A Multi-Layer Framework for Modelling Resilience in Waterway-Dependent Supply Chains Using Reliability Theory: A Case Study of the West German Canal System

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Vorwort des Herausgebers

Binnenwasserstraßen und Kanäle bilden eine tragende Säule leistungsfähiger Transport- und Lieferketten. Sie verbinden über ihre Häfen Absatz- und Beschaffungsmärkte, Produktionsstandorte und Industriezentren miteinander und leisten einen wichtigen Beitrag zu einer energieeffizienten, sicheren und nachhaltigen Güterbeförderung. Aktuelle Störungen globaler und regionaler Logistiksysteme zeigen allerdings, dass die Verlässlichkeit der wassergebundenen Infrastrukturen keineswegs selbstverständlich ist. Sperrungen, Ausfälle, Kapazitätsengpässe, extreme Wetterereignisse, wie Niedrig- oder Hochwasserphasen, sowie unzureichende Redundanzen können weitreichende Folgen für Unternehmen, öffentliche Akteure und ganze Wirtschaftsregionen haben.

Herr Dr.-Ing. Johannes Gast beschäftigt sich vor diesem Hintergrund in seiner Dissertation mit der Resilienz wasserstraßenabhängiger Lieferketten. Damit greift er ein für die Wissenschaft und Praxis hochinteressantes Thema auf. Im Mittelpunkt steht die Frage, wie sich die Auswirkungen von Infrastrukturstörungen systematisch erfassen, quantifizieren, bewerten und reduzieren lassen. Dazu entwickelt er ein umfassendes Vier-Ebenen-Modell, das Infrastruktur, Transportprozesse, Lieferkettenentscheidungen und wirtschaftliche Konsequenzen berücksichtigt und verbindet. Diese Zusammenhänge werden hier erstmalig in dieser Komplexität modelliert und wissenschaftlich durchleuchtet. Durch die Verknüpfung von Reliability Theory, Operations Research, Queueing-Theorie und empirischen Daten entsteht so ein Ansatz, der sowohl wissenschaftliche Erkenntnisse erweitert als auch praktische Entscheidungsgrundlagen für Infrastrukturplanung und Risikomanagement bereitstellt.

Das Westdeutsche Kanalsystem bildet den empirischen Untersuchungsraum der Dissertation. Anhand realer Daten zu Infrastrukturzuständen, Ausfällen und Belastungssituationen macht er sichtbar, wie eng die Leistungsfähigkeit von Lieferketten mit der Verfügbarkeit einzelner Schleusen, Häfen und Wasserstraßenabschnitte verknüpft ist. Herr Dr.-Ing. Gast leitet in der Folge systematisch ab, dass Resilienz nicht nur durch Redundanz entsteht, sondern durch das Zusammenspiel aus frühzeitiger Information, adaptiver Planung, koordinierter Nutzung vorhandener Kapazitäten und zielgerichteten Investitionen.

Herr Dr.-Ing. Gast gibt einen strukturierten Überblick über Motivation, theoretische Grundlagen, methodisches Vorgehen, zentrale Ergebnisse und praktische Implikationen seiner Dissertation. Sie richtet sich an Leserinnen und Leser sowohl aus Wissenschaft, als auch aus Verwaltung und Praxis, die sich mit der Zukunft resilienter, nachhaltiger und leistungsfähiger wassergebundener Transport- und Lieferketten befassen. Ein Ziel ist es, ein besseres Verständnis dafür zu schaffen, wie wasserstraßenabhängige Systeme auf

Störungen reagieren, welche Risiken daraus entstehen und welche Strategien geeignet sind, akute Nachteile von Störungen zu überwinden und die Widerstandsfähigkeit langfristig zu stärken.

Ich wünsche Ihnen viel Freude und interessante Einblicke beim Lesen dieser besonderen Dissertationsschrift, die gleichzeitig Band 11 der Reihe „Innovationen für die Maritime Logistik“ ist.

Hamburg, Juni 2026

Prof. Dr.-Ing. Carlos Jahn

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Johannes Gast

Structured Abstract

Background: Recent disruptions in waterway infrastructure highlight the vulnerabilities of waterway-dependent supply chains (SCs). Although substantial research in various disciplines exists, the effect of infrastructure availability on SC resilience (SCR) remains underexplored. This gap persists despite high-profile infrastructure failures, such as the 2021 Suez Canal blockage.

Objective: This study develops a comprehensive SCR model for waterway-dependent SCs by integrating historical event data, infrastructure states, and dynamic time factors. The primary objective is to *enable* effective SC decision-making (SCDM) and the evaluation of mitigation strategies that preserve SC value during disruptions.

Methods: This dissertation employs a mixed-method design to develop *a multi-layer, multi-state SCR framework* with four layers representing infrastructure, transportation, SCs, and industry. The approach integrates reliability theory to assess infrastructure availability, which informs an operations research model combining vehicle routing. Focusing on the West German canal system, the methods evaluate how availability affects cost, SC performance, and resilience strategies.

Results: The results quantify the critical link between infrastructure state and SC performance, demonstrating how empirical transportation cost increases propagate through the supply chain. Key findings highlight the importance of infrastructure availability in facilitating effective risk mitigation, influenced by the warning times, availability, and SCR. The model further quantifies infrastructure disruption and mitigation effects on SCs' value and determines their viability. The analysis quantifies the system-wide cost of infrastructure disruption for the case study at approximately seven million EUR per day. Further, the model estimates the annual welfare utility of a single secondary lock chamber at one million EUR, demonstrating the scale of economic gains achievable through targeted resilience investments. In addition, the results reveal the novel ‘shuttling effect’: a cyclical phenomenon distinct from the ‘ripple effect’. The shuttling effect arises from repeated, short-term capacity constraints in shared infrastructure.

Conclusion: This research demonstrates that a deep understanding of infrastructure states is vital to strengthening SCR, particularly in waterway-dependent SCs. The resulting model provides actionable insights for SCDM and informs both private and public resilience enhancement strategies. Furthermore, the findings demonstrate that proactive SCDM can mitigate welfare loss more effectively than conventional reactive approaches by incorporating warning time, multimodal strategies, and considering the systemic risk of the ‘shuttling effect’.

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List of Abbreviations

AIS	Automatic Identification System
BN	Bayesian Network
BVWP	"Bundesverkehrswegeplan" (infrastructure plan)
DEK	"Dortmund-Ems-Kanal"
DHK	"Datteln-Hamm-Kanal"
FLP	Facility Location Problem
FMA	Failure Mode Analysis
GDWS	Federal Waterways and Shipping Administration
HRF	Hazard Rate Function
I-O	Input-Output
IW(s)	Inland Waterway(s)
IWT	Inland Waterway Transportation
NtS	Notice-to-Skipper(s)
NRW	North Rhine-Westphalia
QT	Queueing Theory
RHK	"Rhein-Herne-Kanal"
RQ(s)	Research Question(s)
RT	Reliability and Maintainability Theory
SC(s)	Supply Chain(s)
SCDM	Supply Chain Decision-Making
SCEM	Supply Chain Event Management
SCM	Supply Chain Management
SCR	Supply Chain Resilience
SCRM	Supply Chain Risk Management
SLR	Systematic Literature Review
TN(s)	Transportation Network(s)
TPP	Travelling Purchaser Problem
TTA, TTN	Time to Adapt, Time to Note
VRP	Vehicle Routing Problem
VSC	Viable Supply Chain
WDK	"Wesel-Datteln-Kanal"
WdtK	West German Canal Network
WSV	Waterways and Shipping Administration

List of Symbols and Notations

General indices and sets

i, j	General indices for nodes in a network, with i, j ∈ {1, …, N} (e.g. ports, locks)
k, K	Index for transportation mode of set K
t, τ, T	Index for a discrete time point or period with the total planning horizon T and the integral residual τ
n	Total number of records n
N, M	Total number N of nodes in a network, total number of links in a network M or matrix dimensions
V, E	Sets of nodes (vertices) and links (edges) in a graph
G, χ, W	A dynamic alternative multigraph W representing the SC ecosystem with index χ representing a SC
L_χ, l	Set of available SC configurations with index l
WW, a	Set of all waterway infrastructure components a
S, s	State set of available SC structural components s

1) Infrastructure layer (reliability and availability metrics)

$A, A(t)$	Availability of a component or system (at time t)
A_i, A_{ij}	Availability of the i-th node and the link between node i and node j
A_i^{Base}	(Inherent) Base availability of node i assuming no capacity constraints
$R(t)$	Probability of a component operating without failure until time t
$M(t)$	Probability that component is restored in time t
$\lambda(t)$	The instantaneous failure rate at time t (hazard rate)
TN_A	Total availability of the transportation network TN
$P(CF_i)$	Overall failure probability of component i
$P(F_j \mid F_i)$	Conditional probability of component i failing given component j has already failed
$P_x(t)$	Probability of the system being in state x at time t
$P_{xx'}(T)$	Transition probability of moving from state x to x' over a period T

L_i	Congestion load at node i
$Cap, Cap_{max,i}$	Capacity of servers in a queueing system or nodes, maximum capacity of node i
$P_{q,i,j}$	Queueing-induced availability degradation probability at node i due to load from node j
Y_i, Z_i, $\mu_{i,Y}$, $\mu_{i,Z}$,	Servers (e.g. lock chambers) at node with respective service rates μ

2) Transportation layer (generic routing and cost)

C	Total cost of transportation
$OPEX(TN)$	Operating cost function dependent on TN
$CAPEX$	Capital expenditure of transportation agents
$TC(TN)$	Transhipment and handling costs dependent on TN
$\theta(VT, VL)$	Individual cost function for a specific vehicle type VT and vehicle load VL

3) Supply chain layer (Decision-making and value maximization model)

$SCVal(\mathrm{x})$	The objective function value of the SC optimisation model, representing the total accumulated value
p_j	Net earnings generated at stage/node j
x_j	Supply quantity transported to stage j
c_{kij}	Cost of transporting quantity using mode k from origin i to destination j
X_{ijt}, Y_{jt}	Quantity of product shipped from i to j in period t and the consumption Y of product to fulfil demand
D_{jt}	Total demand at location j in period t
I_{jt}	Inventory level at location j at the end of period t
Cap_j	Inventory capacity at location j
h_{jt}	Inventory holding cost per unit at location j in time t
F_j	Shortage cost incurred at location j
θ_j	Penalty rate per unit of shortage at location j
R_{ijk}, R	A specific resilience strategy for the origin-destination-mode triplet (i, j, k) of the set of adaptation strategies R

w_{ijk}	Binary decision variable: 1 if the strategy $\mathrm{R_{ijk}}$ for (i, j, k) is used, 0 otherwise
T_{ijk}	Available period to deploy resilience strategy $\mathrm{R_{ijk}}$
Earn(t, Cap(t)), Cost(t, Cap(t))	Aggregate earning and cost functions at time t for a given capacity, as used in the resilience value integral in equation (22)
W_t	Warning time before a disruption at time t
Dur_t	Duration of a disruption at time t
d_{ijk}	Implementation time of a resilience strategy $\mathrm{R_{ijk}}$

4) industry layer (welfare and economic Impact analysis)

ΔC	Change in cost impact due to TN disruptions
L, I	The Leontief inverse matrix, Identity Matrix
Dem_j	(Historical) Industrial demand data for port j
A, a_{pq}	A is the technical coefficient matrix of $\mathrm{a_{pq}}$ denoting the input required from industry p to produce one unit of output for industry q
$TN(t)$	Historical transportation network state at time t
Fl_{ij}	Export-import flow between regions at ports i and j, used in equation 16 to scale economic activity
BL	Backlog of goods (used in the thought experiments in chapter 4 for the 'shuttling effect')

1 Introduction

Supply chains (SCs) worldwide face unprecedented challenges. The Suez Canal blockage, lengthy port queues, record-high freight rate spikes, and declining schedule reliability spotlight crucial transportation infrastructure bottlenecks and SC disruptions. For example, the aftermath of the Suez blockage continued to affect transportation performance for an additional 12 days (Gast et al. 2021), having already delayed USD 9.6 billion of trade goods daily (see Baker, Watkins, and Osler 2021). In 2023, the shipping challenges involving the Panama and Suez Canals (Jeffrey 2023) further underscored infrastructure-related vulnerabilities. Up to 14% of global shipments were reportedly stuck in transit, while liner schedule reliability fell to an average of 20–30%, as the newspaper DVZ (2023) reports. Addressing these challenges requires novel strategies to mitigate business impacts, enhance SC performance, and secure resilient and sustainable operations in what has been termed the 'new never normal'.

1.1 Motivation

Disruptions to critical infrastructure, such as a transport(-ation) network (TN), can produce severe consequences that ripple across interdependent industries (see Merz, Hiete and Bertsch 2009). Anticipating and mitigating such disruptive events is central to SC risk management (SCRM). Notably, SC resilience (SCR) largely subsumes SCRM and has garnered tremendous attention during the 'new never normal' (see Ivanov, Hägele, and Grosse 2023). Despite this focus, significant gaps remain in how to effectively evaluate and enhance SCR (e.g. Wicaksana et al. 2022), especially with respect to transportation infrastructure networks (Gast, Kirkach and Ivanov 2022). Moreover, understanding the trade-offs between the costs and benefits of mitigation measures is critical for effective resource allocation (e.g. infrastructure maintenance), risk management, and SC value creation (see Aldrighetti et al. 2021; Aldrighetti, Battini and Ivanov 2023). This critical gap in the literature motivates this thesis research, which develops a comprehensive model for evaluating and enhancing SCR in the context of waterway transportation networks.

This dissertation grounds its analysis of SC decision-making (SCDM), SCR and infrastructure availability in reliability and maintainability theory (RT), which provides a robust quantitative basis for modelling component states and multi-network configurations, failure modes, and time-dependent dynamics. SC reliability, which derives from RT, can serve as a framework for SCR (see Chen, Xi and Jing 2017), assess vulnerabilities, and improve SC value by aligning performance targets with SCRM (Gast 2019a). Although the literature in this discipline remains relatively small, it is expanding (see Ha, Jun and Ok 2018; Ebrahimi and Bagheri 2022).

Geographical location and TNs play a crucial role in determining SC's vulnerability to specific disruptions. For example, the Tōhoku earthquake and tsunami caused widespread damage to thousands of transportation infrastructure elements in Japan in 2011, severely impacting the recovery of economic activities (Mimura et al. 2011). Moreover, even seemingly minor but frequent events, such as adverse weather conditions, can incur substantial cumulative costs for transportation infrastructure (see Pekka Leviäkangas et al. 2014).

Canals constitute a major component of inland waterways (IWs). Industries such as chemical parks, construction, and power plants benefit from IW transportation (IWT) for handling bulk chemicals, building materials, hazardous goods, and breakbulk at relatively low cost (Gast, Gross and Binsfeld 2022). Yet, these SCs have limited alternatives, making them highly dependent on infrastructure functionality and availability. Accordingly, they are waterway-dependent, relying on the infrastructure's performance and availability. For example, BASF SE incurred a write-off of around 245 million EUR due to SC disruptions directly stemming from the historically low water levels of the Rhine River in 2018 (BASF 2019). For the purposes of this study, a 'waterway-dependent SC' is operationally defined as one for which IWT constitutes a critical transport leg, characterised by the following attributes: (i) a significant volume of its total freight is moved via IWT, (ii) the cargo type (e.g. bulk chemicals, heavy goods) is economically or practically infeasible to shift entirely to other modes as key production or distribution facilities are geographically tied to waterway access with limited, high-cost alternatives.

The research project PREVIEW and the West German canal system

In February 2012, the chemical park in Marl—and several nearby ports—became inaccessible for nearly two weeks because of ice coverage on the Wesel-Datteln-Kanal (WDK). Various firms, including BASF SE and the Marl chemical park, contemplated relocating to other regions, partly due to escalating energy costs (WiWo 2022). Nonetheless, the competitiveness and viability of these sites also hinge on reliable IWT access and availability (Wehrle et al. 2023).

Recognising the state of IWT infrastructure and its logistical importance, the German Federal Ministry of Education and Research funded the PREVIEW project. Between December 2018 and February 2022, PREVIEW investigated the resilience of IW infrastructure elements across the West German canal network (WdtK). The author of this thesis, with colleagues at 4flow AG, participated as an industrial partner, offering logistics expertise to analyse the WdtK's transportation operations affected by infrastructure failures (see Gast, Gross, and Binsfeld 2022). PREVIEW convened diverse institutions and stakeholders, including the Waterways and Shipping Administration (WSV), which oversees the daily operations of waterway infrastructure, and the Federal Waterways and Shipping Administration (GDWS), which is responsible for the infrastructure's strategic management. Both WSV and GDWS contributed in-depth knowledge of waterway administration and management.

The industrial stakeholders offered key perspectives on the practical demands and benefits of a resilient waterway infrastructure for logistics, represented by the chemical plant in Marl (Evonik Industries AG) and the coal plant in Lünen (Trianel GmbH). Together, the project team investigated resilience factors described by Wehrle, Wiens, and Schultmann (2022). Building on identified infrastructure failure modes—for instance, accidents, ice coverage or regular maintenance clustered in natural/climate events and technical/human errors—PREVIEW analysed how SC disruptions affect public well-being under varying vulnerability conditions and the availability of mitigation measures. Specifically, the project focused on (i) infrastructure closures and the role of public authorities in minimising downtime, (ii) SCR and the costs of risk mitigation strategies, and (iii) population safety and security of essential goods. Figure 1-1 sketches the overall approach where infrastructure failure could be caused by nature or technical / human failure (leaving out malicious measures) that impact transportation, transportation-dependent SCs and ultimately the public.

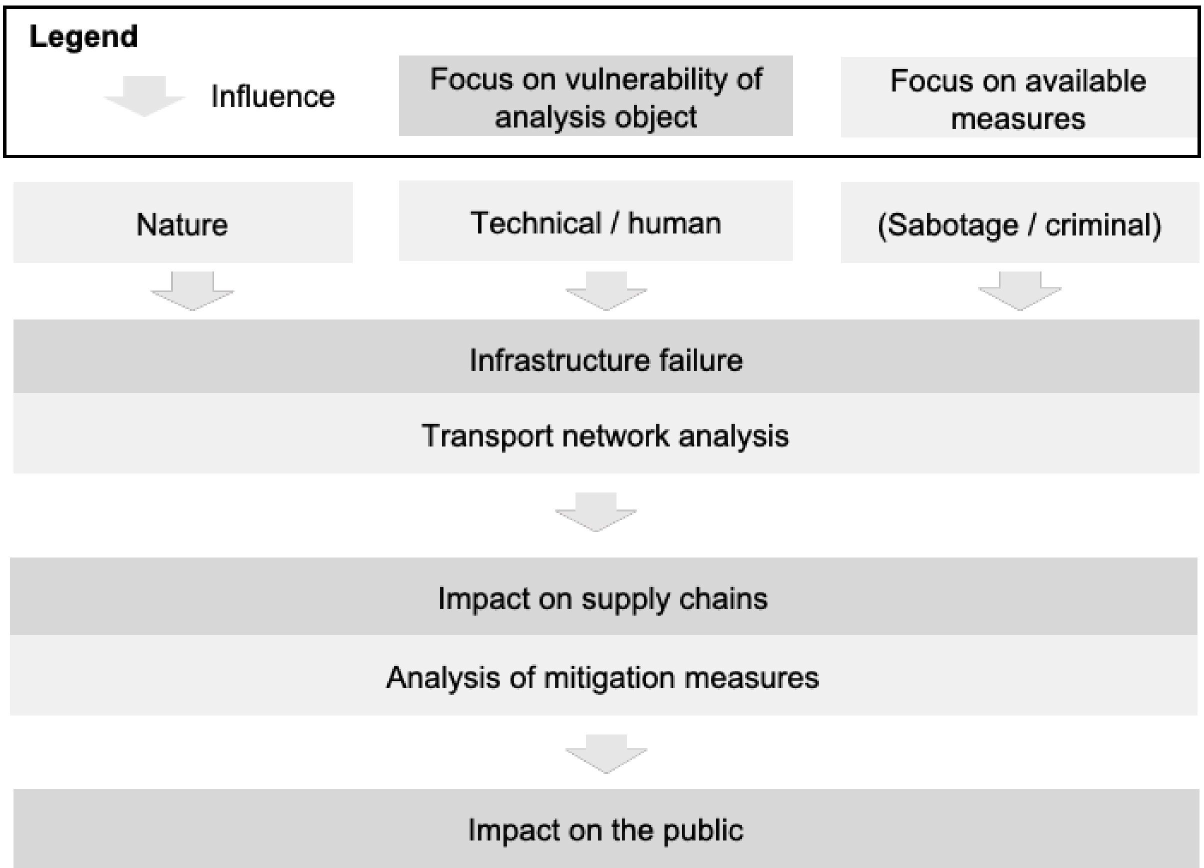

Figure 1-1: Joint research project on waterway infrastructure resilience

The project's outcomes are reflected in six main publications by the author. (i) and (ii) emphasise the condition of infrastructure networks, empirically showing canal network availability and failure modes (Gast and Wehrle 2019; Gast et al. 2020). (iii) The project further examined decision-makers' responses to waterway closures and distinguished between immediate (short-term) disruptions and the longer-term impacts, including lower competitiveness (Wehrle et al. 2023). (iv) Infrastructure bottlenecks are relevant for SCR due to queueing effects (Gast et al. 2021). (v) Infrastructure closures affect transportation quantified via a multimodal transportation model (Binsfeld et al. 2024). (vi) Risk levels of IW infrastructure elements were visually communicated to industrial and public stakeholders (Wehrle and Gast 2022).

While the PREVIEW project established the operational context and stakeholder perspectives, its outcome highlighted a critical research gap: the quantitative connection between infrastructure availability, SCR, and economic value. How can SCDM bolster SCR to cope with inland waterway infrastructure disruptions to mitigate economic value loss?

1.2 Problem formulation and research objective

This thesis addresses the absence of a model for quantifying resilience in waterway-dependent SCs by incorporating historical disruptions, infrastructure states, and dynamic resilience strategies depending on time and SCDM. The thesis further explores how publicly managed infrastructure, transportation, SC operations, and overall welfare interact, which are factors not previously studied in a unified way. To frame the primary research objective (RQ), a detailed literature review is undertaken, followed by secondary RQs derived from identified gaps to clarify the scope and requirements. The main research objective and accompanying RQs and sub-RQs are as follows.

- **Research Objective**: T*o develop and validate a multi-layer, multi-state model quantifying the resilience of waterway-dependent supply chains. The model integrates empirical data on infrastructure states and time dynamics to assess the system-wide impact of disruptions and evaluate available mitigation strategies.*
- RQ1: What is the current state of the literature regarding the main research objective?
    - Is RT a suitable method to pursue the primary research objective?
    - What is the existing link between SCR and transportation?
- RQ2: How can the resilience of waterway-dependent SCs be formalised into a holistic, multi-layer model?

- How can heterogeneous data be integrated to represent IWT and the relationship to SCDM to obtain reasonable as-is parameters and a prognosis of developments?
- What mitigation strategies increase resilience, and what dynamic and quantitative dependencies exist in the IWT context (with emphasis on modal shifts)?
- What are the requisite inputs, expected outputs, and distinct benefits of this model compared with alternative concepts in the literature?

- RQ3: What are the practical applications and utility of the model for public and industrial stakeholders?

1.3 Significance, scope and structure

In addition to incurring higher transportation costs and delays, SCs can face production disruptions—potentially leading to stockouts. Moreover, unavailability or performance degradation caused by deteriorating infrastructure can render SCs untenable in the long run, creating broader welfare concerns (e.g. job losses and reduced tax revenues). Consequently, both private-sector SCDM and public-sector decision-makers stand to gain from evaluating IW infrastructure failures and devising effective resilience strategies. This research is therefore essential to advance the academic understanding by introducing a novel modelling framework for SCR in the IWT context and provides practical tools for decision-makers in both industry and public administration.

The WdtK is selected as the case study for its methodological suitability. The WdtK provides a bounded system to model the causal cascade from infrastructure failure to economic consequence with available historical data. The canal network serves as an ideal natural experiment to test the model's core functionalities: multi-state reliability assessment, queueing at distinct bottlenecks, and the evaluation of modal shift strategies. Furthermore, the WdtK is suited due to its economic significance and relevance regarding infrastructure failures from ageing components, which challenged the SCDM of industries in the Ruhr Valley.

Figure 1-2 below depicts the research framework, comprising three stages: (i) stakeholder insights and literature review delineate real-world challenges, (ii) development of a multi-layer, multi-state resilience model, and (iii) validation of this model via a case study. Validation data draw upon additional sources, including literature and expert assessments.[1] Consequently, the case study parametrisation and application are tailored to the WdtK, generating SCR insights for both industrial and public stakeholders and informing strategies and policy recommendations.

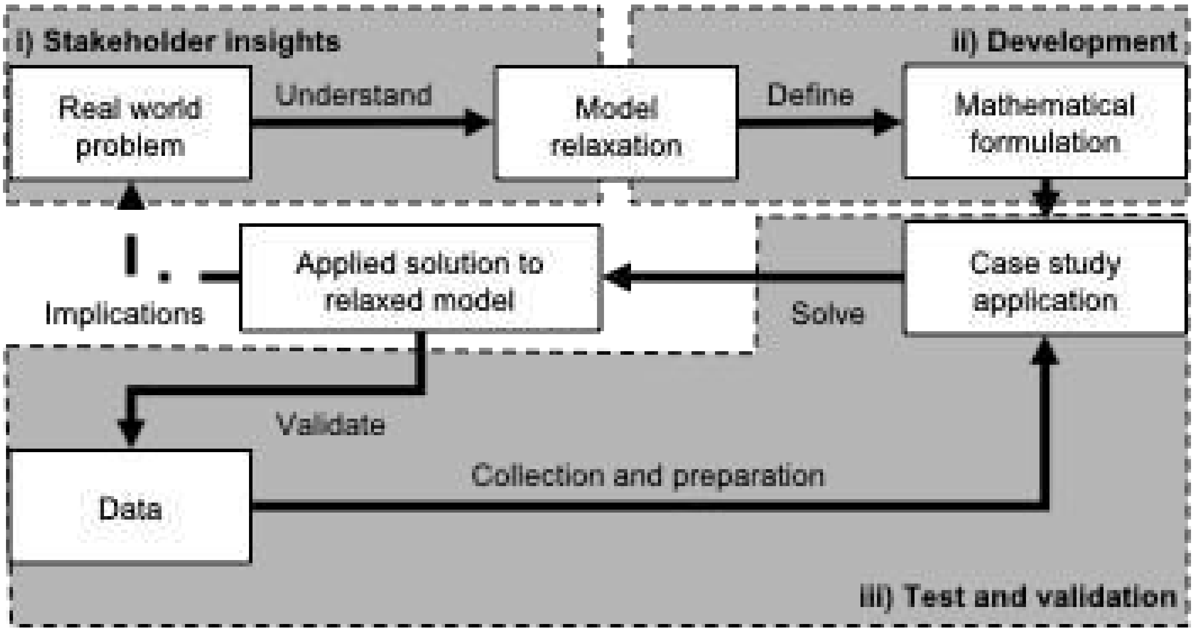

Figure 1-2: Schema of mathematical modelling of real-world problem for dissertation[2]

This research adheres to the established methodological framework, depicted above, moving from problem definition to model development and empirical validation. This thesis achieves its research objective through six chapters, as summarised in Figure 1-3, and features a model implemented in Python using open-source packages (*see Gast 2024 for the code repository*). Following this introduction in chapter 1, chapter 2 reviews the state of the literature in Supply Chain Management (SCM), SCR, SC reliability, transportation, and IWT, highlighting gaps and formulating RQs aligned with the dissertation's main objective. This review uses both narrative and systematic literature review (SLR) techniques to develop a profound overview of the research need and a uniform SCR framework. Furthermore, that chapter extracts the challenges of (inland) waterway-dependent SCs requiring resilience strategies.

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1 The data used for model validation are, by necessity, distinct from those used in the case study application to ensure an independent and robust assessment.

2 Adapted from Rizvanolli (2022)

In chapter 3, a new multi-layer, multi-state SCR model is presented, integrating methods from operations research and RT. Real-world data from the WdtK and empirical assumptions form the basis for parametrising infrastructure states, yielding preliminary calculations. This mixed-methods approach leverages the strengths of both quantitative and qualitative research, capturing both detailed data and broader contextual insights.

Chapter 4 demonstrates the model's feasibility through three case study analyses and their interpretation. Each case offers findings on SCDM and resilience strategies under varying conditions of infrastructure availability, warning times, and queueing effects. Chapter 5 discusses the model's major results, situates them within academic discourse, and proposes practical implications for both public and industrial stakeholders. Finally, chapter 6 summarises key contributions, findings, and prospective pathways for future research.

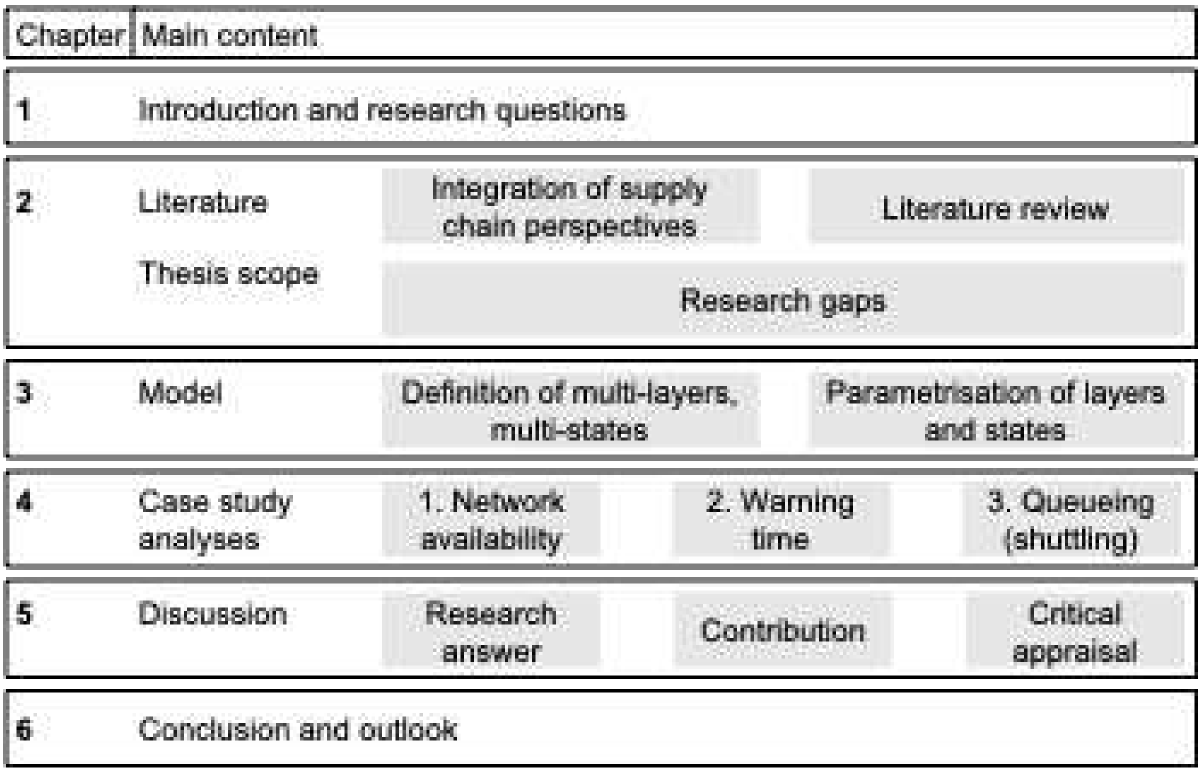

Figure 1-3: Thesis outline

2 Literature and Theory

This chapter provides the current state of the SCM literature regarding modelling SCR in the context of waterways. Firstly, transportation has been a pillar of SCM, emphasising infrastructure that is particularly relevant for IWT. However, transportation infrastructure is prone to disruption. A unified view of SCRM, SCR, and SC reliability, which this thesis synthesises, can manage these disruptions, aligned with the evolving viable SC (VSC) concept within SCM. Then, this chapter elaborates on the field of transportation, where an SLR establishes the link between SCR and transportation. Finally, the chapter concludes with why modelling the resilience of waterway-dependent SCs is beneficial yet remains absent from the literature by presenting a summary of identified research gaps.

2.1 Integration of supply chain management and disruptions

The SCM literature is multi-faceted and influenced by both practitioners and academics, as Ivanov (2018) notes, viewing SCM "as a multi-disciplinary framework of management science, engineering science, and information science." This perspective resonates with open discussions about the terminologies of SC and logistics (see Schulte 2017; see Biedermann and Kotzab 2018) with the concept of the SC as an ecosystem becoming popular in SCM (Ivanov and Dolgui 2022; c.f. Graça and Camarinha-Matos 2017). The SC ecosystem consists of a network of stakeholders (e.g. suppliers, manufacturers, distributors, retailers, end-customers, and public institutions) working together to deliver goods and services subject to environmental effects and market conditions.

SCs are characterised by interconnected companies involved in transforming raw materials into final products for the consumer (Carter, Rogers, and Choi 2015; Mentzer et al. 2001) in a SC network with nodes and links (see Hearnshaw and Wilson 2013). The nodes represent entities and facilities such as suppliers, factories and warehouses, customers, and other agents. The links are how the nodes are connected and may be physical, informational, or financial flows (Christopher 2016; Schulte 2017). This SC ecosystem affects public welfare. According to market theory (Richert 2010), public welfare is maximised alongside market efficiency with an equilibrium of supply and demand, which SCs and their transportation can facilitate. SCs are therefore direct contributors to public welfare: efficient SCs generate positive welfare effects, whereas disrupted SCs that fail to meet demand efficiently result in a tangible welfare loss.

SCM coordinates cross-functional activities and optimises processes to enhance value creation. It manages flows of materials, products, finances, and information across interconnected SC components, each represented as nodes and links in a network (Christopher 2016; Mentzer et al. 2001). Tseng and Yue (2005) highlighted the work of Thomas and Griffin (1996) who divided SCM into the purchase, manufacture, and *transportation* process. A year later, Cooper, Lambert, and Pagh (1997) determined SCM's three key elements: business processes, management components, and *network structure*. Hence, transportation processes, which rely on a network structure, are essential SC business processes and management components within SCM.[3]

2.1.1 Research framework of supply chain management

Figure 2-1 illustrates the evolution of SCM research, driven by shifting business landscapes and emerging academic perspectives. Each phase led to new methodologies, from early transportation studies (1950s) to resilience and VSC concepts (2000s onwards).

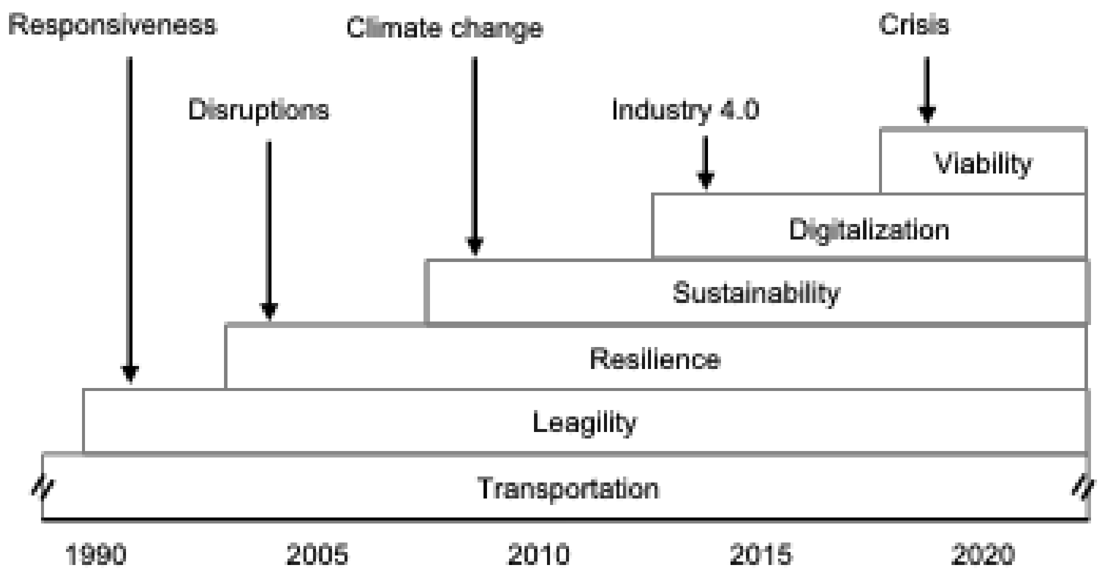

Figure 2-1: Overview of the history of supply chain management research {Ivanov 2020, modified}

3 To emphasise operational considerations such as those affecting cargo transportation, the term "SCM" is extended to "operations," cf. Chopra (2019) or Jacobs and Chase (2024), sometimes referred to as SC and operations management.

Transportation in supply chain management (1956 onwards)

Transportation is vital to SCM, moving goods through space and time (Tseng and Yue 2005; Eriksson, Dubois, and Hulthén, 2022).[4] Furthermore, transportation research precedes SCM (see Ahmed and Dey 2020; Tseng and Yue 2005). While the term "SCM" was first coined in the 1980s, the concept had existed for longer (Biedermann and Kotzab 2018), arguably starting in 1956 with transporting the first intermodal container (Cudah 2006; IMM 2023). Transportation has therefore been a foundational discipline in the evolution of modern SCM.[5]

Leagility (1990 onwards)

The concept of leagility emerged as a combination of the terms "lean" (cost-efficient and process-optimised) and "agile" (flexible and customer-oriented), integrating lean principles with SC agility to remain economically feasible despite competition and changing operating factors (Ivanov 2020). This approach emphasises the importance of lead time and capacity adaptation in response to changing customer demands (Naylor, Naim, and Berry 1999). In addition, leagility includes using modular processes that are easily reconfigured and continuously improved by identifying and eliminating sources of waste and inefficiency (Cooper, Lambert, and Pagh 1997; Christopher 2016), known as the Toyota way (Liker and Meier 2012). Lastly, the approach utilises information and automation technology like radio-frequency identification (Schulte 2017) and demand forecasting (Lee 2002).[6]

Resilience (2004 onwards)

SCs aim to reap the synergies between production and transportation costs yet are vulnerable to disruptions in production and transportation (Lasch 2018). SC disruptions significantly endanger business activities (Aldrighetti et al. 2021; Faertes 2015), like during the COVID-19 pandemic or the Tōhoku earthquake. SCR manifests when the network can withstand and recover from disruptions to ensure performance (Hosseini, Ivanov, and Dolgui 2019). The

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4 . . . — historical trade lanes like the Silk Road have preceded SCs for millennia and require transportation and infrastructure management.

5 Furthermore, Morgenstern (1955) introduced the first logistics theory, which stemmed from military concerns (Schulte 2017) and was concerned with balancing the supply and demand of goods and services with transportation and storage operations.

6 For comprehensive reviews highlighting how design and operation considerations affect various dimensions of SC performance, see Selvaraj and Wesley (2020) and Olugu and Wong (2009). Furthermore, Chopra (2019) provided many case analyses of successful implementation in praxis.

concept of SCR began by mitigating the risks of disruptions while improving overall SC performance (see Christopher and Peck 2004; Blackhurst et al. 2005).

While multiple conceptual approaches to SCR exist, a persistent criticism has been the lack of empirical validation (Hosseini, Ivanov, and Dolgui 2019). Although pre-pandemic research emphasised qualitative success factors like collaboration and transparency, the surge in disruptions since 2020 has intensified the focus on quantifiable SCR capabilities, such as network redundancy and vulnerability analysis (Ivanov, Hägele, and Grosse 2023; Aldrighetti et al. 2021).

Sustainability (2008 onwards)

The focus of SCM has shifted to include sustainability considerations, such as reducing the environmental impact of SCs and promoting social and economic development, see McKinnon (2022) or Amirian, Amiri, and Taghavifard (2022). While customer demands and regulatory restrictions can enforce sustainable operations that dampen performance, internalising externalised costs can resolve this conflict by becoming integrated into the leagility trade-off. Regulatory frameworks or deriving value from sustainability initiatives may also achieve this internalisation. The literature shifted towards network-related issues as a research objective and shows that geographical origin and the industrial sector play significant roles in the relative importance of different sustainability drivers due to their stakeholder requirements (Saeed and Kersten 2019).[7]

Digitalisation (2012 onwards)

The adoption of digital technologies in SCM has witnessed a significant surge, culminating in the evolution of the digital SC leveraging data analytics, automation, and other digital tools for enhanced efficiency and responsiveness (MacCarthy and Ivanov 2022). An intensified data exchange between logistics and other SC components, realised by interoperability, could boost efficiency not only of logistics but the whole value network (Kersten, Von See, and Indorf 2018). Arguably, digitalisation supports all SCM endeavours—academically and practically—and draws various perspectives with digital technologies. As supported by recent research,

7 For a comprehensive overview see Prabodhika, Niwunhella, and Wijayanayake (2020)'s tertiary review involving sustainability trade-offs (i.e. under social, ecological, and economic considerations).

consultants have postulated that data-driven methods enhance SC capabilities (Yu et al. 2018).[8]

Viable supply chain (2018 onwards)

Crises like the COVID-19 pandemic and the Suez Canal blockage have arguably steered new research directions by proposing the VSC. Ivanov and Dolgui (2020) defined viability as the "ability of an SC to maintain itself and survive in a changing environment through a redesign of structures and replanning performance with long-term impacts". The central ideas of the VSC are adaptable structural SC designs for situational supply-demand allocations and, most importantly, the establishment and control of adaptive mechanisms for transitions between structural designs (Ivanov 2020; Ivanov and Dolgui 2022). The VSC model comprises a digital representation of the SC and a business ecosystem responsible for securing society's needs in line with natural, economic, and governance interests (see Ivanov and Dolgui 2020)—i.e. welfare. System dynamics can model the VSC in four ways (Ivanov 2020; see Dolgui, Ivanov, and Sokolov 2022), of which the performance view (later described in Figure 2-2) and the dynamic state view (Figure 2-4) are particularly relevant to this thesis. Existing VSC models, however, while addressing structural adaptability, have largely overlooked the specific impact of transportation network disruptions. Addressing this critical research gap is a central objective of this dissertation.[9]

2.1.2 Links between supply chain management, uncertainty, and disruptions

SCM objectives aim to manage the SC successfully and increase the company's competitiveness (Coyle, Novack, and Gibson 2016; Zsidisin, Petkova, and Dam 2016).[10] Key performance metrics, KPIs, (ASCM 2022) operationalise these objectives and constraints in improvable metrics for individual SCs. Fundamentally, SCM aims to improve SCs through simplification, enhancing process reliability, and reducing both variability and complexity (see

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8 These methods have eventually allowed the use of radio frequency identification records that have filled databases for a decade, such as automated identification system (AIS) data of ships (Yang et al. 2019).

