infrastructure, and of the complexity and interconnectedness of different systems.

This thesis is motivated by the idea that infrastructure systems should remain unnoticed by most people most of the time, adopting Mau’s (2004) view that “the secret ambition of design is to become invisible, to be taken up into a culture, absorbed into the background”. However, in light of foreseeable environmental, societal and technological changes giving rise to new threats and greater uncertainty, it is important to realise that critical infrastructure systems are “precarious achievements” and “processes that have to be worked toward” (Graham, 2010).

The emerging concept of infrastructure resilience is a promising development regarding the future-proofing of infrastructure. This thesis investigates how the full potential of resilience approaches can be unlocked with quantitative modelling and simulation methods for assessing and strengthening the resilience of infrastructure, particularly focussing on the role of interdependencies between different systems.

1.1 Background

Infrastructure systems that are vitally important for the nominal function of a society are also referred to as critical or lifeline infrastructure systems (Chang, 2016). The collapse of these systems is characteristic for disasters (e.g. earthquakes, floods, storms) and can result in catastrophic socio-economic impacts. Between 1998 and 2017, disasters have affected 4.4 billion people and caused 1.3 million fatalities worldwide (CRED and UNISDR, 2018). Figure 1.1 shows that floods have the highest impact in terms of people affected, earthquakes in terms of fatalities, and storms in terms of economic losses.

The direct economic losses estimated by CRED and UNISDR (2018) amount to an average of US\$ 145 billion per annum. These economic losses occur mostly in the world's wealthiest countries, although the number of people affected by disasters is much higher in poorer countries. Therefore, the global impact of disasters is even greater when taking into account socio-economic impacts beyond asset losses. According to the World Bank (2017), disasters cause a global well-being loss that is estimated to exceed US\$ 520 billion per annum.

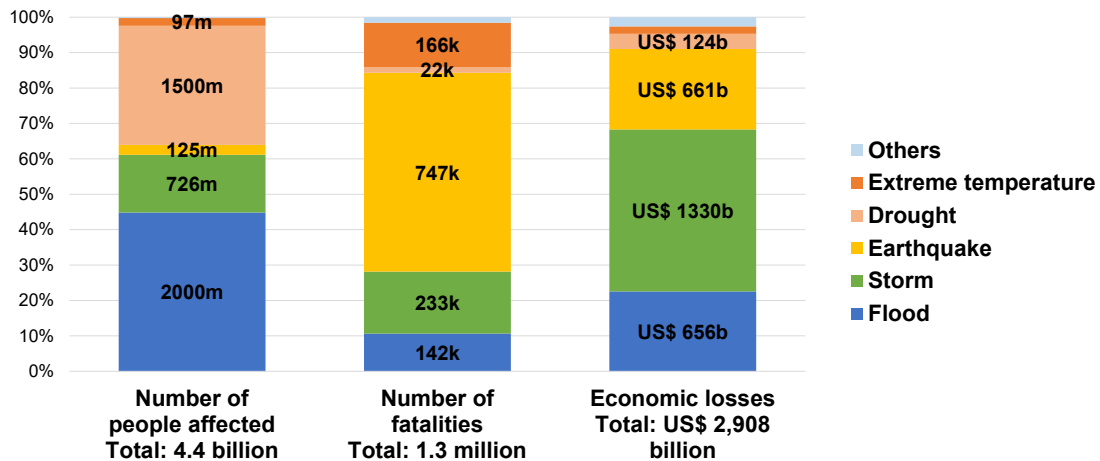


Figure 1.1: Global socio-economic impacts of disasters between 1998 and 2017 based on data from CRED and UNISDR (2018)

Over the coming decades, global climate change is expected to further increase the risk of extreme weather events (IPCC, 2014). For instance, the risk of major fluvial flooding incidents is increasing in many parts of the world (Willner et al.,

2018). More extreme hourly rainfall intensities are expected to increase the risk of flash flooding in the UK (Kendon et al., 2014). In the Atlantic, high-intensity hurricanes are predicted to occur more often (Bender et al., 2010; Knutson et al., 2010). Adapting the protection of critical infrastructure to these environmental changes is particularly difficult because the stakes are extremely high and decisions for very long planning horizons have to be made under great uncertainty.

While climate-related and geophysical disasters result in the most extreme cases of infrastructure collapse, smaller incidents occur much more frequently and can also have severe impacts on local communities. For example, in 2015 a fire started in an underground electrical sub-station in central London (BBC, 2015). The fire damaged a natural gas pipeline, which added more fuel and made it more difficult to get the fire under control. It took 36 hours to extinguish the fire and several thousand people had to be evacuated from surrounding business premises and homes, despite a relatively small geographic area affected. Other infrastructure systems also were disrupted, including a metro station, road transport and telecommunication services. Backup diesel generators had to supply power to the area for two weeks, and the costs for businesses were estimated to be £ 40 million (Evening Standard, 2015).

The fact that a relatively small incident, such as a technical fault, can escalate and cause disruptions in multiple critical infrastructure systems is linked to the existence of complex interdependencies between those systems. The seminal paper by Rinaldi et al. (2001) was one of the first to provide a systematic analysis of critical infrastructure interdependencies and the associated challenges for risk management. The paper identifies an accelerating trend of increasing interconnectedness and highlights the need for interdependency risks to be addressed by strategies for protecting critical infrastructure.

Many factors contribute to the increasing interdependency of infrastructure systems. One is the continued trend of global urbanisation (United Nations, 2014). The concentration of infrastructure assets in dense urban spaces increases interdependency

due to geographic proximity. Another factor is that more and more activities in modern societies are dependent on electric power supply. In the UK, electricity demand is predicted to increase by 26 to 48 % until 2050 (National Grid, 2018). This is mainly due to the electrification of transport, with around 36 million electric vehicles expected to consume 65 to 89 TWh electricity per annum.

Furthermore, infrastructure systems are increasingly reliant on information and communication technologies. In the transport sector, the emerging concepts of mobility-as-a-service, intelligent transportation systems, and connected and autonomous vehicles promise to make mobility more accessible and economic while also reducing environmental impacts. However, the interfaces required by these concepts between transport and other infrastructure systems (e.g. global navigation satellite systems, traffic control, mobile communication networks) also create new vulnerabilities (Zhao et al., 2012; Petit and Shladover, 2015; Saxena et al., 2017; Sheehan et al., 2018). In the energy sector, smart electricity grids increase the efficiency of power supply and facilitate the integration of renewable energy sources, but also increase interdependency and give rise to new risks, such as cyber attacks on electricity distribution networks (Wang and Lu, 2013).

To summarise, changing environmental conditions, the expansion and densification of cities and increasing technological interconnectedness pose great challenges for managing the risks of infrastructure disruptions. If infrastructure planners and operators do not succeed in adapting to these trends, for example by embracing resilience approaches, the socio-economic impacts of infrastructure failure are bound to become even higher.

1.2 Research aim and objectives

As a concept, infrastructure resilience emerged in response to the need for new approaches for critical infrastructure protection in light of greater complexity and uncertainty resulting from environmental, societal and technological changes. Many government authorities and infrastructure companies are currently seeking to develop

resilience strategies. However, they mostly rely on qualitative resilience analysis frameworks, due to the lack of quantitative modelling and simulation methods that are mature enough to support practical decision-making by providing insight (understanding of resilience phenomena) and foresight (resilience predictions).

The aim of this thesis is to develop new methods for analysing the resilience of critical infrastructure systems with the help of quantitative models. A particular focus is put on capturing the effects of interdependencies between different systems. The results of this research contribute to the scientific knowledge about mechanisms that impact the resilience of infrastructure systems and inform the model-based development of resilience improvement strategies. In order to attain this aim, the following research objectives are defined:

1. Survey current quantitative methods for analysing the resilience of interdependent infrastructure systems
2. Develop new modelling and simulation methods, focussing in particular on
 - (a) network components as repairable assets
 - (b) interdependencies on the network and asset levels
 - (c) dynamic effects of cascading failure and system restoration
 - (d) optimal recovery and preparedness strategies
3. Demonstrate the application of the proposed modelling methods

The sub-objectives for developing new methods are based on the limitations of existing methods that were identified in the literature review (ref. Chapter 2).

The primary contribution of this thesis is a new modelling method that considers repairable assets in network flow models of interdependent infrastructure systems. This methodological advancement extends the scope and realism of resilience analysis compared to state-of-the-art modelling approaches, and enables three secondary contributions: i) more detailed analysis of dynamic effects, ii) more realistic representation of interdependency, and iii) mathematical optimisation of recovery and preparedness decisions.

1.3 Thesis structure

The core structure of this thesis is as follows:

Chapter 2 presents a literature survey of current methods for analysing the resilience of interdependent infrastructure systems.

Chapter 3 develops general modelling principles, including a dynamic minimum cost flow (MCF) assignment model for interdependent networks.

Chapter 4 presents a resilience assessment method based on combining an MCF model and stochastic simulation of asset failure and repair using Dynamic Bayesian Networks.

Chapter 5 considers optimal recovery strategies by extending the MCF assignment to repair resource logistics and modelling flow assignment and repair scheduling with a rolling planning horizon.

Chapter 6 further extends the MCF assignment method with a stochastic programming method for optimising capacity investment decisions, enabling the model to analyse resilience trade-offs between redundancy and recovery.

Chapter 7 offers concluding remarks and an outlook on future research.

The modelling principles (Chapter 3) can be seen as building blocks for developing resilience analysis models. They can be implemented and combined according to the requirements of different applications. The most basic building block is the minimum cost flow assignment method, which is used throughout Chapters 4 to 6.

Figure 1.2 illustrates the scope of resilience analysis models presented in this thesis. All three models consider dynamic network flows under the uncertainty of asset operability due to the risk of cascading failures. Chapter 5 additionally addresses the issue of optimal recovery strategies with a model of how infrastructure operators prioritise the allocation of repair resources. In other words, this chapter focusses mainly on post-disruption decision-making.

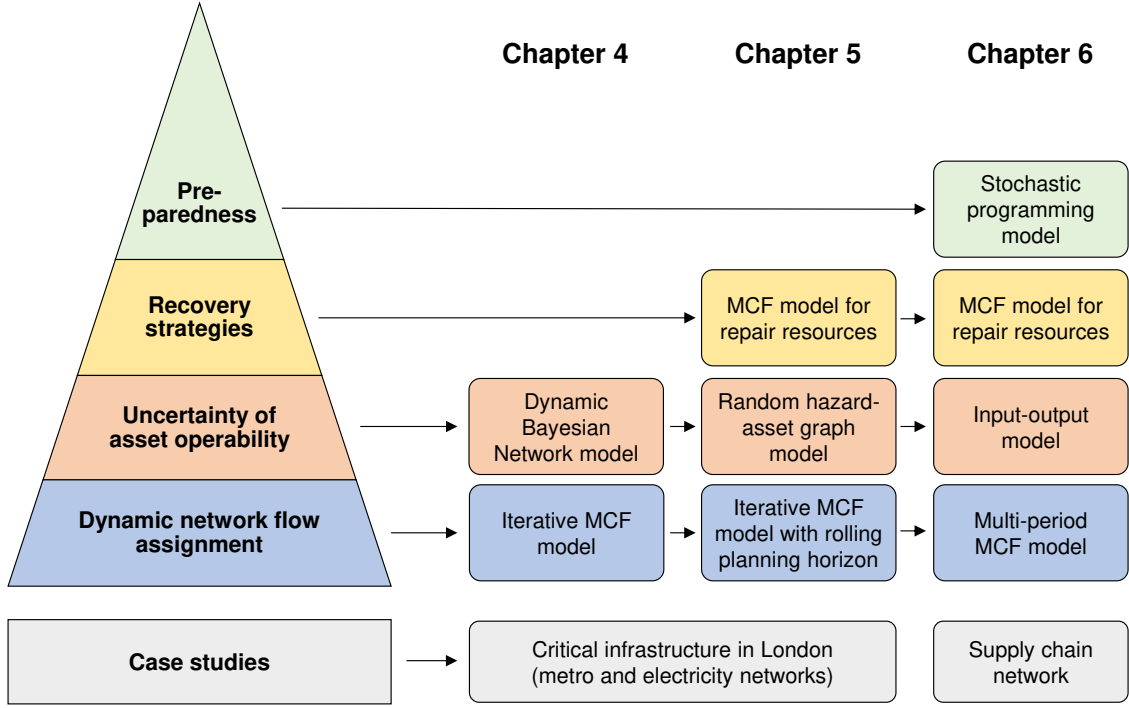


Figure 1.2: Overview of key resilience analysis issues addressed in Chapters 4 to 6

Chapter 6 expands the scope to consider both pre- and post-disruption decision, thereby addressing the issue of preparedness. Pre-disruption decisions include investments in network capacities (i.e. redundancy) and recovery capabilities.

However, this structure does not imply that a more comprehensive resilience analysis is always preferable. Determining the right scope is the first task of every resilience analysis and depends on the goals and constraints of the individual application. This thesis seeks to provide modelling methods that can be applied to different resilience analysis tasks.

The case studies presented in Chapters 4 and 5 demonstrate that the proposed models are capable of analysing the resilience of full-scale, real-world urban infrastructure systems by applying them to two critical infrastructure systems in London, the London Underground and London Power Networks. The purpose of the case study in Chapter 6 is to demonstrate that infrastructure resilience analysis methods can also be applied to analyse the infrastructure underlying modern supply chains.

1.4 Publications related to this work

The research presented in this thesis has led to the following publications:

Papers published in international journals:

- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2019), ‘Resilience assessment for interdependent urban infrastructure systems using dynamic network flow models’, *Reliability Engineering and System Safety* **188**, 62–79. DOI: 10.1016/j.res.2019.03.007
- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2020), ‘Optimal supply chain recovery strategies with consideration of failure propagation and repair logistics’, *Transportation Research Part E: Logistics and Transportation Review* **133**. DOI: 10.1016/j.tre.2019.101830.
- Achurra-Gonzalez, P. E., Angeloudis, P., Goldbeck, N., Graham, D. J., Zavitsas, K. and Stettler, M. E. J. (2020), ‘Evaluation of port disruption impacts in the global liner shipping network’, *Journal of Shipping and Trade* **4**. DOI: 10.1186/s41072-019-0043-8.

Papers currently in review:

- Escribano, J., Goldbeck, N., Hsu, P.-Y., Angeloudis, P. and Ochieng, W. Y. (n.d.), ‘Endogenous stochastic optimisation for relief distribution assisted with UAVs’, *OR Spectrum* (submitted).

Book chapters:

- Goldbeck, N. and Angeloudis, P. (2018), Civil Engineering: Unlocking the potential of future cities through sustainable and resilient infrastructure, in D. Iossifova, C. N. Doll and A. Gasparatos (eds), ‘Defining the Urban: Interdisciplinary and professional perspectives’, Routledge, chapter 11. DOI: 10.4324/9781315576282

Papers published in conference proceedings:

- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2016a), Analysing the resilience of metro systems under consideration of interdependencies: A combined Dynamic Bayesian Network and network flow approach, in ‘Proceedings of the 14th World Conference on Transport Research in Shanghai’.

- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2016*b*), Joint Vulnerability Analysis of Urban Rail Transit and Utility Networks, *in* ‘Transportation Research Board 95th Annual Meeting Compendium of Papers’. URL: <https://trid.trb.org/view/1394243>
- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2017), A Dynamic Network Flow Model for Interdependent Infrastructure and Supply Chain Networks with Uncertain Asset Operability, *in* T. Bektas, S. Coniglio, A. Martinez-Sykora and S. Voß (eds), ‘Computational Logistics. ICCL 2017. Lecture Notes in Computer Science, vol 10572.’, Springer, pp. 513–528. DOI: 10.1007/978-3-319-68496-3_34

Academic presentations at international conferences (posters and talks):

- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2015), ‘Analysis of cascading failures across interdependent dynamic networks’, European Operations Research Conference (EURO) in Glasgow.
- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2017*b*), ‘Modelling the Dynamics of Asset Operability and Network Flows in Interdependent Infrastructure Systems after Disruptive Events’, 3rd International Conference on Dynamics of Disasters (DoD) in Kalamata.
- Goldbeck, N. (2018), ‘Resilience assessment for interdependent infrastructure systems: A dynamic network flow model’, 50th Annual Conference of the Universities’ Transport Study Group (UTSG) in London.
- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2018*a*), ‘A flow-based resilience assessment method for interdependent urban infrastructure networks’, International Conference on Infrastructure Resilience in Zurich.
- Goldbeck, N., Angeloudis, P. and Ochieng, W. Y. (2018*b*), ‘Analysing the effects of interdependency on the resilience of urban transport systems: A dynamic network flow approach’, 7th International Symposium on Transportation Network Reliability (INSTR) in Sydney.

Chapter 2

Critical infrastructure protection

This chapter presents a review of previous research on critical infrastructure protection (CIP), with a particular focus on quantitative modelling and simulation methods. Section 2.1 introduces the concept of infrastructure resilience and Section 2.2 reviews empirical and theoretical research on the role of interdependencies. Section 2.3 discusses the main modelling approaches and Section 2.4 focusses on state-of-the-art network flow models. The chapter concludes with a summary of research gaps in Section 2.5.

Critical infrastructure refers to “assets, networks, and systems in the built environment that provide essential services for social and economic activities” (Chang, 2016). The term “lifeline” systems is also used, highlighting the importance of critical infrastructure during disasters (O’Rourke, 2007).

Services provided by critical infrastructure include protection against natural and man-made hazards, transportation of passengers and freight, the supply of water and energy, disposal of waste and wastewater, communication services, public health and security (Chang, 2016). Many of these infrastructure services have the characteristic properties of a natural monopoly (high capital costs, significant market entry barriers), prompting the need for government intervention in the form of nationalisation or regulation (Mosca, 2008). Thus, most infrastructure systems are owned and operated by government authorities, state-owned enterprises or heavily-regulated private-sector companies.

Critical infrastructure is sometimes divided into hard and soft infrastructure (Egan, 2007; O’Sullivan et al., 2013). Hard infrastructure refers to the built environment and often to large-scale systems, such as transportation networks. Soft infrastructure is better described as a set of institutions, such as health and security services. However, it is important to keep in mind that soft infrastructure also requires physical assets, and that hard infrastructure systems are managed by institutions.

The protection of critical infrastructure is a key responsibility of governments and many countries have national authorities that take responsibility for coordinating CIP efforts. The US launched a national programme for CIP in 1998 with the Presidential Decision Directive PDD-63, drawing attention for the first time to increasing vulnerabilities arising from interdependency (National Security Council, 1998). In the UK, the Centre for the Protection of National Infrastructure (CPNI) coordinates CIP activities. Its mission is “to protect national security by helping to reduce the vulnerability of the national infrastructure to terrorism and other threats” (CPNI, n.d.). Governments also collaborate internationally for the protection of critical infrastructure, for example, in the European Programme for Critical Infrastructure protection (European Commission, 2006).

2.1 Infrastructure resilience

Resilience is derived from the Latin word *resilio*, which means to jump back (Klein et al., 2003). In the 1940s the term became popular in the fields of psychology and psychiatry and in the 1970s it was adopted by researchers in ecology (Manyena, 2006). In the context of infrastructure systems, the term resilience began to be used around the year 2000, as researchers focussed on overcoming limitations of more conventional risk management approaches to critical infrastructure protection.

2.1.1 From risk to resilience

CIP can be seen as a form of risk management. The pre-condition for risk is a hazard, which is a “source of potential harm” (Ayyub, 2014). Hazards can be endogenous (failures within the system) or exogenous (events in the environment).

Hazards become risks if a valuable asset or process is exposed to them and vulnerable. So-called “natural” disasters are only disasters because of man-made socio-economic conditions, such as insufficient precautionary planning (O’Keefe et al., 1976). The following equations are often used to describe risk as a product of risk factors (Roberts et al., 2009):

$$\text{Risk} = \text{Hazard} \times \text{Vulnerability} \quad (2.1)$$

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability} \quad (2.2)$$

$$\text{Risk} = \frac{\text{Hazard} \times \text{Exposure} \times \text{Vulnerability}}{\text{Coping capacity}} \quad (2.3)$$

However, such risk factors are difficult to quantify in practice. For example, coping capacity in Equation (2.3) is defined as “aptitude of an element to reduce negative impact from a threat through short term response” but it is unclear how it is measured (Roberts et al., 2009).

Most quantitative risk assessment methods are based on a risk concept that focusses on probabilities and consequences, rather than sources of risk:

$$\text{Risk} = \text{Probability} \times \text{Consequence} \quad (2.4)$$

Kaplan and Garrick (1981) introduced the notion of risk as a set of triplets, each consisting of a scenario, its probability and its impact. According to this influential concept, risk assessments have to answer the following questions:

1. What can go wrong?
2. How likely is this to happen?

3. If it does happen, what are the consequences?

A two-dimensional plot of this information is referred to as risk matrix or risk map and is a standard feature of most practical risk assessments. For example, Figures 2.1 and 2.2 show risk matrices for the metro and electricity networks in London. Both were created by the infrastructure companies to better understand the risks related to global climate change.

Based on systematic risk assessments, infrastructure companies and government authorities can devise risk management plans, which determine how each individual risk is treated. Risk management options are to avoid (eliminate), reduce (mitigate), transfer (share) or accept a risk (Vose, 2008).

The risk management process is standardised in ISO 31000 (BS ISO, 2018). In addition to risk assessment and treatment, the process also includes communication, consultation, recording, reporting, monitoring and review tasks (ref. Figure 2.3).

The ISO risk management process and similar approaches are widely used in practice by organisations seeking to protect their assets and operations, including owners and operators of infrastructure assets. However, it has the following limitations:

- Uncertainties regarding the probability and impact of hazards as well as the effectiveness of risk treatment measures are not addressed.
- Interdependencies and trade-offs between different risks and treatment options are not considered.
- The possibility of unknown risks is not addressed.

As discussed in Section 1.1, global warming leads to higher uncertainty of climate-related risk. At the same time, the complexity and interdependency of critical infrastructure systems is increasing due to technological developments, such as increasing reliance on ICT and electrification of road transport. In many cities, further complexity is added by the pressure of urban growth, the societal need to reduce environmental impacts and the fragility of ageing infrastructure assets. All these issues threaten the effectiveness of CIP strategies if they are solely based

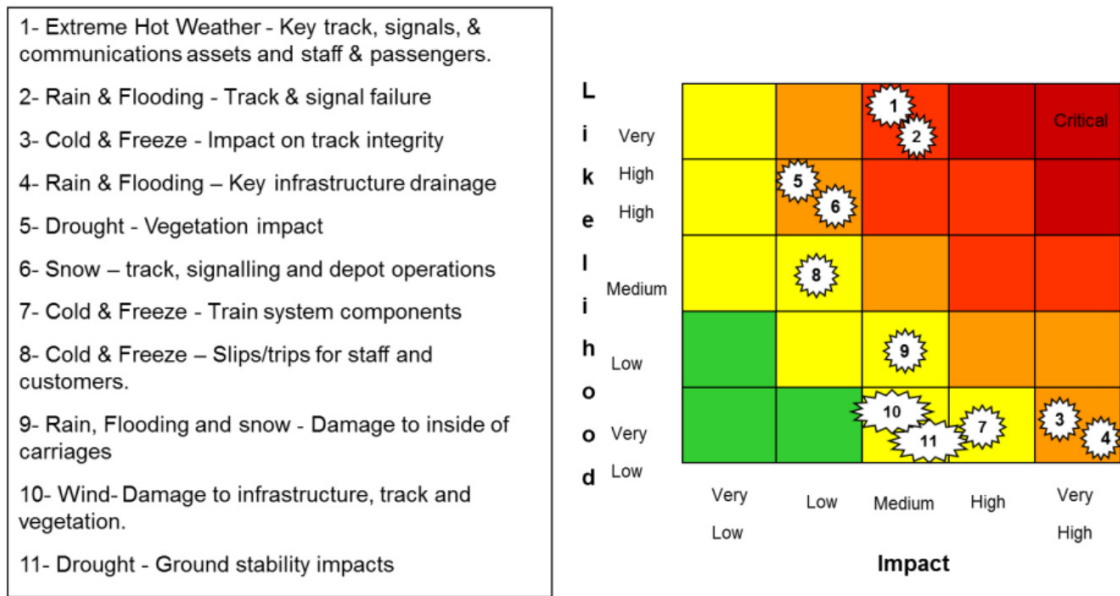


Figure 2.1: Risk matrix showing extreme weather risks for the London Underground system (adapted from Transport for London, 2015b)

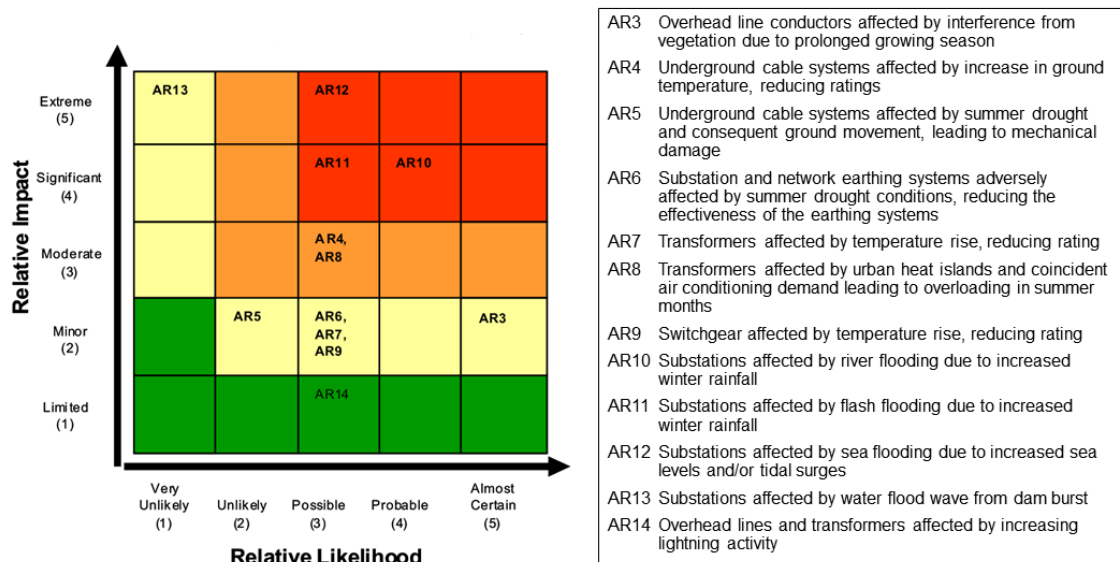


Figure 2.2: Risk matrix showing climate-related risks for the electricity distribution network in London (adapted from UK Power Networks, 2014)

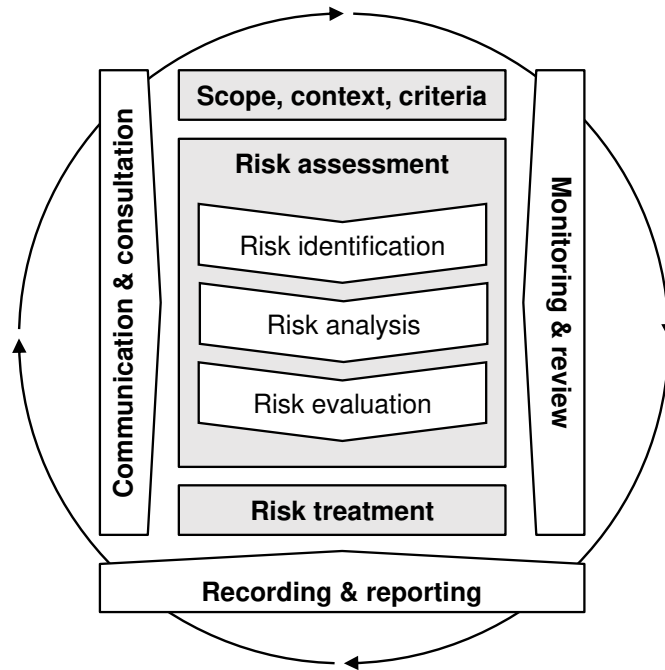


Figure 2.3: ISO 31000 risk management process (adapted from BS ISO, 2018)

on conventional risk management approaches. Future-proof CIP strategies have to embrace resilience approaches that are capable of addressing high levels of uncertainty and interdependency.

2.1.2 Defining resilience

Instead of focussing on assessing and treating all risks, resilience approaches aim to strengthen the capabilities of infrastructure systems to cope with disruptions. This addresses the problem that highly uncertain risks can often not be completely avoided, controlled or transferred (at least with practical budget constraints). However, many of these risks are also too severe to accept because of the potentially very harmful consequences in worst-case scenarios.

There exist different definitions for resilience, as Table 2.1 shows. Most of them address the following four questions:

What is resilient? Many definitions describe resilience as a property of a generic system, leaving it open where to draw the system boundaries. Resilience can also be considered a property of communities or societies (Manyena, 2006;

Table 2.1: Definitions of resilience

Definition	Source
Resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist.	Holling (1973)
Ability of the system to reduce the chances of a shock, to absorb a shock if it occurs (abrupt reduction of performance) and to recover quickly after a shock (re-establish normal performance)	Bruneau et al. (2003)
The ability to respond to singular or unique events.	Kendra and Wachtendorf (2003)
The capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks.	Walker et al. (2004)
The capability of a system to maintain its functions and structure in the face of internal and external change and to degrade gracefully when it must.	Allenby and Fink (2005)
The intrinsic capacity of a system, community or society predisposed to a shock or stress to adapt and survive by changing its non-essential attributes and rebuilding itself.	Manyena (2006)
The ability of a system to withstand a major disruption within acceptable degradation parameters and to recover within an acceptable time and composite costs and risks.	Haimes (2009)
The ability of a system, community or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the preservation and restoration of its essential basic structures and functions.	UNISDR (2009)
The joint ability of infrastructure systems to resist (prevent and withstand) any possible hazards, absorb the initial damage, and recover to normal operation	Ouyang et al. (2012)
City resilience describes the capacity of cities to function, so that the people living and working in cities – particularly the poor and vulnerable – survive and thrive no matter what stresses or shocks they encounter.	Arup (2014)
Resilient cities can absorb shocks (from extreme events, such as natural disasters) while still maintaining function (in terms of providing the basis for well-being of residents).	Chang et al. (2014)
The capacity of individuals, communities, institutions, businesses, and systems within a city to survive, adapt, and grow no matter what kinds of chronic stresses and acute shocks they experience.	100 Resilient Cities (2016)

UNISDR, 2009). When resilience is applied to cities, the term urban resilience is commonly used, and individuals, institutions and businesses could be included in the definition (100 Resilient Cities, 2016).

Against what is it resilient? Definitions vary with regards to how specific they describe the condition or event against which something is resilient. Terms used include “change” (Holling, 1973; Allenby and Fink, 2005), “disturbance” (Walker et al., 2004), “major disruption” (Haimes, 2009), “singular or unique event” (Kendra and Wachtendorf, 2003), “shock” (Bruneau et al., 2003; Chang et al., 2014), “shock or stress” (Manyena, 2006; Arup, 2014; 100 Resilient Cities, 2016), and “hazard” (UNISDR, 2009; Ouyang et al., 2012).

How is it resilient? Different verbs are used to describe the behaviour of resilient systems, including to “absorb” (Holling, 1973), “withstand” (Haimes, 2009) “respond” (Kendra and Wachtendorf, 2003), “recover” (Bruneau et al., 2003), “reorganize” (Walker et al., 2004), and “adapt” (Manyena, 2006). Many definitions make reference to multiple ways in which systems can be resilient.

What is the outcome of resilience? Some definitions include outcomes of systems being resilient, for example, that they survive (Manyena, 2006; Arup, 2014; 100 Resilient Cities, 2016) or that they maintain their core function (Walker et al., 2004; Allenby and Fink, 2005; Chang et al., 2014).

A common theme in the reviewed resilience definitions is the recognition that risk can very rarely be eliminated, and the emphasis on coping and mitigation capabilities. As a synthesis of the available literature, the remainder of this thesis adopts the definition that infrastructure resilience means the ability of infrastructure systems to withstand or absorb disturbances and to recover quickly after potential disruptions, such that the expected loss of system performance for a certain hazard scenario is minimised.

One of the most widely recognisable visual definitions of resilience is the resilience loss triangle, illustrating how the initial loss of system performance and the recovery

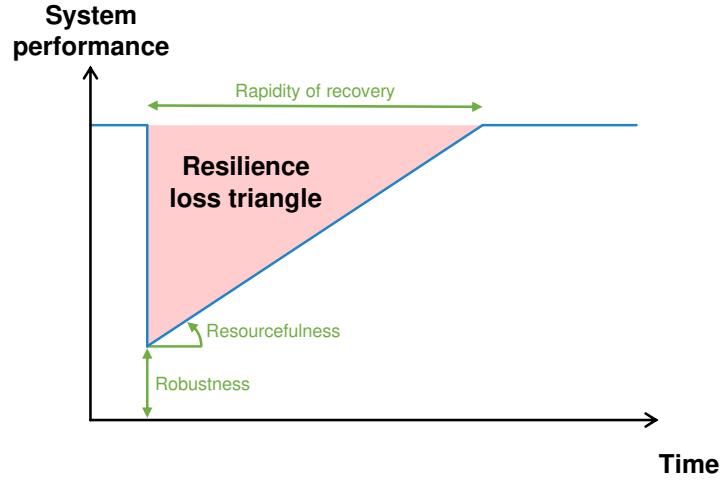


Figure 2.4: Resilience loss triangle

path determine the overall impact of a disruption (Figure 2.4). This concept provides the basis for many quantitative definitions of resilience, which will be discussed further in Section 2.1.5.

2.1.3 Related concepts

In the following section, we discuss related concepts to further clarify the terminology around infrastructure resilience.

Robustness

Robustness of an infrastructure network can be defined as “the extent to which, under pre-specified circumstances, a network is able to maintain the function for which it was originally designed” (Snelder et al., 2012). Robustness is included in the proposed resilience definition as the ability to withstand or absorb disturbances. If it was possible to design a perfectly robust system there would be no need for recovery capability and the system could also be considered perfectly resilient. However, the resilience concept acknowledges that perfect robustness is not realistic and that both robustness and recovery capabilities are needed.

Stability

Systems that are stable in the presence of disruptions can also be considered resilient, but the opposite is not generally true. In his seminal paper on ecological resilience, Holling (1973) points out that systems that regularly change and adapt to new circumstances are often more resilient to acute shocks than stable systems that have not experienced change processes before.

Reliability, availability and dependability

Resilience is related to several concepts in the field of system reliability theory. Rausand and Høyland (2004, p. 5 ff.) provide the following definitions (based on standards like ISO 8402 and BS 4778):

Reliability The ability of an item to perform a required function, under given environmental and operational conditions and for a stated period of time.

Availability The ability of an item (under combined aspects of its reliability, maintainability and maintenance support) to perform its required function at a stated instant of time or over a stated period of time.

Dependability The collective term used to describe the availability performance and its influencing factors: reliability performance, maintainability performance and maintenance support performance.

These definitions overlap and the terms are sometimes used interchangeably. Important quantitative measures for reliability include meant time to failure (MTTF), failure rate and survival probability (Rausand and Høyland, 2004, p. 8).

Reliability engineering focusses on modelling failure and repair processes with statistical methods, which are also useful for resilience analysis. However, several important resilience issues are not addressed by classical reliability engineering, for example, decisions taken during the recovery period or trade-offs between strengthening reliability and recovery capabilities. Thus, resilience can be seen as a concept

that extends classical reliability engineering, much like it extends conventional risk management.

Anti-fragility

The concept of anti-fragility was introduced by Taleb (2012) and describes the characteristic of a system to gain and not to lose from disorder. If resilience describes the ability to "bounce back" then anti-fragility describes the ability to "bounce forward".

2.1.4 Resilience assessment frameworks

Resilience assessment frameworks provide structured approaches for the analysis of resilience, usually by defining performance areas (also referred to as resilience dimensions). Table 2.2 presents four examples of resilience assessment frameworks. The first three examples are from academic publications and rather theoretical. The City Resilience Index (Arup, 2014) is more practically oriented and an online platform has been developed to facilitate the data gathering process. It provides a multi-level structure with four dimensions, 12 goals, 52 indicators and 156 variables.

Resilience assessment frameworks are instrumental in developing a conceptual understanding of mechanisms that make systems more or less resilience. However, it is important to keep in mind that these frameworks are based on prior knowledge and / or value-based decisions regarding the selection and weighting of performance areas and indicators.

2.1.5 Measuring resilience

In this section, we present the results of a literature survey on quantitative assessment methods for resilience. Similar reviews have been carried out by Hosseini et al. (2016) and Sun et al. (2018), whose results were also considered.

Resilience can be measured with indicator systems based on resilience assessment frameworks, such as the City Resilience Index (Arup, 2014). Another example is the

Table 2.2: Resilience assessment frameworks

Framework	Dimension	Description
Framework to quantitatively assess and enhance the seismic resilience of communities (Bruneau et al., 2003)	Robustness	Strength, or the ability to withstand a given level of stress or demand without suffering degradation or loss of function
	Redundancy	Extent to which elements exist that are substitutable
	Resourcefulness	Capacity to identify problems, establish priorities, and mobilise resources when conditions exist that threaten to disturb some elements or systems
	Rapidity	Capacity to meet priorities and achieve goals in a timely manner
Resilience in social-ecological systems (Walker et al., 2004)	Latitude	Maximum amount a system can be changed before losing its ability to recover
	Resistance	Ease or difficulty of changing the systems
	Precariousness	How close the current state of the system is to a limit
	Panarchy	Exposure to influences from states and dynamics at scales above and below a system
Three-stage resilience analysis framework (Ouyang et al., 2012)	Resistant capacity	Hazard frequency and initial damage level
	Absorptive capacity	Maximum impact level
	Restorative capacity	Recovery time and cost
City resilience framework (Arup, 2014)	Infrastructure & environment	Reduced physical exposure, continuity of critical services, increased reliability of mobility and communication
	Economy & society	Finance including contingency funds, social stability and security, collective identity and mutual support
	Health & wellbeing	Safeguards to human life and health, livelihoods and employment, minimal human vulnerability
	Leadership & strategy	Integrated development planning, empowered stakeholders, effective leadership and management

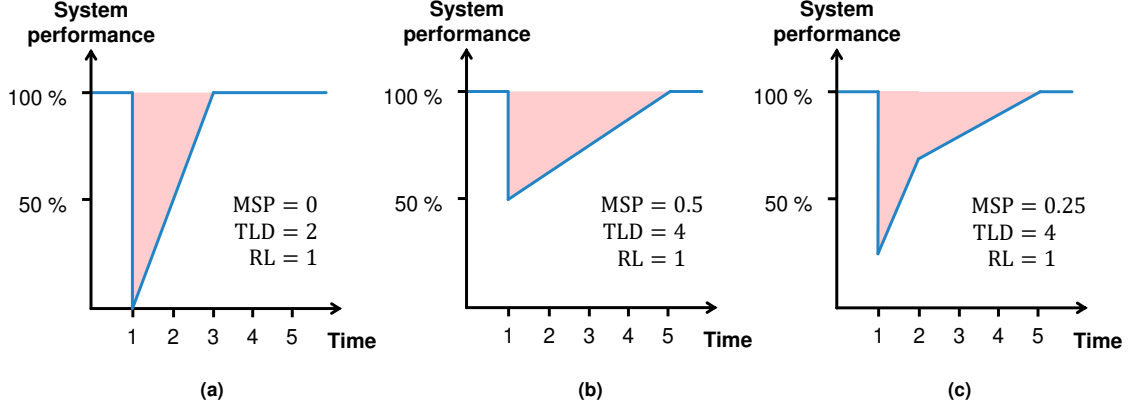


Figure 2.5: Resilience loss triangle concept illustrated with three examples of performance loss and recovery

survey method proposed by Shirali et al. (2013), which is based on a framework with six dimensions and contains 61 indicators. Such indicator systems are mostly used in empirical resilience assessments.

Another common approach to quantify resilience, especially in modelling and simulation methods, is to use a system performance function. This reflects the central role that many resilience definitions give to the system's ability to maintain its functionality. Bruneau et al. (2003) introduced the resilience loss metric, which measures the loss of system performance integrated over the recovery time. We denote the system performance measure with $P(t)$ and assume that it is normalised to values between 0 and 1. The resilience loss metric is then defined as

$$RL = \int_{t_0}^{t_{\max}} (1 - P(t)) dt \quad (2.5)$$

where t_0 is the beginning of the disruption and $t_{\max}$ is the time of full recovery. In cases where the system performance never recovers to a value of 1, the resilience loss metric could either be considered infinite or undefined.

Figure 2.5 depicts three examples of system degradation and recovery, each with the same resilience loss value. The resilience loss metric is also referred to as the area of the resilience loss triangle because the shaded area takes a triangular shape if performance loss is a step change and recovery a linear process, as in sub-figures

(a) and (b). In this case, the resilience loss can be calculated based on the minimum system performance (MSP) and the total length of disruption (TLD):

$$RL = \frac{1}{2} \times (1 - MSP) \times TLD \quad (2.6)$$

This shows how the resilience loss metric incorporates robustness (indicated by the MSP) and recovery capability (indicated by the TLD), the two main resilience factors in many definitions and frameworks.

Similar metrics can be defined by relating the actual system performance to a pre-defined target performance. An example is the time-dependent expected annual resilience metric defined by Ouyang et al. (2012) as

$$AR = E \left[\frac{\int_0^{t_{\max}} P(t)dt}{\int_0^{t_{\max}} TP(t)dt} \right] \quad (2.7)$$

where $TP(t)$ denotes the target performance and $t_{\max} = 1$ year. The annual resilience metric as a probabilistic measures, since E denotes the expected value.

According to Rose (2007), the actual system performance should be compared to an estimated worst-case performance (non-resilient behaviour). This paper defines total static economic resilience (TSER) as the “extend to which the estimated output reduction deviates from the likely maximum potential reduction”, calculated as

$$TSER = \frac{\% \Delta TY^m - \% \Delta TY}{\% \Delta TY^m} \quad (2.8)$$

where $\% \Delta TY$ is the estimated loss of system performance and $\% \Delta TY^m$ is the maximum (worst case) loss of system performance. The total dynamic economic resilience (TDER) is calculated as

$$TDER = \sum_{t=0}^n Y_{DR} - \sum_{t=0}^m Y_{DU} \quad (2.9)$$

where Y_{DR} and Y_{DU} are the resilient and worst-case response paths.

Henry and Ramirez-Marquez (2012) take a conceptually very different approach

and define resilience as a function over time:

$$\mathfrak{R}_F(t_r|e_j) = \frac{\text{Recovery at } t_r}{\text{Loss caused by disruption}} = \frac{F(t_r|e_j) - F(t_d|e_j)}{F(t_0) - F(t_d|e_j)} \quad (2.10)$$

where F is the performance metric, e_j is a disruptive event, t_0 is the time at which the disruption begins, and t_d is the time at which the disruption ends. Visualisation techniques, such as heat maps, can be used to compare different resilience time series (Gama Dessavre et al., 2016).

To summarise, resilience metrics are either based on a system of resilience indicators or measure the expected system performance relative to a certain baseline, such as no-disruption, target or worst-case performance. An advantage of performance-based measures is that they do not require a priori knowledge regarding the importance of certain resilience indicators. Comparing the expected system performance to a no-disruption scenario directly relates to the definition of resilience as the ability to maintain functionality. The selection of a suitable system performance function has a great impact on the resilience assessment and will be discussed in the following section.

2.1.6 Infrastructure system performance measures

System performance functions used in the current literature on infrastructure resilience broadly fall into three categories (Table 2.3). The first group measures performance as the availability of network components. However, they do not consider that some components may be more important than others for the service an infrastructure network provides.

The second group are network connectivity measures, which take into account how important a node or link is in the topology of a network. This importance can be measured with graph centrality metrics, such as degree or betweenness centrality (Stergiopoulos et al., 2015). However, a limitation of connectivity-based performance measures is that they do not consider network capacity. Consider, for example,

Table 2.3: Infrastructure performance measures for resilience analysis

Category	Performance metrics	Examples
Asset availability	Number of available assets	Nan and Sansavini (2017)
	Number of failures	Azzolin et al. (2018); Rahnamay-Naeini and Hayat (2016)
Network connectivity	Existence or size of a giant component	Buldyrev et al. (2010)
	Number of supply nodes connected to demand nodes	Duenas-Osorio, Craig and Goodno (2007); Ouyang (2016); Zio et al. (2012)
	Average or characteristic path length	Duenas-Osorio, Craig and Goodno (2007); Eusgeld et al. (2009); Williams and Musolesi (2016)
Network capacity	Unmet demand or number of affected users	Alderson et al. (2014); Chen and Miller-Hooks (2012); Mostafavi (2018); Thacker et al. (2017); Trucco et al. (2012)
	Travel time, generalized cost, welfare or accessibility	Cats and Jenelius (2015); Faturechi and Miller-Hooks (2014); Fotouhi et al. (2017); Miller and Baker (2016)

the case where an equipment failure partially reduces the capacity of a link. This could cause service disruptions but would not affect connectivity-based performance measures. Research on electricity networks (Ouyang, 2013) and railway networks (Ouyang et al., 2014) suggests that topological performance measures are suitable for extreme events in which large portions of the network collapse, but only indicate lower bounds for the vulnerability in cases of smaller disruptions. Hines et al. (2010) warn that “overly abstracted topological models can result in erroneous conclusions, which could lead to misallocation of risk-mitigation resources.”

The third group of infrastructure performance measures is based on network capacity in relation to demand. A widely-used approach is to measure the fraction of demand a system is able to satisfy during a disruption, which assumes that all components of demand are equally important. Metrics based on total travel time, generalized cost, welfare or accessibility are the most granular infrastructure performance measures, capturing how disruptions differently affect the various users of a system.

2.1.7 Need for further research

Considering the focus of this thesis on infrastructure interdependencies, a gap in the reviewed literature is the lack of research on how to measure the combined performance of interdependent systems. Previous research on individual infrastructure sectors suggests that measures based on the capacity of networks most accurately capture the overall service a system provides to all users. In the case of interdependent infrastructure systems, performance measures have to consider not only different users but also entirely different types of services (e.g. mobility and energy supply).

In order to facilitate the application of resilience approaches in practical decision-support, further research should focus on resilience measures that relate to metrics already used in the industry, such as lost customer hours or monetised disruption impacts. On the other hand, the selection of metrics for analysing resilience also has

to consider which indicators current or future modelling and simulation methods are able to predict.

2.2 Interdependency of critical infrastructure

Infrastructure interdependency is defined as “a bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other” (Rinaldi et al., 2001). The purpose of the following section is to present the state-of-the-art in research on how interdependency affects the resilience of critical infrastructure systems. In the first step, we review empirical studies. In the second step, approaches for modelling different types of dependency relations are discussed.

2.2.1 Empirical evidence

An empirical framework for characterising infrastructure failure interdependencies has been developed by McDaniels et al. (2007) and Chang et al. (2007). It is applied to three cases of major infrastructure disruption in North America: the 1998 ice storm, the 2003 blackout and the 2004 hurricane season. Based on a systematic analysis of newspaper reports, this research shows that interdependencies exacerbate the impacts of infrastructure disruptions, especially in the areas health, safety, social and economic impacts. In the case of the 1998 ice storm, 107 interdependency-induced infrastructure failure events were identified, five of which fall into the category large extent and high impact.

In the 13 weeks following the 2001 World Trade Centre attack, 238 disruptions to eight critical infrastructure systems have been reported, according to Mendonça and Wallace (2006). The analysis in this paper finds that approximately 20 % of disruptions involved interdependency effects, with co-location of assets being the most frequent cause.

Dueñas-Osorio and Kwasinski (2012) analyse cross-correlations of recovery rates

in critical infrastructure systems after the 2010 earthquake in Chile. Considering coupling effects both with and without time lags, this paper identifies the interdependencies between landline, mobile, power and water networks.

2.2.2 Taxonomies of dependency relations

To conceptualise the issue of infrastructure interdependency, different categorisations for dependency relations have been proposed (Table 2.4). A widely-used dependency type is physical dependency, which is defined in Rinaldi et al. (2001) and Dudenhoeffer et al. (2007), and also features in Lee II et al. (2007) as input dependencies and as part of the wider concept of functional dependencies in Zimmerman (2001). Geographic dependencies also appear in all dependency classification schemes, sometimes referred to as spatial, geospatial or co-located.

The dependency types physical, cyber and procedural have in common that they are defined based on a certain domain in which systems interact. In comparison, the dependency types shared and exclusive in Lee II et al. (2007) are defined on a more abstract level as ways in which different systems concurrently access a certain resource. While the domain-based distinction is useful for identifying dependencies or when using models that are organised by the same set of domains, the generic formulation of dependency types aides the development of more widely-applicable models.

However, currently available generic categorisations fall short of capturing some important interdependency aspects. For example, the dependencies defined in Lee II et al. (2007) assume the use of resources to be binary. However, in many cases, resources are available in a certain overall amount and can be partially allocated to different systems or services. Network capacities are particularly complex in this regard, as congestion effects can decrease the level of service for all users if the total demand exceeds certain thresholds.

In order to facilitate resilience analysis with capacity-based performance metrics (ref. Section 2.1.6), dependency types must be defined that include a quantitative

Table 2.4: Types of dependency relations

	Dependency type	Definition	Example
Rinaldi et al. (2001)	Physical	Dependence on the material output(s) of another system	Rail network depends on electricity supply
	Cyber	Dependence on information transmitted through another system	Electricity network depends on SCADA system
	Geographic	A local environmental event can affect several systems	Electric and communication cables running in parallel
	Logic	Mechanisms that are not physical, cyber or geographic	Financial dependencies
Zimmerman (2001)	Functional	Same as physical, cyber and logic dependencies above	
	Spatial	Same as geographic dependency above	
Dudenhoeffer et al. (2007)	Physical	Same as physical dependency above	
	Informational	Same as cyber dependency above	
	Geospatial	Same as geographic dependency above	
	Policy / procedural	A policy or procedure relates the state of one infrastructure to the state of another	Transport system disrupted because of police operation
	Societal	Societal factors such as public opinion, confidence, fear, etc.	Travel demand changes caused by major events
Lee II et al. (2007)	Input	Same as physical dependency above	
	Co-located	Same as geographic dependency above	
	Mutual	Bidirectional dependency between systems	System A depends on system B in the same way as B depends on A
	Shared	Some physical components or activities used in providing different services are shared	Different telecommunication services operated on phone lines
	Exclusive or	Two or more systems require a resource which can only be used by one system at a time	Equipment required to repair damaged buildings after an earthquake

measure for the strength of coupling. In the case of physical or input dependencies, this could be the amount of a certain resource a system requires from another for a certain performance level.

Another gap in the current literature on dependency types is the insufficient consideration of stochastic effects. According to Rinaldi et al. (2001), geographic dependency means a correlation of failures. However, there is no further consideration how such effects could be statistically defined.

2.3 Modelling and simulation approaches

The literature review identified seven distinct approaches that are used to analyse the resilience of interdependent infrastructure networks. The following subsections summarize the key aspects of each approach and a complete list of all models surveyed in this research is provided in Table A.1 in the appendix. A comparative analysis of the modelling approaches is offered in Section 2.3.8. Similar reviews of modelling approaches have been conducted by Ouyang (2014) and Iturriza et al. (2018), whose results were also considered.

2.3.1 Reliability engineering

According to DePoy et al. (2006), the most important reliability engineering methods used for CIP are failure fault tree analysis, event tree analysis, and failure modes and effects analysis. Such logic modelling approaches can be used to quantify failure probabilities of components and multi-component systems but cannot capture network performance. Therefore, Volkanovski et al. (2009) propose to combine fault tree analysis with a network flow model. Fault tree analysis can also be expanded to consider dynamic effects (Čepin and Mavko, 2002; Durga Rao et al., 2009; Gascard and Simeu-Abazi, 2018). However, this approach has not yet been applied in the domain of CIP.

Dynamic failure and repair processes can also be modelled with Markov chains

(Rausand and Høyland, 2004). To model cascading failure in interdependent infrastructure networks, Rahnamay-Naeini and Hayat (2016) propose a method based on coupling different Markov chains. Another stochastic modelling method is Petri net analysis, which has been used by Sultana and Chen (2009) to model the vulnerability of hydro-electric power generation.

A literature review by Weber et al. (2012) finds that the reliability of complex systems is increasingly analysed with Bayesian network models. These can emulate traditional methods, such as fault tree analysis, but offer greater flexibility in modelling additional complexities, such as interdependencies and human factors. Dynamic Bayesian network models have been used to model cascading failure in fire protection systems (Khakzad et al., 2017) and power networks (Codetta-Raiteri et al., 2012), but not in interdependent infrastructure systems.

2.3.2 System dynamics

At least since the influential Limits to Growth study (Meadows et al., 1972), system dynamics is known as a powerful method for the analysis of interdependent systems. It has been applied to CIP in the Critical Infrastructure Protection Decision Support System project (Bush et al., 2005). Min et al. (2007) use a system dynamics approach to predict the shortage of materials and services in different critical infrastructure networks following a disruption. Tonmoy and El-Zein (2014) study the cascading effects in regional infrastructure systems that are triggered by sea level rise.

2.3.3 Agent-based modelling

Agent-based approaches model infrastructure systems as components (agents) that observe certain input variables, make decisions according to their decision logic and interact with other systems or the environment. This approach has been implemented, for example, in the Critical Infrastructure Modeling System (CIMS) project (Dudenhoeffer et al., 2006). The decision logic of agents can be modelled with decision rules or with optimisation methods (Permann, 2007).

Nan and Sansavini (2015) propose to structure agent-based models of critical infrastructure systems into three layers. On the system layers, agents represent components of the infrastructure system itself (e.g. electricity lines). On the operational control system layer, agents represent components of the control systems (e.g. terminals in a SCADA system). On the social system layer, agents represent human operators.

Agent-based modelling is also used to model the decisions of infrastructure users. In transport research, simulation methods that consider the behaviour of individual passengers or vehicles are also referred to as microscopic simulations. An example of such a simulation framework is MATSim (Horni et al., 2016).

2.3.4 Game theory

Game theoretical approaches to resilience analysis are often based on an attacker-defender model. For example, Bell (2003) shows that a two-player, non-cooperative, zero-sum game between a router and a virtual network tester provides a computationally efficient method to identify the most vulnerable links in a network. Further aspects can be investigated by adding a third player. For example, Alderson et al. (2014) use an attacker-defender-operator model and Fang and Sansavini (2017) a planner-attacker-defender model. However, these studies have not considered interdependent systems.

On the other hand, Zhang et al. (2005) analyse optimal budget allocation for three coupled infrastructure systems using a dynamic Stackelberg leader-follower game but this model does not address resilience issues. A reason why game theoretic approaches are not used more widely for the resilience analysis of interdependent infrastructure systems is that the number of relevant stakeholders is usually higher than the two or three players modelled in current game theoretic models and the model complexity increases very fast with the number of players.

2.3.5 Input-output modelling

Input-output modelling is a method from economic theory and was first applied to interdependent infrastructure systems by Haimes and Jiang (2001). The key variable in this modelling approach is the inoperability vector $\mathbf{x}$ whose components $x_i \in [0, 1]$ indicate the inoperability of the individual systems. The perturbation vector $\mathbf{c}$ represents the external disruptive event and the interdependency matrix $\mathbf{A}$ quantifies the strength of interdependency. Inoperability is the combined effect of the disruption and interdependency:

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{c} \quad (2.11)$$

Assuming that $(\mathbf{I} - \mathbf{A})$ is non-singular, the equation can be solved for $\mathbf{x}$:

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{c} \quad (2.12)$$

This general concept has been used to develop physical-based, regional, demand-reduction and dynamic infrastructure inoperability input-output models (Haimes, Horowitz, Lambert, Santos, Lian and Crowther, 2005; Haimes, Horowitz, Lambert, Santos, Crowther and Lian, 2005). It can be combined with Monte Carlo simulation methods to take into account parameter uncertainty.

Most application of the infrastructure inoperability input-output model focus on economic aspects of resilience and interdependencies, modelling the inoperability of entire industry sectors (e.g. Jonkeren and Giannopoulos, 2014; Kelly, 2015; Pant et al., 2014). However, it is also possible to use input-output modelling on a disaggregated scale to model physical or operational interdependencies between components, such as electricity sub-stations (Cagno et al., 2011).

2.3.6 Graph theory

Graph theory is concerned with the structure (or topology) of networks. The origins of statistical and algorithmic graph theory lie in the work by Erdos and Rényi (1960) on random graphs. Further milestones were the discoveries of small world networks (Watts and Strogatz, 1998) and scale-free networks Barabási and Albert (1999). Empirical research has shown that the topology of many real-world networks, including infrastructure systems, can be characterised with these graph theoretical concepts (Albert and Barabási, 2002; Boccaletti et al., 2006).

Graph theory is used to analyse the robustness of networks by measuring how certain connectivity properties change when a fraction of nodes is removed. A widely used connectivity measure is the efficiency of a graph, calculated as

$$E = \frac{1}{N(1-N)} \sum_{i,j \in V, i \neq j} \frac{1}{d(i,j)} \quad (2.13)$$

where $d(i, j)$ is the shortest path distance between nodes i and j Boccaletti et al. (2006).

Scale-free networks are generally known to be robust against the random removal of nodes (Cohen et al., 2000). In contrast, the network disintegrates rapidly when highly connected nodes are removed first (Cohen et al., 2001). However, some infrastructure networks have special topological characteristics. For example, Angeloudis and Fisk (2006) find that in metro networks nodes with a degree of four or six provide most of the connectivity, making such networks relatively robust against attacks targeted at higher degree nodes.

Topological network robustness analysis has recently been extended to interdependent networks. Dueñas-Osorio, Craig, Goodno and Bostrom (2007) model the interdependency of electricity and water networks with conditional failure probabilities based on geographic proximity and find efficiency losses for random component removal increases with a stronger coupling of the networks. Buldyrev et al. (2010) analyse a cascading failure event involving the Italian electricity transmission net-

work and a communication network. They find that “a broader degree distribution increases the vulnerability of interdependent networks to random failure, which is opposite to how a single network behaves”. Poljansek et al. (2012) show that the seismic vulnerability of the European electricity transmission network is exacerbated by the interdependency with the gas network. Topological models have also been used to investigate the optimal balance of benefits and costs of connecting different networks (Ouyang and Dueñas-Osorio, 2011; D’Souza et al., 2014).

2.3.7 Network flow theory

The notion of network flows features prominently in many definitions of critical infrastructure. For example, the US President’s Commission on Critical Infrastructure Protection (1997) defines infrastructure as “systems and processes that function collaboratively and synergistically to produce and distribute a continuous flow of essential goods and services.” Hence, it is not surprising that network flow theory is widely used to analyse infrastructure resilience.

Network flow theory provides different methods for assigning flows to networks (Ahuja et al., 1993). These flows often represent the spatial displacement of people, materials, energy or information. However, flows can also represent any other type of transformation (e.g. the transformation of electric power from one voltage level to another), the provision of services or any allocation of resources, including intangible and abstract resources.

In the case of homogeneous commodities (e.g. electric power, water), the flow assignment has to route flows from a set of source nodes to a set of demand nodes, such that ideally, all demands are satisfied. However, the origin of a commodity that is provided to satisfy a certain demand is not relevant. This case is referred to as single-commodity assignment.

On the other hand, there are networks which serve demands between a set of origin and destination pairs (OD pairs). This case is referred to as multi-commodity assignment because the flow between each OD pairs is considered a separate commod-

ity and these multiple commodity flows are assigned to the same network. Examples of multi-commodity networks are road or public transport networks.

Network flow modelling approaches have been adapted to analyse the resilience interdependent infrastructure networks (e.g. Lee II et al., 2007; González et al., 2016; Fotouhi et al., 2017). The general approach in this type of research is to model interdependency as the coupling of flows in different networks. Such a model can then be used to conduct experiments in which the performance of the network in terms of satisfying a given demand is measured when the network capacity is reduced according to a certain hazard scenario.

2.3.8 Comparison of modelling approaches

Table 2.5 summarises the key features of the seven modelling approaches reviewed in the previous sections. A fundamental difference between them are the main functional entities that are used to represent infrastructure systems (e.g. assets, agents, graphs). This also means that they require different model input data, provide different outputs and can capture different aspects of infrastructure resilience. No individual modelling approach can be deemed generally more advantageous than others because the requirements of a particular application determine which features of a modelling approach are particularly important. Some points to consider when choosing a modelling approach are discussed in the following.

According to a review by Iturriza et al. (2018), system dynamics and agent-based approaches are most frequently used for analysing critical infrastructure. System dynamics can be seen as a top-down approach and agent-based modelling as a bottom-up approach. Both are relatively generic and capable of addressing a wide range of resilience issues. However, the model development with these approaches is a manual process and requires a detailed understanding of the systems to be modelled. This poses epistemological limitations, as the emergent phenomena discovered by these models strongly depend on the causal relationships considered in the model development process. Furthermore, Ouyang (2014) highlights that the calibration

Table 2.5: Comparison of modelling approaches

	Reliability engineering	System dynamics	Agent-based modelling	Game theory	Input-output modelling	Graph theory	Network flow theory
Functional entities	assets	processes	agents	players	linear systems	graphs	flow networks
Model inputs	failure probabilities, dependencies	stocks variables, flows, causal relations	agents, environment, interactions	strategies, pay-offs	interdependency matrix, perturbation	nodes, links	nodes, links, capacity, demand
Model outputs	probability of asset availability	joint effect of dynamic processes	emergent phenomena of distributed decision-making	equilibria arising from distributed decision-making	total effect of linear interdependencies	characteristic path length, clustering	flow distribution on capacitated networks
Aspects considered	failure modes, conditional probabilities	non-linear dynamics, feedback loops	decisions rules, agent interaction	strategic decisions, anticipation	economic ripple effects	network connectivity	transport demand and supply

and validation of system dynamics and agent-based models requires data that is usually not available in resilience analysis applications.

The other modelling approaches are more focussed on specific aspects of resilience analysis. Reliability engineering methods are most suitable for modelling stochastic processes of asset failure and repair. Game theoretic approaches are most suitable for modelling strategic decisions, for example, which network components to protect against targeted attacks. Input-output modelling is most suitable to analyse economic ripple effects of infrastructure failure. Models based on graph theory or network flow theory are particularly suitable for analysing network effects.

An important difference between graph theoretical and network flow approaches is that the former only consider the topology of networks whereas the latter also consider capacity and routing. Previous research compared how topological- and flow-based models evaluate infrastructure performance in disruption scenarios. Analysing electricity networks, Hines et al. (2010) argue that using purely topological metrics for vulnerability analysis can be misleading because they only mildly correlate with network performance. Ouyang (2013) confirms these results but points out that the quality of topology-based approximations increases when the disruption is very large (failure of more than half of the network). Similar results have been found for the Chinese railway network (Ouyang et al., 2014). Also analysing public transport systems, Luo et al. (2019) show that topological properties can be used in combination with regression models to estimate passenger flows. However, the quality of these approximations is relatively low (mean absolute percentage errors between 71 and 248 %). Furthermore, this analysis only considers flow in undisturbed networks.

In addition to greater accuracy, another advantage of network flow modelling approaches is their capability of addressing other resilience aspects, such as operational phenomena or strategic decisions. This flexibility is related to the use of mathematical optimisation methods for calculating the flow assignments. Such models can easily be expanded to capture further details by adding decision variables and / or

constraints. The main limitation of network flow models is their computational cost if detailed network operations are modelled (Ouyang, 2014).

Finally, the literature review also shows that the general modelling approaches are rarely applied in their pure form and that the complexity of resilience analysis is often better captured with combined approaches. Many existing hybrid methods combine a network flow model with other approaches, for example, with reliability engineering methods (Volkanovski et al., 2009), agent-based simulation (Nan and Sansavini, 2015) or game theory (Alderson et al., 2014). According to Ouyang (2014), however, the integration of modelling approaches still requires much further research.

To conclude, network flow modelling is the most suitable modelling approach for this thesis, considering the focus on the transportation of people and goods. In order to advance the field of critical infrastructure resilience analysis, two directions of research should be pursued: i) new methods for capturing interdependency effects with network flow models, and ii) new combined modelling and simulation methods for improving the scope and realism of resilience analysis.

2.4 Network flow modelling methods

Based on the review and comparison of modelling approaches, network flow theory is chosen as the principal modelling paradigm in this thesis. The purpose of this section is to review state-of-the-art network flow models for interdependent networks and identify shortcomings that will be addressed in this thesis. An overview of the nine most relevant existing network flow models is presented in Table 2.6.

2.4.1 Flow assignment methods

Flow assignment is the process of calculating network flows by modelling the interaction of demand and supply. In transport systems analysis, the simplest traffic assignment method is the all-or-nothing approach that assigns all drivers to the shortest route, irrespective of capacity constraints. More realistic results can be

Table 2.6: State-of-the-art network flow models

	Holden et al. (2013)	Chen and Miller- Hooks (2012)	Fotouhi et al. (2017)	Ouyang (2017)	Jin et al. (2014)	González et al. (2016)	Cats et al. (2017)	Lee II et al. (2007)	Sharkey et al. (2015)
Case study	hypothetical	container logistics	Minneapolis	IEEE test system	Singapore	Shelby County	Amsterdam	New York City	New Hanover County
Systems	water, electric power	railway, road	road, electric power	electric power, water	metro, bus	electric power, gas, water	metro, tram	metro, electric power, telephone	electric power, telecom, water, transport
Single-commodity	✓		✓	✓		✓		✓	✓
Multi-commodity		✓	✓		✓		✓	✓	
Network size	6 nodes	8 nodes	8 nodes	23 nodes	77 nodes	125 nodes	216 nodes	100 - 1000 nodes	1,400 – 2,283 nodes
Capacity loss	continuous	continuous	discrete	discrete	binary	binary	discrete	binary	binary
Resilience measure	satisfied demand	satisfied demand	total travel time	satisfied demand	satisfied demand		generalised travel costs	cost (incl. unmet demand penalty)	restored services
Objective function	min cost	min unmet demand	min cost	min unmet demand	min cost	min cost	min cost	min cost	max recovery
Dynamic flows	✓					✓			✓
Integer variables		✓	✓	✓	✓	✓		✓	✓
Linearisation		✓	✓	✓					
Stochastic model		✓	✓		✓				
Game theory				✓					
Preparedness decisions			protection, redundancy	protection	intermodal connections				
Mitigation decisions	emergency supplies retrieval	temporary roads, repair	manual traffic control, repair			repair		temporary connectors	repair
Repair budgets		✓				✓			
Repair operations			✓						✓

achieved with congested assignment methods, such as those based on Wardrop's conditions for user and system optimal equilibria (Wardrop, 1952). Stochastic assignment methods additionally consider differences in individual users' route choices. For public transport networks, there exist schedule- and frequency-based methods. A detailed discussion of traffic assignment methods is beyond the scope of this thesis and the interested reader is referred to relevant textbooks, such as Bell and Lida (1997), Cascetta (2009) or Ortúzar and Willumsen (2011).

In the domain of electricity networks, AC and DC optimal power flow models are used for calculating network flows (Li, 2014). DC power flow models ignore the effects of reactive power but have considerably lower computational cost and are sufficiently accurate for system risk evaluation in most cases.

For the analysis of interdependent infrastructure systems, different types of network flows have to be assigned to different networks while the flows mutually depend on each other. This is achieved in state-of-the-art resilience analysis models by help of the variational principle, which says that in many physical and social systems the equilibrium conditions are also optimality conditions of an optimisation problem (Ahuja et al., 1993, p. 16). For example, Wardrop's user equilibrium can be calculated by minimising the sum of the areas under the cost-flow curve for all links, and the system optimal equilibrium by minimising the total costs for all drivers (Ortúzar and Willumsen, 2011, p. 392 ff.). Optimal power flow models can also be expressed as optimisation problems (Li, 2014, 135 ff.). In their mathematical programming formulation, the flow assignment problems for different networks can be integrated, enabling the simultaneous computation of interdependent flows.

Table 2.6 shows that most reviewed models use cost minimisation approaches with objective functions including different types of costs and penalties (e.g. for unmet demand). In contrast, Chen and Miller-Hooks (2012) and Ouyang (2017) directly minimise the unmet demand, and Sharkey et al. (2015) maximise the recovery rate.

The minimum cost flow models mostly use fixed link costs (i.e. link costs do not depend on the flow) and link capacity constraints (Lee II et al., 2007; Holden et al.,

2013; Jin et al., 2014; González et al., 2016). This means that the models compute system optimal flows on a capacitated network. If congestion occurs, the demand that exceeds the available capacity is assigned to other links, without consideration of the route choice behaviour of individual travellers or the physical laws governing power flows. However, it is possible to extend the minimum cost flow approach to consider such effects, for example, by using the Bureau of Public Roads function as a more realistic estimate of travel time in road networks (Fotouhi et al., 2017).

To conclude, the literature review shows that the minimum cost flow model with fixed link costs and capacity constraints is a suitable flow assignment method for analysing the resilience of interdependent networks. Using more realistic, domain-specific assignment methods for each individual type of infrastructure would mean that only small network instances and few disruption scenarios could be analysed due to computational limitations. On the other hand, the minimum cost flow approach provides a more realistic model of network performance compared to methods without consideration of capacity (topological models, all-or-nothing assignment). Furthermore, minimum cost flow models can be refined according to the requirements of the model application, for example, with more realistic cost functions.

2.4.2 Coupling of flows in different networks

We can distinguish between the discrete and continuous coupling of flows in different networks. For example, Lee II et al. (2007) propose a discrete method with binary coupling variables. If a demand node in one network cannot be supplied with the required amount of a commodity, a switching variable reduces the capacity of nodes or links in other networks that depend on the demand node. Furthermore, binary variables can also couple flows by altering the cost parameters in one network based on flows in another (Fotouhi et al., 2017).

An example of a continuous coupling method is the linear production function in Holden et al. (2013). In this model, the production of a commodity may consume other commodities that are provided by demand nodes in other networks. Thus, the

production capacity depends on the quantities of input commodities that can be provided.

Whether discrete or continuous coupling methods are more realistic is determined by the nature of the interdependency effect. With regards to computational complexity, it is important to be aware that discrete coupling leads to flow assignment methods that are formulated as integer programming problems. In general, such integer-constrained problems are NP-complete, i.e. the computational complexity of solving them can increase exponentially with the size of the problem (Williams, 2009). Thus, discrete coupling methods can be computationally prohibitive when a large number of dependency relations has to be considered.

There are some mechanisms which can lead to the coupling of different infrastructure systems but are not considered in state-of-the-art network flow models, for example, resources required to operate storage facilities for certain goods or the transportation of resources required to repair damaged assets. Further research is needed to investigate how such dependencies can be modelled.

2.4.3 Dynamic flows

The recovery of infrastructure systems after major disruptions may take hours, days, weeks or even longer and the course of recovery is an important aspect of infrastructure resilience. However, only a few papers provide dynamic network flow modelling methods for evaluating system performance during the recovery phase.

For each type of infrastructure, there exist specific methods for modelling dynamic flows, for example, dynamic traffic assignment models for transport networks or transient stability analysis for power networks. However, due to the same complexity reason discussed above, these methods are not suitable for system-of-systems resilience analysis.

With minimum cost flow models, dynamic flows can be analysed through iterative static flow assignment Holden et al. (2013); González et al. (2016). However, this method cannot take into account flows spanning over multiple time-steps. In other

words, it can be considered a myopic assignment method that does not model any planning beyond the current time step.

An alternative approach is to model dynamic flow assignment as a single optimisation problem for the entire simulation period (Sharkey et al., 2015). This method is equivalent to the time-expanded network approach (Fonoberova, 2012, p. 374 ff.). It is based on the assumption of perfect foresight and does not consider that new information may become known at different times in the simulation period. Another drawback is the large size of the resulting mathematical programming instance.

Thus, the main research gap with respect to modelling dynamic flows in interdependent infrastructure networks is the lack of realism in modelling sequential decisions. New dynamic assignment methods are needed that are capable of modelling both unforeseeable events (e.g. component failure) and the future effects of operational decisions (e.g. the planning of repair works).

2.4.4 Network components

Nodes and links in network models of infrastructure systems represent individual assets, such as metro stations, railway tracks or electricity sub-stations. In existing models, the operational characteristics of these assets tend to be condensed into one-dimensional operability variables. Moreover, the operability variables are usually assumed exogenous or modelled with a stochastic process (e.g. random failure).

In reality, assets that form the nodes and links of infrastructure networks are complex systems themselves, composed of interacting sub-systems and components. Thus, the realism of network flow models could be improved by developing methods for modelling the operability of individual assets more realistically, for example, by applying fundamental reliability engineering concepts (e.g. series and parallel systems).

2.4.5 Repair processes

Decisions regarding the repair of damaged assets can be integrated into the mathematical programming model used to calculate the flow assignment. The models in Chen and Miller-Hooks (2012) and González et al. (2016) are parametrised with a repair budget that can represent the financial resources, time and workforce available to carry out repair works. Sharkey et al. (2015) also model dependencies between repair tasks using different types of precedence constraints. Fotouhi et al. (2017) introduce constraints that a repair site must be accessible from a depot via the (potentially disrupted) road network.

The literature review identified three aspects of repair processes that are not sufficiently addressed in state-of-the-art models. The first aspect is the lack of considering the complexity of individual assets, which is related to the literature gap already identified in the previous section. The second aspect is partial repair. Current models do not consider that infrastructure operators facing scarce repair resources may choose temporary fixes that only partially restore an asset's capacity. And third, the issue of repair resource logistics. In addition to considering the accessibility of repair sites, models should also consider the time and costs for transporting repair resources to repair sites, as well as the capacity of the transportation network used.

2.4.6 Preparedness

Another important aspect of resilience is preparedness, i.e. decisions taken prior to a potential disruption in order to mitigate the expected impacts. Jin et al. (2014) model decisions on intermodal connection points between a metro and bus network using a two-stage stochastic programming method. In the attacker-defender model proposed by Ouyang (2017), the defender decides which network components to protect from an attack and which additional links to create in the network. Fotouhi et al. (2017) model decisions on providing backup power generation for substations and traffic signals and on hardening road links.

The papers discussed above have demonstrated how the trade-off between investing

in protection and redundancy can be analysed with network flow models. However, they do not consider preparedness decisions regarding recovery capability, despite this being a central aspect of resilience. For example, the benefit of installing backup power generation at a substation depends on the expected downtime of the substation and, thus, on the overall capability of the system to restore power supply.

2.5 Summary of gaps in current research

The literature review has shown that the topic of infrastructure resilience has attracted the attention of many researchers in the last two decades. Qualitative and semi-quantitative resilience concepts are also beginning to be used by stakeholders in industry and government, for example in the form of resilience indicators. However, despite many publications on quantitative modelling and simulation methods, such approaches are rarely applied beyond research projects. This shows that current methods for quantitative resilience analysis are not yet fit to support practical decision-making. In particular, the following areas have been identified as priorities for further research:

- resilience metrics for interdependent infrastructure systems
- quantitative and probabilistic definitions for different dependency types
- coupling of network flows related to resource requirements for asset repair or commodity storage
- foresight and sequential decisions
- system characteristics of individual assets
- repair resource logistics
- trade-off between robustness, redundancy and recovery capabilities

The following chapters will address these issues by proposing new theoretical concepts and presenting model applications.