9 Refer to Ivanov and Keskin (2023) for recent contributions concerning the VSC model.

10 For an extensive review of SCM objectives and performance measures, such as costs, customers, responsiveness, activity time, and flexibility, refer to Beamon (1998), Gunasekaran and Kobu (2007), and Selvaraj and Wesley (2020).

Christopher 2016). This aligns with the management principle that effective improvement requires robust measurement.[11] SCM must pursue its objectives under known operating constraints and uncertainty, which can be achieved with a variety of methods (Chen et al. 2023).[12]

Uncertainty has inherent variations in outcomes (i.e. *better*, worse, or unexpected). Risks manifest in uncertainty of which disruption is the most severe risk type (Chopra and Sodhi 2014) because SC disruptions foil SCM objectives and require careful management to mitigate their effects. Katsaliaki, Galetsi, and Kumar (2022) described the *three perspectives* on disruptions based on:

- the reason that caused the disruption (see Chopra and Sodhi 2014), such as disasters, delays, system breakdowns, inaccurate forecasts, and capacity limitations;
- whom they affect, from broad to specific (see Rao and Goldsby 2009), such as the environment, SC networks, SC organisations, problem-specific, and decision-makers; and
- the five characteristics: type, intensity, duration (Dolgui, Ivanov, and Rozhkov 2020), source, and impact (Katsaliaki, Galetsi, and Kumar 2022).

These disruption perspectives have resulted in three specific effects on the SC (Ivanov and Dolgui 2022). (i) The 'ripple effect' describes the propagation of an initial disruption, such as natural disaster, through interconnected nodes and links, causing consequential failures downstream (Dolgui and Ivanov 2021). (ii) The 'bullwhip effect' describes how small changes

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11 Besides, an example from RT highlights an important point about this management principle, emphasising the need to consider intangible or mechanistic relationship aspects of SCM. The RT principle suggests that adding redundancy always improves network reliability but accurately measuring the extent of this improvement is difficult without detailed data. Therefore, it is still possible to manage SCs effectively by understanding the underlying mechanisms in a qualitative manner.

12 . . . — like QT, with other alternative methods being stochastic programming, fuzzy and robust optimisation per Nazari-Ghanbarloo and Ghodratnama (2021). Stochastic programming involves estimating probability distribution functions for uncertain parameters, but it may not always be feasible due to the lack of historical data and increased model complexity. Fuzzy and robust optimisation, on the other hand, offers a framework to handle parameter uncertainty while ensuring the optimal solution remains stable to any realisation of uncertainty within a given bounded set.

in customer demand can cause increasingly significant fluctuations in demand further upstream, creating inefficiencies and excess inventory throughout the SC (Lee, Padmanabhan, and Whang 1997; 2004). (iii) *Survivability* refers to an SC's ability to stay viable in the face of deep uncertainty and catastrophic disruptions from which recovery is not foreseeable, such as political instability. Table 2-1 summarises these uncertainty characteristics in the context of SC.

N.b. that this typology, like the others mentioned above, does not address the 'unknown-knowns' category of uncertainty—risks which mechanisms are known to exist but whose current state is unknown. This specific type of uncertainty, such as the real-time congestion level at a key infrastructure node, is central to the operational challenges this dissertation addresses.

Table 2-1: Uncertainty characteristics in supply chains {Dolgui et al. 2022}

Uncertainty type	Knowledge about uncertainty	Disruption type	Uncertainty analysis	Specific effects	Disruption examples
Random	known-known	Event	Stability	Bullwhip effect	Demand fluctuations
Epistemic	known-unknown	Event	Resilience	Ripple effect	Natural disasters
Deep	unknown-unknown	Crisis	Viability	Survivability	Pandemic

SC risk can also be viewed as a vulnerability (see Ivanov, Hägele, and Grosse 2023), a system property that is "at risk". SC vulnerability refers to the degree to which an SC is susceptible to or unable to cope with disruptions, resulting in negative consequences for SC performance. Such vulnerability may arise from three risk sources: (i) environment-related risks due to SC interactions with the environment (e.g. floods and terrorist attacks), (ii) organisational risks within the SC boundary (e.g. strikes and machine failures), and (iii) network-related risks due to firms' interactions within the SC (Jüttner, Peck, and Christopher 2003). Reciprocally, SC robustness refers to an SC's ability to simply withstand disruptions and maintain performance. In addition, companies of different industries experience various vulnerability exposure levels based on their vulnerability and robustness, depending on factors like locations, lead times [relevant for responsiveness—the ability to react and adapt], and customer markets (Durach, Wieland, and Machuca 2015). Hence, SCM facing disruptions must deploy comprehensive and specific risk management strategies to decrease vulnerability or increase robustness and responsiveness (Blackhurst et al. 2005).

2.2 Unified view of managing supply chain disruptions

Concepts dealing with SC disruption are changing and developing. For example, whereas the impact of SC disruptions on shareholder value meant an average loss of more than 10% on the stock market in the 1990s (see Hendricks and Singhal 2009), this average loss was reduced to 2% in the 2000s—partially explained by the increased number of less impactful disruptions reported by companies (Katsaliaki, Galetsi, and Kumar 2022; cf. Coyle, Novack, and Gibson 2016), affecting the reliability of their operations. However, disruptions like pandemics are so impactful that they question the survival of a business and its SC (i.e. catastrophic failures). The SCM literature suggests three management approaches, which overlap. Hence, this thesis integrates them into a unified view of risk, resilience, reliability.

2.2.1 Supply chain risk management

SCRM is an inter-organisational collaboration that utilises quantitative and qualitative risk management methodologies to identify, evaluate, mitigate, and monitor unexpected macro- and micro-level events and conditions that may adversely impact any part of an SC (Ho et al. 2015). SCRM follows five cyclic steps (Schulte 2017): risk identification, risk assessment, vulnerability detection, risk mitigation, and documentation—then review and redo. Amirian, Amiri, and Taghavifard (2022) developed a risk typology from the literature with three distinct categories that extended on the well-known typology by (Ho et al. 2015):

- risk characteristics (e.g. exogenous vs endogenous, intentional vs unintentional, and operational vs disruptive),
- risk locations (e.g. SC structures: supply, manufacturing, and demand; SC flows: information, goods, and finance), and
- risk impacts with two distinct views:
    - SC risks are divided into different groups/layers (Christopher and Peck 2004); and
    - SC risks are sorted into missing targets (e.g. late delivery) and missing quality requirements (Ravindran et al., 2010; Ohmori and Yoshimoto, 2013).

Mapping identified risks with appropriate mitigation strategies depending on SC vulnerabilities is part of the risk assessment (Amirian, Amiri, and Taghavifard 2022). There are four classes of risk mitigation strategies: (i) avoiding risk by addressing risk causes, (ii) alleviating risk effects by increasing resilience, (iii) transferring risks through insurance, and (iv) accepting tolerable risks (Schulte 2017). Tolerable risks primarily arise in daily operations. While they may impact performance, they do not threaten business feasibility. Subsequently, SC event management (SCEM) addresses these risks by, for instance, using a transportation management system.

The goal of SCEM is to minimise the negative impact of such events on the overall performance of the SC to ensure that it can continue functioning as smoothly and efficiently as possible (Ijioui 2008; Liu, Kumar, and van der Aalst 2007). A few early warning systems have been presented in the SC literature considering sensors and web services (e.g. Sommerfeld, Teucke, and Freitag 2018; Fernández et al. 2016; Genc, Duffie, and Reinhart 2014). These systems aim to identify adverse trends and operational risks for SC as early as possible while deploying operative measures to prevent a reduction in sales, damage, or even bankruptcy by utilising SCs' responsiveness—they notify at the time a known disruption impacts SC operations. Therefore, SCEM measures align well with SCRM. Furthermore, SCEM considers the "crucial question of how much time is lost until the deployed measures become effective" (Romeike 2018). There seems to be no SCEM research on waterway-dependent SCs. Yet, these SCs could benefit, for instance, by utilising automatic identification system (AIS) data to track transportation performance (Mulkidzhanyan 2020).

Major literature reviews have highlighted the extensive contributions to SCRM, covering the remaining steps of how risks are assessed and linked to the vulnerabilities of the SC to derive appropriate risk mitigation strategies (e.g. Wicaksana et al. 2022; Bier, Lange, and Glock 2020; Ho et al. 2015; Ravindran et al. 2010). Recently, Mosayebi et al. (2024) pointed out the effect of time-criticality on SCDM's risk mitigation strategies, suggesting exploring the "time to adapt" (TTA) in specific contexts. However, the literature on SCEM and SCRM has neglected the notion of warning time—a notification period between the start of disruption and the time it impacts SC operations, which is present in disaster research (see Gast et al. 2020), representing a critical temporal dimension of resilience this thesis will quantify.

In addition, SCRM allows various responses to tackle disruptions, including repair/recovery, prevention, and detection; however, economic reasons often limit the availability of these risk-mitigating responses (Dolgui, Ivanov, and Sokolov 2022). Hence, there is a need to document and justify SCRM actions for shareholders and stakeholders.[13] However, a key limitation of traditional SCRM is its focus on pre-defined risks, offering less guidance for managing unexpected, high-impact disruptions for which no plan exists. Nevertheless, restoring links to

13 Furthermore, the "Lieferkettensorgfaltspflichtengesetz" (Supply Chain Act) steers business attention to documenting risks that were not necessarily relevant for SCM operations before, for example, legal compliance of third tier suppliers since 2023.

operation resembles the recovery aspect of SCR literature (see Hosseini, Ivanov, and Dolgui 2019).

2.2.2 Supply chain resilience

In contrast to SCRM's focus on pre-empting known risks, SC resilience (SCR) is fundamentally concerned with the capacity of a SC to withstand, adapt to, and recover from disruptions (Christopher and Peck 2004; Melnyk et al. 2015), particularly those that are unexpected. Starting with the paper titled ‘Building the Resilient Supply Chain’ (Christopher and Peck 2004), the field of SCR has been continually extended since. According to Katsaliaki, Galetsi, and Kumar (2022), "resilience has grown to be a major determinant in SCM for the last two decades". Per Melnyk et al. (2015),[14] SCR is "the ability of an SC to both resist disruptions and recover operational capability after [disruptions] occur". Successfully managed and resilient SCs shift to reaction and recovery instead of pure risk minimisation (see Biedermann and Kotzab 2018).

SCR aims to build and enhance resilient capabilities by understanding and assessing vulnerability factors. By developing resilience strategies, SCs can adapt to environmental changes and remain functional under adverse conditions. Ivanov, Hägele, and Grosse(2023) outlined SCR's various vulnerabilities and capabilities in their tertiary study. Supported by Ivanov, Hägele, and Grosse (2023); Katsaliaki, Galetsi, and Kumar (2022); Hosseini, Ivanov, and Dolgui (2019); Tukamuhabwa et al. (2015), there are three main capabilities:

1. *resistance and risk management* identify potential risks and disruptions that may impact the SC and assess these events' likelihood and potential impact on risk mitigation and management. Then, aligned strategies are developed to mitigate the impact of disruptions, such as developing contingency plans and redundancies in the SC and managing risks as they occur (see Aldrighetti et al. 2021).
2. *recovery and adaptation* employ processes for quickly recovering from disruptions and adapting the SC to be more resilient. Strategies include investing in SCR assets, such as reliable suppliers (see Hosseini, Ivanov, and Dolgui 2019).
3. *flexibility* enables companies to quickly and efficiently respond to changes in their operating environment (Biedermann and Kotzab 2018; Tukamuhabwa et al. 2015).

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14 In the author's mind, this source is the best introduction to SCR in terms of approachability, compactness, and content.

SCR capabilities are operationalised and assessed through a set of core capacities (Pettit, Croxton, and Fiksel 2013) that determine the SC's performance trajectory amidst disruptions. SCR elements are the objectives managed to increase the resilience capacities and decrease the vulnerability of disruptions with dedicated strategies. Arguably, each factor contributing to SCR is an element of resilience, and there are many. Indeed, Biedermann and Kotzab (2018) identified 176 in the literature. A prominent example is stability, which is an object of analysis in system dynamics: the ability to return to a pre-disturbance state and ensure continuity (Demirel et al. 2019). Furthermore, SC can withstand disruptions and maintain its operation if they are *robust* against disruption (Durach, Wieland, and Machuca 2015), as mentioned above.

Navigating the balance between elements is crucial to enhance SCR and avoid creating inefficiencies. For instance, building up redundant structures with additional warehouses is costly but potentially beneficial if supply is delayed. Flexibility alleviates disruptions by drawing on redundancies or shifts of goals. For instance, if there is *flexibility* in the SC, for example, to postpone its services until the disruption effects have vanished, there is no need for costly *resistance and risk management* or *recovery and adaptation* measures. In contrast, an information system might primarily support anticipating disruptions, but if lacking management capabilities, it will not support the containment or return process. The links between capabilities and capacities are schemed in Figure 2-2.

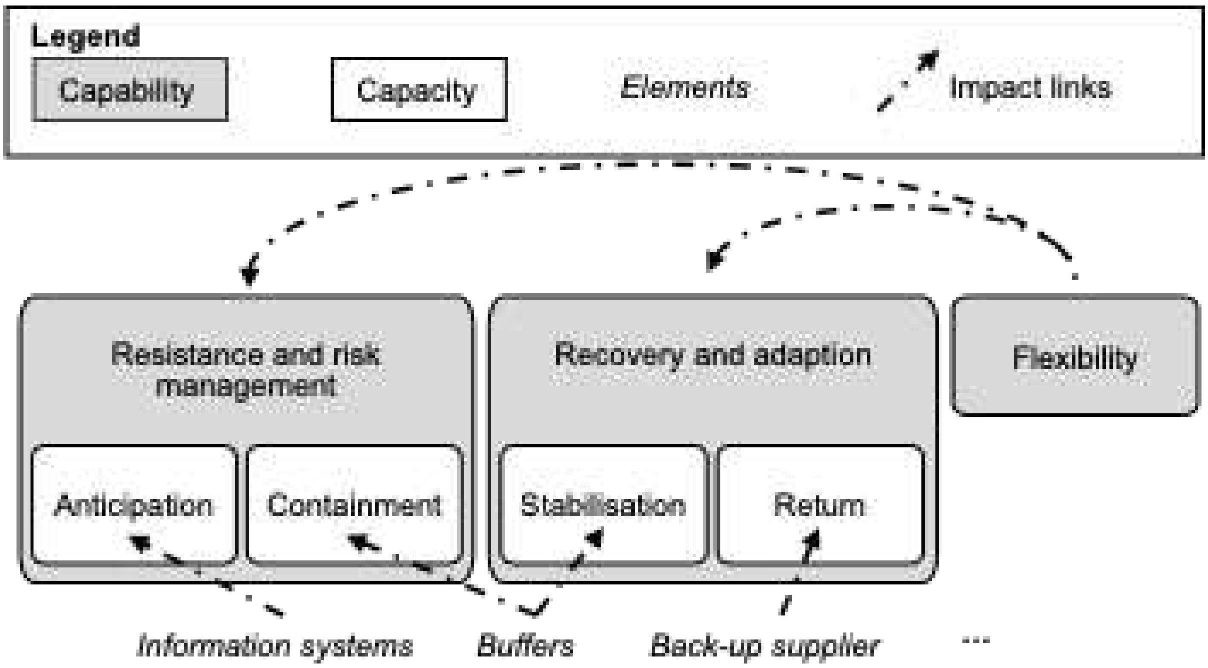

Figure 2-2: The relationship between supply chain resilience capabilities and capacities

The well-known SCR triangle (first encountered by Bruneau et al. 2003; cf. Bevilacqua, Ciarapica, and Marcucci 2018) in Figure 2-3 illustrates the capacity types while quantifying performance loss over time. Resistance capacity (a proactive approach) is the ability of a system to minimise the impact of a disruption by dodging it entirely (*avoidance*) or by minimising the time between the start of the disruption and the recovery (*containment*). Recovery capacity (a reactive approach) is the ability of a system to return to functionality once the disruption has started to impact performance. The system recovery process is characterised by what is ideally a brief *stabilisation* phase, after which a *return* to a steady performance state follows. Stabilisation ensures survival, after which resilient SCs recover. Indeed, some SCs may even thrive, achieving better performance than before (Tukamuhabwa et al. 2015; Biedermann and Kotzab 2018). However, failing to stabilise SC performance results in the collapse. To prevent this, SCDM can respond at various points in time to turn around performance.

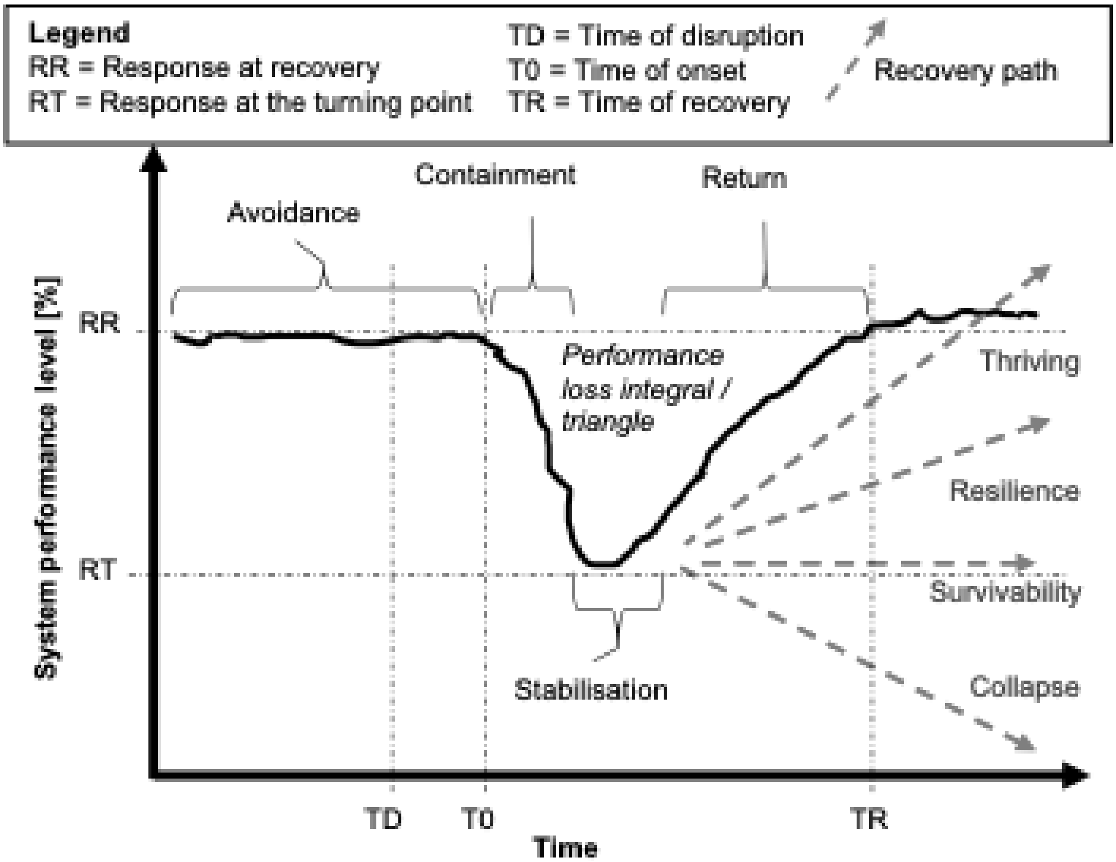

Figure 2-3: The performance view of supply chain resilience {Melnyk et al. 2015, modified}

"Reacting to and recovering from a severe risk event [i.e. disruption] cost-efficiently is essential for SCR" (see Aldrighetti et al. 2021). SC reliability can achieve a cost-efficient balance between risk-reducing investments and SC performance (see Gast 2019a).

Generally, SCDM should minimise the (expected) performance loss integral by efficiently investing in SCR elements to achieve a SC state with high output.

Supply chain reconfiguration with state transition

From the perspective of an SC system, a new state will be reached if the environment changes significantly enough to require new feedback loops for optimal control of SCDM. The analytical derivations can be found in Ivanov, Pavlov, and Sokolov's (2016) study. Their approach allowed for a detailed understanding of how different states evolved and the sequences that facilitated these transitions within the system which, e.g. can be modelled with Markov chains.

For a general SC setting, Pavlov et al. (2018) emphasised identifying a reconfiguration or 'transition' path minimising the performance loss integral (the area within the resilience triangle depicted in Figure 2-3 above), thereby maximising the SC performance area below the curve. Figure 2-4 demonstrates the multi-states with various possible transition sequences indicated by the arrows, which may be uni- or bidirectional. On the vertical axis, moving down indicates a performance degradation of the SC output X with higher costs, while moving up recovers performance. There may be unrecoverable states like X_L, indicating SC collapse. On the horizontal axis, the multi-structural states describe the current configuration leading to the same output level, for instance, X_2. However, the multi-structural state S_{21} may not necessarily be reachable from S_{22}. SCDM aims to identify and take the best recovery path, involving the fewest costs to change the current structural state to a better one depending on the provided opportunities.

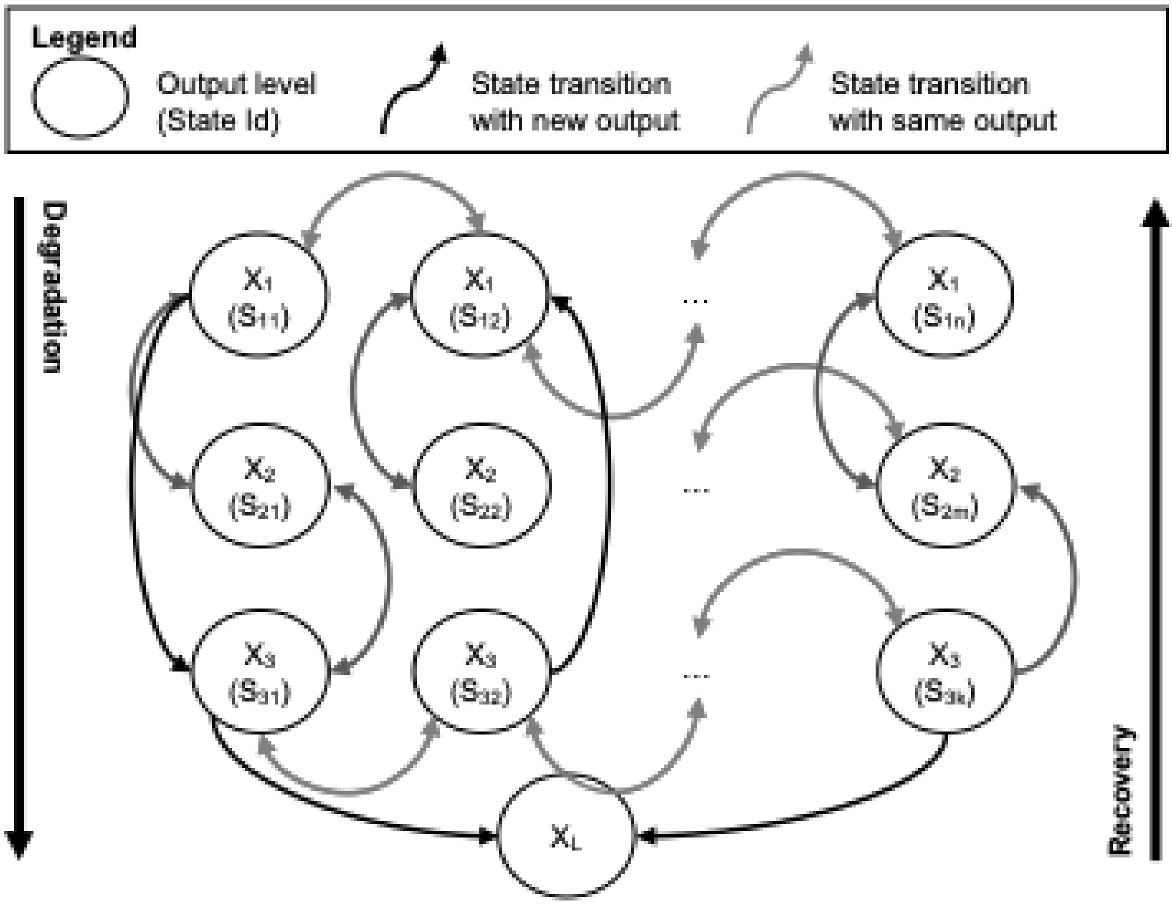

Figure 2-4: Dynamic state view of a supply chain with degrading and recovering states due to a disruption and risk mitigation, respectively resilience adaptation strategies {Ivanov 2020}

2.2.3 Supply chain reliability

The principle that all systems are subject to eventual failure is a fundamental premise of RT. RT provides a toolkit with a sound scientific basis to model the failures of almost all systems with *a single metric—reliability* (Ebeling 1997). SC reliability is a branch of the SC literature (Amirian, Amiri, and Taghavifard 2022) that effectively coordinates SCs with a single metric—reliability.[15] According to Chen et al. (2017),

> SC reliability is the ability of an SC to continually fulfil end-customer demand to the desired level over the planning horizon, despite the risks of external and/or internal shocks to the system and prior to any risk mitigation efforts.

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15 In a service-oriented view, the end-customer can also be internal departments of, e.g. subsequent processes downstream.

Distinct from the structural capability focus of SCR, SC reliability offers a performance-oriented perspective, defined as the ability of an SC to fulfil end-customer demand to a desired level over a planning horizon. SC reliability utilises methods from RT (Ha, Jun, and Ok 2018), generally classifying the SC based on three criteria: the frequency of operations, failure response, and the relationship between the components provided (Lukinskiy, Lukinskiy, and Churilov 2014). Unlike RT, where time is the *main variable*[16] (see Ebeling 1997), *time and quantity* are the main variables of SC reliability (Ha, Jun, and Ok 2018). In addition, Ha, Jun, and Ok (2018) argued that using a throughput capacity unit per time unit as a decision variable rather than component lifetime better represents the impact on SC. Because a failure no longer concerns all or nothing but discrete intervals, which has also been suggested for intralogistics systems (see Maier 2011).

The ability to fulfil the SC mission to reliably deliver a given quantity for a given time and recover operations quickly in case of failure is essential for achieving SCM objectives because availability extends reliability with recovery considerations. Besides, the mission might not become at risk of failure due to disruptions because buffers and redundancies like safety stocks mitigate the failures. However, since buffers lead to excess and inventory holding costs, Gast (2019) suggested that adding shortage costs if demand cannot be met to manage SC reliability aligns with SCRM and SCR to determine the balance between lean performance and excess. Zokaee et al. (2017) suggested accepting a certain degree of shortage costs since too much conservationism [i.e. excess with, e.g. high safety stocks], would diminish SC performance.

RT's *primary metric* is reliability, and SC reliability's main metric is availability (per discrete quantity per time period until a new SC planning period). Nevertheless, SC reliability has only recently gained attention, primarily as an adjunct in the context of SCRM (Ha, Jun, and Ok 2018; Ohmori and Yoshimoto 2013; Gast and Wehrle 2019; see Miman and Pohl 2008)—presumably due to more available data usable for RT. According to Faertes (2015), RT offers tools that ensure several advantages for SC network design and operations by, for instance, considering the trade-off between capital, operational expenditures and lost revenue. Modelling-wise, SC reliability extends RT with network considerations relevant to SCM, such as flow networks, SC configuration (e.g. supplier-manufacturer relationships), and ecosystem parameters not necessarily leading to a failure (e.g. weather conditions). *However*, a network

16 . . . — to evaluate the reliability metric.

reliability approach is necessary to capture complex structures like the SC system with all its components (see Pérez-Rosés 2018).

The SC reliability literature covers the dimension of disruptions (in contingency logistics) and the logistic process dimension of delivery reliability (i.e. service levels). Previous SC reliability approaches had three weaknesses, as Gast (2019a) detailed: (i) they did not link their data requirements to SC data, particularly performance data; (ii) they mainly focused on SC risks, while the quality of SC processes could have been described with SC reliability methods; and (iii) they lacked a management perspective on SC reliability objectives. In addition, the SC reliability literature has provided concepts untested in real-world logistics systems (cf. Ha, Jun, and Ok 2018; Gast and Wehrle 2019; see Ebrahimi and Bagheri 2022).

2.2.4 A unified viable supply chain view

This section integrates the elaborations above about SCRM, SCR, and SC reliability by emphasising the perspectives of SCR and VSC (i.e. survivability, digitalisation, and ecosystem thinking). According to Ha, Jun, and Ok (2018),

> SC reliability contributions to SCRM have mainly focused on structural reliability analysis without providing a clear mathematical definition of SC reliability. Using throughput capacity per unit time as a decision variable, SC reliability can deal with safety stock, backlog, and load-sharing.

This approach represents the lean performance measurement of ‘inventory days’, hedging against stock-out costs (Christopher 2016). Subsequently*,* SCRM integrates various aspects of SCM. Moreover, SCRM aims to optimise SC performance by investing in mitigating known risks (Esmizadeh and Mellat Parast 2021). Ohmori and Yoshimoto (2013) argued that a reliability perspective can manage SC risks through SCDM by defining the risks of SC disruption as "whether the SC processes can be recovered by the specified target time", not simply whether SC processes are disrupted. Gast (2019) opined that supply-side disruptions considered in SCRM could be transferred to a customer-centric view to "fulfil the mission" under various environmental, operational, and product quality parameters by SCDM. Ha, Jun, and Ok (2018) considered RT to be part of quantitative research on SCRM. Hence, a unified perspective on SCM with SC reliability and SCRM is possible for SCDM.

Designing SCs to improve their resilience and reliability has been discussed and modelled in the literature (Chen, Xi, and Jing 2017). For instance, Chen et al. (2017) created a framework integrating SCR and SC reliability, resulting in the following definition: "SCR is the ability of an SC to fulfil end customer demand to the desired level within an acceptable time period after any pre- or post-disruption mitigation efforts". Gast (2019a) extended the framework by adding performance from a management perspective, including cost, quality, and time. Furthermore, failure mode analysis (FMA) from RT provides a powerful tool to integrate SC risks into the hazard rate function (HRF) that can be linked to SC vulnerabilities and addressed with SC reliability management (Gast 2019a). Hence, a unified perspective on SCM with SC reliability and SCR is possible for SCDM.

The resilience and performance trade-off is integral to SCR. Katsaliaki, Galetsi, and Kumar (2022) showed how resilience could address disruptions and other risks, concluding six propositions for academic research presented in SCRM. The authors (2022) connected these propositions to three SC design characteristics – density, complexity, and node criticality – which are determinants in assessing SCR (see Falasca 2008). These propositions include all aspects of SCRM and SCR because recovery and warning are SCRM mitigation strategies and a part of SCR capabilities, according to Katsaliaki, Galetsi, and Kumar (2022). Subsequently, a unified perspective on SCM with SCR and SCRM is possible for SCDM.

Unifying risk and reliability promotes a proactive approach to mitigating risks in SCM. Rather than managing only known risk events and reacting to each realised risk, SCDM can use this approach to manage deviations and take steps to ensure mission fulfilment for a given network configuration despite unknown risks by, for instance, adding redundancies like extra inventory for a critical path (e.g. bottlenecks). In a dynamic, open system, these redundancies make the critical paths less severe, allowing SCDM to shift focus to other areas with the new capability of extra inventory to counter future disruptions.

The most popular indicators for evaluating the impact of uncertainty on SC execution regarding coordination are reliability and stability (for operational and technical uncertainties), robustness (for environmental uncertainties), and resilience (Lukinskiy et al. 2023). According to Ivanov, Pavlov, and Sokolov (2016), "the ability to execute SC operations (in other words, to survive) despite the disturbances caused by disruption is considered as SC design reliability", foreshadowing the VSC concept. Due to considerable overlap, this thesis argues that a holistic view of SCRM and SC reliability applies to the model's scope, with the central perspective of SCR. Table 2-2 provides a comparison of the unified view, summarising the elaboration above to show the resemblance. SC reliability focuses on mission fulfilment under uncertainty, while SCRM primarily identifies and assesses risk events. SCR extends beyond these by incorporating proactive, recovery, and adaptive capabilities. It aligns well with the VSC model, integrating the rather closed SCR framework into a dynamic SC ecosystem (Ivanov and Dolgui 2020).

Table 2-2: Contrasting combination of the unified view supply chain resilience view

Attribute	**Risk**	**Reliability**	**Resilience**
Primary Focus	Pre-empting known risks and specific failure modes	Fulfilling demand (quantity over time) under uncertainty	Recovering system performance after any disruption
Core Question	What can go wrong, is it acceptable or how can we prevent it?	Will we meet the required output level?	How quickly can we bounce back?
Key Metric(s)	Risk probability x impact (risk matrix)	Availability (probability of meeting demand)	Time-to-recover; performance loss integral
Analytical Tools		See Table 2-3	
Handling Disruptions	Proactive mitigation of specific, identified threats	Buffering against performance deviation (e.g. safety stock)	Adaptive capacity and structural flexibility with various elements

Methods used in a unified way

A unified way must be to utilise an RT toolkit instead of an SCRM toolkit. Gast and Wehrle (2019) identified three main clusters of limitations in SCRM that SC reliability could address:

- *context sensitivity* is needed to account for the affected SC's state and environment (e.g. current utilisation and external effects);
- *network character* must account for not only static but also risk anticipation and detectability before activation (see Gast et al. 2020) and propagation; and
- *time* is not inherent to the definition of risk in SCRM, prompting the call for dynamic models. On the contrary, time is an inherent attribute of RT and SC reliability, as elaborated above.

SCR and SC reliability provide ample methods for coping with SC disruptions and ecosystems. Katsaliaki, Galetsi, and Kumar (2022) presented a review of used methods and quantitative approaches to model SCs based on risk factors, their impacts, mitigation strategies, costs, and benefits: quantitative, mathematical optimisation models are most common, including stochastic, mixed-integer, and multi-objective programming, followed by simulation techniques that can handle more uncertainty and complexity, including system dynamics, discrete-event simulations, agent-based models, Monte Carlo simulations, and Markov chains.

Table 2-3 provides the operations research methods for coping with disruptions in SC control, planning and networks, and the ecosystem (cf. Dolgui, Ivanov, and Sokolov 2022). Here, RT can be utilised to capture the ecosystem with network modelling tools. Building a multi-state Markov model from Markov chains is used in RT to model a network's availability, capable of addressing multiple component failures and varying HRF (see Pérez-Rosés 2018) and also suited to represent SCs (Ivanov, Pavlov, and Sokolov 2016). Then, graph theory is one approach to analyse the physical networks, further utilising simulation for processes to assess their SCR (Falasca 2008) or linear programming for planning scenarios (Taki, Barzinpour, and Teimoury 2016). In addition, a unified view integrates process control from SCRM respectively SCEM within a resilience context.

Table 2-3: Operations research methods for addressing disruptions in supply chains {modified}

Supply chain scope and method:	Process control with simulation	Planning decisions with mathematical optimisation	Network and ecosystem modelling	Network and ecosystem analysis
Method examples	Agent-based simulation, discrete-event simulation, system dynamics	Mixed-integer linear programming, robust optimisation, stochastic optimisation	RT, Markov chains, complexity theory, Bayesian networks	RT, Markov chains, graph theory

2.3 Role of freight transportation

This thesis focuses on SCs that depend on and are vulnerable to waterway TNs while still managing to achieve goods flow. This section elaborates on the role of freight transportation for the research objective with a brief overview of the discipline, emphasising intermodal transport. Moreover, a SLR elaborates on the relationship between SCR and TNs.

2.3.1 Links between transportation and supply chain management

Transportation is a fundamental aspect of logistics, crucial for moving goods and services between locations. Transportation in the SCM context aims to connect suppliers, manufacturers, distributors, and customers. Consequently, transportation has shifted from a reactive function to a strategic one, where decisions regarding network design, mode selection, and vehicle routing are integral to an organisation's ability to compete in global markets (Schulte 2017; Coyle, Novack, and Gibson 2016; Ballou 2004).

Aldrighetti et al. (2021) argued that decision-making in designing resilient SC networks must consider transportation. Transportation is the major cost driver of logistics relevant in the SCM of many industries (see Schwemmer 2021). Since transportation contributes the highest cost among the related elements in logistics systems, improving transportation efficiency can change overall SC performance (Tseng and Yue 2005). Therefore, logistics managers must thoroughly comprehend the transportation system's operations (see Tseng and Yue 2005).

Eriksson, Dubois, and Hulthén (2022) showed that considerations of the performance of transportation activities have developed from a focus on efficiency (i.e. using transportation resources as much as possible) to other aspects such as service effectiveness for shippers and consignees, energy efficiency, and reducing emissions and cost over time. These authors (2022) illustrated how transportation performance is an integrated activity in SC and analysed as a function of how business relationships are connected vertically (i.e. transportation activities are sequentially related in SCs) and horizontally (i.e. how to connect activities in their joint use of equipment across SCs). Moreover, regarding disruptions, their relationship can be represented horizontally (a disruption of shared resources like a port affecting multiple SCs) and vertically (subsequent delays, e.g. in intermodal transportation). As Eriksson, Dubois, and Hulthén (2022) contend, enhancing transportation performance requires the scop identification of collaboration in the SC and/or TN settings.

Surprisingly due to its criticality and thus supportively, Eriksson, Dubois, and Hulthén (2022) found that the focus on transportation and logistics within the SCM literature had been relatively limited. Nevertheless, SCDM authors had made various considerations regarding transportation. For instance, Coyle, Novack, and Gibson (2016) indicated that higher levels of safety stocks were required depending on the performance reliability of transportation. Furthermore, depending on demand-driven or transport-driven SC, considerations like a minimum order quantity, customer profitability analysis, replenishment orders, stock in transit, and consumption forecast aligned with production activities are used to decrease uncertainty (Günther and Tempelmeier 2016).

Various social, economic, and environmental factors drive transportation demand, so understanding them is required to manage transportation systems effectively. Eriksson, Dubois, and Hulthén (2022) expanded on Hesse and Rodriguez's (2004) notion that transportation is not (only) a derived demand of various exogenous factors but an integrated demand. As integrated demand, transportation services can be demand- or transport-driven. On the one hand, SCs buy themselves into established transportation capacities (e.g. scheduled liner service) in the TN market for transport-driven transportation, thereby driving the transportation demand of SCs—the TN perspective. On the other hand, SCs acquire the capacity to fulfil transportation needs in demand-driven transportation—the SC perspective. In both perspectives, there are four main service components of freight demand, which can be affected by the infrastructure and the number of transportation agents utilising it (Coyle, Novack, and Gibson 2016). Each of these service components is a direct determinant of SCR; a failure in any one of them constitutes a disruption that requires a resilience response:

- reliability (e.g. switching to a more reliable carrier using more reliable infrastructure),
- accessibility (e.g. including intramodal and multimodal transportation with multiple legs),
- capability (e.g. track and trace or certifications like the "Rheinpatent"), and
- security (e.g. lost and damaged shipments).

Due to lower transportation costs, SCs can expand their reach, resulting in higher time utility. In addition, consumer goods related to special sales events (e.g. at Halloween) and fresh food have a high time utility in opposition to low-value, non-degrading bulk goods (e.g. hard coal and deadwood). For this reason, transportation infrastructure networks and SC networks must be considered together to enable efficient and sustainable economies (Yamada and Febri 2015), thereby maximising welfare. Coyle, Novack, and Gibson (2016) highlighted further TN considerations, namely the welfare dimensions:

- TNs can enhance welfare by providing population easier access to services like health and education (*social significance)*;
- TNs require government regulation and finance to provide services feasibly (*political significance /governance)*; and
- TNs are critical in economic development, enabling trade and access to resources and markets (*Economic significance)*.

To account for the welfare dimensions also present in the VSC (see section 2.1.2), Eriksson, Dubois, and Hulthén (2022) emphasise the role of policy actors: they require an understanding of how a market ecosystem embeds transportation to assess how SCs respond to policies targeting TNs. The dependency on transportation for a market provides a rationale for policy actors to regulate by three means (Coyle, Novack, and Gibson 2016): Firstly, regulators can incentivise certain markets to achieve societal goals through the players (e.g. subsidies for sustainable transportation means to facilitate modal shift). Secondly, policy actors provide a regulatory framework for a marketplace, like safety regulations.[17] Thirdly, to provide non-discriminatory services to the market players (Coyle, Novack, and Gibson 2016; BMDV 2016;

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17 Transportation security and security-related topics are beyond the scope of this thesis. These include C-TPAT, the TSA Transportation Security Administration, the Maritime Transportation Security Act, the SAFE Security and Accountability for Every Port Act, and the CSI Container Security Initiative, which are not considered in assessing the resilience of waterway-dependent SCs because they take a legal position (beyond the scope) or security engineering perspective (where RT might be helpful but generally SCM is not).

EU monitor 2008), regulators can exercise direct ownership, such as with postal offices or by *operating transportation infrastructure* like road, waterway and rail networks.