Chapter 3

Modelling principles

The purpose of this chapter is to lay the theoretical foundations for analysing the resilience of interdependent infrastructure systems with network flow models. We focus on novel modelling concepts that address limitations of state-of-the-art methods. The key results can be summarised as follows:

- A bi-level modelling architecture is presented that distinguishes the network and asset layer of infrastructure systems to enable a more realistic representation of asset operability and network flow aspects (Section 3.1).
- Minimum cost flow assignment models are suggested to simulate dynamic and coupled flows in interdependent infrastructure networks (Section 3.2).
- A new system performance function for resilience assessment is proposed based on the value of infrastructure services provided (Section 3.3).
- Deterministic and stochastic methods for modelling cascading failure are discussed (Section 3.4).
- Recovery capability can be modelled by incorporating repair resource networks in the interdependent flow assignment model (Section 3.5).
- Preparedness can be considered as optimal investment into robustness and repair capabilities (Section 3.6).

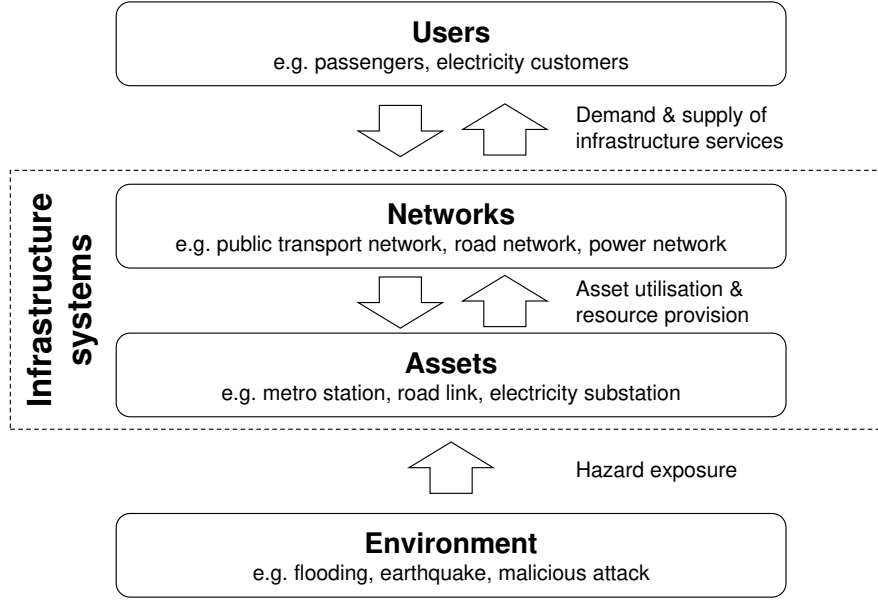


Figure 3.1: Basic modelling framework

The modelling principles introduced in this chapter include several new methods for representing dependency relations between infrastructure systems. The asset layer model features methods for modelling interdependent failure modes, also referred to as cascading failure (Section 3.4). On the network layer, the principle of coupling flows in different networks (Section 3.2.3) enables the modelling of dependencies related to resource requirements for operating the systems and repairing damaged assets. The value-based system performance measure (Section 3.3) provides an aggregated metric for assessing the resilience of interdependent infrastructure systems. Considering interdependencies in all parts of the modelling architecture does justice to the variety of different dependency types found in the literature (Section 2.2).

3.1 Network and asset layer

An important first modelling principle is separating the network and asset layers of infrastructure systems, as illustrated in Figure 3.1. The interaction of users with infrastructure systems is modelled on the network layer as demand for and supply of infrastructure services. On the other hand, the interaction of infrastructure systems with their environment (e.g. impacts of a hazardous event) is modelled on the asset

layer. The two layers are closely interlinked, as networks rely on the operability of assets to provide infrastructure services and assets may require certain infrastructure services to be operable.

Separating the network and asset layers enables us to extend the scope of the model with respect to network and asset effects independently of each other. Consider the example of a metro station: in the first instance, it could be represented as a node in the network. However, the flow of passengers through the station could be modelled in greater detail by representing entrances, exits and platforms as separate nodes. Similarly, the metro station could be represented either as a single asset or as a system of assets, such as building structures, ventilation systems and escalators. There is no limit to increasing the granularity of the model by adding further components to the asset and network layers.

3.2 Minimum cost flow assignment

Let $G = (V, E)$ be a directed network with nodes $i \in V$ and links $(i, j) \in E$. We formulate the basic minimum cost flow problem for static single-commodity assignment as a linear programming problem (Ahuja et al., 1993):

$$\text{minimise} \quad \sum_{(i,j) \in E} c_{i,j}^f f_{i,j} \quad (3.1)$$

$$\text{subject to} \quad \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} = b_i \quad \forall i \in V \quad (3.2)$$

$$f_{i,j} \leq \hat{f}_{i,j} \quad \forall (i,j) \in E \quad (3.3)$$

$$f_{i,j} \geq 0 \quad \forall (i,j) \in E \quad (3.4)$$

The decision variables $f_{i,j}$ represent directional link flows. Cost parameters $c_{i,j}^f$ are unit costs that are multiplied with the flow variables to form the objective function (3.1). Capacity parameters $\hat{f}_{i,j}$ pose upper limits for link flows in constraints (3.3). The

parameters b_i in the balance of flow constraints (3.2) indicates the supply and demand in the form of network in- and out-flows.

The basic minimum cost flow problem becomes infeasible if the network capacity is not sufficient to satisfy the total demand. To analyse resilience, however, network flow models need to be able to calculate flows for disruption scenarios in which the demand can only partially be satisfied. Therefore, we modify the basic minimum cost flow problem by modelling network in- and out-flows with decision variables g_i and u_i . Network in-flows may incur costs denoted with parameters c_i^g . The commodity demand at each node is represented with parameters $\check{u}_i$. A penalty of c_i^{SC} per unit of unmet demand is added to the cost function, so that the demand is satisfied unless the network capacity is insufficient or the costs for satisfying the demand would be higher than the penalty c_i^{SC} . With this, we can formulate the minimum cost flow problem as follows:

$$\text{minimise} \quad \sum_{(i,j) \in E} c_{i,j}^f f_{i,j} + \sum_{i \in V} \left(c_i^g g_i + c_i^{SC} (\check{u}_i - u_i) \right) \quad (3.5)$$

$$\text{subject to} \quad g_i - u_i + \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} = 0 \quad \forall i \in V \quad (3.6)$$

$$f_{i,j} \leq \hat{f}_{i,j} \quad \forall (i,j) \in E \quad (3.7)$$

$$g_i \leq \hat{g}_i \quad \forall i \in V \quad (3.8)$$

$$u_i \leq \check{u}_i \quad \forall i \in V \quad (3.9)$$

$$f_{i,j}, g_i, u_i \geq 0 \quad \forall (i,j) \in E, i \in V \quad (3.10)$$

Multi-commodity flows could be analysed by formulating the minimum cost flow problem with separate decision variables for each commodity. However, this approach is not practical for large transportation networks that serve the demand between many thousands of OD pairs. For each OD pair, a separate commodity would have

to be modelled, which would inflate the size of the optimisation problem beyond computational limitations.

As an alternative, this research uses a k shortest path approach in order to determine attractive routes. Yen's (1971) algorithm in combination with the A* algorithm (Hart et al., 1968) is used to calculate the k shortest paths between each OD pair, where k is a parameter indicating how many possible paths the model considers. This is a computationally efficient method because the shortest path calculation can be carried out as a pre-processing step and the resulting set of paths can be used in the flow assignment computations for different time steps and scenarios. A limitation of this method is that flows are not assigned to paths that are longer than the k -th shortest path. However, for most transportation networks it is realistic to assume that travellers will only consider a finite number of route options (e.g. $k = 10$) and decide not to travel or use a different mode of transport if all known route options are congested.

For an OD pair $(o, d) \in OD$, let $c_{o,d}^{\text{MC}}$ denote the penalty for unmet demand and $P_{o,d}$ the set of k shortest paths. Path flows are denoted with decision variables f_p . To relate path and link flows, $Q_{i,j}$ is defined as the set of all paths that include the link (i, j) . With this, we can formulate the minimum cost flow problem for multi-commodity assignment as follows:

$$\text{minimise} \quad \sum_{(i,j) \in E} c_{i,j}^f f_{i,j} + \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \left(\check{f}_{o,d} - \sum_{p \in P_{o,d}} f_p \right) \quad (3.11)$$

$$\text{subject to} \quad g_i - u_i + \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} = 0 \quad \forall i \in V \quad (3.12)$$

$$f_{i,j} = \sum_{p \in Q_{i,j}} f_p \quad \forall (i,j) \in E \quad (3.13)$$

$$f_{i,j} \leq \hat{f}_{i,j} \quad \forall (i,j) \in E \quad (3.14)$$

$$\sum_{p \in Q_{i,j}} f_p \leq \check{f}_{o,d} \quad \forall (o,d) \in OD \quad (3.15)$$

$$f_{i,j}, f_p, g_i, u_i \geq 0 \quad \forall (i,j) \in E, i \in V, p \in P \quad (3.16)$$

3.2.1 Multiple networks

The minimum cost flow approach can be applied to multiple infrastructure networks by modelling them as sub-graphs in G . In the first instance, we consider the networks to be independent, i.e. the sub-graphs are disjoint. In this case, the flow assignment could also be calculated for each network individually. However, since we will introduce coupling mechanisms later we formulate the flow assignment as a joint minimum cost flow problem:

$$\text{minimise} \quad \sum_{(i,j) \in E} c_{i,j}^f f_{i,j} + \sum_{i \in V^{\text{SC}}} \left(c_i^g g_i + c_i^{\text{SC}} (\check{u}_i - u_i) \right) + \quad (3.17)$$

$$\sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \left(\check{f}_{o,d} - \sum_{p \in P_{o,d}} f_p \right)$$

$$\text{subject to} \quad g_i - u_i + \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} = 0 \quad \forall i \in V \quad (3.18)$$

$$f_{i,j} = \sum_{p \in Q_{i,j}} f_p \quad \forall (i,j) \in E^{\text{MC}} \quad (3.19)$$

$$f_{i,j} \leq \hat{f}_{i,j} \quad \forall (i,j) \in E \quad (3.20)$$

$$g_i \leq \hat{g}_i \quad \forall i \in V^{\text{SC}} \quad (3.21)$$

$$u_i \leq \check{u}_i \quad \forall i \in V^{\text{SC}} \quad (3.22)$$

$$\sum_{p \in Q_{i,j}} f_p \leq \check{f}_{o,d} \quad \forall (o,d) \in OD \quad (3.23)$$

$$f_{i,j}, f_p, g_i, u_i \geq 0 \quad \forall (i,j) \in E, p \in P, i \in V \quad (3.24)$$

The set V^{SC} contains all nodes that belong to a single-commodity network. Note that the capacity constraints (3.21) and (3.22) could also be applied to multi-commodity networks if required. The set E^{MC} in Equation (3.19) contains all links that belong to a multi-commodity network.

3.2.2 Dynamic flows

As discussed in Section 2.4.3, previous research has modelled dynamic network flows either with iterative static or with integrated multi-period assignment methods. The iterative static assignment method is adequate if all decisions taken in one time-step are independent of events or decisions in future time steps.

However, the restoration of infrastructure systems after major disruptions requires planning over multiple time steps, for example, to consider certain preparations that need to be completed before a repair task can begin. Sharkey et al. (2015) address

this issue with a multi-period assignment method. However, a limitation of this approach is that it cannot model unanticipated events.

For this study, we developed two alternative methods that enable a more realistic representation of sequential decision making. The first method is a rolling planning horizon approach. For each time step in the simulation period, a multi-period assignment problem is solved for the current time step t_c to the end of the planning horizon $t_c + t_h$. The parameter settings for this multi-period assignment problem represent the available information at time t_c . As t_c iterates through the simulation period, new information, such as random failures, may become available. This method is presented with further detail in Chapter 5.

The second method is a stochastic programming approach that is based on solving a single optimisation problem for the entire simulation period and considers the evolution of uncertainty with a scenario tree. This method is described in Chapter 6.

3.2.3 Coupled flows

In previous research, the coupling of flows has been modelled with different methods, for example, using binary coupling variables (Lee II et al., 2007) or linear production functions (Holden et al., 2013). In this thesis, we generalize these approaches by introducing decision variables v_i that indicate the amount of a commodity that nodes $i \in V$ provide to other systems (or other parts of the same system). These variables represent an additional network out-flow and have to be included in the model by modifying the balance of flow constraints (3.18) as follows:

$$g_i - u_i - v_i + \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} = 0 \quad \forall i \in V \quad (3.25)$$

The new decision variables v_i are constrained to non-negative values, like all other decision variables.

We can now model different interdependency effects by introducing constraints that relate the values v_i to variables belonging to other infrastructure systems. For

example, the linear production function in Holden et al. (2013) would be modelled as

$$v_i = \sum_{k \in V: (i,k) \in D^I} \alpha_{i,k}^g g_k \quad \forall i \in V \quad (3.26)$$

where D^I is the set of input dependencies, each described by a parameter $\alpha_{i,k}^g$ for the quantity of a commodity that node i must provide to enable the generation of one unit of another commodity at node k .

The input dependency in Lee II et al. (2007) could be modelled with binary switching variables as follows:

$$v_i = \sum_{k \in V: (i,k) \in D^I} \alpha_{i,k}^g \gamma_k \quad \forall i \in V \quad (3.27)$$

$$g_i(1 - \gamma_i) = 0 \quad \forall i \in V \quad (3.28)$$

$$\gamma_i \in \{0, 1\} \quad \forall i \in V \quad (3.29)$$

This generalised method for modelling the coupling of flows enables the analysis of additional dependency effects. For example, in Chapter 5 we present a model that considers resources required for asset repair by linking v_i to repair rates. The model in Chapter 6 considers resources required for the storage of commodities.

3.3 Resilience metrics

To address the need for a resilience measure that considers the joint performance of interdependent infrastructure systems (ref. Section 2.1.7), this thesis proposes a new measure based on estimating the monetised value of infrastructure services. We define the value of demand (VoD) as the total value of all infrastructure services that would be provided without any infrastructure disruptions. The value of supply (VoS) measures the total value of infrastructure services that are actually provided in a disruption scenario. The joint performance of interdependent infrastructure systems

at time t is then calculated as follows:

$$P(t) = \frac{\text{VoS}^t}{\text{VoD}^t} \quad (3.30)$$

In the network flow modelling framework, the demand for infrastructure services is given by parameters $\tilde{u}_i^t$ for single-commodity networks and $\tilde{f}_{o,d}^t$ for multi-commodity networks. Without loss of generality, we assume here that the penalty parameters c_i^{SC} and $c_{o,d}^{\text{MC}}$ indicate the monetary value for fulfilling one unit of the respective demand with the expected quality of service. The total value of fulfilling the demand in all systems is then calculated as follows:

$$\text{VoD}^t = \sum_{i \in V^{\text{SC}}} c_i^{\text{SC}} \tilde{u}_i^t + \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \tilde{f}_{o,d}^t \quad (3.31)$$

The total value of services actually provided can be calculated as follows:

$$\text{VoS}^t = \sum_{i \in V^{\text{SC}}} c_i^{\text{SC}} u_i^t + \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} f_{o,d}^t \quad (3.32)$$

The system performance function $P(t)$ takes the value one if $\text{VoS}^t = \text{VoD}^t$, i.e. if the entire demand is satisfied. This corresponds to the demand-based performance functions commonly used in resilience analysis (e.g. in Alderson et al., 2014; Chen and Miller-Hooks, 2012; Mostafavi, 2018; Thacker et al., 2017; Trucco et al., 2012).

However, our generalised formulation based on estimating the monetary value of infrastructure services provides two advantages: First, the weighting of services in different infrastructure systems and within the same system can be adjusted with parameters c_i^{SC} and $c_{o,d}^{\text{MC}}$. Second, the approach can be extended to consider additional aspects, such as the deterioration of service quality in the event of infrastructure disruptions. Resilience assessments based purely on the fraction of demand that systems are able to satisfy do not consider, for example, increased travel times. In the approach used here, this can easily be taken into account by introducing discount

factors α_i^t and $\alpha_{o,d}^t$:

$$\text{VoS}^t = \sum_{i \in V^{\text{SC}}} c_i^{\text{SC}} \alpha_i^t u_i^t + \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \alpha_{o,d}^t f_{o,d}^t \quad (3.33)$$

For instance, in multi-commodity systems the expected generalised cost for travel between an OD pair divided by the actual generalised cost could be used as a discount factor. In the network flow model, the discount factor for each path is equal to the shortest path length $c_{o,d}$ divided by the actual path length c_p and the value of supply is calculated as follows:

$$\text{VoS}^t = \sum_{i \in V^{\text{SC}}} c_i^{\text{SC}} \alpha_i^t u_i^t + \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \left(\sum_{p \in P_{o,d}} \frac{c_{o,d}}{c_p} f_{o,d}^t \right) \quad (3.34)$$

The performance-based resilience metrics (ref. Section 2.1.5) can then be evaluated as follows:

$$\text{RL} = \sum_{t=1}^{t_{\max}} \left(1 - \frac{\text{VoS}^t}{\text{VoD}^t} \right) \quad (3.35)$$

$$\text{MSP} = \min_{t=1 \dots t_{\max}} \left(\frac{\text{VoS}^t}{\text{VoD}^t} \right) \quad (3.36)$$

$$\text{TLD} = \sum_{t=1}^{t_{\max}} \mathbb{1}_{x < 1} \left(\frac{\text{VoS}^t}{\text{VoD}^t} \right) \quad (3.37)$$

The resilience measures formulated above focus on impacts on infrastructure users. A disruptive event is likely to also result in additional cost for infrastructure providers (e.g. recovery and repair costs) and externalities (e.g. environmental impacts). While such effects can be analysed with network flow models, they are not included in the main resilience metrics because they are considered costs of (non-)resilience rather than outcomes.

3.4 Cascading failure

Let A be the set of assets in the interdependent infrastructure systems. Assets can represent specific pieces of equipment (e.g. electricity transformers), buildings (e.g. metro stations) or entire sub-systems (e.g. train control systems). An asset is a hierarchical system if it consists of sub-assets. For example, metro station assets could be considered to have sub-assets, such as power supply, ventilation systems, elevators, etc.

Variables $z_k \in [0, 1]$ denote the operability of assets $k \in A$, where $z_k = 1$ means that an asset is in its normal, fully functional state. Asset failure is represented with damage variables x_k , which measure the loss of operability. Asset damage variables can be binary, discrete or continuous, depending on the asset failure model used.

In the following, two modelling approaches are discussed. Deterministic methods model logical dependencies in hierarchical systems. Stochastic methods model the correlation of failure probabilities, for example, due to spatial proximity.

3.4.1 Deterministic models

The process of modelling assets as hierarchical systems is conceptually similar to the fault tree analysis method. Assets can be either series or parallel systems. Series system assets correspond to OR gates in fault trees because the failure of any sub-asset is sufficient to cause failure propagation. On the other hand, parallel system assets are equivalent to AND gates because all its sub-assets must fail to cause failure propagation. Figure 3.2 illustrates this concept with the example of a metro station that is modelled as a hierarchical system of assets.

The concept of deterministic failure propagation is formalised by introducing the set of logic dependencies D^L . If a dependency (m, k) exists in D^L , the asset m is a sub-asset of k . If k is a series system asset it is part of the set A^S and its operability

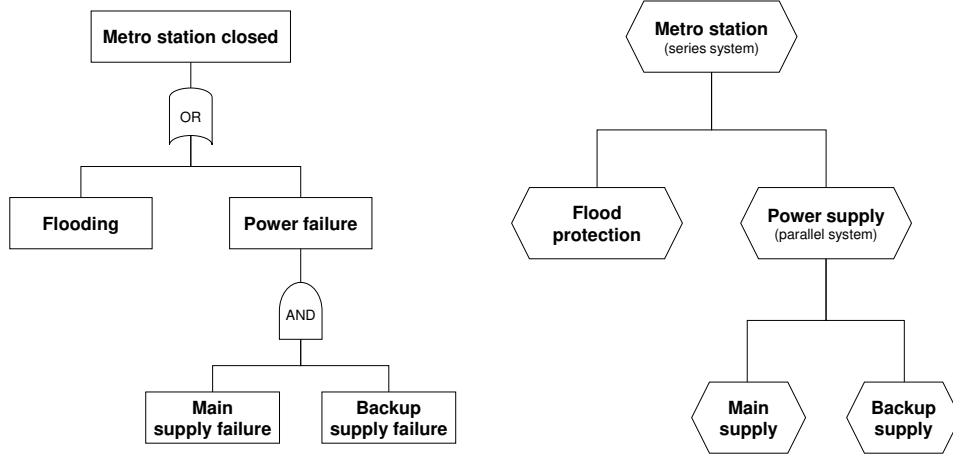


Figure 3.2: Fault tree (left) and equivalent hierarchical system of assets (right)

is bound by the minimum operability of its sub-assets:

$$z_k \leq \min_{(m,k) \in D^L} \{z_m\} \quad \forall k \in A^S \quad (3.38)$$

If k is a parallel system asset it is part of the set A^P and its operability is bound by the maximum operability of its sub-assets:

$$z_k \leq \max_{(m,k) \in D^L} \{z_m\} \quad \forall k \in A^P \quad (3.39)$$

Equation (3.38) is equivalent to the following set of constraints:

$$z_k \leq z_m \quad \forall k \in A^S, (m,k) \in D^L \quad (3.40)$$

We will use this transformation in Chapter 5 to consider series system assets in a linear programming model. For parallel system assets, an equivalent transformation of Equation (3.39) would require the use of integer variables. However, under certain conditions the operability of parallel system assets can be modelled as a linear

combination of its sub-assets' operability:

$$z_k \leq \sum_{(m,k) \in D^L} z_m \quad \forall k \in A^P \quad (3.41)$$

If all operability variables are binary, constraints (3.41) are equivalent to (3.39). Furthermore, constraints (3.41) may be used if the operability of sub-assets is substitutable. For example, if two sub-assets represent redundant ventilation systems and their operability indicates the flow rate of fresh air they provide, the main asset can be assumed fully operable if both ventilation systems operate at 50 % operability or any other combination that sums up to a value greater than or equal to one.

3.4.2 Stochastic models

In stochastic system reliability models, dependent failures are failures of one component that occur with a higher or lower probability if another component fails (Rausand and Høyland, 2004, p. 207 ff.). The following equations apply for the damage variables x_1 and x_2 of two dependent assets:

$$\text{Positive dependency: } \Pr(x_1 > 0 \wedge x_2 > 0) > \Pr(x_1 > 0) \times \Pr(x_2 > 0) \quad (3.42)$$

$$\text{Negative dependency: } \Pr(x_1 > 0 \wedge x_2 > 0) < \Pr(x_1 > 0) \times \Pr(x_2 > 0) \quad (3.43)$$

Positive failure dependency can be related to common cause failure or cascading failure. In dynamic modelling frameworks, failure propagation may also occur with delays. In this thesis, three different methods are explored to simulate dependent asset failure processes, namely a Dynamic Bayesian Network method (Chapter 4), a random graph method (Chapter 5) and an input-output method (Chapter 6).

Optimisation	Deterministic optimisation models	Stochastic programming models
	Deterministic simulation models	Stochastic process models
Simulation		
	Deterministic	Stochastic

Figure 3.3: Basic types of recovery models

3.5 Recovery

Analysing the resilience of infrastructure includes considering the recovery process. Thus, assets that can fail have to be modelled as repairable or replaceable. Figure 3.3 proposes a basic classification of recovery modelling approaches.

The literature review in Chapter 2 found that the logistics of recovery resources are not currently considered in state-of-the-art resilience analysis methods. In stochastic process models, this issue can be addressed by considering repair rates to be dependent on the availability of repair resources. A method following this approach is proposed in Chapter 4.

Sharkey et al. (2015) show how the optimisation of repair decisions can be integrated into a network flow model by adding decision variables that represent the progress of repair tasks. Their method considers precedence relationships between different repair tasks and the overall availability of work crews. In this thesis, we seek to further advance this approach by considering the logistical aspects of how work crews or repair resources in general are transported to assets that require repair.

The basic concept of the proposed method is that the provision of each repair resource is modelled with a separate flow network. Flows on these repair resource networks are assigned with the same minimum cost flow model that is also used to assign flows on infrastructure networks. Hence, the general method for flow coupling

proposed in Section 3.2.3 can also be applied to repair networks and we can model the demand in the repair resource networks to be dependent on the repair rates in other networks. Chapters 5 and 6 present two models that implement this approach.

3.6 Preparedness

Preparedness means to optimise pre-disruption decisions regarding investments that strengthen robustness or recovery capabilities. The proposed modelling framework considers this as a problem of finding the optimal flow capacities. In infrastructure networks, these capacities determine the robustness, i.e. the ability of infrastructure systems to absorb disruption. On the other hand, capacity limits in the repair resource networks determine the recovery capabilities. To model preparedness, the minimum cost flow formulation in Section 3.2.1 will be expanded to a stochastic programming model in Chapter 6.

3.7 Concluding remarks

This chapter discussed fundamental issues regarding the use of network flow models for analysing the resilience of interdependent infrastructure networks. The key findings can be summarised as follows:

- Dynamic flows have been modelled in previous research with iterative static or integrated multi-period assignment methods, which do not adequately represent sequential decision making. Two approaches were outlined to address this issue: a planning horizon and a stochastic programming approach.
- A generalised method for coupling flows in different networks has been proposed that is capable of representing several coupling mechanisms in previous network flow models for interdependent infrastructure networks.
- A resilience metric has been proposed that can be evaluated using network

flow modelling and considers the quantity and quality of infrastructure services provided by different systems.

- Deterministic and stochastic methods for modelling cascading failure have been discussed.
- For modelling the recovery of interdependent infrastructure systems, the concept of repair resource networks has been proposed. This approach enables the detailed representation of repair resources by considering them in the minimum cost flow assignment.
- Considering nominal capacities as decision variables in the model provides a method for analysing trade-offs between strengthening the robustness and preparedness of infrastructure networks.

The next step in this research is to apply and evaluate the theoretical concepts proposed in this chapter. This will be the focus of the models presented in the following three chapters.

Chapter 4

Stochastic simulation of asset failure and repair

This chapter introduces a novel asset operability model that uses a Dynamic Bayesian Network approach. The model simulates the failure and repair of interdependent infrastructure assets as a stochastic process. It is combined with a minimum cost flow assignment model to evaluate the impacts of asset failure on services provided to infrastructure users. The application of the model is demonstrated with the example of London's metro and electricity networks.

The chapter begins with a review of Bayesian network modelling approaches (Section 4.1) before using this method to develop a model of stochastic asset failure and repair in interdependent infrastructure systems (Section 4.2). Data sources are described (Section 4.3) that are then used to apply the model to a case study of London (Section 4.4). Simulation results are presented (Section 4.5) and discussed (Section 4.6).

The findings reported in this chapter are also published in a paper at the World Conference on Transport Research (Goldbeck et al., 2016*a*).

4.1 Review of Bayesian Network models

Bayesian Networks are increasingly used in engineering applications due to several advantages they offer over conventional methods of dependability and risk analysis (Weber et al., 2012). For example, Bayesian Networks have the flexibility to be used for predictions as well as diagnostics and can be updated according to new evidence. Most importantly, Bayesian Networks are polyvalent in the sense that it is possible to represent other reliability engineering tools, such as fault trees and Markov chains, with Bayesian networks. For instance, Weber and Jouffe (2006) present a case study on how a failure mode and effect analysis (FMEA) translates into a Bayesian network. Furthermore, Bayesian networks have proven to be a useful modelling language for machine learning approaches (Dehmer and Basak, 2012).

Bayesian Networks are directed acyclic graphs in which nodes represent variables and edges represent relations between them (Jensen and Nielsen, 2007). The value of each variable depends on variables connected to it through incoming edges in the network (parent variables) and this relationship is described with conditional probability distributions. Following the notation of Acharya et al. (2012), we formally define a Bayesian network as $BN = (G, \Theta)$ where G is a directed, acyclic graph with nodes X_i^t and Θ denotes the set of conditional probability distributions. For each realization x_i^t of X_i^t , the conditional probability distributions define

$$\Theta_{x_i^t | \text{Pa}(X_i^t)} = \Pr(x_i^t | \text{Pa}(X_i^t)) \quad (4.1)$$

where $\text{Pa}(X_i^t)$ are the parents of X_i^t in G . Note that $\text{Pa}(X_i^t)$ can contain nodes from the same time slice or from the previous time slice.

Variables in Bayesian Networks can be stochastic or deterministic. Stochastic variables are random variables with non-degenerate probability distributions whose parameters are determined by the node's parents in the Bayesian Network. Deterministic variables are defined by a deterministic function of their parents. In other words, their conditional probability distributions are degenerate.

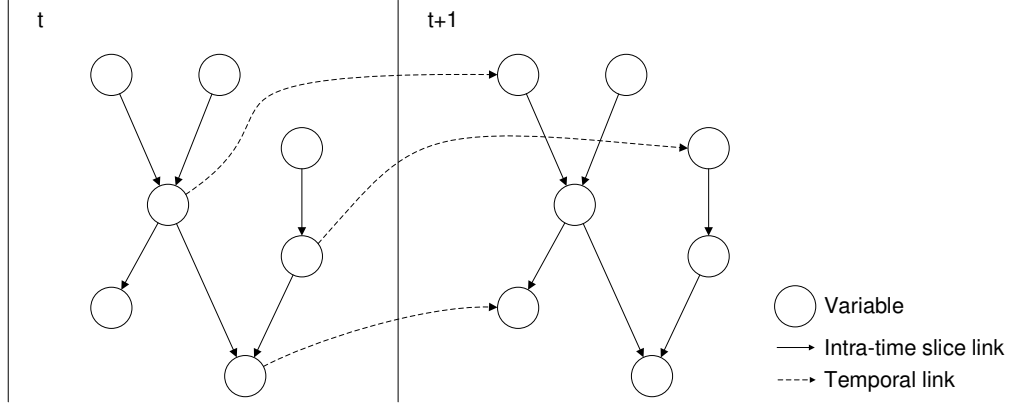


Figure 4.1: Graph representation of a Dynamic Bayesian Network (DBN)

Furthermore, we distinguish between discrete variables, where the conditional probability distributions are represented with conditional probability tables, and continuous variables, where they are represented with probability density functions.

Dynamic Bayesian networks (DBN) extend the concept of Bayesian networks by expanding the network into the dimension of time and modelling discrete-time stochastic processes. In a DBN, the structure of variables and links, as well as the conditional probability distributions, are identical for all time steps (Jensen and Nielsen, 2007). DBNs are usually visualised by drawing the nodes and links for two time steps, as shown in Figure 4.1.

DBNs have been used in previous studies to quantify the vulnerability of infrastructure networks. For example, Di Giorgio and Liberati (2012) propose a DBN approach with three distinct levels (atomic events, propagation and services). The authors present a case study in which they model an electricity distribution network and a control system as a DBN with 231 nodes. It is demonstrated how such an approach can be used to calculate reliability, predict the propagation of adverse events and diagnose the causes of failure. However, this method does not consider restoration and repair processes. Furthermore, it only uses discrete variables.

Codetta-Raiteri et al. (2012) also analyse an electricity system and propose a DBN model based on decomposing a network into modules that are connected in series or parallel. The failure rates in this model are dependent on the system state whereas the repair rates are assumed to be constant. By applying the method to a

benchmarking network of 118 nodes, the paper demonstrates that it is capable of approximating network flow effects without the need to conduct computationally expensive optimal power flow calculations.

The dynamics of repair processes have been captured in greater detail in Neil and Marquez (2012), albeit not specifically for infrastructure networks. This study analyses the dependency of a repair process on a four-event logistics chain with a mixture of normally-distributed delay times and discrete delay events, such as the need for and availability of resources.

The papers discussed above show that there is great potential in using DBN approaches to analyse the resilience of infrastructure networks. However, many issues remain to be addressed in order to advance this methodology. For instance, a more detailed representation of damage and repair processes in distributed systems is needed. Furthermore, the infrastructure DBN models identified here stem from the electric power sector and are therefore tailored to the specific characteristics of that industry. There is currently no study available on the application of DBNs for the resilience analysis of transportation networks or systems-of-systems containing networks from different infrastructure sectors. Finally, the scalability of the DBN modelling approach to real-world infrastructure networks is yet to be shown.

4.2 DBN-based asset operability modelling method

The principal challenge of using DBN approaches to analyse the resilience of inter-dependent infrastructure systems is the large number of assets (denoted here with the set A), which are usually distributed over a large geographic area. Instead of modelling each asset individually, the approach proposed here defines types of assets and develops corresponding DBN classes, which then serve as blueprints from which instances of individual asset DBNs are created. The DBN classes define interface variables, through which the DBNs for different assets can be connected to each

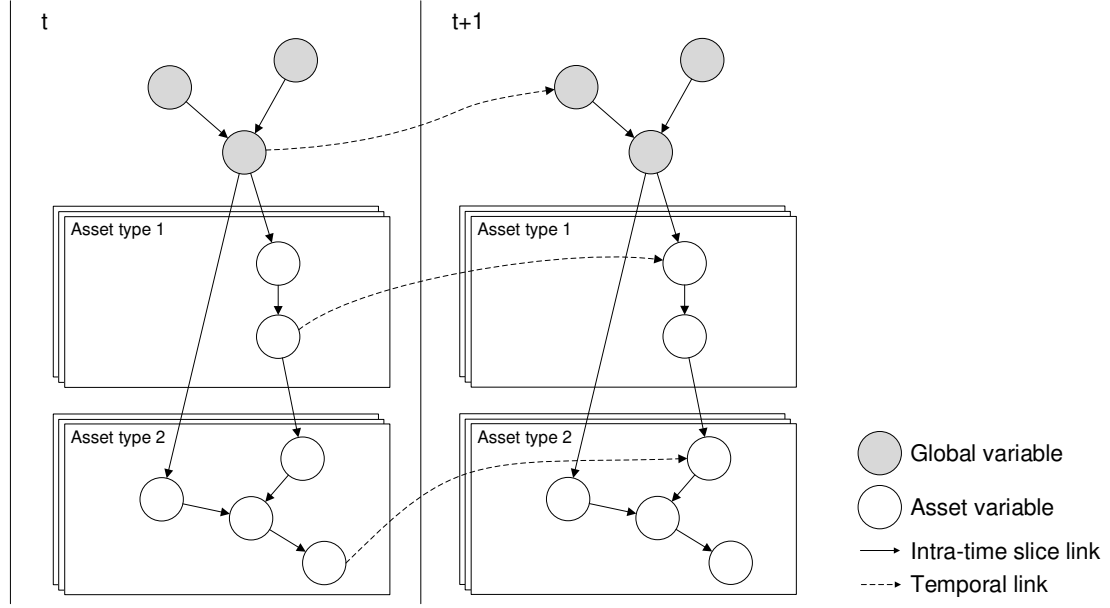


Figure 4.2: Asset operability DBN with two asset types

other or to variables describing environmental conditions. This modelling approach is illustrated in Figure 4.2 with an example involving two asset types.

4.2.1 Global and asset variables

The proposed modelling approach distinguishes two types of variables in the DBN. Global variables represent the environment (e.g. hazards) and state of the overall system (e.g. availability of recovery resources). Global variables do not belong to an asset class and are instantiated only once in every time step. On the other hand, asset variables are instantiated for each asset of the type they belong to and are denoted with sub-scripts $i \in A$.

4.2.2 Dependencies

The edges in Bayesian networks are directed links which show that the parent node appears as a parameter in the conditional probability distribution of the child node, thus making the latter dependent on the former. In the case of deterministic variables, the conditional probability distributions are degenerate. For example, a deterministic variable could be defined simply as the sum of two other variables.

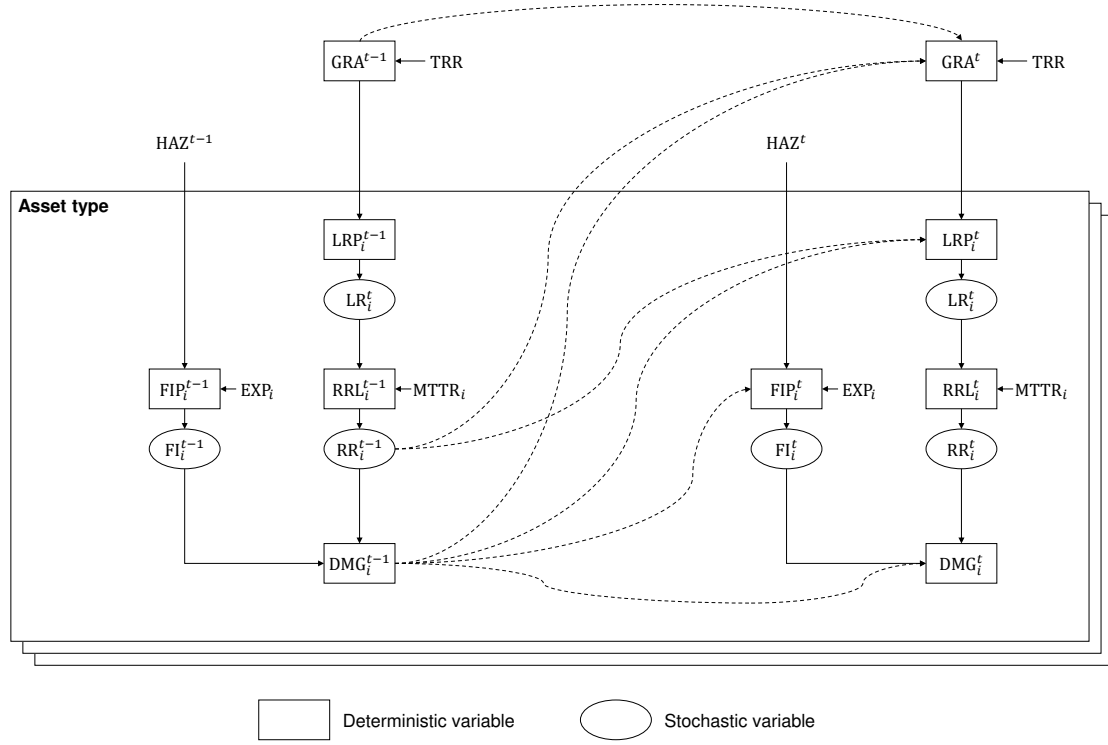


Figure 4.3: DBN model for the failure and repair of a generic asset type

For stochastic variables, the conditional probability distribution could be discrete or continuous and contain one or more parameters. The number of parameters must correspond to the number of incoming edges. For example, a stochastic variable with a Bernoulli distribution has one parameter p and, therefore, must have one incoming link in the Bayesian Network.

While the representation in Figure 4.2 gives the clearest overview of the DBN asset operability, it has the limitation that it cannot show dependencies between different instances of the same asset type. This can only be achieved by drawing all individual assets but the DBN then quickly becomes too large for a clear visualisation.

4.2.3 Damage and repair

The DBN presented in Figure 4.3 serves as a basic building block that can be used to capture damage and repair of a generic asset type. The DBN updates damage variables DMG_i^t for time steps t and assets $i \in A$. The current damage level is a

deterministic asset variable that depends on the damage in the previous time step DMG_i^{t-1} , the failure incident variable FI_i^t and the repair rate variable RR_i^t :

$$DMG_i^t = \begin{cases} DMG_i^{t-1} + FI_i^t - RR_i^t & \text{if } DMG_i^{t-1} + FI_i^t - RR_i^t > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4.2)$$

The failure incident variable FI_i^t indicates whether asset i is damaged at time t ($FI_i^t = 1$) or not ($FI_i^t = 0$). The failure incident probability is denoted with FIP_i^t . Thus, the conditional probability distribution of FI_i^t is a Bernoulli distribution with parameter FIP_i^t :

$$FI_i^t \sim \text{Bernoulli}(FIP_i^t) \quad (4.3)$$

The failure incident probability FIP_i^t is a deterministic asset variable that takes the value of the exposure parameter EXP_i if the global hazard variable H^t has a value of one and the asset is not already damaged:

$$FIP_i^t = \begin{cases} EXP_i & \text{if } HAZ^t = 1 \wedge DMG_i^{t-1} = 0 \\ 0 & \text{otherwise} \end{cases} \quad (4.4)$$

In other words, the exposure parameter EXP_i is the failure probability of asset i if a certain hazard event occurs, which is indicated by the variable HAZ^t taking a value of one. However, an asset failure cannot occur if the asset is still damaged from a previous failure.

If a failure occurs, the damage level DMG_i^t increases by 1 according to Equation (4.2). To mitigate the damage, the asset must be repaired, which is modelled with repair rate variables RR_i^t . Repair rates are assumed to be stochastic asset variables following uniform probability distributions with upper limits RRL_i^t :

$$RR_i^t \sim \text{Uniform}(0, RRL_i^t) \quad (4.5)$$

The model assumes that the mean time to repair for each asset can be estimated

with parameters $MTTR_i$, which translates into a mean repair rate of $1/MTTR_i$. Thus, the upper limit RRL_i^t for the uniformly distributed repair rate variable RR_i^t must be $2/MTTR_i$.

However, the normal repair rate is only achieved if all resources required for repairing the asset are available. This is modelled in the conditional probability distribution of the repair rate with

$$RRL_i^t = \begin{cases} \frac{2}{MTTR_i} & \text{if } LR_i^t = 1 \\ 0 & \text{otherwise} \end{cases} \quad (4.6)$$

where LR_i^t is a stochastic asset variable indicating the local resource availability. This variable is assumed to be Bernoulli distributed with parameter LRP_i^t :

$$LR_i^t \sim \text{Bernoulli}(LRP_i^t) \quad (4.7)$$

LRP_i^t denotes the probability that repair resources are available and is only greater than zero if the asset is damaged. If the asset has been repaired in the previous time step the resources are already available and $LRP_i^t = 1$. If the asset is damaged but repair has not yet started the probability that repair resources are dispatched to the asset depends on the global variable GRA^t :

$$LRP_i^t = \begin{cases} 1 & \text{if } DMG_i^{t-1} > 0 \wedge RR_i^{t-1} > 0 \\ GRA^t & \text{if } DMG_i^{t-1} > 0 \wedge RR_i^{t-1} = 0 \\ 0 & \text{otherwise} \end{cases} \quad (4.8)$$

The global variable GRA^t models the overall repair capability of the system. According to Equation (4.8), a low value of GRA^t means a low probability that repair resources are dispatched to an asset awaiting repair and vice versa.

The value of GRA^t depends on the total number of assets requiring repair and a parameter TRR setting the maximum number of assets that can be repaired at any

time, i.e. the system's overall repair capacity. If the number of assets requiring repair resources is less than TRR minus the number of assets that are already being repaired minus one, it is certain that repair resources are available and $\text{GRA}^t = 1$. Otherwise, GRA^t is the ratio of unused resources and the number of damaged stations. To prevent oscillation, a moving average of this ratio and the previous global resource availability is used:

$$\text{GRA}^t = \begin{cases} 0 & \text{if } \sum_{i \in A} \text{sgn}(\text{RR}_i^{t-1}) > \text{TRR} \\ 1 & \text{if } \sum_{i \in A} \text{sgn}(\text{RR}_i^{t-1}) < \text{TRR} \\ -\sum_{i \in A} \text{sgn}(\text{DMG}_i^{t-1}) & \\ \frac{1}{2}(\text{GRA}^{t-1} + \frac{\text{TRR} - \sum_{i \in A} \text{sgn}(\text{RR}_i^{t-1})}{1 + \sum_{i \in A} \text{sgn}(\text{DMG}_i^{t-1})}) & \text{otherwise} \end{cases} \quad (4.9)$$

To summarize, the DBN described above models the failure and repair of a set of infrastructure assets based on the following key assumptions:

1. Each asset has one failure mode that occurs with probability EXP_i if a certain hazard condition is active.
2. Assets are repaired with continuous repair rates that are uniformly distributed between 0 and $2/\text{MTTR}_i$ if the required repair resources are available.
3. The probability that repair resources for a damaged asset are available depends on the the overall number of damaged and repaired assets in the previous time step, as specified in Equation (4.9)

This DBN can be seen as a generic starting point for modelling asset failure and repair. The assumptions can be modified according to concrete application requirements. For example, considering different failure modes would be a matter of adding additional failure incident variables to the asset type DBN class. Different probability distributions could be considered for failure and repair rates.

The DBN presented above already captures an important interdependency effect related to the repair of assets: if many assets are damaged some repair tasks may

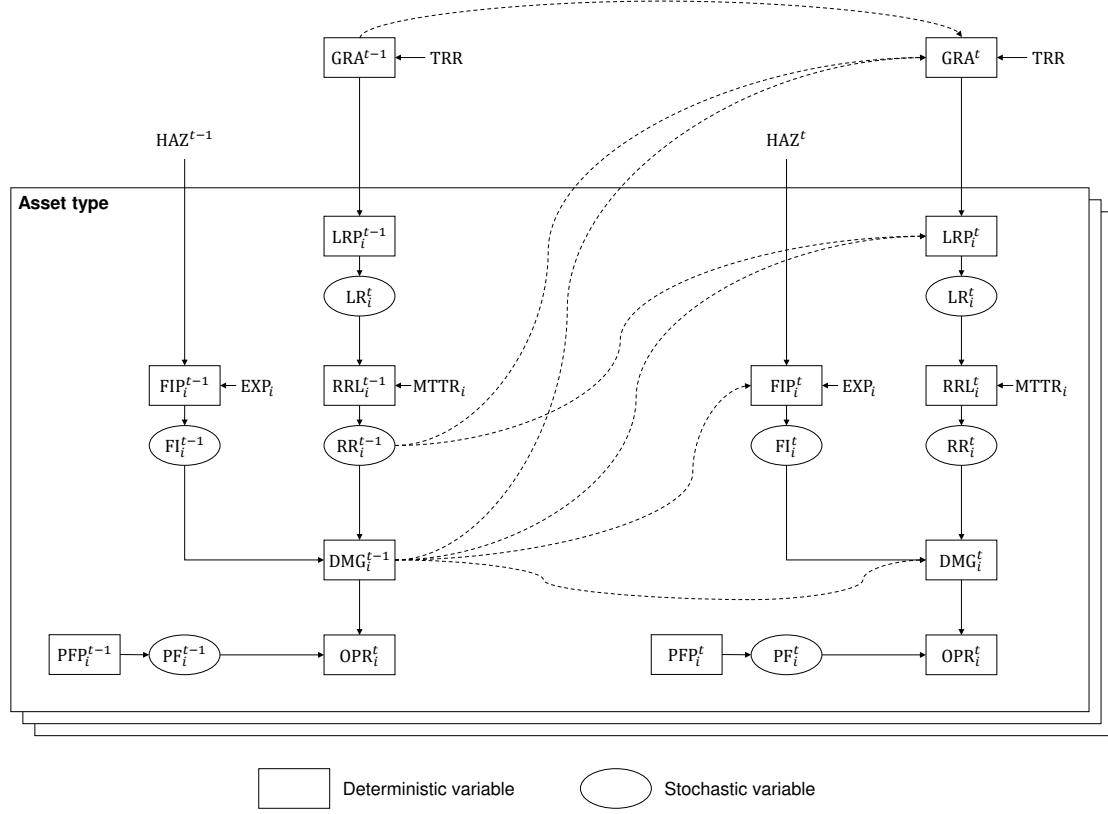


Figure 4.4: DBN model for the failure and repair of one asset with dependency

have to be delayed due to the unavailability of resources. In the following section, we introduce a second type of dependency, namely stochastic failure propagation.

4.2.4 Failure propagation

To model failure propagation dependencies, we extend the basic damage and repair DBN with asset variables PFP_i^t , PF_i^t and OPR_i^t , as shown in Figure 4.4. The deterministic variable OPR_i^t is binary and indicates whether the asset is operable ($OPR_i^t = 1$) or not ($OPR_i^t = 0$). Inoperability can be caused either by damage to the asset ($DMG_i^t > 0$) or by a propagated failure, represented with another asset variable $PF_i^t > 0$:

$$OPR_i^t = \begin{cases} 0 & \text{if } DMG_i^t > 0 \vee PF_i^t > 0 \\ 1 & \text{otherwise} \end{cases} \quad (4.10)$$

A propagated failure is assumed to occur with a probability PFP_i^t . Therefore, PF_i^t has the following conditional probability distribution:

$$\text{PF}_i^t \sim \text{Bernoulli}(\text{PFP}_i^t) \quad (4.11)$$

The asset variable PFP_i^t models failure propagation dependency. Its conditional probability distribution could be, for example:

$$\text{PFP}_i^t = \begin{cases} 1 & \text{if } \exists k \in A : k \text{ is co-located with } i \wedge \text{DMG}_k^t > 0 \\ 0 & \text{otherwise} \end{cases} \quad (4.12)$$

The conditional probability distribution for failure propagation can take many forms. In the remainder of this chapter, we will develop the model further using the example of two critical infrastructure systems in London, the London Underground metro network and an electric power supply network.

4.3 Data sources and modelling assumptions

The case study presented in this chapter acts as a proof-of-concept for the modelling method rather than an actual resilience assessment, and the emphasis is not on completeness but on clarity and demonstrating the capabilities of the modelling approach. As such, the case study considers only two key asset types (metro stations and electricity substations) whereas a comprehensive resilience analysis would have to consider other types, such as railway tracks and electricity cables.

4.3.1 London Underground Network

The main data source for the London Underground metro network was the Rolling Origin and Destination Survey (RODS), which is publicly available (Transport for London, 2016). This data set contains the travel demand for the network consisting of 268 metro stations and 731 directed links. Due to different lines running in parallel

between some stations, the network is a multi-graph. It was transformed into a simple graph, which reduces the number of edges to 617 and enables the use of more efficient shortest path algorithms, such as the A* algorithm (Hart et al., 1968).

The data set contains the travel demand for 32,918 OD pairs, which sums up to 4.3 million passenger journeys on a typical weekday. The demand is disaggregated into six time slots:

- early morning: beginning of service - 7 am
- morning peak: 7 am - 10 am
- midday: 10 am - 4 pm
- evening peak: 4 pm - 7 pm
- evening: 7 pm - 10 pm
- late evening: 10 pm - end of service

The minimum cost flow assignment model assumes that passengers do not travel on the metro network if the expected travel time is higher than a certain cut-off value, either because they cancel their journey or because they use another transport mode. The cut-off travel time was calculated for each OD pair by obtaining the unimpeded driving time from the Google Maps API (Google, n.d.), increasing it by 25 % for congestion that is likely to occur if the metro network is disrupted, and adding 15 minutes to account for the time it takes to change modes of transport.

The peak and off-peak travel times between adjacent stations were obtained from Transport for London (2013). Link capacities were estimated by multiplying the capacity of the train model used on that link with the maximum service frequency (trains per hour) according to the current timetable, resulting in capacity values between 6,488 and 34,920 passengers per hour.

4.3.2 London Power Network

The London Power Network (LPN) is owned and operated by UK Power Networks and is the largest electricity distribution system in London. According to UK Power Networks PLC (2017), the LPN covers 656 square kilometres and receives power inputs from the National Grid's 400 and 275 kV networks at six supergrid transformer sites. Through a succession of voltage levels ranging from 132 kV to 230 V, LPN distributes electricity to 2.3 million customers with a peak demand of almost 5,000 MVA. The LPN consists of more than 35,000 kilometres of cables and 6,000 transformers.

UK Power Networks provide a website with live information on power outages (UK Power Networks PLC, n.d.). The high voltage incidents published on this website were logged over a period of five months between May and September 2015. For each incident, the data includes incident type, time of reporting, estimated recovery time, geographic location and affected postcodes. The geographic location is the location of the substation at which the incident occurred. A total of 149 high voltage incidents at 97 different substations were recorded.

This set of 97 substations serves as asset set for the case study presented here. The set is not a complete representation of LPN substations, since there may be substations at which no incident occurred during the period the data was recorded. However, for the proof-of-concept that we seek to establish the 97 substations are a sufficiently representative set of assets.

4.3.3 Flood hazard and recovery resources

According to the London Climate Change Partnership (2005), local flooding is a major risk for London Underground, with more than 1,200 flooding incidents and 200 station closures recorded between 1992 and 2003. As an effect of climate change, extreme rainfall incidents are expected to become more frequent and intense. Since climate change adaptation is a major application area of resilience assessment models, local flooding was chosen as a hazard for the case study presented here.

A comprehensive flood risk assessment for individual assets was beyond the scope of this study. Therefore, the flood risk exposure parameter for the 268 metro stations and 97 electricity substations was estimated using the Environment Agency's Updated Flood Maps for Surface Water (UK Department for Environment Food & Rural Affairs, n.d.). These maps show the extent of land that could be affected by surface flooding with a 1 in 30, 100 and 1,000 years probability of occurrence.

Metro stations where the platforms are above the surrounding ground level according to Transport for London (2011) are less likely to be damaged by flooding and the corresponding exposure parameters were set to $EXP_i = 0$. In the absence of further information on flood risk exposure, we assume that the fraction of surfaces within 100 metres that is at risk of flooding according to the Environment Agency's flood map is a sufficient proxy for the probability of flood damage to an underground station. We use a proportional scaling factor σ to related this proxy to the model parameter EXP_i :

$$EXP_i = (\text{Proportion of surface at flood risk within 100 m of } i) \times \sigma \quad (4.13)$$

In this case study, we assume $\sigma = 0.1$ because it is estimated that an underground station that is fully surrounded by surfaces marked at flood risk will suffer flood damage with a probability of 10 % in the case of an extreme weather event. Figure 4.5 depicts the empirical distribution function of the EXP_i parameter values for metro stations and electricity substations for three different return periods, calculated with Equation (4.13).

Since the two networks are managed by different organisations, recovery resource availability was modelled separately. In the absence of information on recovery capabilities in the public domain, each infrastructure operator was assumed to be capable of repairing up to 10 assets simultaneously, denoted with parameter settings $TRR^{LUN} = TRR^{LPN} = 10$.

For electricity substations, the estimated recovery time recorded from the UK Power Networks map of power outages was used to calculate the MTTR parameter.

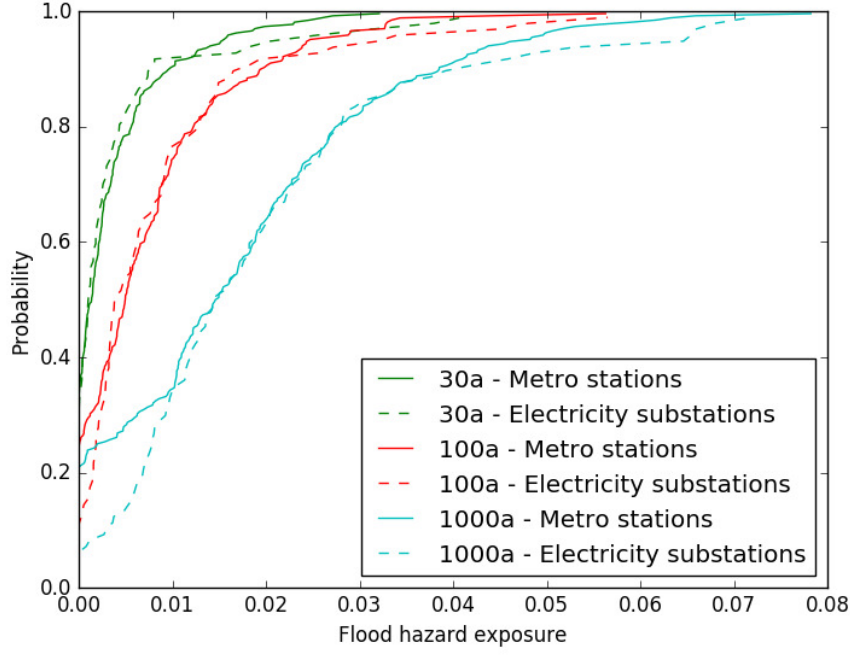


Figure 4.5: Cumulative distribution functions for flood hazard exposure

For metro stations, it was considered that evacuating flood water from depths of more than 10 metres requires pumps to be placed underground. We assume that removing flood damage, in this case, takes on average 2.5 hours whereas it takes only 1 hour if the metro station is less than 10 metres underground. In addition, we consider the time it takes to access the station from the nearest engineering depot with an assumed average speed of 25 kilometres per hour. Thus, the MTTR parameter for metro stations was calculated as follows:

$$\text{MTTR}_i = \begin{cases} 1.0 + \frac{\text{Distance from } i \text{ to the nearest depot in km}}{25} & \text{if depth of } i < 10 \text{ m} \\ 2.5 + \frac{\text{Distance from } i \text{ to the nearest depot in km}}{25} & \text{otherwise} \end{cases} \quad (4.14)$$

An overview of modelling assumptions in this case study is provided in Table 4.1.

Table 4.1: Overview of modelling assumptions

Assump- tion	Description	Parameter values
A1	Passengers decide to use an alternative transport mode or reschedule their journey if the expected travel time is greater than $(1 + a)x + b$, where x is the usual travel time.	$a = 0.25$ $b = 15 \text{ min}$
A2	The fraction of surfaces that is marked at risk of flooding within a distance r from an asset is a sufficient proxy for flood hazard exposure and the probability of flood damage can be calculated by multiplying this fraction by σ .	$\sigma = 0.10$
A3	Each infrastructure operator has the capacity to carry out repair works on up to n assets simultaneously.	$n = 10$
A4	The mean time to repair flood damage at a metro station is t_1 if the platforms are less than 10 m underground and t_2 otherwise. In addition, the time to reach a damaged asset from the nearest engineering depot at an average speed of v kilometres per hour is considered.	$t_1 = 1.0 \text{ h}$ $t_2 = 2.5 \text{ h}$ $v = 25 \text{ km/h}$

4.4 Model development

Based on the data and assumptions described in the previous section, we create a model of the two critical infrastructure systems considering the following interdependencies:

Hazard exposure The extreme rainfall event is assumed to equally affect the entire city, meaning that all infrastructure assets are exposed to the same hazardous event. While there are differences in how exposed assets are, the fact that flood damage can only occur during the hazardous event creates a temporal interdependency of asset failure.

Common repair resources Repair processes of assets belonging to the same infrastructure system are interdependent because they require the same resources.

Metro station power supply In addition to closure due to flood damage, metro stations are at risk of becoming inoperable due to power supply failure. Where possible, London Underground seeks to achieve redundancy by supplying sta-

tions from two different grid sources (London Underground, n.d.). Nevertheless, local power failure remains a frequent cause of station closure.

Congestion Congestion effects can cause interdependency on the network level. For example, the closure of a station could force passengers to evade to alternative routes, which could then become congested.

4.4.1 Asset operability model

The asset operability model is created based on the generic DBN for failure and recovery introduced in Section 4.2. Figure 4.6 depicts the DBN for two asset types. Failure incident probabilities of all assets depend on the global hazard variable HAZ. Repair resource availability is modelled separately for each infrastructure system using variables $\text{GRA}_{\text{LUN}}^t$ and $\text{GRA}_{\text{LPN}}^t$.

The representation of metro stations includes variables PFP_i^t for the propagated failure probabilities. These are dependent on the operability of the nearest electricity substation, indicated in Figure 4.6 with an incoming link from the PFP_i^t variable of the electricity substation asset type.

The fact that many metro stations are connected to two different grid supply points or have backup power supply equipment reduces the risk of cascading failure. This is taken into account in the calculation of the propagated failure probability:

$$\text{PFP}_i^t = \begin{cases} 1/2 & \text{if } \text{OPR}_k^t < 1 \text{ where } k \text{ is the nearest electricity substation} \\ 0 & \text{otherwise} \end{cases} \quad (4.15)$$

4.4.2 Network flow model

The purpose of this case study is to illustrate how even a simple network flow assignment approach with few parameters and low computational requirements can be used to evaluate value-based resilience measures. Thus, accuracy of flow assignment is not the main focus here, which justifies certain simplifications. In

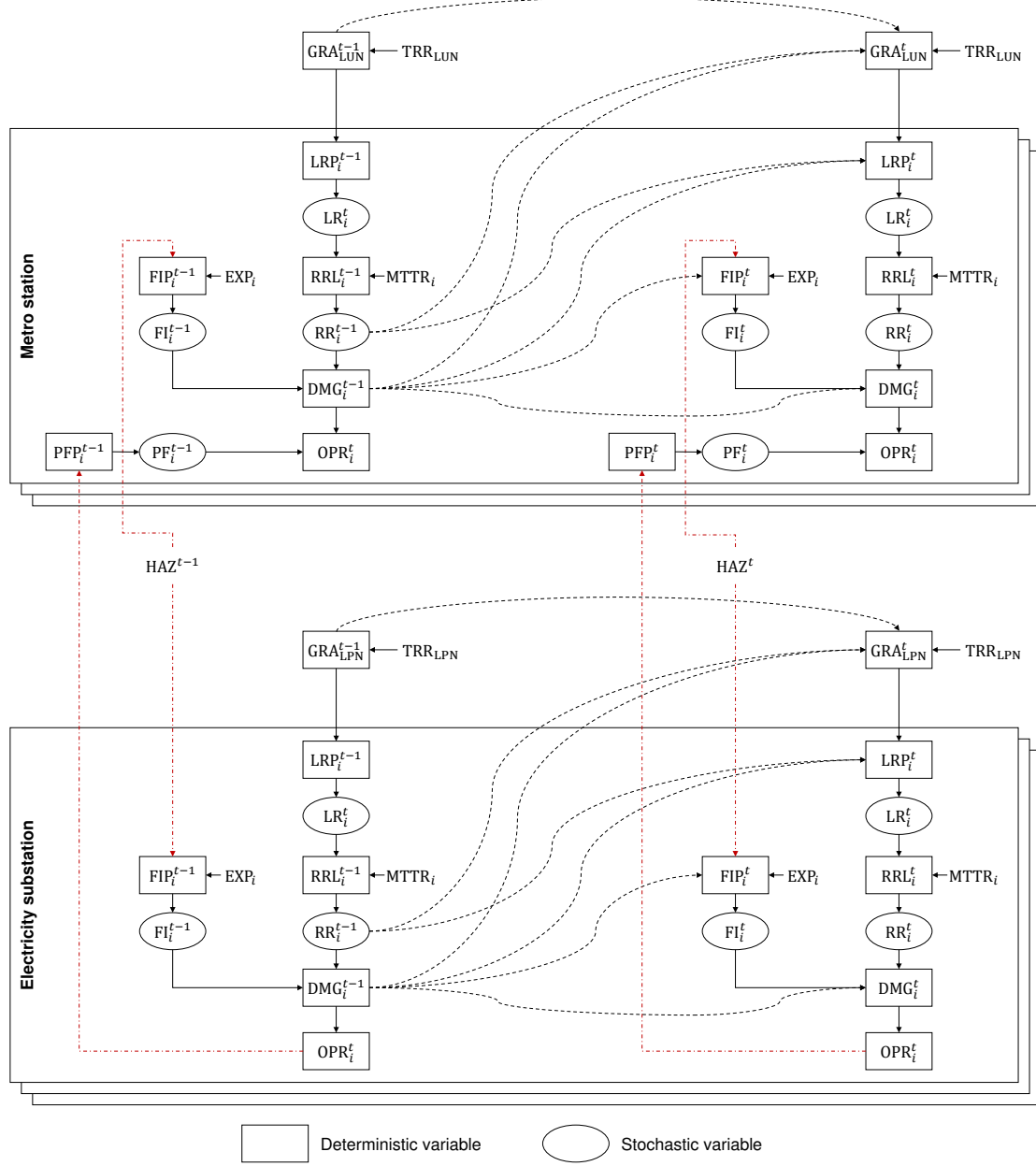


Figure 4.6: Asset operability DBN

Chapter 5, the network flow model will be expanded and its accuracy will be discussed in more detail.

Here, we consider only passenger flows on the metro network and use a relatively aggregated network representation in which all link flows represent passenger journeys between adjacent stations. The model does not include links for boarding, alighting or other passenger movements within stations. The flow assignment is carried out iteratively by solving a minimum cost flow problem for each time step.

The minimum cost flow problem is formulated as a linear program in Equations (4.16) to (4.22). The decision variables are link flows $f_{i,j}$, path flows f_p , network entries g_i and network exits u_i . Since a separate linear program is solved for each time step, we omit time step superscripts for the benefit of a clearer notation.

$$\text{minimise} \quad \sum_{(i,j) \in E} c_{i,j}^f f_{i,j} + \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \left(\check{f}_{o,d} - \sum_{p \in P_{o,d}} f_p \right) \quad (4.16)$$

$$\text{subject to} \quad f_{i,j} \leq \tilde{f}_{i,j} \quad \forall (i,j) \in E \quad (4.17)$$

$$g_i \leq \tilde{g}_i \quad \forall i \in V \quad (4.18)$$

$$u_i \leq \tilde{u}_i \quad \forall i \in V \quad (4.19)$$

$$g_i - u_i + \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} = 0 \quad \forall i \in V \quad (4.20)$$

$$f_{i,j} = \sum_{p \in Q_{i,j}} f_p \quad \forall (i,j) \in E \quad (4.21)$$

$$f_{i,j}, f_p, g_i, u_i \geq 0 \quad \forall (i,j) \in E, p \in P, i \in V \quad (4.22)$$

The objective (4.16) is to minimise the total travel time plus the penalty for demand that could not be assigned to the network due to insufficient capacity. This penalty is measured in terms of the travel time of an alternative transport mode (ref. 4.3.1).

Equations (4.17) to (4.19) represent capacity constraints for link flows, network

entries and network exits respectively. Equation (4.20) ensures the balance of flows at each node. Equation (4.21) ensures that link flows correspond to path flows, using sets $Q_{i,j}$ that contain all paths that link (i, j) is part of.

Capacity parameters $\tilde{f}_{i,j}$, $\tilde{g}_i$ and $\tilde{u}_i$ are determined by the asset operability model. This is modelled with asset utilisation dependencies contained in the set D^U . For each metro station, there is an asset utilisation dependency between the node and the asset representing this station. Links are not represented with separate assets but depend on both of the metro station assets that they connect.

If a metro station closes due to flood damage or power failure, passengers can no longer board or alight at this station. Therefore, the capacity parameters for network entries and exits are

$$\tilde{g}_i = \text{OPR}_k \times \check{g}_i \quad i \in V, (k, i) \in D^U \quad (4.23)$$

$$\tilde{u}_i = \text{OPR}_k \times \check{u}_i \quad i \in V, (k, i) \in D^U \quad (4.24)$$

where $\check{g}_i$ and $\check{u}_i$ are the capacities when the station is fully operable. As traction power supply is separate from station power supply, trains are normally able to pass through stations even if they are closed due to local power failure. However, if a station is affected by flooding, it is assumed that trains can no longer pass through. Thus, if the metro station asset at either side of a link becomes damaged the capacity of that link is set to zero:

$$\tilde{f}_{i,j} = \text{DMG}_k \times \check{f}_{i,j} \quad (i, j) \in E, (k, i, j) \in D^U \quad (4.25)$$

Equations (4.23) to (4.25) connect the asset operability and network flow models and we can now proceed to simulation experiments.

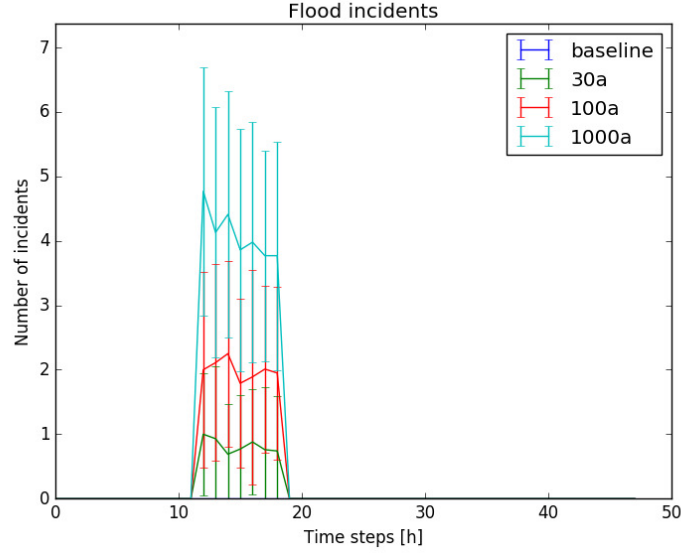


Figure 4.7: Number of flood incidents (mean over 100 simulation runs with error bars indicating standard deviation)

4.5 Simulation results

The model was implemented in a bespoke modelling and simulation environment, developed using the C# programming language. The commercial software Gurobi was used to solve the linear programming models. First, a baseline scenario was simulated in which no flood event occurs. Then, 100 stochastic simulation runs were carried out for each hazard level, denoted with 30a, 100a and 1000a.

The extreme rainfall events were assumed to occur between 12 midday and 6 pm on a typical weekday. The simulation period was set to 48 days, as no disruption effects were found to last for longer than this time period.

4.5.1 Asset failure

According to the simulation results, the expected number of metro stations experiencing flood damage is 5.8, 14.0 and 28.7 in the three hazard scenarios respectively. These flooding incidents are evenly distributed over the time of the rainfall event, as shown in Figure 4.7. The expected number of damaged electricity substations in the three scenarios was found to be 2.1, 4.9 and 11.6.

Direct flood damage and power loss cause the closure of metro stations as shown

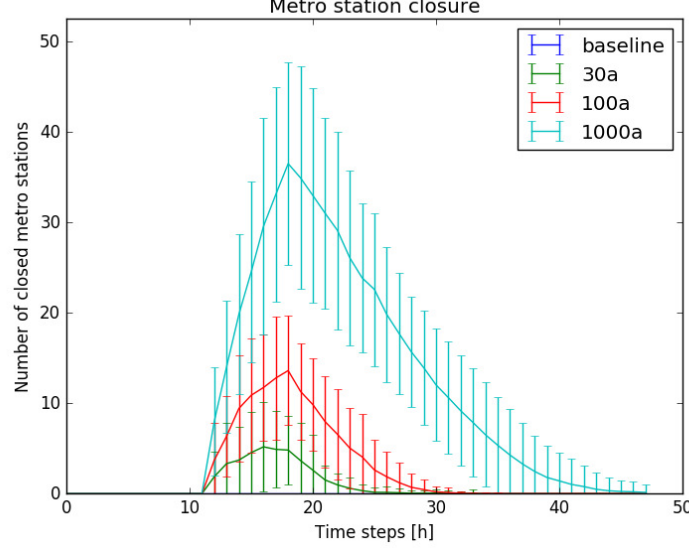


Figure 4.8: Number of closed metro stations (mean over 100 simulation runs with error bars indicating standard deviation)

in Figure 4.8. The expected number of station closures peaks at the end of the assumed extreme rainfall events, with 5.2, 13.6 and 36.5 stations expected to close in the three scenarios.

In the 30a scenario, 41.3 % of station closures were caused by local power failures. For the more severe flooding scenarios 100a and 1000a this proportion decreased to 28.4 % and 24.8 % respectively, indicating that closure due to power failure is less sensitive to increasing flood hazard than closure due to flood damage. In all three scenarios, some station closures were caused by both direct flood damage and power loss but these closures represent less than 2 % of all closures.

4.5.2 Asset repair

Figure 4.9 plots the values of flood damage variables DMG_k^t in a typical simulation run with 30a hazard severity. In this simulation run, five metro stations and three electricity substations experience flood damage, with the first incident occurring at $t = 12$ and the last at $t = 17$. As the number of damaged assets does not exceed the maximum number of assets that can be repaired simultaneously, all repair

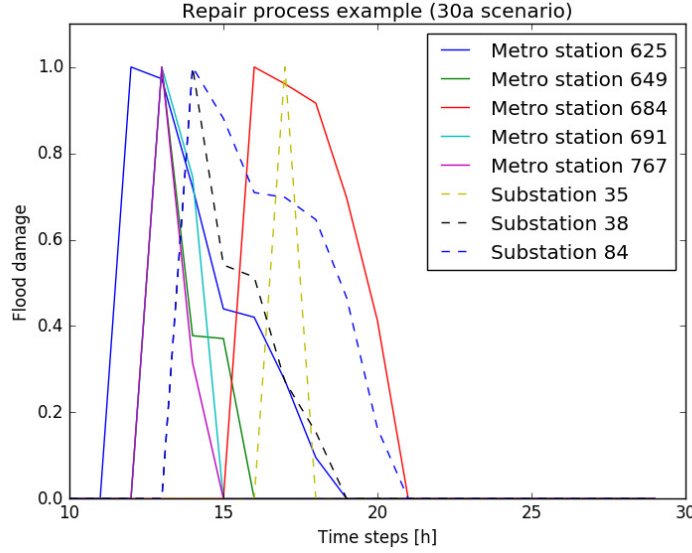


Figure 4.9: Asst failure and repair in a typical 30a simulation run

processes start without delay. The duration of repair processes ranges from one hour (substation 35) to seven hours (substation 84 and metro station 625).

In the 30a hazard scenario, the availability of repair resources in the metro system $\text{GRA}_{\text{LPN}}^t$ never falls below 90 %. Thus, it is very unlikely that repair processes are delayed in this scenario and the repair capacity of 10 simultaneous repair tasks can be regarded as sufficient. However, in the 100a and 1000a scenarios, the repair resource availability is drastically depleted, as shown in Figure 4.10. In the extreme scenario of a 1000a rainfall event, the probability of delayed repair rises up to about 80 %.

The flood damage probabilities and expected repair times for individual metro stations are depicted in Figure 4.11 for the 100a scenario. The marker size indicates the number of passengers travelling through each station in the baseline scenario. These results could be used to target investments for improving component-level resilience. For instance, the results suggest that some of the most-used stations, like Bond Street, Kings’s Cross St. Pancras and Victoria, could be at risk of flood damage with a probability greater than 10 %. Additionally, the expected repair times are relatively long. Thus, it should be evaluated whether additional protection measures or repair resources could be put in place.

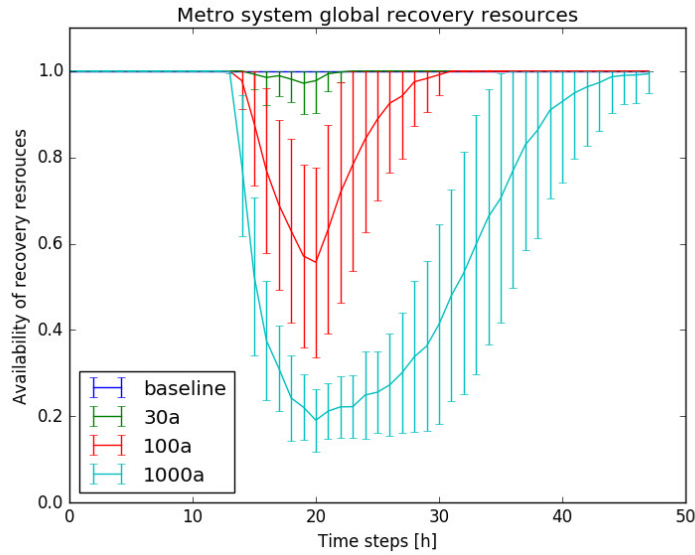


Figure 4.10: Recovery resource availability in the metro system (mean over 100 simulation runs with error bars indicating standard deviation)

4.5.3 Unmet demand

The outputs of the network flow model show the overall ability of the metro system to meet travel demand. In the baseline scenario, the demand is fully met and the number of journeys shows clear morning and evening peaks (Figure 4.12). In the flooding scenarios, the number of journeys is up to 50 % lower than in the baseline.