2.3.2 Links between freight transportation modes and infrastructure

Transportation infrastructure is interdependent on critical infrastructure systems and affects transportation; it comprises the physical components built to facilitate the movement of people and goods, such as roads, highways, railways, airports, seaports, and canals with their supporting facilities such as fuel stations (Ahmed and Dey 2020). Studies about the impacts of infrastructure developments on economic productivity reveal positive externalities of infrastructure investments, including in companies' productivity; consequently, infrastructure is considered the essential location factor of business locations and a key driver of economic growth, especially in the long run (Wehrle et al. 2023). Therefore, transportation infrastructure is crucial for economic growth and development within and between regions.

Because competition is no longer between companies but entire SC networks (Cai et al. 2009), the priority order of project realisation should affect SC competitiveness: if SCs rely on shared transportation infrastructure, disparities in infrastructure performance can influence their overall success. For example, two identical SC configurations planned with the same expectations about infrastructure performance (respectively, cost levels) may encounter varying outcomes if one SC contends with deteriorating infrastructure, raising risks of delays and costs due to unavailability. Sharing infrastructure with competitors has two implications: (i) it establishes a level playing field or opportunity for all companies if the infrastructure performance is homogeneous, and (ii) SCs must adapt to capitalise on the most advantageous infrastructure.

Freight transportation has four primary modes: road, rail, water, and air. Additionally, pipelines represent a specialised mode for specific cargo types. Each mode possesses distinct characteristics, making it suitable for various cargo and transportation scenarios within a region (Coyle, Novack, and Gibson 2016; Aberle 2009; Rodrigue 2024) and requires a dedicated transportation infrastructure network:

- *road transportation* is appropriate for small and high-value shipments and provides door-to-door service with extensive network coverage;
- *rail transportation* suits large and heavy shipments, though its network resilience is a subject of ongoing research *(Bešinović 2020)*
- *IWT* offers a cost-effective and environmentally friendly alternative to other transportation modes for long-distance and large-scale shipments (Caris et al. 2014), which is elaborated below; and

- *Pipelines,* which require significant investments, enable large-scale transportation of specific products, such as oil and natural gas (Ulvestad and Overland 2012).

These modes are combined in intermodal transportation that relies on large-scale operations using fixed terminals such as rail tracks and ports combined with predetermined timetables and dedicated equipment. Arguably, intermodal transportation requires even more SCM practices like stakeholder management as operators of transhipment points participate in SC operations but are often outside the direct control of SCDM as other parties operate the infrastructure. Nonetheless, intermodal transportation provides multiple benefits: reduced CO2e and consolidation, leading to an economy of scale for long-distance (Coyle, Novack, and Gibson 2016; Kubanova and Schmidt 2016; Aberle 2009). Generally, there are six options of SCDM for delivering freight cargo through a network, depending on transportation class (direct or broken into corridors [respectively, SC "legs"]), the hub structure and the routing approach, as highlighted in Woxenius (2007) and depicted in Figure 2-5:

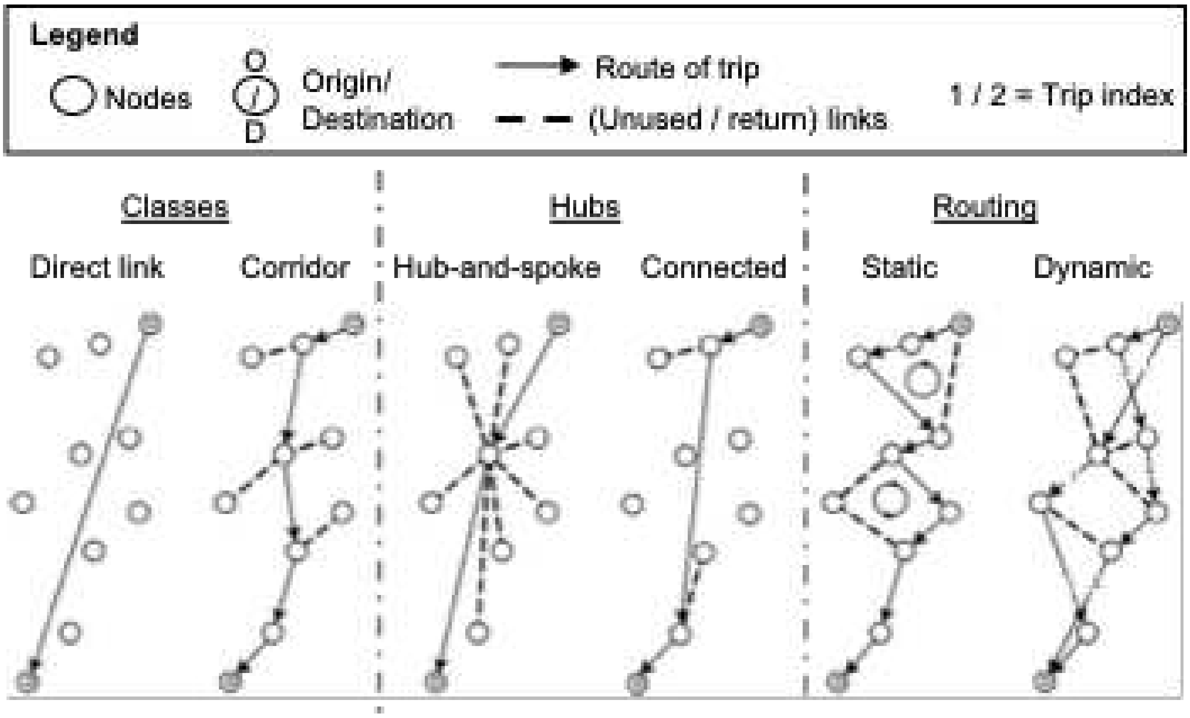

Figure 2-5: The six network design options for routing freight from origin–destination {Woxenius 2007, modified}

The choice among these network designs is driven by a trade-off among several key factors. Flodén, Bärthel, and Sorkina (2017) identified four key factors in selecting the transportation mode in their literature review: cost, transit time, reliability, and the quality of goods where cost was the most important factor. Furthermore, Sommar and Woxenius (2007) distinguished time elements further, including (i) the transportation time between legs, (ii) the required order time before departure to guarantee capacity or a certain price or service level, and (iii) the frequency of departures during a specific time. Considering these time elements is relevant in SCDM to, for example, order enough transportation capacity at reasonable prices despite disruptions, especially for multimodal transport.

Further key factors influencing transportation mode selection include accessibility, capacity, safety (i.e. shipment condition upon arrival),[18] and cargo characteristics (Coyle, Novack, and Gibson 2016; Meers and Macharis 2015). Each mode provides various forms of transportation equipment (Schwemmer 2021) and adds secondary product characteristics like the consideration of packaging because it is easier to fill a van with parcels than a container, let alone a barge. Hence, multimodal transportation often exploits the advantages of each mode in an SC network (e.g. shipping raw materials in bulk and distributing finished goods with trucks). Arguably, emerging risks (e.g. infrastructure failures and climate change resulting in lower availability) also impact the transportation mode choice, but the literature has omitted them.[19]

2.3.3 Systematic literature review of supply chain resilience and transportation

Historically, transportation risk management has addressed disruptions within transportation pertaining to disturbances and issues interfering with a model event, activity, or process. Transportation disruptions encompass considerable delays, interruptions, and stoppages in trade flow caused by natural disasters, heightened threat levels, and transportation security incidents. The uncontrolled risk of disruption produces adverse outcomes ranging from minor delays to significant product losses affecting financial performance (Coyle, Novack, and Gibson 2016).

Unlike SC disruptions, transportation disruptions occur at the operational level, thus bridging to reliability metrics and SCEM. Risk management practices in transportation follow the same procedures as SCRM (see Coyle, Novack, and Gibson 2016; Aberle 2009). Formulating planned responses to high-probability risks like delays caused by weather and traffic is far

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18 Safety and security in the sense of danger mitigation seem only present in combination of hazardous goods transportation in freight transportation literature, see, e.g. Huang et al. (2021).

19 Readers may refer to the topic's SLR by Elbert, Müller, and Rentschler (2020) or the review of case studies on multimodal transportation addresses minimising transportation costs and risks (see Delbart et al. 2021).

more effective than waiting until problems occur to develop solutions (Coyle, Novack, and Gibson 2016). Accessibility metrics respectively reliability networks can measure transportation network resilience (Mohaimani, Mohammadian, and Kalantari 2006). Subsequently, research on transportation and network resilience has emerged, albeit it lacks the SCM or SCR perspective (Kiani Mavi et al. 2022; cf. Ahmed and Dey 2020; cf. Zhou, Wang, and Yang 2019).

The role of transportation has been acknowledged and developed in the SCRM literature (among others; see Ho et al. 2015; Bak 2018; Bier, Lange and Glock 2020). Furthermore, the literature suggests that transportation and infrastructure could significantly impact SC vulnerability (Pettit, Croxton and Fiksel 2013; Bak 2018). However, the literature remains vague about the effect of a disrupted transportation network on the capacities of SCR. Thus, Gast, Kirkach, and Ivanov (2022) conducted an SLR to identify and increase understanding of the relationship between transportation and SCR, reviewing 36 relevant papers from 251 identified abstracts. As a result, the authors (2022) identified six clusters of specific strategies to build and enhance SCR in relationship to TN. The SLR confirmed that while the literature acknowledges that TNs are qualitatively linked with SCs (cluster 1), TNs are quantitatively linked with SCs (cluster 2), and that TN disruptions affect SC performance (cluster 3), the link remains underdeveloped in key areas such as mode-specificity and evidence. The review revealed that while decision-makers have choices, such as rerouting and modal shifts and trade-off between CO_2 and costs (cluster 4), the specific impact of infrastructure failure on these choices is not well quantified (cluster 5). Crucially, while empirical studies confirm a link between poor infrastructure and degraded SCR, there is a lack of evidence quantifying how investments in infrastructure enhance resilience (cluster 6).

These identified clusters show that a quantitative model can link infrastructure availability to SC performance, and that such a model can quantify the economic value of resilience investments regarding economic value. Modelling and assessing these links is the central problem this dissertation addresses. Additionally, the SLR highlights that operation research methods (i.e. graph theory and linear optimisation) are the most common, supporting Table 2-3, next to vehicle routing.

Gast, Kirkach, and Ivanov (2022) further note that most papers have proposed measures to assess, alleviate, and manage the consequences of transportation disruptions by intensifying private SCR investments—not public infrastructure. However, empirical validation is lacking (Gast, Kirkach, and Ivanov 2022), especially in the context of IWT. Dolgui and Ivanov (2021) also highlighted the problem of not precisely defining a specific setting for the research objective. Subsequently and surprisingly, only a few relevant papers have specified the mode of transportation influenced by infrastructure characteristics and vulnerability. For example, extreme weather effects more easily disrupt IWT networks than road networks (see Gast, Kirkach, and Ivanov 2022). Therefore, an empirical case study regarding IWT compared to road transportation would contribute to the literature.

Gast, Kirkach, and Ivanov (2022) have also supported the three potential assets enhancing SCR for SCDM identified by Hosseini, Ivanov and Dolgui (2019). These are "(i) redundancies such as risk mitigation inventories, subcontracting capacities, backup supply and transportation infrastructures, (ii) data-driven, real-time monitoring and visibility systems, and (iii) contingent recovery plans". Furthermore, Gast, Kirkach, and Ivanov (2022) uncovered a fourth one, specifically relevant to transportation infrastructure: *(iv)* finding the right balance between public and private investments to enhance SCR and minimise the economic performance loss, respectively, welfare loss. Therefore, investigating the welfare perspective would be a worthwhile contribution.

2.3.4 Infrastructure constraints of supply chain ecosystems

While established SCRM frameworks categorise risks by their point of origin, such as supply-side, demand-side, or production-side (Tang 2006; Wicaksana et al. 2022), this approach is insufficient for analysing disruptions to shared transportation infrastructure. Such disruptions are ecosystem-level risks that do not originate from a single firm but from the environment in which multiple SCs operate, simultaneously affecting all actors who depend on the network. Meanwhile, the VSC emphasises the ecosystem, thereby presenting a holistic view between multiple SCs, external stakeholders and the transportation link. This consideration is crucial for infrastructure-dependent SCs because environmental risks like infrastructure disruptions potentially affect not only the supply or demand side (i.e. the purchaser) but all other components by affecting the TN, too. Subsequently, enhancing ecosystem components like TN availability would benefit such SCs. Figure 2-6 summarises risks from uncertainty affecting SC supply, organisation/processes, demand, and the environment from a VSC ecosystem perspective. In addition, the figure below positions shared transportation infrastructure as prone to disruption by environmental risks (cf. Kersten et al. 2011 highlighting Christopher and Peck 2004).

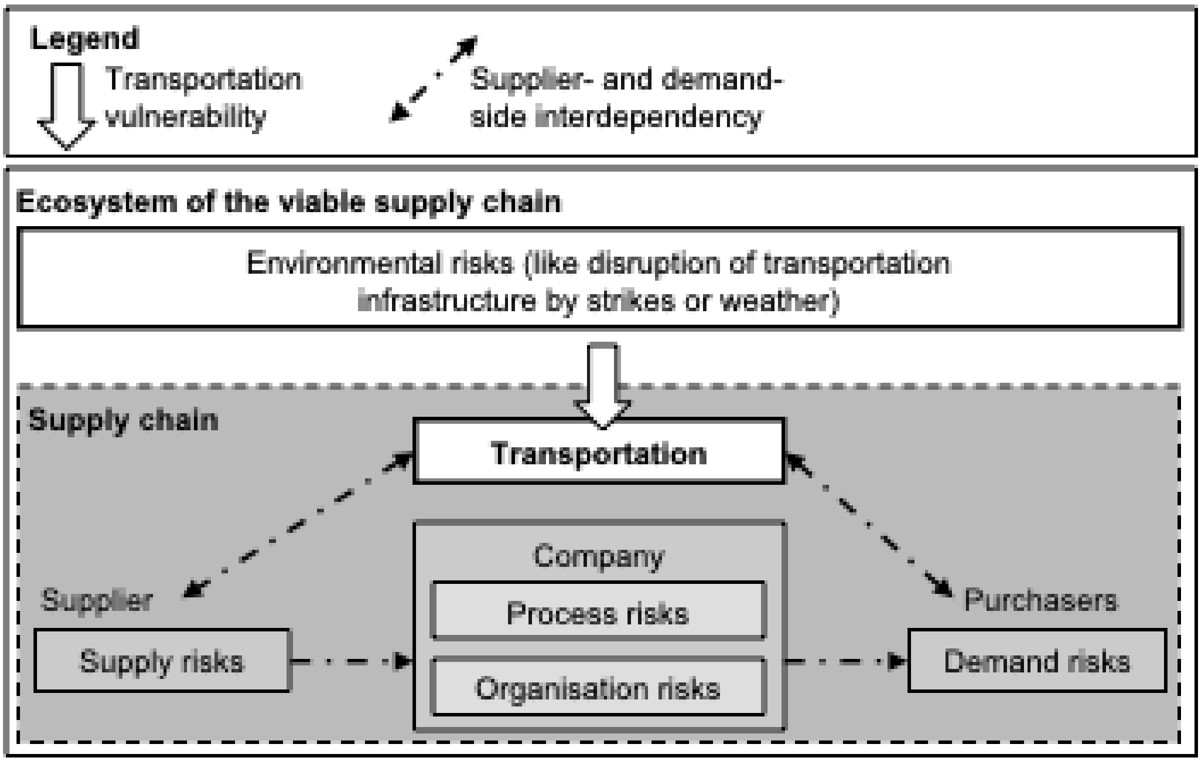

Figure 2-6: The viable supply chain ecosystem with emphasis on transportation vulnerability {cf. Kersten et al. 2011, modified}

2.4 Supply chains dependent on inland waterway transportation

Historically, IWs have provided dwelling and ancillary benefits such as flood protection, power generation, recreation, water supply, and habitats for fish and wildlife (Gast 2019b; OECD 2018). IW systems are vital in transportation, embedded in various SCs (see Schwemmer 2021; Wehrle et al. 2022). Transportation activities of waterway-dependent SCs have the following stakeholders: waterway authorities, (public/private) port operators, carriers, and shippers (see Eriksson, Dubois, and Hulthén 2022). Today's data landscape allows for new businesses (Ninnemann, Tesch, and Werner 2019) and provides an empirical basis for studying the IWT system, especially since the data interfaces are harmonised (see Euris 2023).

2.4.1 Introduction to inland waterway transportation

Under typical operating conditions, waterways are reliable and flexible transportation systems, assuming the full functionality of the infrastructure for which government and administration are predominately responsible. In addition, they provide advantages like high energy/fuel efficiency, relatively low transportation costs for bulk goods, the possibility of transporting breakbulk and hazardous goods, and savings in storage time and fees while reducing the number of accidents. Therefore, IWs should be maintained efficiently to enhance the sustainable development of regional business locations dependent on IWT. (Oztanriseven and Nachtmann 2020; BMVI 2019)

IWT requires multiple components: Wiegmans and Konings (2015) and Roso et al. (2020) highlight inland ports as transportation infrastructures along waterways with terminals, storage facilities, and equipment for handling cargo. Moreover, communication infrastructure supports operations and interaction with SC stakeholders. Locks are particularly critical infrastructure components; they function as capacity-constrained nodes that enable navigation across changes in elevation while also serving as crucial data collection points for traffic volume (Colling et al. 2022). Indeed, space limitations and congestion in port areas have led to the emergence of inland ports to enable more reliable connections and increase the geographical scope of the hinterland (Caris et al. 2014). Therefore, developing infrastructure plans with modern standards in mind is essential.[20]

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20 Distinction between IWT and maritime transportation (next pages)

Maritime transportation and IWT are interrelated in many ways and share characteristics, such as multimodal logistics infrastructure and navigability constraints. Wiegmans and Konings (2015) analysed IWT as a port hinterland, claiming that if the inland port were highly accessible by road, it would stimulate growth in the IWT and maritime port throughputs. Furthermore, Acciaro and McKinnon (2015) saw three main segments of the hinterland SCs and their corresponding infrastructure that affected the ability of container terminals to create SC value: container gate systems, hinterland transportation by road or rail, and dry (inland) ports. The authors (2015) distinguish specific policy, management, and environmental challenges characterising each hinterland SC component with the common tendency of coordination minimising the risk of bottlenecks developing.

Tseng and Yue (2005) named three clusters of maritime transportation: liner shipping, tramp shipping, and industry shipping. Liner shipping is based on the same ships, routes, prices, and regular voyages, while tramp shipping exhibits unsteady transportation routes and schedules. Industry shipping supplies raw materials, sometimes requiring specialised containers, such as high-pressure containers for natural gas. This thesis argues that the three clusters correspond to IWT, too. In addition, estuary shipping blurs the line between maritime and inland shipping. Verschuur et al. (2023) quantify direct supply chain losses and asset damage due to maritime network disruptions but do not consider further economic spillovers. For approaches to model the resilience of maritime transportation and logistics systems, refer to Omer et al. (2012), Wendler-Bosco and Nicholson (2020), and Dui, Zheng, and Wu (2021).

2.4.2 Drivers and barriers to inland waterway transportation

SCM chooses the best fitting modes of transportation to fulfil transportation-requiring objectives and must address the challenges of utilising IWT (Caris et al. 2014). Rail transportation and IWT share commodity groups, which are coal and stones, dry and liquid chemicals, farm products, and breakbulk (Wehrle et al. 2022; Destatis monthly; Martin Schwemmer 2021). Ongoing and continual discussions argue how to realise the modal shift towards rail and IWT and prevent cannibalisation between both systems to relieve roads and promote sustainable growth (BMVI 2019). This debate is not new; as early as 1908 optimising public welfare deemed an integrated approach, where "no railman would not support enforcement of IWT" and the modes would act as supporters rather than competitors (Smith 1908).[21]

With its ecological nature, IWT offers up to a 3.7-fold cost decrease compared to road transportation and single vessel replaces up to 120 trucks, effectively mitigating traffic congestion; furthermore, IWT presents the lowest external costs, including greenhouse gas emissions, air pollution, noise, and accidents (Planco 2007). IWT naturally depends on suitable waterways constraining navigation. The main drivers of IWT are congestion relief, cost reduction [per ton-kilometre], and lower environmental impact; the main barriers are the slow pace of development, high investment costs, and poor hinterland connectivity (Roso et al. 2020).

Further disadvantages named by Roso et al. (2020) are associated with transportation time and terminal transhipments: Weather and climate effects restrict the vessels' load factor because the ship needs to pass between the depth of the navigable channel depth and the height of the lowest-hanging bridge on the voyage, impacting transportation costs and reliability as the water level fluctuates. In addition, the level of reliability and capacity of the ports tend to be limited, leading to congestion. Garberg (2016) finds that [in Sweden] an obstacle to "IWT development is poor coordination between the business sector and governmental authorities, resulting in conflicting objectives". For an extensive list of the drivers and barriers of IWT, refer to Roso et al. (2020).

Numerous public and private stakeholders are concerned with operating and maintaining IWT infrastructure, and thus goal conflicts arise. While companies seek financial returns for

21 . . . — a historical letter already highlighting synergies of multimodal transportation systems. Eventually though, the rail lobby lobbied to enact user charges on waterways to better compete against them instead of proliferating with the IWT system (Coyle, Novack, and Gibson 2016).

themselves, public planning agencies compare the total societal cost to total societal benefits (i.e. welfare), be they monetary or nonmonetary. The tool typically used in public planning is the benefit-cost ratio, considering the time value of funds (Coyle, Novack, and Gibson 2016; Aberle 2009). While planners could consider the collected tax volume of companies and their employees for refinancing, available human resources and construction equipment significantly restrict project realisation in praxis (see PREVIEW 2019a), requiring prioritisation.

(Public) Investments in IWT infrastructure to increase IW performance and availability lead to positive economic spillovers (Bedoya-Maya, Beckers, and Van Hassel 2023) while demand changes and system disruptions lead to adverse economic spillovers like exodus of capital (Wehrle et al. 2023). The public can enact measures to protect critical infrastructure to limit the potential of escalating disruptions (see Merz, Hiete, and Bertsch 2009). Disruptions can occur as a result of port or lock unavailability due to repairs and maintenance, natural disruptions (e.g. droughts, earthquakes, and floods), human-made attacks, and labour strikes (Pant, Barker, and Landers 2015). The literature has heavily studied port unavailability, bridging transport, SCs, and industries (see Hosseini and Barker 2016; Pant, Barker, and Landers 2015). However, the availability of waterway infrastructure elements like locks has been rarely considered (Wehrle et al. 2023; cf. Roso et al. 2020). This public-private tension is compounded by data challenges. Because accurately modelling an IWT network to assess these trade-offs requires granular data on vessel movements and cargo loads, which is often difficult to obtain (Al Enezy et al. 2017).

2.4.3 Waterway-dependency of supply chains

The state of IWT infrastructure affects SCs in two distinct ways. On one side, IWT infrastructure affects “port processing times, lockage times, unscheduled unavailability (i.e. failures/disruptions), scheduled unavailability (e.g. planned repairs and maintenance), and transportation times" (Oztanriseven and Nachtmann 2020) that require SCRM responses. On the other side, scheduled unavailability falls not under the reactive scope of SCRM but rather the proactive planning scope of SCDM because a vessel does not have to wait but could fulfil its transportation order at another time (Wang, Tao, and Schonfeld 2006; Gast et al. 2020). A comprehensive model must therefore be able to account for both stochastic failures and deterministic closures.

Indeed, utilising available historical data on IWT navigation may support both SCRM and utilising IW infrastructure (Huang et al. 2021) because SCDM can assess failure modes and hedge against them. Investments in maintaining and improving IWs can enhance SCR, such as dredging to maintain navigable depths, repairing and upgrading locks and dams, and implementing advanced technologies for improved communication and monitoring. Such investments can reduce the likelihood of disruptions and improve the overall efficiency of waterway transportation (BMVI 2019).

Environmental factors significantly shape the relationship between the total, used, and available capacity. For instance, low tides reduce the average river draft (Scholten and Rothstein 2012), limiting vessel utilisation (Rieken et al. 2015) while resulting in more vessels required to fulfil demand and limiting available vessel capacity while raising freight rates. Infrastructure disruptions can significantly impact businesses, mainly when there is a lack of alternative road and rail capacities (Chen, Xi, and Jing 2017).

The capability to dynamically add logistics infrastructure is helpful as, for example, ports suited for transhipment on the Rhine and WdtK are an average of only 20 km apart (see Colling et al. 2022) and assessments explore whether mobile logistics unloading infrastructure is feasible (Alias et al. 2020). While infrastructure operators can influence infrastructure availability either by adding redundancy or increasing service, SCDM's influence on the infrastructure layer is limited as the public runs the infrastructure. Further discussions also revolve around public financing to invest in the availability of the waterway infrastructure (PREVIEW 2019b) and increasing the access points of logistics infrastructure (see Alias et al. 2023), thereby increasing transportation availability by, e.g. new modal shift opportunities without changing waterway infrastructure availability. Further ways to adapt SC operations include:

- obtaining prioritised service at locks and ports,[22]
- prioritising the modal shift towards IWT to benefit SCs in their configuration the most (Meers and Macharis 2015), and
- upgrading the logistics equipment at ports (see Wendler-Bosco and Nicholson 2020; Cimpeanu, Devine, and O'Brien 2017).

Binsfeld et al. (2024) demonstrated a way to link IWT to infrastructure failure with a travelling purchaser problem (TPP). Binsfeld et al. (2024) used the approach, which is similar to a multi-objective vehicle routing problem (VRP), to estimate transportation time, emissions, and costs associated with infrastructure failures in an IWT system with tramp shipping, providing valuable insights into the potential impacts of disruptions on waterway-dependent SCs (see Binsfeld et al. 2024) utilising cost data from the German Federal Transportation Infrastructure

22 Extending the current prioritisation of certain vessels like waterway police or passenger crafts for certain goods or companies is seen controversially and shall be more carefully considered for beneficiaries as schedules are disrupted (BAW 2023).

Plan (BVWP).[23] Figure 2-7 exemplary illustrates the TPP approach with a set of vehicles k tramping between port nodes to fulfil demand Dem via routes Fl (Binsfeld et al. 2024). The assumption of tramping results in a system equilibrium that is most efficient cost-wise due to the highest utilisation; in reality, costs and, thus, disruption costs are higher.

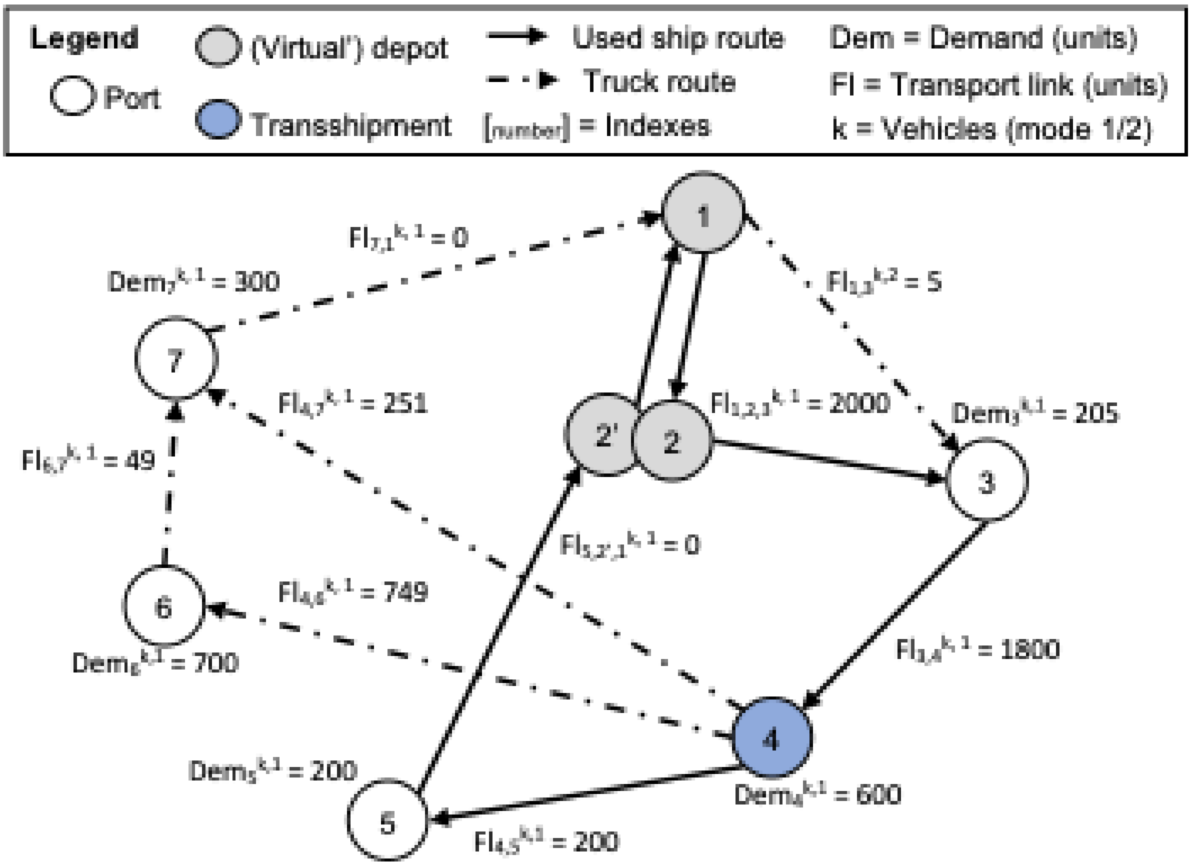

Figure 2-7: Illustration of vehicle routing with the travelling purchaser problem approach {Binsfeld et al. 2024, modified}

Binsfeld et al. (2024) validated the formal correctness and significance of the TPP approach and concluded four primary observations: (i) "Using IWT is more attractive if demand increases". (ii) Multimodal transportation contributes to system stability and equilibrium by mitigating the effects of longer lock times. (iii) "Infrastructure failures impose higher costs of nearly 28% per day [for the whole system by disrupting a single most critical node]; in this case, multimodal transportation is more efficient than a single transportation mode". (iv)

23 For an extensive classification of vehicle routing approaches in the SCR context, refer to Philipp Müller (2021), or in the tramp shipping context, refer to Pache, Kastner, and Jahn (2019).

"Multimodal transportation provides a faster emission reduction rate when the total cost increases by 1%". Saving 1% of emissions increases costs by 0.89% on average. Interestingly, reducing costs by 1% saves only 0.34% of emissions for trucks but 1.17% for IWT, emphasising the environmental benefits of IWT.

Methods from the BVWP help reflect realistic cost structures and investment priorities in the canal system, its infrastructure operators and users. The BVWP outlines investment priorities and provides cost and utility models for infrastructure projects.[24] Every ten years, the BVWP calculates utility benefits (i.e. welfare) for planned federal infrastructure projects like new highways and infrastructure replacements requiring significant investments for the next decade. The welfare calculation includes utility factors stemming from (opportunity) costs, time, place, and emissions, including expected modal shift effects. If the benefit-cost difference is positive, endeavours commence, usually prioritised by the highest benefit-cost ratio.[25] Furthermore, the plan allows the calculation of IWT costs per tonne considering vehicle capacity, distance and time-related costs, an empty return cost factor, and other relevant costs, such as maintenance or fixed costs (e.g. insurance and financing) by providing empirical data such as capacity and cost parameters per vessel characteristics, distance (i.e. fuel costs), and time (i.e. wage costs). While accounting for *reliability* provides additional utility for new road transportation infrastructure, the factor is not directly considered in the IWT models (see Rieken et al. 2015).

Strategies of waterway-dependent supply chains

Infrastructure operators play a critical role in determining the resilience of SC through accessibility, availability, and cost considerations. Strategies of operators are extending infrastructure service time or prioritisation of maintenance and prioritising the (un)loading of cargo (also regarding modal shift) based on economic impact and societal requirements as outlined by Campo, Mayer, and Rovito (2012). Wehrle et al. (2023) highlighted the crucial relationship between infrastructure availability, short-term business reactions, and strategic options like relocation. In summary, infrastructure availability affects SC in the long term due to the combination of repair backlogs, maintenance durations, and scarce resources in

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24 On a side note, the BVWP utilises additionally maintained traffic prognosis for the different transportation modes like the Travis.de data for calculating the infrastructure utility; hence Travis.de date gets renewed accordingly.

25 The project with the highest ratio of the 2015 plan has been deepening centre parts of the Rhine River, which involves multiple states and stakeholders not related to infrastructure planning.

infrastructure construction. In addition, the findings link infrastructure maintenance with a region's attractiveness and competitiveness for more transparent industries. The following strategies affect SCR and address unique characteristics of IWT as discussed in the literature (Wehrle, Wiens, and Schultmann 2022; Wehrle et al. 2022):

- providing timely warning and accurate state of the infrastructure,
- increasing maintenance efficiency (e.g. having spare parts available), and
- increasing service efficiency (e.g. additional equipment or increasing capacities).

The procurement of raw materials often involves extended lead times, making short-term changes to the procurement schedule particularly challenging for suppliers and carriers. Consequently, high demand volatility can result in delivery disruptions, especially when reported just before the call-off (Adelhardt 2020). The call-off and transportation activities of waterway-dependent SCs is affected by the following stakeholders: waterway authorities, port operators (public/private), carriers, and shippers (cf. Eriksson, Dubois, and Hulthén 2022). A closer look at modal shift preferences from the WdtK stakeholder survey (see Gast 2020) revealed that "the short-term shift to the road is the most considerable resilience strategy. On the other hand, rail plays only a minor role" (cf. Wehrle et al. 2022, 18ff). This finding was explained by (i) capacity limitations and (ii) the required time to plan the transports. Surprisingly, the capacity limitations between road and rail are similar and general concern. Hence, (ii) is a crucial differentiating factor as SCs require at least two weeks to prepare using rail cargo capacity.

Warning time is the interval between an operator communicating about an impending restriction and the enactment of the restriction. This interval is critical to preparing efficient mitigation strategies (Genc, Duffie, and Reinhart 2014). For example, Tomlin (2006) introduced response time rerouting and ordering from suppliers with shorter lead times. Therefore, Gast et al. (2020) analysed failure modes of IW disruptions and introduced the concept of warning time from disaster management to extend the implications of response time as an enabler for resilience strategies. Warning time supports Costa et al. (2019) who suggest that real-time tracking and predictive analytics can improve SC visibility and facilitate faster responses to disruptions, thereby enhancing resilience. By considering the concept and failure modes, SCDM is equipped with a tool for optimising SC performance and mitigating the impact of infrastructure failure communicated by public authorities. This enables industries to deploy risk mitigation measures, reorganise their transports, and enhance the effectiveness of available resilience strategies. Within the scope of this thesis and its unified framework (see section 2.2), risk mitigation and resilience strategies are considered equivalent for the purpose of this model.

The extent to which sufficient early warning times mitigate the adverse effects of reduced infrastructure availability largely depends on a company's vulnerability (Gast et al. 2020; see Wehrle et al. 2022). The opportunity cost between industry characteristics, such as transporting gas, coal, or containers, and the second-best mitigation strategy can be affected by the lost value and the flexibility buffers provided. The following strategies affect resilience, attributed to the SC layer (also see Tomlin 2006; Dolgui, Ivanov, and Sokolov 2022):

- postponing transportation and consuming safety stock,
- postponing transportation and adapting production levels (resulting in shortage costs), and
- depending on the notification time in conjunction with the failure mode by
    - preponing and then holding inventory, or
    - reserving capacities for modal shift

Methods of modelling waterway-dependent supply chains

Comprehensive modelling techniques are required to accurately represent the relationships among IWT system components because, according to Oztanriseven and Nachtmann (2020),

- the system is dynamic and has tightly coupled components,
- feedback relationships among system components (e.g. locks, ports) and the environment (e.g. markets and SCs) cause system decisions and outcomes, and
- the effects are not proportional to the causes (i.e. nonlinear) due to capacity and budget constraints, system delays, and the subjective nature of decision-making processes.

Consequently, system dynamics are valuable for analysing and modelling SCs dependent on waterways for this thesis. Due to the complex nature of these SCs, involving multiple stakeholders and various interconnected factors, system dynamics allow for a holistic system view while simulating different scenarios and their potential outcomes. System dynamics allow modelling of the impacts of disruptions to waterway infrastructure on transportation and dependent SC to identify potential solutions to mitigate these impacts.

As elaborated above, network graph representations are well-suited for representing both SCs and transportation infrastructure, allowing for adequate analysis of the complex interactions between nodes and links in the SC ecosystem. Furthermore, they capture nonlinear dynamics and facilitate the identification of critical components and vulnerabilities within the system, enabling targeted improvements and risk mitigation strategies via SCDM (see Wang and Zhang 2018). However, individual components necessitate multiple network graphs (i.e. infrastructure, transportation, and SC configuration), and components with unique attributes demand specific models. For instance, simulation can determine attributes of congested infrastructure attributes, and econometric models can assess the welfare impacts of economic regions. Hence, a model of waterway-dependent SCs requires a comprehensive but manageable system representation.

Dimensions essential to IWT are the infrastructure network, multiple public and private stakeholders, and the relevancy of port infrastructure in common point-to-point SCs requiring large-scale transportation. Therefore, defining layers of the IWT ecosystems seems reasonable for determining risks and resilience (see Wehrle, Wiens, and Schultmann 2022). Furthermore, such a layered model aligns with the VSC structure and Chopra (2019)'s cycle view and SCDM model on SCM by capturing the ecosystem and component interaction both up and downstream.

2.4.4 Research gaps in supply chain resilience and inland waterway transportation

Colling et al. (2022) used the research taxonomy outlined in Caris et al. (2014), indicating limited novel research endeavours over the last decade. Thus, refer to both papers for a comprehensive literature overview. IWT has been successfully studied from different perspectives, such as its integration with other modes of transport, barriers to implementation, cost analysis, network perspectives, and infrastructure issues (Roso et al. 2020). However, the scope of SCM in IWT has been scarce. Instead, the consequences of disruptions of IW ports on industries have been analysed, along with the immediate risk associated with the navigation of inland cargo vessels (cf. Wehrle et al. 2022). Furthermore, Caris et al. (2014) saw a lack of integrating IWT in the SC as one of the reasons for poor IWT performance.

Pant, Barker, and Landers (2015) showed the economic impact of IW logistics infrastructure disruption in a case study of the Mississippi, highlighting how port failures impacted economies across multiple regions severely. However, they neglected the mitigating capability of SCDM and the consideration of empirical failure modes. Nachtmann et al. (2020) extended Pant et al. (2015)'s model by considering the impact of deteriorating infrastructure on multiple economic factors (e.g. taxes). However, the model neglected SCDM considerations, too, and merely derived industrial demand from transportation demand instead of an integrated view or the usual other way around. Furthermore, their assumption of linear infrastructure state deterioration to just 5% availability by 2050 (cf. Nachtmann et al. 2020) is both empirically questionable and fails to capture the multi-state, probabilistic reality of infrastructure performance.

Hossain et al. (2019) modelled the resilience of IW ports, considering the relationship with affected SCs contributing to the field but leaving other elements like TNs open for further research. Baroud et al. (2014) applied stochastic network resilience measures in a Mississippi case study without considering infrastructure states. However, Baroud et al. (2014) suggested further research potential by applying graph theory. While all these models above have provided insights for U.S. decision-makers, no economic models exist for German IWs. Overall, the literature has omitted considerations of multi-states like differing failure scenarios and their characteristics affecting SC performance.

Wang, Tao, and Schonfeld (2006) speculate the impact of warning time for scheduled maintenance operations of a waterway intersection, demonstrating how a modal shift to rail or preponing shipments minimises transportation costs. The authors (2006) argued that their model, which is grounded in economics combined with queueing theory (QT), could produce longer warning times that allowed shippers to depart earlier—hence, a relevant study on warning time. However, the paper offered simplified assumptions that were unfeasible, like evenly distributed traffic after scheduling announcements, while not elaborating on its contribution despite these great ideas: (i) rail requires minimum preparation time; (ii) shippers do not evenly distribute shipments up to 60 days but either use the days before or after the closure or right when anticipating a higher traffic load; (iii) empirical validation, SC considerations apart from transportation scheduling, as well as risk and resilience considerations were missing. While their work provided a valuable conceptual precedent for the mechanisms of warning time and modal shift, it left open the need for empirical validation and integration with broader SC dynamics. This dissertation aims to fill the gap by formalising and testing these concepts with real-world data.

The transportation and SC literature has featured many applications for queueing in waterway transportation (Griffiths 1995; Passchyn et al. 2016; Zhang, Rossi, and Pavone 2019). However, QT has not been applied in the risk context (cf. Worthington 2009; cf. Nazari-Ghanbarloo and Ghodratnama 2021; cf. X. Li et al. 2022). Gast et al. (2021) suggest its relevance in the SCR context. Queueing effects occur at various SC points as operational uncertainty impacts transportation schedules (Nazari-Ghanbarloo and Ghodratnama 2021).[26]

Though Nazari-Ghanbarloo and Ghodratnama (2021) omitted their model's implications for SCR and SCRM, they indicated the need for a realistic model for SC network optimisation considering queueing in future studies.

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26 Refer to Nazari-Ghanbarloo and Ghodratnama (2021) for a structured overview of queueing applications in SC networks. Furthermore, in (public) transportation science, the term "knock-on" is often used, describing, similar to the ripple effect, how delays propagate throughout a network affecting system's performance and potentially disrupting its schedules.

Gast et al. (2021) analysed waiting vessels due to the Suez Canal blockage with QT, introducing non-empty queueing models to the SCR literature. The literature on the operational transportation effect of queueing is extensive, but the SCR perspective is lacking (Gast et al. 2021). Queueing has not been considered in the SCR literature before (Gast et al. 2021) but is relevant in the case of ITW, where transportation capacities and rerouting choices are limited. Thus, chapter 3's model answers the call and demonstrates relevancy in the context of uncertainty and disruption.