The greatest impact on passenger journeys occurs during the evening peak hour on the first day of the simulation period. In the 30a hazard scenario, the metro system recovers completely before the beginning of service on the second day. In the 100a scenario, there is a very small probability that service disruptions affect the morning peak hours. In the 1000a scenario, the disruption could last until the evening peak hours of the second day.

To analyse congestion on the metro network, we compare the number of links that operate at full capacity (Figure 4.13). Some congestion can be observed even in the baseline scenario, with 11 and 13 links at capacity during the morning and evening peak hours respectively. The number sharply increases in the flooding scenarios due to the deterioration of network capacity.

Although in many cases passengers can deviate from their shortest route to

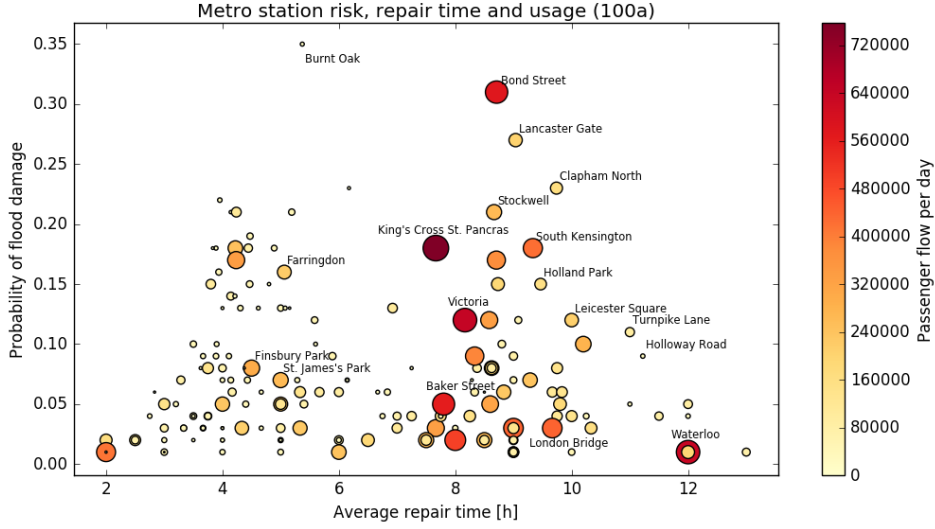


Figure 4.11: Damage probability, repair time and passenger flows for metro stations in the 100a scenario (mean over 100 simulation runs)

circumvent closed or congested parts of the networks, this is not always feasible or practical. The simulation results in Figure 4.14 show that during the peak of disruption 8.5, 24.0 and 48.2 % of journeys are not assigned to the network in the three hazard scenarios.

A key performance indicator for metro systems is the lost customer hours estimate. This measure can be derived from the simulation results by subtracting the baseline optimal value of the linear programming instances from the optimal value in the disruption scenarios. Figure 4.15 depicts the lost customer hours over time, which sum up to about 83,000, 260,000 and 820,000 lost customer hours in the three hazard scenarios.

For a simple plausibility check, we compare the lost customer hour estimates with data available from a two-day closure of the entire metro system due to industrial action in August 2015. The operator quantifies the impact of this closure to be 3.94 million lost customer hours (Transport for London, 2015a). Considering that in the 1000a flood risk scenario 36 % of travel demand over two days was not satisfied, the simulation result of 820,000 lost customer hours seems plausible.

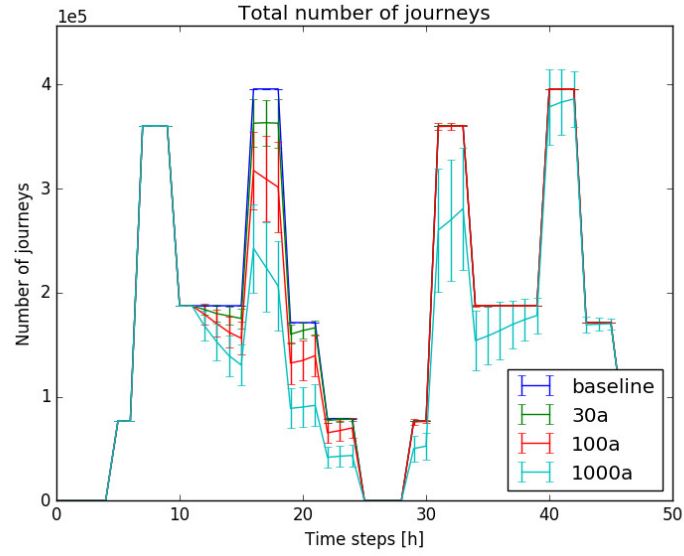


Figure 4.12: Total number of journeys (mean over 100 simulation runs with error bars indicating standard deviation)

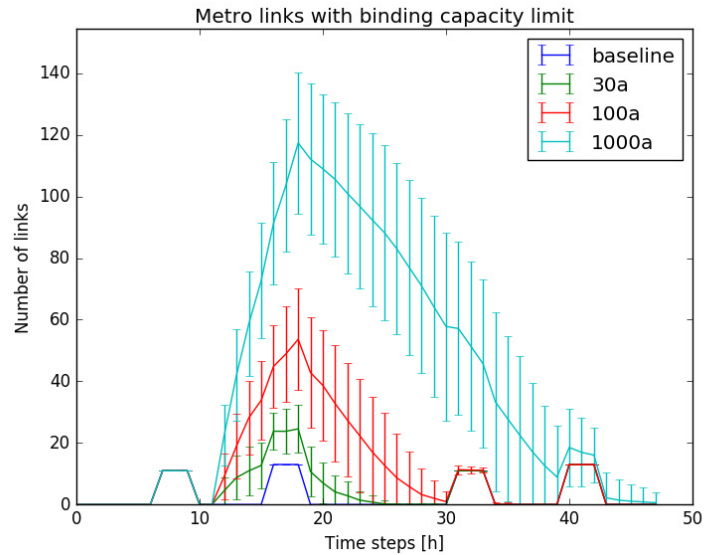


Figure 4.13: Metro network links operating at full capacity (mean over 100 simulation runs with error bars indicating standard deviation)

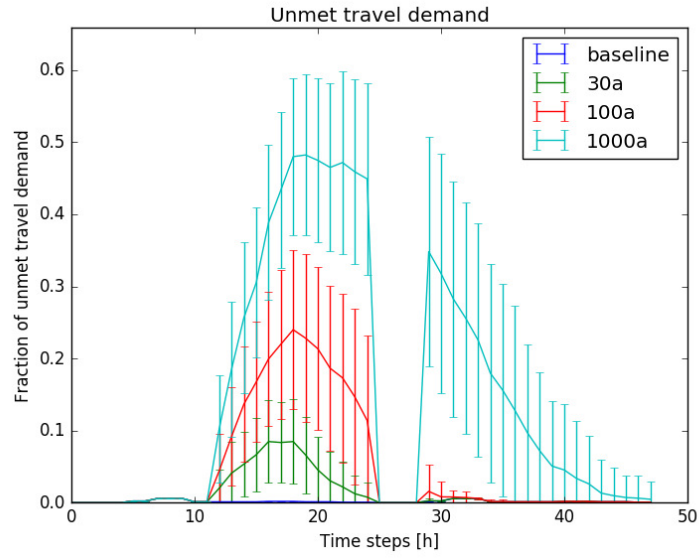


Figure 4.14: Unmet travel demand (mean over 100 simulation runs with error bars indicating standard deviation)

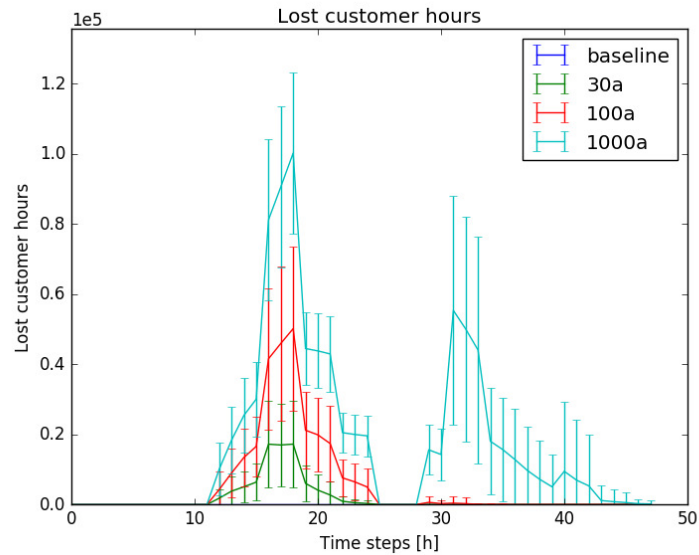


Figure 4.15: Lost customer hours (mean over 100 simulation runs with error bars indicating standard deviation)

4.6 Discussion and concluding remarks

This chapter contributes to the advancement of quantitative resilience analysis methods by investigating how a dynamic network flow assignment method can be combined with a stochastic model for simulating the failure and repair of network components. A novel network-of-networks approach for DBN models is proposed. The overall DBN consists of several interconnected networks, each representing an individual asset. It was found that this DBN modelling method is particularly useful for interdependent infrastructure systems, as shared hazard exposure, common repair resources and input dependencies can be represented as links in the DBN. The modelling of such interdependencies as conditional probabilities addresses the lack of stochastic definitions of dependency relations in the current literature and improves the possibilities to analyse highly uncertain dependency effects.

The method proposed in this chapter has been applied to model the metro and electric power networks in London. Key results of this case study include quantitative resilience assessments for the two interdependent critical infrastructure systems against severe flooding events with return periods of 30, 100 and 1,000 years. Under certain assumptions regarding the extend of asset damage and speed of repair, the model predicts the expected impact of these three flooding scenarios to amount to 83, 260 and 820 thousand lost customer hours respectively. The case study results demonstrate that owners and operators of infrastructure systems can use the proposed model to better estimate the impact of disruptive events and inform decisions on investments to protect their assets and operations.

The model's realism depends largely on the selection of probability distributions and their parameters. For high-impact low-probability scenarios, historical data that could be used for model validation is by definition rarely available. An alternative approach is to validate the model structure and parameters with the help of subject-matter experts. However, this is time-consuming and was not possible within the scope of this research.

Another limitation is that the probabilistic approach to modelling inputs

provided by one infrastructure system to another does not consider the quantity of inputs required and supplied. Furthermore, the stochastic repair model ignores that infrastructure operators would prioritise the allocation of repair resources to those assets that are most important for the functioning of the overall network. Both of these issues are addressed in the next chapter.

Chapter 5

Optimal recovery strategies

With increasing severity of asset damage, the scarcity of repair resources becomes more and more relevant, as we observed in the case study in the previous chapter. Therefore, resilience models should be able to capture the ability of infrastructure operators to efficiently manage repair resources and prioritise repair tasks that contribute most to overall network recovery.

To address this issue, the following chapter proposes two new modelling methods. Both methods are extensions of the basic minimum cost flow assignment introduced in Section 3.2. The first method is the iterative computation of network flows over a rolling planning horizon. This captures the optimal planning of infrastructure operations over several time steps under anticipation of future demand. The second method is the modelling of repair resource networks and the use of flow coupling constraints to link the recovery performance of infrastructure systems to the allocation and logistics of repair resources. This enables a joint optimisation of infrastructure operations and recovery planning.

The chapter is structured as follows. Section 5.1 presents the stochastic part of the methodology that is used to simulate the interdependent failure of assets. Section 5.2 presents the optimisation model that is used to simulate dynamic flow assignment and optimal repair resource allocation. The practical application of the modelling methodology is demonstrated by continuing the resilience analysis for London’s metro and electricity networks. Data sources used for this case study

are presented in Section 5.3. The model is validated for the baseline scenario in Section 5.4. Simulation results are presented in Section 5.5 and their sensitivity for changes in key parameters are analysed in Section 5.6.

5.1 Failure propagation scenarios

The stochastic scenario generation in this chapter only considers asset failure, since repair is modelled as part of an optimisation problem. Therefore, a relatively simple random graph approach can be used instead of the DBN-based modelling method in the previous chapter. The following section introduces the time-expanded asset-hazard graph and Section 5.1.2 describes how it is used to generate scenario trees for cascading asset failure.

5.1.1 Time-expanded asset-hazard graph

The central idea of the scenario generation method used in this chapter is to create a random graph in which nodes represent hazards and assets. Sampling is carried out by randomly adding edges to the graph and if an asset is directly or indirectly connected to a hazard it fails. By expanding the random graph in the dimension of time, the method can also take into account that some failures may propagate with a delay.

Each hazard $h \in H$ is assumed to occur at a certain time in the simulation period, denoted with t_h . In this time step, the hazard is referred to as active and can cause the failure of assets that are exposed to it.

The edges in the time-expanded asset-hazard graph are referred to as failure propagation dependencies, contained in the set D^F . These dependencies can connect an asset to a hazard or to another asset. In other words, they model both the exposure to hazards and the risk of cascading failure.

In the model development process, the set D^F is created by identifying all the possibilities of how a hazardous event could damage assets and how the failure of

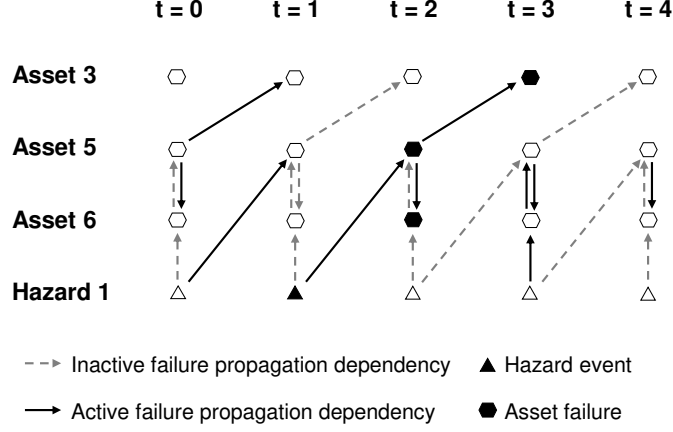


Figure 5.1: Time-expanded asset-hazard graph for the example in Figure 5.3

one asset can trigger the failure of another. If the failure of two assets is known to be correlated but the causal relation is unknown, this is modelled with two failure propagation dependencies in opposite directions.

For each failure propagation dependency $(k, m) \in D^F$, the parameters $p_{k,m}$ and $t_{k,m}$ are required, defining the probability and delay of failure propagation. These parameter values could be estimated based on historical data or subject-matter expertise.

An example asset-hazard graph is depicted in Figure 5.1. Hazard 1 is active at $t_h = 1$. In the particular sample shown, the failure propagation dependency from Hazard 1 to Asset 5 is also active for $t = 1$. It has a delay of one time step, which means that the failure of Asset 5 occurs at $t = 2$. This triggers further failures of Assets 5 and 3. Thus, hazard event causes direct damage to one asset and indirect damage to two further assets.

Given a sample of the time-expanded asset-hazard graph, the asset damage variables x_k^t are defined as follows:

$$x_k^t = \begin{cases} 1 & \text{if } (k, t) \text{ can be reached} \\ & \text{from any } (h, t_h), h \in H \\ 0 & \text{otherwise} \end{cases} \quad k \in A, t = 1 \dots t_{\max} \quad (5.1)$$

For ease of notation, we combine these asset damage variables into vectors $\mathbf{x}^t$.

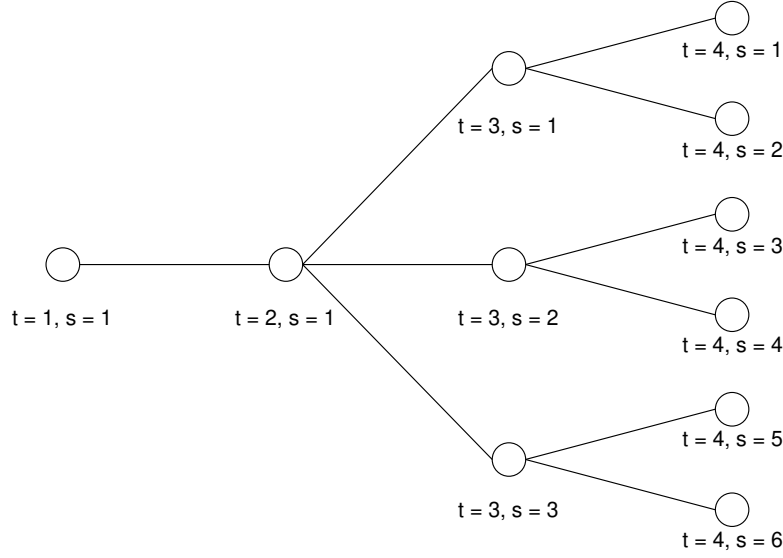


Figure 5.2: Example scenario tree

5.1.2 Scenario tree generation

The propagation of failure modelled with the asset-hazard graph method means that uncertainty increases over the simulation period. Representing this uncertainty as a scenario tree rather than a set of scenarios enables our methodology to avoid unnecessary network flow calculations. Figure 5.2 depicts an example scenario tree. We denote the number of tree nodes in time step t with s_t and in the following model variables will be indexed superscripts t, s , where $t = 1 \dots t_{\max}$ and $s = 1 \dots s_t$.

There exist two basic approaches for scenario tree generation: depth-first and breadth-first. Algorithm 1 describes a depth-first method. With the outer for-loop starting in line 3, the algorithm samples n_{scn} time series of asset damage vectors and adds them to the scenario tree. The inner for-loop starting at line 5 iterates through the simulation time steps and tests whether a new asset damage sample already exists in the scenario tree (line 7). If this is the case, the probability of the existing branch is increased (line 8). Otherwise, a new branch is created (lines 11 to 14).

The probability that a scenario is included in a scenario tree generated with this method is equal to its probability of occurrence. For the analysis of resilience and cascading failure, however, we are particularly interested in low-probability

Algorithm 1 Depth-first scenario tree generation

Input: set of assets A , asset failure model AFM, number of simulation time steps $t_{\max}$, maximum number of scenarios n_{scn}

Output: probabilities $p^{t,s}$, damage vectors $\mathbf{x}^{t,s}$

```

1:  $p^{1,1} \leftarrow 1$  ▷ Create root node
2:  $\mathbf{x}^{1,1} \leftarrow \text{Zeros}(|A|)$ 
3: for  $i = 1 \dots n_{\text{scn}}$  do
4:    $(t, s)_{\text{cur}} \leftarrow (1, 1)$  ▷ Set root node as current node
5:   for  $t = 2 \dots t_{\max}$  do
6:      $\mathbf{x}^{\text{spl}} \leftarrow \text{AFM.SampleAssetFailure}((t, s)_{\text{cur}})$ 
7:     if  $\text{ChildNodes}((t, s)_{\text{cur}})$  contains  $(t, s)_{\text{idn}}$  where  $\mathbf{x}^{(t,s)_{\text{idn}}} = \mathbf{x}^{\text{spl}}$  then
8:        $p^{(t,s)_{\text{idn}}} \leftarrow p^{(t,s)_{\text{idn}}} + 1/n_{\text{scn}}$  ▷ Increment probability of existing node
9:        $(t, s)_{\text{cur}} \leftarrow (t, s)_{\text{idn}}$ 
10:    else
11:       $(t, s)_{\text{new}} \leftarrow (t, |\text{ChildNodes}((t, s)_{\text{cur}})| + 1)$  ▷ Create new node
12:      Add  $(t, s)_{\text{new}}$  to  $\text{ChildNodes}((t, s)_{\text{cur}})$ 
13:       $p^{(t,s)_{\text{new}}} \leftarrow 1/n_{\text{scn}}$ 
14:       $\mathbf{x}^{(t,s)_{\text{new}}} \leftarrow \mathbf{x}^{\text{spl}}$ 
15:       $(t, s)_{\text{cur}} \leftarrow (t, s)_{\text{new}}$ 
16: return  $p^{t,s}, \mathbf{x}^{t,s}$ 

```

high-impact scenarios. In other words, we would like to control the branching of the scenario tree so that more low-probability scenarios are considered while ensuring that the scenario tree still accurately represents the probability space.

For this purpose, the breadth-first scenario generation method described in Algorithm 2 has been developed, which creates the same number of samples for each branch of the scenario tree. The outer for-loop starting at line 4 iterates through the simulation time steps the second for-loop (line 6) iterates through nodes in the current time steps. With the for-loop starting at line 8, the algorithm samples n_{spl} new asset damage vectors. If the current node already has a child node with an identical damage vector the probability of this node is increased (line 11). Otherwise, a new child node is created (lines 14 to 17).

To prevent the algorithm from creating more than n_{scn} scenarios, lines 18 and 19 stop the sampling if a node has reached the maximum number of child nodes,

calculated as the number of remaining scenarios ($n_{\text{scn}} - s_t$) divided by the number of current leaves s_t . If sampling is stopped before the maximum number of samples n_{spl} is reached, the child node probabilities have to be normalised, which is achieved with lines 20 and 21. This method of controlling the branching of the scenario tree increases the likelihood of including extreme scenarios without impacting the overall representativeness of the scenario tree.

Algorithm 2 Breadth-first scenario tree generation

Input: set of assets A , asset failure model AFM, number of simulation time steps t_{max} , maximum number of scenarios n_{scn} , number of samples per parent node n_{spl}

Output: probabilities $p^{t,s}$, damage vectors $\mathbf{x}^{t,s}$

```

1:  $p^{1,1} \leftarrow 1$  ▷ Create root node
2:  $\mathbf{x}^{1,1} \leftarrow \text{Zeros}(|A|)$ 
3:  $s_1 \leftarrow 1$ 
4: for  $t = 1 \dots (t_{\text{max}} - 1)$  do
5:    $s_{t+1} \leftarrow 0$ 
6:   for  $s = 1 \dots s_t$  do
7:      $(t, s)_{\text{cur}} \leftarrow (t, s)$ 
8:     for  $i = 1 \dots n_{\text{spl}}$  do
9:        $\mathbf{x}^{\text{spl}} \leftarrow \text{AFM.SampleAssetFailure}((t, s)_{\text{cur}})$ 
10:      if  $\text{ChildNodes}((t, s)_{\text{cur}})$  contains  $(t, s)_{\text{idn}}$  where  $\mathbf{x}^{(t,s)_{\text{idn}}} = \mathbf{x}^{\text{spl}}$  then
11:         $p^{(t,s)_{\text{idn}}} \leftarrow p^{(t,s)_{\text{idn}}} + 1/n_{\text{spl}}$  ▷ Increment probability of existing node
12:      else
13:         $s_{t+1} \leftarrow s_{t+1} + 1$  ▷ Create new node
14:         $(t, s)_{\text{new}} \leftarrow (t + 1, s_{t+1})$ 
15:        Add  $(t, s)_{\text{new}}$  to  $\text{ChildNodes}((t, s)_{\text{cur}})$ 
16:         $p^{(t,s)_{\text{new}}} \leftarrow p^{(t,s)_{\text{cur}}} / n_{\text{spl}}$ 
17:         $\mathbf{x}^{(t,s)_{\text{new}}} \leftarrow \mathbf{x}^{\text{spl}}$ 
18:      if  $s_{t+1} \geq \lceil \frac{n_{\text{scn}} - s_t}{s_t} \rceil$  then
19:        break
20:      for  $i = 1 \dots s_{t+1}$  do
21:         $p^{t+1,i} \leftarrow p^{t+1,i} / \sum_{j=1}^{s_{t+1}} p^{t+1,j}$  ▷ Re-normalise probabilities
22: return  $p^{t,s}, \mathbf{x}^{t,s}$ 

```

5.2 Optimal repair and flow assignment

Given a scenario tree for failure propagation, the next task is to model the optimal repair of assets. Since our aim is to consider repair resource logistics, the optimisation of repair is integrated into the minimum cost flow assignment model.

5.2.1 Rolling planning horizon

To consider repair resource management, we seek to model multi-period planning, for example, the optimal sequencing of repair tasks. This cannot be achieved with iterative static minimum cost flow assignment methods, such as the one used in Chapter 4, because they consider network flows in each time step independently and could only model myopic decisions.

On the other hand, multi-period minimum cost flow assignment methods are based on the assumption of perfect information, including on the occurrence of future events. Therefore, they would allow unrealistic anticipation, for example, the pre-emptive deployment of repair resources before random asset failures occur.

A rolling planning horizon method combines the iterative and multi-period assignment approaches. The basic idea is to model that decision makers anticipate the results of their own actions but not random events, such as asset failures. The current time step t_c iterates from 1 to $t_{\max}$. In each time step, the optimal flow assignment is calculated for a planning horizon of length t_p . The current time step is the first time step of the planning horizon and decisions for this time step are saved as final values of the flow variables. Decisions for future time steps indicate what the decision makers anticipate at time t_c . These predictions are updated in subsequent iterations until the final value is determined when the respective time step becomes t_c .

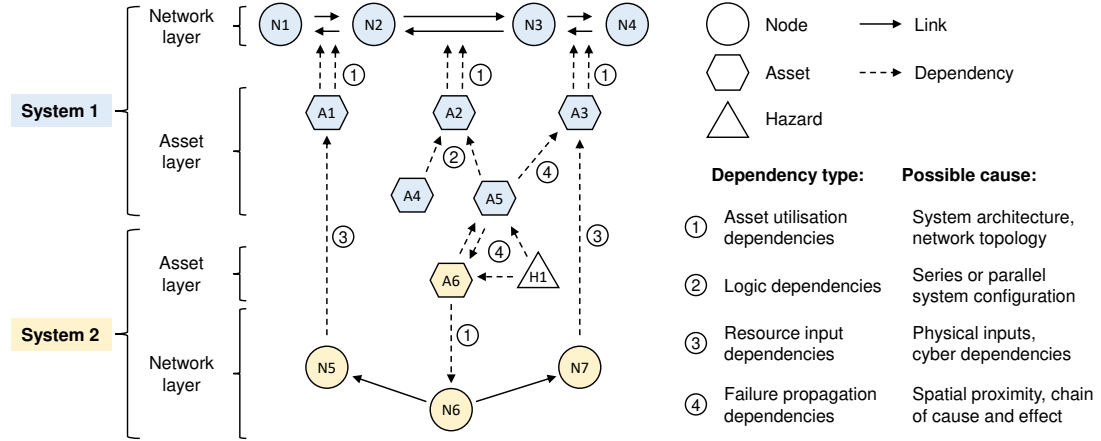


Figure 5.3: Example illustrating different types of dependency relations

5.2.2 Interdependency

Consider the toy model depicted in Figure 5.3. It consists of two infrastructure systems, both are represented with an asset layer and a network layer. The scenario generation model captures that assets A5 and A6 are both exposed to hazard H1, i.e. their failure probability is correlated. Furthermore, the risk of stochastic failure propagation to asset A3 is considered.

Another type of dependency considered in this chapter is deterministic failure propagation due to hierarchical relations between assets. In the example in Figure 5.3, assets A4 and A5 are sub-assets of A2. Equations (3.40) and (3.41) can be used to include these dependency relations as constraints in the optimisation problem (ref. Section 3.4.1).

Two further types of dependency are introduced to link the network layer to the asset layer and vice versa. Asset utilisation dependencies model how nodes and links rely on the operability of certain assets. Resource input dependencies model how assets rely on the supply of products and services provided by certain nodes. In the example in Figure 5.3, the links in system 1 require the operability of assets A1, A2 and A3. These assets, in turn, are dependent on inputs supplied by nodes N5 and N7 in the other system. These inputs are provided by node N6, which requires the operability of asset A6.

Let D^U denote the set of all asset utilisation dependencies. Asset utilisation is denoted with variables w_k^t and defined as the maximum capacity utilisation of all nodes and links that are connected to the asset via dependencies contained in D^U :

$$w_k^t = \max \left\{ \max_{(i,j) \in E: (k,i,j) \in D^U} \left\{ \frac{1}{\hat{f}_{i,j}} f_{i,j}^t \right\}, \max_{i \in V: (k,i) \in D^U} \left\{ \frac{1}{\hat{g}_i} g_i^t \right\} \right\} \quad (5.2)$$

If an asset is damaged it cannot be used. This is modelled by setting asset operability as upper limit for asset utilisation:

$$w_k^t \leq z_k^t \quad (5.3)$$

Resource input dependencies are denoted with the set D^I . Following the generalised method for coupling network flows (ref. Section 3.2.3), we use variables v_i^t to measure the amount of resources that node i provides to dependent assets. This amount is a linear function of the utilisation w_k^t and the repair y_k^t of the asset:

$$v_i^t = \sum_{k \in A: (i,k) \in D^I} \left(\alpha_{i,k}^w w_k^t + \alpha_{i,k}^y y_k^t \right) \quad (5.4)$$

Parameters $\alpha_{i,k}^w$ and $\alpha_{i,k}^y$ determine the coupling strength, i.e. how many units of the input resource node i has to provide to enable the full utilisation or repair of asset k .

5.2.3 Linear programming formulation

Now that we have defined the asset variables required to model interdependency, we can integrate the optimisation of repair into the minimum cost flow assignment model. The objective function (5.5) is the objective from the standard minimum cost flow model (3.17), summed up over the entire planning horizon.

Constraint (5.6) sets the asset operability at the beginning of the planning horizon according to the asset damage vector x_k^{tc} of the scenario tree node for which the flow assignment is calculated. A damaged assets can recover its operability if it is

repaired (5.7), but the maximum operability is one (5.8). Operability cannot decrease in the planning horizon, i.e. the model does not anticipate future asset failures.

Constraints (5.9) and (5.10) are based on Equations (3.40) and (3.41). They implement logic dependencies (series and parallel systems) that can lead to deterministic failure propagation.

Constraint (5.11) model the relation of asset utilisation and operability as per (5.3). Constraints (5.12) and (5.13) transform Equation (5.2) into equivalent linear constraints. Since capacity constraints also apply to nodes and links that do not depend on any assets, Equations (5.14) and (5.15) are added.

Constraint (5.16) models the amount nodes supply to dependent assets depending on their utilisation and repair, as per Equation (5.4). This supply is then taken into account in the balance of flow constraint (5.17), alongside the net flow over connected links and the balance of network in- and out-flows.

As in the standard minimum cost flow model (ref. Section 3.2), constraint (5.18) is required for consistency between link and path flows in multi-commodity networks, and constraints (5.19) and (5.20) ensure that supply does not exceed demand. Finally, constraints (5.21) to (5.24) set all decision variables to be non-negative.

$$\begin{aligned} \text{minimise} \quad & \sum_{t=t_c}^{t_c+t_p} \left(\sum_{(i,j) \in E} c_{i,j}^f f_{i,j}^t + \sum_{i \in V^{\text{SC}}} \left(c_i^g g_i^t + c_i^{\text{SC}} (u_i^t - u_i^t) \right) \right) + \\ & \sum_{(o,d) \in OD} c_{o,d}^{\text{MC}} \left(\check{f}_{o,d}^t - \sum_{p \in P_{o,d}} f_p^t \right) \end{aligned} \quad (5.5)$$

$$\text{subject to} \quad z_k^{t_c} \leq 1 - x_k^{t_c} \quad k \in A \quad (5.6)$$

$$z_k^t + y_k^t = z_k^{t+1} \quad k \in A, t=t_c \dots t_c+t_p-1 \quad (5.7)$$

$$z_k^t \leq 1 \quad k \in A, t=t_c \dots t_c+t_p \quad (5.8)$$

$$z_k^t \leq z_m^t \quad k \in A^S, (m,k) \in D^L, t=t_c \dots t_c+t_p \quad (5.9)$$

$$z_k^t \leq \sum_{(m,k) \in D^L} z_m^t \quad k \in A^P, t=t_c \dots t_c+t_p \quad (5.10)$$

$$w_k^t \leq z_k^t \quad k \in A, t=t_c \dots t_c+t_p \quad (5.11)$$

$$\frac{1}{\hat{f}_{i,j}} f_{i,j}^t \leq w_k^t \quad (k, (i,j)) \in D^U, t=t_c \dots t_c+t_p \quad (5.12)$$

$$\frac{1}{\hat{g}_i} g_i^t \leq w_k^t \quad (k, i) \in D^U, t=t_c \dots t_c+t_p \quad (5.13)$$

$$f_{i,j}^t \leq \hat{f}_{i,j} \quad (i,j) \in E, t=t_c \dots t_c+t_p \quad (5.14)$$

$$g_i^t \leq \hat{g}_i \quad i \in V, t=t_c \dots t_c+t_p \quad (5.15)$$

$$v_i^t = \sum_{k \in A: (i,k) \in D^I} \left(\alpha_{i,k}^w w_k^t + \alpha_{i,k}^y y_k^t \right) \quad i \in V, t=t_c \dots t_c+t_p \quad (5.16)$$

$$g_i^t - u_i^t - v_i^t + \sum_{j \in V: (j,i) \in E} f_{j,i}^{t-t_{j,i}} - \sum_{j \in V: (i,j) \in E} f_{i,j}^t = 0 \quad i \in V, t=t_c \dots t_c+t_p \quad (5.17)$$

$$f_{i,j}^t = \sum_{p \in Q_{i,j}} f_p^{t-\delta_{p,i}} \quad (i,j) \in E^{\text{MC}}, t=t_c \dots t_c+t_p \quad (5.18)$$

$$\sum_{p \in P_{o,d}} f_p^t \leq \check{f}_{o,d}^t \quad (o,d) \in OD, t=t_c \dots t_c+t_p \quad (5.19)$$

$$u_i^t \leq \check{u}_i^t \quad i \in V^{\text{SC}}, t=t_c \dots t_c+t_p \quad (5.20)$$

$$w_k^t, y_k^t, z_k^t \geq 0 \quad k \in A, t=t_c \dots t_c+t_p \quad (5.21)$$

$$g_i^t, v_i^t, u_i^t \geq 0 \quad i \in V, t=t_c \dots t_c+t_p \quad (5.22)$$

$$f_{i,j}^t \geq 0 \quad (i,j) \in E, t=t_c \dots t_c+t_p \quad (5.23)$$

$$f_p^t \geq 0 \quad p \in P, t=t_c \dots t_c+t_p \quad (5.24)$$

Assuming a valid network topology, the linear program formulated in Equations (5.5) to (5.24) is always feasible because the slack variables allow demands to remain unsatisfied if network capacity is insufficient. Networks in which all capacity and demand parameters are integers are guaranteed to have an integer minimum cost flow solution (Ahuja et al., 1993, p. 318). However, in our case the asset operability variables can turn integer capacity parameters into real-valued effective capacities and, therefore, the integrality property does not apply.

The size of the linear program is considerable for city-scale infrastructure networks with hundreds or thousands of nodes, links, OD pairs and assets. The number of decision variables is $t_{\text{ph}}(2|V^{\text{SC}}| + |E| + k|OD| + 2|A|)$ and an upper bound for the number of constraints is $t_{\text{ph}}(3|V^{\text{SC}}| + |OD| + 2|E| + 3|A| + |D^{\text{L}}| + |D^{\text{U}}|)$. Owing to the computational efficiency of the simplex algorithm, solutions to LP problem instances of this magnitude can be obtained within seconds or minutes, thus enabling the analysis of a large scenario tree.

5.3 Data sources and modelling assumptions

In the remainder of this chapter, the case study introduced in Chapter 4 is expanded to demonstrate the simulation of optimal repair with the methodology presented above. In addition to the London Underground Network (LUN) and the London Power Network (LPN), two repair resource networks are considered (LUN repair and LPN repair). An overview of the nodes, links and assets in these four systems is presented in Table 5.1. Figure 5.4 depicts a geographic map of the systems.