Delays due to infrastructure failure for vessels pose significant costs, especially due to inventory-carrying (Tran et al. 2025). Hence, considering lock infrastructure states to mitigate queueing might be worthwhile for waterway-dependent SCs. In QT, a busy period state occurs when the system has customers waiting or being served. Therefore, the system's behaviour must be analysed over time as it transitions from a busy period with a non-empty initial queue to a steady state (Vahdani et al. 2012; Gast et al. 2021). A steady state refers to the long-term behaviour of the queueing system, where queue lengths and waiting times reach equilibrium. For example, in a single-server queueing system with an arbitrary arrival rate and service rate μ, the system is stable if the arrival rate is lower than μ, indicating that customers like vessels are served faster than they arrive on average. In this case, the system eventually reaches a steady state and recovers.

Non-steady-state queueing has significant implications for TN infrastructure disruptions, where vehicles wait until the link gets repaired or need to reroute, depending on what is a better strategy in the transportation or SC layer outlined below. Depending on the analysis objective, Monte Carlo simulation methods provide sufficiently accurate performance metrics because an analytical solution is too hard to obtain (Worthington 2009). For instance, the queueing situation observed at seaports and disruptions caused by lockdowns lead to long-term unavailability of transportation capacity and schedule unreliability not seen before (see DVZ 2023). Importing and exporting goods stuck in transit poses further efforts in coordinating not only their ongoing transportation or ordering replacements but also planning for the available transportation capacity at later periods. These delays likely aggregate if a tight schedule without time buffers requires the same vehicles and containers that are still stuck in transit.

Li et al. (2015) emphasised the need for a collaborative, end-to-end approach in SCRM. Subsequently, Pettit, Croxton, and Fiksel (2013) identified collaborative approaches for disruption management as a key success factor for SCR. Nevertheless, the literature lacks information on how collaboration relates to SCR and the factors required to establish successful collaborative resource-sharing (Duong and Chong 2020). Furthermore, Dolgui, Ivanov, and Sokolov (2022) saw that supply shortage and shrinking demand could result in disruptions propagating forwards and backwards simultaneously or sequentially. However, no approach considers collaboration in transportation to deal with disruptions of transportation capacities (e.g. too little container capacity leading to freight rate spikes) or the network layer (e.g. blocked canals). Collaboration is relevant in the IWT context because SC agents share the same infrastructure and likely depend on the same vessel tramping between ports. Using QT and TPP in the model allows insights into the resource limitations and sharing mechanisms.

Chapter summary of research gaps

This review reveals a fundamental disconnect in the literature: while the strategic importance of transportation infrastructure for SCR is acknowledged, its performance is rarely modelled with the probabilistic, multi-state granularity necessary to quantify its impact on dependent SCs. While the fields of SCRM, SCR, and SC reliability have grown, their focus has remained predominantly on firm-level or supplier-centric risks. The critical role of shared, publicly managed transportation infrastructure as a primary source of systemic risk and a key enabler of resilience remains significantly underexplored. Existing research either treats transportation as an abstract link with uniform costs and availability or focuses on catastrophic, single-point failures. This overlooks the complex, multi-state reality of infrastructure performance, where partial closures, performance degradation, and cascading delays are the more frequent, yet analytically challenging, sources of disruption.

The VSC concept, particularly the dynamic alternative multigraph proposed by Ivanov and Sokolov (2010), offers a conceptual starting point by accommodating multiple system states and ecosystem interactions. However, this framework has remained largely theoretical. Therefore, Ivanov and Dolgui (2022) suggested testing the multigraph approach empirically for a VSC to assess whether and to what extent SC components are affected—e.g. regarding reliability. Making the framework operational for waterway-dependent SCs requires quantitative methods capable of capturing the specific dynamics of infrastructure. Traditional SCR frameworks lack the tools to model probabilistic component states, while classical transportation models often fail to account for the economic impact of disruptions on SC value and welfare. Therefore, a unified framework is needed that systematically connects infrastructure state to transportation cost, and transportation cost to SC performance and economic value.

Linking transportation with SCDM and SCR is worthwhile but needs to be mode-specific. While prior research has modelled the economic impact of IWT disruptions, existing models have significant limitations. For example, the seminal work on the Mississippi by Pant et al. (2015)

and its extension by Nachtmann et al. (2020) demonstrated the scale of economic losses but neglected the mitigating capabilities of SCDM and relied on impractical assumptions about infrastructure deterioration. Crucially, these models derive industrial demand from transport demand, rather than treating them as integrated components of a single ecosystem. Similarly, network resilience models like Baroud et al. (2014) have not incorporated the multi-state nature of infrastructure failures, which is critical for realistic performance assessment. These omissions highlight the need for a model that integrates empirical, multi-state infrastructure data with dynamic SCDM and a holistic ecosystem perspective.

RT offers a way to model the behaviour of complex systems and estimate the likelihood of different types of failures. RT is handy for modelling complex systems with dependencies between components or subsystems (Ebeling 2017), as in SC networks, highlighting the need for research in SCR that RT methods (with usable non-RT methods in brackets) potentially address in the scope of this thesis' research objective to close methodological and empirical research gaps '(G)' while exploring future research pathways outlined by the literature '(P)', as outlined in Table 2-4 below.[27]

Table 2-4: Identified research directions to consider for the model

27 Comparing it with Table 5-1 (section 5.2.1) shows the research contribution to these gaps.

Gaps (G) and Pathway (P)	Source	RT (non-RT)
Lack of empirical research: (G/P) Recognising the distinct challenges posed by simultaneous demand, supply, and logistics infrastructure disruptions calls for an innovative SCRM approach. (P) Implementing more complex networks considering transportation disruptions and (G) load-dependent states can enhance SCR analysis.	see Chen, Xi, and Jing 2017; Aldrighetti et al. 2021	Multi-state reliability networks (and TPP system equilibrium)
Short- and long-term implications of disruptions: (G) Examining how recovery processes differ from *instantaneous* disruptions, such as earthquakes, is necessary for comprehensive SCR analysis. (G) Accounting for geo-location factors can enable more precise modelling of SCR. (P) Communication and market location can play an important role in the event of looming resource limits.	Aldrighetti et al. 2021; Chen, Xi, and Jing 2017; Gast et al. 2021, Bak 2018; Wehrle et al. 2023, Ivanov, Hägele, and Grosse2023	Multi-state, FMA, reliability networks (and queueing)
The link between TN and SCR: (G/P) Linking SC performance to transportation disruptions can provide valuable insights for enhancing SCR strategies.	Lukinskiy et al. 2023; cf. Gast and Wehrle 2019, Gast, Kirkach, and Ivanov 2022	Component hierarchy (multi layers with shortage cost)

Gaps (G) and Pathway (P)	Source	RT (non-RT)
Responsiveness / Adaptability: (G) The impact of warning time depending on failure modes on SC operations and (A) simulation-based analyses of SCR.	cf. Wang, Tao, and Schonfeld 2006; Gast et al. 2021; Huang et al. 2021; Ivanov, Hägele, and Grosse2023	Dynamic states with different reliability and risk strategies
Public investments, collaboration and SCR: (G) Investigating the potential trade-offs achievable through minimal efforts, such as public safety nets, can address concerns about high investment and operational costs associated with SCR. (P) Research should explore collaboration and resource-sharing as cost-effective alternatives to traditional, passive SCR capabilities.	cf. Aldrighetti et al. 2021; Pettit, Croxton, and Fiksel 2013; Duong and Chong 2020; Li et al. 2015	FMA (and welfare optimisation)
Lack of SC reliability application: (P) Limited SC reliability literature and (G) the lack of case study applications; (G) A scarcity of real data for TN parametrisation demands enhancing modelling accuracy and to formulating SCR costs.	Adenso-Diaz et al. 2012; Ha, Jun, and Ok 2018; Chen, Xi, and Jing 2017; Aldrighetti et al. 2021; Gast, Kirkach, and Ivanov 2022	RT with a case study

SC survival in the current ecosystem: (P) Addressing damage and recovery or restoration (repair) costs from an ecosystem perspective. (G) Research on survivability concerns and (P) continuing business models in crises is necessary to ensure long-term SC viability. (G) Modelling demand sensitive to SC responsiveness and disruption risk calls for further analysis to improve SCM practices. (P) Complex multi-regional interdependent risk analysis along inland waterways.	Aldrighetti et al. 2021; Gast, Kirkach, and Ivanov 2022; Ivanov and Dolgui 2022; Wehrle et al. 2023; cf. Oztanriseven and Nachtmann 2020; cf. Pant, Barker, and Landers 2015	Multi-state reliability networks (and robust optimisation; I-O modelling)

This thesis aims to address the RQs and close the mentioned gaps supported by a vast body of literature collected until 2023 and relevant additions from 2024, which is summarised as follows: While most references belong to SCM literature, further disciplines include (IW) transportation and research reports while RT foremostly provides methodological papers. Figure 2-8 shows the publication timeline of the 257 literature references reviewed and included in this thesis. The initial wave of foundational SCR research (circa 2004–2014) was followed by a significant increase in publications after 2015 both in SCR and IWT, confirming the timeliness and relevance of this dissertation's research focus.

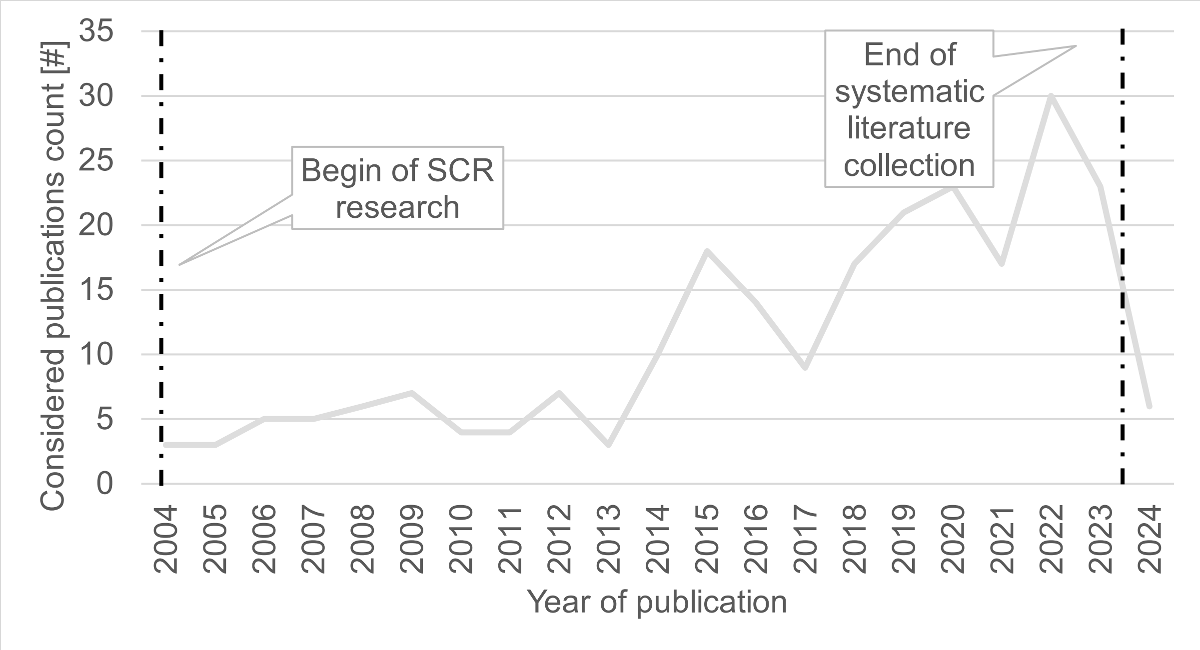

Figure 2-8: Overview of the relevant publications since 2004 used in this thesis[28]

In summary, the literature illustrates several open research pathways concerning SCR in waterway-dependent SCs. A systematic review (section 2.3.3) underscores the absence of mode-specific, multi-state analyses, real-time warning and queueing considerations. This chapter thus concludes that integrating RT with SCRM can address these gaps, particularly by:

- accounting for multiple disruption states,
- capturing dynamic warning times and adaption with risk/resilience strategies, and
- linking infrastructure availability to SCDM and SC value.

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28 Literature references before 2004 are not plotted. Also, due to the cut of the systematic literature review in the end of 2023, only highly relevant papers of 2024 are included.

3 Resilience Model for Waterway-Dependent Supply Chains

This chapter presents a resilience model for waterway-dependent supply chains that integrates real-world data, structural infrastructure condition states, and time dynamics for IWT mitigation strategies. Sections 3.1–3.2 describe the layered modelling approach, showing how system dynamics (structural state and time) inform resilience strategies. Section 3.3 then parametrises the model for the WdtK case study, drawing on the author's research and relevant literature to demonstrate real-world applicability ahead of the next chapter's case analysis.

3.1 Ecosystem representation in a multi-layer model

This thesis hypothesises that infrastructure failure affects waterway-dependent SCs by causing unavailability at the infrastructure layer, which directly impacts transportation and, in turn, triggers higher costs, delays, or stock-outs in the SC that demand consideration by SCDM.[29] Ultimately, these failures reduce public welfare. To capture these interactions, this thesis adopts a four-layer model affecting waterway-dependent SCs' resilience. This decomposition is necessary to isolate the distinct causal mechanisms and decision-making processes at each level of the ecosystem, from physical infrastructure to economic welfare:

1) the transportation infrastructure layer
2) the transportation network layer,
3) the SC layer, and
4) the industry (and public welfare) layer.

The preceding literature review identifies the need for a holistic, dynamic, and ecosystem-aware framework. The proposed four-layer model directly operationalises these theoretical requirements:

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29 The thesis methodology considers the following distinction. A failure is the underlying physical or technical event (e.g. a gate motor breaks, a crack appears in the concrete), a closure / Unavailability is the operational state resulting from a failure or planned maintenance, where a component is not navigable. This can be partial or full. Lastly, a disruption is the SC-level consequence of a closure.

- the VSC concept, with its emphasis on the wider ecosystem, informs the overall four-layer structure, particularly the inclusion of the industry and public welfare layer;
- SCR principles, focusing on recovery and adaptation, are primarily embodied in the SC layer, where SCDM makes decisions on inventory and modal shifts;
- RT provides the core mathematical grounding for the infrastructure layer, allowing for the empirical, multi-state modelling of physical assets; and
- SCRM, with its focus on proactive measures, is operationalised through the model's use of warning time and the analysis of queueing, bridging the infrastructure and transportation layers.

3.1.1 Disruptions in the 1) waterway infrastructure layer

IWT networks are not as fine-meshed as rail networks, mostly lacking any form of parallelism with ports as access points to multimodal transportation networks for rerouting SC flows. Nevertheless, canals (and their parallel two-chambered locks) provide higher transportation volume capacities than road or rail networks. A reliability network model can assess the reliability of the transportation infrastructure by incorporating infrastructure availability, failure modes, and capacity constraints.

Component availability

Infrastructure elements need to be available if they are relevant to transportation functions. Repairs can restore them to a navigable state if they become non-navigable due to reliability problems or scheduled closures. Then, the availability A of a system is the probability that the system is functioning. A is related to the reliability and maintainability of the system by the following formula:

Equation (1): Availability function

$$\mathrm{A} = \frac{\mathrm{MTBF}}{\mathrm{MTBF} + \mathrm{MTTR}}$$

Here, $MTBF$ is the mean time between failures (MTBF),[30] $MTTR$ is the mean time to repair the preceding failure. Assuming that failures and repairs occur at a constant rate, the time-to-failure and time-to-repair can be modelled using an exponential distribution. $MTBF$ derives from the reliability function, shown in equation (2) below, which is the probability that the

30 . . . — assuming the recovery operation restores operations. Otherwise, the mean time to failure (MTTF) describes average time until the component reaches its end of life. In an infrastructure network, component replacement is possible. Hence modelling the MTTF is not reasonable.

system will operate without failure for a given time as related to the HRF denoted with $\lambda(t)$, which represents the rate at which failures could occur in a system at the time t. The reliability function $R(t)$, or the probability of surviving until time t, is therefore given by:

Equation (2): Reliability function

$$\mathrm{R(t)} = \mathrm{e}^{-\frac{\mathrm{t}}{\mathrm{MTBF}}} = \mathrm{e}^{-\int_0^t \lambda(\tau)d\tau}$$

The maintainability function $M(t)$ is the probability that the system can be restored to an operational state within a given time after a failure and is related to the $MTTR$:

Equation (3): Maintainability function

$$\mathrm{M(t)} = \mathrm{e}^{-\frac{\mathrm{t}}{\mathrm{MTTR}}}$$

$$\text{with } \mathrm{MTTR} = \frac{\sum_{i=1}^{n} T_i}{n}$$

Where $MTTR$ is the mean time to repair, n is the total number of repairs performed in the observed period, and $\mathrm{T_i}$ is the time taken to complete the i-th repair. Then, the availability assessment for a given period captures reliability and maintainability is as follows:

Equation (4): Availability of a period

$$\mathrm{A(t)} = \frac{\mathrm{R(t)M(t)}}{\mathrm{R(t)M(t)} + \int_0^t \mathrm{R}(\tau)\lambda(\tau)\mathrm{M}(t-\tau)d\tau}$$

Availability in a reliability network

While equation (4) assesses the availability of a single component, transportation infrastructure comprises a network of interdependent assets. To evaluate the network system, one must account for structural properties like redundancy, which provides multiple pathways between locations. This built-in redundancy maintains overall reliability and resilience because the flow of goods and services is seldom fully impaired due to available alternative paths next to providing shorter paths for arbitrary point-to-point transports. In contrast, waterways seldom have red*unda*ncy, making multimodal transportation and transhipment nodes indispensable. The mathematical formula for a network configuration with a reliability network of multiple component nodes typically employs graph theory or a structure function (Φ). Here, TN_A represents the availability of the entire network configuration and a directed graph, with the set of nodes V, respectively n, signifying the components or subsystems in the network and the set of edges E, respectively m, representing the interconnections between nodes with $A_i \in V$ and $(i, j) \in E$.

For a baseline case assuming statistical independence between component failures, the transportation network availability TN_A in series is the product of the availabilities of its individual components. Equation (5) presents the series-system case with node and link reliabilities:

Equation (5): Reliability network with availability

$$TN_A = \prod_{i=1}^{n} A_i * \prod_{i,j \in E}^{m} A_{ij}$$

Here,

- n is the total number of nodes;
- m is the total number of links;
- A_i is the availability of the i-th node; and
- $A_{i,j}$ is the set of edges E that could either be available or not in the graph TN_A.

The formula accounts for cascading failures, common failure modes, and other factors influencing network reliability. The network configuration is relevant and usually modelled by a structural component functions: For example, if two links connect nodes i and j, represented by $A_{i1,j1}$ and $A_{i2,j2}$, the system possesses redundancy. This redundancy allows the network to maintain functionality even if one link fails, as there still is a path between nodes i and j. Modulating link and edge attributes consider common failure modes and other factors like capacity restrictions, as described below.

Failure types

In practice, failures may be interdependent. Equation (6) refines the availability calculation by incorporating the conditional probability of component failure, respectively interdependency: For instance, ice coverage is less likely to be a failure mode during summer. Comprehending and analysing diverse factors causing reliability issues and their unique failure modes, described in equation (6), is crucial for evaluating resilience strategies based on the current network states and partial unavailability as well as the failure's time, impact, and location.

Equation (6): Interdependent failure modes

$$P(C, F_i) = \sum_{j \in N(i)} P(F_i \mid F_j) \cdot P(F_j)$$

Here, the overall component failure probability $P(CF_i)$ signifies the overall failure likelihood at the node i where $N(i)$ represents the set of nodes connected to the node i and F_i denotes its failure. $P(F_j|F_i)$ is the conditional probability of node i failing, given that node j has already failed $P(F_j)$ if it is in the set $N(i)$ of connected nodes. In the model's case, the conditional probability can be 100% if scheduled unavailability links between ports are unavailable. As a result, all other links in the sequence become unavailable.[31] Expert knowledge is often required to understand the complex interactions between failures, and sufficient empirical data is lacking.

Capacity restrictions

In the context of waterway-dependent SCs, capacity limitations occur at various points in the infrastructure network. For example, they can limit the number of vessels passing through a lock and limited space at transhipment points such as ports. Reaching the capacity limit of network components does not necessarily prevent further transportation.[32] Instead, queueing effects occur, resulting in increased costs and time depending on each network node and link's current load levels and capacity. Therefore, the model considers capacity constraints by adjusting each node's base availability according to queueing-induced congestion, as in equation (7):

Equation (7): Load-dependent capacity restrictions of availability component

$$A_{\mathrm{i}} = \mathrm{A}_{\mathrm{i}}^{\mathrm{Base}} \times (1 - P_{q\ i,j}(L_i/\mathrm{C}_{\mathrm{max,i}}))$$

Here, A_i^{Base} is the base availability of the node A_i assuming no capacity constraints, and load $P_{q,i,j}$ is the queueing-induced availability degradation probability at node *i*, dependent on congestion load L_i (i.e. number of ships) from a connecting node *j* and $C_{max,i}$. $C_{max,i}$ is the maximum capacity of the node i. If the load exceeds capacity, availability does not necessarily have to be reduced, but waiting times increase. To determine specifically how the node and its availability are affected by congestion, QT offers insights. QT has not been considered in

31 Various failure modes exist; for a comprehensive list and modelling techniques, see Ebeling (2017). For instance, a completely random disruption can result from accidents, while a planned failure would be scheduled maintenance. Some failures can be observed long in advance, such as wear-out failures (i.e. state deterioration). On-demand failures can only happen at the time of using the component; an exploding lightbulb would be an illuminating example.

32 . . . — in case of a load overflowing the vehicle's capacity, security considerations might prevent transportation.

the SC resilience context before, as section 2.4 above elaborates. Congestion load due to infrastructure bottlenecks or disrupted capacity can be determined by QT.[33]

3.1.2 Routing in the 2) transportation network layer

The infrastructure layer directly impacts the transportation network layer—the TN—by affecting the efficiency of carriers' use of the infrastructure. When a link is unavailable, or its capacity is reduced, the transportation network layer must adapt and find alternative routes or modes of transportation to ensure the uninterrupted flow of goods. Furthermore, multimodal transportation options could utilise other transportation modes via transhipment nodes in the TN.[34] However, the TN also introduces constraints, as some modes may be incompatible with specific types of goods, capacity, or geographic conditions requiring consideration in the node and link attributes.

Cost of transportation

A multi-state model can provide a better understanding of the cost structure in TNs, such as distance- or time-dependent operating costs, capital expenditure, and transhipment costs. Excess costs due to rerouting or waiting time are incorporated by having longer distances and/or travel-time-dependent operating costs like labour wages. Considering these cost components, the stylised transportation cost equation (8) of transporting goods in a TN is as follows:

Equation (8): Cost of waterway transportation

$$\mathrm{C} = \mathrm{OPEX(TN)} + \mathrm{CAPEX} + \mathrm{TC(TN)} + \theta(\mathrm{VT}, \mathrm{VL})$$

Here,

- OPEX represents the operating cost function depending on the TN;
- CAPEX represents capital expenditure (usually partitioned for a year);
- TC represents transhipment costs and handling depending on the TN; and
- $\theta(\mathrm{VT}, \mathrm{VL})$ represents an individual cost function that accounts for vehicle type VT and vehicle-specific loading and handling of goods VL.

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33 Case 3 in chapter 5 provides the simulation setup of applying QT in the transportation network to reveal insights in the TN and SCR context.

34 Arguably, you would have to define a TN containing multiple bipartite TN graphs connected at transhipment points.

3.1.3 Decision-making in the 3) supply chain layer

The SC layer is crucial, as it translates infrastructure availability into SCDM: When the network's state impacts transportation costs, reliability, and resource allocation, SCDM must adjust accordingly. For example, consider a simplified case with an earning margin of 5% of revenue and transportation costs accounting for 5%. A twofold increase from 5% to 10% due to infrastructure unavailability would consume all the earnings. Moreover, unavailability could lead to production delays or outages (i.e. shortage costs).

The goal of each supply chain

The primary objective of each SC is to maximise value. This involves a continuous trade-off analysis between performance (output, customer satisfaction) and costs (procurement, transportation, inventory), all under conditions of uncertainty and disruption. The SC value function, equation (9), serves as the objective function for this optimisation, representing the accumulated difference between earnings, the *SC performance*, respectively *SC output*, and costs for a given product at SC stage j.

Equation (9): Supply chain value function

$$\text{SCVal} = \sum_{j=1}^{M} (p_j \cdot x_j) - \sum_{k=1}^{K} \sum_{i=1}^{N} \sum_{j=1}^{M} (c_{kij} \cdot x_j)$$

Here,

- j is the index representing each stage, respectively component node, in the SC, such as a supplier, manufacturing, distribution centre, or customer. Within the scope of this thesis, it is the port of destination;
- $\mathrm{p_j}$ are the net earnings generated at j as it either gets sold or new value-adding processes occur, and goods prices remain constant within the scope of this thesis;
- $\mathrm{x_j}$ is the supply quantity transported to the stage j; and
- $\mathrm{c_{kij}}$ is the cost of transporting $\mathrm{x_j}$ using transportation mode k between origin i and destination j.

Shortage costs

The need to manage shortage costs arises when SC cannot satisfy customer demand due to insufficient supply or disruptions at location j for maintaining customer satisfaction and profitability. Thus, SCDM must minimise these costs through SCR, respectively resilience strategies. Equation (10) represents linear shortage costs, F, associated with not meeting demand $\mathrm{D_j}$ with the supplied amount X_{ijt}. These shortage costs are induced by failures in the infrastructure network preventing main supply if there is no inventory available or limited alternative modes.

Equation (10): Shortage cost function for supply chains

$$F_j = \begin{cases} (D_j - x_j) \cdot \theta_j & \text{if } D_j > x_j \\ 0 & \text{otherwise} \end{cases}$$
$$\text{with } x_j = \sum_i x_{ij} + I_j$$

θ_j is the penalty rate per shortage unit. If the demand is met $(D_j \leq X_j)$, the penalty is 0. If demand exceeds supply $(D_j > X_j)$, the penalty is calculated as the difference between the demand and supply multiplied by the penalty rate. The supply consists of the sum of supplied goods between the origin-destination pair (i, j) and available inventory at the destination j. Not meeting demand leads to SC performance degradation, as not only less is earned but additional costs occur at the penalty rate.

Modelling the supply chain layer with a single-echelon SC model

To isolate the impact of infrastructure disruptions, the SC layer employs a stylised, single-echelon SC model in equations (11)–(15) that maximises SC value considering shortage costs and inventory for multiple time periods between $[0, T]$ that have their own demand and supply characteristics while inventory balance is conserved. The model is deliberately simplified to focus on the core trade-offs between transportation costs, inventory holding costs, and shortage costs F which are the primary levers affected by transport availability. With the single-echelon model, SCDM implements the economic order quantity, which determines the optimal inventory replenishment order size in each period (Chopra 2019). The SC model is formalised as follows:

Equation (11): Objective function of the supply chain model

$$\max\left\{\sum_{t=1}^{T}\left(\sum_{j=1}^{M}(p_j \cdot x_{jt}) - F_{jt} - (h_{jt} \cdot I_{jt}) - \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=1}^{M}(c_{kij} \cdot x_{ijt})\right)\right\}$$

subject to

Demand constraints

Equation (12): Demand constraints of supply chain

$$Y_{jt} = D_{jt}, \quad \forall j, \forall t$$

Inventory capacity constraints

Equation (13): Inventory capacity constraints of supply chain

$$I_{jt} \leq C_j, \quad \forall j, \forall t$$

And inventory balance constraints

Equation (14): Inventory balance constraints of supply chain

$$I_{jt} = I_{j,t-1} + \sum_{i=1}^{N} (X_{ijt} - Y_{ijt}), \quad \forall j, \forall t$$

Finally, stock, demand, and transported/sold units cannot be negative.

Equation (15): Non-negativity constraints of model parameters

$$X_{ijt}, Y_{ijt}, I_{jt} \geq 0, \quad \forall i, \forall j, \forall t$$

Here, Y_{ijt} represents the consumption of a product to fulfil overall demand D at location j in period t. X_{ijt} represents the quantity of product shipped from the location i to location j in period t. The model aims to maximise SC value by minimising the total cost of inventory holding $(\sum_{j=1}^{M} h_{jt} \cdot I_{jt})$, transportation and shortages over the planning horizon T, subject to meeting the (consumption) demand under capacity constraints at each location. The inventory balance constraint ensures that inventory levels are consistent with consumption and shipments to j while considering available inventory. The shortage cost term penalises the model for failing to satisfy demand if the sum of supply and inventory is not sufficient.

3.1.4 Welfare implications in the 4) industry layer

The industry layer represents the sum of economic activities benefiting the public and, therefore, is an essential component of welfare significantly impacted by other layers. Arguably, the sum of all waterway-dependent SCs' activities comprises the economic activities related to IWs in each region. Ideally the sum of all SC activities in the SC layer is the industrial layer's economic activity. The public decision-maker can finance excesses like TN redundancies to reduce welfare loss and increase companies' SCR[35] by ensuring that no shortage costs occur and that transportation costs only increase insignificantly in case of infrastructure failure.

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35 . . . — not necessarily the taxpayers'.

Input-output modelling

The Leontief input-output (I-O) matrix (Leontief 1951) provides a comprehensive framework to understand the interdependencies between industries, enabling the estimation of the cost impact of TN disruptions at each port node in the network (Pant, Barker, and Landers 2015; Oztanriseven and Nachtmann 2020). The matrix approximately calculates aggregated industry shortage costs, i.e. inoperability due to disrupted nodes in the TN in the multi-layer model—the sum of the shortage costs of affected economic activity. Therefore, the following steps were undertaken by Pant, Barker, and Landers (2015) for the US Arkansas IWT ecosystem, deploying a matrix for analysing the cost impact at each port node based on industrial demand:

1. Construct the technical coefficient matrix $A = [a_{pq}]$, where a_{pq} denotes the amount of output from the industry p needed to produce one unit of output in industry q.
2. Calculate the Leontief inverse matrix L by using the formula $L = (I - A)^{-1}$, where I is the identity matrix.
3. Evaluate the cost impact at each port node j resulting from TN disruptions, including the inoperability and tax loss effects, by incorporating the port-specific industrial demand D_j[36] and trade flows Fl into the Leontief input-output matrix.

Then, the cost impact can be estimated using the following formula:

Equation (16): Economic cost impact estimate of network availability

$$\Delta\mathrm{C} = \mathrm{L} \cdot \left(\mathrm{Dem_j} \cdot \mathrm{TN(t)}\right) \cdot \mathrm{Fl_{ij}}$$

Here, ΔC represents the change in cost impact at each port node due to TN disruptions. Dem_j is the historical demand data for each port, $\mathrm{TN(t)}$ is the historical TN state at the time t reflecting disruptions or significant delays in transportation, and Fl_{ij} is the export-import flow between trading regions at ports i and j.

3.2 Resilience strategies in a multi-layer, multi-state model

Unavailable canal infrastructure not only changes the infrastructure layer but also allows transportation in the transportation network layer to require rerouting. This results in SCDM changing plans as transportation costs are expected to be higher by, for instance, increasing

36 . . . — which is consistent with demand D that the SC layer fulfils for a location j considered time period t.

inventory. Hence, the infrastructure, transportation network, and SC layer are in different states, affecting the states of other layers. System dynamics modelling offers a holistic view of waterway-dependent SCs, capturing these interactions and feedback loops, making it ideal for policy analysis and scenario planning.[37] Furthermore, a comprehensive understanding of the interplay between various factors in waterway-dependent SC is achievable by combining system dynamics with other modelling techniques, such as network analyses and multi-state Markov models, see Table 2-3 above.

3.2.1 System dynamics and dynamic structure approach

The model employs dynamic alternative multigraphs, connecting the states of the four layers to the resilience level and strategies of SCDM, enabling state-dependent resilience strategies, see equation (17). Consequently, the SC is defined as a set of different structures in a dynamic alternative multigraph $\mathrm{G} = \{\mathrm{G}_\chi, \chi \in \mathrm{W}\}$, where W is a set of alternative structures following the implementation principles (c.f. Dolgui, Ivanov, and Sokolov 2020):

Equation (17): Multi-state multi-graph of supply chains

$$\mathrm{G}_\chi^\mathrm{t} = \langle \mathrm{Elem}_\chi^\mathrm{t}, \mathrm{K}_\chi^\mathrm{t}, S_\chi^\mathrm{t}, \mathrm{TN}_\chi^\mathrm{t} \rangle$$

Here, subscript χ characterises the possible alternative SC structures, and time point t belongs to a given set T, denoting the considered periods. $Elem_\chi^t = \{elem_{\langle\chi\rangle}^t, \chi \in L_\chi\}$ is a set of elements of the structure actively used in the SC of L_χ^t (the set of location nodes, e.g. actual and potentially usable suppliers) at time point t. $K_\chi^t = \left\{k_{<\chi,l,l'>}^t, l, l' \in L_\chi\right\}$ is the set of arcs of the dynamic alternative multigraph representing how a transportation channel and carrier connect to the SC layer with the set of considerable SC components L at time t. Finally, $S_\chi^t = \left\{S_{<\chi,l,l'>}^t, l, l' \in L_\chi\right\}$ is a set of attributes, such as capacity and inventory for the SC components L resulting in an SC output x (see equation (9) above) at time t. As an addition, the TN of the transportation network layer represents the state of the waterway infrastructure run by public authorities as a multigraph:

Equation (18): Transportation network consideration in a multi-state multi-graph

$$\mathrm{TN}_\chi^\mathrm{t} = \{\mathrm{k}_{<\chi,\mathrm{a},\mathrm{a}'>}^\mathrm{t}, a, a' \in WW_\chi\}$$

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37 For example, applying system dynamics has been suggested to model IWT (Roso et al. 2020) and SCR (Ivanov 2018) as elaborated in sections 2.2.4 and 2.4.3.

WW is the set of all the possible states of all waterway infrastructure elements a that impact transportation. Each infrastructure element can be available, unavailable (i.e. closed or disrupted), or something-in-between (e.g. canal usage restricted by a speed limit) denoted by a'. Thereby, the TN fully considers the waterway infrastructure layer. The TN does not have resilience states but reliability/availability states in which recovery is determined by repair time and failure based on failure modes, as outlined below. SCDM applies resilience strategies depending on the TN state, allowing the alternative multigraph to describe the resilience of waterway-dependent SCs in hindsight of multiple TN disruptions co-occurring.

State transitioning

Time and events can change the structure, leading to decisions such as increasing inventory to hedge operations in the SC layer. This thesis assumes that SC output X depends on the availability states of its used TN. The probability of the component being in a state x' at time t, denoted by $P_{x'}(t)$, is expressed as in the equation (19):

Equation (19): Probability of a component being in a state x

$$P_{x'}(t) = \sum_{x=1}^{S} P_x(t-T) \cdot P_{xx'}(T)$$

Here, $P_x(t-T)$ is the probability of the network being in a state x at time T. During the time interval *[T,t]*, $P_{xx'}(T)$ is the transition probability from state x to state x'—a preceding to a succeeding state. Let TN_A be the current availability state of the TN at the time t, with $TN_A \in 1,2,3,\dots,S$ where S is the total number of states. Then, the TN availability, is a function of the state probabilities as follows:

Equation (20): State-probability for availability of a transportation network

$$TN_A(t) = \sum_{x=1}^{S} A_x P_x(t)$$

Here, A_x is the availability of the x-th state. Thus, the transition probability matrix to incorporate the effect of the environment, network state, and network utilisation on the transition probabilities is as follows:

Equation (21): Transition probability matrix

$$P(t) = \begin{bmatrix} p_{11}(t) & p_{12}(t) & \cdots & p_{1x'}(t) \\ p_{21}(t) & p_{22}(t) & \cdots & p_{2x'}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{x1}(t) & p_{x2}(t) & \cdots & p_{xx'}(t) \end{bmatrix}$$

Here, $p_{xx'}(t)$ represents the transition probability from state x to state x' at time t. The dimensions of this matrix should equal the number of states *(S x S)*, where *S* represents the total number of states possible with the dynamic alternative multigraph of the SC, see equation (17). The environment, network state, and network utilisation determine the transition probabilities. The probability can be set to 1.0 if the next specific state is known or assumed for simulation analysis. Contrary, these probabilities can also be *zero* if no way leads from one state to the other.

For example, the probability of transitioning from a 'fully operational' state (x) to a 'partially closed due to ice' state (x') could be calculated based on historical meteorological data for a given month. The probability $p_{xx'}(t)$ would be a function of the historical frequency of icing events in that time period *t*. Similarly, a transition to a 'congested' state could be determined by the numbers of IWT agents in the network rate exceeding a certain threshold. While this thesis uses deterministic state transitions for the case study in chapter 4 (i.e. probabilities are 1 or 0 based on historical events), this matrix provides the formal structure for a fully stochastic implementation.

3.2.2 Resilience strategies in supply chain decision-making

Each layer may be vulnerable to disruptions or adverse decisions of other layers and their stakeholders. Conversely, disruption in the infrastructure layer affects the TN configuration of SCDM, leading to increased costs due to the additional waiting time or rerouting time.[38] However, the criticality of disruptions' impact and consequence depends on whether the disrupted element/component is relevant to the other layer's input and whether resilience measures are in place. For instance, the IWT paths to a coal plant are still vulnerable to network disruptions in the transportation network layer. Still, large inventory stocks mean that in the SC layer, the path disruption is usually not critical until a certain threshold of the disruption duration, where shortage costs occur.

38 . . . — or no transportation at all, meaning no costs but SCDM and welfare will suffer as the economic activity falls away.

Resilience of value capacity per time throughput

A combined system dynamics optimisation approach is used to assess and test the resilience of waterway-dependent SCs, capturing interactions among system components. As depicted in equation (22) and illustrated in Figure 2-3, the SC triangle measures the SC performance and SC value by considering the costs to generate said performance. In this context, this thesis proposes a value function based on the reliability of value capacity per time throughput unit to model the resilience of waterway-dependent SCs. To capture the dynamic nature of resilience, the static SC value function, equation (9), must be extended. The following resilience value function transforms the SCR concept into a time-dependent integral. Equation (22) assesses the cumulative value generated over a planning horizon, explicitly weighting the performance in each time step by availability of the transportation network. This formulation directly links infrastructure state to the potential for value creation over time, allowing both a probabilistic and empirical quantification:

Equation (22): Availability-dependent supply chain value function for time and capacity

$$\mathrm{SCVal}_{\mathrm{SCR}}\big(\mathrm{t}, Cap(\mathrm{t})\big) = \int_0^{\mathrm{T}} \big[\mathrm{Earn}\big(\mathrm{t}, Cap(\mathrm{t})\big) - \mathrm{Cost}\big(\mathrm{t}, Cap(\mathrm{t})\big)\big] \cdot \mathrm{TN}_{\mathrm{A}}(\mathrm{t})\ \mathrm{dt}$$

Here depending on the SC output state,

- $SCVal_{SCR}\big(t, Cap(t)\big)$ represents the value of considering resilience and relevant capacity units Cap at time t;
- $Earn\big(t, Cap(t)\big)$-*Cost*$\big(t, Cap(t)\big)$ represents the net value generated by the volume of goods successfully transported and delivered in period t; and
- $TN_A(t)$ represents the availability of the network, see equation (5), where either infrastructure failures incur costs for resilience strategies (e.g. higher transportation costs for modal shift) or shortage costs and less earnings.

The multiplication by $\mathrm{TN}_{\mathrm{A}}(\mathrm{t})$ thus models the probabilistic expectation of this value, correctly scaling the potential earnings and associated costs by the likelihood that the transportation network is functional enough to permit the delivery. The integral is calculated over a specified time horizon $[0, T]$ to account for the temporal aspect of SCR. The values can be normalised according to a single capacity throughput per time to allow comparability for various SC scenarios. The objective is to maximise the $SCVal_{SCR}$ function, considering earnings and costs under the reliability constraints, by reaching the optimal target state $x^* :=$ *argmax* $\Big(SCVal_{SCR}\big(t, Cap(t)\big)\Big)$ by SCDM, particularly available resilience strategies.