5.3.1 London Underground Network

The metro network model in Chapter 4 did not consider parallel tracks between adjacent stations and interchange times. To increase the realism of the model in this respect, we expand the network and add 778 nodes representing platforms at the 267 stations. Each platform node is connected to the station node with links in both

Table 5.1: Overview of the system-of-systems

London Underground Network			London Power Network		
	LUN	LUN repair		LPN	LPN repair
V	1,045 nodes	392 nodes	1,379 nodes	404 nodes	
	267 stations	19 depots	1,099 busbars	12 depots	
	778 platforms	373 repair sites	67 super grid transformers	392 repair sites	
			128 demand nodes		
			6 bulk supply points		
			79 traction power sub-stations		
E	2,315 links	959 links	1,742 links	784 links	
	759 on-train links		828 connectors		
	778 entrance-to-train links		394 two-winding transformers		
	778 train-to-exit links		80 three-winding transformers		
			440 reverse flow links		
A	389 assets		392 assets		
	267 metro stations		19 grid supply points		
	79 track sections		247 high-voltage sub-stations		
	8 rolling stock fleets		126 low-voltage sub-stations		
	8 line control systems				
	8 control centres				
	19 depots				

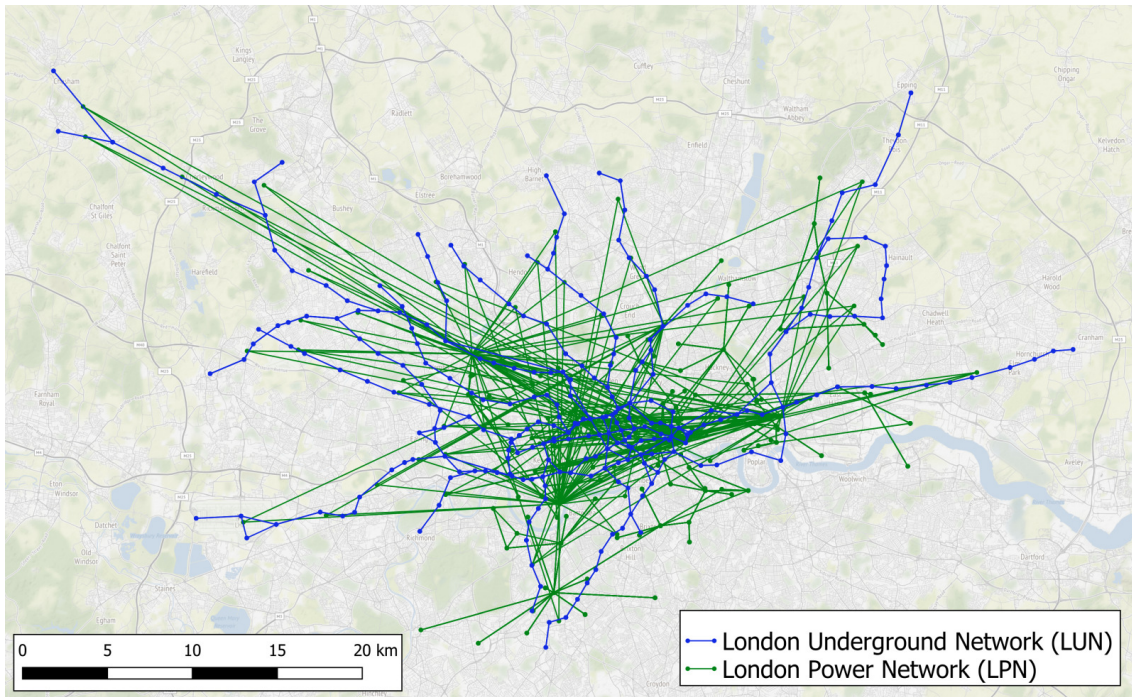


Figure 5.4: Map of the critical infrastructure systems

directions, referred to as entrance-to-train and train-to-exit links. As an example, Figure 5.5 depicts the representation Piccadilly Circus.

The cost parameters for the London Underground network were calculated using on-train travel times between adjacent stations (Transport for London, 2013) and within-station walking times (Transport for London, 2012). All travel times were valued at £11.21 per hour, based on estimates by the UK Department for Transport (2015). As in the previous chapter, travel demand data from the Rolling Origin and Destination Survey (RODS) was used (Transport for London, 2016).

A detailed account of model parameters is provided in Table B.1 in the appendix. For some parameters, real-world data was not available and assumptions had to be made. The capacity of intra-station walking links was assumed to be 10 % higher than their peak usage observed in the data. While this may not be very accurate, especially for less used stations, the impact on simulation results is deemed to be low because network flows on the London Underground network are much more constrained by the capacity of on-train links. Justification for some further parameter assumptions is provided in Table B.4. Overall, the impact of uncertainty regarding

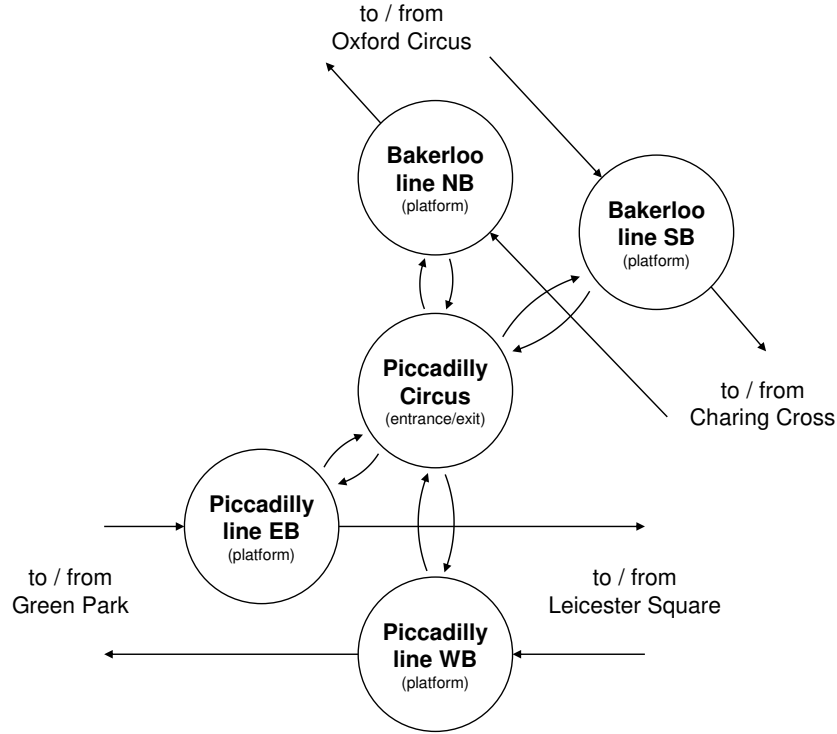


Figure 5.5: Representation of a metro station with platform nodes, on-train links and walking links

the parameters of the network flow model is relatively low compared to the impact of uncertainty regarding asset damage and repair times.

5.3.2 London Power Network

The case study in Chapter 4 considered sub-stations in the London Power Network (LPN) as assets that can be damaged by flooding, resulting in the failure of power supply to metro stations. However, the model did not calculate power flows and did not consider the supply of power to other end-users.

In this chapter, we develop a more detailed model of the LPN using data taken from the long term development statement (LTDS) published by the network operator UK Power Networks PLC (2017). This dataset contains 1,379 nodes, including 67 super-grid transformers (where power is fed into the LPN from the national grid), and 138 demand nodes (mainly sub-stations at the 11 kV level). A typical feeder circuit is depicted in Figure 5.6. There are 1,742 links in the network, representing connectors

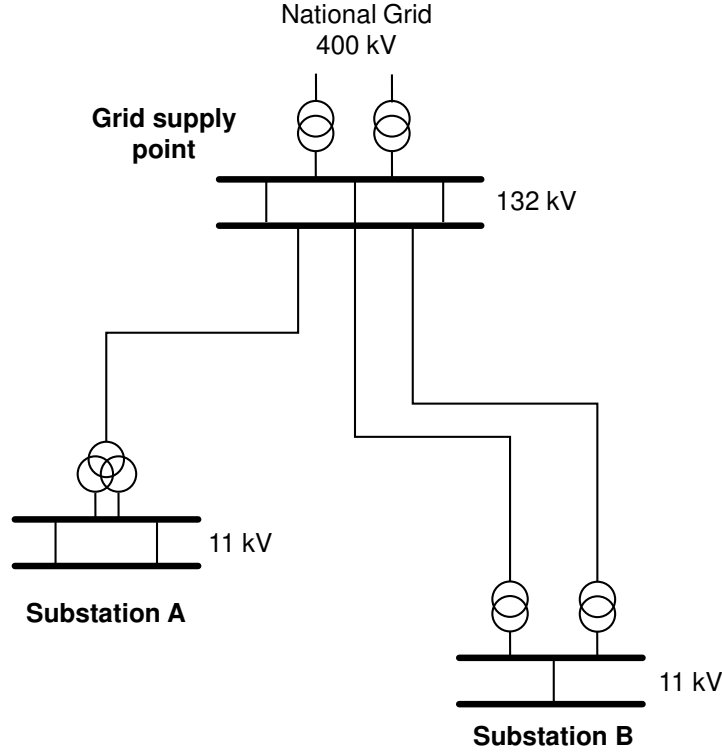


Figure 5.6: Single-line diagram of a grid supply point with two substations

and transformers. The transformers are located at 392 different sub-station sites, and for the purpose of this case study, these are considered as assets of the system.

5.3.3 Repair networks

For the LUN, depots play an important role in emergency engineering because this is where technical staff and equipment are based. For the LPN, it is assumed that grid supply points play a similar role, as they are much larger facilities compared to sub-station sites.

Due to the unavailability of data on specific repair resources for the two infrastructure systems, an abstract repair resource commodity was modelled that represents all staff, equipment and spare parts required to carry out repair tasks. The complete repair of an asset requires one unit of this abstract repair resource.

5.3.4 Dependency relations

Asset utilisation and logic dependency relations follow directly from the system architecture. For example, all within-station walking links depend on the asset representing the metro station. Track section assets are connected via logic dependencies with line control and rolling stock assets.

Input dependencies model the supply of electricity to operate metro stations and trains. Furthermore, each asset is connected to its repair site node via an input dependency. Failure propagation dependencies are added based on the geographic distance of an asset to another asset or to the hazard (see next section).

In total, the model contains 16,295 dependency relations. An overview of the different types of dependency relations is presented in Table 5.2. A more detailed description, including parameter values where applicable, is available in Table B.3 in the appendix.

5.3.5 Hazard exposure

The borough of Brent was chosen as site for a hypothetical flooding incident in this case study because several infrastructure assets in this area are located close to a potential source of flooding, the Welsh Harp reservoir. The borough's strategic flood risk assessment (London Borough of Brent, 2007) and flood risk management strategy (London Borough of Brent, 2015) identify a failure of this reservoir as the most catastrophic, yet unlikely flooding incident. The reports do not quantify the probability of such an incident, but they state that the failure probability for similar reservoirs is estimated to be one in 50,000 years. This is substantially lower than the probability of flooding scenarios considered in current flood protection policies. Nevertheless, it was deemed a suitable example for this case study because it demonstrates how the proposed method is particularly apt for exploratory analysis of high-impact, low-probability events.

It is not in the scope of this paper to carry out detailed flood risk assessments for individual assets. Instead, we assume that the risk of flood damage depends only on

Table 5.2: Dependency relations

	From	To	No. of instances
Failure propagation	Flood hazard	Assets in flood zone 1	9
	Flood hazard	Assets in flood zone 2	30
		Assets located less than 100 m apart	1,598
		Assets located 100 to 1,000 m apart	5,940
Asset utilisation	Electricity substation	Generation nodes and outgoing connectors	4,837
	Metro station asset	Entrance-to-train and train-to-exit links	1,556
	Track section assets	On-train links	759
Logic	Line control assets	Track section assets	79
	Rolling stock fleet assets	Track section assets	79
	Control centre assets	Line control assets	10
	Depot assets	Rolling stock fleet assets	20
Input	Low-voltage electricity substation node	Metro station asset	534
	Traction power supply substation node	Track section asset	79
	Repair site node	Asset	765

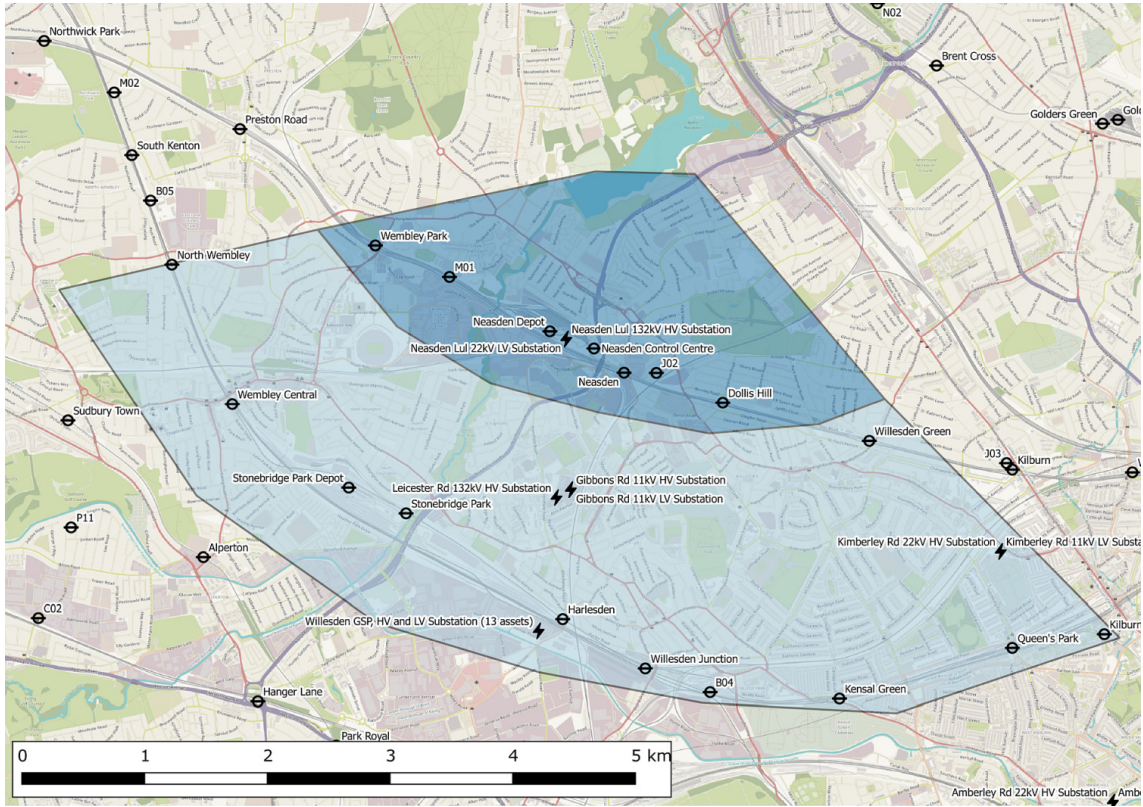


Figure 5.7: Infrastructure assets in the two impact zones of the hypothetical flooding incident

whether an asset is located in one of the two flood zones shown in Figure 5.7. Flood zone 1 extends 2,000 m downstream of the reservoir and contains 9 infrastructure assets. Flood zone 2 encompasses the area between 2,000 and 4,000 m downstream of the reservoir and contains 30 assets.

Hazard exposure is modelled with failure propagation dependencies between the hazard node and assets at risk. Assets in flood zone 1 are assumed to be affected by flooding with a probability of 25 % and assets in flood zone 2 with a probability of 5 %. The hazardous event is assumed to occur at 8 a.m. on a typical weekday. A time lag of one hour is considered until the potential flooding affects assets in flood zone 2.

5.4 Model validation

Considering that the minimum cost flow assignment does not model passengers' route choice behaviour beyond shortest-path seeking or physical laws governing power

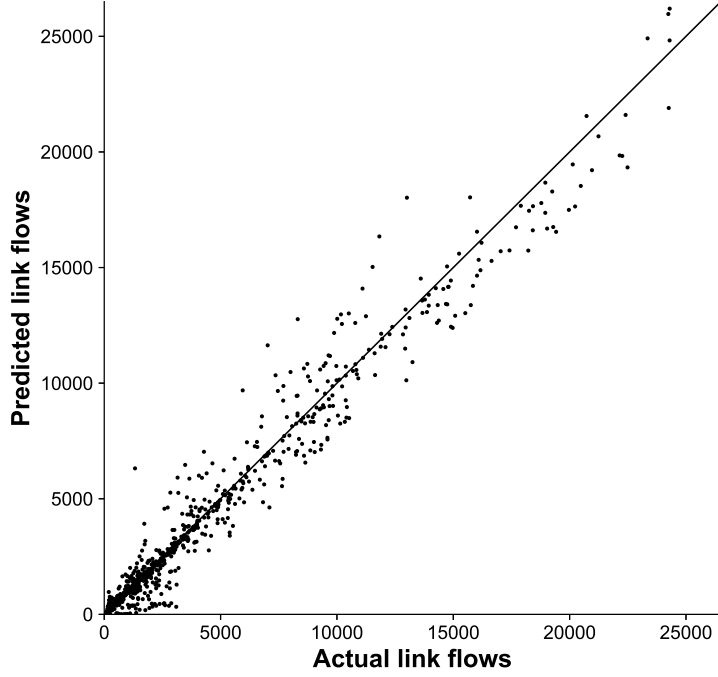


Figure 5.8: Actual and predicted link flows (passengers per hour) in the London Underground Network (LUN) for $t = 8$. Points closer to the diagonal line have lower error values.

flows, we expect some error in the predicted link flows. For the baseline scenario, in which no asset damage occurs, we can compare the predictions with survey-based estimates for line loading in the RODS dataset (Transport for London, 2016). The mean absolute percentage error for time step t is calculated as

$$\text{MAPE}_t = \frac{1}{|E|} \sum_{(i,j) \in E} \frac{|f_{i,j}^{t*} - f_{i,j}^t|}{f_{i,j}^{t*}} \quad (5.25)$$

where $f_{i,j}^{t*}$ are the actual link flows. Since the line loading data was not used in the network flow model, this is an out-of-sample validation approach.

For the morning peak hour, MAPE_8 was found to be 14.1 %. In comparison, state-of-the-art public transport assignment models that use only topological features only achieve MAPE values between 71.9 and 248.3 % (Luo et al., 2019). A plot of predicted and actual link flows (Figure 5.8) reveals that relative errors tend to be higher for links with comparatively low passenger flows, which is in line with the results of Luo et al. (2019).

For evaluating the resilience metrics defined in Section 3.3, the total travel time of all passengers is more relevant than the distribution of flows on individual paths. The predicted total travel time for the hour between 8 and 9 a.m. is 129,000 hours, which is 2.7 % lower than the actual travel time according to the RODS dataset.

For the LPN, actual line loading data was unavailable and the power flow assignment could only be validated by checking that the demand at all substations is fully satisfied in the no disruption case without exceeding the maximum power rating for any connector or transformer.

With a 2.7 % error in total travel time predictions, the minimum cost flow assignment is sufficiently accurate for evaluating the resilience of the LUN. While power flow prediction errors may be higher, the assignment method is still deemed adequate for the purpose of this case study, considering that uncertainty regarding network capacity in low-probability, high-impact scenarios is expected to be a much greater source of errors. In a comprehensive resilience assessment, the initial analysis of a large number of scenarios with the computationally efficient minimum cost flow assignment should be followed by additional analysis of selected scenarios with infrastructure-specific assignment models.

Asset failures and repairs simulated in this case study are verified against the modelling assumptions, for example, by checking that the frequency of certain failure patterns in the set of scenarios corresponds to the probability defined by the failure propagation parameters. Validating failure and repair predictions using real-world data is not possible because the model was parametrised for a hypothetical flooding incident.

A general problem regarding the validation of resilience analysis models is that, by definition, there exist insufficient historical data to validate predictions for high impact, low probability events. Therefore, the validation of the model for baseline scenarios should only be seen as a first step. When using the proposed methodology in practice, additional validation measures should be taken, for example, checking

Table 5.3: Simulation parameters

Parameter	Description	Value
k	Paths per OD pair	10
$t_{\max}$	Length of simulation period	24 hours
t_h	Begin of hazardous incident	8
t_{ph}	Length of planning horizon	5 hours
n_{scn}	Maximum number of scenarios	150
n_{spl}	Samples per scenario tree node	10

the plausibility of individual modelling and parameter assumptions with the help of subject matter experts.

5.5 Simulation results

With the model of the two interdependent infrastructure systems in place, the study proceeds with simulations to assess their resilience against the flood hazard scenario described above. The parameters for the simulation runs are presented in Table 5.3.

With the parameter values $n_{\text{scn}} = 150$ and $n_{\text{spl}} = 10$, Algorithm 2 generated 74 unique asset failure scenarios. The linear programming instances had on average 230,000 decision variables, 100,000 constraints and 4 million non-zero constraint matrix coefficients. They were solved using the Gurobi dual simplex solver (version 8.0.0). On a 3.50 GHz CPU, the average runtime was 30 seconds per LP problem instance. The model lends itself to parallel computing, as the calculations for each branch in the scenario tree are independent of each other. On a CPU with six cores, it took approximately one hour to pre-calculate the shortest paths and 3 hours to run the simulation.

5.5.1 Asset failure and repair

Asset inoperability caused by direct and propagated failure after the flooding incident is shown in Figure 5.9. In the first hour after the incident ($t = 8$), the expected number of asset failures over all scenarios is 1.4 and 0.5 in the LUN and LPN

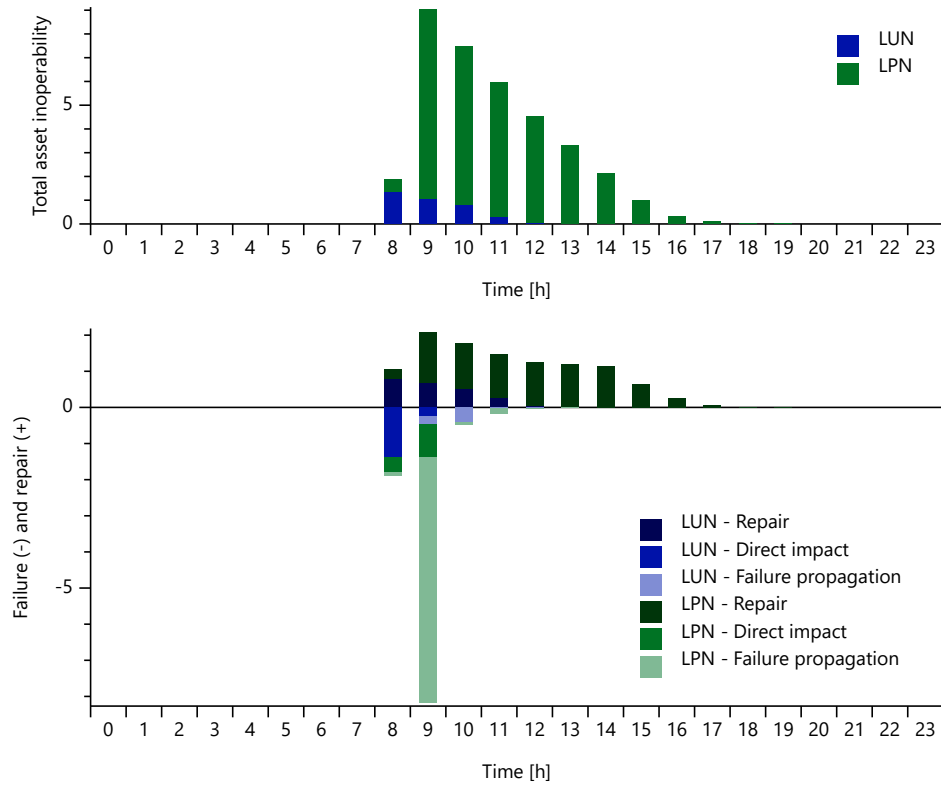


Figure 5.9: Total asset inoperability (top) and changes in asset operability (bottom)

respectively. In the second hour after the incident, the total inoperability in the LUN system is expected to decrease to 1.1 due to the effective deployment of repair resources which outweighs the additional damage caused by direct damage in flood zone 2 (0.2) and failure propagation (0.2). In contrast, the total inoperability in the LPN system is predicted to rise sharply to 8.0, mainly due to failure propagation (6.8) and also to direct damage in the second flood zone (0.9). Due to the large number of asset failures, the LPN system is predicted to take 10 hours until full recovery of asset operability whereas the LUN network is predicted to take only 5 hours.

5.5.2 Unmet demand

The asset inoperability predicted by the model would severely affect the systems' ability to meet the demand of a typical weekday. Although the flood damage is contained to a relatively small area of the city, its effects spread widely, as shown on the maps of unmet demand in Figure 5.10.

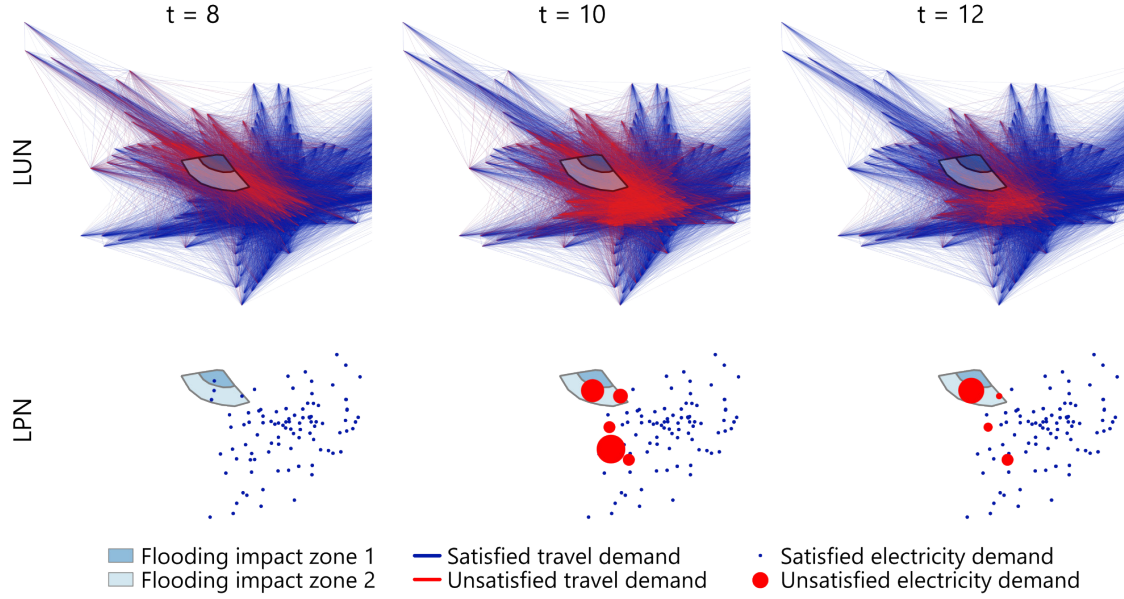


Figure 5.10: Geographic distribution of disruption impacts zero, two and four hours after the beginning of the flooding incident

The expected loss of electric power supply to two demand nodes located within the second flood zone amounts to 172 MWh over the duration of the disruption. Additional 253 MWh of unmet demand are expected to occur at three substations which are located south of the area affected by flooding.

The disruptions in the metro network mainly affect the Jubilee, Metropolitan and Bakerloo lines, which run through the area affected by flooding and also depend on rolling stock, train control and electric power supply assets located there. Hence, most journeys that are cancelled or delayed are to or from areas served by these lines, most notably the Northwest of London. In total, the model predicts that journeys between 7,321 OD pairs with a combined travel volume of 66,166 passenger journeys would be affected by the disruption.

5.5.3 Value of demand and supply

The model predicts the expected loss (the difference between the value of demanded and supplied infrastructure services) to amount to £1.3 and 7.2 million in the transport and energy sectors respectively. These results depend strongly on

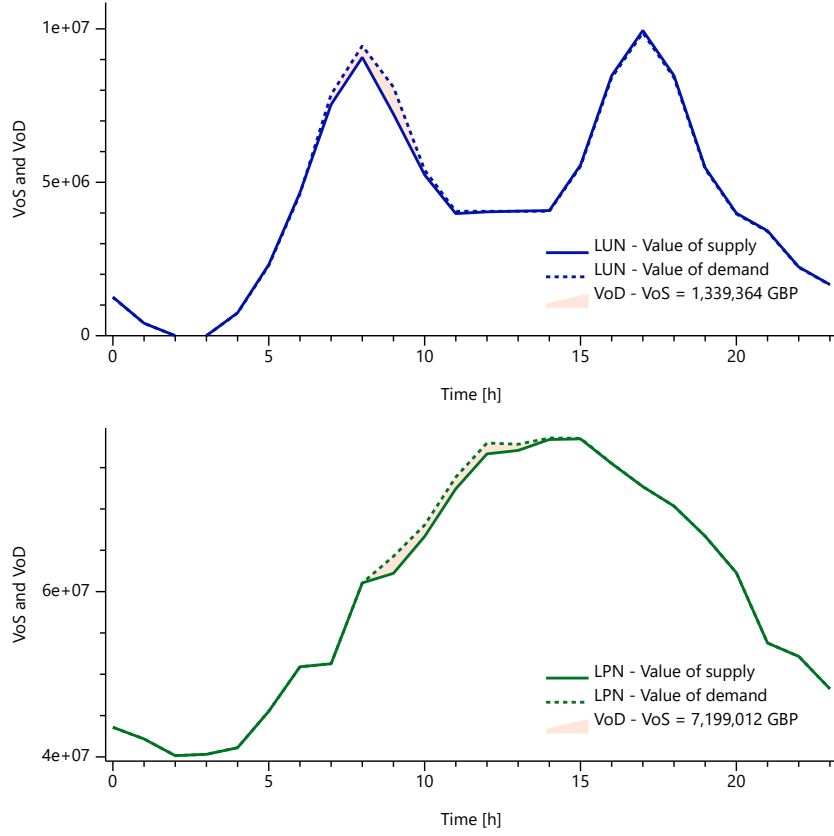


Figure 5.11: Value of demand (VoD) and expected value of supply (VoS)

our assumptions regarding the value of infrastructure services (A3, A4 and A9 in Table B.4). Figure 5.11 shows that although the estimated loss is in the range of millions, it is still relatively small compared to the overall value of services provided by the infrastructure networks.

The simulation experiment enables us to quantify the resilience of the two interdependent infrastructure systems in terms of the resilience measures introduced in Section 3.3. Figure 5.12 plots the value-based system performance $1 - \frac{VoS_t}{VoD_t}$ for the 74 individual scenarios and its probability-weighted average over all scenarios. The model predicts an average resilience loss triangle area (RLT) of 0.11, an expected minimum system performance of 0.96 and a total length of disruption of 9 hours.

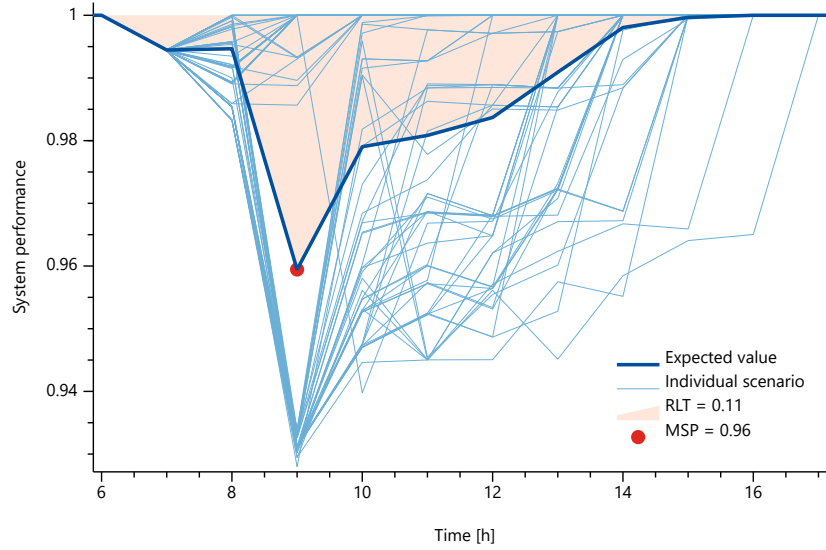


Figure 5.12: Value-based system performance index

5.6 Sensitivity analysis

The simulation experiment was repeated with different parameter settings to analyse sensitivity. The parameter for the capacity of engineering depots providing repair services was varied over the set $\{0, 1, 2, 3\}$. Furthermore, three different levels for failure propagation probabilities were assumed. In the first setting, the probability for short-range failure propagation (from the hazard to assets in flood zone 1 or between assets less than 100 m apart) is 0.125 and the probability for long-range failure propagation (from the hazard to assets in flood zone 2 or between assets 100 to 1,000 m apart) is 0.025. In the second setting, the probabilities are 0.250 and 0.050 respectively, and in the third setting they are 0.500 and 0.100. The predicted RLT values for the resulting 12 parameter configurations are presented in Figure 5.13. As expected, the sensitivity analysis shows that increasing the probability of failure propagation increases the RLT area whereas increasing the capacity to provide repair services decreases it.

The sensitivity analysis also demonstrates how the modelling framework presented in this paper could be used to inform decision-making on how to improve the resilience of interdependent infrastructure systems. For example, assume that the status quo is best represented by the parameter setting $[1, 0.250, 0.050]$ with an RLT area of 0.11.

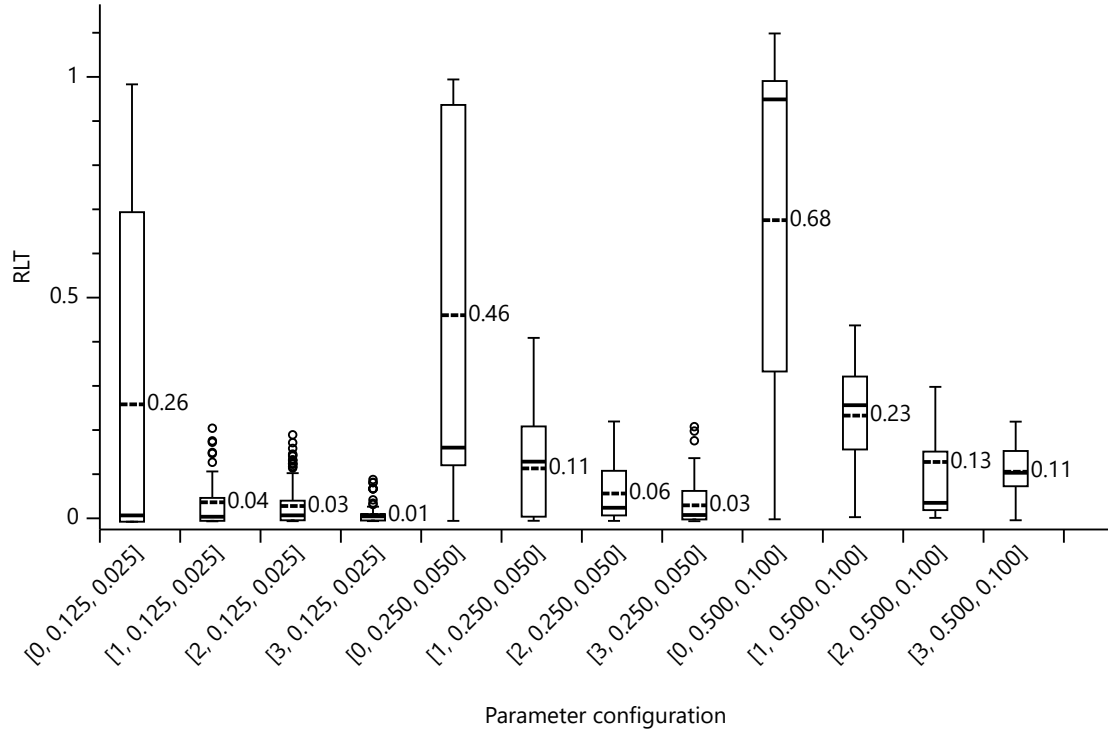


Figure 5.13: RLT area for 12 parameter configurations denoted by [repair capacity, probability of short-range failure propagation, probability of long-range failure propagation]

The model suggests that resilience could be improved by 45 % percent (i.e. reducing the resilience loss from 0.11 to 0.06) at the cost of doubling the resources available for asset repair. In comparison, resilience could be improved by 64 % (i.e. reducing the resilience loss from 0.11 to 0.04) by investing in the protection of assets so that they are 50 % less likely to suffer flood damage (e.g. able to withstand a flood hazard event with a 200 instead of a 100 year return period).

A cost-benefit analysis based on such modelling and simulation results could help decision-makers optimise strategies for strengthening infrastructure resilience and save considerable financial resources compared to interventions not based on such evidence.

5.7 Discussion and concluding remarks

The contribution of this chapter is a method for analysing the recovery capability of interdependent infrastructure networks. The method expands the minimum cost flow

assignment model with a representation of repairable infrastructure assets, enabling the following methodological advancements:

1. The model captures that repair efforts are prioritised where they contribute most to restoring the ability of interdependent networks to meet a certain demand.
2. Repair resource logistics are modelled as network flows, i.e. under consideration capacity, time and cost aspects.
3. Logic dependencies in complex assets with sub-assets on multiple hierarchical layers are considered in the cascading failure model as well as in the repair optimisation.
4. The rolling horizon approach models planning over multiple time steps, while ensuring non-anticipativity of random events.

The case study presented in this chapter demonstrates how the method can be applied to real-world infrastructure systems. In this study, power supply and underground railway assets were modelled in order to analyse London's electric power distribution and metro networks. However, the mathematical description of the modelling method is not specific to these types of infrastructure systems. For example, road networks could be added to the analysis by modelling key assets, such as road links, intersections, signals, traffic control systems, and processes, such as incident response and highway maintenance. Telecommunication networks are another important class of critical infrastructure networks that could be added to the model as multi-commodity networks. Pipeline networks (e.g. for fresh water supply, urban drainage and natural gas distribution) could be considered with some additional constraints regarding pressure.

The minimum cost flow approach enables the modelling of sub-systems that provide similar infrastructure services. For example, if a road network is added to the London case study, passengers have a choice between different transport modes. Different cost functions can be introduced to model individual preferences affecting

mode choice, for example, a segmentation of passengers regarding their valuation of travel time and comfort. Additional transport services that use the same physical infrastructure, e.g. road freight, can also be modelled. The combined minimum cost flow approach ensures that the capacity constraints of the shared network infrastructure are respected. Moreover, the joint flow assignment also captures demand-side interdependencies between sub-systems, such as higher traffic volumes on the road network in case of disruptions to the underground metro network.

Some assumptions were made in the case study regarding hazard exposure, costs and repair resources. However, it can be expected that industry stakeholders with access to business sensitive information could replace most of these assumptions with empirical data.

Even with the high level of operational detail captured by the proposed methodology, a dynamic, city-scale model of two infrastructure systems with several thousand assets, nodes, links and dependency relations can be modelled and simulated with the computational resources of a standard desktop computer. Compared to case studies presented for previous network flow models for interdependent infrastructure networks, the system-of-systems analysed here is considerably larger and the results offer more detailed insights into the phenomena determining infrastructure performance after disruptive events.

While it was not possible to validate the model predictions for the disruption scenarios analysed, the flow assignment for the baseline scenario was shown to be more accurate than state-of-the-art methods that only consider topological features.