Mission fulfilment under disruptions

The proposed unified metric, expressed in equation (22), operationalises the concept of resilience by quantifying the reliability of value generation over time. It represents the cumulative SC value, explicitly weighted by the probabilistic availability of the transportation network in each time period. Now, SCDM must effectively manage disruptions to minimise their negative impact on SC performance and maximise value under uncertainty. x denotes the state vector in the multi-state model achievable from the current state with SCDM. SCDM aims for the optimal state x^*, maximising SC value and SCR. This can be achieved by deploying resilience strategies that respond to disruptions and realised risk events, altering the system dynamics and SC optimisation. To check whether an SCR strategy is used, the equation (23) introduces a binary decision variable constraint:

Equation (23): Binary variable of decision-making between network nodes and its supply mode

$$\mathrm{w_{ijk}} \in 0{,}1$$

where 0 indicates that a particular strategy is not used. In contrast, 1 indicates that SCDM uses the strategy for origin-destination pairs (i, j) with supply mode k. These variables can be used to determine which resilience strategies are feasible for a given infrastructure failure scenario. Nonetheless, buffers reduce the recovery time (related to the resilience of SCM and RT maintainability). As SC vulnerability depends on transportation availability, consider, for example, if the excess daily inventory (above the safety stock) is five days, and the time-to-repair disruptions are eight days, the criticality of the SC impact is as severe as a three-day disruption without excess inventory. The set of decision variables in the equation (24) determines which resilience strategy R_{ijk} to implement when an infrastructure failure occurs to optimise SCVal compared to not deploying any strategy:

Equation (24): Resilience strategies to enhance supply chain value

$$\mathrm{R_{ijk}} \in \mathrm{R};\ \mathrm{C}\left(\mathrm{R_{ijk}}\right) > 0$$

$$\sum_{T} \mathrm{SCVal}\left(\mathrm{R_{ijk}}\right) \geq \sum_{T} \mathrm{SCVal}(\mathrm{x_d})$$

Where the sets of decision variables are:

- R_{ijk} describes the resilience strategy for the origin-destination-mode triplet (i, j, k), chosen from the set of available adaptation strategies R;
- $C\left(R_{ijk}\right)$ denotes that the resilience strategy's relative costs must be larger than zero;

- $SCVal(R_{ijk})$ determines that the resilience strategy must yield a better outcome compared to not adapting to the disrupted state x_d in the full planning period;

R_{ijk} represents a specific set of parameter changes within the model actively steered by SCDM—be it modal shift or procuring additional inventory. These resilience strategies add the following constraint to the SCDM model in equations (11)–(15) to ensure the adoption of resilience strategies leading to an equally good or better outcome with:

Equation (25): Constraints to enable resilience strategies for supply chains

$$\sum_{i=1}^{N}\sum_{\mathrm{j}=1}^{\mathrm{M}}\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{d_{ijk}} \cdot \mathrm{w_{ijk}} \leq \mathrm{W_t} + \mathrm{Dur_t}$$

$$\forall\, \mathrm{t} \in 1, \ldots, \mathrm{T_{ijk}};\ \mathrm{T_{ijk}} \geq 0$$

Here, d_{ijk} represents the required implementation time (e.g. in days) for the specific strategy R_{ijk} to ensure SC operations across all considered modes of transportation K between the network relations. R_{ijk} can only happen if there is sufficient warning time W_t about a network state change or the disruption duration Dur_t is long enough. T_{ijk} determines whether there is enough time to deploy R_{ijk}. Note that modes k and $\mathrm{k}+1$ could also represent same-mode carriers with distinct characteristics, such as lead times, capacities, and costs.

Control system representation of the multi-layer, multi-state model

The model allows SCDM to build and enhance resilience, as described in the equations (22)–(25). The proposed multi-layer, multi-state model dynamically adjusts the TN state *x* represented by the parameters of cost levels (for time and distance) and transportation capacities between origin–destination depending on infrastructure disruptions, thereby affecting the SC configuration with its parameters like routing policy and associated cost levels, inventory levels and so on. In response, SCDM can alter the SC configuration, transitioning to a different state by controlling inventory levels and routing policies. Incorporating feedback mechanisms on the disruptions enables plan adaption by applying resilience strategies R to maximise value for the current period until the maximum planning horizon.

The model operates as a closed-loop control system. Figure 3-1[39] illustrates how the environment at the time t affects the TN state x. SCDM of waterway-dependent SCs affects SCVal(x) in changing the SC configuration If the TN state changes from x to x', SCDM adapts the single-echelon model, accordingly, changing the SC configuration with SCR and leading to another value level. Lastly, the SC value, results in the welfare contribution in the industrial layer.

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39 The SCDM block acts as the controller, making decisions (the control variables) of ‘Resilience strategies’ based on feedback from the system's state. For example, monitoring the 'TN(x, t)' state provides feedback on infrastructure availability and transport costs. If costs exceed a threshold due to disruption resulting in TN(x’,t), the controller can issue a new resilience strategy R1 (e.g. enact modal shift), which alters the 'Supply chain configuration’ in the next period to (x’, t+1, R1)'. This new configuration, in turn, affects the 'SCVal(x’, t+1)', creating a feedback loop where decisions are continuously adjusted to optimise value in response to a changing environment.

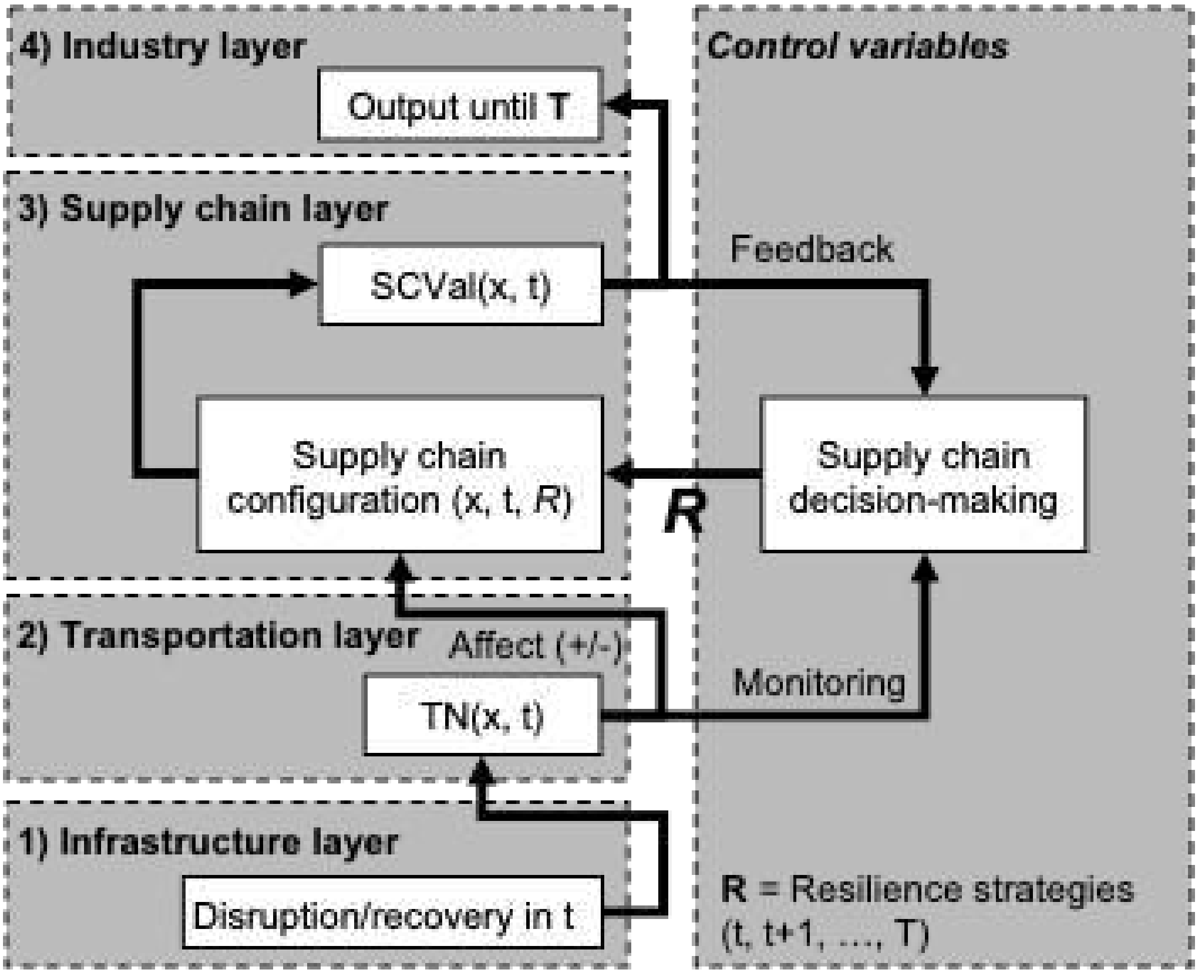

Figure 3-1: A control system view of the multi-layer, multi-state model

Figure 3-2 schematises the causal cascade at the core of this dissertation's logic. Following a disruption originating in the 1) infrastructure layer, the model quantifies how impacts propagate upwards: through altered transport costs and routes in the 2) transportation layer, to adapted SCDM and SC value calculations in the 3) SC layer and culminating in the aggregated economic consequences assessed in the 4) industry layer. This schema acts as the blueprint for the case study parametrisation that follows.

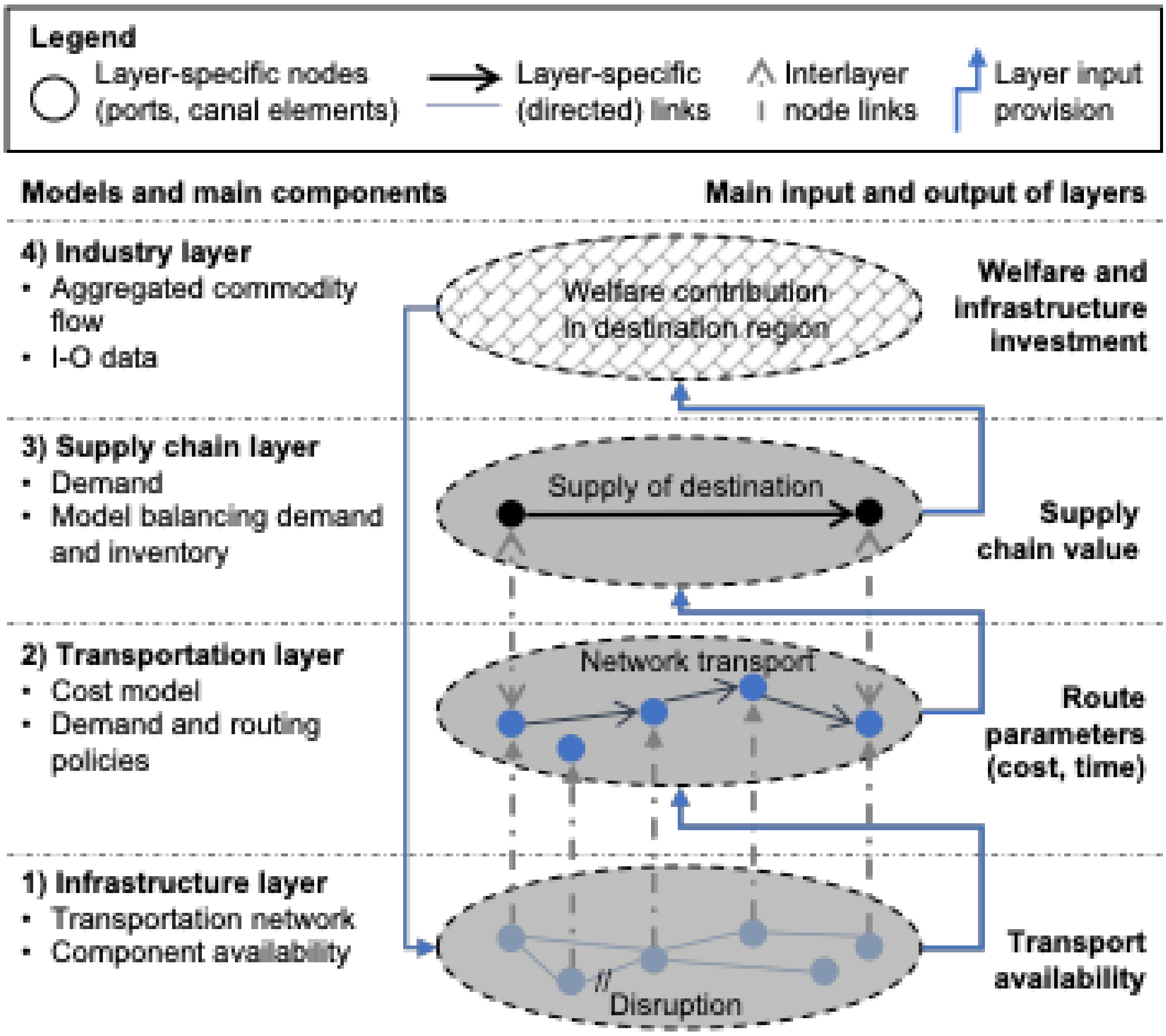

Figure 3-2: A schema of the four layers for modelling waterway-dependent supply chains

3.3 Case study parametrisation of multi-layers in multi-states

This section demonstrates the model's four layers for the WdtK, detailing historical infrastructure availability, additional transportation costs, and industrial shortage costs. As Germany's second busiest inland waterway system after the Rhine, the WdtK is a focal point for infrastructure debates and carries substantial freight volumes (see Witte 2019; WSV 2021). Nationally, IWT accounts for about 7% of freight movement while producing only 2.5% of CO_2e emissions per transported tonne (see DLR 2021). It connects 54 of Germany's 80 major cities—often through small-scale "Partikuliere" operators—and a few large shipping firms, especially those linked to the Netherlands via the Port of Rotterdam. IWT capacity remains robust (Seidenfus 1994; Planco 2007; BAW 2023), with federal authorities once targeting a rise to 12% modal share by 2030 (cf. BMVI 2019).

North Rhine-Westphalia (NRW) is Germany's most populous region and a prominent economic hub, encompassing the Ruhr Valley's metal, chemical, energy, construction, and breakbulk industries. The WdtK, built over 120 years ago during the Wilhelmine era for coal and steel transport, now features the world's largest inland container port in Duisburg. Development plans envision an urban riverfront regeneration (Nemo 2019) alongside cleaner energy transition with using IWT for 'green steel' production and hydrogen infrastructure. Figure 3-3 locates the WdtK as a gateway between different IWT regions like Rhine/Maas, Weser, and Elb. The canal system comprises the "Wesel-Datteln-Kanal" (WDK), "Rhein-Herne-Kanal" (RHK), "Datteln-Hamm-Kanal" (DHK), and DEK. The top three top freight ports are Duisburg, Marl, and Dortmund. Furthermore, the figure pictures the 16 ports and 17 locks— note that the Port of Mulheim was not considered for this case study as it is a river port. These nodes form the basis of the case study analysis.

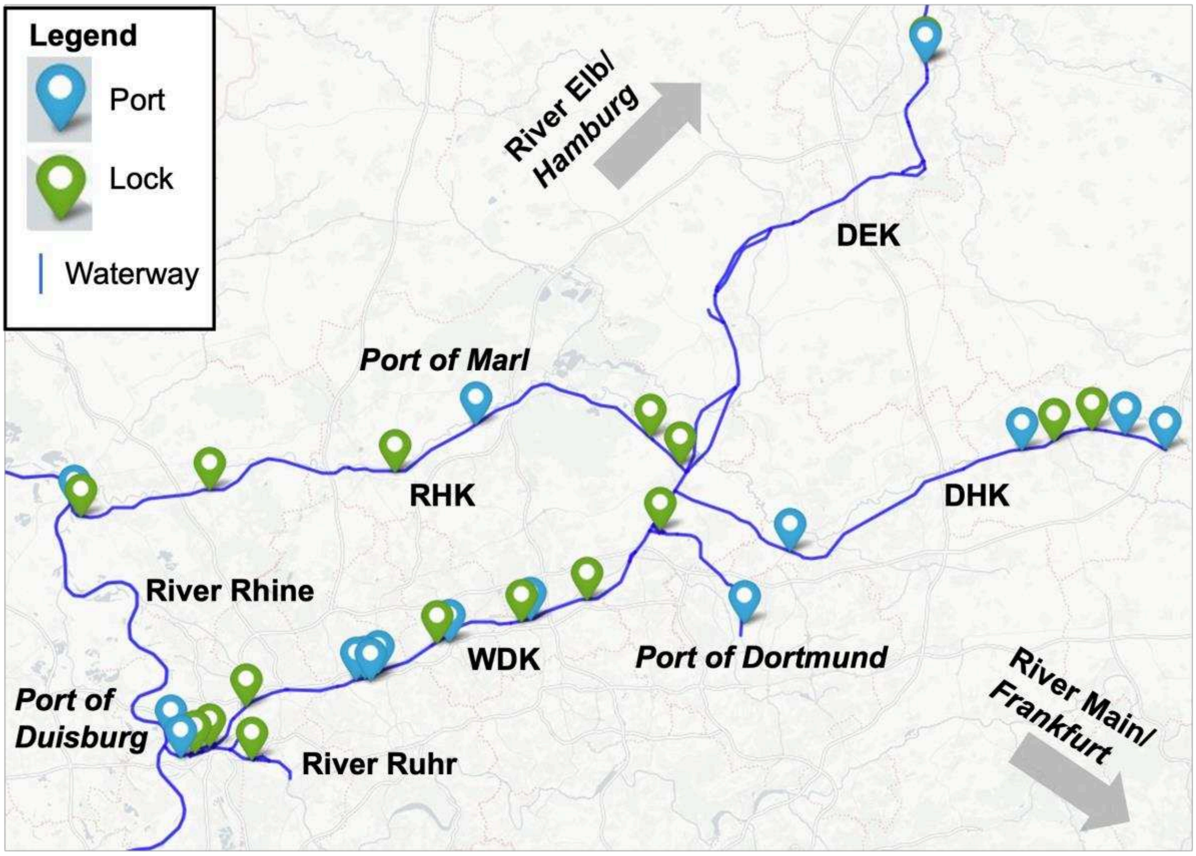

Figure 3-3: The West German canal system {author, ©Leaflet, ©OpenStreetMap, ©CartoDB}

3.3.1 Infrastructure layer

Geospatial data on the WdtK comes primarily from BWaStr (2023) with Euris (2023) and Unece (2023) adding logistics details like port locations and transportation restrictions. However, translating physical waterway data into a graph that retains navigable topology, path lengths, and other key attributes is non-trivial. Even dedicated algorithms for parsing navigable rivers may struggle to incorporate port and lock nodes accurately for cost/time estimations. Consequently, Figure 3-4 schemes the overcome challenge for the geospatial data of the WdtK (top left). While state-of-the-art algorithms like Momepy (Fleischmann 2019) can parse general network topology, they are not designed to integrate specific logistical nodes such as ports and locks with their unique attributes, nor can they easily correct topological errors observed in the raw data (e.g. the disconnected Rhine segment shown in Figure 3-4). Therefore, a custom graph algorithm was developed allowing for an arbitrary addition of additional infrastructure elements (see Gast 2024 get_infrastructure_network using Hagberg, Schult, and Swart 2008); in this case, the locks are in green, and the ports are in blue and visualised by The Matplotlib Development Team (2024), while bridges and other canal elements have been omitted in the current scope.

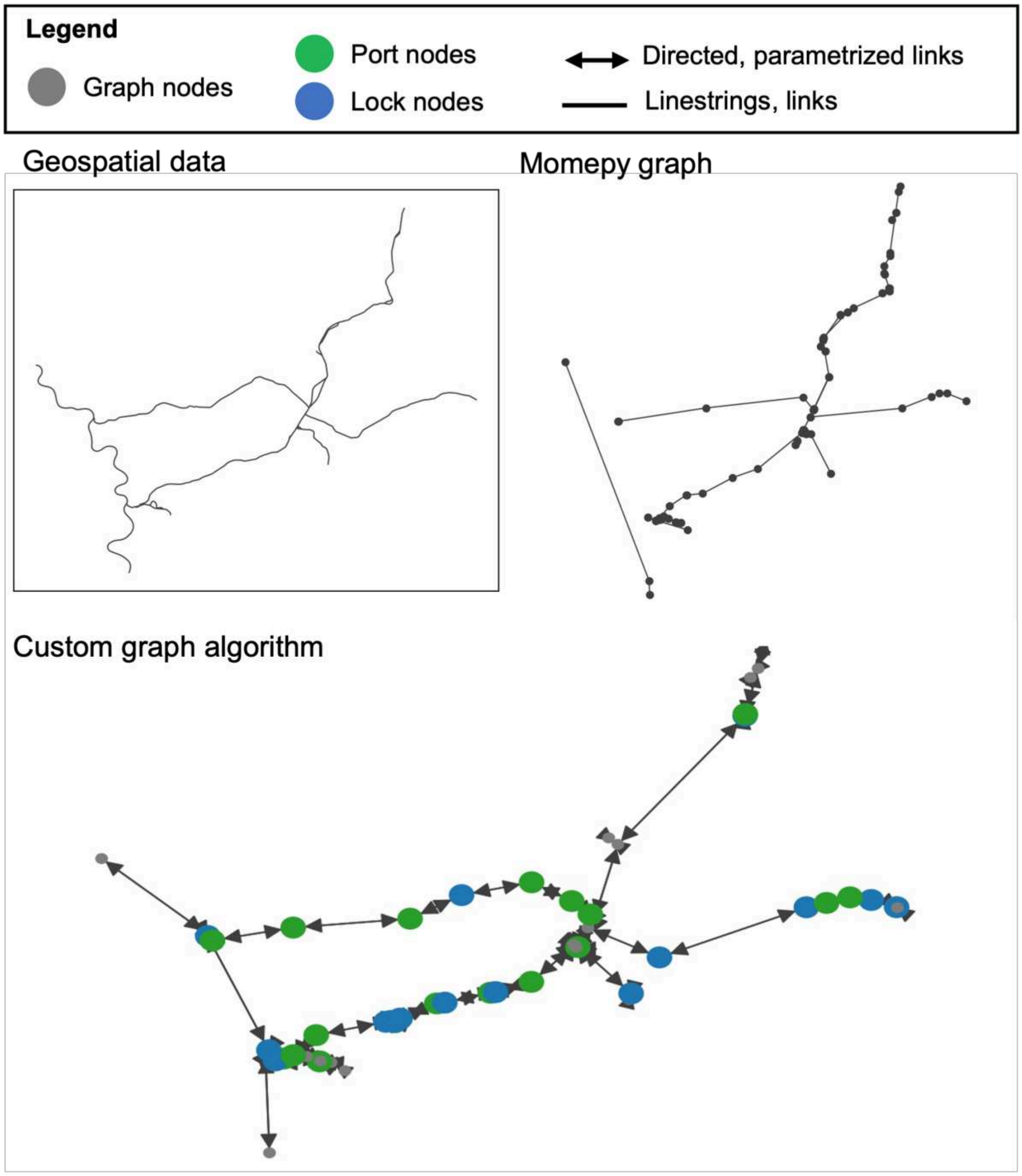

Figure 3-4: The graph creation from the geospatial IWT network with custom algorithm

The adapted graph now contains the proportional canal network and relevant infrastructure elements as nodes. After adding nodes of logistic interest (i.e. locks and ports), the graph can be aggregated only to include waterway intersections and the nodes of interest relevant for an availability assessment from data of notices to skippers (NtS). NtS data were obtained by scraping and processing (WSV 2023) to determine the historical availability of multi-states of the graph network (see Gast 2024 get_multistates).

Results of historical failures

Frequent or prolonged unavailability adversely impacts SC competitiveness by raising mitigation costs (Wehrle et al. 2023). Building on Gast and Wehrle (2019), this thesis compiles a new, more extensive dataset of around 1,900 full-closure records (March 2012–February 2023) for WdtK infrastructure elements. A zero-inflated Weibull distribution was selected to model the time-to-failure data to account for the significant number of infrastructure components that recorded zero failures during the observation period, which would otherwise bias a standard Weibull fit.

Table 3-1 presents aggregated availability metrics for the WdtK's locks and the canals' channels with a dedicated id, the number of observations n, Weibull distribution fit p-values, and MTBF. See Gast (2024, get_failure_data) for further details. The HRF of all infrastructure elements accepts a Weibull distribution indicated in the column "$p < 0.05$" with a "Yes", while the normal distribution is rejected in 50% of all cases, as indicated in the brackets with a “No”.

The MTBF column indicates that failures occur on average every few months, and the MTTR shows that average closures are relatively short. The percental availability of each infrastructure object is in the last column, meaning that 99% corresponds to 1% non-navigability per year on average. N.b. how parallel redundancies, like two lock chambers from a network perspective, increase availability, unlike the mere relationship between MTBF and MTTR. This finding provides empirical validation for the use of a network reliability model, as formulated in equation (5), which accounts for such structural redundancy.

Table 3-1: Calculation of reliability parameters for the WdtK

ID	Elements	n	$p < 0.05$	MTBF [d]	MTTR [d]	Availability
1	Waterway DEK	191	Yes (No)	25.54	2.39	0.957
2	Waterway DHK	53	Yes (No)	97.64	3.07	0.985
3	Waterway RHK	182	Yes (No)	24.70	0.78	0.985
4	Waterway WDK	75	Yes (No)	66.55	0.69	0.995
5	Lock Ahsen	53	Yes	88.90	14.08	0.932
6	Lock Datteln	59	Yes	82.76	3.24	0.981
7	Lock Dorsten	56	Yes	85.07	8.98	0.952
8	Lock D.-Meiderich	62	Yes	68.20	14.05	0.915
9	Lock Flaesheim	46	Yes	101.10	4.88	0.977
10	Lock Friedrichsfeld	110	Yes (No)	45.58	3.64	0.963
11	Lock Gelsenkirchen	43	Yes	120.59	5.50	0.978
12	Lock Hamm	24	Yes (No)	184.80	4.62	0.975
13	Lock Henrichenburg	47	Yes	107.47	3.27	0.970
14	Lock Herne-Ost	26	Yes	172.82	13.32	0.964
15	Lock Münster	13	Yes (No)	342	3.6	0.995
16	Lock Oberhausen	53	Yes (No)	120	4	0.984

The reliability parameters for each object parametrise the reliability structure function for a route through this component system. The network availability function, see equation (5), provides historical states for an arbitrary SC configuration using the waterways by considering the active closures at each point in time, whereas warning time indicates state transitioning. Figure 3-5 below illustrates the unavailability of an extract of the WdtK infrastructure elements in 2015, showing the duration of (partial) closures and the warning time period before closure, visualised with Plotly Technologies Inc. (2015). As evident, this was the year the Lock Friedrichsfeld had been undergoing prolonged repairs. The failure behaviour differed between objects, ranging from sporadic to regular restrictions. *In sum,* 105 multi-states of closures[40] were identified from the different failure combinations of the WdtK from the historical failure records.

40 Including a baseline case without any closure.

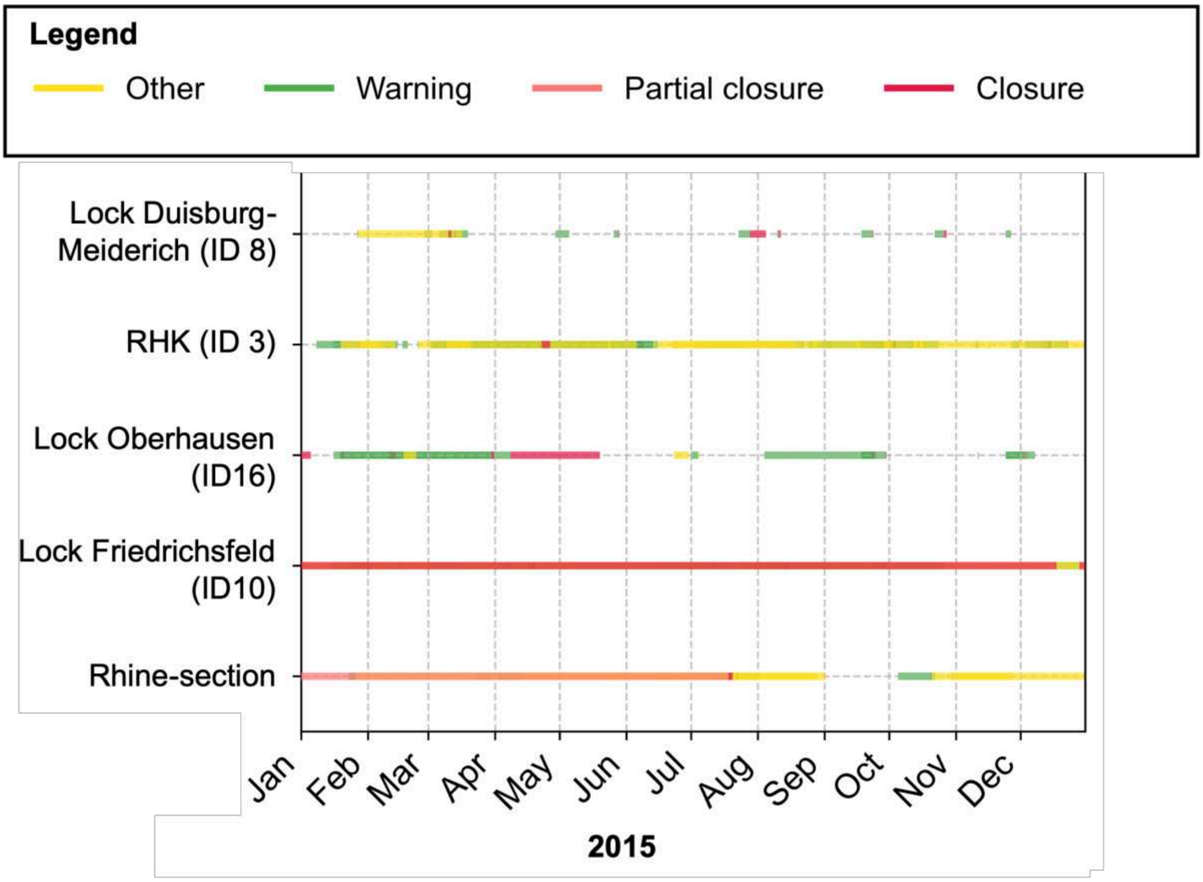

Figure 3-5: Extract of historical failure event schedules in 2015

3.3.2 Transportation network layer

This layer bridges the infrastructure and SC layers, emphasising how SCDM depends on waterway availability. By modelling the movement of goods, it *draws on data* about a commodity flow survey (CFS) from Travis.de (Travis and Peter Weinmann 2016), infrastructure from Euris (2023), NtS from WSV (2023) and monthly volumes from Statistisches Bundesamt (2022). See Gast (2024 tpp_data) for the incorporation of the cost factors according to the BVWP.

Insights of applying commodity flow analysis

The model evaluates how infrastructure unavailability affects a region by mapping port accessibility and origin–destination (O–D) flows. Travis (2016) provides 2010 German IWT flows as aggregated WdtK inflows and outflows, shown in Figure 3-6. The gray sub-flows indicate individual contributions, e.g. from the DEK. Further details on data parsing and aggregation appear in Gast (2024, get_cfs_data).[41] As seen, coal is primarily handled or transits while chemicals and metals also exhibit export behaviour. Containers are included in "Other" and are primarily exported emptily (see Statistisches Bundesamt 2022).

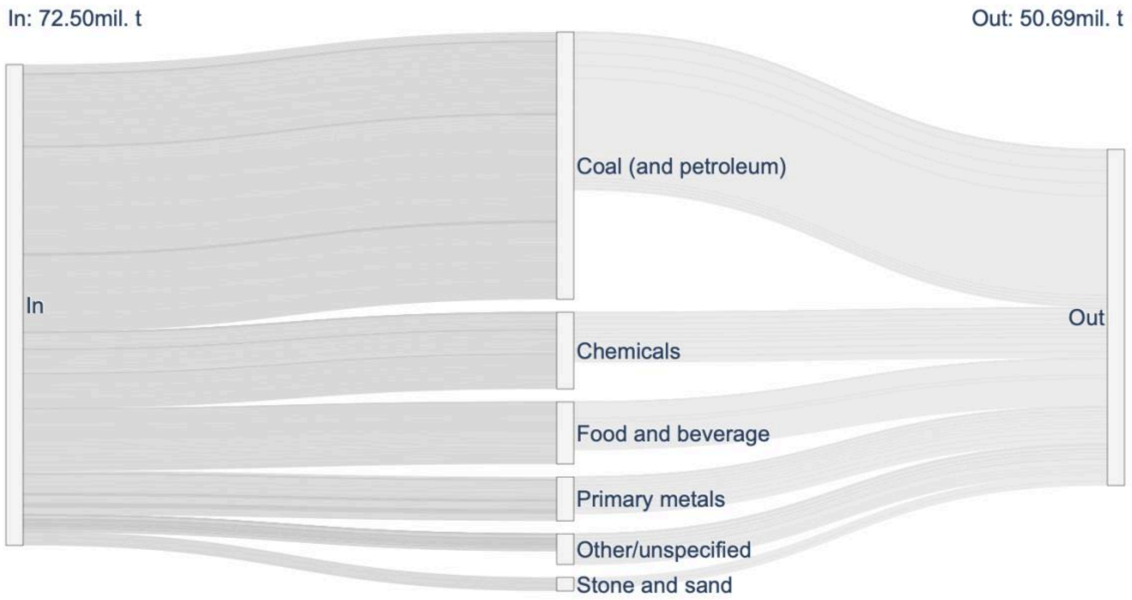

Figure 3-6: The aggregated commodity flow in and out of the West German canal system by waterways in 2010[42]

There is no CFS to identify which vehicles transport specific goods between origin-destination pairs; there are only monthly statistics of IWT cargo loading and unloading in German regions. However, the transported goods can be mapped according to the NST-2007 transport classification used by the UN and EU (cf. Pant, Barker, and Landers 2015), as demonstrated in Table 3-2, determining goods value and required vessel type for transportation. The commodity flows were aggregated into broader industry categories relevant to the WdtK to link it with the NST2007 goods detailed in Gast (2024), get_cfs_data. Furthermore, monthly statistics on port demand are available, see Statistisches Bundesamt (2022). Still, a historical routing estimate is required to determine disruption impacts on TN, as elaborated in the next section.

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41 As flows overlap, they can be counted muliple times. Aggregating the in and out commodity flows at port nodes results in the 24.52MT used in Table 3-2. At the time of writing, a refresh of this data for 2019 and beyond is conducted but not yet published.

42 Note that the commodity flows of Travis (2016) data are aggregated into the top five categories by volume; all other categories are grouped into 'Other/unspecified'.

Table 3-2: Mapping goods classifications to transportation equipment[43, 44]

NST2007 goods	WdtK volume [MT]	Value [€/t]	Vessel type (VT)
Primary metals	0.11	570	Dry bulk
Machinery	0.08	7190	Dry bulk
Fabricated metals	1.62	576	Dry bulk
Containers	0.49	-	Dry bulk
Stone and sand	2.06	35	Dry bulk
Waste	1.94	11	Dry bulk
Coal (and petroleum)	5.44	175	Dry bulk
Food and beverage	4.68	252	Dry bulk (grains)
Chemicals	8.1	430	Liquid tanker

Insights of applying the travelling purchase problem approach

Port-handling data enables a TPP analysis that weighs all possible transportation options for a given infrastructure network (see Binsfeld et al. 2024). The TPP derives origin–destination flows and costs of IWT based on monthly port demand data. The TPP considers time, cost, demand constraints, and vehicle capacity as well as modal shifts (at different cost levels) and allows flexible routing of partial loads (i.e. optimal tramp shipping).

Running the TPP for different disrupted network states produce lower-bound estimates of disruption costs. Because actual costs in real-world settings are likely higher, as market frictions such as limited carrier competition can amplify price spikes. This assumption is a deliberate methodological choice. By modelling a 'perfectly outsourced market', the TPP establishes a robust, best-case cost baseline. Consequently, the disruption costs calculated by the model represent a *conservative*, lower-bound estimate of the true economic impact of disruptions.

For the given 105 infrastructure multistates, the transportation cost to fulfil general demand ranges between 26,500 and 39,100 EUR. Figure 3-7 illustrates these identified states in order of first occurrence. Each point represents the total network transport cost under a unique infrastructure state for chemical or general transport which have different demand patterns at the WdtK's ports. As conceptualised in the multi-state model (cf. Figure 2-4), the system

43 . . . — aggregated data for DEK, DHK, WDK, RHK calculated from Travis (2016).

44 See Robinson et al. (2014).

transitions between these cost states are based on historical failure events. The figure reveals that while most states cluster around a baseline cost, some states drive system-wide cost increases to over 54%. This highlights the importance of identifying which failure combinations pose the greatest systemic risk, thereby extending established disruption criteria focusing on individual components (see section 2.1.2 and 2.2.1).

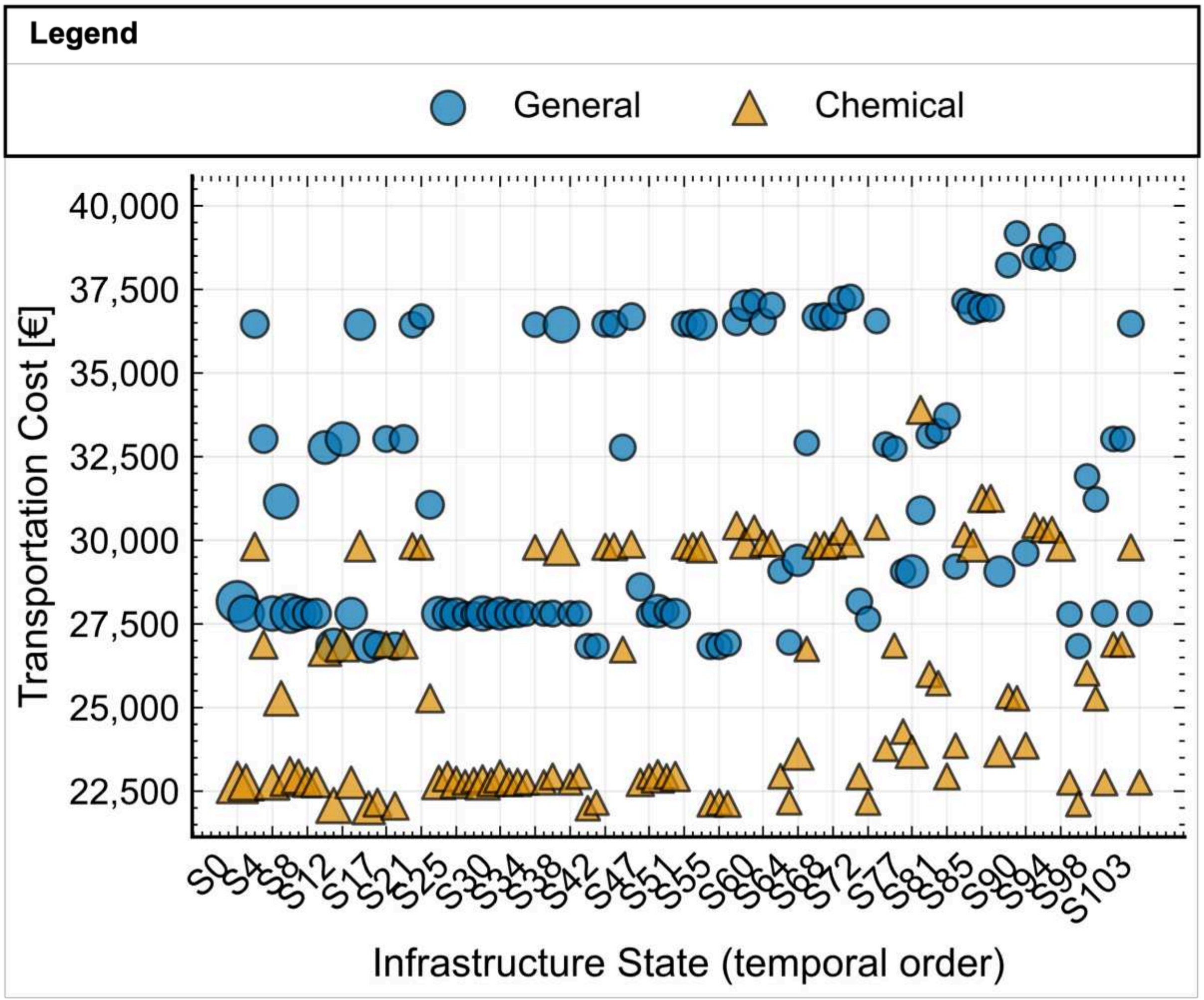

Figure 3-7: The 105 infrastructure multi-states linked transportation cost for fulfilling demand

Using the TPP (Gast 2024, analyse_transportation_in_multistates), Figure 3-8 below displays the relative cost increase for the analysed period based on the multi-states provided by the NtS for general cargo and chemicals (liquid transportation), which have varying demands at the ports and different transportation cost parameters. Also, the states affect destination ports due to rerouting costs differently.

The TPP optimisation model was solved using Gurobi. To ensure computational tractability across over 100 network states, a time limit of 300 seconds and a MIP Gap of 5% were set representing a deliberate trade-off. A barrier method (Method=2) was selected for its numerical stability with this problem structure.

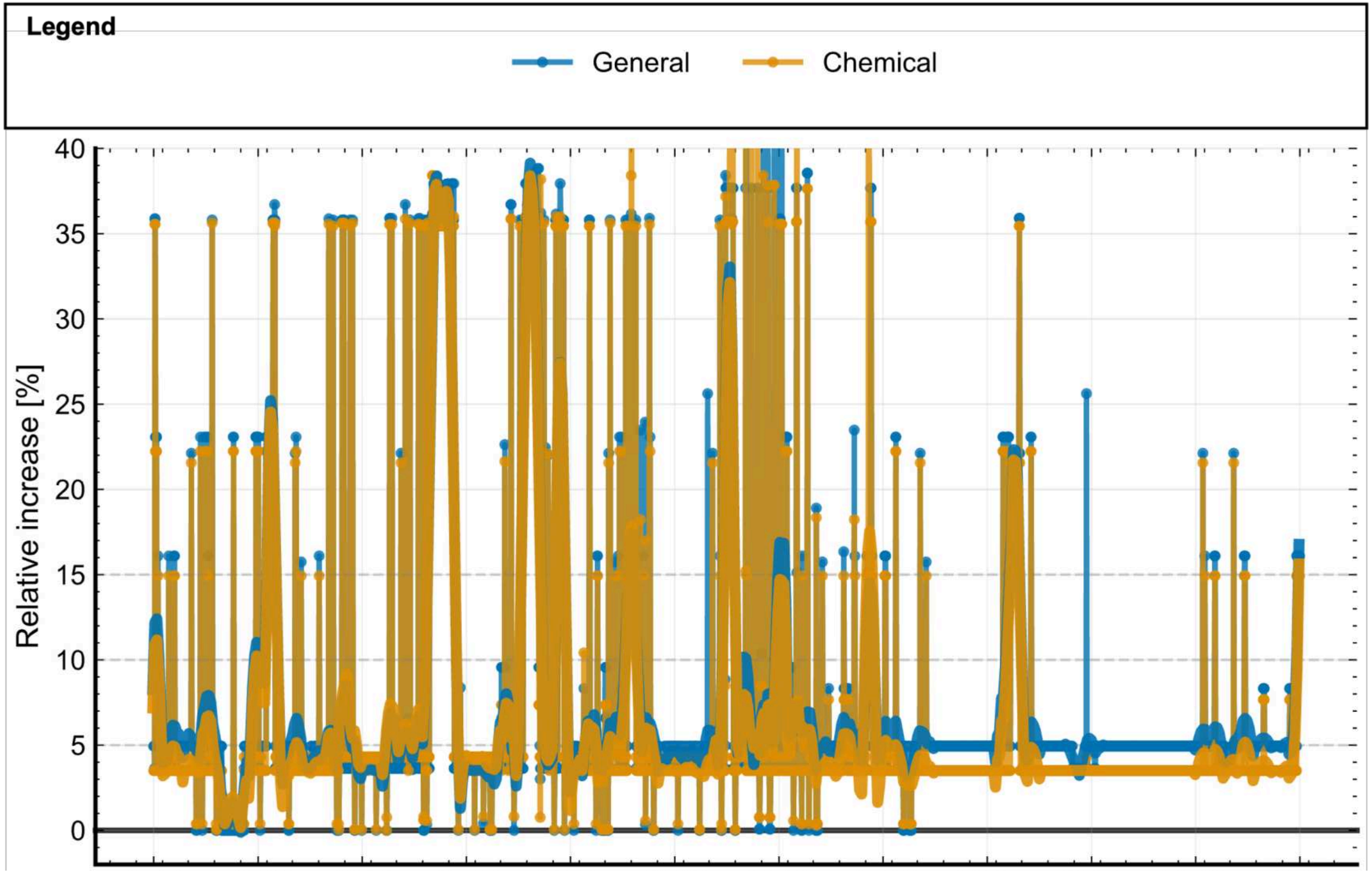

Figure 3-8: Cost increases due to historical failure states in the WdtK

3.3.3 Supply chain layer

Minor service-level drops in these hubs can magnify competitiveness risks across the region. The SC layer exhibits various interdependencies with other layers comprising a simple SC model that incorporates procurement, production, transportation, and inventory as defined in equation (11)–(15). The analysed theoretical SC is stylised to focus on a single, representative product whose flow is subject to waterway availability across multiple periods. The SC pursues mission fulfilment, optimising the trade-off between multi-objectives. The procurement and inventory model that SCDM uses to fulfil missions stems from the economic order quantity principle to satisfy the demand with consideration of industrial inventory holding costs and transportation costs.

Primarily, the enactment of resilience strategies through SCDM occurs in this layer. Maintaining additional inventory can be another resilience strategy, providing a buffer against disruptions in waterway transportation. However, inventory holding costs and capacity constraints limit buffering strategies. Waterway-dependent SCs benefit from diversifying their transportation routes to avoid reliance on a single waterway achievable by a modal shift in response to infrastructure disruptions. This layer demonstrates the direct integration of parameters from the infrastructure layer into SCDM. Analysis of the NtS failure data in the infrastructure layer reveals that approximately one-third of disruptions have a warning time exceeding 14 days (see Gast 2024, get_failure_data). For further differentiation of warning time and failure modes, refer to Gast et al. (2020). Chapter 4 will provide further in-depth analysis and elaboration on SC scenarios in the SC layer considering further SC configurations like inventory and available resilience strategies.

Cases definition of supply chain performance and supply chain value

The RT approach provided the metrics to determine costs and delays due to the TN state and a shortage cost estimate. The cases utilised the unit ‘value capacity throughput per time’, defined as earnings minus other running costs if manufactured minus state-dependent transportation and shortage costs, as defined in the equation (22). SCDM aims to maximise value by transitioning to states through resilience strategies to respond to the state of the infrastructure (equations 17–21). SC performance was defined and modelled assuming a 5% profit margin on turnover and transportation costs equivalent to 5% of turnover. This represents a typical business scenario where operational disruptions can rapidly erode profitability.

The direct impact of infrastructure state on SC viability becomes visible when comparing the failure timeline (Figure 3-5) with a generic SC performance (Figure 3-9). While the prolonged closure of the Friedrichsfeld lock in mid-2015 elevates transport costs around 4% (Figure 3-

8), its impact on SC performance (Figure 3-9) appears relatively contained to the same level. Because traffic can be more easily re-routed via the River Ruhr or the northern RHK. In contrast, the shorter, more sporadic closures affecting the RHK in March/April and October cause far more severe performance drops. Furthermore, SC performance is not a simple function of disruption duration but is highly sensitive to the location of the failure and the availability of alternative routes. For instance, the unavailability of the waterway between the ports Duisburg–Dortmund, former Hansa towns, results in a 270% increase in transportation costs if everything needs to be transported by truck, which happened in 2019 and 2021 as the lock Henrichenburg was undergoing six weeks of maintenance. Such situation would become economically unfeasible for low-value, high-volume goods in the long run. Ultimately, the specific SC configuration determines viability as elaborated in chapter 4. For the complete data, refer to Gast 2024, analyse_transportation_in_multistates.

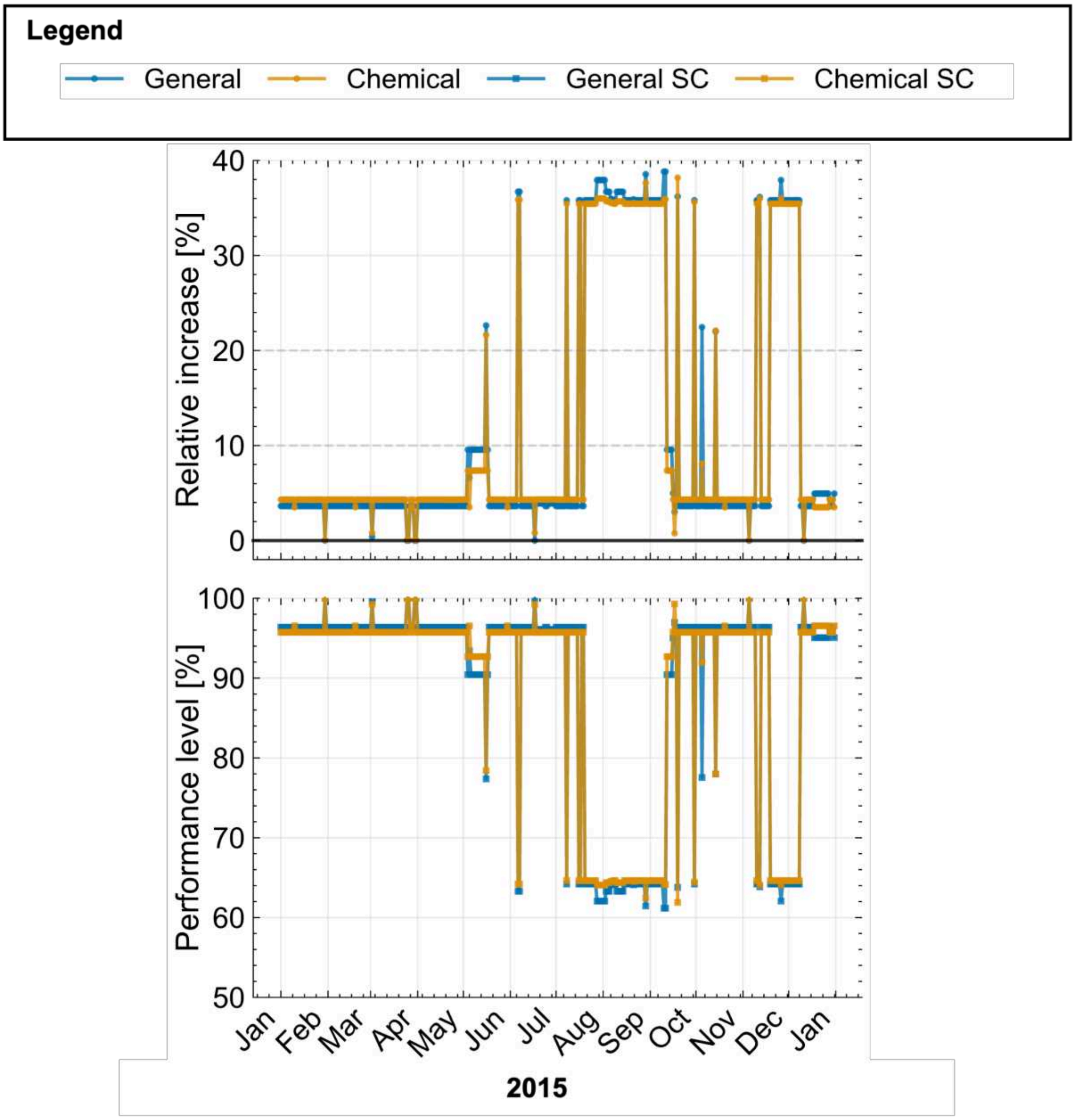

Figure 3-9: Supply chain performance impact of historical availability in the West German canal system in 2015

3.3.4 Industry layer

By mapping disruptions to specific port nodes in the WdtK, this thesis connects SC reliability to economic geography, wherein clusters of heavy industry rely heavily on canal infrastructure. This layer consolidates economic activities linked to the WdtK, encompassing import/export volumes, industrial sectors, and welfare. Drawing on national/regional data (cf. Pant, Barker, and Landers 2015; OECD 2018), the layer represents two core components:

1. public authorities who manage the waterway infrastructure and aim to preserve navigability (BAW 2023), security, and broader socio-economic benefits (BMVI 2019);[45] and
2. industrial sectors with companies reliant on IWT for raw materials and distribution, directly or indirectly affected by closures and disruptions.

Infrastructure failures, leading to higher SC costs due to increased transportation costs, result in a market efficiency loss (i.e. welfare loss). These higher losses likely lead to an adaptation of production levels, resulting in an unsatisfied demand for SCs downstream. Therefore, according to Pant, Barker, and Landers (2015), an industry input-output value model was utilised to capture the unsatisfied demand costs (i.e. shortage costs in terms of lost import/export values in transportation and production). This approach allowed for a comprehensive assessment of the financial welfare loss implications of disruptions on the WdtK and its stakeholders. Table 3-3 provides the shortage cost estimates per relevant industry in the WdtK based on disrupted import/export volumes. The calculations use the input-output table for NRW and Germany and the technical coefficients matrix provided by Többen and Kronenberg (2011). As the production vector, the origin-destination volume flows of transported goods (see Travis 2016) identify the multi-regional relations. The approach mapped all product categories and utilised commodity flow data for the IWT ports (cf. Wehrle, Wiens, and Schultmann 2022).

Multiplying the affected goods transported by IWT and their volume with the inoperability vector calculates the direct loss vector as seen in equation (16). See Gast (2024, calculate_io) for the derivation of the economic inoperability, providing an estimate of the total daily economic impact, which is composed of direct losses within affected industries, indirect losses propagated through the supply network, and induced losses resulting from reduced economic activity (including taxes and social security contributions) for the West-German canal system. Table 3-3 contains the results. Note that no reasonable value estimate can be provided for containers in Table 3-3 in available statistics[46] —hence, the results omit their shortage costs.

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45 The objectives are mandated by respective laws like the "BWastrG", but I am not a jurist.

46 Mostly, IWT handles empty containers but recently, a trend of containerization of bulk good emerged (see Alias et al. 2023).

Table 3-3: Shortage cost estimates per industry in NRW due to waterway unavailability

NST2007 Goods	Volume [MT]	Value [€/t]	Inoperability factor	Daily loss [million EUR]		
				Direct	Indirect	Value
Primary metals	0.11	456	0.293	0.039	0.016	0.050
Machinery	0.08	5752	0.293	0.396	0.166	0.104
Fabricated metals	1.62	460	0.293	0.619	0.260	0.163
Containers	0.49	n/a	n/a	n/a	n/a	n/a
Stone and sand	2.06	28	0.017	0.002	0.001	0.003
Waste	1.94	8.8	0.047	0.002	0.001	0.001
Coal	5.44	140	0.050	0.612	0.257	0.085
Food/beverage	4.68	201	0.073	0.339	0.142	0.114
Chemicals	8.10	344	0.293	2.301	0.970	0.608
Total	24.52	-	-	**4.324**	**1.816**	**1.083**

This I-O analysis quantifies the maximum potential welfare loss under a theoretical, complete shutdown of the IWT system that would lead to an adverse economic effect at the end-point regions. Based on the 2010 flow and I-O data, the complete disruption of the IWT system would daily result in 4.32 million EUR in direct loss for NRW, 1.82 million EUR in indirect loss in the trade regions (mainly Amsterdam, Antwerp, Rotterdam, and Hamburg and to some extent Bremen via the "Mittellandkanal" and Weser), and 1.08 million EUR in value-added loss for welfare if not mitigated. The sum of SC shortage costs equals the industrial welfare loss.

Generally, from a public perspective, shortage costs can have broader economic and societal implications. For example, supply shortages in industries can lead to price hikes, the reduced availability of essential goods and services, and tax losses. In extreme cases, significant SC disruptions can result in economic instability, job losses, and eroded public trust in the affected industries. Therefore, both business and infrastructure planners should consider the potential societal impacts of SC disruptions and strive to establish a reliable and resilient TN to minimise shortage costs and their consequences.

However, as the reliability analysis of the infrastructure layer demonstrates, such a complete failure is a low-probability event. The true analytical power of the multi-layer model lies in its ability to connect these layers: by weighting the potential economic impacts from the industry layer with the state probabilities derived from the infrastructure layer, the model can generate a more realistic, probability-weighted expectation of welfare loss, moving beyond a simplistic worst-case scenario.

At best, welfare loss equals the added carrier transportation and SC inventory costs due to effective SCDM and SCR. Yet, while simply choosing extra inventory or rerouting may effectively mitigate a one-day disruption, several days of shortage may result in a cascading effect and unfeasibility of business at this location. Furthermore, disruptions in the canal system can potentially cause a shortage of available transportation capacity in transit, increasing transportation rates further, e.g. by imposing low-tide surcharges to compensate for the reduced loading capacity. While carriers may not experience losses in the transportation network layer due to these surcharges, SCs and industries depending on the waterway system are adversely affected by the increased transportation costs.

The layered model enables SCDM to test various IWT resilience strategies drawn from both literature and practice. By distinguishing infrastructure disruptions (their source, intensity, and duration) from the resulting effects on transportation and SCDM, it covers the three disruption perspectives (section 2.1.2). Consequently, each stakeholder group (i.e. infrastructure operators, carriers, SC decision-makers, and the public sector) can evaluate tailored responses to optimise SC value or welfare.

4 Case Study: West German Canal System

This chapter demonstrates and validates the model's capabilities through three case analyses; each designed to isolate and quantify a distinct dimension of waterway-dependent resilience. The common denominator of the case studies is the demonstration of how an SC is affected by the multi-state infrastructure and transportation layers and how SCDM maximises value despite disruptions by deploying mitigation strategies. The methodology for the cases 1–3 was built on the parametrisation in section 3.3; refer to Gast (2024, run_case_analyses) for the configurations:

- case 1 examines the impact of historical failures to quantify the direct economic value of the core resilience strategy ‘inventory’;
- case 2 explores the role of warning time, demonstrating how advance information enables proactive modal shifts; and
- case 3 investigates the non-linear consequences of network load and queueing, revealing how second-order effects could become the primary determinant of SC survival

To ensure comparability across the case studies, a standard performance metric was established utilising the SC performance parametrisation of 3.3.3. SC value in the performance integral in the resilience triangle depicted the sum of the difference between margin and transportation costs in the shortest period, with higher values indicating better relative performance in the overall planning horizon (i.e. simulation) for 50 time periods, resulting in a maximum achievable SC value of *250 units* standardised across experiments (calculated as a 5% profit margin over 50 time periods: 50 × 5 = 250). The relative performance level begins at 100% and gets modified by changing availability states. Also, the cases were configured with distinct shortage cost parameters to test the model's sensitivity and demonstrate how a SC’s resilience interacts with infrastructure availability.

4.1 Case 1: impact of historical failures

Case 1 demonstrated the established link between infrastructure availability, SC performance, and resilience capabilities during times of failure. The Port of Dortmund and its accessibility through the one-chamber lock, Henrichenburg, is analytically significant due to its graph-terminal position in the WdtK. Unfortunately, the ship lift was decommissioned in 2007, leaving the lock as the sole access point for the port. Additionally, scheduled maintenance of the lock chambers rendered the port inaccessible for six weeks in 2019 and 2020 (WSV 2023). Despite intermodal rail access, the closure necessitated the use of approximately 2,000 trucks per week through Dortmund during the maintenance periods (DVZ 2019). This specific case therefore provides an ideal empirical setting to test the model's ability to quantify the relationship between a well-defined infrastructure vulnerability and the resulting SC performance and economic viability.

4.1.1 Results of availability assessment

Three SC scenarios were developed, each with a different sensitivity to shortage costs (i.e. penalty rate), to test the model. Figure 4-1 demonstrates the direct link between infrastructure availability and SC viability. While SC A (95% availability) maintains high performance, reduced availability (60%) causes the collapse of the unbuffered SC C (value: -10) due to negative profit margin at their penalty rate of 8%. Crucially, SC B remains economically viable under the same 60% availability scenario (value: 90) due to a penalty rate of only 3% during disruptions.

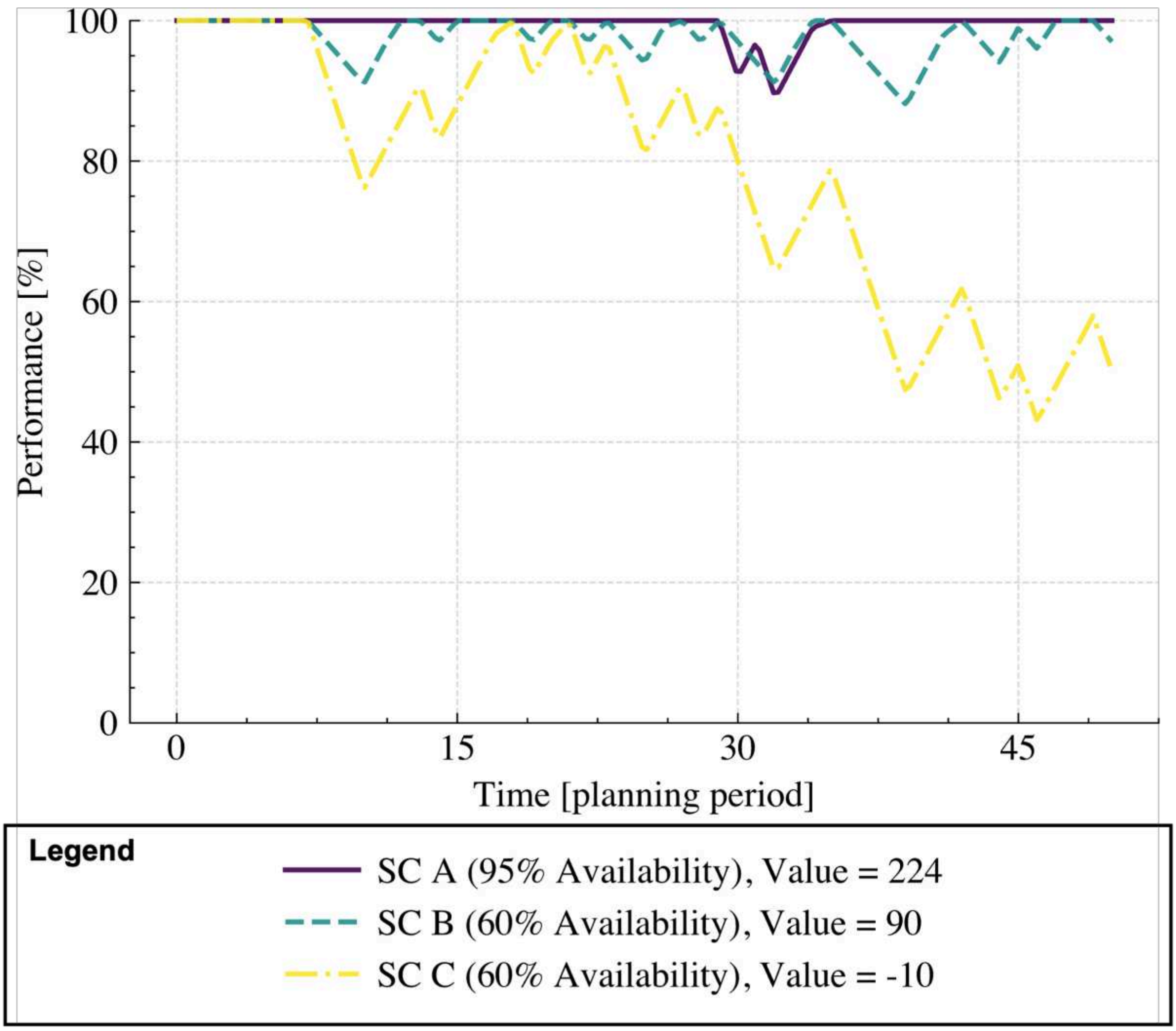

Figure 4-1: The effects of various levels of infrastructure availability on supply chain performance and supply chain resilience regarding availability

Energy security of a coal plant

Therefore, with high TN availability levels, SC B value would be higher if inventory holding costs diminish SC performance margin. However, an availability level of 60% would result in SC B's collapse equivalent to SC C above. Figure 4-2 presents the case of a coal plant SC A with a one-period inventory range and SC B with no spare inventory capacity, isolating the SCR impact of inventory strategies and transportation. With high infrastructure availability (95%), the cost of holding inventory of 1 value unit per period makes SC A about 22 value units less profitable than the leaner SC B (without inventory). However, under a disruption scenario (60% availability), SC A maintains its viability, while SC B collapses. This illustrates the classic risk management trade-off: the trade-off between resilience and excess in a spectrum ranging from manageable cost increases to collapse, all directly related to infrastructure availability.

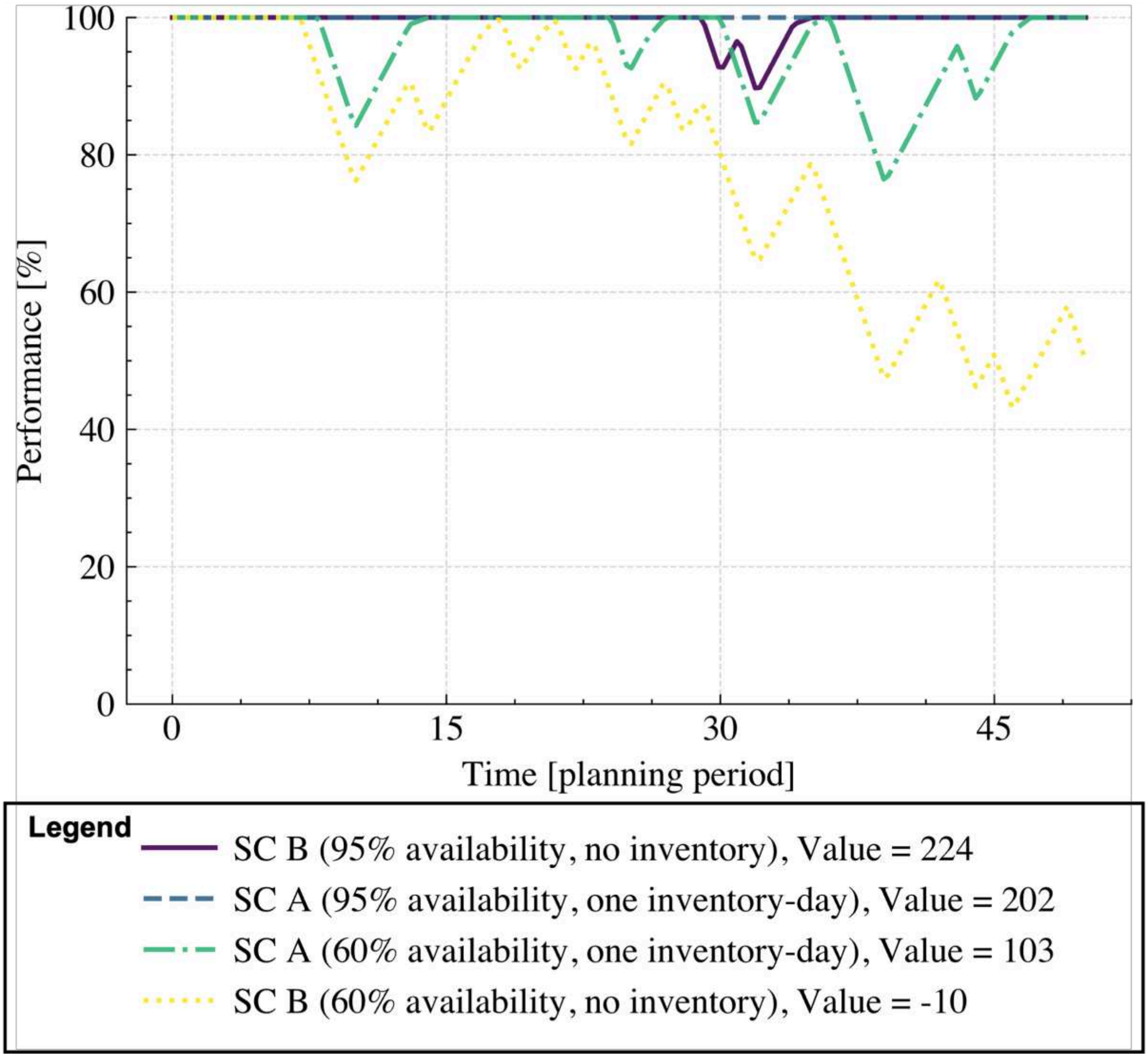

Figure 4-2: The resilience of high inventory capacities in comparison to no inventory range

Impact between low and high inventory ranges on resilience

During the peak of the German energy crisis, gas prices suddenly slumped due to arriving LNG ships needing to unload to redo their voyage and the German gas storage was full, requiring wholesale prices to make room.[47] The storage of gas and liquids is exceptionally costly due to high material costs for low capacity. Moreover, there is a product loss due to dispersion (Gast 2016). The educt feedstock tanks are then used for products, meaning that resupply can only happen after export, which might also be with vessels. Consequently, storage tanks are usually designed to hold only a few days' worth of inventory.

Therefore, assuming only three days of inventory range, the effect of long-term infrastructure failure becomes more severe. Figure 4-3 demonstrates the case of how industry-specific characteristics fundamentally alter resilience profiles. The figure demonstrates that a liquid SC with low inventory capacity is more vulnerable to TN disruptions at various availability levels than a coal SC with high inventory ranges. While inventory allows the SC Coal to maintain viability even at 30% infrastructure availability, the SC Liquid, with its inherently lower and more costly storage capacity, collapses under the same conditions.

47 Indeed, handling non-solid goods is challenging and has some fascinating considerations. For example, optimal routing and replenishing may not involve filling the tank to the max (see Q. Zhang and Grossmann 2016).

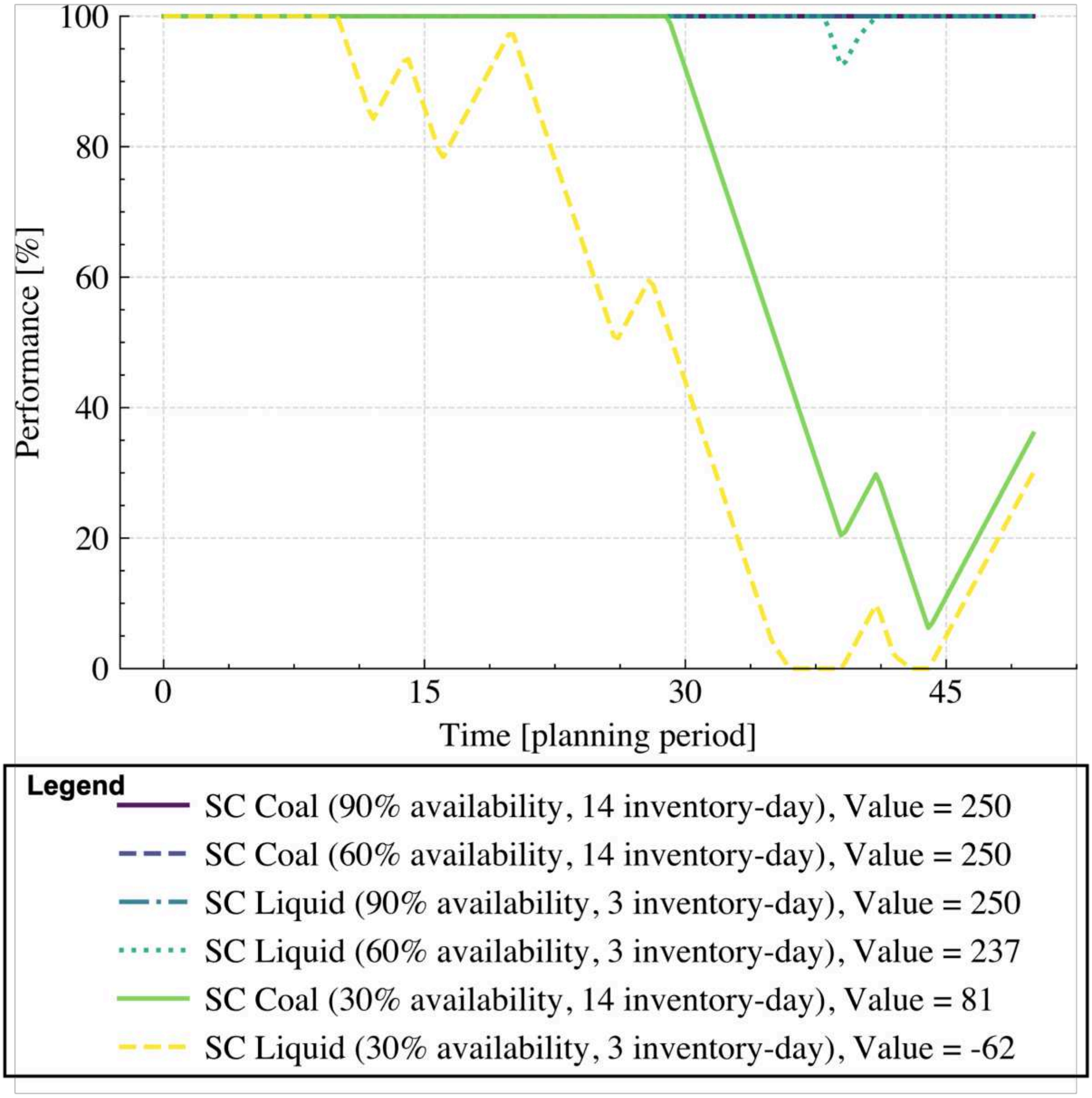

Figure 4-3: Differences in the resilience of a liquid supply chain with low inventory capacity compared to a coal supply chain with high inventory capacity

4.1.2 Interpretation and conclusion

The case showed the interplay between availability, performance and value generation, and inventory. The case also compared the SCs for coal and liquid products showing the distinguished behaviour between dry bulk and liquid bulk storage. Managing liquids required considering the trade-off between stocking inventory to fulfil demand and incurring high holding and procurement costs—including energy feedstock—since their storage capacities were severely limited (Gast et al. 2020; see Gast, Gross, and Binsfeld 2022). Ultimately, this case demonstrates that the viability threshold, the point at which an SC collapses, is not a fixed line but an emergent property of the interaction between infrastructure state and the SC's own resilience capabilities.

A strategy for enhancing the energy security of a coal plant could involve utilising load-sharing with suppliers and providing a steady supply with a scheduled line that could accommodate accumulated delays. The model assumes static earning, yet energy becomes more expensive in times of energy shortage. Hence, the market provides also justification for SC survival.

4.2 Case 2: impact of warning time

Platforms like Euris and Elwis,[48] run by public entities, provide information on the current state of IWT networks while projecting future network conditions based on scheduled restrictions (e.g. planned maintenance and rowing events) and forecasted restrictions (e.g. estimated duration of ongoing repairs and 30-day water level forecasts). These data provide an empirical basis for real-life state transitioning and monitoring and support SCDM in choosing appropriate mitigation strategies by adjusting transportation planning. A modal shift to rail is justifiable when either the notification time or the failure duration is expected to exceed two weeks even due to the failure mode requiring a lengthy repair time, for example, for severe accidents (PREVIEW 2019b; 2019a). This case tests the hypothesis that quantifiable economic value can be derived from proactive warning time, which enables less costly resilience strategies than purely reactive responses.

4.2.1 Results of risk communication

Figure 4-4 presents the performance gains achieved by different SC scenarios using a modal shift to rail transportation. The historically usable rail capacity, expressed as a percentage of the demand, is shown over ten years for the three SC scenarios: A, B, and C. SC C did not use rail transportation as an alternative mode, so its generated value remained unchanged at 198 due to TN unavailability. SC B utilised rail transportation to cover 50% of its demand. At the same time, SC A relied on rail transportation for 100% when capacity was available, resulting in a value of 219. If rail capacity was exceeded, trucks were used as an alternative mode instead.

48 See www.euris.eu or www.elwis.de.

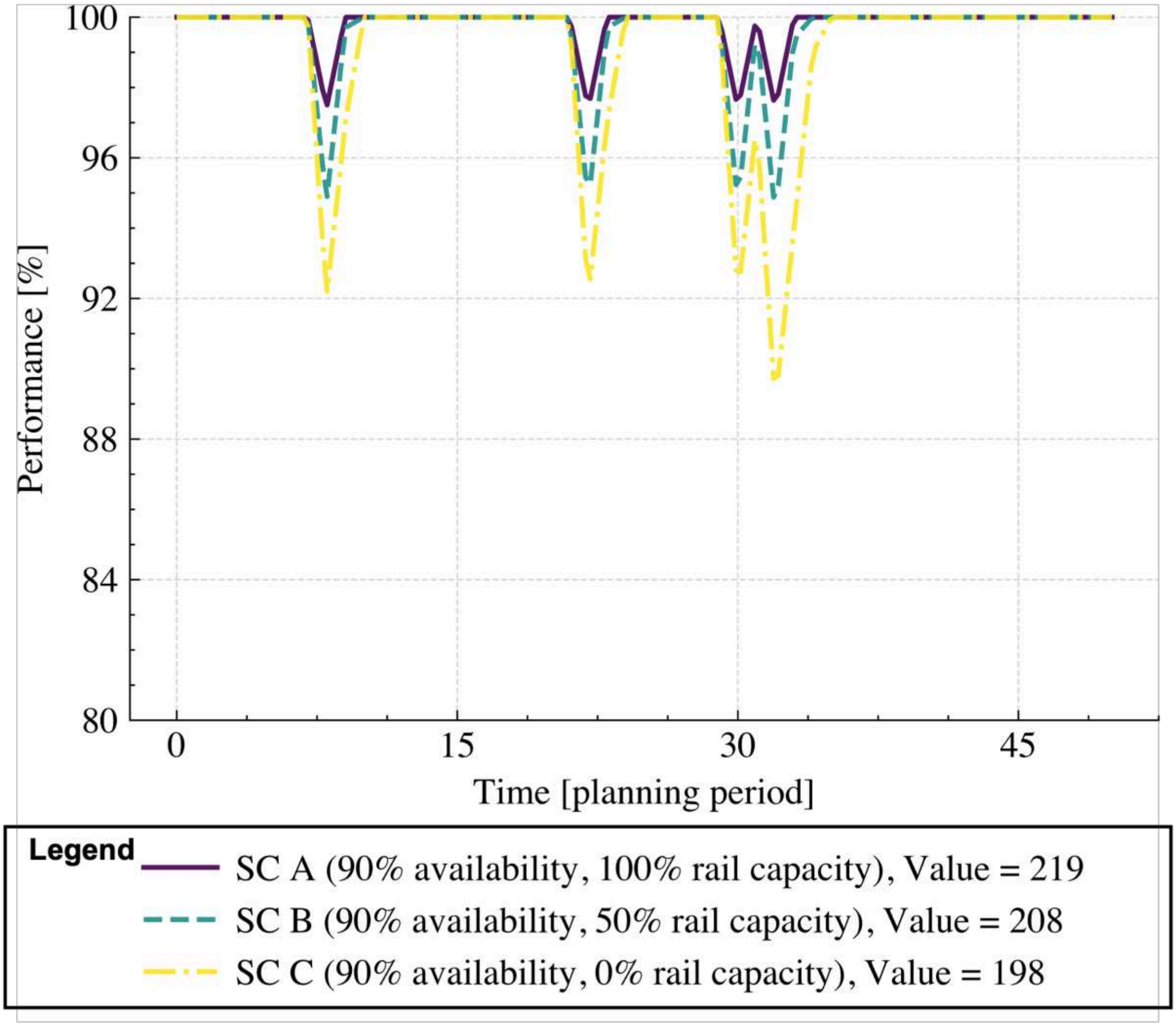

Figure 4-4: The effect of supply chain resilience via the modal shift to rail based on relative levels of transportation capacity

The results demonstrate that warning time functions as a critical enabler for proactive resilience strategies. By providing SCDM with advance notice of an impending disruption, SCDM can pre-emptively book alternative rail capacity. This transforms the response from a costly reaction into a planned, optimised reconfiguration, thereby smoothing throughput and preserving SC value during the disruption period. Figure 4-5 highlights the difference in SC value and the costs of mitigation strategies (red area) before the disruption occurred due to higher modal shift costs. However, during and after the disruption, there is a payout (green area): Whereas SC B has to fully shift to trucks lowering performance at a rate of 8% per disruption period, SC A utilises rail transport lowering performance at a factor in-between normal state and emergency truck supply (i.e. 4%). Furthermore, one can see that for short disruptions, SC B performs better because preparing rail shift is more expensive as the outweighing red area indicates.

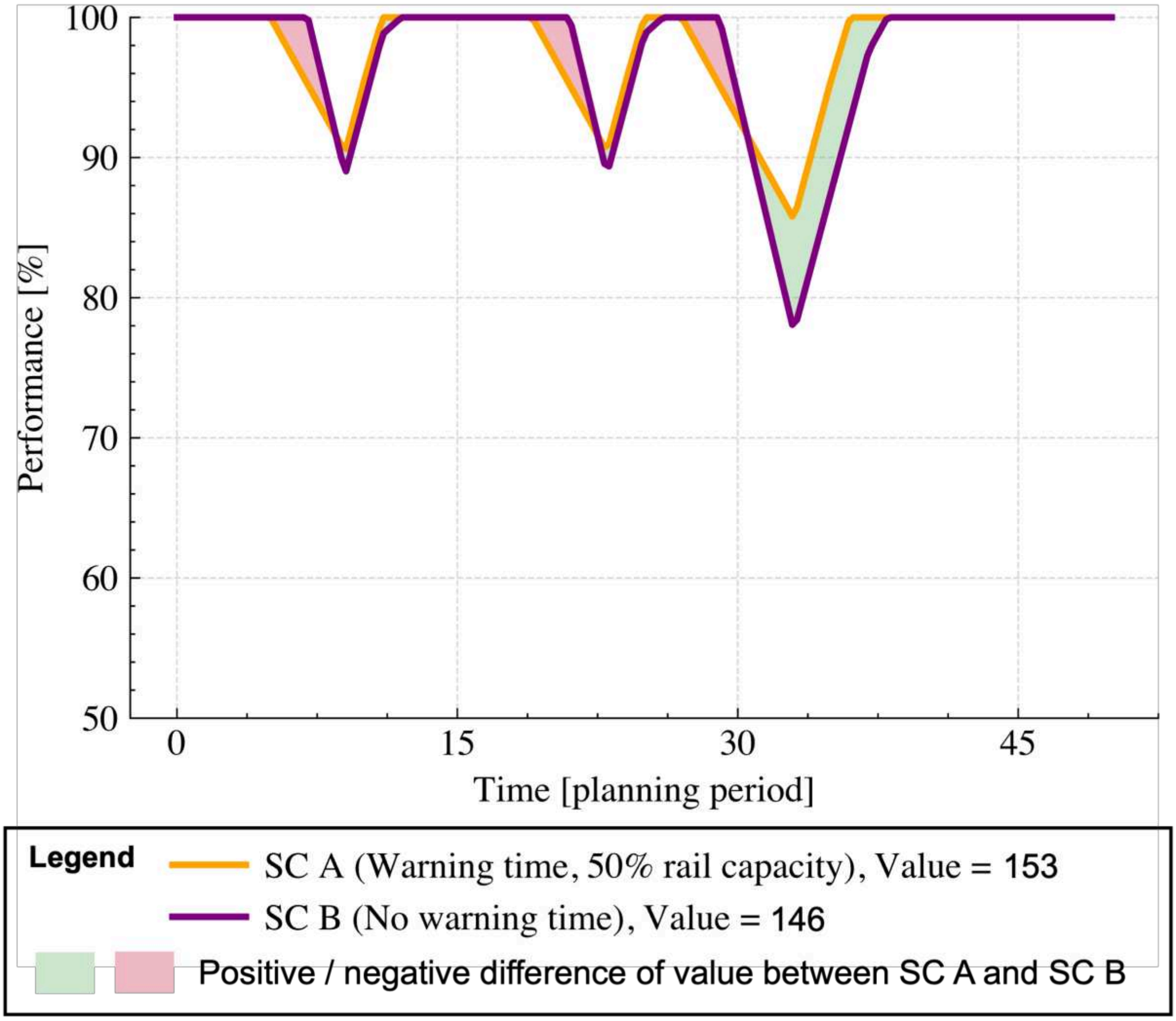

Figure 4-5: Warning time as an enabler of effective resilience strategy in a given period

4.2.2 Interpretation and conclusion

Warning time is relevant in disaster management but not present in SCR and IWT. However, scheduled partial lock closures can increase SC vulnerability, causing more stress on the other chamber. Stakeholders react differently to disruptions depending on available mitigation strategies and their SC requirements. Hence, SCs can react and find a better optimum by reducing uncertainty (see Chopra 2019), with sufficient warning time allowing for feedback loops in system dynamics.