The optimisation problems in this chapter can be solved efficiently with standard solver software packages because they are formulated as linear programming problems. Therefore, even for large network instances, the method is capable of analysing many disruption scenarios. However, this comes at the cost of not being able to model discrete or non-linear interdependency effects. For example, the metro system's electric power base load that is not proportional to network flows could not be

considered. Further research should investigate how the introduction of integer variables would affect the computation complexity of the optimisation problems.

The assumption that planners cannot anticipate stochastic failure propagation may not always be realistic. This could be addressed by including asset failures that are anticipated according to a foresight model in the constraints of the flow assignment problem.

Regarding the practical relevance of this study, it is worth highlighting the results obtained by varying some of the key parameter assumptions, like asset failure rates and the capacity to provide repair resources. The model predicts that doubling the repair capability reduces the resilience loss by 45 % compared to the baseline scenario (from 0.11 to 0.06). In comparison, additional asset protection reduces the resilience loss by 64 % (from 0.11 to 0.04). These are only two examples of what-if comparisons that could inform the optimal planning of measures to improve critical infrastructure resilience.

Chapter 6

Optimal network capacities

The models presented in Chapters 4 and 5 focus on passenger transport and utility networks. Another important part of critical infrastructure are supply chains for goods that are essential for human well-being (e.g. food, medical products) and economic prosperity (e.g. key industrial products). The resilience of these supply chains should be analysed jointly with the resilience of other infrastructure systems, considering the complex interdependencies between them (Chang, 2016). Therefore, this chapter extends the proposed modelling approach to include supply-chain-specific aspects, such as commodity storage and inventory planning.

Moreover, this chapter extends the scope of methodology to preparedness decisions. The models presented in Chapters 4 and 5 use optimisation methods to analyse how resilient interdependent infrastructure systems can be if they make best use of existing network assets and repair capacities, which are specified by exogenous parameters. In the following chapter, we also investigate which configurations of network capacities and contingency repair resources achieve optimal resilience, in the sense that they minimise the total expected costs of the supply chain (including penalties for unmet demand) for a set of hazard scenarios. This leads to a model capable of analysing important trade-offs regarding the development of resilience strategies, for example, between investing in redundant network capacity and improved recovery capability.

The remainder of this chapter is structured as follows: First, an overview of the modelling method is presented (Section 6.1). Then, an input-output model for the

generation of asset failure scenarios is introduced (Section 6.2). These scenarios serve as an input for a multi-stage stochastic programming model (Section 6.3). This model is then applied to a supply chain example (Section 6.4), for which simulation results are presented (Section 6.5) and discussed (Section 6.6).

6.1 Model overview

The model presented in this chapter builds upon the basic minimum cost flow model from Section 3.2.1 but includes some additional variables. To model commodity storage, decision variables $h_i^{t,s}$ are introduced, indicating the current inventory level at nodes $i \in V$.

Furthermore, we introduce decision variables for nominal network capacities: $\bar{f}_{i,j}$ for link capacities, $\bar{g}_i$ for commodity production capacities and $\bar{h}_i$ for commodity storage capacities. These variables are not scenario-specific and represent pre-disruption capacity investments, which are associated with cost parameters $c_{i,j}^{\bar{f}}$, $c_i^{\bar{g}}$ and $c_i^{\bar{h}}$.

The methods used in Chapters 4 and 5 involve solving a separate optimisation problem for each time step and scenario or scenario tree node. This separation, however, is no longer possible with the global capacity decision variables introduced above, as they would appear in every individual optimisation problem. In other words, the optimisation of preparedness decisions requires an integrated, multi-period problem formulation.

The optimisation has to consider the uncertainty of asset damage and decisions over multiple time steps. Hence, it is a stochastic, multi-stage programming problem. In the first stage, decisions are taken regarding the global capacity limits $\bar{f}_{i,j}$, $\bar{g}_i$ and $\bar{h}_i$. The subsequent stages $1 \dots t_{\max}$ represent the simulation period during which the model seeks to optimise link flows, production rates, inventory levels and repair rates under consideration of global capacity limits and scenario-specific asset damage.

Since the main focus in this chapter lies on network effects, we do not consider a separate asset layer. For the purpose of presenting the key modelling concepts

Table 6.1: Model variables

	Symbol	Description
Global decision variables	$\bar{f}_{i,j}$	Nominal link flow capacities
	$\bar{g}_i$	Nominal production capacities
	$\bar{h}_i$	Nominal storage capacities
Stochastic variables	$x_{i,j}^{t,s}$	Damage to links
	$x_i^{t,s}$	Damage to nodes
Time- and scenario-dependent decision variables	$\tilde{f}_{i,j}^{t,s}$	Available link flow capacities
	$\check{f}_{i,j}^{t,s}$	Repair of link flow capacities
	$f_{i,j}^{t,s}$	Link flows
	$\tilde{g}_i^{t,s}$	Available production capacities
	$\check{g}_i^{t,s}$	Repair of production capacities
	$g_i^{t,s}$	Production rates
	$\tilde{h}_i^{t,s}$	Available storage capacities
	$\check{h}_i^{t,s}$	Repair of storage capacities
	$h_i^{t,s}$	Inventory levels
	$u_i^{t,s}$	Supply to end-users
	$v_i^{t,s}$	Supply to dependent assets
	$q_i^{t,s}$	Supply shortfalls below service level targets
	$r_i^{t,s}$	Supply shortfalls below demand

more clearly, each node and link in the supply chain network is considered to be one asset. Asset damage is modelled directly as capacity losses instead of using asset operability variables and asset utilisation dependencies, as in Chapter 5. However, the model could easily be implemented with a separate asset layer if the application demands greater granularity on the asset side.

An overview of all model variables is presented in Table 6.1. Another difference compared to the previous chapters is that we use two different sets of slack variables: $r_i^{t,s}$ for the shortfall of supply below the demand of end-users and $q_i^{t,s}$ for the shortfall below a certain service level target. These service level targets are given by parameters β_i , measuring the fraction of end-user demand that has to be satisfied for meeting the target.

Variables $\tilde{f}_{i,j}^{t,s}$, $\tilde{g}_i^{t,s}$ and $\tilde{h}_i^{t,s}$ denote the available capacities in time steps $t = 1 \dots t_{\max}$ and scenarios $s = 1 \dots s_t$. In the first time step, available capacities are

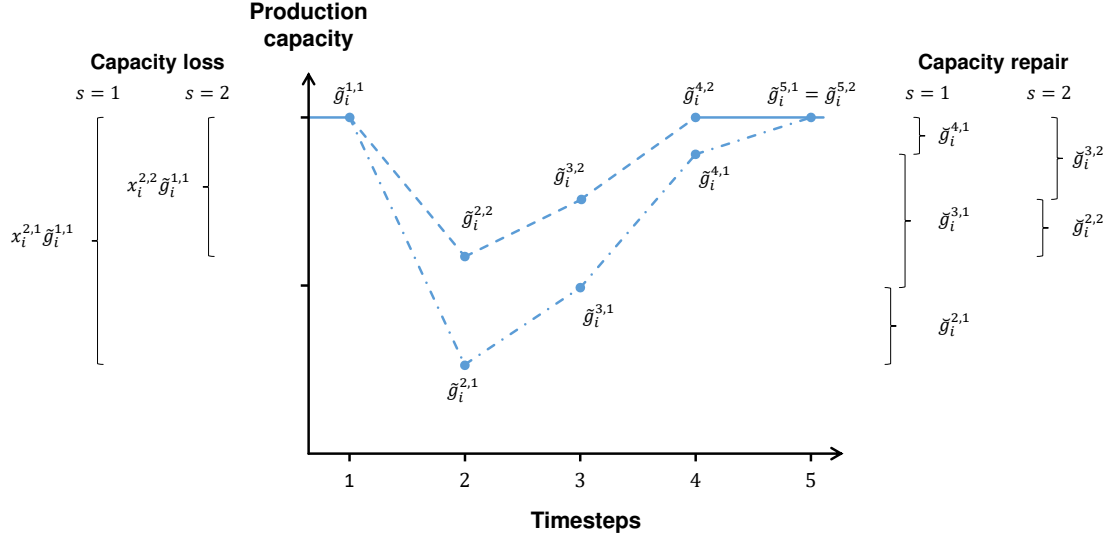


Figure 6.1: Two example scenarios of loss and repair of production capacity at a node

set to the nominal capacities $\bar{f}_{i,j}$, $\bar{g}_i$ and $\bar{h}_i$. During the simulation period, available capacities can decrease due to damage or increase due to repair. The amount of capacity that is restored by repairing damaged assets is modelled with another set of decision variables: $\check{f}_{i,j}^{t,s}$, $\check{g}_i^{t,s}$ and $\check{h}_i^{t,s}$.

The change of available capacity over time through damage and repair is captured in the following equation for updating available link flow capacities:

$$\tilde{f}_{i,j}^{t,s} = (1 - x_{i,j}^{t,s}) \left(\tilde{f}_{i,j}^{\delta_{t,s}(1)} + \check{f}_{i,j}^{\delta_{t,s}(1)} \right) \quad (6.1)$$

The predecessor function $\delta_{t,s} : \Delta t \mapsto (t_{\text{pred}}, s_{\text{pred}})$ outputs the scenario tree node $(t_{\text{pred}}, s_{\text{pred}})$ that is a predecessor to (t, s) with distance Δt time steps. Thus, $\tilde{f}_{i,j}^{\delta_{t,s}(1)} + \check{f}_{i,j}^{\delta_{t,s}(1)}$ is the available capacity plus capacity repair in $t-1$, which is multiplied with the damage factor $(1 - x_{i,j}^{t,s})$ to obtain the available capacity in t . Production and storage capacities are updated in the same way. Figure 6.1 depicts two example scenarios in which a node partially loses its production capacity and is repaired over multiple time steps.

6.2 Scenario generation using an input-output modelling approach

The time-expanded hazard-asset graph method used in the previous chapter for generating asset damage scenarios considers binary asset failure. In the context of supply chains, it is often more realistic to also consider the possibility of partial damage. For example, a production facility or warehouse may partially loose capacity. To address this issue, we propose a novel method for generating damage scenarios, using an input-output approach.

As introduced in Section 2.3.5, input-output modelling is a method that originated in economic theory and was applied to interdependent infrastructure systems for the first time by Haimes and Jiang (2001). Most input-output models abstract from different types of dependency relations and assume that the interdependency matrix $\mathbf{A}$ captures their overall effect. In the hybrid modelling approach proposed here, however, functional dependencies are captured more realistically by the network flow model because it takes into account operational aspects, such as capacity and costs. Therefore, we use the input-output modelling approach only for failure propagation dependencies, which cannot be captured by the network flow model.

Another adaptation is that our method distinguishes between the probability and degree of inoperability so that it can be used for generating random samples rather than calculating expected outcomes. This is achieved by considering the perturbation vector $\mathbf{c}$ and interdependency matrix $\mathbf{A}$ to be composed of random variables. The probability that a random variable in $\mathbf{c}$ or $\mathbf{A}$ is greater than zero corresponds to the probability of initial damage or failure propagation, respectively. The observed value in a simulation experiment is the severity of the corresponding effect.

Random variables in $\mathbf{c}$ and $\mathbf{A}$ can be discrete, continuous or mixed-type. The choice of probability distributions depends on the method for quantifying the risks of initial damage and failure propagation, for example, by statistical analysis of historical data or by elicitation of subject matter expertise.

Let $\mathbf{c}^{t,s}$ and $\mathbf{A}^{t,s}$ denote the sample values for the perturbation vector and interdependency matrix. Using on Equation (2.12), we can calculate the corresponding inoperability or damage vector:

$$\mathbf{x}^{t,s} = (\mathbf{I} - \mathbf{A}^{t,s})^{-1} \mathbf{c}^{t,s} \quad (6.2)$$

The input-output equation calculates the effects of failure propagation within one time step and, therefore, only dependency relations without delay are considered in the interdependency matrix. Failure propagation dependencies with delay are considered in the perturbation vector, as they have the same effect as direct hazard exposure.

In Section 5.1.2, we presented two scenario tree generation methods, a depth-first and a breadth-first approach. With a continuous stochastic process, such as the input-output-based sampling method introduced above, the branching control mechanisms of the breadth-first algorithm does not work because it is very unlikely that two child nodes have exactly the same damage vector. Therefore, both methods are equivalent in this case and for simplicity we use the depth-first method (Algorithm 1) in this chapter.

6.3 Multi-stage stochastic programming model

In this section, we formulate the multi-stage stochastic programming model that optimizes the preparedness and recovery of supply chain networks, given a scenario tree that captures asset damage uncertainty.

$$\text{minimise} \quad \sum_{(i,j) \in E} \bar{c}_{i,j}^f \bar{f}_{i,j} + \sum_{i \in V} \left(\bar{c}_i^g \bar{g}_i + \bar{c}_i^h \bar{h}_i \right) + \quad (6.3)$$

$$\sum_{t=1}^{t_{\max}} \sum_{s=1}^{s_t} p^{t,s} \left(\sum_{(i,j) \in E} c_{i,j}^f f_{i,j}^{t,s} + \sum_{i \in V} \left(c_i^g g_i^{t,s} + c_i^h h_i^{t,s} + c_i^q q_i^{t,s} + c_i^r r_i^{t,s} \right) \right)$$

$$\text{subject to} \quad f_{i,j}^{t,s} \leq \tilde{f}_{i,j}^{t,s} \leq \bar{f}_{i,j} \leq \hat{f}_{i,j} \quad (i,j) \in E, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.4)$$

$$g_i^{t,s} \leq \tilde{g}_i^{t,s} \leq \bar{g}_i \leq \hat{g}_i \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.5)$$

$$h_i^{t,s} \leq \tilde{h}_i^{t,s} \leq \bar{h}_i \leq \hat{h}_i \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.6)$$

$$(1 - x_{i,j}^{t,s}) \left(\tilde{f}_{i,j}^{\Delta_{t,s}(1)} + \check{f}_{i,j}^{\Delta_{t,s}(1)} \right) = \tilde{f}_{i,j}^{t,s} \quad (i,j) \in E, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.7)$$

$$(1 - x_i^{t,s}) \left(\tilde{g}_i^{\Delta_{t,s}(1)} + \check{g}_i^{\Delta_{t,s}(1)} \right) = \tilde{g}_i^{t,s} \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.8)$$

$$(1 - x_i^{t,s}) \left(\tilde{h}_i^{\Delta_{t,s}(1)} + \check{h}_i^{\Delta_{t,s}(1)} \right) = \tilde{h}_i^{t,s} \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.9)$$

$$\sum_{(j,i) \in E} f_{j,i}^{\Delta_{t,s}(\delta_{j,i})} - \sum_{(i,j) \in E} f_{i,j}^{t,s} + h_i^{\Delta_{t,s}(1)} - h_i^{t,s} + \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.10)$$

$$g_i^{t,s} - u_i^{t,s} - v_i^{t,s} = 0$$

$$\beta_i \check{u}_i^t - u_i^{t,s} \leq q_i^{t,s} \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.11)$$

$$\check{u}_i^t - u_i^{t,s} \leq r_i^{t,s} \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.12)$$

$$v_i^{t,s} = \sum_{(j,k) \in E: (i,j,k) \in D} \left(\alpha_{i,j,k}^f f_{j,k}^{t,s} + \alpha_{i,j,k}^{\check{f}} \check{f}_{j,k}^{t,s} \right) + \quad i \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.13)$$

$$\sum_{k \in V: (i,k) \in D} \left(\alpha_{i,k}^g g_k^{t,s} + \alpha_{i,k}^h h_k^{t,s} + \alpha_{i,k}^{\check{g}} \check{g}_k^{t,s} + \alpha_{i,k}^{\check{h}} \check{h}_k^{t,s} \right)$$

$$\bar{f}_{i,j} \geq 0 \quad (i,j) \in E \quad (6.14)$$

$$\tilde{f}_{i,j}^{t,s}, \check{f}_{i,j}^{t,s}, f_{i,j}^{t,s} \geq 0 \quad (i,j) \in E, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.15)$$

$$\bar{g}_i, \bar{h}_i \geq 0 \quad k \in V \quad (6.16)$$

$$\tilde{g}_i^{t,s}, \check{g}_i^{t,s}, g_i^{t,s}, \tilde{h}_i^{t,s}, \check{h}_i^{t,s}, h_i^{t,s}, q_i^{t,s}, r_i^{t,s}, u_i^{t,s}, v_i^{t,s} \geq 0 \quad k \in V, t=1 \dots t_{\max}, s=1 \dots s_t \quad (6.17)$$

The objective function (6.3) seeks to minimize capital expenditure in the first stage and operational costs in the subsequent $t_{\max}$ stages. Capital expenditure is calculated as the sum of first stage decision variables, weighted with cost coefficients $\bar{c}_{i,j}^f$, $\bar{c}_i^g$ and $\bar{c}_i^h$, which are per unit capital costs adjusted to a planning horizon of $t_{\max}$ time steps.

The operational expenditure is calculated as sum over all time steps and scenarios, weighted by the scenario probabilities $p^{t,s}$. Operational costs include those for link flows, commodity production and inventory holding. Furthermore, the objective function includes the penalty $c_i^q q_i^{t,s}$ for unmet service level targets and the lost revenue $c_i^r r_i^{t,s}$.

Constraints (6.4) to (6.6) model that capacity utilisation has to be less than or equal to the available capacity, which in turn has to be less than or equal to the nominal capacity, which in turn has to be less than or equal to the maximum capacity parameter. Constraints (6.7) to (6.9) model the loss and recovery of capacity based on Equation (6.1).

Equation (6.10) enforces the balance of flows and ensures for each node that the net flow over connected links, net inventory change, production, supply to end-users and dependent assets would sum up to zero.

We use parameters $\beta_i \in [0, 1]$ to indicate service level targets for nodes $i \in V$, measured as fraction of the demand that has to be met. Slack variables $q_i^{t,s}$, calculated in Equation (6.11), measure by how much the supply to end-users $u_i^{t,s}$ falls below the service level target $\beta_i \check{u}_i^t$. The second set of slack variables $r_i^{t,s}$, calculated in Equation (6.12), measure by how much the supply $u_i^{t,s}$ falls below the demand $\check{u}_i^t$.

The concept of flow coupling via input dependencies (Section 3.2.3) is implemented in Equation (6.13). Since assets are not modelled on a separate layer in here, the coupling variables $v_i^{t,s}$ are a function of the utilisation and repair rates of dependent flows and links. Whereas in Chapter 5 asset utilisation is only determined by link flows and commodity generation, the model presented here also considers input

requirements for commodity storage. This enables the model to consider, for example, the electricity supply required by a cold storage warehouse.

6.4 Data sources and modelling assumptions

To demonstrate the modelling method proposed above, we use an example from the real-world multi-echelon supply chains published by Willems (2008) as a dataset for testing and benchmarking supply chain optimization models.

6.4.1 Infrastructure and supply chain network

Supply chain example number 3 from the dataset was chosen for the case study in this paper because it allows the demonstration of all important modelling aspects while its relatively small size and clear structure facilitate the analysis and interpretation of simulation results.

The supply chain (Figure 6.2) consists of four demand nodes, four factories and five suppliers. Each supplier and factory is represented with an ensemble of two nodes and one link in order to model the duration of the production process and the ability to store the output. Transport links T1 to T4 are for parts and intermediate products, whereas transport links D1 to D4 model the distribution of final products to end-users.

The data set published in Willems (2008) contains the expected demand as well as expected durations and unit costs for manufacturing and transportation steps. The value of intermediate and final products can be calculated by summing up the costs of all previous manufacturing and transportation steps. Some additional input parameters for our model have been derived based on the following assumptions:

Value of lost revenue The market value of final products was calculated as the total cost of production multiplied by an assumed profit margin of 25 %.

Penalty for unmet service level targets Service level targets are given in Willems (2008) as $\beta_i = 95\%$. The penalty parameter was set to the market value of the

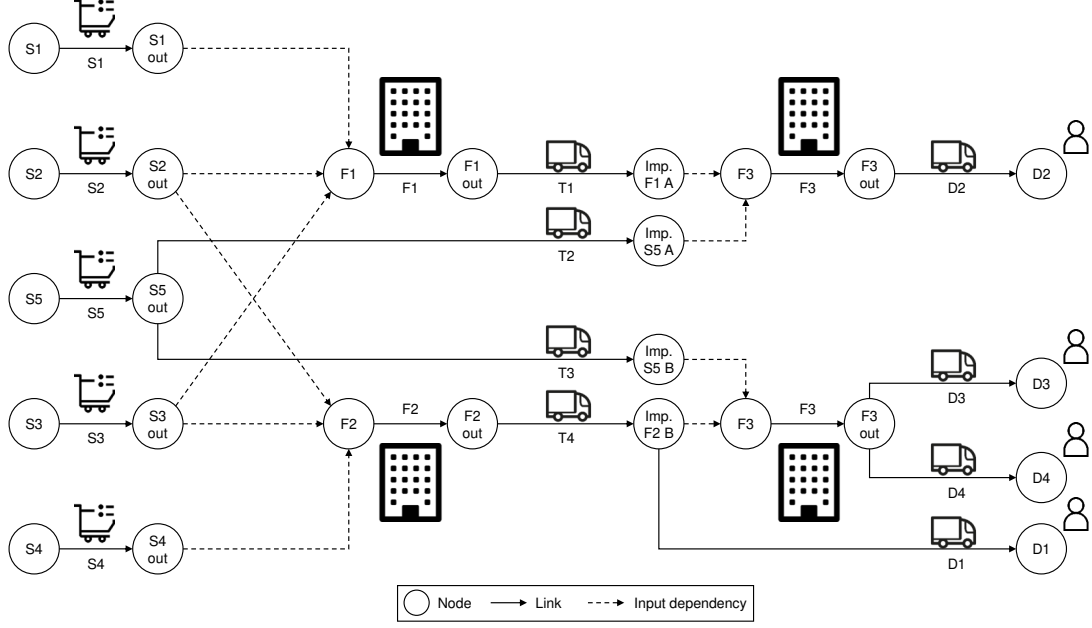


Figure 6.2: Example supply chain network

commodity because we assume that substitute products are bought from the market if the supply chain is unable to meet its service level targets.

Inventory cost Data on inventory costs are not included in the dataset, and we assumed the cost to be 1 % of the commodity value per day.

Opex and capex Willems (2008) does not distinguish between fixed and variable costs. In order to demonstrate the capacity optimization in our model, we assume a fixed-cost ratio of 50 %.

An overview of all model parameters is provided in 6.2 and 6.3. As Willems (2008) primarily intended to test models for inventory optimization under demand uncertainty, some additional assumptions were made in this study regarding asset hazard exposure, failure propagation risks and repair resources.

6.4.2 Hazard and failure propagation dependencies

The structure of the supply chain example suggests that there are three geographic regions. All of the suppliers and factories F1 and F2 are assumed to be located in the same region because they are not separated by transportation links. In this case

Table 6.2: Node parameters

Node	$c_i^{\bar{s}}$	c_i^g	$c_i^{\bar{h}}$	c_i^h	$\tilde{u}_i$	$c_i^q = c_i^r$
	USD	USD	USD	USD	units	USD
S1	96250.00	550.00				
S2	52500.00	300.00				
S3	35000.00	200.00				
S4	96250.00	550.00				
S5	131250.00	750.00				
Out S1			962.50	5.50		
Out S2			525.00	3.00		
Out S3			350.00	2.00		
Out S4			962.50	5.50		
Out S5			1312.50	7.50		
F1	26250.00	150.00				
F2	21875.00	125.00				
F3	4375.00	25.00				
F4	5250.00	30.00				
Out F1			2100.00	12.00		
Out F2			2056.25	11.75		
Out F3			3458.88	19.77		
Out F4			3423.00	19.56		
Import F1 A			2100.00	12.00		
Import F2 B			2056.25	11.75		
Import S5 A			1315.13	7.52		
Import S5 B			1314.25	7.51		
D1			2406.25	13.75	70.00	3437.50
D2			3590.13	20.52	126.00	5128.75
D3			3641.75	20.81	57.00	5202.50
D4			3716.13	21.24	46.00	5308.75

study, we seek to analyse and optimize the resilience of the supply chain against a disruptive event in this region.

We consider a simulation period of length $t_{\max} = 260$ business days. For demonstration purposes and without loss of generality, we assume that the hazardous event occurs at time $t_h = 100$ and damage occurs only during this time step, i.e. the scenario tree has one single branch for $t = 1 \dots t_h - 1$ and S_{t_h} branches for $t = t_h \dots t_{\max}$.

The direct damage vector $\mathbf{c}$ and failure propagation matrix $\mathbf{A}$ for $t_h = 100$ were populated with mixed-type random variables that are parametrized by a probability of being non-zero, and mean and standard deviation parameters for a normal distribution that is truncated to values between 0 and 1. In this case study, we assume that all assets in the affected region are exposed to the same level of risk and the parameter values for the random variables in $\mathbf{c}$ are presented in Table 6.4.

Table 6.3: Link parameters

Name	From	To	$\bar{c}_{i,j}^f$ USD	$c_{i,j}^f$ USD	$t_{i,j}$ days
S1	S1	Out S1			45
S2	S2	Out S2			38
S3	S3	Out S3			54
S4	S4	Out S4			26
S5	S5	Out S5			31
F1	F1	Out F1			12
F2	F2	Out F2			10
F3	F3	Out F3			10
F4	F4	Out F4			10
T1	Out F1	Import F1 A			2
T2	Out S5	Import S5 A	262.5	1.5	2
T3	Out S5	Import S5 B	175.0	1.0	2
T4	Out F2	Import F2 B			2
D1	Import F2 B	D1	35000.0	200.0	1
D2	Out F3	D2	13125.0	75.0	1
D3	Out F4	D3	21875.0	125.0	4
D4	Out F4	D4	29312.5	167.5	4

Table 6.4: Random variable parametrisation

Variable	Assets	Probability of damage or propagation	Severity of damage mean	standard deviation
c	S1-5, F1-2, T1-4	0.1	0.5	0.5
A	Within site (e.g. S1 to Out S1)	0.25	0.5	0.5
	Within region (e.g. S1 to F2)	0.1	0.1	0.25

For failure propagation, we use two sets of parameter values: one for failure propagation within the same site (e.g. from the production to the storage node of the same supplier) and another for failure propagation between sites (e.g. from one supplier to another). The corresponding parameter values for random variables in **A** are also given in Table 6.4.

6.4.3 Repair network

In this case study, we model one abstract repair resource that can be seen as a proxy for staff, equipment and parts required to repair damaged supply chain assets. This repair resource is measured in monetary units.

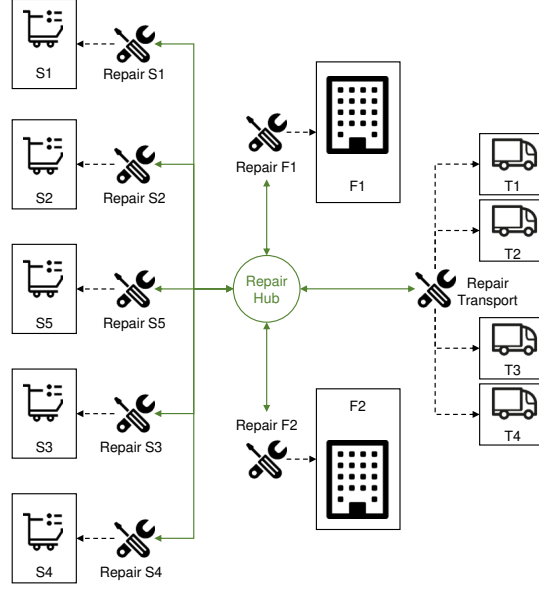


Figure 6.3: Repair network

As depicted in Figure 6.3, the example network contains a repair resource node for each of the five suppliers and two factories that are at risk of damage. A joint repair node is considered for the four transport links leaving the affected region because they are assumed to make use of the same physical infrastructure asset, for example, a sea- or airport.

In order to demonstrate how the proposed method can be used to assess alternate contingency plans for providing repair resources, we analyse two alternative configurations of the repair network:

Individual repair resources Each repair node provides repair resources exclusively to the asset it is directly associated to.

Shared repair resources A repair hub is introduced and connected to each repair node so that repair resource can be shipped from one repair node to another.

With these two alternative configurations, we can investigate how the sharing of repair resources would affect the resilience of the supply chain and optimal capacity investments.

The repair nodes are connected to the associated node or link in the supply chain network via functional dependencies. In the absence of further information

on the types of assets and repair resources, it is sensible to assume that the amount of repair resources required is related to the capital value of the asset. Therefore, we set the input dependency coefficients $\alpha_{i,j,k}^{\check{f}}$, $\alpha_{i,k}^{\check{g}}$ and $\alpha_{i,k}^{\check{h}}$ to the capital cost of flow, production and inventory capacity, multiplied with a markup of 10 % to take into account that the cost for emergency capacity restoration is likely to be higher compared to planned procurement.

6.5 Simulation results

The linear program formulated in Equations (6.3) to (6.16) has

$$(10n + 2)|V| + (3n + 1)|E| \quad (6.18)$$

decision variables, where $n = \sum_{t=1}^T |S_t|$ is the number of scenario tree nodes. For the case study presented here, $T = 260$ and $S_T = 100$. With the branching at $t_h = 100$, the resulting scenario tree has $n = 16,199$ nodes.

The combined supply chain and repair network has $|V| = 34$ nodes and $|E| = 33$ links, resulting in a linear program instance with approximately 7.1 million decision variables. However, the problem size can be reduced to 3.4 million decision variables by excluding decision variables with an upper and lower bound of zero. The linear programming solver Gurobi 8.1 is able to solve the model with a barrier method in 4 hours 22 minutes on a desktop computer with a 3.40 GHz CPU.

The model was solved for three cases: i) baseline case with no hazard occurrence, ii) individual repair resources, and iii) shared repair resources. The results include optimal network capacities and the expected supply chain performance in each of the 100 scenarios.

6.5.1 Resilience performance

For the case of individual repair resources, Figure 6.4 shows the supply chain performance, measured as the total value of products supplied divided by the total

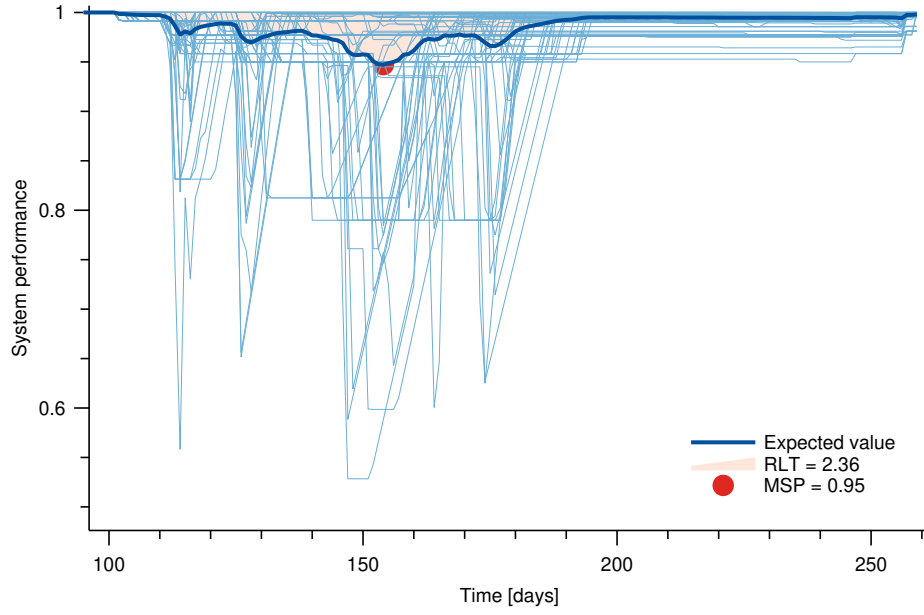


Figure 6.4: Supply chain performance for 100 scenarios and individual repair resources

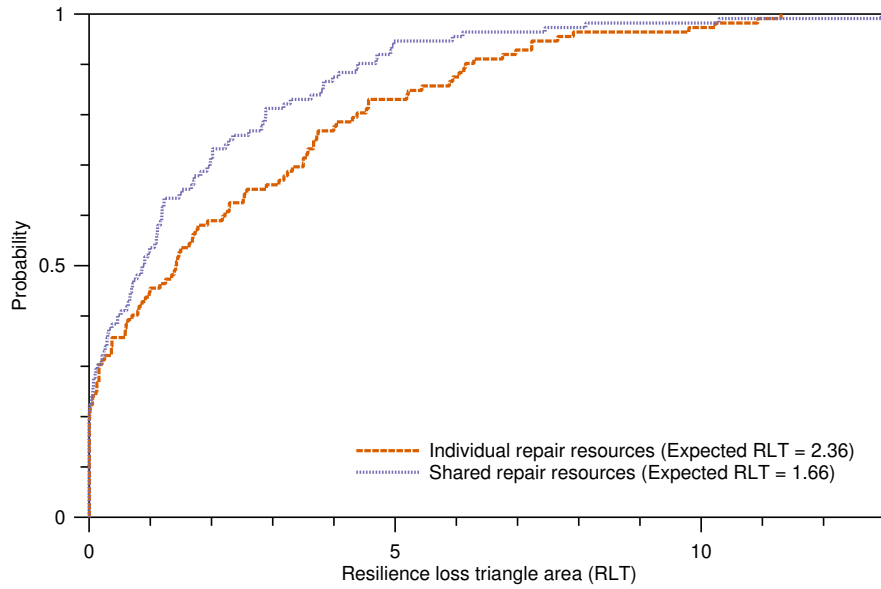


Figure 6.5: Cumulative probability function for the RLT area

value of products demanded, as described in Section 3.3. The shaded area between the expected performance curve and full performance has an area of 2.36 and corresponds to the resilience loss introduced in Equation (3.35).

Figure 6.5 compares the distribution of RLT values for the cases of individual and shared repair resources. The sharing of repair resources reduces the expected RLT area from 2.36 to 1.66. The 95 % percentile is reduced from 7.66 to 5.94. Thus, the model suggests that sharing repair resources improves the resilience of the supply chain. However, we also note that the worst-case RLT value in the shared repair resources case is 12.94, which is higher than the value of 11.30 for individual repair resources.

6.5.2 Optimal capacities

Figure 6.6 shows the optimal capacities calculated for all three cases. Optimal capacities for production nodes and transport links to the demand nodes are almost the same in all three cases. However, there are substantial differences in optimal storage capacities. As expected, the optimal supply chain configuration in the no-hazard case is a just-in-time operation, which eliminates the need for storage. In the two other cases, storage is needed at the import and supplier nodes. At all storage locations, the optimal capacity in the case of shared repair resources is lower than in the case of individual repair resources.

Optimal capacities to provide repair resources are depicted in Figure 6.7. We find that the sharing of repair resources reduces the optimal production capacity at nodes providing repair resources. The results show that for factories F1, F2 and the transport infrastructure it is not justified to invest in local repair resources if they have access to the pool of shared resources.