One crucial aspect is the economies of scale for different transportation modes. The cost-effectiveness of each mode may vary depending on the scale of operations, and thus, SCDM should consider them for modal shifts. By leveraging rail transportation, SC can achieve higher performance levels and better manage the impact of disruptions on their operations. The results from case 2 indicated that the resilience strategy of using rail as an alternative could reduce cost increases by saving on trucks and provide additional transportation capacities.

Subsequently, the industry layer would obtain less welfare loss due to TN disruptions. Hence, the available rail transportation system increases the resilience of waterway-dependent SCs. Even in cases where warning time is not sufficient, the length of the restriction might provide the rationale for rail shift. Furthermore, an SCDM might find an optimum with load-sharing between rail and IWT, as the previous figure suggests, where rail is still beneficial in pre-disaster periods.

The findings of this case highlight a crucial distinction, often overlooked in the literature: between the mere notification of a disruption and the practical window for SCDM response. The time-to-note (TTN) is the moment stakeholders are first informed of a potential disruption—warning time. However, the effective resilience of the SC is determined by the time-to-adapt (TTA), the actual window in which meaningful adaptations can be implemented. TTN represents the moment when stakeholders are first informed about a potential disruption, providing awareness but not necessarily enabling immediate action. Conversely, TTA defines the actual window in which meaningful resilience adaptation, can be implemented *during* the disruption.

The distinction between TTN and TTA becomes critical when the practical adaptation window (TTA) is too short to implement effective resilience strategies. Then, TTN impacts SCR. For instance, if a notification is early (long TTN) but the lead time for securing alternative capacity is even longer, the effective TTA may be insufficient to enact the optimal strategy. This case demonstrates that by enabling a shift to rail, sufficient warning time makes the TTA viable, directly impacting SCR and mitigating welfare loss in the industry layer. This case thus distinguishes between the TTN, when a disruption is announced, and the TTA, the practical window for executing a mitigating strategy like a modal shift. The strategic value of a warning system, therefore, is not merely to inform, but to create viable decision-space. Its effectiveness is measured by its ability to expand the TTA sufficiently for cost-effective action to be taken within the TTN. This critical distinction between the information period TTN and the feasible action window TTA is precisely what equation (25) is designed to capture, where a strategy is only viable if its implementation time (d_{ijk}) is less than the available TTA.

4.3 Case 3: impact of the network load

Numerous real-world cases highlight how network load can disrupt SC performance. For example, in maritime shipping, multiple U.S. executive orders targeted congestion at the Port of Los Angeles where ships needed to wait more than 30 days for unloading (Swanson, Smialek, and Tankersley 2021), while an IWT incident in 2019 saw 129 vessels stranded at the Main-Donau-Danube channel's Riedenburg lock (Ammer 2019). Likewise, the *Nord-*

Ostsee-Kanal, the world's busiest canal, often requires vessel operators to decide whether to invest extra hours circumventing the waterway (Andersen et al. 2021). This case tests the effect of congestion from other SCs or users of the shared TN infrastructure on SCDM.

4.3.1 Results of queueing effects

Complete waterway inaccessibility for an entire network is uncommon. However, partial failures such as closing a single lock chamber for maintenance reduce serving capacity and can trigger queueing that persists even after repair. To investigate this, this thesis simulates lock chamber availability under one- or two-chamber conditions, observing how capacity variations influence vessel waiting times and congestion. See Gast (2024, s03d_queueing) for the details.

Simulation approach for lockage performance

Equation (26) denotes an IWT queueing network in Kendall notation focusing on locks:

Equation (26): Queueing network of locks in Kendall notation

$$\left[\mathrm{Y_i}\middle|\mu_{\mathrm{i,Y}}\middle|\mathrm{Z_i}\middle|\mu_{\mathrm{i,Z}}\middle|\mathrm{Cap}_{\text{chamber},\mathrm{Y_i}}\middle|\mathrm{Cap}_{\text{chamber},\mathrm{Z_i}}\right]_{\mathrm{i}=1}^{\mathrm{n}}$$

Here,

- i, the index of each network component, ranging from 1 to n;
- $\mathrm{Y_i}$ and $\mathrm{Z_i}$ are the servers (lock chambers) with $\mu_{\mathrm{i,Y}}$ and $\mu_{\mathrm{i,Z}}$, their service rates; and
- $\mathrm{Cap}_{\text{chamber},\mathrm{Y_i}}$ and $\mathrm{Cap}_{\text{chamber},\mathrm{Z_i}}$ their respective capacities.

Figure 4-6 below demonstrates how varying lock chamber availability between one vs. two operational chambers changes waiting times by showing the average queueing metrics from 10,000 runs with Monte Carlo simulation. For instance, this thesis simulated the Oberhausen lock with Euris data providing the average lockage times (ID: DEOBE04001LOCKS00057). The simulation has the following parameter: a Poisson distributed interarrival time of "number of vessels" per a 16 hour day, lockage time (north chamber): 17.14 min upstream, 16.15 min downstream, lockage time (south chamber): 16.98 min upstream, 17.8 min downstream, vessel distribution: 50% large vessels, 50% small vessels, and lockage time increases by five minutes for each additional vessel in the same chamber (see BAW 2023). Each lock chamber measures 190 m, accommodating either one large and one small vessel or up to three small vessels. When system utilisation approached 100%, having two chambers buffered busy periods more effectively, especially after about 55 vessels per day. With two chambers, throughput reached 130 vessels daily (double-chamber capacity). In contrast, a single-chamber scenario struggled to handle the same volume, magnifying average waiting times by a factor of 6–9 at 130 vessels from the 5–10min with two chambers. Consequently, network load strongly influences both transit times and costs.

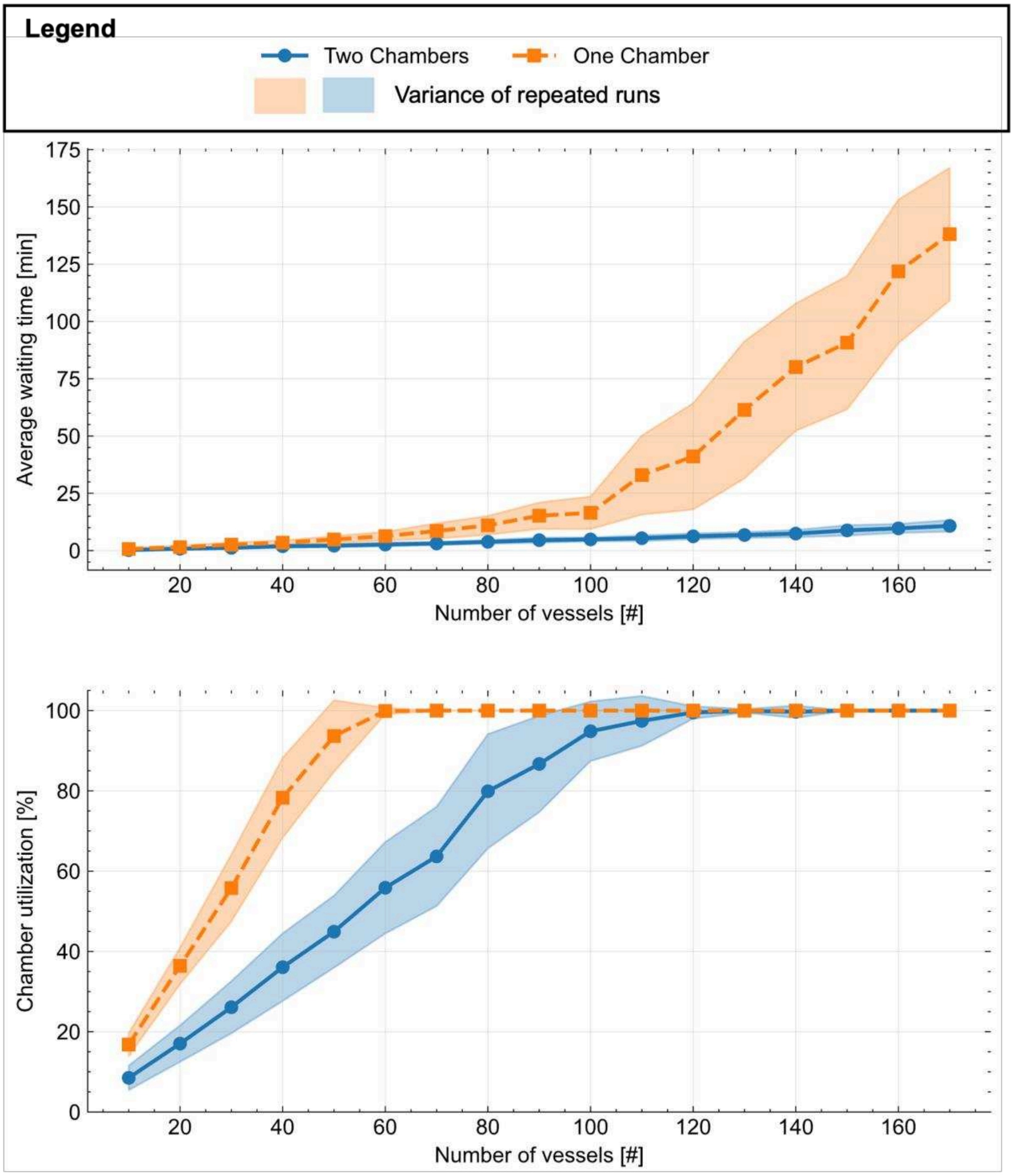

Figure 4-6: The waiting time and utilisation of the lockage process in a two-chamber lock against a one chamber lock

A generalisation of the single lock simulation from the network perspective

The network load factor affects SC transit times and costs beyond a single lock. Because the TPP is not agent-based, the model estimates lockage loads under chamber unavailability via a separate queueing simulation (Gast 2024, get_queueing_model). Testing various initial queue lengths and waiting strategies revealed that, even once a waterway reopened, existing vessel backlogs prolonged delays. Consequently, SC strategies (e.g. rerouting vs. waiting) alter overall performance.

Optimising with knowledge about delays can lead to better SCDM, such as preferring rerouting or, in the worst case, shifting to truck transportation. However, without adapting to this information, an SC may suddenly suffer additional time-related costs unaccounted for in the initial planning. Therefore, queueing delays were added to the SC analysis with reasonable assumptions based on lockage time sensitivity for each lock on the way based on the number of daily vessels. This resulted in an increased lockage time anticipated in routing decisions. Figure 4-7 quantifies the non-linear cost impact of network load, expressed as lockage time, showing that as network load increases beyond a threshold (~80 vessels/day), the cost penalty for not shifting away from IWT grows exponentially. A proactive modal shift can mitigate over 25% of these congestion-induced costs, demonstrating a clear economic case for anticipatory SCDM.

Transferring this insight to the case 3 analysis, there is roughly a cost increase of 5% at 80, 10% at 100, and 20% at 130 daily vessels. If modal shift to truck is available, the impact of longer lockage time is reduced by roughly 25% compared to the case where vessels must wait it out or reroute to an alternative route with fewer locks possible, which is possible in the unique West German canal setup with redundancy. A model that incorporates queueing dynamics can therefore identify this threshold and trigger a modal shift strategy before such non-linear costs are incurred, creating significant value.

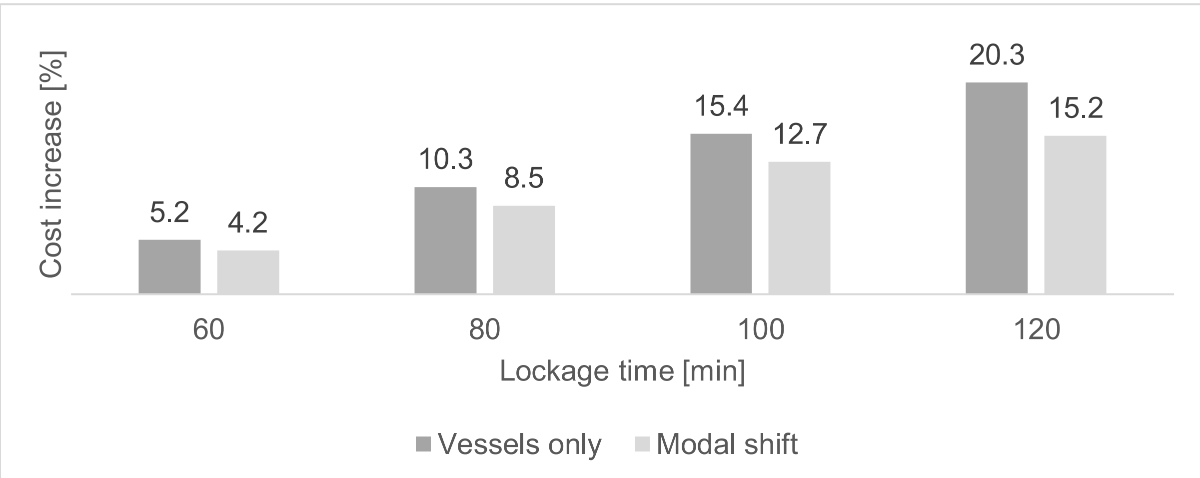

Figure 4-7: Lock time impact on transportation system costs depending on multiple considerations {Binsfeld et al. 2024, author, modified}

Implications of the network load factor for supply chain decision-making

Anticipating queueing effects enables SCDM to adjust inventory and demand in targeted time windows. Figure 4-8 compares three SCs under the same configuration:

- SC A remains a reference scenario without queueing constraints.
- SC B has foreknowledge of network load;
- SC C does not and hence experiences queueing fully without rerouting; and

By factoring in lock congestion, SC B shifts to a different mode during short closures and avoids prolonged wait times. The effect seems minor as the transportation layer already optimises to account for disruption. Yet, it becomes vital in busy periods, paralleling the scenarios seen in Figure 4-6, where there could be delays by days if initial backlogs need to be resolved.

The ability to anticipate queueing effects (e.g. by lock congestion) could become a decisive factor in SC viability under stress. Figure 4-8 shows that with foreknowledge of network load (SC B), SCDM can proactively use alternative modes to circumvent short-term congestion, maintaining higher performance than a reactive SC C that fully bears the additional congestion costs. While this effect appears minor under normal conditions, it becomes critical as infrastructure availability degrades. Figure 4-9 illustrates this at an edge case: at 64% availability, the foreknowledge of queueing is the difference between survival (SC B, value of 1) and collapse (SC C, value of -12). This demonstrates the existence of a critical 'tipping point' where the ability to anticipate second-order queueing effects becomes the primary determinant of SC survival.

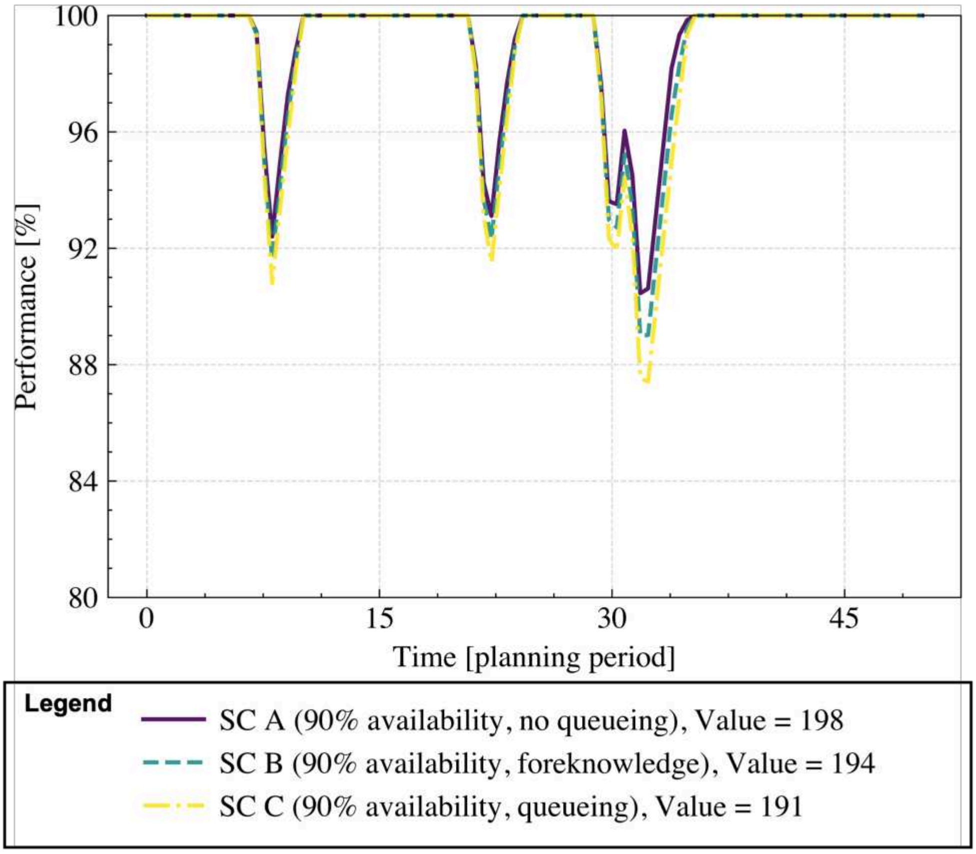

Figure 4-8: The effect of the knowledge about queueing

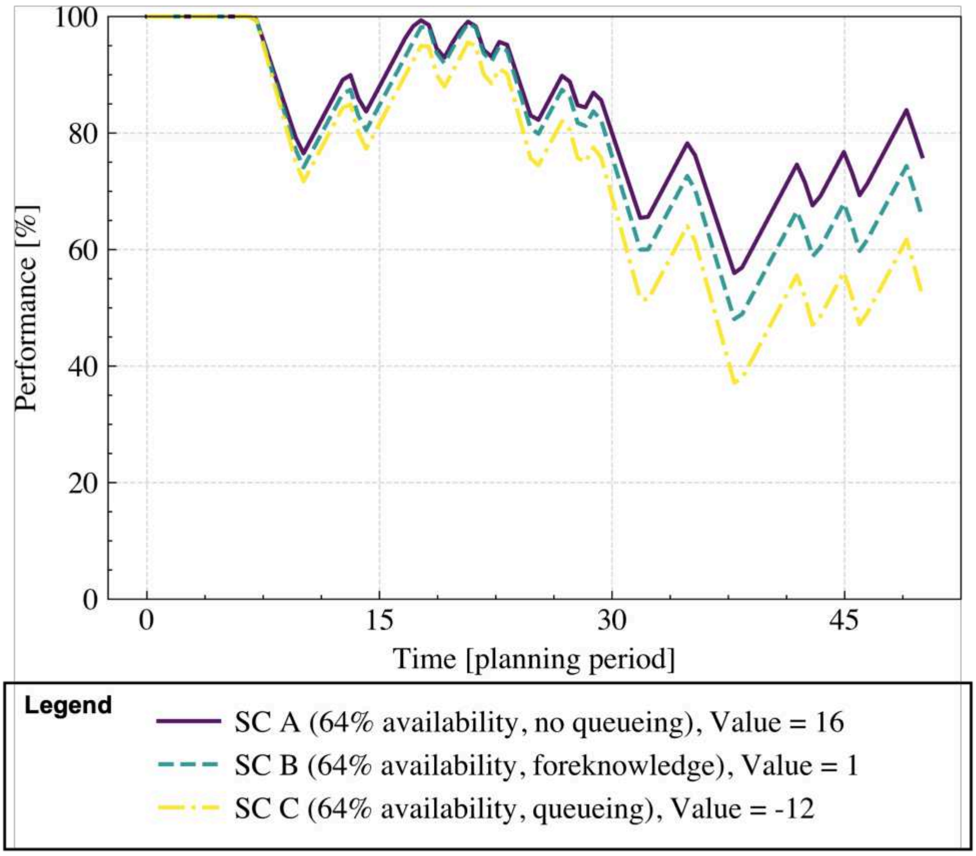

Figure 4-9: The effect of the knowledge about queueing in an edge case

Minimum reliable requirements and cost sensitivity in TPP modelling

The TPP framework also yields a minimum network load required to satisfy port demand by vessel. Exceeding infrastructure capacity escalates queues, delays, and eventual cost spikes. QT aids in quantifying these risks (Gast et al. 2021; Nazari-Ghanbarloo and Ghodratnama 2021). Sensitivity analysis further clarifies at which point added traffic diminishes vessel throughput that causes disproportionate cost rises (e.g. reduced economies of scale, modal shifts).

In addition, the TPP provides insights on a minimum network load on the transportation infrastructure elements to fulfil port demand with vessels. Determining the minimum number of required vessels enables an assessment of whether infrastructure capacity is sufficient if all traffic must use the same paths. Limited infrastructure capacity increases the risk of backlogs, queues, and transportation delays if too many users use these path links in the TN. QT can model the impact of limited transportation capacity on SC using Little's Law and standard QT (Gast et al. 2021; Nazari-Ghanbarloo and Ghodratnama 2021).

A mechanistic thought experiment of partial disruptions

To isolate the core mechanism of this ‘shuttling effect’, which is difficult to disentangle from other variables in the historical data, the following thought experiment of vessels shuttling between a supply and demand port triggered by SCDM and SC demand under different capacity assumptions was designed. In this setup:

- There is a steady demand of 5 units per day for 50 periods that if not met, incurs backlog *BL* units equivalent to vessels not yet arrived;
- arrivals follow a Poisson process of 5 vehicles per period;
- transportation capacity is either ‘unlimited’ (instantly clearing backlog once disruptions end) or ‘limited’ by 6 vessels that can potentially fulfil 6 demand units reliably in a single day, i.e. capacity per time throughput in a single day; and
- the configuration of the SCs can contain a schedule or inventory buffer of certain days or inventory so that vessels do not immediately have to fulfil their next trip; and
- closures intermittently disrupt the system reducing supplied capacity to zero while the vessels are waiting to finish their trip and their load is stuck in transit.

As shown in Figure 4-10 and Figure 4-11, the simulated backlog *BL* remains modest with unlimited capacity, since each ‘backlog spike’ clears immediately after the closure. The sum of BL is calculated for each subplot. Under unlimited capacity, each backlog surge vanishes soon after a closure event. In contrast, when capacity is capped at six vessels, any short-term disruption leaves a residual backlog that lingers without schedule buffer. If these disruptions occur in succession, an initial wave of backlog triggers a series of secondary backlogs, impacting overall system stability. Adding vessel buffers or additional shifts significantly reduces the accumulated queue and subsequent backlog by compressing the catch-up period. These experiments demonstrate how even small time or inventory buffers reduce backlog risks in capacity-limited systems. Thus, SCDM must respond with strategies, such as proactive modal shifts, to maintain system equilibrium and mitigate the risk of exacerbating backlogs in the transportation layer.

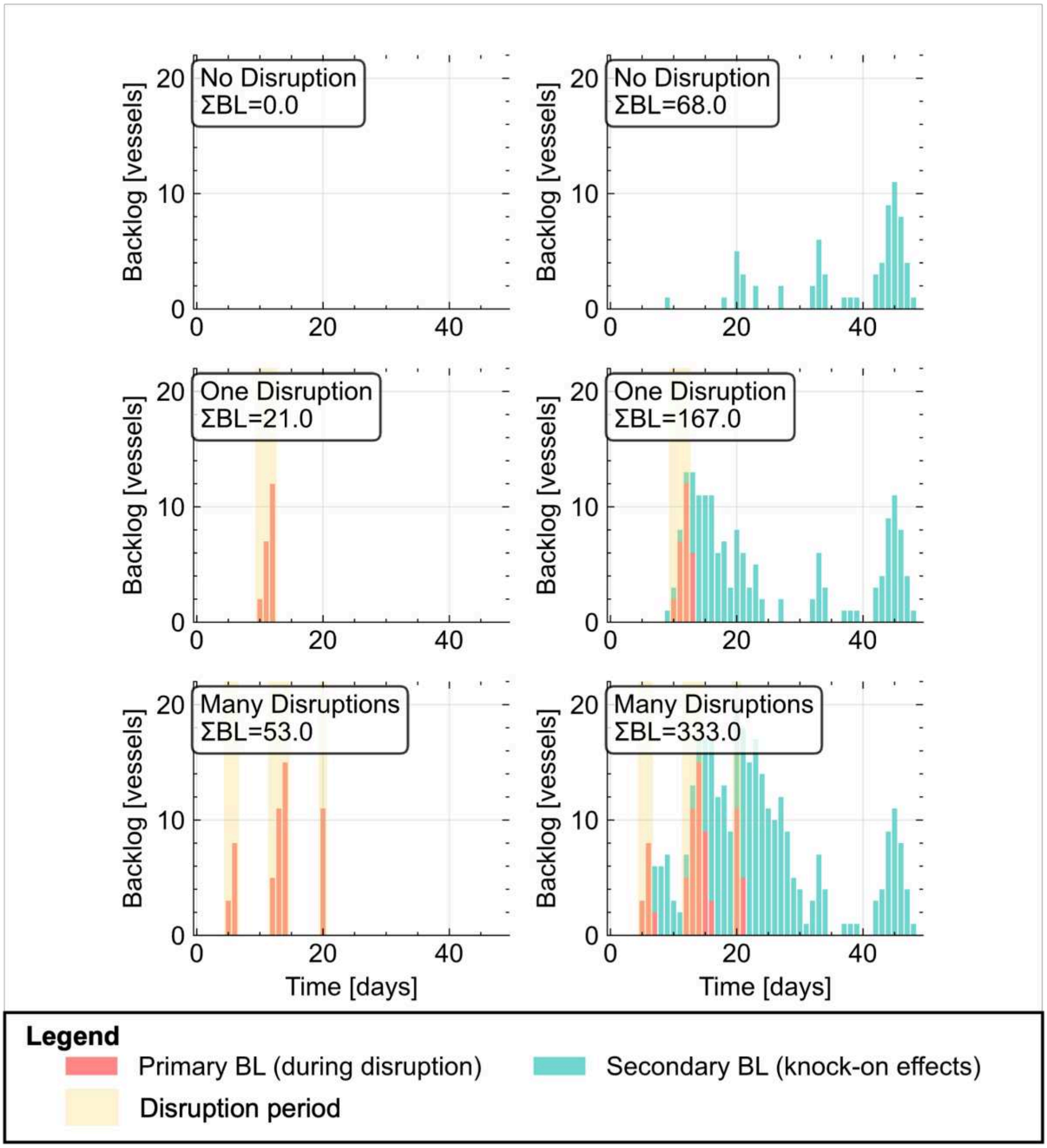

Figure 4-10: Shuttling effect comparing unlimited and limited transportation capacity (left: unlimited capacity units; right: capacity = 6 units with no buffer). With unlimited capacity, backlog spikes clear immediately after each closure; under the capped capacity of six vessels per day, residual backlog accumulates across successive disruptions.

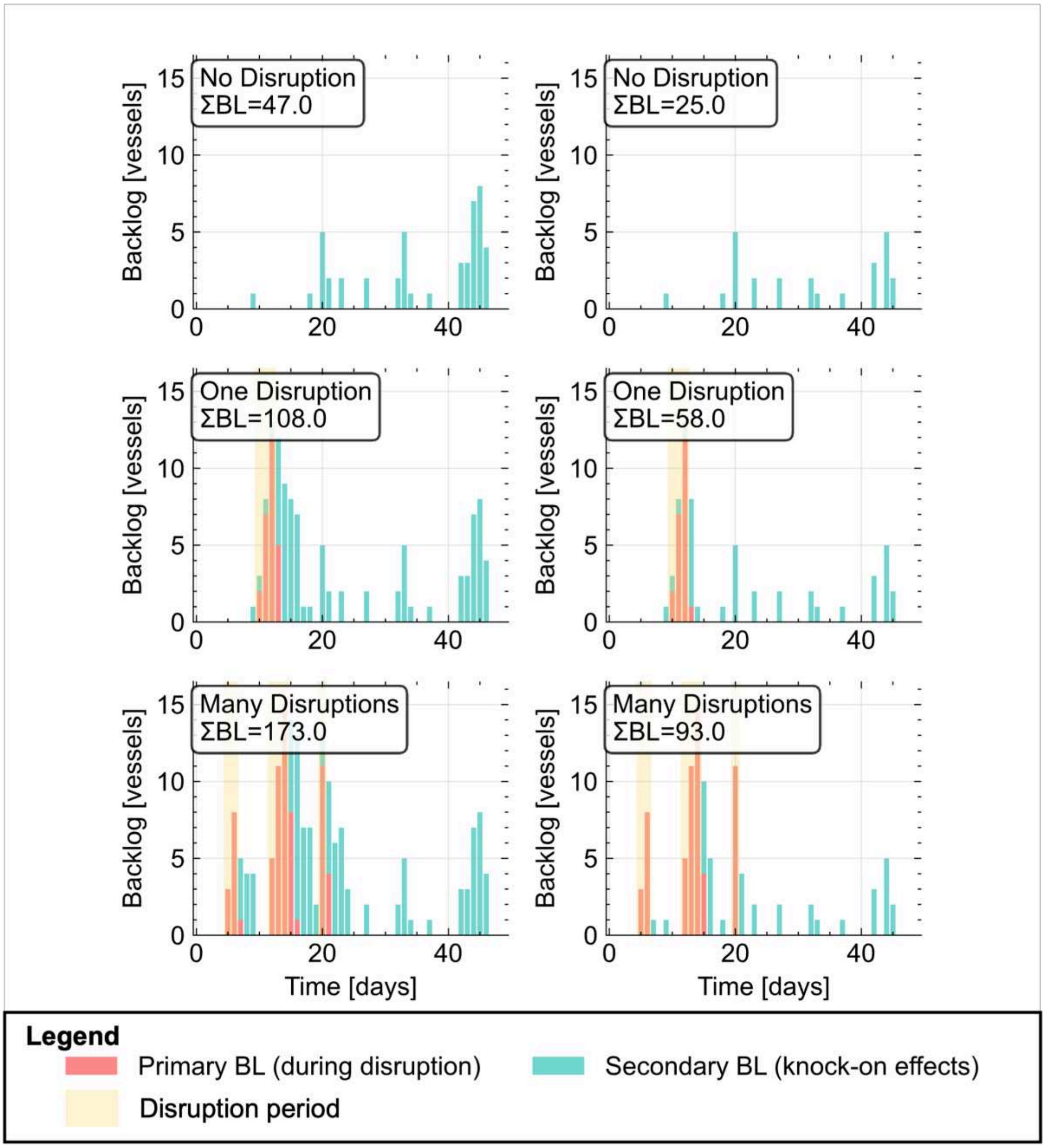

Figure 4-11: Shuttling effect comparing different buffer size in schedule (left: capacity = 6 and buffer = 1 units; right: capacity = 6 and buffer = 5 units)

4.3.2 Interpretation and conclusion

Case 3 highlights how network load can profoundly influence resilience. While complete waterway unavailability is rare, this case demonstrates that partial disruptions, such as single-chamber lock failures, are sufficient to reduce serving capacity and trigger significant queueing effects. In turn, these queues can persist long after a waterway reopens, as vessels initially delayed form substantial backlogs that intensify congestion under high arrival rates. These scenarios mirror the choices SCDM of waterway-dependent SCs often confront when a lock chamber is unavailable: they can allow vessels to queue and exacerbate congestion, or they can redirect traffic to alternative modes.[49]

An essential factor in managing network load is infrastructure reliability. Simulation insights demonstrate that a two-chamber lock operating at or near 100% utilisation provides crucial buffering against busy periods. As seen in Figure 4-6 and Figure 4-7, a single-chamber failure can yield exponential congestion once throughput demand surpasses ~55–60 vessels/day. A second lock chamber mitigates these effects, delivering tangible welfare benefits considering reliability. The tangible welfare benefit of a second lock chamber can be quantified by applying established public-planning valuation methods. Following Rieken et al. (2015), an average time saving of 20 minutes per vessel, combined with BVWP weightings for improved plannability, and a flow of 65 vessels/day over 350 operating days, yields an annual benefit calculated as: (65 vessels/day) × (350 days/year) × (70 EUR/hour) x ((20 min/vessel) × (1.7 / 60 min/hour) + (10 min/vessel) x (0.7 / 60 min/hour)) ≈ 1.08 million EUR in estimated welfare gains per year—conservatively estimated as not accounted for inflation and cost increases. Furthermore, it reduces the risk of total unavailability of the WdtK due to failure at entry locks that would cost seven million EUR per day, as calculated in section 3.3.4. This calculation provides the empirical basis for the one million EUR annual welfare utility cited for a secondary lock chamber.

From a SCDM perspective, queueing simulations offer tangible tools to anticipate and mitigate congestion effects. In waterway networks where certain locks are unavoidable, capacity shortfalls can become major bottlenecks. Although modal shifts can bypass those locks, such strategies bring new costs for SC managers. The TPP framework helps quantify these trade-offs, indicating that switching away from waterways prematurely may spare companies from severe lock queues, reducing disruption-induced value losses by as much as 25%. However, these tactics require robust information on expected queue length, arrival rates, and closure duration—hence, forecasting and real-time monitoring become essential.

From a policy and infrastructure planning perspective, these findings reinforce the value of two-chamber locks and targeted investments that align lock capacity with actual traffic demand. In many waterway corridors, passenger vessels also compete for the same, shared infrastructure (e.g. pleasure crafts on the Danube), adding further complexity to queueing analyses. Incorporating them into these models can help capture both time-dependent

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49 . . . — at potentially congested transhipment nodes as other carriers do the same.

disruptions and system interdependencies. Planners can then better assess whether new locks, chamber expansions, or scheduling initiatives will sufficiently enhance reliability.

Shared infrastructure congestion, such as port queues, leads to systemic delays. A lock chamber failure immediately creates vessel backlogs, exacerbated during peak traffic periods. The delay increase is non-linear, influenced by vessel volume and system adaptability. To mitigate this, coordinated route planning can reduce waiting times. This is relevant for liner schedules. For instance, a coal plant owns a ship panelling between Rotterdam and Lünen within three days for a constant supply of feedstock. Those some-hour-long delays may lead to the ship being unloaded the next day, wasting the night time during which it cannot navigate (PREVIEW 2019b). Hence, in the worst case, even a delay of some hours could lead to becoming out of sync with the schedules despite time buffers requiring an expedited order of coal from the spot market to adhere to the plant's production plan.

Repeated modal shift IWT-to-rail to avoid IWT queueing can address short-term lock failures but may lead to secondary congestion and higher costs in rail. A critical question is whether large-scale mode shifting eventually becomes counterproductive, negating the SC benefit gained by avoiding lock delays, or if a modal shift is always beneficial. Identifying these tipping points helps maintain a balanced multimodal system. In sum, case 3 demonstrates the importance of load-aware resilience strategies in inland waterway transportation. By integrating QT with SC cost models, researchers and practitioners can:

- evaluate how partial lock failures shape throughput and congestion;
- quantify the trade-offs of rerouting vs. inventory buffering; and
- design infrastructure and policies that minimise waiting times.

5 Discussion of Model Usage

This chapter first addresses the research objective and its related questions (section 5.1). Section 5.2 then highlights the model's contributions to the literature, with a particular focus on the shuttling effect. Eventually, section 5.3 discusses implications for key stakeholders, including policymakers, transportation agencies, and industry actors. Finally, section 5.4 provides the critical appraisal of this thesis.

5.1 Research objective and research questions

RQ1: What is the current state of the literature regarding the primary research objective?

As chapter 2 details (sections 2.1–2.2), SCM disruptions and resilience remain crucial topics, but TN considerations in SCR, particularly regarding waterway infrastructure, are underexplored (section 2.3.4). Identifying this gap (section 2.4.4) shaped this thesis's scope.

RQ2: How can the resilience of waterway-dependent SCs be formalised into a holistic, multi-layer model?

Chapter 3 introduced the multi-layer, multi-state model using the WdtK as a case. This layered approach supports a modular analysis of the SC ecosystem, highlighting interdependencies between infrastructure, transportation, and SCDM. By combining RT (section 3.1) with mixed methods (sections 3.2–3.3), the model incorporates dynamic factors (e.g. warning time) and adopts a VSC perspective. The WdtK parametrisation (section 3.3) demonstrates how this holistic approach surpasses prior SCRM and SCR frameworks in scope and detail.

RQ3: What are the practical applications and utility of the model for public and industrial stakeholders?

Chapter 5 further examines how the model aids public agencies and industry, particularly in infrastructure planning and SCDM. By offering open-source code for model parametrisation plus a thorough critical appraisal (section 5.4), stakeholders can assess the model's suitability for varied use cases.

5.2 Contributions to the literature

This dissertation's multi-layer, multi-state model makes three key contributions by bridging previously disconnected research domains, moving from theory to empirical validation, and demonstrating how probabilistic infrastructure states directly influence the economic viability of dependent SCs. The key contributions are:

1. The model provides the first empirical quantification, for a waterway system, of the direct link between probabilistic infrastructure availability and the financial performance and viability of dependent SCs (sections 3.3.3 and 4.1).
2. The framework operationalises and quantifies the economic value of dynamic resilience capabilities. Specifically, it demonstrates how incorporating warning time into SCDM enables proactive mitigation strategies (section 4.2) and how anticipating queueing effects allows for the avoidance of non-linear cost escalations (section 4.3).
3. Simulation reveals that repeated, short-term capacity constraints in shared networks induce a cyclical backlog phenomenon termed the 'shuttling effect' which is distinct from the directed propagation of the ‘ripple effect’. This identifies a new mechanism for systemic disruption in capacity-constrained transportation networks (section 4.3).

In the following Table 5-1, these contributions are mapped against the key research gaps from chapter 2, clarifying which aspects represent entirely new insights, which apply specifically to waterway-dependent SCs, and validate empirically in the WdtK case. The outcome differentiates between (i) newly proposed as a universal contribution to the literature, (ii) suggested as relevant for waterway-dependent SCs as demonstrated in the WdtK case, and (iii) empirically elaborated in the case study.

Table 5-1: Addressed research directions

Gap and pathways	**Contribution and section**	Outcome
Lack of empirical research on simultaneous disruptions in demand, supply, and logistics infrastructure	**Introducing the shuttling effect as a novel resilience mechanism (section 4.3)**	Newly proposed
Short- and long-term implications of disruptions (e.g. geo-location and recovery processes)	**Integrating spatial network topology in the model and analysing short-term and long-term disruption impacts (sections 3.3, 4.2)**	Suggested for the WdtK
Link between TN and SCR	**Connecting infrastructure availability with transportation decisions through the TPP framework (section 4.1)**	Suggested for the WdtK
Responsiveness / adaptability	**Modelling warning time effects on resilience strategies (section 4.2) and knowledge about load (section 4.3)**	Suggested for IWT
Public investments, collaboration, and SCR	**Layered model approach illustrating industry and policy implications (section 3.3)**	Elaborated for the WdtK
Limited application of SC reliability and lack of case studies	**First empirical application of the model to WdtK (chapter 4)**	Elaborated for the WdtK
SC survivability and long-term risk assessment	**Assessing SC viability through infrastructure and demand-sensitive resilience modelling (sections 3.3, 4.1)**	Elaborated for IWT
Integration of transportation into SCR	**Demonstrating the role of transportation network redundancy and disruption costs in resilience planning (sections 4.1, 4.2)**	Elaborated for IWT

5.2.1 Literature findings relevance

Integration of transportation into SCR; link between TN and SCR

This thesis extends earlier IWT studies (e.g. Pant, Barker, and Landers 2015; Oztanriseven and Nachtmann 2020) by empirically demonstrating how infrastructure availability influences SCDM (sections 3.3 and 4.1). Its modular approach encompasses diverse stakeholder needs, reflecting public-private interdependencies in multimodal settings, thereby enhancing SCR and ultimately benefiting public welfare, which is a gap per Gast, Kirkach, and Ivanov (2022). This multi-layer approach operationalises a 'system of systems' perspective, recognising that disruptions propagate through interlinked subsystems, like port infrastructure and SC demand nodes, creating effects across all layers rather than affecting each layer in isolation.

This study also illustrates how multimodal networks can bolster waterway-dependent SCR, confirming observations in Rieken et al. (2015) about the complexities of pure cost-based multimodal assessments. Since modal shifts require preparation time, the thesis partially addresses this by showing historical cost-savings potential (section 4.1) and broader welfare impacts. Though not all SCs can adopt multimodal capacity easily (e.g. Delbart et al. 2021; see Zokaee et al. 2017), large-volume, low-value goods may benefit substantially from such flexibility.

Limited application of SC reliability and lack of case studies; SC survivability and long-term risk assessment; short- and long-term implications of disruptions

The thesis significantly advances prior research through empirical case analyses. By factoring in value and industrial shortage costs for SC reliability, plus a multi-state model to capture expected infrastructure states (section 3.1), SCDM can smooth transitions by preponing or postponing procurement (section 4.1). Furthermore, the model highlights adverse impacts when shifting from disrupted/busy states back to normal, an aspect often overlooked (see Gast et al. 2021, and section 4.3). The framework developed in this thesis integrates SC reliability to quantify time-dependent failure probabilities, which are then used as inputs to a multi-layer optimisation model that assesses the impact on SC value while acknowledging the trade-off between lean performance and excess, addressing this theorised research gap by Ivanov (2022).

While typical SC reliability studies focus on the TN network level, with metrics like "perfect order reliability" (Lukinskiy et al. 2023; Cai et al. 2009; Selvaraj and Wesley 2020) the thesis' model extends this literature by, first, discarding normal distribution assumptions in favour of a Weibull-distribution of failure modes (Nazari-Ghanbarloo and Ghodratnama 2021; Ha, Jun, and Ok 2018), and, second, focusing on transportation infrastructure. This model also addresses risk mitigation for critical suppliers at minimum edge cuts (Ha, Jun, and Ok 2018), which suits IWT's inherent infrastructure constraints.

The availability assessment revealed that the cost increases from disruptions were less severe than anticipated, falling within the range of cost deviations rather than constituting catastrophic SC disruptions. Partly because the WdtK exhibited high levels of availability and redundancy compared to the Rhine River, the navigation unavailability was approximately 5–6% (Colling et al. 2022), potentially blocking the route access to the Lower Rhine area, not considered in this analysis. However, even in cases where SCs could *adapt* effectively to avoid disruptions and minimise shortage costs, they still faced additional expenses, attributed to increased transportation expenses, inventory holding and depreciation, and the efforts required for event management.

By establishing alternative flows even with limited capacities at higher costs, the load-sharing mechanism found in SC reliability enhances SC value. This approach affirms that network redundancy is a potent resilience strategy, but with a critical caveat demonstrated by case 3 analysis for queueing knowledge (section 4.3): if load-sharing among redundant assets is not coordinated, it can induce congestion that degrades, rather than enhances, overall system performance. Effective resilience therefore requires not just redundancy, but also visibility and coordination across shared assets.

Shortage costs and preventing backlogs play a critical role in SCDM processes and affect SCR by influencing actions such as building inventory and safety stock, waiting out delays, decreasing production, and diversifying sources. The model provided a novel approach to analysing the impact of shortage costs on SCDM regarding infrastructure availability, adding to Lukinskiy et al. (2023) with the SCR value integral. Leveraging macroeconomic data through input-output analysis enabled a more comprehensive assessment of maximum shortage costs and their granular implications on SCDM (section 3.3).

Link between TN and SCR; responsiveness / adaptability

A network perspective is vital because potential shortages simultaneously affect supply- and demand-side operations (Nazari-Ghanbarloo and Ghodratnama 2021). Determining minimum path sets in the infrastructure network is crucial for evaluating transportation costs and transit times. Some SCs in the WdtK face greater disruption severity, prompting potential reconfiguration or divestment. The layered approach underscores these interdependencies, with the TPP linking infrastructure availability and SCR, while SCDM directs performance outcomes. This model also considers the long-term influence of infrastructure conditions on SC viability, e.g. via survival analysis and identification of availability thresholds (section 4.1; Wehrle et al. 2023), showing how location-specific conditions shape SC performance and resilience.

Incorporating warning time and multi-state elements from infrastructure operators into the resilience cycle offers more robust SC mitigation responses, saving on IWT transportation in more than 35% of cases. Although warning time was traditionally limited to disaster management, applying it to daily SC operations broadens SC responsiveness (see Berbner

2017). In parallel, the model supports SC digitalisation (Dolgui, Ivanov, and Sokolov 2022) by integrating Euris-data to anticipate disruptions and refine SCDM decisions.

5.2.2 The shuttling effect: a novel contribution

This dissertation identifies and formalises the shuttling effect as a distinct SC disruption phenomenon:

> Distinct from the directed propagation of a singular disruption (the 'ripple effect') or of demand variance (the 'bullwhip effect'), the shuttling effect is a cyclical, oscillatory phenomenon of congestion. ‘Shuttling’ emerges in capacity-constrained, shared networks subjected to repeated, short-term disruptions and is characterised by the system’s inability to clear backlogs fully between disruptive events. This generates self-reinforcing waves of congestion that propagate through and remain in the network for a prolonged time while making further disruptions more critical.

Concurrent events, such as the Suez Canal blockage and pandemic-related demand surges, highlight how multiple factors can create conditions analogous to the shuttling effect. Cf. Ivanov, Hägele, and Grosse(2023) attribute this to the ‘ripple effect’. However, the Suez Canal blockage itself primarily caused queueing (Gast et al. 2021; see Maersk 2021), not a classic ‘ripple effect’. The broader stress on global maritime SCs reflected a complex interplay of pandemic-related lockdowns, surging demand, and capacity imbalances. These are precisely the conditions of intermittent unavailability and high load in a shared, capacitated system which give rise to the shuttling effect, e.g. resulting in vessels waiting for over 30 days at the Port of Los Angeles.

Accordingly, the multi-layer, multi-state model suggests strengthening infrastructure resilience by raising service rates or adding redundancy. This thesis thus recommends viewing transportation in shared-user infrastructure, especially if operated by public stakeholders, as an SCR element to be managed by SC reconfigurations such as diversifying routes to alternate ports. Table 5-2 extends existing uncertainty types to incorporate the shuttling effect, depicting unknown-known disruptions that frequently stress the system. Once the load is measured (via QT), targeted measures (extra work shifts, flexible scheduling) can curtail busy periods sooner.

Table 5-2: Uncertainty characteristics in supply chains (addition to Table 2-1)

Uncertainty type	Knowledge about uncertainty	Disruption type	Uncertainty analysis	Specific effects	Disruption examples
Random	known-known	Event	Stability	Bullwhip effect	Demand fluctuations
Epistemic	known-unknown	Event	Resilience	Ripple effect	Natural disasters
Deep	unknown-unknown	Crisis	Viability	Survivability	Pandemic
System stability	**unknown-known**	**Frequent events**	**Reconfiguration**	**Shuttling effect**	**Congested logistics infrastructure**

The ‘shuttling effect’ captures repetitive waves of congestion that surface when cyclical disruptions repeatedly reduce a system’s effective transportation capacity. During each disruption, vessels may be forced to wait mid-transit or remain idle, thereby underutilising available capacity. As these partial failures recur in quick succession, residual backlog persists, creating further congestion with each new wave. In this sense, the shuttling effect extends beyond isolated crisis events; it instead characterises a systemic phenomenon that emerges from a sequence of smaller disruptions in capacity-limited settings exacerbated by its users sharing the same infrastructure.

Employing QT to analyse these backlog spikes reveals how relatively short closures can cascade into large-scale instability if capacity does not recover fully between events. Timely interventions, such as enabling extended operating hours at lock chambers or employing flexible schedules, can alleviate queues before the next disruption wave hits. Nevertheless, deep uncertainties remain as no single catastrophic event triggers the cycle. Repeated minor failures collectively push the network out of its steady-state equilibrium. Compounding matters, abrupt backlog waves can also produce secondary ‘bullwhip effects’ on suppliers because shippers and consignees attempt to compensate for lost time by placing additional or expedited orders, further straining the transportation network, where companies overcompensate for disruptions by placing accelerated orders, exacerbating volatility in procurement cycles and causing additional transports in the system, as seen in the case of energy supply in section 4.1.2.

Arguably, the shuttling effect is a counterpart of deep uncertainty: instead of a single crisis event with unknown effects causing the SC disruption, multiple events put stress on the system with an unknown stability equilibrium. Once the stress is determined, QT methodologically analyses the impact, and measures could be enacted like adapting the regulatory framework for extra shifts for employers to end the *busy period* as soon as possible.

The proposed model demonstrates how SC delays can accumulate within shared transportation networks, where limited capacity and repeated partial disruptions amplify inefficiencies. Central to this dynamic is the shuttling effect in systems operating near or at capacity limits. Under this effect, each minor interruption prompts a backlog that forces ongoing rescheduling and congestion, which can persist in subsequent operating cycles. By incorporating simultaneous demand shifts, supply variability, and infrastructure outages, the model clarifies how network capacity constraints (e.g. port and lock throughout) reshape origin–destination flows and stress system capacity. This approach goes beyond the conventional 'ripple effect' by emphasising the cyclical nature of repeated bottlenecks—particularly when disruptions recur quickly and the potentially available number of vessels and their cargo remain trapped in transit.

Implications of the 'shuttling effect' for supply chain decision-making

Treating the SC as an interconnected ecosystem invites reconfiguration to restore transportation capacity and stabilise demand with minimal disruption.

- Strategic sourcing and network design:
    - diversifying transportation providers and infrastructure entry points to reduce dependency on single nodes or corridors (strategic sourcing and network design).
- SC business process control and coordination:
    - maintaining in-house logistics or fostering partnerships for increasing available resilience strategies, their efficiency and the respective TTA / TTN; and
    - fostering public-private collaboration to ensure infrastructure operators' actions (e.g. maintenance schedules) are aligned with industrial needs.
- Adaptive policy and regulation:
    - implementing regulatory flexibility (e.g. pre-approved overtime for infrastructure services) to increase throughput under crisis conditions and proactively prevent shuttling.

While the model represents solutions to the shuttling effect through abstract concepts like 'increased capacity' or 'schedule buffers,' these represent complex human and organizational actions in the real world. Implementing these solutions requires negotiation between public infrastructure operators and private carriers, potential labour agreements for overtime, and dynamic pricing mechanisms. Quantifying the value of enabling these socio-technical solutions might provide an economic justification for developing the policies and agreements needed to manage congestion proactively due to direct consequences for both industrial strategy and public policy.

5.3 Further implications of the findings

The underlying issues addressed in this research are well-known and have prompted calls for action. Germany's master plan "Binnenschifffahrt" (BMVI 2019) echoes many of the concerns that are addressed and quantified by this thesis with the demonstration of a complete, quantifiable pathway from an infrastructure failure to a macroeconomic welfare loss due to its impact on SCs. By linking the probabilistic failure states of 1) infrastructure components to 2) network-wide transportation costs, then to the financial viability of 3) individual SCs, and finally aggregating these impacts into 4) industrial inoperability, this model provides an integrated, end-to-end assessment. The model moves beyond analysing either infrastructure reliability or SC resilience in isolation providing the following benefits:

Benefits for business stakeholders

Every SC is unique, so universal assumptions rarely hold. This research is adaptable, offering scenario-based guidance for large-volume/low-value cargo or capacity investments of stakeholders like IWT carriers and chemical parks. Infrastructure data (Euris, Elwis) integrated with SC attributes (inventory, demand) can forecast disruptions and optimise warning time usage. Kersten and Koch (2010) underscore the value of timely reordering and securing capacity.[50] Even road carriers—ostensibly independent of IWT—can plan around modal shift surges triggered by waterway closures.[51] Moreover, robust risk communication fosters trust, a crucial SCR element (Ivanov, Hägele, and Grosse2023), a key SCR dimension.[52]

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50 . . . — for instance, Apple's rapid reaction to the 2003 tsunami in Thailand (Keynote by Sophia Velastegui at the "IfM Supply Chain Symposium", Cambridge, 25.09.2019).

51 . . . — just as individual vehicle routing decisions (e.g. by app-based taxi drivers) are optimised based on real-time data about disruptions in the public transit network.

52 How accurate are the warning/notification times provided for repair durations? An anecdote from a workshop suggests that if a bridge collapses in a canal, it takes a maximum of two weeks to remove it. For instance, a bridge did collapse in the DEK, and it took 12 days to recover, as mentioned in WSV (2023) for NtS (0342/2022).

Case 2 showcased how warning time affects SC parameters. Heightened complexity from digital SC platforms (Blecker, Kersten, and Meyer 2005) underscores the notion that “digital SC ecosystems” (Dolgui, Ivanov, and Sokolov 2022) can improve viability if integrated well. Decision-makers should adopt a proactive stance, leveraging expert knowledge about failure modes, SC performance, and demand levels to anticipate the shuttling effect. As seen in ex-post validation, the concurrency of canal congestion and freight rate spikes can be catastrophic. This phenomenon suggests that transportation may again become a core competency of businesses (Capgemini 2023).

Distinguishing accessibility from availability further refines resilience: more loading/unloading points mean greater rerouting flexibility. According to Dolgui, Ivanov, and Sokolov (2022), failing a delivery (in terms of scope, time, cost, or quality) without justification degrades trust, threatening long-term supplier feasibility. Hence, reliability tools involving public infrastructure operators, advanced notifications, and integrated data platforms reinforce a synergy of multimodal carriers and contract frameworks. This synergy avoids relying on spot markets under duress and fosters stable transportation rates, especially for essential goods (i.e. energy and food).

Incorporating such layered approaches lets planners comprehend the infrastructure and SC interdependencies, ultimately improving public welfare. For instance, Rieken et al. (2015) advised against a generic reliability factor, partly because prior studies on rivers, such as Coffeng (2012), deemed lead times less critical for IWT. Such analysis, however, neglects the distinct characteristics of canal systems, particularly the role of locks as capacity-defining bottlenecks. Furthermore, lead time delays would increase costs possibly rippling through the SC downstream. In contrast, the delay accumulation remains in the system for an extended period due to capacity constraints—the shuttling effect. Consequently, the thesis model analysed the effect for locks and found that incorporating the parameter would, for example, increase the welfare utility of a second lock chamber by approximately one million EUR annually, as demonstrated in section 4.3.

Benefits for public decision-makers (operators and policy)

This model offers a direct methodological contribution to public infrastructure planning frameworks, such as the German Bundesverkehrswegeplan (BVWP). By moving beyond static cost-benefit analysis to integrate probabilistic reliability and queueing dynamics, the model becomes a tool to quantitatively challenge policy assumptions and refine investment decisions. For example, the model can demonstrate that the long-term welfare gains from a second lock chamber as a resilience investment may significantly outweigh the projected costs of several smaller, seemingly unrelated maintenance projects, a nuance potentially missed by current assessment methods. For another example, stakeholders can use the model to quantitatively compare the long-term welfare effects of competing policy choices: dismantling underused infrastructure versus expanding bottlenecked infrastructure. Also, recognising resilience from multiple transportation modes can strengthen a region's competitiveness and SC performance might steer more targeted financial investments and ensuring synergies across transportation corridors. Planning frameworks may mandate the inclusion of probabilistic availability analysis (as demonstrated in Section 3.3.1) for critical infrastructure components like locks, moving beyond static cost-benefit.

Public dialogues (e.g. BMDV 2025) could incorporate citizen/industry input on open-data methods (see Wehrle and Gast 2022). Recognising the public infrastructure operators as SCR enablers provides a foundation for pursuing shared objectives, such as coordinated maintenance scheduling and data sharing—at least increase trust (Gast et al. 2020; Leven and Kersten 2021).[53] Public stakeholders may enhance funding and data-sharing mandates for platforms like Euris and Elwis to improve the quality of real-time and predictive state information, which enhances private sector resilience. Furthermore, the model provides a framework for dynamic policy-making. Instead of static regulations, authorities could use real-time network state data (as modelled) to implement flexible policies, such as temporarily waiving certain restrictions or activating pre-approved overtime for lock operators during periods of high congestion, thereby proactively mitigating the shuttling effect before it escalates.

IWT planners and operators may utilise the model to identify infrastructure whose failure leads to non-linear cost increases (as shown in case 3) and prioritise these for resilience investments (e.g. planning a secondary lock chamber). Beyond regional infrastructure, relevant trading partners must also be considered (section 3.3). Weighing risks linked to degrading infrastructure or shifting competitiveness shapes public decisions. The model can handle multiple objectives, informing VSC and public investments with a sustainability outlook. For instance, IWT can support road cargo by absorbing empty containers, raising overall efficiency. A minimum service level (e.g. via a local carrier financed by public stakeholders) might secure critical capacity, stabilising the market from abrupt underloads (see Liu, Han, and Zhu 2022). In case of abrupt overload of nodes due to unavailability of alternatives, the

53 . . . — in case of German IWT; a novel Charta was implemented to address this (see GDWS 2023).

prioritisation of goods depending on their criticality in the industrial layer might reduce welfare loss.

5.4 Critical Appraisal and model validation

This section presents a comprehensive appraisal of the multi-layer, multi-state model, discussing its validation procedures, key assumptions, simplifications, and overall applicability. The section consolidates and structures the model's boundary adequacy, parametrisation steps, choice of methods, and limitations, thus clarifying its strengths, weaknesses, and paths for future research. The model underwent systematic tests regarding boundary conditions, parameter coherence, structure assessment, dimensional consistency, and cross-method comparisons.

5.4.1 Mixed-method approach with a case study

The model was validated through a four-dimensional process consistent with best practices in system modelling (see Sterman 2002): (i) Boundary adequacy was addressed through a systematic review of the literature and extensive expert consultations within the PREVIEW project to ensure all causally significant components of the waterway-dependent ecosystem were included. These insights (e.g. Gast, Gross, and Binsfeld 2022; see Binsfeld et al. 2024; Wehrle and Gast 2022) guided which infrastructure elements, TN links, and SCDM parameters would be included.[54] The multi-year data collection from 2012–2023 and expert validation from WSV/GDWS (PREVIEW 2019b, PREVIEW 2019a, Gast 2023) reinforce the model's real-world grounding.

For (ii) parameter reliability, the cost models and parameters that are crucial for evaluating SC performance were drawn from Rieken et al. (2015) and Binsfeld et al. (2024), ensuring a solid empirical foundation. Where necessary, further calibration employed industry data (Travis 2016) or expert judgments (Wehrle and Gast 2022), thus reflecting region-specific IWT characteristics. Assumptions made in the simulation studies in chapter 4 are outlined and reviewed in Gast 2024.

(iii) Validity of structural assessment was considered by utilising existing models from SC or SCRM in their dedicated layers to ensure the model's core mechanisms. The PREVIEW

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54 Furthermore, the results were presented at PhD workshops (especially at Kühne Logistics University) and conferences.

context examined the model's relational assumptions—for instance, how canal availability influences transportation mode choice. They confirmed that feedback relationships (e.g. liner schedules can get out of schedule due to queueing) were faithfully represented. Meanwhile, code-level checks and logging enforced (iv) dimensional consistency across multi-layer elements (see Gast 2024), ensuring units (tonnes, kilometres, EUR costs, and time) aligned within computations and the computation is documented.

A mixed-methods approach enhanced confidence in the thesis model reducing the risk of unacknowledged biases in the final outputs. On the qualitative side, semi-structured discussions with WdtK experts (see Gast et al. 2020) validated the reasonableness of system boundaries. On the quantitative side, Monte Carlo simulations examined how in the case of case 3 vessel numbers using the same infrastructure would affect transportation and SCR.

Usage of alternative methods

While various approaches exist for SCR modelling (Hosseini et al. 2019; Dolgui and Ivanov 2022), the thesis intentionally applied a reliability-theory-based framework combined with Markov chains for spanning the multi-state logic. The following alternatives were deemed less suitable:

- Though robust optimisation is advocated in some SCRM contexts (Dolgui and Ivanov 2021), it was not pursued here due to the comparatively known resilience mitigation strategies for waterway-dependent SCs. Only the infrastructure layer could be truly stochastic but based on identified states from historical data, so a multi-state Markov approach was sufficient. Adding high-complexity robust constraints could obscure managerial insights.
- Bayesian Networks (BNs) are strong in forward/backward propagation but disallow cycles (Hossain et al. 2019; Qazi et al. 2018). As the proposed model requires returning to initial states, BNs would not handle cyclical or time-variant transitions well (Hosseini, Ivanov, and Dolgui 2020; Garvey, Carnovale, and Yeniyurt 2015). Markov chains and queueing methods proved more apt for capturing repeated disruptions and partial repairs over time.
- While agent-based simulation or game theory can provide fine-grained interactions because the analytical solution is likely unfeasible but also unnecessary for a network of locks (Ji et al. 2022; Gong, Lai, and Wang 2008), the thesis focused on higher-level SC reliability for waterway infrastructures. Future expansions could incorporate agent-level strategies or facility-level competition, but the Markov-based reliability structure, TPP-based cost modelling, and queueing sub-model already handle critical capacity constraints. Adding an agent-based layer could reveal how numerous independent

carriers affect SCR—each with unique policies—amplifying or dampening the shuttling effect.

In sum, the chosen mixed-method approach (RT + TPP + QT + parametrisation with empirical data and expert assumptions) better fits the complexity of IWT disruptions than purely qualitative or purely robust-optimisation-based methods.

5.4.2 Limitations

Every model is a purposeful simplification of reality, respectively relaxation. The limitations outlined below represent deliberate scoping decisions made to maintain analytical tractability and focus sharply on the dissertation's core research questions. While reflecting standard practice in large-scale modelling (see Sargent 2020), they necessarily define the boundaries of the model's precision and may present pathways for future research.

Infrastructure layer

- Following Hossain et al. (2019) or Oztanriseven and Nachtmann (2020), the model omits port-equipment failures. This assumption suits the canal/lock scope but neglects onsite crane or handling downtime and thus the model likely underestimates reliability impacts.
- The model intentionally focuses on the multi-states of the IWT network and therefore always assumes alternative (road/rail) capacities are possible. Even though Unece (2023) data allows for railway cost/time parameters, the thesis highlights waterway infrastructure element availability as the prime disruption source.
- The NtS required parsing freeform text. Potential revision errors can distort real closure durations. The use of generative AI and future Euris (2023) expansions promise more accurate machine-readable states.
- A Weibull HRF is standard in reliability analysis (Ebeling 2017) with zero-inflation accounting for infrastructure elements with no recorded disruptions. Meanwhile, normal distribution assumptions are rejected (significance $p < 0.05$), see Table 3-1. Nevertheless, assuming such distributions omit complex infrastructure failure behaviours and might not be sufficient for a forecast.
- Some lock-level capacity data is absent. The historical state approach lumps “full closures” as identical to disruptions; partial closures or restricted operations remain underrepresented. This can moderate real impacts (Wang et al. 2022).
- Multiple versions and revisions of disruption data are often communicated, with errors possibly present in these datasets, making it challenging to draw accurate conclusions.

For instance, NtS before 2012 were initially communicated via radio[55] but only later entered the system, causing revisions. Furthermore, the analysis of failure modes should consider that not all closures are equal. The situations and restrictions can impact SC operations in non-quantifiable ways.

Transportation network layer

- The TPP computations rely on annual or monthly port statistics. Seasonal fluctuations or day-to-day spikes are smoothed out, potentially underestimating short-term congestion (c.f. Statistisches Bundesamt 2022).
- The model addresses lock-chamber queueing (section 4.3), leaving port-terminal queues or multi-terminal scheduling (refer to Cimpeanu, Devine, and O'Brien 2017) out of scope.
- Although the model includes IWT modal shifts, it treats truck capacity proportionally, ignoring real constraints on vehicle availability (PREVIEW 2019a). For short closures, many SCs prefer trucks, a preference that is captured in this model only as an aggregated cost differential.
- The model simplifies the heterogeneous waterway fleet into a more homogeneous vessel capacity for IWT, meaning the calculated congestion and rerouting costs may not capture the more extreme effects on specific vessel classes or added congestion by other waterway traffic.
- Depending on the vessel utilisation, multiple trucks and trains are required. While truck loads can be assigned proportionally, the model also just considers rail cargo proportionally – single wagon loads equivalent – as a simplification to prevent complexities. Because a full train comprises a variable number of rail cars, and liquid tank capacities are often crucially constrained (PREVIEW 2019b; 2019a).
- For simplification, the cost is determined as the essential factor in IWT, while the lead time is not as relevant, as the literature supports (e.g. Vermeiren and Macharis 2016). The quality of bulk goods is not an issue and will not result in a higher IWT risk. Moreover, all suppliers offering different product qualities use the same TN. Transportability risk factors favour IWT compared to road and rail, especially concerning hazardous goods (see Huang et al. 2021). Finally, tramp shipping or complete outsourcing to a third-party logistics, “3PL”, carrier can lead to market efficiency in transportation planning and procurement, reducing transportation costs of the SC but remaining at least as high as transportation costs in the TN; see equation

55 . . . — and postings at the black board of the local WSV stations across Germany.

(9). Arguably, this assumption is sound because IWT has a market premium of only 1–3% above total transportation costs (ViaDonau 2019), supporting a cost-based approximation in opposite to invoiced service costs for which data is not easily available.

Supply chain layer

- The thesis focuses on waterway disruptions as the main driver of SC risk. Detailed multi-echelon production/distribution is simplified to highlight IWT characteristics.
- Demand is allocated weekly (see Woxenius 2007), but sub-week closures are handled proportionally, ignoring "lumpy" actual orders. This could slightly underestimate the shock from sudden closure for extremely time-sensitive goods. Yet, half of all closures in the WdtK are less than one day (Gast et al. 2020), potentially overestimating the effect of brief closures on goods with less time-criticality.
- Penalty rates are broad approximations (Lukinskiy et al. 2023), ignoring intangible reputational costs or fixed overhead. SC decision-makers might refine them using real contract data.
- The model assumes rational economic decision-making, where SCDM acts to optimise a defined value function which not necessarily accounts for non-economic human factors such as organisational inertia, cognitive biases, or pre-existing commercial relationships that might prevent a firm from selecting the mathematically optimal resilience strategy. The model's output should therefore be interpreted as a normative benchmark for best-practice response, highlighting the potential value that can be unlocked by overcoming such organisational barriers.

Industry layer

- The approach suits typical IWT cargo (coal, chemicals), often inputs to manufacturing, not wholesale (see Schwemmer 2021). Potentially, the actual welfare loss is understated if downstream SCs produce high-value outputs.
- The model anchors on NRW's demand patterns and economic data. Transfer to other regions or SC contexts requires verifying local infrastructure states and industry linkages.
- A limitation of the current framework is the static link between the SC and industry layers. Future work could explore a dynamic integration where the specific shortage costs calculated in the SC layer for each period would serve as a direct input to modify the final demand vector in the I-O model, allowing for a more granular analysis of propagating welfare impacts.

Model limitations and remaining gaps

SCs are complex systems, making it challenging to consider control systems with a single model (Ivanov 2018). However, focusing on the TN and applying the layered model to describe the interrelationships significantly reduced complexity systematically. The proposed model incorporated dynamic modelling through simulation, capturing the time-dependent settings and situational behaviour changes inherent in SC disruptions. Multi-criteria decision-making methods were employed in this study with the SCDM optimisation model and the bi-objective TPP, considering all factors relevant for modal choice and shift in IWT elaborated by Meers and Macharis (2015). For simplification, the thesis' TPP omits unloading/loading costs because the BVWP also omits handling costs in the modal choice between the origin-destination (Rieken et al. 2015).

Simulation outputs heavily depend on accurate parameters (Sargent 2020). Minor input changes (e.g. on reliability or queue times) can yield large cost differentials. Repeated runs and stable calibrations (e.g. Rieken et al. 2015) help reduce random variance, but perfect forecasting remains elusive. Deep uncertainties, like sudden geopolitical shocks or severe climate events, can push the SC beyond known states, limiting the model's predictive capability (Hosseini, Ivanov, and Dolgui 2020). Coupling RT with the TPP enabled direct linking of network availability to transportation performance—and by extension, SCDM outcomes. Monte Carlo simulations confirmed that raising reliability (e.g. fewer closures) consistently improved SC performance. Moreover, safety-stock modelling and multi-supplier load-sharing informed which cargo volume shifts truly cut costs. The heuristic runtime of 90 seconds yields a solution within 10% of the optimum. This gap must be recognised alongside the model's simplifying assumptions outlined in Binsfeld et al. (2024). In the best case, the suboptimal heuristics result might provide better real-world estimates of a not-perfect transportation market.

The data sources are valid due to the effort required to collect and maintain them. Furthermore, public decision-making depends on them. However, the level of aggregation likely leads to inaccuracies at the granular level. Comparing Travis' (2016) and TPP's equilibrium monthly analyses helps determine the unload factor of each port for 2010. This comparison can be seen as a bottom-up versus top-down approach or, more specifically, as the source-sink versus relational approach. The difference between the Destatis and Travis data for the WdtK is less than 5%, meaning that the databases fit well, and the amount of goods transported within the WdtK is negligible as they are either exported, imported, or roughly 10% is just passing through to other IWT regions (Gast 2024, get_cfs_data). Furthermore, port data is only available annually even though the seasonality of goods exists, as the aggregated monthly statistics suggest (see Statistisches Bundesamt 2022, chap. 2 in contrast to 5). Hence, the model splits demand proportionally, assuming 50 weeks and five workdays (same as Pant, Barker, and Landers 2015).

Comparisons of monthly statistics (Travis 2016) helped identify the spectrum of goods moved via IWT, while the author's earlier publications tested key effects—availability assessment, notification time, queueing models, TPP, and FLP—flagged by the SLR. Because data and methods were interlinked, linking NST2007 goods to specific vehicles or industries proved challenging. For instance, the case study classified coal and petroleum as 'dry bulk', justified by the WdtK's pipeline transportation of crude oil/natural gas (Travis 2016; Statistisches Bundesamt 2023), implying vessels predominantly carry coal. Future work might leverage datasets like the CFS for finer-grained analysis.

Recent commodity flow data is missing,[56] Moreover, only a few other European countries publish the utilisation of lockage data.[57] However, the anonymised AIS data (Euris 2023) allows for a granular assessment of the traffic situation and allows assumptions about the cargo classifications, as Franzkeit, Pache, and Jahn (2020) suggested. While the model does not consider this data, it can potentially be used to parametrise and validate the case study further and is generally valuable for future research.

The industry I-O framework (Pant et al. 2015) provided a macroeconomic anchor, aligning well with standard IWT policy studies. Although some prior work treats port closures as a total loss of goods in transit, this thesis model demonstrated actionable resilience (e.g. alternate routes, shift strategies) to lessen acute impacts. As a result, the inoperability matrix can gauge shortage costs at an industrial scale, supporting more nuanced policy or business decisions. However, the data from 2010 might not necessarily reflect current industrial output in the Ruhr Valley.

While Wang et al. (2022) note how multi-state network disruptions often demand difficult-to-obtain failure probabilities, the WdtK case offered a unique dataset supporting multi-state decomposition. Theoretically, 60! multi-states could arise from combinatorial product expansions, but a scenario reduction ("min-span" approach) shrank the factorial permutations into only 105 network states drawn from historical full-closure data (March 2013–February 2023), omitting minor failure types beyond the thesis scope or unidentified situations.

56 . . . — Travis currently gets renewed for 2020 but is not available as of December 2023.

57 The US go one step beyond and further collect lockage data based on tonnage of goods classification, see https://www.swt.usace.army.mil/Missions/Navigation.aspx

Yet, a compelling visualisation of the multi-states is lacking, and further states could be identified.

5.4.3 Generalisation and transferability

The findings from the WdtK case study yield several generalisable principles, while the model's architecture ensures its methodological transferability.

Generalisable principles

This research demonstrates that the economic character of resilience is contingent on the underlying reliability of the infrastructure. In a robust system like the WdtK, where catastrophic failure is rare, resilience manifests primarily as a cost optimisation problem—mitigating disruptions that cause cost deviations rather than total collapse. In more fragile systems, the same model would frame resilience as a question of survival. This establishes a general principle: the strategic value of resilience investments (e.g. inventory vs. modal shift flexibility) is a direct function of the infrastructure's baseline failure probability.

Furthermore, this work proposes and formalises the ‘shuttling effect’ as a general phenomenon in any shared, capacitated logistics network. Unlike the linear ripple effect, which models the propagation of a singular failure, the shuttling effect describes the cyclical, systemic congestion that emerges from repeated, minor capacity reductions. This principle is generalisable to other shared infrastructures, such as seaport container yards, rail terminals, or cross-docking facilities, where multiple users compete for limited throughput capacity.

Methodological transferability

Beyond these principles, the model’s modular, multi-layer architecture facilitates its transferability to other contexts. Tang (2006) and Chopra (2019) described *adaptation* to uncertainty through knowledge about market conditions. The thesis model extends the SCDM scope with knowledge about shared-user infrastructure state and availability as relevant environmental parameters. Despite focusing on WdtK waterway-dependent SCs, the model’s layered architecture and modular design facilitate adaptation to other contexts:

- The framework is directly applicable to any canal or river system where infrastructure reliability data (e.g. collected from Euris 2023) and commodity flow data are available. For natural river systems, the framework remains highly relevant but might require adaptation. For instance, the Danube or Rhine could be modelled to assess the impact of water-level-related disruptions, incorporating specific parameters for queueing and scheduling.

- The failure mode analysis would allow the assessment of, e.g. the impact of climate change (see Scholten and Rothstein 2012) by appropriately linking failure modes to SCR and welfare if their impact on infrastructure availability is understood.
- The core logic of the model—linking probabilistic component states to network performance and economic value—can be abstracted to other transport modes. Although originally geared to waterway locks, the reliability/queueing insight can extend to bridge or railway reliability issues. For instance, for Germany, a data service similar to Elwis (2023) is available for rail networks (see DB Netz 2023). While network characteristics differ (e.g. the denser mesh of a road network may offer more rerouting options), the fundamental methodology for quantifying the economic impact of unavailability remains valid.
- At its most abstract, the model provides a template for linking any system of physical assets with probabilistic failure modes to the economic ecosystems interdependency. This approach could be adapted to analyse the resilience of energy grids to power plant outages or the stability of digital SCs subject to server or data link failures.

6 Main Findings and Outlook

This thesis presents a novel multi-layer, multi-state model to assess the resilience of waterway-dependent SCs facing infrastructure failures. Applied to the WdtK, the model highlights the critical role of infrastructure availability, warning time, and queueing dynamics in mitigating IWT disruptions. Notably, it introduces the shuttling effect to the literature, offering new insights into resilience strategies. The findings underscore the necessity for enhanced data integration, stronger stakeholder collaboration, multimodal transportation considerations, and capacities at shared-user infrastructure, paving the way for a more resilient and sustainable SC ecosystem.

6.1 Summary

This thesis was motivated by a fundamental disconnect in the literature: the link between probabilistic infrastructure failure and the viability of dependent SCs remained unquantified. To address this, a multi-layer, multi-state model was developed to trace the causal cascade from infrastructure state to SC performance and welfare. The SLR in chapter 2 summarised SCM frameworks and highlighted the importance of transportation as a crucial element of SCM and resilience. Moreover, it revealed that the link between SCR and transportation has been under-researched in the literature, prompting the need for a model to capture SCs' resilience capabilities and vulnerability to transportation (infrastructure) networks.

Chapter 3 introduced a multi-layer, multi-state model that systematically assesses vulnerabilities in waterway-dependent SCs. Integrating system dynamics, network analysis, and multi-state Markov models, the approach captures complex interactions and feedback loops, identifying critical weak points. The incorporation of SCDM feedback loops enables testing resilience improvements and mitigation strategies based on model parameters demonstrated in chapter 4 case analyses.

The infrastructure layer provided the model's foundation. The layer calculated historical infrastructure states using historical data for availability assessments and considered known failure modes. This layer allowed for a detailed understanding of a network's reliability, capacity constraints, and potential bottlenecks possibly affecting an SC's overall resilience. The transportation layer extended the model by incorporating a transportation flow graph with associated costs and constraints, statistical data on transportation volume per class of goods, and queueing behaviour at infrastructure elements and transhipment points (i.e. ports). In addition, the transportation layer utilised a TPP approach to determine a system equilibrium for optimising welfare by considering the effects of multiple transportation agents and their potential impact on SC performance.

The SC layer introduced a range of factors affecting the resilience of individual SCs, including transportation costs and inventory costs, the flexibility to adapt production, and vulnerability to infrastructure failures. Moreover, the industry layer connected the model to the broader context, considering the interactions between SC ecosystems, TN infrastructure operators, and public stakeholders utilising I-O matrices that considered regional interconnectedness. This layer highlighted the role of regulatory frameworks in facilitating efficient markets, the importance of critical industries, and the potential consequences of infrastructure failures on public welfare. The case analyses also emphasised the role of public and private infrastructure operators in maintaining and investing in SCR and infrastructure.

The optimisation problem sought to maximise the total value generated by an SC ecosystem while considering various constraints. Hence, the model implemented a mixed-integer linear programming problem for multimodal vehicle routing adaption and SC resilience strategies under disruption. Simulation techniques elaborated on queueing effects. Throughout the research process, the model was validated and discussed in a chosen case study of the WdtK due to its economic significance and relevance regarding infrastructure failures from ageing components, which challenged the SCDM of industries in the Ruhr Valley.

6.2 Main findings

Modelling the resilience of waterway-dependent SCs emphasised three novel insights: (i) the link between infrastructure availability and SC performance and welfare, (ii) warning time as an enabler of resilience strategies, and (iii) disruptions due to queueing behaviour, the ‘shuttling effect’. The study proposed and investigated the new concept of the shuttling effect, which emerged from the relationship between known and unknown uncertainties within a resilience context. The application of QT was instrumental in understanding this effect, revealing the benefits of managing non-empty queues and busy-period transitions. Furthermore, incorporating notification or warning time as a new phase of resilience capacities provides newly available resilience strategies.

The case study on the WdtK, involving public and industrial stakeholders, demonstrates the significance of the transportation layer in strengthening the resilience of geographically constrained waterway-dependent SCs. The thesis *elucidates* how SCDM can proactively manage disruptions, sustain operations, and minimise cascading failures by leveraging the TN. These core findings translate into several actionable insights for both policymakers and industry stakeholders. At the same time, the provided code (Gast 2024) can streamline its adoption, replicating the main insights in the following.

Insights for businesses

- *Leveraging data services for early warning systems*. By utilising infrastructure data such as Euris and Elwis combined with proprietary data (e.g. inventory, demand, and transportation capacity), businesses can establish early warning systems to anticipate disruptions and help implement resilience strategies. Furthermore, creating more transparency in the transportation market can lead to more proactive SCM.
- *Considering infrastructure states to anticipate impact and adapt performance*. Understanding the complex adaptive nature of critical infrastructure and applying the layered approach can help businesses identify relevant relationships and dependencies within their SCs. This knowledge supports determining failure modes and developing tailored resilience strategies to adapt to the future TN states and potential disruptions.
- *Consideration of shared-user infrastructure and multimodal transportation frameworks*. Knowing the impact of congestion at shared-user infrastructure next to exploring multimodal transportation options can provide businesses with more flexibility during disruptions, allowing them to adapt operations. By becoming familiar with various transportation alternatives, SCDM can secure capacity and maintain service level agreements, ultimately improving overall SCR.

Insights for policymakers

- *Enhancing data platforms and public consultation*. Policymakers should encourage the usage and development of data platforms such as Euris and Elwis to provide valuable insights for stakeholders involved in SCM. By promoting public consultation, policymakers can foster a more collaborative environment for discussing improvements and adjustments to the existing systems, infrastructure, and regulatory frameworks.
- *Facilitating collaboration between infrastructure operators and stakeholders*. Recognising the role of infrastructure operators in SCR can promote trust and better coordination between the IWT stakeholders. A cooperative approach can ensure that essential goods and services are prioritised during disruptions, mitigating potential negative impacts on other critical industries.
- *Extending infrastructure planning frameworks to account for reliability in waterway transportation*. Integrating the proposed model into the methodology provides a more comprehensive understanding of the interplay between SCR and waterway infrastructure, which can lead to the development of a more resilient, welfare-oriented TN in the long term.

6.3 Future research and outlook

Building and enhancing resilience is a critical future issue for SCs. The findings from the WdtK case study have several implications for policymakers and practitioners (section 5.3), including integrating various TNs like rail and road. For example, this research contributes to the public debate by analysing shared-user infrastructure and its impact on individual SCDM (section 4.3). Because cost-benefit analyses in infrastructure planning already value time savings and reliability, the multi-state model offers a direct methodological extension to these frameworks by quantifying how a second lock chamber or proactive maintenance scheduling boosts welfare, enabling a robust quantification of the welfare created by investments in infrastructure availability and resilience. While the model and effects address multiple research gaps (section 5.2.1), there remains room for further exploration. Future research should build on this work along three pathways.

Methodological and data framework enhancement

Future work can enhance the model's temporal dynamics and stochastic features. A stress test exploring multi-week closures on the WdtK would serve to benchmark resilience strategies in extreme scenarios. This requires integrating additional data sources, such as rail delay data, and leveraging tools like generative AI to interpret unstructured infrastructure data. To tackle missing commodity flow and handling data in some regions, which is a known barrier to application (Al Enezy et al. 2017), expanding data platforms like Euris (2023) is vital.

Theorising and validating the 'shuttling effect'

A second research stream can explore the relevance of the shuttling effect in SCR. Building on the queueing insights from events like the Suez Canal blockage (Gast et al. 2021), researchers should gather evidence from other systems, such as congested ports or rail terminals. Future research must refine the conceptualisation of queueing within SCR and examine its link to the supply-side bullwhip effect, where goods stuck in transit induce compensatory procurement, particularly in identifying cascading network effects caused by underload or overload (see Liu, Han, and Zhu 2022). A rigorous theoretical and empirical review (e.g. by adapting this model to other case studies) is required to test the concept's robustness.

Extending the application domain

The model's framework can be extended to new domains to test its generalisability.

- The (re)configuration of SCs with SCDM shares methods with TN resilience (see Esmizadeh and Mellat Parast 2021), yet the literature has not thoroughly examined TNs in the SCR context (see Gast, Kirkach, and Ivanov 2022). The model's layered approach can be applied to other networks, like rail, using available data services (see DB Netz 2023) to determine their effect on the resilience of dependent SCs and enhance the realism of SCR models (e.g. see Kim, Chen, and Linderman 2015).

- TNs are highly relevant in humanitarian relief logistics (see Thompson and Anderson 2021). The model's emphasis on warning time and infrastructure states provides a basis for transferring these considerations to disaster relief settings. While not a primary focus, the RT methods applied herein could also be useful for safety engineering analysis, such as accident analysis related to water levels.

- While the SCDM model does not strictly require them, regional input-output matrices are beneficial for determining the effects for public stakeholders when extending the model to other regions. This would allow for a more precise quantification of the impact of infrastructure states in different IWT trading regions, requiring enhanced commodity flow and multi-regional I-O data.

Feedback and comments on this dissertation model are highly welcome to incite a discussion.

Closing remark

In synthesis, this dissertation demonstrates that the resilience of waterway-dependent SCs is an emergent property of a complex, multi-layer system. By integrating probabilistic infrastructure states with SCDM, the model proves that resilience can be quantified. This quantification reveals the tangible welfare benefits of public investment (e.g. a second lock chamber), the economic value of foresight (warning time), and the systemic risk posed by phenomena such as the 'shuttling effect'. Ultimately, the research establishes that effective SCR benefits from a unified view, where public infrastructure management and private SC strategy are not separate domains but intertwined components of a viable ecosystem.

In conclusion, this thesis contributes to the academic literature on SCR by offering a comprehensive and robust model for capturing the complex dynamics of infrastructure, TNs, and SCDM. The insights gained from the case study provided a solid foundation for future research, particularly in the field of IWT, where a further investigation into the interplay between public authorities, business relations, and intermodal SCs is possible. This work provides a robust framework for developing more viable—resilient, and sustainable—SC ecosystems in the 'new never normal'.

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