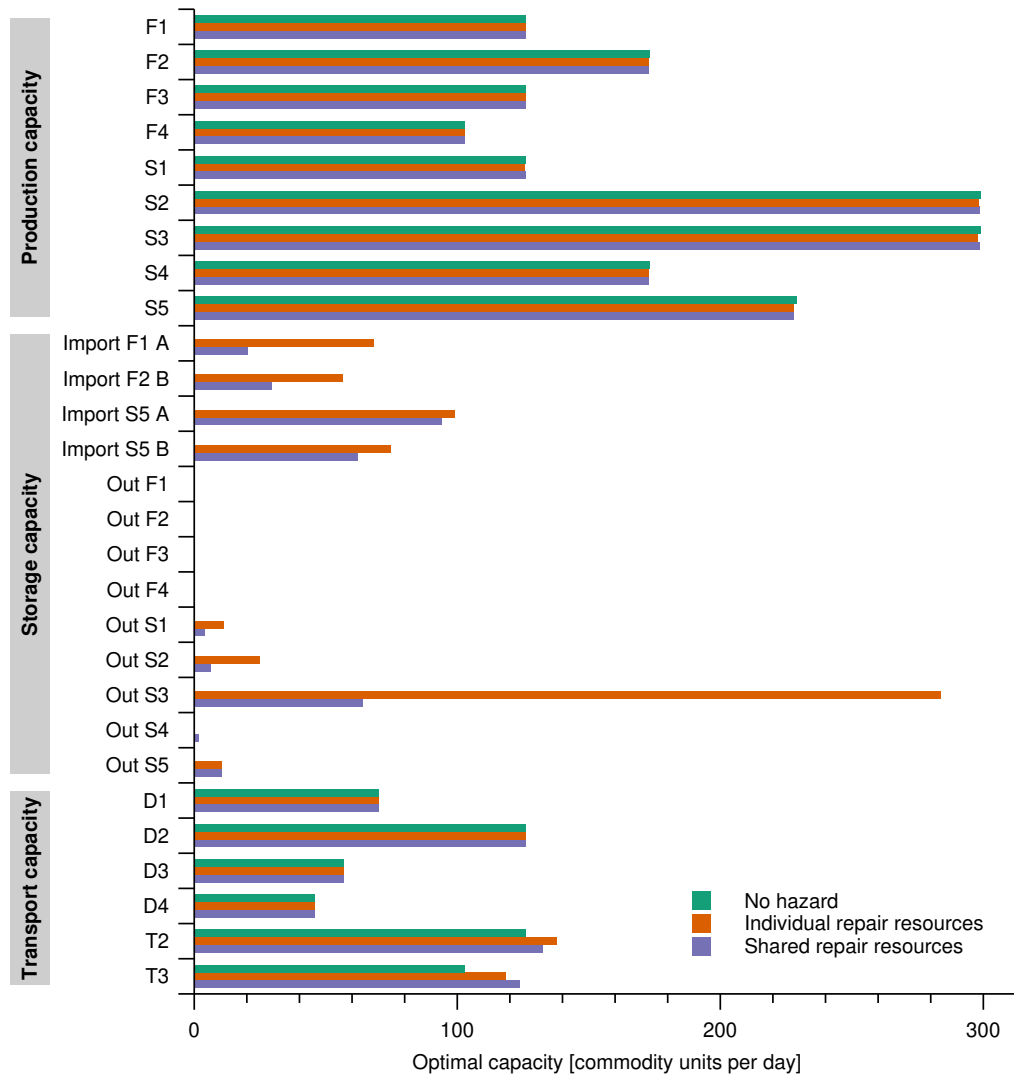


Figure 6.6: Optimal capacities in the supply chain network

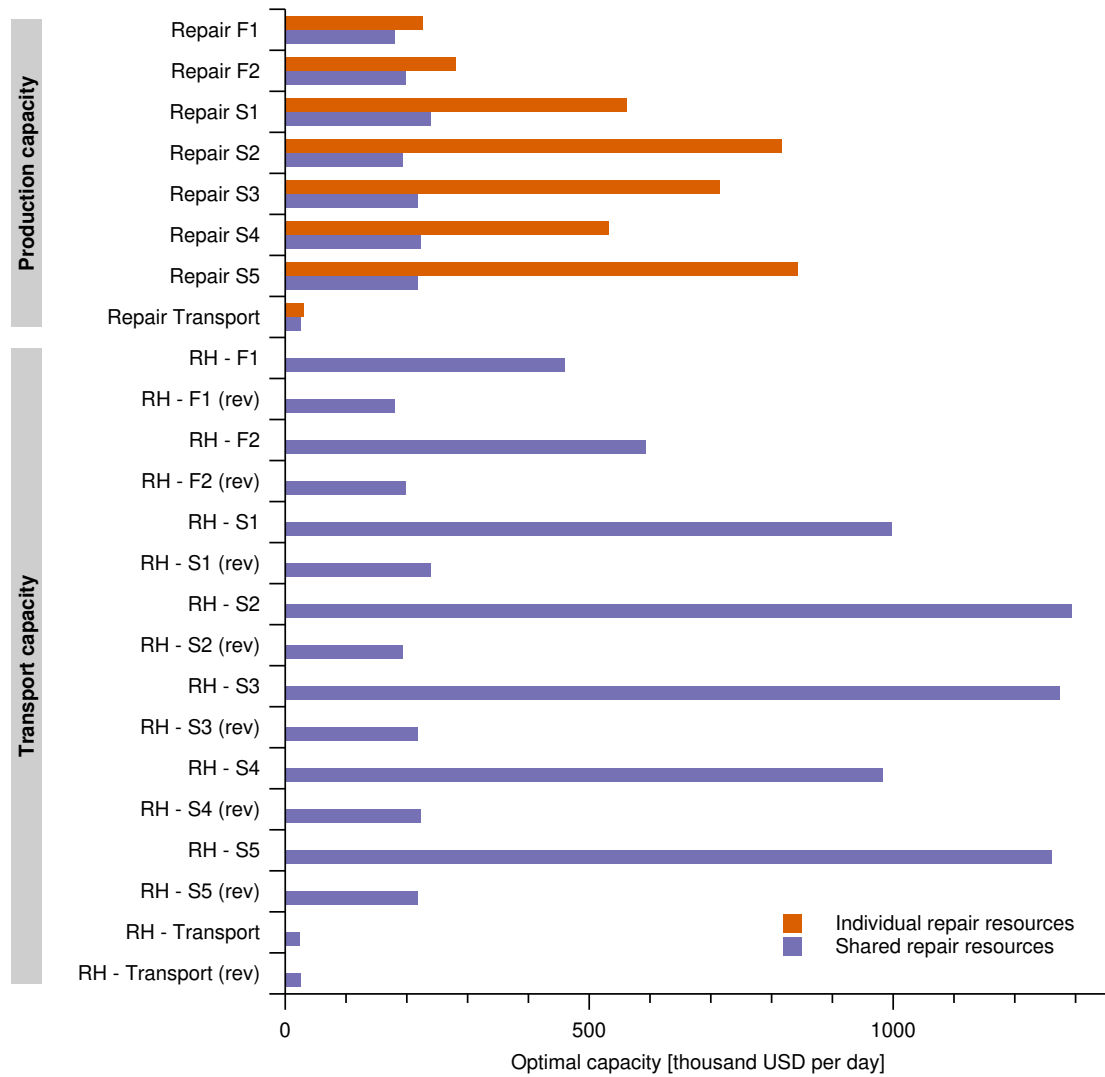


Figure 6.7: Optimal capacities in the repair network

6.5.3 Cost analysis

Finally, we analyse the costs predicted by the simulation model. Figure 6.8 shows cost differences compared to the no-disruption baseline scenario. The expected total costs are approximately USD 18.3 million higher in the case of individual repair resources, and USD 15.1 million higher in the case of shared repair resources, compared to the no-disruption case. The main driver for the cost increase is in both cases operational expenditure for asset repair.

The USD 3.2 million lower total cost in the case of shared repair resources compared to the case of individual repair resources means that the model predicts savings of 17 % that can be linked to the introduction of repair resource sharing. These savings are mainly due to lower investments in repair capacity as well as lower revenue losses and penalties.

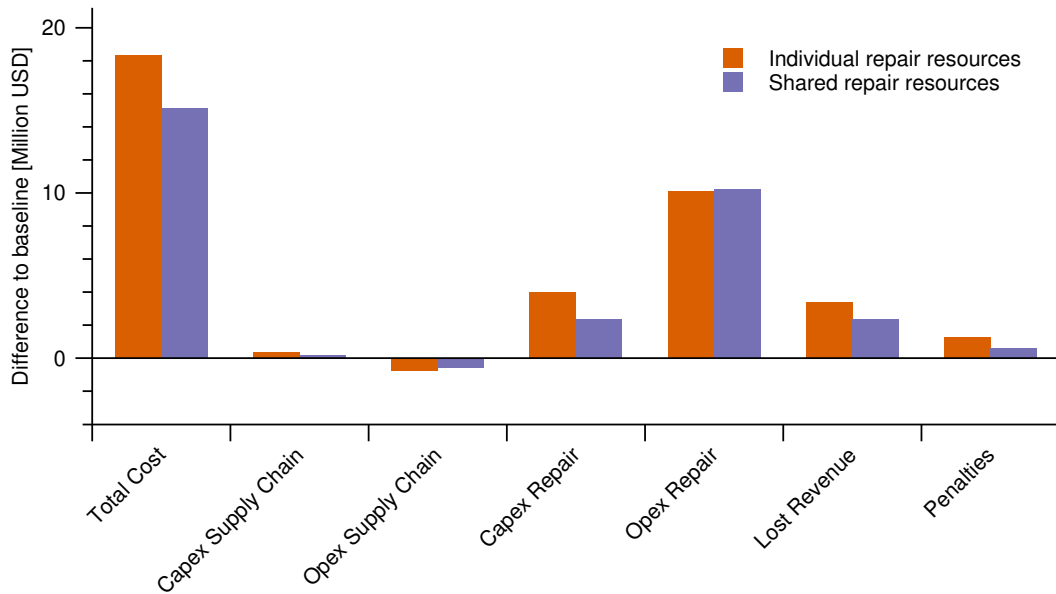


Figure 6.8: Cost compared to the no-disruption scenario

6.6 Discussion and concluding remarks

We presented a case study that demonstrates the application of the proposed method to a real-world supply chain from a benchmarking dataset that provides topology, demand, cost and process duration parameters. The cost breakdown into capital and operational expenditure, as well as penalty costs for unmet demand, are parameter assumptions that could easily be replaced by an analyst with access to business sensitive data.

Parameter assumptions regarding the risk of initial damage and failure propagation could not be verified with the information provided by the generic benchmarking dataset. Considering that the method is geared towards analysing extreme event scenarios with little or no historical precedence, it is expected that the required parameters will be set based on subject matter expertise rather than statistical analysis of previous incidents. Extensive sensitivity analysis should be carried out before making decisions based on the simulation results.

Predicting repair processes and resource requirements is a challenging task, especially for complex assets, such as entire production systems. The case study shows that even in the most aggregated case of modelling one abstract repair resource, the proposed network flow method for optimizing repair capabilities and operations leads to a better understanding of repair resource logistics and can help to improve preparedness and mitigation decisions. For example, the model can be used to find the optimal distribution of repair capacities in a network. The method has the potential to offer more detailed insights if parameters for different types of repair resources can be estimated.

There exist two types of dependency relations in the case study supply chain: i) functional dependency of production and assembly nodes on input parts, and ii) stochastic risk of failure propagation resulting in correlated failure probabilities. While such interdependency mechanisms were considered separately in previous research, the proposed methodology can capture both owing to a novel combination

of a stochastic network flow model and a scenario tree generation method based on input-output modelling.

In the case study, we used the proposed method to optimize the resilience of a supply chain considering 100 possible scenarios for initial damage and failure propagation. The initial capacity design of the network was optimized together with sequential mitigation decisions over the simulation period of 260 time steps. Differences between scenarios in terms of system performance degradation and recovery show the importance of considering a greater temporal resolution with multi-stage stochastic programming compared to two-stage approaches used in many previous papers.

The multi-stage stochastic programming model is based on the assumption that decisions are taken based on knowledge of the scenario tree, i.e. past events are known and future events are anticipated with known probabilities for the branching of the scenario tree. This realistically represents real-world conditions, assuming that the subject matter expertise used to parametrize the scenario tree generation model is also available to supply chain managers.

Within each time step, the decision model assumes perfect information on the state of the supply chain. Furthermore, the method assumes system-optimal decisions and not distributed decisions of individual stakeholders. For this reason, the proposed methodology is most suitable for the analysis of supply chains that are sufficiently integrated, such that all stakeholders have a mutual interest and ability to share information and collaborate in order to achieve the system optimum.

The model is capable of considering non-linear cost functions, such as unmet demand penalties comprising lost revenues and additional penalties if a certain service level threshold is exceeded. Moreover, the model captures economies of scale, as it distinguishes between capital and operational expenditure, and seeks to optimize capacity utilisation. However, modelling economies of scale resulting from increasing marginal returns from resource inputs for production or repair processes would lead to a non-convex optimization problem, which is substantially more difficult to solve.

In the case study, we found that under the assumptions discussed above, sharing of recovery resources among different facilities in the supply chain reduces the expected impact of the disruption by 17 %. This result is relevant for practical decision-making because it supports the argument for more collaboration and coordinated contingency planning when developing supply chain resilience strategies.

Chapter 7

Conclusions and further research

In this final chapter, we revisit the research objectives defined Chapter 1 and summarise how they have been addressed (Section 7.1). We also provide recommendations for further research (Section 7.2) and comments on how the results of this thesis can impact practical decision-making (Section 7.3).

7.1 Main findings and contributions

Critical infrastructure protection is an increasingly complex problem due to rising uncertainty of environmental conditions and manifold trends towards integrating different systems. Improving infrastructure resilience requires mathematical modelling methods for creating digital twins of real-world systems. Simulation experiments with such models serve to generate insight (understanding of resilience phenomena) and foresight (prediction of resilience performance), that can then inform the development of resilience strategies. The main findings of this thesis and contributions to improving the system-of-systems modelling methods for analysing infrastructure resilience can be summarised as follows:

Survey of current resilience analysis methods (Chapter 2)

- Infrastructure resilience is an emerging field of research, characterised by the co-existence of different definitions and analytical frameworks.

- Quantitative resilience analysis methods are rarely applied beyond research projects, indicating that current methods are not mature enough to support practical decision-making.
- Interdependencies are known to affect the resilience of critical infrastructure systems but current analytical methods are limited in their capabilities to consider them. In particular, there is a lack of suitable resilience metrics for interdependent infrastructure systems and of quantitative and probabilistic definitions for different types of dependency.
- State-of-the-art resilience analysis methods do not sufficiently address issues related to the system-characteristics of individual network components, sequential decision-making during the recovery phase, repair resource logistics and trade-offs between different options for improving infrastructure resilience.

Methodological contributions (Chapters 3 to 6)

- A general formulation of a minimum cost flow assignment model for dynamic, coupled flows in interdependent infrastructure networks.
- A method for modelling the failure and repair of interdependent infrastructure assets with Dynamic Bayesian Networks, considering failure propagation and the probabilistic assignment of repair resources.
- An iterative minimum cost flow model with a rolling planning horizon that includes repair resource logistics and models optimal recovery strategies with a realistic degree of anticipation.
- A stochastic programming model for the optimal investment in network capacities and repair capabilities under consideration of cascading failure risks, enabling the analysis of trade-offs between different preparedness strategies.

Model application (Chapters 4 to 6)

- A case study on distributed local flooding incidents affecting the metro and electricity networks throughout London.
- A case study on a hypothetical catastrophic reservoir failure resulting in flood damage in a geographically confined part of London with knock-on effects throughout the metro and electricity networks.
- A case study analysing the preparedness of a supply chain by modelling optimal investments into infrastructure and repair capabilities.

The methods developed in this thesis can be used by infrastructure companies and government authorities to inform decisions on how to improve the resilience of critical infrastructure systems. For instance, the model proposed in Chapter 4 predicts damage probabilities and recovery times for distributed assets that form a system-of-systems. Such estimates are useful for efficiently targeting investments into protecting assets.

In Chapter 5, we show how stochastic simulation experiments with different parameter settings can be conducted to evaluate the effectiveness of resilience improvement strategies. For the specific case study network, it was found that doubling the capacity to repair damaged assets would increase the resilience performance by 45 %, compared to a 64 % improvement achieved by protecting vulnerable assets so that they are 50 % less likely to be damaged. Since the resilience metric proposed in this thesis is based on estimates of the expected monetary losses due to infrastructure disruptions, the model outputs can directly be used in the cost-benefit analysis of infrastructure planning.

The analysis in Chapter 6 demonstrates how the proposed methodology can be used to directly derive optimal investment plans that minimise the expected the impacts of cascading infrastructure failure for a certain hazard exposure scenario. Moreover, the proposed model can also be used to compare optimal solutions for

different incident response regimes. In the example considered, a shared pool of repair resources was found to reduce the overall costs in the supply chain by 17 %.

The areas in which the results of this research can be applied extend beyond issues addressed in the case studies. In the context of smart city projects, they can help to better understand impacts of new technologies. Resilience issues also play an important role in planning urban expansion projects (Daudey and Matsumoto, 2017) or even completely new urban settlements, such as Masdar City (Lee et al., 2016). Another use case are planning tasks related to rebuilding infrastructure after disasters. For example, New York City made resilience a guiding principle for infrastructure investments after hurricane Sandy (The City of New York, 2013).

Finally, the Dynamic Bayesian Network approach used in Chapter 4 also lends itself to develop machine learning models (Dehmer and Basak, 2012). The lack of training data makes this approach less suitable for the analysis of rare events but it could be instrumental in analysing smaller disruptions that occur more frequently.

7.2 Further research

The following sections outline opportunities to build upon the research presented in this thesis by addressing methodological limitations and by extending the application of the proposed modelling methods to further practical decision problems.

7.2.1 Addressing methodological limitations

Some limitations of the models presented in this thesis are linked to assumptions made due to unavailable input data (e.g. cost parameters, hazard exposure). These could easily be addressed by practitioners with access to additional data sources. Other limitations are related to assumptions that were made in order to keep model complexity manageable. Such limitations could be addressed by future research focusing, in particular, on the issues of non-linear coupling of network flows, infrastructure-specific assignment methods and distributed decision-making.

Non-linear coupling of network flows

Using linear approximations for the additional demand through which we model the coupling of flows in interdependent networks enables us to efficiently solve the flow assignment problems with linear programming methods and simulate dynamic flows on city-scale infrastructure networks for a large number of hazard scenarios. This is an advantage of great practical relevance over approaches based on mixed integer programming.

However, in some cases, linear approximations are clearly unrealistic, for example, when it comes to modelling control or telecommunication systems. In Section 3.2.3 we outlined how discrete and non-linear functions could be considered in the generalised method for flow coupling. Further research should focus on investigating the effect this would have on the computational performance of the methodology and whether specialised solution techniques (e.g. heuristic methods) could be used to improve it.

Infrastructure-specific assignment methods

The minimum cost flow assignment method has proven useful for simultaneous flow assignment on interdependent networks and the consideration of repair resource logistics. It was shown to be more accurate than models based purely on network topology. However, it cannot achieve the same accuracy as infrastructure-specific assignment models, such as frequency-based public transport assignment or power flow models.

For the resilience analysis problems addressed in this research, the minimum cost flow approach is justified because the flow assignment errors are relatively small compared to the uncertainties related to asset operability and interdependency effects. However, in other applications, the uncertainty of capacity availability may be lower, for example, when there are only few possibilities of cascading failure. In such cases, the flow assignment error would be more significant for the resilience assessment. Future research should investigate how infrastructure-specific assignment models could be used while still considering the coupling of flows between networks.

Distributed decision-making

The models presented in this thesis focus on system-optimal solutions and neglect aspects related to different actors making decisions based on different information. Without the assumptions of complete information and coordinated decision-making, resilience performance is expected to be lower due to inefficient planning. Hence, the resilience predictions based on methods developed in this thesis should be seen as upper-bound estimates.

For decisions taken by infrastructure providers, research considering distributed decision-making is needed to evaluate strategies for improving information sharing and collaboration between system operators. For instance, Rio de Janeiro has created an integrated control centre to coordinate monitoring and incident response in all critical infrastructure systems (Luque-Ayala and Marvin, 2016). An unexplored research question is how the benefits of this system integration compare against the potential risks arising from additional interdependency.

On the side of infrastructure users, it would be particularly important to investigate the effect of providing information about disruptions to passengers and customers. However, the prediction of user behaviour in extreme event scenarios is particularly challenging.

7.2.2 Addressing further resilience analysis problems

The purpose of the case studies presented in this thesis is to demonstrate the practicality of the proposed modelling methods. The next step is to apply these methods to further examples of interdependent infrastructure systems and hazard scenarios. The following two lines of research are suggested to further improve our ability to develop effective resilience strategies.

Component criticality assessment

Methods for criticality assessment are mainly based on enumerating different scenarios of asset failure or on game-theoretical concepts (attacker-defender models). The

modelling methods presented in this thesis have the potential to improve the system performance assessment required for such approaches.

Furthermore, the minimum cost flow approach developed in this thesis provides additional model outputs in form of the dual values for the linear programming constraints, also referred to as shadow prices as they indicate the scarcity of a certain resource. It is yet to be investigated if and how dual values of minimum cost flow models of coupled networks could be used in assessing the criticality of individual network components.

Comparative analysis of real-world systems

In Chapter 6, we used the methodology developed in this thesis to compare two alternative contingency planning regimes, individual and shared provision of repair resources. Continuing this line of research with other real-world systems-of-systems will further improve our understanding of resilience. The aim of such comparative approaches should be to identify fundamental aspects of system design that make systems more or less resilient. A very relevant question in this regard is whether an optimal level of interdependency can be analytically determined.

7.3 Pathways to impact

The case studies in this thesis present a first proof-of-concept for the proposed mathematical modelling methods. The software developed for this research is currently at Technology Readiness Level 4 and the next steps towards its practical implementation require the creation of standardised interfaces with real-world systems. Model inputs related to the normal operation of infrastructure systems (e.g. network, cost and demand data) could be extracted from existing information systems. On the other hand, the automation of model inputs regarding the risk of failure propagation, incident response and repair processes necessitates user interfaces for the systematic elicitation of relevant information from subject matter experts.

A greater challenge than technical data management issues is to engage all

relevant stakeholders in the development and application of the envisioned resilience analysis tools. Many different organisations are involved in the ownership, operation and regulation of critical infrastructure systems. A clear business case has to be presented to each one of them, addressing the particular needs of their operational and strategic planning.

Local government authorities could play a key role in facilitating the collaboration of different infrastructure providers for the development of resilience strategies. Global resilience networks (e.g. The Resilience Shift, ICLEI, 100 Resilient Cities) could be instrumental in sharing best practices of adopting quantitative resilience analysis approaches amongst infrastructure planners around the world. Further momentum could be gained from financial service institutions who are considering resilience bonds as the next innovation frontier in financing resilience investments. Of crucial importance for this concept are scientific approaches to quantifying the effects of policy interventions and environmental changes on infrastructure resilience.

Appendix A

Review of resilience analysis models

Table A.1: Models for analysing the resilience of interdependent infrastructure systems

Publication	Keywords		Methods	Systems	Geo.	Time	Scope	Dependencies	Hazards	Data used
		Theory Application	Failure analysis Network topology Network flows Demand and capacity Institutional Wider impact analysis	Transport Energy Control systems Telecommunication Water and sanitation Soft infrastructure	National or regional Urban	Static Minutes or hours Days Years	Individual system System-of-systems Assets Operations	Geographic Physical Cyber Functional Socio-economic	Earthquake Malicious attack Flooding Other	Network topology Network utilisation Interviews Incidents News reports Demographic data Economic data
Reliability engineering										
Krings and Oman (2003)	SPN, common failure mode	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sultana and Chen (2009)	SPN	✓	✓	✓	✓	✓	✓	✓	✓	✓
Di Giorgio and Liberati (2012)	Dynamic Bayesian Network	✓	✓	✓	✓	✓	✓	✓	✓	✓
System dynamics										
Tonmoy and El-Zein (2014)	Vulnerability to sea level rise	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bush et al. (2005)	National security decision support system	✓	✓	✓	✓	✓	✓	✓	✓	✓
Martí (2014)	Resource allocation problem	✓	✓	✓	✓	✓	✓	✓	✓	✓
Min et al. (2007)	Functional models, nonlinear optimization	✓	✓	✓	✓	✓	✓	✓	✓	✓
Agent-based simulation										
Barrett et al. (2010)	Human indicated cascades, evacuation	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table A.1: Models for analysing the resilience of interdependent infrastructure systems (continued)

Publication	Keywords	Theory	Application	Methods				Systems				Geo.	Time				Scope				Dependencies					Hazards				Data used										
				Failure analysis	Network topology	Network flows	Demand and capacity	Institutional	Wider impact analysis	Transport	Energy		Control systems	Telecommunication	Water and sanitation	Soft infrastructure	National or regional	Urban	Static	Minutes or hours	Days	Years	Individual system	System-of-systems	Assets	Operations	Geographic	Physical	Cyber	Functional	Socio-economic	Earthquake	Malicious attack	Flooding	Other	Network topology	Network utilisation	Interviews	Incidents	News reports
Bompard et al. (2009)	Information impact analysis	✓		✓					✓	✓			✓		✓														✓				✓							
North (2002)	Social and organisational modelling						✓		✓				✓					✓																					✓	
Schoenwald et al. (2004)	Agent-based simulation laboratory for economics and infrastructure interdependence	✓			✓	✓	✓								✓		✓	✓	✓		✓	✓																		
Dudenhoeffer et al. (2006)	Critical sub-networks	✓		✓																✓	✓																			
Game theory																																								
Bell (2003)	Attacker defender model for measuring network vulnerability	✓		✓	✓	✓		✓									✓												✓				✓	✓						
Zhang et al. (2005)	Dynamit game theoretic model of multi-layer infrastructure networks	✓		✓	✓	✓		✓			✓		✓					✓					✓	✓	✓	✓	✓						✓	✓						
Alderson et al. (2014)	Attacker defender operator model	✓	✓	✓	✓	✓		✓					✓		✓														✓				✓	✓						
Nagurney et al. (2016)	Cyber security of supply chains	✓		✓	✓	✓	✓	✓									✓				✓				✓				✓				✓	✓					✓	
Fang and Sansavini (2017)	Planner attacker defender model	✓	✓	✓	✓	✓			✓				✓		✓														✓				✓	✓						

Table A.1: Models for analysing the resilience of interdependent infrastructure systems (continued)

Publication	Keywords			Methods				Systems				Geo.	Time				Scope				Dependencies					Hazards				Data used											
		Theory	Application	Failure analysis	Network topology	Network flows	Demand and capacity	Institutional	Wider impact analysis	Transport	Energy	Control systems	Telecommunication	Water and sanitation	Soft infrastructure	National or regional	Urban	Static	Minutes or hours	Days	Years	Individual system	System-of-systems	Assets	Operations	Geographic	Physical	Cyber	Functional	Socio-economic	Earthquake	Malicious attack	Flooding	Other	Network topology	Network utilisation	Interviews	Incidents	News reports	Demographic data	Economic data
Input-output modelling																																									
Haimes and Jiang (2001)	Inoperability input-output model	✓					✓		✓							✓							✓																✓	✓	
Haimes, Horowitz, Lambert, Santos, Lian and Crowther (2005)	Regional, physical, demand and dynamic input-output models	✓					✓		✓							✓		✓		✓			✓															✓	✓		
Cagno et al. (2011)	Underground urban infrastructure	✓	✓		✓		✓		✓	✓	✓	✓	✓	✓		✓		✓					✓	✓		✓	✓					✓		✓				✓			
Jonkeren and Giannopoulos (2014)	Economic resilience	✓					✓	✓	✓											✓			✓									✓						✓			
Pant et al. (2014)	Economic resilience of interdependent infrastructure and industry sectors	✓					✓	✓	✓	✓						✓				✓			✓									✓						✓			
Graph theory																																									
D'Souza et al. (2014)	Random graph models of connectivity, sandpile model	✓			✓																		✓																		
Chassin and Posse (2005)	Scale-free electric networks	✓			✓					✓						✓							✓																		

Table A.1: Models for analysing the resilience of interdependent infrastructure systems (continued)

Publication	Keywords			Methods				Systems				Geo.	Time				Scope		Dependencies					Hazards				Data used																	
		Theory	Application	Failure analysis	Network topology	Network flows	Demand and capacity	Institutional	Wider impact analysis	Transport	Energy		Control systems	Telecommunication	Water and sanitation	Soft infrastructure	National or regional	Urban	Static	Minutes or hours	Days	Years	Individual system	System-of-systems	Assets	Operations	Geographic	Physical	Cyber	Functional	Socio-economic	Earthquake	Malicious attack	Flooding	Other	Network topology	Network utilisation	Interviews	Incidents	News reports	Demographic data	Economic data			
Dueñas-Osorio, Craig, Goodno and Bostrom (2007)	Clustering coefficient, redundancy ratio	✓	✓		✓					✓		✓			✓						✓	✓			✓	✓														✓					
Duenas-Osorio, Craig and Goodno (2007)	Inverse characteristic path length, connectivity loss, fragility curves	✓	✓		✓					✓		✓			✓						✓					✓	✓			✓										✓					
Ouyang and Dueñas-Osorio (2011)	Interface topologies for electricity and gas networks	✓	✓		✓					✓						✓					✓					✓					✓								✓						
Poljansek et al. (2012)	Spatial distribution of network structures and hazard exposure	✓			✓					✓					✓						✓					✓	✓			✓											✓				
Winkler et al. (2011)	Interface network models	✓	✓		✓					✓		✓			✓						✓					✓					✓									✓					
Gutiérrez-Pérez et al. (2013)	Spectral-clustering, ranking algorithms	✓	✓		✓							✓				✓					✓																		✓						
Herrera et al. (2012)	Spectral-clustering, ranking algorithms, district metered areas	✓	✓		✓							✓			✓						✓																		✓						
Hines et al. (2010)	Comparison of topological and linearized network flow models	✓			✓	✓				✓					✓						✓																		✓	✓					

Table A.1: Models for analysing the resilience of interdependent infrastructure systems (continued)

Publication	Keywords	Theory	Application	Methods	Systems	Geo.	Time	Scope	Dependencies	Hazards	Data used
				Failure analysis Network topology Network flows Demand and capacity Institutional Wider impact analysis	Transport Energy Control systems Telecommunication Water and sanitation Soft infrastructure	National or regional Urban	Static Minutes or hours Days Years	Individual system System-of-systems Assets Operations	Geographic Physical Cyber Functional Socio-economic	Earthquake Malicious attack Flooding Other	Network topology Network utilisation Interviews Incidents News reports Demographic data Economic data
Ouyang (2013)	Comparison of topological and linearized network flow models	✓		✓ ✓	✓	✓		✓			✓ ✓
Rosato et al. (2009)	Comparison of topological and linearized network flow models	✓		✓ ✓	✓	✓		✓			✓
Lee et al. (2012)	Random networks, correlated multiplexity	✓		✓				✓			
Moreno et al. (2002)	Node breaking avalanches in scale-free networks	✓		✓				✓			✓
Moreno et al. (2003)	Congestion failures in scale-free networks	✓		✓	✓			✓			✓
Motter and Lai (2002)	Congestion failures in scale-free networks	✓		✓							✓
Wang et al. (2012)	Long-term and focused vulnerability	✓		✓	✓	✓		✓	✓		✓
Network flow theory											
Lee II et al. (2007)	Mathematical programming, network flows, restoration	✓	✓	✓ ✓ ✓	✓ ✓ ✓	✓	✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓	✓ ✓ ✓ ✓
Sharkey et al. (2015)	Value of information-sharing for restoration	✓		✓ ✓ ✓ ✓	✓ ✓ ✓	✓	✓ ✓	✓ ✓ ✓			

Table A.1: Models for analysing the resilience of interdependent infrastructure systems (continued)

Publication	Keywords	Theory	Application	Methods	Systems	Geo.	Time	Scope	Dependencies	Hazards	Data used
				Failure analysis Network topology Network flows Demand and capacity Institutional Wider impact analysis	Transport Energy Control systems Telecommunication Water and sanitation Soft infrastructure	National or regional Urban	Static Minutes or hours Days Years	Individual system System-of-systems Assets Operations	Geographic Physical Cyber Functional Socio-economic	Earthquake Malicious attack Flooding Other	Network topology Network utilisation Interviews Incidents News reports Demographic data Economic data
Trucco et al. (2012)	Dynamic functional modelling, integrity modulation function	✓	✓	✓ ✓ ✓	✓ ✓	✓	✓ ✓	✓ ✓	✓ ✓ ✓ ✓ ✓		✓ ✓ ✓
Holden et al. (2013)	Network flow model as linear optimisation problem	✓		✓ ✓ ✓	✓ ✓	✓	✓	✓	✓ ✓		

Appendix B

Model parameters used for the case study in Chapter 5

Table B.1: Parameters for the London Underground Network (LUN) model

Parameter	Value / description	Data sources	Assumptions
A	389 assets including: 267 stations, 79 track sections, 8 line control systems, 8 rolling stock fleets, 8 control centres, 19 depots	D1, D2	
V^{MC}	1,045 nodes including: 267 stations, 778 platforms	D2	
E^{MC}	2,315 links including: 759 on-train links, 778 entrance-to-train links, 778 train-to-exit links	D2	
$\hat{f}_{i,j}$	On-train links: scheduled train frequency multiplied with rolling stock capacity	D3	
	In-station links: maximum station entries and exits	D2	A1
$\check{f}_{o,d}^t$	Travel demand profiles for 32,109 OD pairs	D2	A2
$c_{i,j}^f$	On-train links: station-to-station journey time	D4	
	Train-to-exit links: walking time from platform to ticket hall	D5	
	Entrance-to-train links: walking time ticket hall to platform plus average waiting time for first train	D3, D5	
	All travel times valued a 11.21 GBP per hour	D6	A3
$v_{o,d}^{MC}$	Cost of alternative transport estimated based on geographic distance		A4
<i>Repair network:</i>			
V^{SC}	392 nodes including: 19 engineering depots, 373 repair sites	D1	
E^{SC}	957 repair resource deployment links		A5
$\hat{g}_i$	Repair resources for the repair of one asset per hour and engineering depot		A6
$\hat{f}_{i,j}$	0.25 if distance is less than 10 km, 0.20 if distance is between 10 and 25 km, 0.17 if distance is greater than 25 km		A7

Data sources:

- D1 Detailed map of London Underground (Carto Metro, 2017)
- D2 Rolling Origin and Destination Survey (RODS) (Transport for London, 2016)
- D3 London Underground timetable (Transport for London, n.d.)
- D4 Inter-station train times (Transport for London, 2013)
- D5 Gate-to-platform and interchange walking times (Transport for London, 2012)
- D6 Market research for value of travel time (UK Department for Transport, 2015)

Assumptions: ref. Table B.4

Table B.2: Parameters for the London Power Network (LPN) model

Parameter	Value / description	Data sources	Assumptions
A	392 assets including: 19 grid supply points, 247 high-voltage sub-stations, 126 low-voltage sub-stations	D7	
V^{SC}	1,379 nodes including: 67 super grid transformers, 128 demand nodes, 6 bulk supply points for traction power, 79 traction power sub-stations	D7	
E^{SC}	1,742 links including: 828 connectors, 394 two-winding transformers, 80 three-winding transformers, reverse direction links where applicable	D7	
$\hat{f}_{i,j}$	Connectors and transformers: rated capacity Intra-substation connectors: no capacity limit	D7	
$\hat{g}_i$	Rated capacity of super-grid transformers	D7	
$\tilde{w}_i^t$	Load profiles for 128 demand nodes generated using peak demand and minimum load scaling factors	D7	A8
v_i^{SC}	16,940 GBP per MWh (weighted average value of lost load for peak winter workdays in the UK)	D8	A9
<i>Repair network:</i>			
V^{SC}	404 nodes including: 12 engineering depots, 392 repair sites		
E^{SC}	784 repair resource deployment links		A5
$\hat{g}_i$	Repair resources for the repair of one asset per hour and engineering depot		A6
$\hat{f}_{i,j}$	0.25 if distance is less than 10 km, 0.20 if distance is between 10 and 25 km, 0.17 if distance is greater than 25 km		A7

Data sources:

- D7 Long term development statement (UK Power Networks PLC, 2017)
- D8 Value of Lost Load (VoLL) for Electricity in Great Britain: Final report for OFGEM and DECC (London Economics, 2013)

Assumptions: ref. Table B.4

Table B.3: Dependency relations

	From	To	No. of instances	Parameters	Assumptions
Failure propagation	Flood hazard h	Assets k in flood zone 1	9	$p_{h,k} = 0.250$ $t_{h,k} = 0$	A10
	Flood hazard h	Assets k in flood zone 2	30	$p_{h,k} = 0.050$ $t_{h,k} = 1$	A10
	Assets $k \in A$	Assets located less than 100 m from k	1,598	$p_{h,k} = 0.250$ $t_{h,k} = 0$	A11
	Assets $k \in A$	Assets located less than 1,000 m from k	5,940	$p_{h,k} = 0.050$ $t_{h,k} = 1$	A11
Asset utilisation	Electricity substations k	Generation nodes located at k and links starting or ending at k	4,837		
	Metro station assets k	Entrance-to-train and train-to-exit links at k	1,556		
	Track section assets k	On-train links using k	759		
Logic	Line control assets k	Track section assets	79		
	Rolling stock fleet assets	Track section assets	79		
	Control centre assets	Line control assets	10		
	Depot assets	Rolling stock fleet assets	20		
Input	Low-voltage electricity substation node i	Metro station asset k	534	$\alpha_{i,k}^U = 0.10$	A12
	Traction power supply substation node i	Track section asset k	79	$\alpha_{i,k}^U = 4.00$	A13
	Repair site node i	Asset k	765	$\alpha_{i,k}^R = 1.00$	

Assumptions: ref. Table B.4

Table B.4: Modelling assumptions

	Assumption	Justification
A1	Capacities of intra-station links are 10 % higher than maximum usage according to D2, but not less than 5,000 passengers per hour	Near-capacity usage of core network during rush hour
A2	Hourly travel demand is a 3-hour moving average over the values given for six time slots per day in D2	Standard smoothing method for demand forecasting
A3	The average value of travel time (11.21 £/h) applies to all passengers	Unavailability of data on purpose of trips
A4	The value of transportation services can be estimated as $5 \text{ £} + \frac{[\text{Distance in km}]}{5 \text{ km/h}} \times 11.21 \text{ £/h}$	A relatively high value is justified because in case of a major disruption the cost of alternative travel is likely to be above average due to congestion
A5	Depots can be repaired with local resources, control centres with resources from any depot, track sections with resources from depots belonging to the respective metro line, metro stations and electricity sub-stations with resources from the two geographically nearest depots	Estimate based on subject matter expertise
A6	Each engineering depot can provide resources to repair one asset per hour	Estimate based on subject matter expertise, sensitivity analysis provided
A7	Asset repair times depend on distance to the engineering depot providing repair resources (4 h if less than 10 km, 5 h if between 10 and 25 km, 6 h if greater than 25 km)	Estimate based on subject matter expertise
A8	Electricity demand follows a generic sub-station load profile adjusted to the peak and minimum load specified in D7	Standard demand forecasting method
A9	The weighted average value of lost load (16,940 £/MWh) applies to all demand nodes	Best available estimate for economic costs of power outages
A10	Assets located less than 2 km from the reservoir are damaged directly after it fails with a probability of 25 %, assets located between 2 and 4 km from the reservoir are damaged one hour after it fails with a probability of 10 %	Hypothetical flood risk exposure
A11	Failure propagation occurs with 33 % probability and no time lag if assets are located less than 100 m apart, and with 5 % probability and one hour time lag if assets are between 100 and 1,000 m apart	Hypothetical failure propagation risk
A12	Metro stations require 0.1 MW power when used at full capacity	Non-traction power consumption of 200 GWh/a (Transport for London, 2017) divided by the number of stations, assuming a peak-to-average ratio of 1.2
A13	Track sections require 4.0 MW power supply when being used at full capacity	Traction power consumption of 1,363 GWh/a (Transport for London, 2017) divided by the number of sections, assuming a peak-to-average ratio of 2.0

Appendix C

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